The Dynamic Efficiency of Policy Uncertainty: Evidence from Wind Industry*

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April 15, 2023

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Abstract

This paper investigates the dynamic efficiency of policy uncertainty in the US wind energy industry. Policy deadlines embedded in the Production Tax Credit induced uncertainty among wind farm investors and expedited investment. I compile a comprehensive data set of the investment, production, and long-term contracts on the US wind energy market. I find a significant bunching in the number of new wind farms at the expiration dates of the short policy windows and a large mismatch between the timings of investment and technological advancement. I then develop an empirical model featuring the bilateral bargaining of long-term contracts and the dynamic wind farm investment under policy uncertainty. Model estimates reveal that a lapse in policy extension reduced the perceived likelihood of policy renewal to 40%, and counterfactual simulations demonstrate that removing policy uncertainty reduces the number of new wind farms in 2008-2011 by 52.7% and increases the number of new wind farms in 2012-2017 by 55.3%. Overall, the net benefits of wind energy increase by around 20% once policy uncertainty is removed.

Keywords: Wind energy; policy uncertainty; dynamic model

*This draft is preliminary and comments are welcome.

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1 Introduction

Industrial policies have been widely adopted to boost infant industries. However, given limited government resources, political cycles, or uncertainty, many industrial policies start off by committing to a short period with a deadline and might get renewed later. This common implementation pattern of "enactment – expiration – renewal" segments the policy into short time windows, induces policy uncertainty at the expiration time, and steers investors to near-term incentives who should otherwise plan for longer.

This paper explores the dynamic efficiency of policy uncertainty, using the US wind energy industry as the empirical setting. Wind energy grew from a marginal share in 2000 to the biggest renewable energy source in 2019. This industry is featured by a huge irreversible investment cost, and the boom of wind energy has been heavily supported by federal tax incentives, known as the Production Tax Credit (PTC) in a form similar to long-term output subsidies. The PTC has been active since 1992, but when implemented, it was segmented into a series of shorter policy windows with deadlines. A lack of government commitment combined with occasional lapses between expiration and renewal caused policy uncertainty among wind farm investors about the future extension.[1] Under policy uncertainty, investors expedited their investment and bunched investment timing near the deadlines. Consequently, it leads to two opposing forces shaping social welfare. On the one hand, the expedited investment reaps environmental benefits earlier. On the other hand, the bunching of investment at the deadlines creates a mismatch with continuously improving upstream turbine technology. The overall welfare effect is ex-ante ambiguous.

I compile a comprehensive data set of the investment, production, and long-term contracts on the US wind energy market and document two key data patterns. First, I find significant bunching of the investment timing for wind farms at the expiration dates of the short policy windows, especially in 2012, mainly due to a lapse between expiration and renewal. Second, while the investment was bunched at deadlines in earlier years, the upstream wind turbine technology is quickly improving and becoming cheaper. It creates a large mismatch between the timings of investment and technological advancement.

Motivated by the stylized facts and institutional details, I next develop a structural model of the wind energy market in the US. The structural model consists of a dynamic part and a static part. In the dynamic part, the wind farm investors form beliefs about the probability of the future renewal of PTC. Given the turbine technology and turbine procurement cost exogenously evolving, those investors decide whether to invest in the current period or wait until the next period. If they decide to invest in this period, there are two channels to sell wind capacity, and the discounted sum of flow profits from selling capacity is determined in the static part of the model. First, most wind farms

[1] "Wind farm" and "wind project" are used interchangeably.

negotiate with utilities over a long-term power purchase agreement (PPA), in which they jointly determine power purchase prices and procured capacity simultaneously. If the negotiation fails, wind farms would earn an expected payoff from selling capacity to alternative utilities. Second, some wind farms could also sell their capacity to other non-utility buyers such as corporations or sign financial contracts.

For the first channel, I model the profit function for both utilities and wind farms. Utilities obtain profits with procured wind energy from both selling electricity and obtaining renewable credits, while the profits for wind farms are the revenues generated from PPA net total turbine cost. The optimal procured wind capacity maximizes the joint profit, while the negotiated price maximizes the Nash product of the surplus for the two parties. The optimal produced capacity, conditional on a rich set of controls for utilities' willingness-to-pay and other demand shifters, identifies the turbine cost function. Moreover, the relative path-through ratio of utilities' willingness-to-pay as well as wind farms' turbine cost to the negotiated PPA price, identifies the bargaining weight. For the second channel, I model a linear demand curve, combining information for both the corporate buyers and merchant/hedge contracts. I instrument the wind energy price with supply-side shifters as well as state policies.

For the dynamic part of the model, the key empirical challenge is how to separately identify the distribution parameters of entry cost and the policy belief parameters. My identification argument hinges on the temporal structure of the policy. There are years when there is no policy uncertainty, which helps identify parameters of entry cost distribution given the perceived likelihood of policy renewal to be one for the next year. Moreover, any deviation in those deadline years from the "smooth" trend of investment predicted by the model would be rationalized with the belief parameters. The key identification assumption for the policy belief is that conditional on observables, the residual entry cost distribution moves smoothly in the deadline years of the policy windows.

I first estimate the static part of the model. For the bilateral bargaining model, both turbine productivity and willingness to pay for utilities are important shifters for the optimal capacity equation and negotiated price functions. I directly construct indexes for turbine productivity and willingness to pay for utilities from the data. Turbine productivity is measured by the annualized capacity factor.[2] The willingness to pay for utilities includes both the effective market price of wind energy (compounding the electricity price and the renewable credit price), as well as the energy composition of the utility. I estimate the optimal capacity equation and the optimal negotiated price equation simultaneously via non-linear least square estimators. I find that utilities have a larger bargaining power than wind farms and the total turbine cost is convex in the capacity. If I remove PTC from

[2]Capacity factor is defined as "the ratio of the electrical energy produced by a generating unit for the period of time considered to the electrical energy that could have been produced at the continuous full-power operation during the same period." The definition is a direct quote from the EIA website.

the market, around 30% wind farms will fail or earn a negative profit, which further corroborates the importance of this federal incentive in supporting the industry. I estimate the demand curve for non-utility buyers using supply-side shifters and state-level policies as instruments. The demand elasticity at the median price and capacity is around -1.4.

I next estimate the dynamic part of the model in two steps. To tackle the aforementioned identification challenge as well as the non-stationarity issue introduced by the policy uncertainty, I first focus on a policy window when the policy was announced to cover a relatively long period. I assume the problem to be stationary for the policy window. I follow Arcidiacono and Miller (2011) and apply the discrete Euler methods to estimate the parameters of the entry cost distribution. I take advantage of the fact that the investment decision in my model is terminal and thus yields the "finite dependence" property to the Bellman equation. I use the estimated cost parameters to solve the stationary dynamic programming problem and simulate the firm value functions when the PTC is *certain* to be renewed and when the PTC is *certain* to be terminated. I then focus on policy windows when there was policy uncertainty. I match the predicted entry probability with the observed entry rate in the data and the policy belief parameters are estimated as the relative weights on the firm value functions when the PTC is *certain* to be renewed.

I estimate the mean entry cost conditional on entry is around 16.9 million dollars. Moreover, I find higher land price exacerbates the entry cost for new wind farms. More importantly, there was enormous uncertainty with respect to the policy renewal in deadline years, especially for the 2009 and 2012 deadlines. The average perceived probability of policy renewal is around 0.4 for the 2012 deadline, which largely explains the rushed entry at the end of that year.

In the counterfactual analysis, I quantify the consequences of policy uncertainty. I recompute the optimal investment decision with all policy belief parameters set to one; thus completely removing the policy uncertainty induced by the policy deadlines. Given more stable and longer-term incentives provided by PTC, there is a much smoother investment flow with wind projects entering the market later than observed. Removing policy uncertainty reduces the number of new wind farms in 2008-2011 by 52.7% and increases the number of new wind farms in 2012-2017 by 55.3%. The total number of new wind farms is decreased by around 5% as wind farms delay their entry further beyond without policy deadlines. However, the total capacity increases by around 3%. Despite the fewer wind farms, the total capacity increases because the average size of delayed wind farms is bigger since turbine productivity is higher. Moreover, the total electricity output, a discounted sum for a 20-year operation, increases by an even larger margin, due to a better match between technology and investment timing. I evaluate the benefits of wind energy following Callaway et al. (2018) and estimate the average marginal operating emissions rate (MOER) of coal- or gas-fueled power plants in each state and year. Overall, removing policy uncertainty increase the total benefits of wind energy by 5.7%, indicating that the efficiency gain from a better match between technology and investment dominates the benefit loss from the delayed entry. Moreover, as delayed investment takes advantage of cheaper technology, the total turbine costs are also lower by 5%. The net benefits of wind energy increase by 4.1 billion dollars without policy uncertainty, a 21.2% increase from the baseline number. The net benefits increase for wind energy in all markets, and the increase is the largest for MISO. In future versions of the paper, I plan to further explore the interaction of temporal policy segmentation with local policies and investigate the optimal trajectory of subsidy levels.

This paper contributes to the following three strands of literature. First, this paper directly speaks to the literature about industrial policies in the energy sector. Specific to the power and clean energy industry, there are recent papers about the timing of subsidies (Langer and Lemoine, 2018; Armitage, 2021), policy uncertainty (Dorsey, 2019; Johnston and Yang, 2019; Gowrisankaran et al., 2022; Johnston and Parker, 2022), and commitment in the climate policy (Hsiao, 2021). Different from the previous papers, I focus on the dynamic efficiency implications of policy uncertainty. My paper highlights the (in-)efficiency of the matching between technology and investment induced by the discontinuity of policy incentives.

Second, this paper relates to the literature on the renewable energy market. Recent work has covered a wide range of topics, including the intermittency (Gowrisankaran et al., 2016), the spatial misallocation (Callaway et al., 2018; Sexton et al., 2021), the value of wind energy (Cullen, 2013; Novan, 2015), the upstream innovation (Covert and Sweeney, 2022; Gerarden, 2023), the storage technology (Butters et al., 2021), the transmission congestion (Fell et al., 2021), carbon taxes (Elliott, 2022), contract risks (Ryan, 2021), and different tools of subsidies (Johnston, 2019; Aldy et al., 2021). I use the US wind market as a policy laboratory to investigate the consequences of policy uncertainty. Moreover, my paper provided a new empirical structural model for the wind energy market in the US.

Third, this paper also contributes to the literature on the dynamic model and firm beliefs (Doraszelski et al., 2018; Jeon, 2018; Gowrisankaran et al., 2022). I follow the structural approach to estimate the investors' belief under policy uncertainty in the industrial dynamic model, but with a different identification strategy from Gowrisankaran et al. (2022). Gowrisankaran et al. (2022) relies on the heterogeneity in the state regulation, while my paper utilizes different policy windows.

The rest of this paper is organized as follows: Section 2 provides policy background information on wind industry and government policies in the US. Section 3 summarizes the data as well as the key empirical patterns. Section 4 presents the empirical model, and Section 5 discusses the identification argument and the estimation procedures. Section 6 provides model estimates and Section 7 presents counterfactual results. Section 8 concludes.

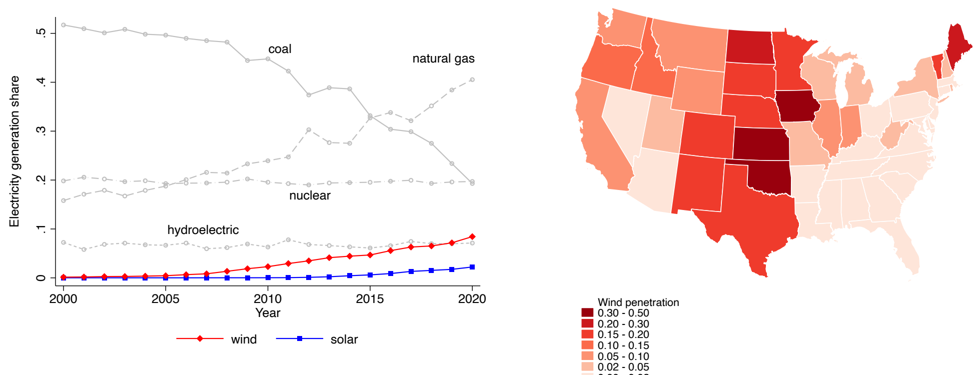
2 Wind Industry and Government Policies in the US

2.1 Wind Industry in the US

Wind energy has become America's biggest renewable energy source. It provided 8.3% of the total electricity generation and 42% of new power plant installation in 2020 (Wiser and Bolinger, 2021). As shown in Figure 1, wind energy grew from a very marginal share in 2000 to the fourth most important energy source in the US in 2020. The booming renewable energy, together with the fast-growing gas-fired power, gradually takes up the market share of coal-fired power plants. Geographically, wind energy concentrates in Texas, Midwest, and the Plains. Texas enjoyed the largest wind generation, taking up around 28% of the total wind power generation of the entire nation in 2019. Meanwhile, Iowa and Kansas have the highest wind energy penetration rates of more than 40% in their state-level total electricity generation.

Figure 1: Share and Penetration Rate of Wind Energy

(a) Wind Share **(b)** Wind Penetration



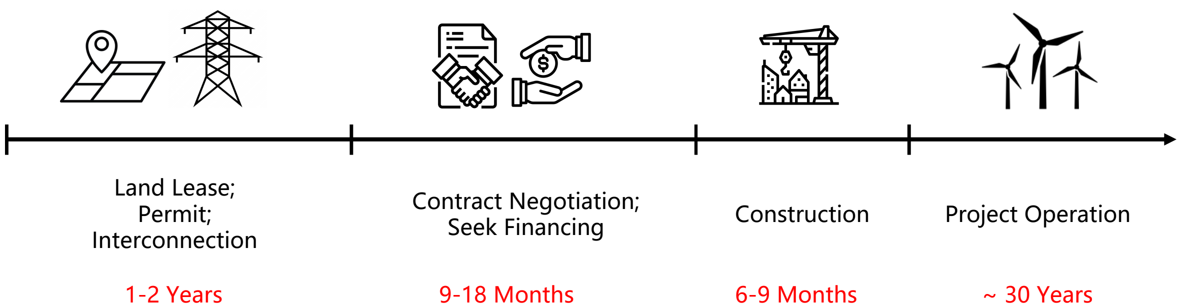
Notes: This figure shows the electricity generation share and penetration rate of wind energy. Panel (a) presents the share of electricity generation in 2000-2020 by different energy sources based on data from EIA-906, EIA-920, and EIA-923. The red line denotes the time trend of the share of electricity generation from wind farms, while the blue line denotes the time trend of the share of electricity generation using solar thermal and photovoltaics. Panel (b) presents the wind penetration rate in 2019 for each contiguous state.

A wind farm requires enormous investment upfront. Investors had to spend more than 100 million dollars to construct an average-sized wind farm in 2019 just for the turbine procurement, leaving alone the transportation cost of wind turbines, the construction cost of the wind farm, the land lease cost, and the expenditures to obtain permits and access to the power grid.[3] It also takes a long time to plan and construct a wind farm as summarized in Figure 2. First, investors need to

[3] In 2019, an average wind farm had 65 turbines with an average turbine nameplate capacity of 2,550 kW. The market price of wind turbines is $700/kW, and thus the turbine cost alone would be $116 million.

sign up for a land lease, acquire government permits, and apply for the interconnection agreement after lengthy waiting in the interconnection queue. Next, investors negotiate with the upstream wind turbine manufacturers for equipment procurement, negotiate with utilities or corporations for power offtake, and seek financing for the projects. Finally, with contracts secured, investors could start the construction process. The typical wind development process takes a total of 3-4 years, and the construction process alone takes around 6-9 months. Once the wind farm starts operation, it could be in service for around 30 years. Large sunk costs, together with a long time to build, indicate the importance of dynamic incentives in wind investment.

Figure 2: Timeline of Building a Wind Farm



Notes: The main source of the time statistics is the Wind Powers America Annual Report 2019 by AWEA.

There are two types of investors on the market, independent power producers (henceforth, IPPs), and utilities, and they together own over 99% of wind energy. The wind farms owned by the IPPs take up around 80% of the total capacity. They typically sign a long-term wind procurement contract with utilities or non-utilities (for example, corporations). These contracts are known as the power purchase agreement (henceforth, PPA). Negotiating and signing a PPA is critical for project financing as it secures a long-term revenue stream. A typical PPA includes the price term, the procured capacity, and the time length of the agreement, among other details. Moreover, wind energy owned by IPPs could also sign merchant or hedge contracts.[4] As shown in Figure A.1, utility PPAs are the most common offtake type, while more non-utility PPAs emerged in the market after 2015.

Wind capacity directly owned by utilities is around 20% of the total capacity, and they will supply electricity to the wholesale market (in restructured states) or the consumers (in regulated states). This paper focuses mainly on wind farms invested by IPPs due to their dominant market shares. As utilities could either own wind farms or procure wind energy from IPPs, endogenizing

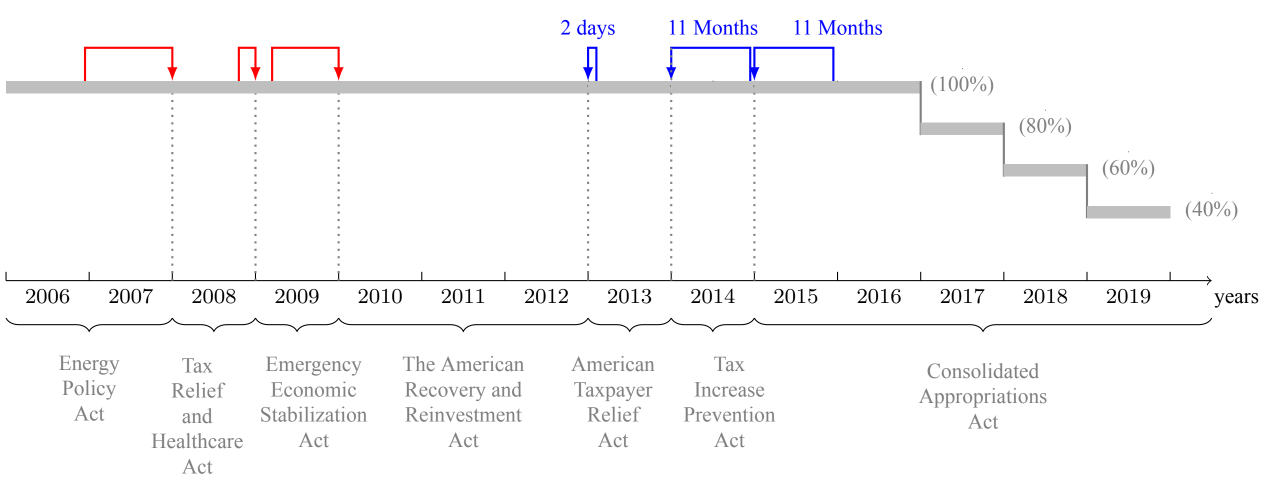
[4]One of the most common forms of merchant/hedge contracts in ERCOT is a physical fixed-volume hedge. Under this contract, the wind project owner sells its actual energy generated at the floating price at the node, and the hedging counter-party pays the wind project owner for the fixed signed energy amount at the price difference between the pre-negotiated fixed price and the floating price at the node (Bartlett, 2019).

wind capacity under direct utility ownership requires a model of make-or-buy choices of utilities, which is beyond the scope of this paper.

2.2 Government Policies

The wind power industry in the US crucially relies on the tax credit from the federal government, upon numerous state-level policies. The most influential and long-standing tax credit is the production tax credit (PTC), which was initially established in 1992. It provided qualified wind farms with a 10-year inflation-adjusted tax credit for wind power generation and stood at $24/MWh in 2018. Although PTC has been in effect for most of the time since 1992, the incentives provided by PTC were segmented into smaller policy windows, with an explicit deadline at the end of each time window. The essential condition to quality for PTC is tied to these deadlines: a wind farm was required to start operation before the deadline prior to 2012, while after 2013, a wind farm was required to start a significant portion of construction (15%) before the deadline. As shown in Figure 3, the PTC is enforced by different acts during different sample periods. For example, from February 2009 to December 2012, the PTC was enacted in the American Recovery and Reinvestment Act. Subsequently, the PTC was enacted in the American Taxpayer Relief Act (2013), the Tax Increase Prevention Act (2014), and the Consolidated Appropriations Act (after 2015).

Figure 3: Timeline of Production Tax Credit



Notes: This figure shows the timing of the production tax credit. The starting points of blue/red arrows indicate the announcement time of the renewal for the next act, while the endpoints are the start time of the new act. There were 2-day, 11-month, and 11-month lapses between the expiration of the previous act and the announcement of the next act at the end of 2012, 2013, and 2014, respectively, though the policy was retroactive.

Since 2005, there have been seven different acts enacting PTC sequentially, which segments the policy into windows of 1-5 years. Before 2009, the renewal of PTC in the next act was announced several months before its expiration. However, at the end of 2012, 2013, and 2014, the renewal of PTC was announced after the deadline passed. Although the lapse between policy expiration and renewal could be as short as two days at the beginning of 2013, it still disturbed the market incentives and creates policy discontinuities. With a lack of government commitment, wind investors were faced with policy uncertainty before the deadlines about whether the PTC would be extended or not. I quoted the following paragraph from the 2011 Wind Technologies Market Report (Wiser and Bolinger, 2012), which was published in August 2012 by the Department of Energy. It suggested that investors were uncertain about the renewal of the PTC, and tended to rush into the market in order to qualify for the tax credit.

Key factors driving growth in 2011 included continued state and federal incentives for wind energy, recent improvements in the cost and performance of wind power technology, and the need to meet an end-of-year construction start deadline in order to qualify for the Section 1603 Treasury grant program...At the same time, the currently-slated expiration of key federal tax incentives for wind energy at the end of 2012 – in concert with continued low natural gas prices and modest electricity demand growth – threatens to dramatically slow new builds in 2013.

The concerns about the expired PTC were ex-post proven to be unnecessary, as only 2 days after the expiration of the PTC, it was extended again in the American Taxpayer Relief Act. Similar things happened again in 2014 and 2015, although the lapses were much longer, and wind farms that started construction during those lapses were always granted PTC as long as they made enough progress before deadlines. From 2015 on, the incentives provided by the PTC gradually stabilized despite the decreasing magnitude of the tax credit.

Along with the production tax credit, there was also the Section 1603 grant, which provided an upfront investment subsidy equal to 30 percent of the investment costs. Between 2009-2012, investors could opt in for either PTC or Section 1603 grant. Unlikely PTC, the Section 1603 grant was announced to expire for sure after 2012. Johnston (2019) and Aldy et al. (2021) study the selection and efficiency consequences of having both production tax credits and investment subsidies on the market. Since there were many wind farms under either subsidy, I assume that these two policies provided similar incentives to new wind farms on average and study the uncertainty and discontinuity under this federal policy bundle.

Apart from federal policies, there are also various state-level policies. One important state-level policy is the Renewable Portfolio Standards (henceforth, RPS). RPS stipulates the minimum share of electricity generation using qualified renewable energy for utilities. If utilities fail to satisfy the requirement, they have to buy renewable credit from the credit market. Otherwise, they can also sell credits for profits. RPS provides important incentives to utilities to procure wind energy.

Abito et al. (2022) studies the consequences of cross-state trading restrictions and state-specific interim annual targets under RPS. States could also have corporate/sales tax incentives, property tax incentives, feed-in tariffs, bond/loan programs, and other industry recruitment policies for wind farms. As shown in Appendix Figure A.2, states with RPS are also more likely to have different kinds of state incentives for wind energy.

This paper focuses on the expiration and renewal patterns of federal incentives and studies the dynamic consequences of policy uncertainty introduced by temporal policy segmentation. Policy uncertainty disrupts the dynamic decision of wind investors, especially given that wind energy requires large irreversible investment costs, a long time to build, and is highly reliant on the support of federal subsidies.

3 Data and Stylized Facts

3.1 Data

I compile several different data sets in the US wind industry. The first two data sets come from the United States Wind Turbine Database (USWTDB) maintained by USGS and the EIA-860 maintained by the Department of Energy's Energy Information Administration, respectively. These two data sets provide universal information on the investment and the characteristics of utility-scale wind farms that were online between 2003 and 2019. USWTDB has more comprehensive coverage and is more accurate in terms of detailed wind turbine characteristics, while EIA-860 also includes information about the owners and interconnections for wind farms as well as rich information for other energy sources. Moreover, I supplement these two data sets with EIA Form-923, which covers the monthly electricity generation and enables me to measure the production efficiency of wind projects.

One key piece of information missing from USWTDB and EIA-860 is the time of investment for wind farms. Both USWTDB and EIA-860 record the month when a wind farm starts to supply electricity, however, as illustrated in Figure 2, there is a lag between finalizing the investment decision and starting operation, including a construction period of 6-9 months. I follow Johnston and Yang (2019) to use the information from the Federal Aviation Administration (FAA) Obstruction Evaluation/Airport Airspace Analysis (OE/AAA) database. The FAA data reports the scheduled dates of starting construction. I match the FAA data with EIA-860 and measure the time of investment as the time when a wind farm starts construction.[5]

[5]FAA data started from 2008 and many projects didn't report the scheduled time to begin construction. Overall, for wind farms online between 2003-2018 from EIA-860, around 42% can be matched with the FAA data. For the rest of the sample, I calculate the average length construction period by the online year and impute the scheduled time to begin construction by subtracting the construction period from its online time.

The second data set is the detailed power purchase agreement (PPA) data from the American Clean Power Association (formerly AWEA), including the offtake amount, capacity suppliers, capacity purchasers, PPA rates, and term length. The data is at the contract-offtaker level and covers the universe of wind capacity as compared with EIA Form-860 data (shown in Panel (a) of Appendix Figure A.3). The modal contract length of PPAs is 20 years as shown in Panel (d) of Appendix Figure A.3. There were around 60% of PPAs with term lengths between 18 years and 22 years. Moreover, around 40% of the utilities signed one contract, and 22% signed two contracts. Meanwhile, 88% of wind farms signed contracts with one utility. Therefore, multiple wind farms match with one utility in general, as shown in Appendix Figure A.4. For more detailed data processing, please refer to Appendix Section A.

Apart from these main data sets, I connected the interconnection queue data from the websites of ISOs/RTOs. I use the renewable credit data from a financial service platform Marex, and I construct the renewable credit prices following Aldy et al. (2021). I use retail electricity price data from EIA-861, agricultural land price data from USDA National Agricultural Statistics Service, the average labor cost for wind turbine technicians from IPUMS, the average wind speed for each wind farm location from the National Renewable Energy Laboratory (NREL), and the annual turbine procurement price from Lawrence Berkeley National Laboratory. I hand-collected the state-level policies including RPS from DSIRE.

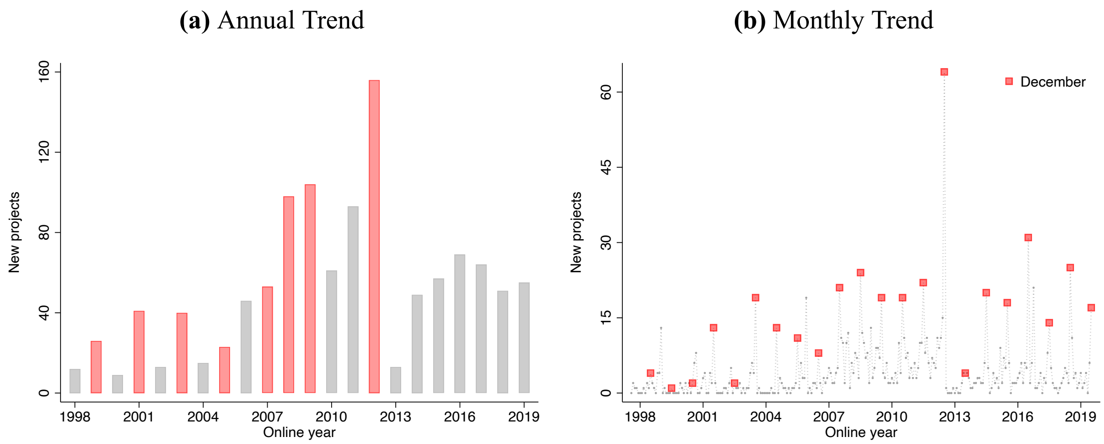
3.2 Stylized Facts

3.2.1 The Timing of Investment

I first investigate the time trend of wind farm investment. Figure 4 presents the annual and monthly numbers of wind farms that are newly online. We observe a clear bunching whenever there was a policy deadline. A mass of wind farms started operation between 2008 and 2012, especially in 2012. There were 174 new wind projects in 2012 with a total capacity of around 13,400 MW, which exceeds the sum of investment in 2001-2006. Following the huge spike in 2012, there was a significant dip in new investment in 2013. It was only after 2015 that the annual level of investment got recovered, and the time trend stayed stable afterward.

This time pattern aligns well with the timing of policy implementation as well as the required time to build in the wind industry. As shown in Figure 3, the Emergency Economic Stabilization Act and the American Recovery and Reinvestment Act were enacted in October 2008 and February 2009 respectively. During the time window between 2009 and 2012, in addition to the production tax credit, there was also the Section 1603 grant, which lent extra flexibility of funding to investors and partly explained the surge of wind projects during this time period. By the end of 2012, it was clear that the Section 1603 grant would be discontinued, but there was enormous uncertainty about

Figure 4: Time Trend for Wind Projects Newly Online



Notes: This figure shows the annual and monthly time trends of the number of wind projects that are newly online. We construct the annual and monthly time trends based on the data from EIA-860. The red bars in Panel (a) represent the deadlines of policy windows, while the red square in Panel (b) represents the new projects that are online in December.

whether PTC would be extended or not due to the time lapse in renewal. Consequently, there was a rushed inflow of new wind projects before the deadline to qualify for the subsidies, as we observe the bunching in the online time in 2012. This distortion owing to the subsidy expiration is more obvious when we examine the monthly trend of new wind projects. As shown in Panel (b) of Figure 4, the bunching in 2012 was mainly driven by a massive entry in the December of 2012, which was ten times as large as the average monthly investment from January 2001 to November 2012.[6]

Although the PTC was renewed shortly after its expiration in 2013, the volume of investment didn't bounce back immediately. The main reason is that it takes a relatively long time to build new wind farms. After 2015, the PTC was planned for relatively long terms and the incentives provided by PTC were also stabilized. Therefore, we observe a flat time trend of new wind projects since 2015. I plot the time trend of new wind capacity in Appendix Figure A.5, and find the bunching pattern robust for the aggregate capacity as well. The average capacity per wind farm was stable in 2012 and displays an increasing trend over time.

There could be different channels for the bunching in the online timing. First, wind farms might expedite the construction process to meet the deadline of PTC, which was tied to the online time of wind projects before 2012. However, as shown in Panel (a) of Appendix Figure A.6, the average construction time remains stable at around 9 months across different online years. Panel (b) further plots the average construction time across years when wind farms start construction. There was suggestive evidence that wind projects starting construction in 2012 were more likely

[6]I exclude the month without any wind farm investment in this calculation.

to have a shorter construction period to meet the end-of-year deadline. However, this difference is relatively small in magnitude, and thus the rushed construction is unlikely to be the main driver in the bunching.

Alternatively, the massive entry in 2012 might reflect the expedited waiting process in the interconnection queue. However, as shown in Panel (a) of Appendix Figure A.7, the total years spent between entering into the interconnection queue and starting construction are also stable across different years when wind farms start construction. Moreover, Panel (b) shows that many projects that started construction in 2011 entered the interconnection queue as early as before 2006. Therefore, the bunching in the online years is achieved mainly through the expedited investment decision, instead of merely reflecting the shortened construction process or the interconnection approval time.

3.2.2 Timing Mismatch

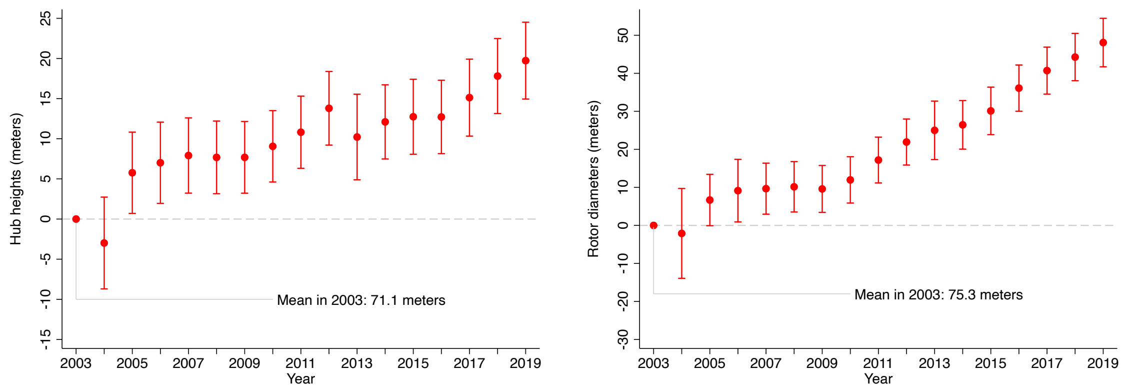
In contrast to the bunched timing of investment, the technology of wind turbines is continuously improving over time. There are three key components of a typical horizontal-axis wind turbine, a tower, a nacelle, and three rotor blades. The potential of wind power generation crucially depends on the height of the tower and the length of the rotor blades. Taller towers enable the turbine to access better wind resources up in the air, while longer rotor blades lead to larger swept areas and capture more wind energy inputs (Covert and Sweeney, 2022). I present the time trend of average tower heights and rotor diameters of new wind farms in Figure 5. As is evident from Panels (a) and (b), the hub heights and rotor diameters are getting larger, and almost follow linear trends after 2009. The average hub height for newly invested wind farms in 2008-2013 was 80.13 meters, while the average hub height for newly invested wind farms in 2014-2019 increased by 6.5% to 85.30 meters. Similarly, the average rotor diameter for newly invested wind farms in 2008-2013 was 88.04 meters, while the average rotor diameter for newly invested wind farms in 2014-2019 increased by 24.6% to 109.69 meters.

Bunched investment timing and improving turbine technology lead to the mismatch between the timings of investment and technology. Panel (a) of Figure 6 plots the contrast of these time trends. I plot the number of new wind farms across different construction start years as well as the technological efficiency of each cohort. I measure the technological efficiency with the capacity factor (the ratio of average power output and maximum power capability) at the age of one. Newly invested wind farms in 2008-2013 had an average capacity factor of 0.32, while that number in 2014-2018 rose to 0.41, increasing by 27.2%. While the investment was made and bunched in earlier years, the upstream wind turbine technology is continuously and quickly improving, thus there might be too many wind farms with old vintage technology as a result of policy uncertainty.[7]

[7]One concern is that the average productivity of a wind farm is also affected by the wind resources of its location, and later entrants might be faced with locations with worse wind resources. However, as shown in Appendix Figure

Figure 5: Time Trend of Wind Turbine Technology

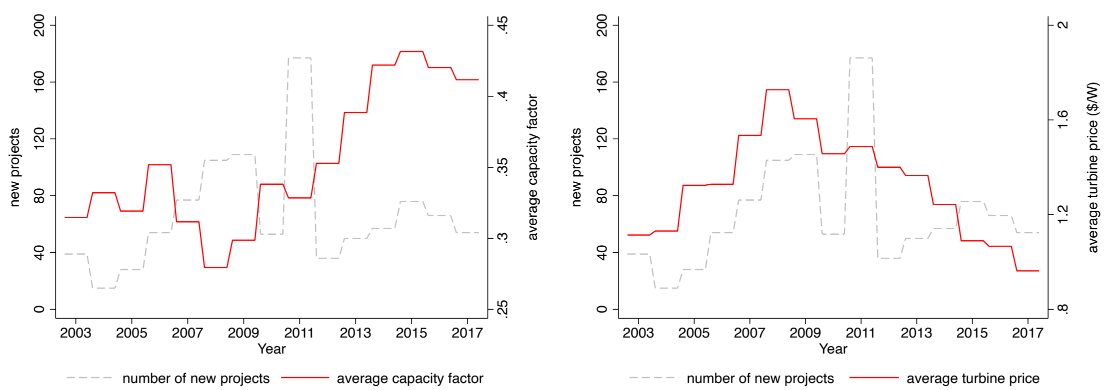
(a) Hub Heights **(b)** Rotor Diameters



Notes: This figure shows the annual time trends of turbine technologies for new wind projects. We construct the annual time trends of hub heights and rotor diameters from The U.S. Wind Turbine Database (USWTDB) published by USGS.

Figure 6: Mismatch between Investment and Turbine Technology

(a) Capacity Factor **(b)** Turbine Price



Notes: This figure shows the time trend of turbine technology for newly installed wind projects. Panel (a) shows the time trend of the capacity factor, measured as the ratio of total output to the nameplate capacity scaled by 24×365, based on the data from EIA Form 923. I plot the investment time trend as the gray dashed line for comparison. Panel (b) shows the time trend of the turbine price, based on the data from Lawrence Berkeley National Laboratory.

Moreover, the average turbine prices are also decreasing over time. As shown in Panel (b), since peaking in 2008-2009 at around 1,700 dollars per kilowatt, the average turbine price has been declining. On average, the turbine price fell below 1,000 dollars per kilowatt after 2015. Therefore, early investment in 2008-2011 largely foregoes later cheaper technology. Decreasing turbine procurement prices and increasing turbine production efficiency together indicate a substantial option value of delaying entering the market for better and cheaper technology. However, policy uncertainty expedited investment, foregoing the benefits of technological improvement and leading to inefficiency in the vintage allocation.

Motivated by industry background and descriptive data patterns, I build an empirical model of US wind energy in which I model the dynamic investment timing decision of wind farms under changing technology and policy uncertainty. Through the lens of the model, I explore the key determinants of profitability of wind farms, as well as how policy beliefs held by investors evolve over time.

4 Model

The structural model consists of a dynamic part and a static part. In the dynamic part, wind farm investors form beliefs about the probability of the future renewal of PTC. Given the turbine technology and turbine procurement cost exogenously evolving, those investors decide whether to invest in the current period or wait until the next period. If they decide to invest in this period, the discounted sum of flow profits from investment is determined in the static part of the model.

There are two different channels for wind farms to sell their capacity. First, a wind farm could negotiate with a utility about a long-term power purchase agreement (PPA), in which the wind farm and the utility jointly decide power purchase prices and the procured capacity simultaneously. If the negotiation fails, the wind farm would earn an expected payoff from selling capacity to alternative utilities, while the utility would earn an expected payoff from its existing capacity mix without procuring new wind capacity in this period. Second, wind farms could also sell capacity to buyers other than utilities such as corporations, or sign financial agreements such as hedge and merchant contracts.

I assume time t is discrete at the annual level. I further denote a wind farm as i and a utility as j. Wind farm investors make the dynamic decision about when to enter the market, while utilities procure wind capacity from wind farms through PPAs.

A.8, the average wind speed for each cohort is generally stable over time. The wind resources are more stable for later entrants, as the standard deviation of the daily average wind speed is lower.

4.1 Static Part

Profit Function for Utilities Utility j generates electricity using different fuel sources, including fossil fuels (f), procured wind (w), other renewable sources (or), or other sources (o). I denote generation capacity as k_{jt}^{a} for utility j, year t, and type a, and the corresponding electricity generation as Q_{jt}^{a}. I endogenize the procured wind capacity k_{jt}^{w} in the model but leave the other three types of energy sources to be exogenous. The total electricity generation Q_{jt} can be expressed as $Q_{jt} = Q_{jt}^{f} + Q_{jt}^{w} + Q_{jt}^{or} + Q_{jt}^{o}$.

Utility j could obtain revenues from selling electricity generated from the procured wind capacity and fulfill the requirement of renewable portfolio standards but have to pay the power purchase agreement price. I define the state as the geographical market m and assume both the electricity market and the renewable credit market to be competitive. Therefore, utility j is faced with the retail electricity price r_{mt}, the renewable portfolio standard z_{mt}, and the renewable credit price λ_{mt}. If the share of electricity generation using renewable energy $\frac{Q_{jt}^{w}+Q_{jt}^{or}}{Q_{jt}}$ falls short of z_{mt}, utilities need to buy renewable credits at the price λ_{mt} to fulfill the requirement; otherwise, they can also sell renewable credits to earn revenues. I suppress the subscript m for the remainder of the section.

Suppose utility j begins a power purchase agreement with wind farm i in year t for a length of T years at the negotiated price of p_{ij}. The profit function for utility j from this contract is

$$\pi^{U}(p_{ij}, k_{ij}^{w}) = \sum_{s=t}^{t+T} E_t \beta^{s-t} \{ \underbrace{r_s Q_{js} - p_{ij}\alpha_{is}k_{ij}^{w} - c(Q_{js}^{f}, Q_{js}^{or}, Q_{js}^{o})}_{\text{profit from electricity generation}} + \underbrace{\lambda_s(\alpha_{is}k_{ij}^{w} + Q_{js}^{or} - z_s Q_{js}) - h_{js}}_{\text{profit from renewable credits}} \}. \tag{1}$$

I assume the production function for independent power producer i as $Q_{ijt}^{w} = k_{jt}^{w} \times \alpha_{it}$, where α_{it} is the annualized capacity factor. The linear functional form fits data well as shown in Appendix Figure A.9. I define $c(\cdot)$ as the annual cost function for the rest three types of energy sources. Another feature I add to the profit function of utility is the hassle cost h_{js}, which captures the frictions on the renewable credit market as well as dynamic incentives of credit banking that I abstract from. I assume the hassle cost to be a quadratic function of the utility's energy composition such that

$$h_{js} = \frac{\kappa}{2}(\alpha_{is}k_{ij}^{w} + Q_{js}^{or} - z_s Q_{js})^2.$$

The hassle cost is higher for utilities that are further away from the RPS goals and thus need to transact a large number of renewable credits. Incorporating h_{js} allows the energy composition to directly shift the willingness to pay for utilities.

Profit Function for Independent Power Producers The profit that the wind farm i receives, given the power purchase agreement price p_{ij}, the production tax credit d_t, and the turbine cost per capacity c_{it}, can be expressed as the follows

$$\pi^W(p_{ij}, k_{ij}^w) = \sum_{s=t}^{t+T} E_t \beta^{s-t} p_{ij} \alpha_{is} k_{ij}^w + \sum_{s=t}^{t+10} E_t \beta^{s-t} d_s \alpha_{is} k_{ij}^w - c_{it} k_{ij}^w. \tag{2}$$

Wind farms receive flow revenues from PPAs for the contract length of T years, but the production tax credit only lasts for 10 years. I allow for the turbine cost per capacity c_{it} to depend on the capacity k_{ij}^w as well as a set of turbine cost shifters $\boldsymbol{X_{it}}$,

$$c_{it} = \boldsymbol{\mu X_{it}} + \frac{k_{ij}^w}{2\gamma} + \xi_{it}. \tag{3}$$

$\boldsymbol{X_{it}}$ includes turbine brands and the average annual turbine price, ξ_{it} denotes the unobserved cost shocks, and γ captures the convexity of the total turbine cost.

Bilateral Bargaining Wind farm i and utility j participate in the bilateral bargaining process to negotiate over the procured capacity k_{ij}^w and the contracted price p_{ij} simultaneously. If the negotiation fails, I assume that wind farms would earn an expected payoff from selling capacity to alternative utilities, while utilities would generate electricity with their current energy mix. Since the price and capacity are negotiated at the same time, the optimal k_{ij}^w will maximize the joint profit such that $k_{ij}^w = \text{argmax } \pi^U(k_{ij}^w, p_{ij}) + \pi^W(k_{ij}^w, p_{ij})$, while the negotiated price p_{ij} will maximize the Nash product of their surpluses from contracting such that

$$p_{ij} = \text{argmax } [\pi^U(k_{ij}^w, p_{ij}) - \pi^U(p_{ij} = \infty)]^\rho \times [\pi^W(k_{ij}^w, p_{ij}) - \pi^W(p_{ij} = \infty)]^{1-\rho}$$

where ρ denotes the bargaining weight of utilities (Chipty and Snyder, 1999). $\pi^U(p_{ij} = \infty)$ and $\pi^W(p_{ij} = \infty)$ denote the bargaining leverages for utilities and wind farms respectively.

Solving the first-order condition to maximize the joint profit $\pi^U(k_{ij}^w, p_{ij}) + \pi^W(k_{ij}^w, p_{ij})$ with respect to the capacity k_{ij}^w yields the optimal capacity function as follows

$$k_{ijt}^w = \gamma(d_t \times \Omega_{it}) + \beta_1 \underbrace{(\Theta_{jt} - \kappa\Phi_{jt})}_{\text{WTP shifters}} \times \alpha_{it} + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\beta_3 Z_{jt}^1} + \epsilon_{ijt} \tag{4}$$

I use Θ_{jt} to represent the discounted sum of the effective market price, which combines the retail electricity price and renewable credit price. Moreover, I denote the utility's energy composition as Φ_{jt}.

$$\Theta_{jt} = \sum_{s=t}^{t+T} E_t \beta^{s-t} (p_s + \lambda_s(1 - z_s)). \tag{5}$$

$$\Phi_{jt} = \sum_{s=t}^{t+T} E_t \beta^{s-t}(1 - z_s)(\alpha_{is} k_{ij}^w + Q_{js}^{or} - z_s Q_{js}). \tag{6}$$

Both Θ_{jt} and Φ_{jt} are important shifters of utilities' willingness to pay for procured wind energy: if the wind energy is more valuable due to either higher electricity prices or higher renewable credit values, or if the utilities have relatively lower shares of renewable capacity compared with the state-level Renewable Portfolio Standard, utilities are willing to pay more for additional wind capacity.

I leverage the fact that capacity factors vary by the cohort of wind projects, but remain stable with respect to the ages of projects even 10 years after entry, as discussed in Appendix Section B.1. Therefore, I use the capacity factor upon entry to measure turbine productivity and assume it to be constant as the turbine ages. I use Ω_{it} to denote the discounted sum of the annual capacity factor during the 10 years under subsidy, such that

$$\Omega_{it} = \sum_{s=t}^{t+10} E_t \beta^{s-t} \alpha_{it} = \frac{1 - \beta^{10}}{1 - \beta} \alpha_{it}. \tag{7}$$

As shown in Equation (4), the optimal procured capacity depends on turbine productivity, utilities' willingness to pay, turbine cost per capacity, as well as a rich set of demand-side controls $\boldsymbol{Z}_{jt}^{1}$. If $\gamma > 0$ such that the total turbine cost is convex, the optimal capacity increases with subsidies per capacity, as a higher subsidy could balance a larger marginal cost. ϵ_{ijt} is a random shock that includes the measurement errors in Θ_{jt} and Φ_{jt}, as well as the unobserved turbine cost shifters ξ_{it}.

Solving the first-order condition of the Nash product of profits from two parties with respect to the price p_{ij} yields the optimal price function.

$$\tilde{p}_{ij} = \frac{p_{ij}(1 - \beta^T)}{1 - \beta^{10}} = \frac{(1 - \rho)(1 - \beta)}{1 - \beta^{10}}(\Theta_{jt} - \kappa \Phi_{jt}) + \rho\left(\frac{c_{it}}{\Omega_{it}} - d_t + \frac{\pi^W(p_{ij} = \infty)}{\Omega_{it} k_{ij}^w}\right). \tag{8}$$

The optimal pricing equation (8) has intuitive interpretations. If the utility has a larger bargaining power, the negotiated price will be low enough to only cover the rescaled turbine cost net government subsidy. If the wind farm has a bigger bargaining power, the negotiated price will be closer to the willingness to pay for utilities. Higher outside option $\pi^W(p_{ij} = \infty)$ gives wind farms better bargaining positions such that the negotiated price will be larger. The capacity function (4) and pricing function (8) together define the optimal solution to the bargaining problem.

Demand of Non-Utility Buyers An alternative channel for selling wind capacity is to sell to non-utility buyers such as corporations or to enter hedge and merchant contracts. Due to a lack of data on the characteristics of both corporate buyers and these financial contracts, I model this second channel using a linear demand curve. To follow the same structure as the bargaining problem, I assume non-utility buyers demand capacity k_i^W at the price of p_i from the wind farm i. The demand function is

$$k_i^w = -\zeta_1 p_i + \zeta_3 \Omega_i + \boldsymbol{\zeta_2 X_i} + \boldsymbol{\zeta_4 Z_i^2} + \upsilon_i. \tag{9}$$

Similar to Equation (4), $\boldsymbol{X_i}$ includes average turbine prices as well as dummies for turbine brands. $\boldsymbol{Z_i^2}$ denotes a set of demand shifters including dummies for different balanced authorities and different types of buyers (corporate buyers, hedge contracts, and merchant contracts). υ_i represents other unobserved demand shifters.

4.2 Dynamic Part

At the beginning of the period t, a potential entrant i draws a random entry cost ψ_{it} from a common distribution and decides whether to invest in this year or wait until the future, by comparing the expected profit from entry and the expected option value of waiting. As pointed out by Fan and Xiao (2015), it's crucial to model potential entrants as long-run players and incorporate the identities of potential entrants to recover the distribution of the entry cost in this type of optimal stopping problem. The identities of potential entrants are observed as wind farm investors need to enter the interconnection queue, get approved by all studies, and sign the interconnection agreements before they are eligible to enter the market. Therefore, I define projects that have been in the interconnection queue for two or more years as the set of potential entrants and model their optimal investment decision.[8]

Dynamic Decision of Potential Entrants Potential entrant i decides whether to invest in year t or wait until later. If it decides to invest, the expected net profit will be the gross profit $\pi^W(p_{ij}, k_{ij}^w)$ as shown in Equation (2), net the entry cost ψ_{it}. I assume that

$$\psi_{it} = \mu W_{it} + \nu_{it}, \quad \nu_{it} \sim F(\nu) = 1 - e^{-\frac{\nu_{it}}{\phi}},$$

where W_{jt} denotes a set of observed entry cost shifters. ν_{it} is the IID entry cost shock, which follows an exponential distribution with the mean parameter ϕ.

I denote the state variables potential entrant i condition for the dynamic decision as $\boldsymbol{s}_{it}$. To avoid the curse of dimensionality in the state space, I construct a linear combination of demand shifters such that $l_{it} = \boldsymbol{\beta_3 Z_{jt}^1}$ for wind farms under utility PPAs, and $l_{it} = \boldsymbol{\zeta_3 Z_{jt}^2}$ for wind farms with corporate buyers and financial contracts. The state variables $\boldsymbol{s}_{it}$ include the willingness to pay for the paired utility $(\Theta_{jt} - \kappa\Phi_{jt})$, a linear combination of demand shifters l_{it}, turbine cost per

[8]For example, PJM has one of the most congested interconnection queues, and the minimum and maximum time between entering the queue and obtaining an interconnection agreement are 2.25 and 2.54 years respectively.

capacity c_{it}, average capacity factor Ω_{it}, the PTC level d_t, as well as observed entry cost shifters W_{it}.[9] Therefore, the net profit for independent power producers is defined as

$$\pi(\boldsymbol{s}_{it}) = \pi^W(p_{ij}(\boldsymbol{s}_{it}), k_{ij}(\boldsymbol{s}_{it})) - \mu W_{it}.$$

I use a dummy D_t to represent whether the PTC is present in year t. D_t is always 1 *ex post* in this industry as the PTC was always extended. However, wind farm investors will form an *ex-ante* belief for the probability of $D_t = 1$ due to policy uncertainty, denoted by $\mathcal{P}_t^*(D_{t+1} = 1|D_t)$. I assume $\mathcal{P}_t^*(D_{t+1} = 1|D_t = 0) = 0$ so that wind investors will expect PTC to be terminated forever once paused. The dynamic optimization problem is as follows

$$V_t(\boldsymbol{s}_{it}, D_t, \nu_{it}) = \max\{\pi(\boldsymbol{s}_{it}) - \nu_{it}, \beta E_t[V_{t+1}(\boldsymbol{s}_{it+1}, D_{t+1}, \nu_{it+1})|\boldsymbol{s}_{it}, D_t, \nu_{it}]\} \tag{10}$$

If the net profit of entry in year t exceeds the option value of waiting, the potential entrant i will choose to enter the market during this period and invest in a wind farm of the size determined either by bilateral bargaining with utilities or by the demand of non-utility buyers. The option value is the expected firm value with respect to the distribution of unobserved entry cost shock $F(\nu_{it})$ and the transition dynamics of state variables $G(\boldsymbol{s}_{it+1}|\boldsymbol{s}_{it})$.

$$E_t[V_{t+1}(\boldsymbol{s}_{it+1}, D_{t+1}, \nu_{it+1})|\boldsymbol{s}_{it}, D_t, \nu_{it}] = \oint_{\boldsymbol{s}_{it+1}, \nu_{it+1}} E_t[V_{t+1}(\boldsymbol{s}_{it+1}, D_{t+1}, \nu_{it+1})|D_t] dG(\boldsymbol{s}_{it+1}|\boldsymbol{s}_{it}) dF(\nu_{it+1}).$$

Moreover, the policy belief $\mathcal{P}_t^*(D_{t+1} = 1|D_t)$ is also embedded in the option value of waiting. As $\mathcal{P}_t^*(D_{t+1} = 1|D_t)$ varies by year, policy uncertainty leads to the non-stationarity of the dynamic problem. Therefore, $V_t(\cdot)$ and $EV_t(\cdot)$ are both indexed by t. If we further expand the expression for $E_t[V_{t+1}(\boldsymbol{s}_{it+1}, D_{t+1}, \nu_{it+1})|D_t]$, it is the weighted average of expected firm value when PTC is certain to be extended $U^1(\boldsymbol{s}_{it+1}, \nu_{it+1})$ and when PTC is certain to be terminated $U^0(\boldsymbol{s}_{it+1}, \nu_{it+1})$, and the weight is the belief of policy renewal in the next period $\mathcal{P}_t^*(D_{t+1} = 1|D_t)$.

$$\begin{aligned} E_t[V_{t+1}(\boldsymbol{s}_{it+1}, D_{t+1}, \nu_{it+1})|D_t] = & \, U^1(\boldsymbol{s}_{it+1}, \nu_{it+1}) \times \mathcal{P}_t^*(D_{t+1} = 1|D_t) \\ & + U^0(\boldsymbol{s}_{it+1}, \nu_{it+1}) \times \mathcal{P}_t^*(D_{t+1} = 0|D_t). \end{aligned}$$

The two boundaries $U^1(\boldsymbol{s}_{it+1}, \nu_{it+1})$ and $U^0(\boldsymbol{s}_{it+1}, \nu_{it+1})$ are by construction from two stationary dynamic problems, where $\pi(\cdot)$ denotes the profit when PTC is present, and $\pi^0(\cdot)$ denotes the

[9] Wind farms that sell capacity to corporate buyers or enter financial contracts don't have the willingness to pay for the paired utility as a state variable. The rest set of the state variables is the same as those under utility PPAs.

profit when PTC is absent.

$$U^1(\boldsymbol{s}_{it}, \nu_{it}) = \max\{\pi(\boldsymbol{s}_{it}) - \nu_{it}, \beta E[U^1(\boldsymbol{s}_{it+1}, \nu_{it+1})|\boldsymbol{s}_{it}, \nu_{it}]\}. \tag{11}$$

$$U^0(\boldsymbol{s}_{it}, \nu_{it}) = \max\{\pi^0(\boldsymbol{s}_{it}) - \nu_{it}, \beta E[U^0(\boldsymbol{s}_{it+1}, \nu_{it+1})|\boldsymbol{s}_{it}, \nu_{it}]\}. \tag{12}$$

I denote the entry decision as a dummy variable E_{it} such that

$$E_{it} = 1 \Leftrightarrow \pi(\boldsymbol{s}_{it}) - \nu_{it} \geqslant \beta E_t[V_{t+1}(\boldsymbol{s}_{it+1}, D_{t+1}, \nu_{it+1})|\boldsymbol{s}_{it}, D_t, \nu_{it}]$$

The entry probability function (the policy function) is denoted by $P_t^E(\boldsymbol{s}_{it}, D_t)$

$$P_t^E(\boldsymbol{s}_{it}, D_t) = P(E_{it} = 1|\boldsymbol{s}_{it}, D_t, t) = 1 - exp(\frac{\pi(\boldsymbol{s}_{it}) - \beta E_t[V_{t+1}(\boldsymbol{s}_{it+1}, D_{t+1}, \nu_{it+1})|\boldsymbol{s}_{it}, D_t, \nu_{it}]}{\phi})$$

As PTC shifts up firm value such that $U^1(\boldsymbol{s}_{it}, \nu_{it}) > U^0(\boldsymbol{s}_{it}, \nu_{it})$, if potential entrants believe there is a weak possibility of policy renewal, then the option value of waiting would be small and potential entrants are more likely to enter in the current period. The entry cost distribution parameters μ and ϕ, as well as policy belief parameters $\mathcal{P}_t^*(D_{t+1} = 1|D_t)$ are key primitives I want to identify and estimate in the dynamic model.

5 Identification and Estimation

I state the identification assumptions and discuss how data variations identify the model in this section. I also discuss the estimation procedures undertaken to uncover model parameters. I start with the static part of the model and the key primitives including the turbine cost function, utilities' bargaining power parameter, as well as the demand function for non-utility buyers. Based on the parameter estimates from the static part, I then discuss how to identify and estimate model primitives in the dynamic part, including parameters governing the entry cost distribution and the policy beliefs.

5.1 Static Part

Bilateral Bargaining There are two key equations from the bilateral bargaining problem: the optimal capacity function (4) and the optimal pricing function (8). In the optimal capacity function, ϵ_{ijt} mainly captures the measurement errors in the willingness to pay, as well as the unobserved turbine cost shifters, both of which are assumed exogenous to the observables.

In the optimal pricing function, I assumed $\pi^W(p_{ij} = \infty)$ as the expected payoff that wind farms would have earned from selling capacity to alternative utilities. Instead of calculating the exact dollar value of $\pi^W(p_{ij} = \infty)$, I control for a flexible function of several key shifters of this bargaining leverage. I find that conditional on all other observables in Equation (8), the residual variation in negotiated prices is positively correlated with the average effective market prices of nearby alternative utilities $\bar{\Theta}_{-jt}$, and negatively correlated with their average energy composition $\bar{\Phi}_{-jt}$, as shown in Appendix Figure A.10. This data pattern is intuitive as $\pi^W(p_{ij} = \infty)$ increases with the average willingness to pay for nearby alternative utilities. Motivated by the data fact, I rewrite Equation (8) for estimation, where $f(\cdot)$ is a fully saturated quadratic function.

$$\tilde{p}_{ij} = \frac{p_{ij}(1-\beta^{T_0})}{1-\beta^{10}} = \frac{(1-\rho)(1-\beta)}{1-\beta^{T_0}}(\Theta_{jt} - \kappa\Phi_{jt}) + \rho(\frac{c_{it}}{\Omega_{it}} - d_t) + f(\frac{\bar{\Theta}_{-jt}}{\sqrt{\Omega_{it}k^w_{ij}}}, \frac{\bar{\Phi}_{-jt}}{\sqrt{\Omega_{it}k^w_{ij}}}) + \upsilon_{ij}. \tag{8'}$$

Demand for Non-Utility Buyers I estimate the linear demand function for non-utility buyers (9) with instruments. As υ_i captures unobserved demand shifters, it's correlated with the price p_i, which introduces bias to the price coefficient ζ_1.

I use three instruments to tackle the identification challenge. The first instrument is the average land price. As the locations of wind farms are exogenously given in the model, land prices are orthogonal to the demand shifters for non-utility buyers, but might be incorporated into the wind energy price for wind farm investors to break even. The second instrument is a dummy variable indicating whether a state implemented wind power recruitment policies. These policies are implemented by the state government to boost renewable energy. As wind energy is only part of the renewable energy mix, and non-utility buyers demand no more than 30% of the total wind capacity, these supply-side policies are unlikely to be correlated with the unobserved demand shifters of non-utility buyers. The third instrument is the renewable credit price in each state. As renewable credit is a product of the Renewable Portfolio Standard which targets utilities, its price is less likely to be correlated with demand shifters for non-utility buyers.

5.2 Dynamic Part

The key identification challenge in the dynamic part of the model is how to separately identify the parameters of the entry cost distribution (μ and ϕ) and the policy belief parameters $\mathcal{P}^*_t(D_{t+1} = 1|D_t)$. The main identification argument is to exploit the temporal structure of the policy. There are years when there was no policy uncertainty, which helps identify parameters of entry cost distribution μ and ϕ given $\mathcal{P}^*_t(D_{t+1} = 1|D_t) = 1$. Moreover, any deviation in those deadline years from the "smooth" trend of wind investment predicted by the model would be rationalized by $\mathcal{P}_t^*(D_{t+1} = 1|D_t)$. The key identification assumption for the policy belief parameters is that conditional on observables, the entry cost distribution moves smoothly in the deadline years of the policy windows.

Following the logic of my identification strategy, I take two steps to estimate the dynamic model. First, I focus on policy windows when there was no policy uncertainty. I follow Arcidiacono and Miller (2011) and apply the discrete Euler methods to estimate the parameters of the investment cost distribution. I take advantage of the fact that the investment decision in my model is terminal and thus yields the "finite dependence" property of the Bellman equation.[10]

Second, I use the estimated entry cost parameters to solve the dynamic programming problem and focus on policy windows with deadlines to estimate the policy belief parameters. As policy uncertainty leads to the non-stationarity of the dynamic problem, I take a full solution approach and solve the dynamic model period by period. I simulate the firm value functions when the PTC is *certain* to be renewed and when the PTC is *certain* to be terminated. I then match the predicted entry probability with the observed entry rate from the data, and the policy belief parameters are estimated as the relative weights on the firm value functions when the PTC is *certain* to be renewed.

Step 1: Entry Cost Parameters I focus on the policy windows in which there was no policy uncertainty such that $\mathcal{P}_t^*(D_{t+1} = 1|D_t) = 1$. As the main source of non-stationarity is policy uncertainty, I exploit the feature that the policy was announced at the end of 2015 to cover through at least 2019 and assume the policy window between 2016 and 2018 is stationary. The stable investment trend as shown in Figure 4, in contrast to the jumping numbers in earlier years, provides another piece of supporting evidence that the policy environment was largely stationary in this period. Following Pakes et al. (2007), I write the ex-ante value function $U(\boldsymbol{s}_{it})$ as follows, under the assumption that the unobserved entry cost ν_{it} is distributed exponentially with the mean parameter ϕ.

$$U(\boldsymbol{s}_{it}) = \pi(\boldsymbol{s}_{it}) - \phi + \phi\ exp(-\frac{\pi(\boldsymbol{s}_{it}) - \beta EU(\boldsymbol{s}_{it})}{\phi}) = \pi(\boldsymbol{s}_{it}) - \phi P^E(\boldsymbol{s}_{it})$$

I denote the choice-specific value function as $U(E_{it}; \boldsymbol{s}_{it}, \nu_{it})$. If the potential entrant i decides to invest in year t, the firm value would be

$$U(1; \boldsymbol{s}_{it}, \nu_{it}) = \pi(\boldsymbol{s}_{it}) - \nu_{it}$$

[10] The recent empirical papers using the discrete Euler method include De Groote and Verboven (2019), Hsiao (2021), Almagro and Dominguez-Iino (2022), et al. Among them, De Groote and Verboven (2019) exploits the terminal nature in the adoption of solar photovoltaic (PV) systems, similar to my setting.

If the potential entrant i instead decides to wait in year t, the firm value would be

$$\begin{aligned} U(0; \boldsymbol{s}_{it}, \nu_{it}) &= \beta E[U(\boldsymbol{s}_{it+1}, \nu_{it+1}) | \boldsymbol{s}_{it}, \nu_{it}] \\ &= \beta E[\pi(\boldsymbol{s}_{it+1}) | \boldsymbol{s}_{it}] - \beta \phi E[P^E(\boldsymbol{s}_{it+1}) | \boldsymbol{s}_{it}] \end{aligned}$$

Therefore, the predicted entry probability is

$$P^E(\boldsymbol{s}_{it}) = 1 - exp(\frac{\pi(\boldsymbol{s}_{it}) - U(0; \boldsymbol{s}_{it}, \nu_{it})}{\phi})$$

The estimation equation is

$$\log(1 - P^E(\boldsymbol{s}_{it})) + \beta E[P^E(\boldsymbol{s}_{it+1}) | \boldsymbol{s}_{it}] = -\frac{\pi(\boldsymbol{s}_{it}) - \beta E[\pi(\boldsymbol{s}_{it+1}) | \boldsymbol{s}_{it}]}{\phi} + \frac{\mu[W_{it} - \beta E(W_{it+1}) | W_{it}]}{\phi} \tag{13}$$

If the gap between the total profit of investment in t and the expected profit of investment in $t+1$ grows wider, the investment will substitute from $t+1$ to t. The elasticity of the investment timing substitution with respect to the profit gap is affected by entry cost parameters. I exploit Equation (13) to identify ϕ and μ.

I use the policy windows between 2016-2018 as the *Consolidated Appropriations Act* was announced at the end of 2015 to cover the policy window until 2019. I first estimate the policy function $P^E(\boldsymbol{s}_{it}, D_t)$ and transition dynamics of state variables $G(\boldsymbol{s}_{it+1} | \boldsymbol{s}_{it})$, following the two-step methods by Hotz and Miller (1993). I estimate the conditional entry probability via function approximation with linear basis functions with data only from 2016-2018 due to data sparsity. I estimate the transition dynamics of state variables using AR(1) models. I then simulate the expected policy function and static profits and feed them into the discrete Euler equation (13) to estimate ϕ and μ. I include the average land price as the entry cost shifter W_{it}.

Step 2: Policy Belief Parameters I use the estimated cost parameters to solve the stationary value functions. I approximate the value functions when the PTC is *certain* to be renewed and when the PTC is *certain* to be terminated using quadratic basis functions $u_n(\boldsymbol{s}_{it})$ such that $U^1(\boldsymbol{s}_{it}) = \sum_n \varphi_n^1 u_n(\boldsymbol{s}_{it})$ and $U^0(\boldsymbol{s}_{it}) = \sum_n \varphi_n^0 u_n(\boldsymbol{s}_{it})$ following Sweeting (2013) and Barwick and Pathak (2015). I solve for the set of parameters φ_n^1 and φ_n^0 by finding the fixed points to the Bellman equations (11) and (12).

I then solve for the policy belief parameters $\mathcal{P}_t^*(D_{t+1} = 1 | D_t)$ year by year, constructing the option value using the stationary value functions. I match the model-predicted entry rate to the data so that the objective function is as follows.

$$G_t(\boldsymbol{s}_{it}) = \pi(\boldsymbol{s}_{it}) - \oint_{\boldsymbol{s}_{it+1}} [U^1(\boldsymbol{s}_{it+1}) \times \mathcal{P}_t^*(D_{t+1} = 1|D_t) + U^0(\boldsymbol{s}_{it+1}) \times \mathcal{P}_t^*(D_{t+1} = 0|D_t)] dG(\boldsymbol{s}_{it+1}|\boldsymbol{s}_{it})$$

$$L_t = \sum_{it} \{1 - exp[-\frac{G(\boldsymbol{s}_{it}, D_t)}{\phi}] - \hat{P}_t(E_{it})\}^2 \tag{14}$$

I minimize Equation (14) to estimate $\mathcal{P}_t^*(D_{t+1} = 1|D_t)$. Moreover, since the *American Recovery and Reinvestment Act* was announced to be valid until the end of 2012 so the policy renewal should be perceived with certainty at the end of 2010 and 2011, I solve the value functions via backward induction for this policy window and estimate the policy beliefs toward the 2012 deadline for investors in 2011 and 2010 respectively.

6 Results

6.1 Static Parameters

I first estimate utilities' effective market price Θ_{jt}, energy mix Φ_{jt}, and turbine productivity Ω_{it} directly from the data. For utilities' effective market price Θ_{jt} and energy mix Φ_{jt}, I assume utilities to hold rational expectations with respect to the transition dynamics of electricity price, renewable credit price, RPS, and their energy source composition. I estimate the transition dynamics of each component using AR(1) models with trend breaks and heterogeneous time trends across states, and then aggregate them according to Equation (5) and (6).

Moreover, I find that capacity factors evolve systematically with the cohort but display limited variation with respect to the age of wind farms (in Panels (a) and (b) of Appendix Figure A.9), and that the annual total output on average is linearly increasing with the nameplate capacity (in Panel (c) of Appendix Figure A.9). Therefore, I treat the annualized capacity factor as constant and calculate it at the age of one for each wind farm for the best data coverage. Ω_{it} is then calculated according to Equation (7) and the discount factor β is assumed as 0.95. I defer a detailed discussion of the estimation of Θ_{jt}, Φ_{jt}, and Ω_{it} to Appendix Section B.

I proceed to estimate the static model using these estimated shifters. Table 1 presents the estimation results of the bilateral bargaining model. I estimate the optimal capacity equation (4) and optimal pricing equation (8) simultaneously using the non-linear least square estimators. I control for a rich set of fixed effects Z_{jt} in Equation (4), including state effects, contract term length fixed effects, as well as the utility type fixed effects. I categorize the contract lengths into three groups: shorter than 15 years, between 15-20 years, and longer than 20 years. I also group utilities into three types: investor-owned, cooperatives, and the others (such as municipal, etc). I incorporate these fixed effects to control for other demand shifters. Moreover, as I explained in Section 5.1, I include a saturated quadratic function of the average effective market prices of nearby alternative utilities $\bar{\Theta}_{-jt}$ and their average energy share $\bar{\Phi}_{-jt}$ in Equation (8) as controls for $\pi^W(p_{ij} = \infty)$.

Column (1) presents the baseline estimates. The estimated coefficient β_1 of utilities' willingness to pay is around 0.2, as utilities with a higher willingness to pay for wind energy, will demand a larger capacity. The estimated hassle cost parameter κ is positive, which captures the incurred frictions for utilities to participate in the renewable credit market, as well as the dynamic incentives of credit banking that I don't explicitly model.

For cost parameters, γ is estimated to be positive, which indicates that the total capacity cost is convex in the procured capacity volume. Therefore, it would be disproportionately more costly to construct a larger wind farm, since the challenges to transport, install, operate, and maintain wind turbines escalate with taller towers and longer blades. Moreover, I include the time series of the average Vestas turbine prices and allow the turbines manufactured by GE, Siemens-Gemasa, and other smaller brands to vary in unit prices. I find higher turbine prices significantly reduce the optimal negotiated capacity. Although GE and Siemens-Gemasa seem to share similar turbine prices with Vestas, the unit capacity cost is significantly higher for other smaller brands, conditional on the turbine efficiency.

I back out unit capacity cost with cost parameter estimates from Table 1 according to Equation (3). The results are shown in Figure 7. The estimated unit capacity cost is around 1000 to 2000 dollars per kilowatt, which on average aligns with the average turbine procurement price across different brands. The estimated unit capacity cost rose above the average turbine procurement price after 2015, as a result of both an increasing average capacity volume per contract and the convexity in the total capacity cost function.

I estimate the bargaining weight of utilities ρ to be around 0.64. Therefore, utilities have two-thirds of the bargaining power compared with wind farms. ρ is also significantly different from 1, thus the change in PTC will not be perfectly passed through on the negotiated price, and assuming a take-it-or-leave-it model and imposing full rent extraction by utilities will overestimate the importance of PTC to the industry. I check the model fit in Appendix Figure A.11 and the model performs well in fitting the average capacity and prices. Column (2) further incorporates the interaction term between the willingness to pay $(\Theta_{jt} + \kappa\Phi_{jt})$ and the annualized capacity factor (α_{jt}). However, all the key parameter estimates remain quantitatively robust. Column (3) leaves out the controls for $\pi^W(p_{ij} = \infty)$, and the bargaining weight parameter estimate decreases by around 10%, which further illustrates the importance of incorporating these controls. Consequently, I proceed with the rest of the model estimation using the baseline estimates in Column (1).

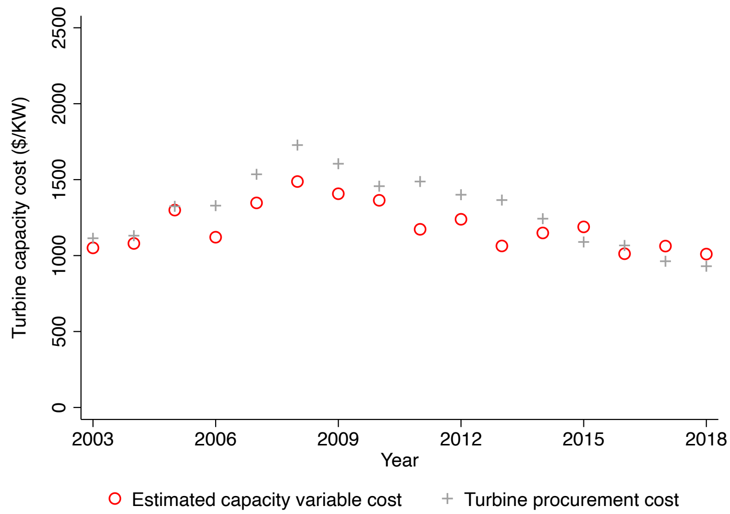
I calculate the discounted sum of profit $\pi^W(D_t = 1)$ for each wind farm and simulated the counterfactual negotiated price $p_{ij}(D_t = 0)$ and the discounted sum of profit $\pi^W(D_t = 0)$ when

Table 1: Estimation Results: Bilateral Bargaining

	(1)	(2)	(3)
Willingness to Pay, β_1	0.186	0.166	0.192
	(0.003)	(0.003)	(0.003)
Hassle Cost, κ	3.323	3.715	3.258
	(0.652)	(0.710)	(0.619)
Unit Capacity Cost Convexity, γ	0.098	0.097	0.097
	(0.008)	(0.008)	(0.008)
Bargaining Weight, ρ	0.639	0.638	0.578
	(0.004)	(0.004)	(0.004)
Turbine Price, $\beta_{2,\text{Turbine Price}}$	-0.048	-0.046	-0.051
	(0.005)	(0.005)	(0.005)
GE, $\beta_{2,\text{GE}}$	-0.170	-0.409	-0.798
	(6.265)	(6.280)	(6.371)
Siemens, $\beta_{2,\text{Siemens}}$	-5.581	-5.758	-5.869
	(8.822)	(8.822)	(8.955)
Other Brands, $\beta_{2,\text{Other Bands}}$	-19.160	-19.719	-21.114
	(6.098)	(6.096)	(6.231)
Interaction: WTP and Capacity Factor		-0.007	
		(0.003)	
Observations	503	503	503
Control for $\pi^W(p_{ij} = \infty)$	✓	✓	
State FE, Term-Length FE, Utility-Type FE	✓	✓	✓

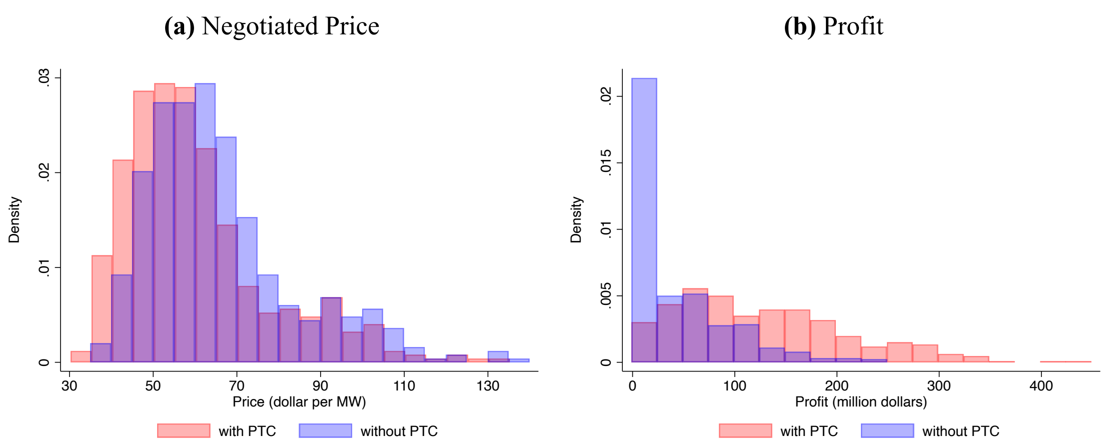
Notes: This table shows the estimation results of the bilateral bargaining model (Equations (4) and (8)). Column (1) presents the estimation result of the baseline model, while Column (2) includes the interaction terms between the effective market price/utility energy mix and the capacity factor. I include a saturated quadratic function of the average effective market price and average energy mix of other utilities within 500 miles as the control for $\pi^I(\mu_{ij} = \infty)$. Standard errors are in parentheses. *p < 0.10; **p<0.05; ***p<0.01.

Figure 7: Estimated Unit Capacity Cost



Notes: This figure shows the time trend of the estimated unit capacity cost and the average turbine procurement prices for Vestas respectively. The unit capacity cost is calculated using estimates in Table 1 according to Equation (3).

Figure 8: Estimated Profit and Price w/o PTC



Notes: This figure shows the distributions of profits and negotiated prices when the PTC is present or absent.

PTC is absent. The distributions are shown in Figure 8. The discounted sum of profit $\pi^W(D_t = 1)$ is 126.5 million dollars on average, 177.8 million dollars at the 75^{th} percentile, and 253.9 million dollars at the 90^{th} percentile. Only 2.0% of wind farms earn a negative profit. When PTC is removed, bilateral bargaining will yield a lower negotiated capacity, but a higher negotiated price. The negotiated price without PTC $p_{ij}(D_t = 0)$ is 8.9% higher compared with $p_{ij}(D_t = 1)$. I assume that a negative negotiated capacity will lead to the failure of the project such that $k^w_{ij} = 0$. Around 31.6% of wind farms will fail or earn a negative profit without PTC, which further corroborates the importance of this federal incentive in supporting the industry. Even conditional on positive profits, $\pi^W(D_t = 1)$ on average is 118% larger than $\pi^W(D_t = 0)$. This result highlights the potential cost of missing deadlines and losing the qualification of PTC, and explains the rushed entry when there is a lower belief for PTC renewal.

The estimation results of the demand function for non-utility offtakers are shown in Table 2. I control for the balancing authority fixed effects as well as the offtake type fixed effects as X_i in Equation (9). I categorize all balancing authorities into four groups: ERCOT (37%), PJM (17%), SPP (15%), and the rest (31%). I also group the offtake type fixed effects into four groups: merchant contracts (44%), PPAs with non-utilities (27%), hedge contracts (10%), and the rest (19%). Column (1) presents the OLS estimates. The price coefficient ζ_1 is around -0.5. Conditional on price, the annualized wind farm capacity and average turbine price are both negatively related to the procured wind capacity, and both coefficient estimates are significant. I use three instruments to deal with the endogeneity issues associated with the wind price: the annual agricultural land price at the state level, a dummy variable indicating whether a state implemented wind power recruitment policies, and the renewable credit price in each state. IV estimate of the price coefficient is larger in magnitude than the OLS result by around 10%. I further regress log capacity on log price, and the estimated average elasticity is around -1.4. There is a sparse reference for the demand elasticity in the wind capacity, but the magnitude roughly aligns with the previous estimates in liquefied natural gas industry (Zahur, 2022) and solar panel industry (Gerarden, 2023).

6.2 Dynamic Parameters

I first estimate the profit function $\pi^W(\cdot)$ and the policy function $P^*(\cdot)$. I further estimate the transition dynamics of state variables using AR(1) models. For detailed results on the first-stage estimation, please refer to Appendix Section C.

I then estimate the parameters of the entry cost distribution ϕ and μ following Equation (13). I use the policy windows between 2016 and 2018 when there is no policy uncertainty. The estimation results are shown in Table 3. The mean parameter ϕ of the entry cost distribution is estimated to be around 88, thus the mean entry cost conditional on entry is around 16.87 million dollars. Moreover,

Table 2: Estimation Results: Demand for Non-Utilities

	Capacity		log(Capacity)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Price	-0.495***	-0.546***		
	(0.082)	(0.122)		
log(Price)			-1.028***	-1.422***
			(0.141)	(0.249)
Productivity (Ω_{it})	-1.241**	-1.284**	-0.015	-0.020
	(0.572)	(0.582)	(0.014)	(0.014)
GE	1.291	1.666	-0.055	-0.023
	(11.328)	(11.243)	(0.201)	(0.202)
Siemens	-10.716	-10.498	0.007	0.009
	(12.598)	(12.566)	(0.200)	(0.200)
Other Brands	-32.783***	-32.095***	-0.817***	-0.749***
	(12.113)	(12.083)	(0.236)	(0.242)
Turbine Price	-3.054*	-3.047*	-0.054	-0.052
	(1.747)	(1.748)	(0.035)	(0.036)
Observations	330	330	330	330
R^2	0.381	0.107	0.561	0.228
Balance-Authority Dummies	✓	✓	✓	✓
Offtake-Type Dummies	✓	✓	✓	✓

Notes: This table shows the estimation results of the linear demand curve for non-utility offtakers (Equation (9)). Column (1) shows the OLS estimates, while Column (2) shows the IV estimates. I use three instruments for the price: the annual agricultural land price at the state level, whether the state offers property tax incentives to wind farms, and whether the state provides industry recruitment support to the wind industry. Robust standard errors are in parentheses. *p < 0.10; **p<0.05; ***p<0.01.

Table 3: Dynamic Model Estimates

Parameter	Estimate	SE
ϕ (mean of entry cost dist.)	88.06	2.64
μ (coef. of land price)	0.02	0.01
$\mathcal{P}^*_{2006}(D_{2007} = 1)$	0.87	0.03
$\mathcal{P}^*_{2007}(D_{2008} = 1)$	0.56	0.10
$\mathcal{P}^*_{2008}(D_{2009} = 1)$	0.48	0.09
$\mathcal{P}^*_{2009}(D_{2012} = 1)$	0.99	0.02
$\mathcal{P}^*_{2010}(D_{2012} = 1)$	0.86	0.03
$\mathcal{P}^*_{2011}(D_{2012} = 1)$	0.42	0.10
$\mathcal{P}^*_{2012}(D_{2013} = 1)$	0.88	0.10
$\mathcal{P}^*_{2013}(D_{2014} = 1)$	0.94	0.04
$\mathcal{P}^*_{2014}(D_{2015} = 1)$	0.91	0.11

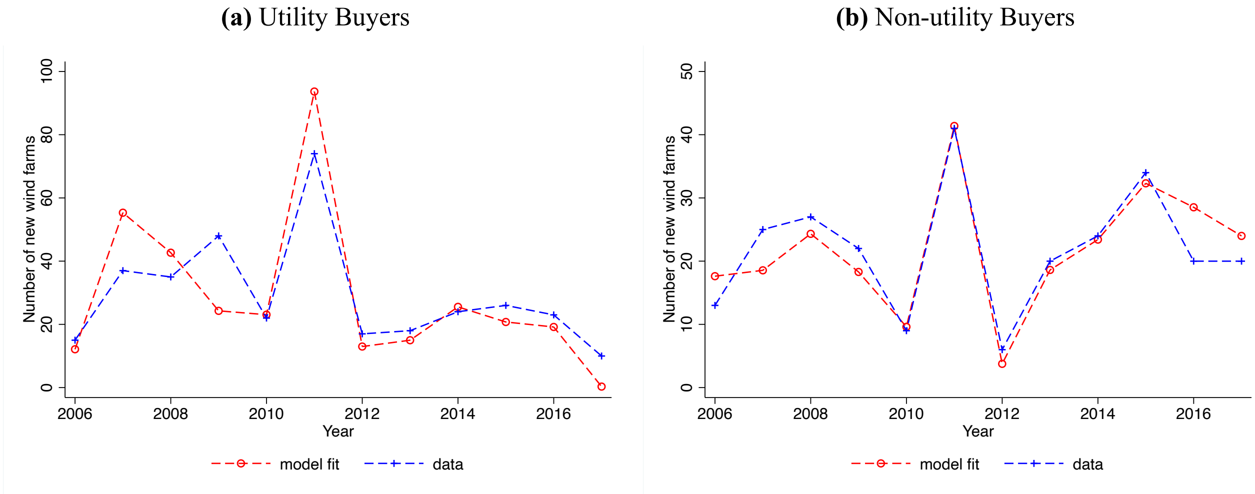
Notes: This table shows the estimation results of the dynamic part of the model.

I include the average state-level annual agricultural land price as W_{it}. The coefficient μ is estimated to be positive, and thus higher land price exacerbates the entry cost for new wind farms.

Next, I use the estimated cost parameters to solve the dynamic programming problem and simulate two firm value functions: the value function when the PTC is *certain* to be renewed and when the PTC is *certain* to be terminated. I use function approximation to solve the coefficients of the quadratic basis functions as the fixed point solution to the Bellman equation. In the final step, I focus on policy windows when there was policy uncertainty and estimate the policy belief parameters as the relative weights on the firm value functions when the PTC is *certain* to be renewed. The results are presented in Table 3. The average perceived probability of policy renewal is around 0.87 in 2006 for the 2007 deadline, as the policy was announced to be extended in the second half of 2006. However, there is relatively large policy uncertainty in 2007 and 2008, as the policy renewal was announced quite close to deadlines in 2008 and 2009. Moreover, as the policy extension was announced in 2009 to cover 2010-2012, I find the perceived likelihood of policy renewal to be gradually decreasing in 2009, 2010, and 2011. The largest policy uncertainty occurred in 2011 for the 2012 deadline as the estimated policy belief is around 0.4. After 2011, although the policy renewal was still accompanied by a lapse in time, the perceived likelihood has been much larger, partly reflecting the learning of investors about the government's objectives.

I test the model fit by drawing the entry cost shocks randomly 500 times and simulating the entry decision of wind farms. The results are shown in Figure 9. The model fits the overall investment time trend and captures the investment spikes and dips well. I examine the model fit separately for two offtake types of wind farms, and the model performs well for both wind farms that match with utilities and those that sell capacity to non-utility buyers.

Figure 9: Model Fit



Notes: This figure shows the test for model fit. Red circles denote the model-predicted number of wind projects, while blue squares denote the number of wind projects in the raw data.

7 Counterfactual Analysis

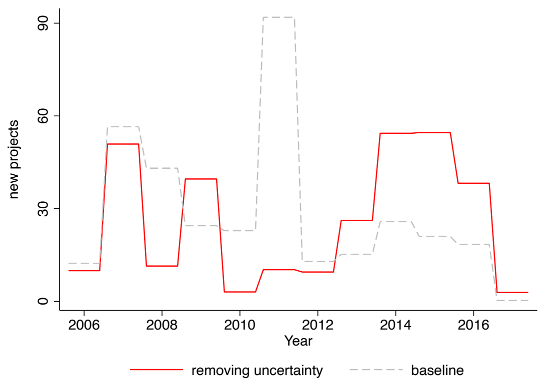
I recompute the optimal investment decision with all $\mathcal{P}_t^*(D_{t+1} = 1|D_t)$ set to one, thus policy uncertainty is entirely removed. The simulation results are shown in Figure 11. Compared to the baseline level, I find that removing policy deadlines delayed entry in the early years due to a substantial option value of waiting for better and cheaper technology in later years.

For wind farms that match with utilities, the total number of new wind farms in 2008-2011 decreased by 64.7%, while the total number of new wind farms in 2012-2017 increased by 98.4%. For wind farms that sell capacity to non-utility buyers, the total number of new wind farms in 2009-2011 decreased by 29.5%, while the total number of new wind farms in 2012-2017 increased by 24.2%. Overall, the total number of new wind farms in 2008-2011 decreased from 277 to 131, while the total number of new wind farms in 2012-2017 increased from 223 to 347. The decreasing ratios are consistent with the parameter estimates of policy beliefs. The investment is delayed to a larger extent in 2008 and 2011 since investors had lower perceived beliefs of policy renewal in these two years. These ratios also match the option value of waiting.

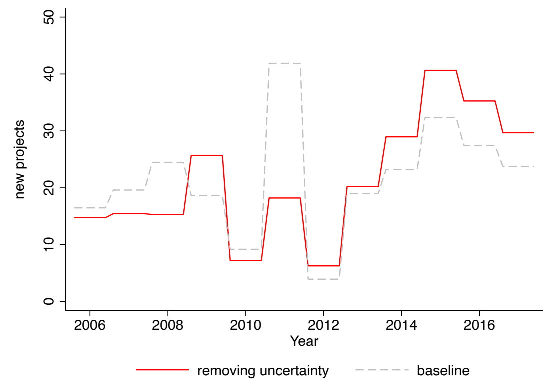
I next evaluate the overall welfare implications of policy uncertainty. Although the investment is delayed to later years and matched better with technological improvement, the environmental benefits will also be delayed. I focus on five ISOs/RTOs including ISONE, CAISO, PJM, MISO, and ERCOT to evaluate the welfare consequences due to data availability. These five markets account for around 70% of the total wind capacity on the market. As shown in Table 4, removing policy uncertainty decreases the total number of new wind farms in 2006-2017 from 448 to 428 by

Figure 10: Counterfactual Analysis: Removing Policy Uncertainty

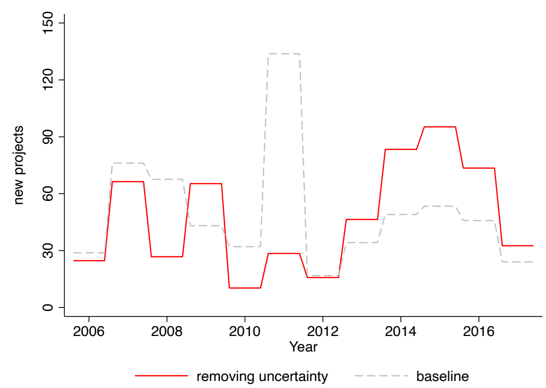
(a) Bilateral Bargaining



(b) Non-utility Buyers



(c) Aggregate



Notes: This figure shows the counterfactual results when policy uncertainty is removed.

around 5%, because wind farms delay their entry further beyond without policy deadlines. On the contrary, the total capacity increases by around 3%. Despite the fewer wind farms, the total capacity increases because the average size of delayed wind farms is bigger since turbine productivity is higher. Moreover, the total electricity output, a discounted sum for a 20-year operation, increases by an even larger margin, due to a better match between technology and investment timing. I evaluate the benefits of wind energy following Callaway et al. (2018). Wind energy substitutes fossil fuels in generating electricity and thus there are three sources of benefits of bringing more wind energy online: reducing carbon emissions, avoiding fossil input costs, and adding capacity values. I estimate the average marginal operating emissions rate (MOER) of coal- or gas-fueled power plants in each state and year and assume the social cost of carbon to be $30 per ton. The statistics of the avoided operating costs and capacity values are taken directly from Callaway et al. (2018). Overall, removing policy uncertainty brings more environmental benefits. Although the entry of wind farms is delayed, the investment matches better with technology. Therefore, both the total capacity and outputs increase, and thus more carbon emission is avoided. The total benefits of wind energy increase by 5.7%. Moreover, as delayed investment takes advantage of cheaper technology, the total turbine costs are also lower by 5%. The net benefits of wind energy increase by 4.1 billion dollars without policy uncertainty, a 21.2% increase from the baseline number.

Table 4: Counterfactual Analysis

	Baseline	Removing Uncertainty	Difference	Percentage
Number of Projects	447.7	427.6	-20.1	-4.5%
Total Capacity (MW)	30383.7	31257.3	873.6	2.9%
Total Output (10^6 MWh)	1226.7	1332.2	105.5	8.6%
Environmental Benefits (Billion $)	20.0	21.1	1.1	5.7%
Total Benefits (Billion $)	51.8	54.3	2.5	4.8%
Turbine Costs (Billion $)	32.6	31.0	-1.6	-5.0%
Net Benefit (Billion $)	19.3	23.4	4.1	21.2%

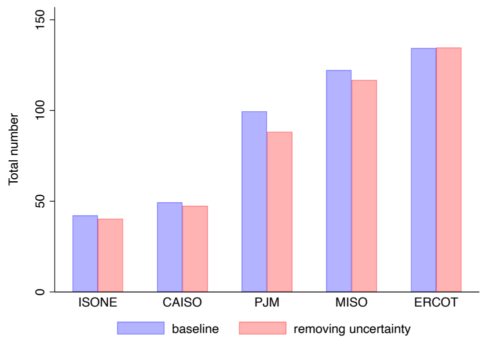
Notes: This figure shows the welfare consequences when policy uncertainty is removed. The environmental benefits only account for the avoided social cost of carbon, while the total benefits further include the avoided fossil input costs and capacity values.

I next explore the heterogeneity of welfare effects across markets. Removing policy uncertainty reduces the total number of wind farms for all the markets except ERCOT, while MISO and ERCOT both enjoy a larger total capacity. The total benefits are smaller for PJM due to reduced total capacity, while a larger share of turbine costs are saved. MISO experiences a slight increase in turbine costs because of a bigger total capacity, which is dominated by the increase in total benefits. ERCOT, on the other hand, has enjoyed both larger total benefits and smaller total costs. Overall, the net benefits increase for wind energy in all markets, and the increase is the largest for MISO.

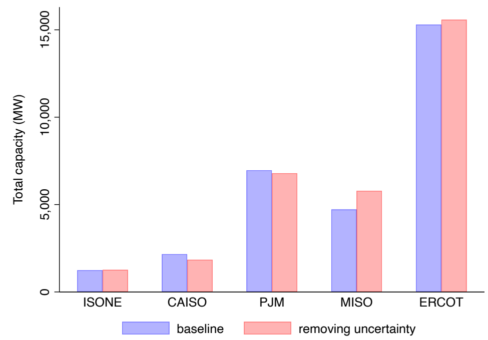
In future versions of the paper, I will explore the interaction of federal policy uncertainty with

Figure 11: Counterfactual Analysis: Removing Policy Uncertainty

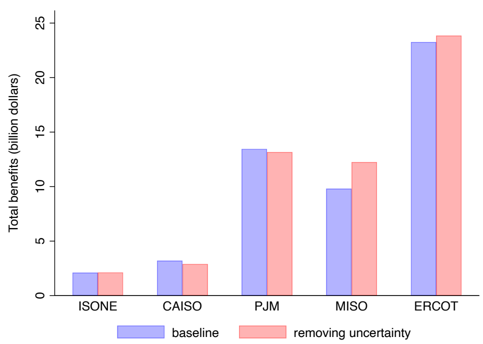
(a) Total Number



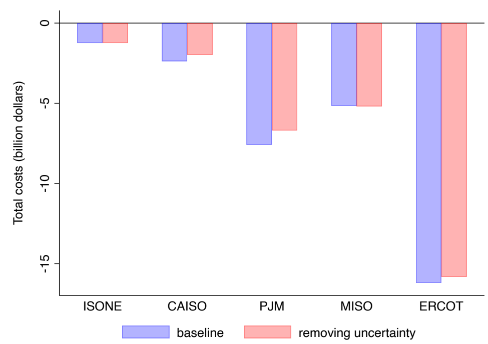
(b) Total Capacity



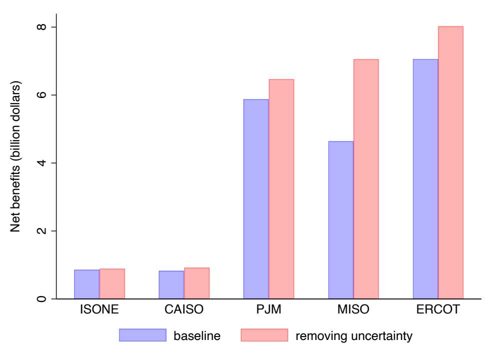
(c) Total Benefits



(d) Total Costs



(e) Net Benefits



Notes: This figure shows the welfare consequences when policy uncertainty is removed for ISONE, CAISO, PJM, MISO, and ERCOT.

local policies. I plan to compare how other local policy features, such as state-level subsidies, renewable portfolio standards, and congestion in interconnection queues, shape the welfare consequences of policy deadlines. My model enables me to answer the question of how state-level policies could mitigate federal policy uncertainty. Finally, I will explore the optimal trajectory of subsidy levels. I solve for a set of optimal c_t to maximize social welfare. Redesigning the subsidy levels combined with policy windows might steer investment toward a better balance between environmental benefits and production efficiency. I also plan to decompose the welfare effect to quantify how much welfare gain is from changing subsidy levels.

8 Conclusion

This paper investigates the dynamic efficiency of policy uncertainty in the US wind energy industry. Policy deadlines embedded in the Production Tax Credit induced uncertainty among wind farm investors and expedited investment. Consequently, it leads to two opposing forces shaping social welfare. On the one hand, the expedited investment reaps environmental benefits earlier. On the other hand, the bunching of investment at the deadlines creates a mismatch with continuously improving upstream turbine technology. The overall welfare effect is ex-ante ambiguous.

I compile a comprehensive data set of the investment, production, and long-term contracts on the US wind energy market. I find a significant bunching of the investment timing for wind farms at the expiration dates of the short policy windows and a large mismatch between the timings of investment and technological advancement. I develop an empirical model featuring the bilateral bargaining of long-term contracts and the dynamic wind farm investment under policy uncertainty. I find that a lapse in policy extension reduced the perceived likelihood of policy renewal to 40%, and counterfactual simulations demonstrate that removing policy uncertainty reduces the number of new wind farms in 2008-2011 by 52.7% and increases the number of new wind farms in 2012-2017 by 55.3%. Overall, the net benefits of wind energy increase by around 20% once policy uncertainty is removed.

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Online Appendix (Not for Publication)

A Data Cleaning

The main data set I use for demand estimation is from AWEA. I keep the PPA data for wind energy with utilities being the power purchasers from 2003 to 2019. The data is at the contract-purchaser level, and there are in total of 738 observations. However, 15% of the observations don't have valid utility names to be matched with the EIA data, and 9% of the observations don't have valid wind farm IDs to be matched with the EIA data. Among observations without valid utility names, 18% only label the power purchasers as "City", and 12% are flagged as "Undisclosed" or "Unknown". Among observations without valid wind farm IDs, 28% have a total capacity of less than 5 MW. Otherwise, the missing pattern seems quite idiosyncratic. Comparing the offtake amounts and contract lengths between sub-samples with and without missing IDs as shown in Appendix Figure A.3, the overall distributions resemble each other.

The offtake capacity amount is complete in the AWEA data. Comparing the aggregate capacity with that from EIA data, I find that AWEA offtake data set covers all wind capacity on the market (Appendix Figure A.3). There are 37% contracts missing price information among contracts with valid utility names and wind farm IDs (604). My strategy of imputation for PPA prices follows that of Aldy et al. (2021). I backed out the PPA prices from the resale revenues and quantities reported in 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 Figure A.3, I find they align well with each other.

B Estimation Details for Static Part

B.1 Estimation of α_{it} and Ω_{it}

I parameterize the wind power generation Q^w_{ijt} as a linear function of the procured capacity k^w_j. Though it is a simplification to assume a linear functional form, I find that the annual total output on average is linearly increasing with the nameplate capacity. I residualize both the annual total generation and the nameplate capacity on the entry cohort dummies and age dummies and then plot the linear fit and local polynomial approximation between these two variables. As shown in Figure A.3, the non-parametric relationship is very close to the linear fit, and the linear function has explanatory power as high as 0.83. Under the assumption of the linear production function, I define the annualized capacity factor $\alpha_{it} = \frac{Q^w_{ijt}}{k^w_j}$.

I then explore how the annualized capacity factor evolves with age by estimating the following model, where age_{it} denotes the age of wind farm j in year t. I further control the entry cohort of wind farms cohort_j. I set the group of age one as our baseline group, and β_a measures the differences in capacity factors between other age groups and the baseline group within an entry cohort.

$$\alpha_{jt} = \sum_{a=2}^{10} \beta_a \times 1(\text{age}_{jt} = a) + \sum_{c=2004}^{2018} \beta_c \times 1(\text{cohort}_j = c) + \epsilon_{jt} \tag{15}$$

I plot the age effects β_a in Panel (a) of Figure A.9. The overall average capacity factor is relatively stable even for the 10 years after entry. The capacity peak arrives at age 5. However, the difference is only around 5% compared to the level of the baseline group. Moreover, I divide the sample into two groups: wind farms of age 1 and wind farms of age 2-5. I estimate the Equation (15) without age dummies and plot β_c for two age groups in Panel (b) of Figure A.9. We find that capacity factors evolve systematically with the cohort, but display limited variation with respect to the age of wind farms. This is further corroborated by the fact that the cohort dummies alone explain 84.3% of the variations of the average capacity factor at the cohort-age level, while the age dummies alone only explain 5.5%. Therefore, we treat the annualized capacity factor as constant and calculate it at the age of one for each wind farm for the best data coverage. We could further calculate Ω_{jt} as follows.

$$\Omega_{it} = \sum_{s=t}^{t+10} E_t \beta^{s-t} \alpha_{it} = \frac{1-\beta^{10}}{1-\beta} \alpha_{it}.$$

B.2 Estimation of Θ_{jt}

I denote the effective market price as Θ_{jt}, which is a combination of wholesale electricity prices and renewable energy credit (REC) prices. I assume that utilities have a rational expectation of the future evolution of both wholesale electricity prices and renewable energy credit (REC) prices. I use the annual average retail electricity price at each state m to measure p_{mt}. As shown in Figure A.12, the average inflation-adjusted electricity price, weighted by the annual sales in each state, increased before 2009 but was declining since then due to plummeting natural gas prices. In order to capture the time trend, I model the evolution of electricity prices using an AR(1) process.

$$\begin{aligned} p_{mt} = {} & \gamma_1 p_{mt-1} \times 1(t \leqslant 2009) + \gamma_2 p_{mt-1} \times 1(t > 2009) + \gamma_3 t \times 1(t \leqslant 2009) \\ & + \gamma_4 t \times 1(t > 2009) + \gamma_5 1(t > 2009) + \xi_m + \epsilon_{mt} \end{aligned} \tag{16}$$

I allow the AR(1) coefficient and the time trend to vary before and after 2009. ξ_m is the state dummy. The estimation results are shown in Table A.1. The time trend of electricity prices varies sharply before and after 2009, and the empirical model captures the data variation in prices adequately as the R^2 is as high as 0.963.

Renewable energy credit (REC) prices are the prices that clear the REC market. State-level renewable portfolio standards (RPS) typically stipulate a minimum share of renewable-sourced electricity out of the total generation for each utility. The demand for renewable energy credit comes from RPS as well as the volume of electricity generated by non-renewable sources, while the supply of renewable energy credit comes from new wind capacity addition, as well as other renewable sources. As shown in Figure A.13, I find REC prices to be positively correlated with the RPS, as more stringent renewable portfolio standards boost the demand for renewable energy credits. Meanwhile, REC prices are negatively correlated with existing wind capacity, because existing wind capacity expands the supply of renewable energy credits. Moreover, REC prices are also positively correlated with the share of electricity generated out of non-renewable sources such as fossil fuels and nuclear energy. A higher non-renewable share of electricity generation shifts the demand curve of renewable energy credits outwards. I further confirm that RPS and cumulative wind capacity are important shifters of the REC prices as shown in Table A.2. Conditional on RPS and cumulative wind capacity, the electricity share by non-renewable sources has only a small and insignificant impact on the REC prices.

I construct the REC prices from the bid-ask data on REC trades provided by Marex, following Aldy et al. (2021). As the data covers 15 states and only after 2006, I extrapolate the REC prices using a linear projection on the three shifters in Table A.2. The RPS data is from DSIRE. I also assume that utilities have a rational expectation of the future evolution of cumulative wind capacity and the electricity share by non-renewable sources, both of which I model as AR(1) processes. I include the state dummies for cumulative wind capacity to capture the rich variation in wind investment across states. I further allow the autoregressive coefficient and time trend to vary before and after 2009 for the electricity share by non-renewable sources, to account for the shale boom.

The effective market price Θ_{jt} therefore can be constructed as

$$\Theta_{jt} = \sum_{s=t}^{t+T_0} E_t \beta^{s-t}(p_s + \lambda_s(1 - z_s)).$$

B.3 Estimation of Φ_{jt}

I denote the utility's energy composition as Θ_{jt}, which is the discounted sum of the flow differences between electricity generation using renewable energy sources (excluding the procured wind energy) and the requirement stipulated by the state Renewable Portfolio Standards.

I first describe the overall time trend of electricity generation by energy source, for all the utilities and utilities in the PPA sample, respectively. The share of coal-fired electricity is decreasing over time, while the share of gas-fired electricity is increasing at the national level as shown in Figure A.14. Despite limited volumes, procured wind and other renewables (including solar, biomass, geothermal, and utility-owned wind) are both increasing. Meanwhile, total generations from nuclear, petroleum, hydroelectric, and other energy sources are almost stable. Compared to the entire sample of utilities, those from my PPA sample have a much larger coal power share compared to the national average and a smaller natural gas power share.

I next estimate the transition process of energy mix at the utility level. I categorize different energy sources into four types: coal, natural gas, other non-renewables (including nuclear, petroleum, and others), and other renewables (including solar, biomass, geothermal, and wind directly owned by utilities). I exclude hydroelectric power following Hollingsworth and Rudik (2019), as many RPSs excluded hydroelectric power built before the implementation to count toward the RPS. We use AR(1) model to capture the evolution process of net generations from these four different energy sources. For other non-renewables and other renewables, I model the transition as a simple AR(1) process with state-specific time trends. For coal and natural gas, I additionally allow heterogeneous transition dynamics before and after 2009. The results are shown in Table A.3.

The utility's energy Φ_{jt} therefore can be constructed as

$$\Phi_{jt} = \sum_{s=t}^{t+T_0} E_t \beta^{s-t} (Q_{js}^{or} - z_s Q_{js}).$$

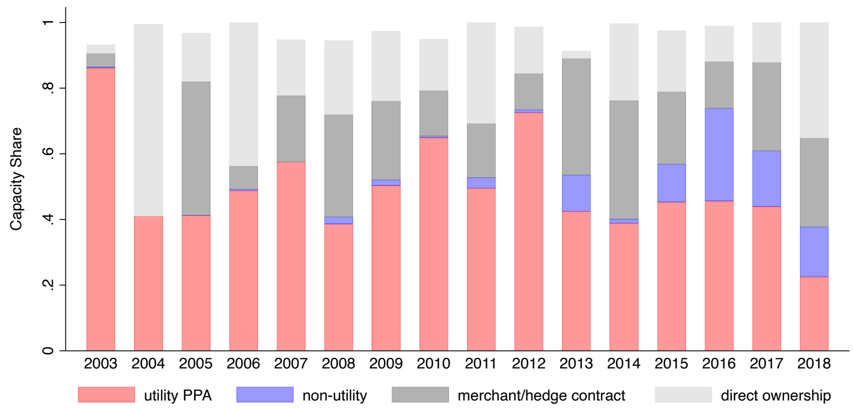
C Estimation Details for Dynamic Part

I estimate the policy function and transition dynamics of state variables via function approximation. I use linear basis functions to approximate the policy function. I estimate the transition dynamics of state variables using AR(1) models. I present a linear approximation of the profit function and policy function for wind farms under utility PPAs and non-utility offtake types, respectively, as shown in Appendix Tables A.4 and A.5. I also present the estimation results for the transition dynamics of state variables in Appendix Tables A.6.

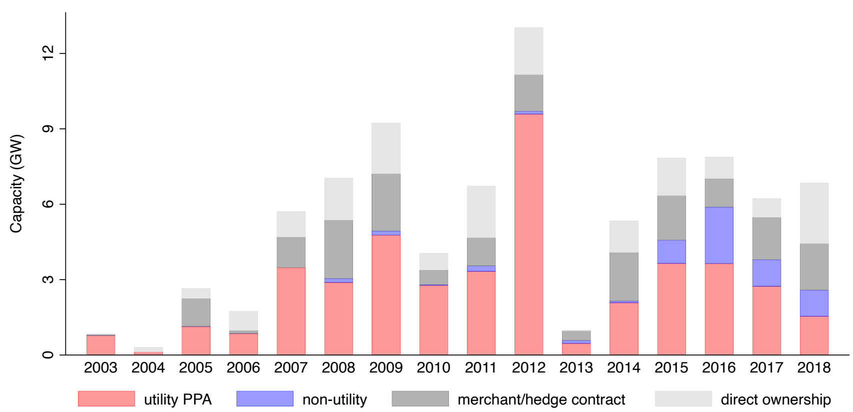
Additional Figures/Tables

Figure A.1: Capacity by Offtake Types

(a) Capacity Share



(b) Capacity Volume

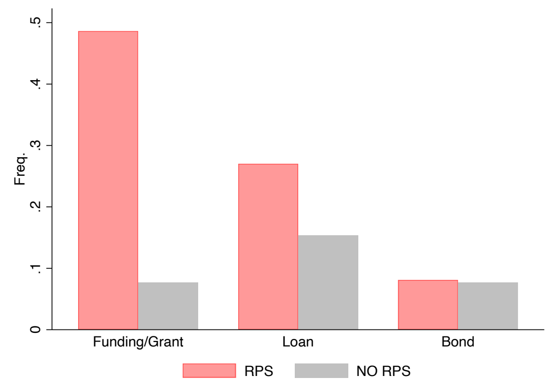


Notes: This figure shows the capacity distribution by offtake types across years. There are four offtake types: utility PPA, non-utility offtaker, merchant/hedge contracts, and direct ownership. Panel (a) describes the share of capacity, while Panel (b) shows the volumes.

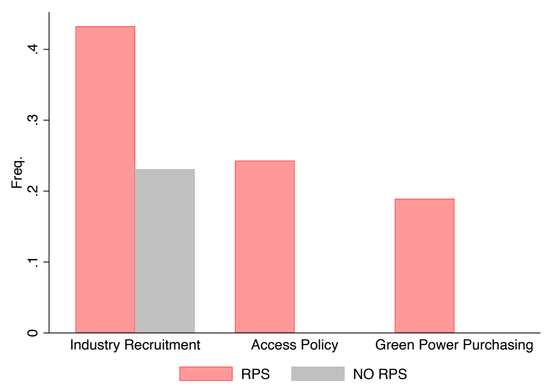
Figure A.2: State-level Policies

(a) Tax Policies

(b) Financing Policies

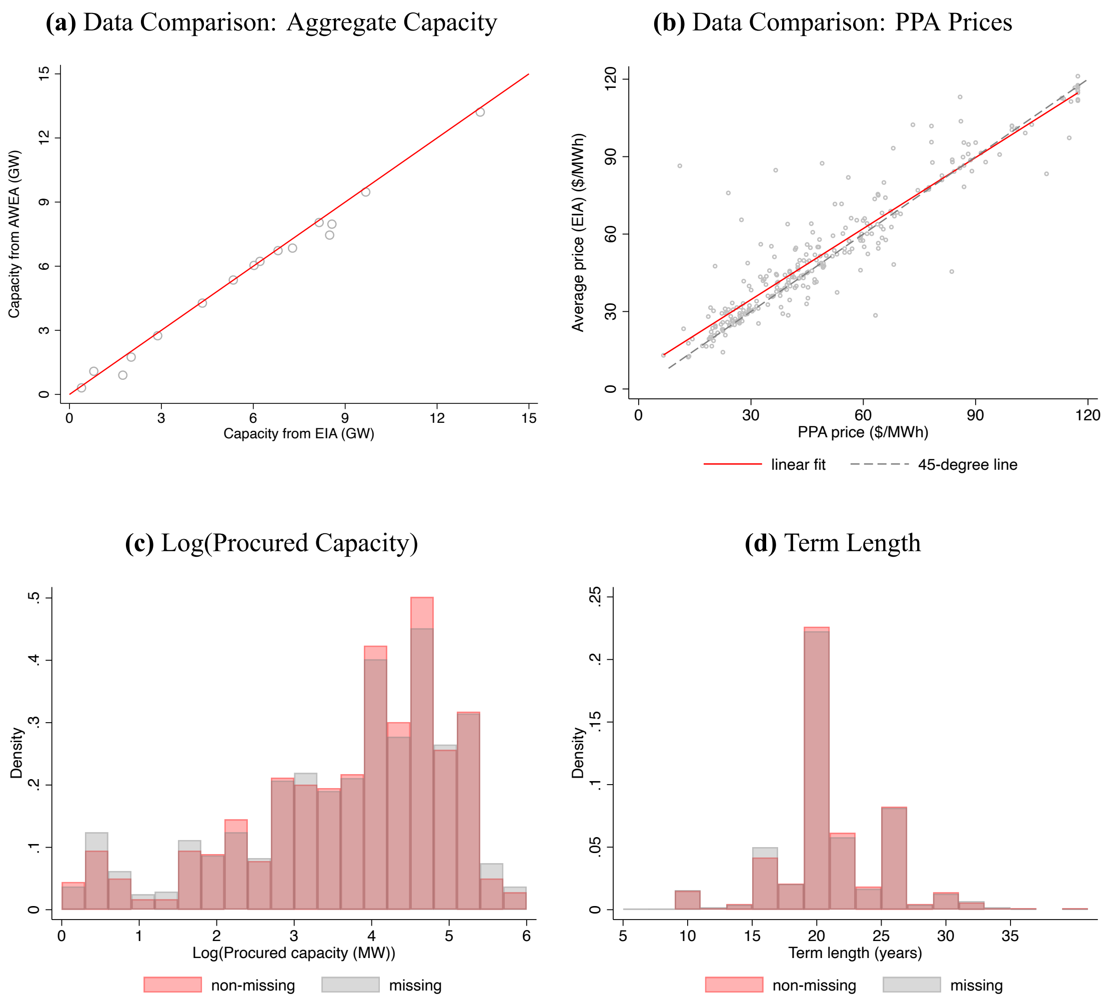


(c) Other Policies



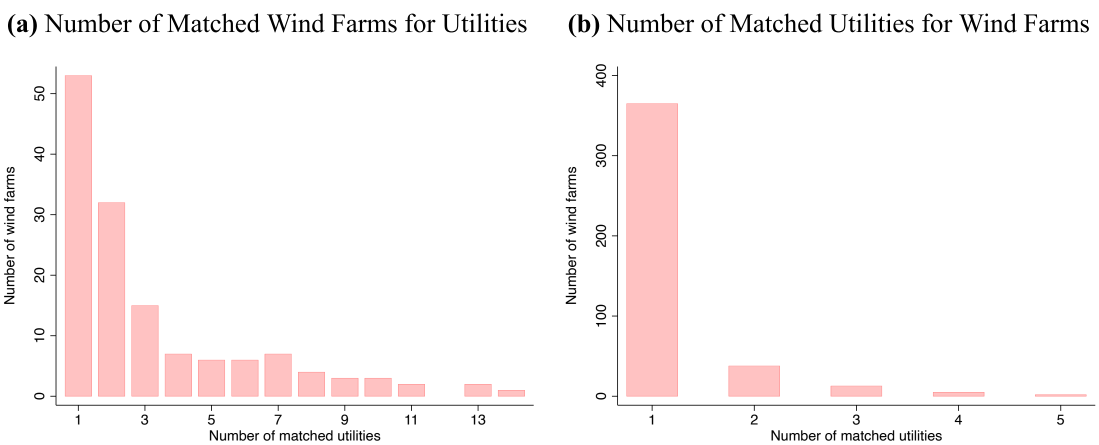
Notes: This figure shows the frequencies of different types of state policies for states with or without RPS. State policies, including RPS, are hand collected by the author from DSIRE (`https://www.dsireusa.org/`).

Figure A.3: Data Description of the PPA Sample



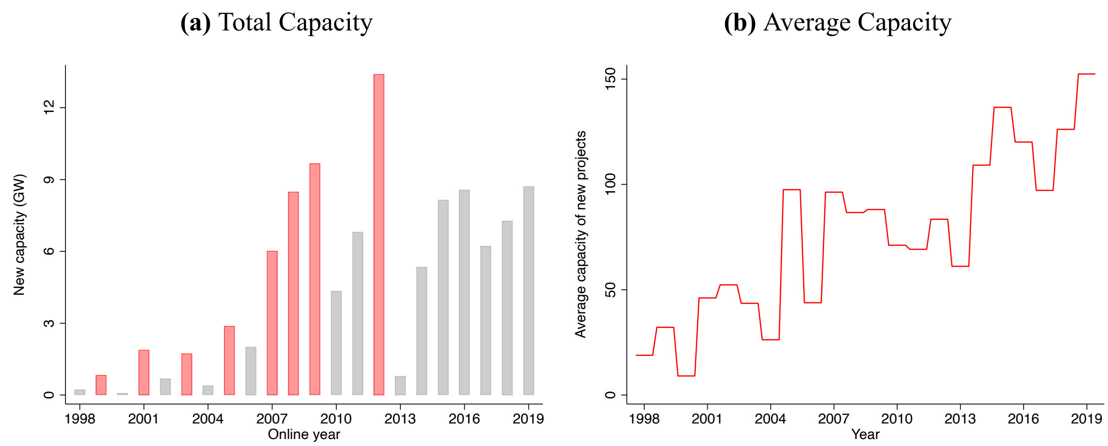
Notes: This figure presents the data description of the PPA sample. Panels (a) and (b) show the results of the data quality cross-check between AWEA and EIA. Panel (a) plots the annual aggregate new capacity from EIA and AWEA. The red solid line denotes the 45-degree line. Panel (b) plots the PPA prices 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 EIA 923 using the resale price in 2011-2019 for each wind farm following Aldy et al. (2021). Panels (c) and (d) show the distributions of the log of procured wind capacity and the contract term length for two sub-samples respectively. The "non-missing" sub-sample denotes the one that matches both utility IDs and wind farm IDs with EIA, and the "missing" sub-sample denotes the one with either unmatched utility IDs or unmatched wind farm IDs.

Figure A.4: Matching between Utilities and Wind Farms



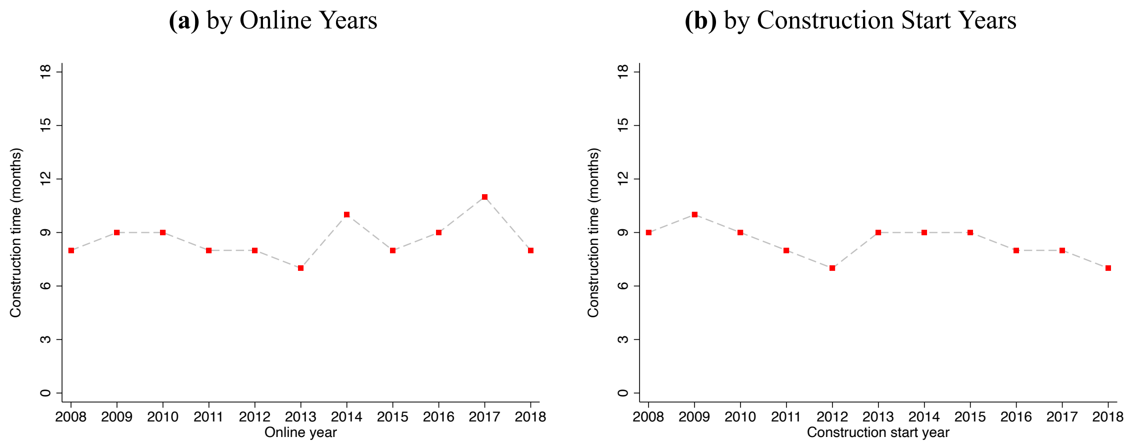
Notes: This figure shows the matching pattern between utilities and wind farms for the PPA sample. Panel (a) plots the distribution of the number of matched wind farms for each utility, and Panel (b) plots the distribution of the number of matched utilities for each wind farm.

Figure A.5: Time Trend for Investment: Capacity



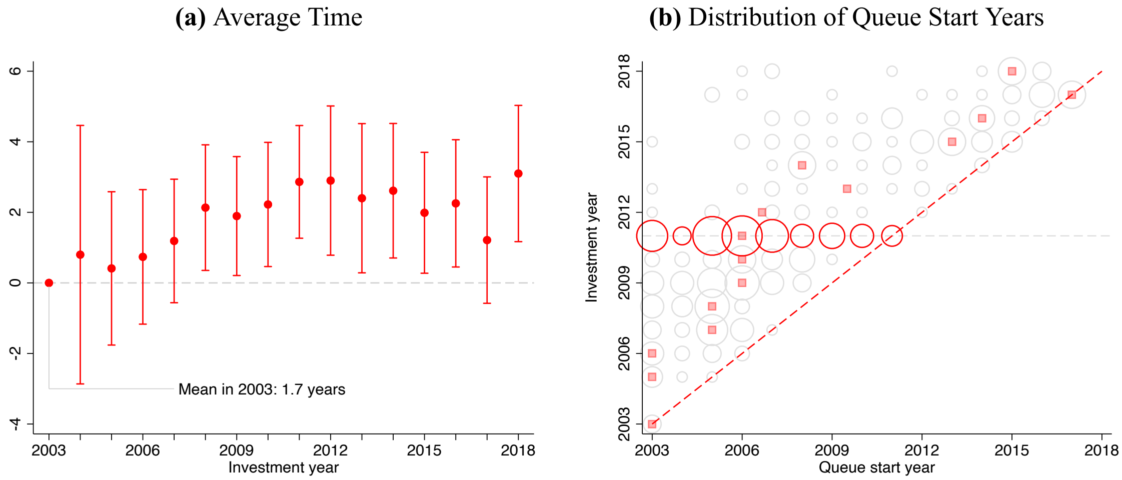
Notes: This figure shows the annual trends of the total capacity and average capacity of new wind projects. We construct the time series based on the data from EIA-860. The red bars in Panel (a) represent the years with policy deadlines.

Figure A.6: Construction Time



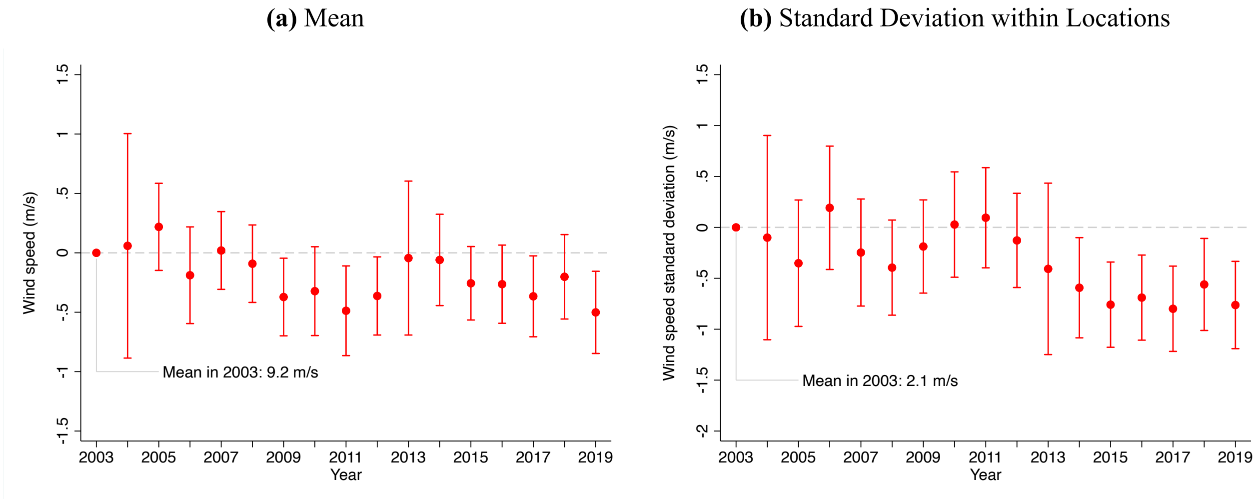
Notes: This figure shows the time trends of the construction time for new wind projects by their online years (Panel (a)) and construction start years (Panel (b)). We construct the annual time trends of the average construction time from FAA data and EIA-860.

Figure A.7: Interconnection Queues



Notes: This figure shows the descriptive evidence for the interconnection queues. Panel (a) plots the average time spent between entering into the interconnection queues and starting construction. Panel (b) plots the distribution of years to start construction and start the queues, where the size of the circles represents the number of wind projects. The interconnection queue data is from ISOs/RTOs including MISO, SPP, PJM, ISONE, NYISO, and CAISO.

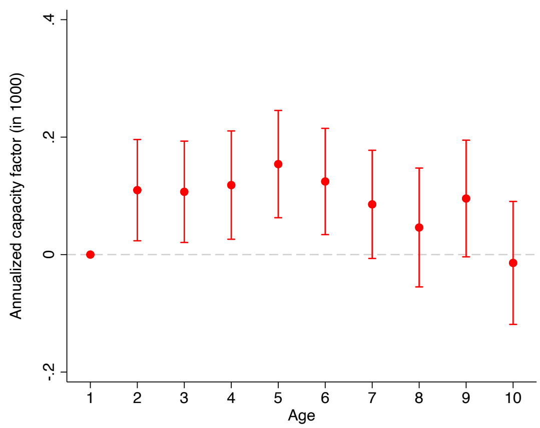
Figure A.8: Time Trend of Wind Speeds



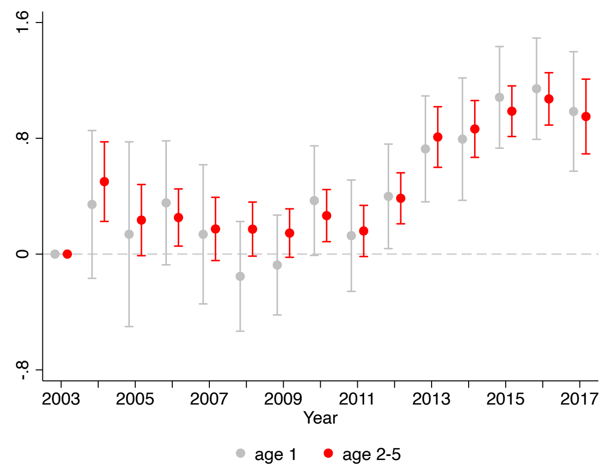
Notes: This figure shows the annual time trends of wind speed at locations of new wind projects. The wind speed is measured at 80 meters at sites nearest to the wind project location based on the Wind Toolkit Data from National Renewable Energy Laboratory (NREL). The mean and standard deviation for each wind project is measured using hourly wind speed in 2007-2013.

Figure A.9: Description of Annualized Capacity Factor

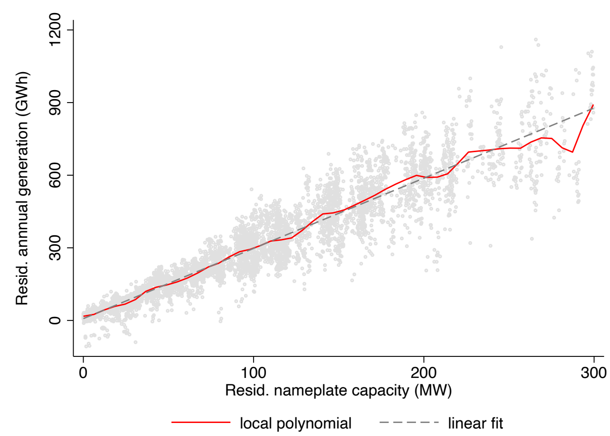
(a) Capacity Factor and Age



(b) Capacity Factor, Age, and Cohort

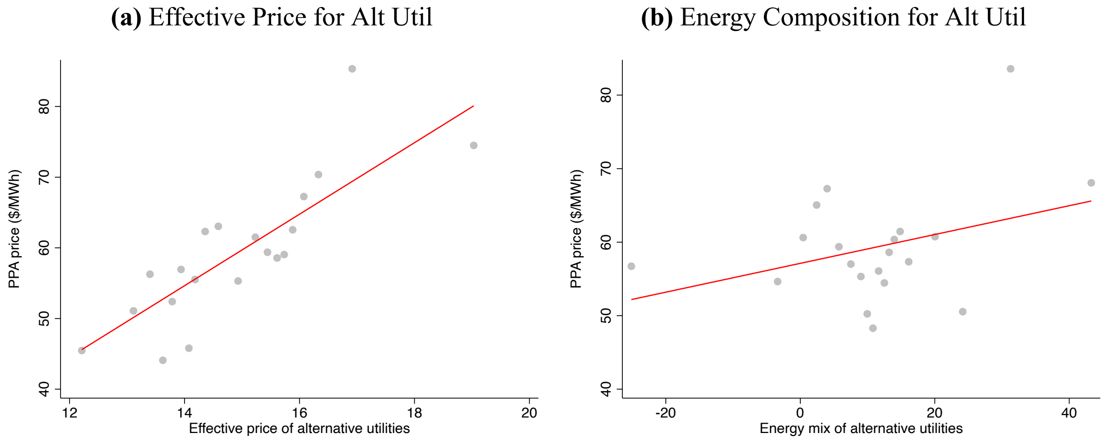


(c) Annual Output and Nameplate Capacity



Notes: This figure presents the descriptive data patterns of the annualized capacity factor of wind farms. Panels (a) and (b) explore the relationship among the capacity factors, ages, and cohorts of wind farms. I rescale the annualized capacity factor and divide it by 1000. The average annualized capacity factor is 2.82×10^3 at the wind farm and year level. Panel (a) plots the coefficient estimates of β_a in Equation (15), controlling for the entry cohort dummies. Panel (b) plots the coefficient estimates of β_c in Equation (15), for the groups of wind farms of age 1 and age 2-5 separately. For both Panels (a) and (b), the 95% confidence intervals are constructed from the robust standard errors. Panel (c) shows the relationship between the annual output and the nameplate capacity of wind farms. I residualize both the annual output and the nameplate capacity on entry cohort dummies and age dummies. The scatter plot is at the wind farm and year level. The red dashed line is the local polynomial approximation, while the blue solid line is the linear fit between these two variables.

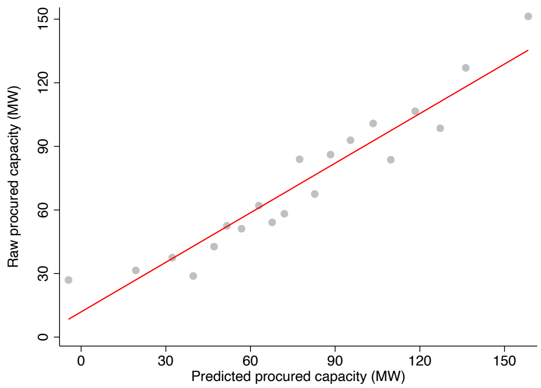
Figure A.10: Negotiated Price and WTP of Alternative Utilities



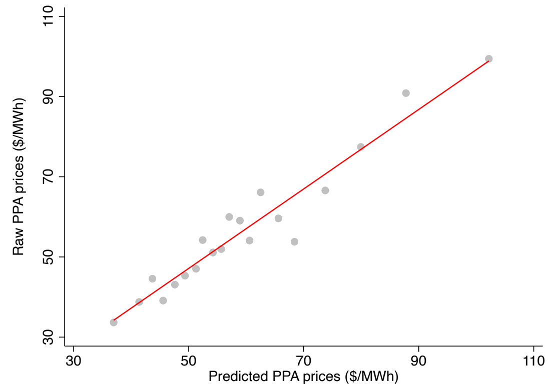
Notes: This figure shows the conditional relationship between PPA prices and two willingness to pay shifters for the alternative utilities within 500 miles. Panel (a) shows the relationship between PPA prices and the average effective prices for alternative utilities, while Panel (b) shows the relationship between PPA prices and the average energy share for alternative utilities, which is scaled by $-\kappa$ estimated in Table 1. Both Panels (a) and (b) control for the utility energy mix, effective market price, estimated unit capacity price, turbine cost, as well as the total capacity for the wind farm and the utility participating in the bilateral negotiation.

Figure A.11: Model Fit for the Static Part

(a) Capacity

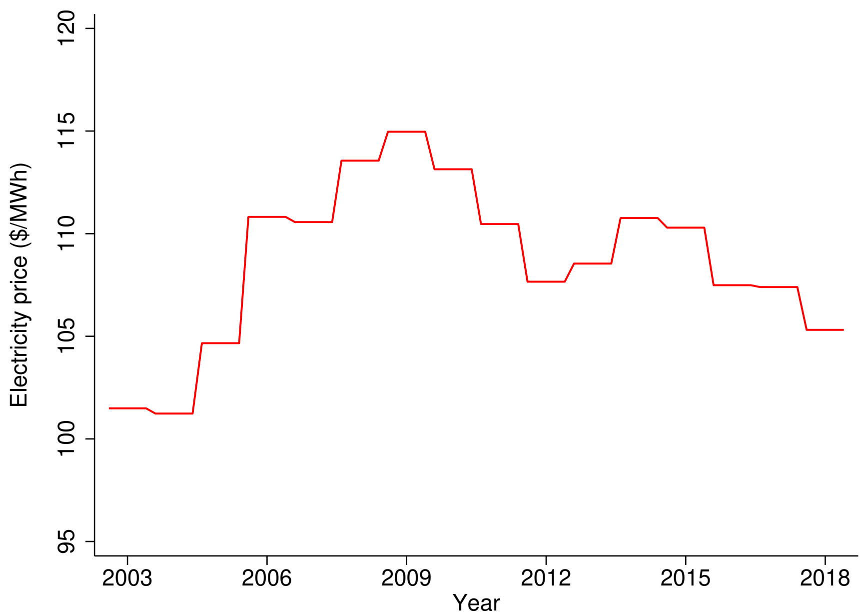


(b) Price



Notes: This figure shows the static model fit for the capacity function (4) and the negotiated price equation (8).

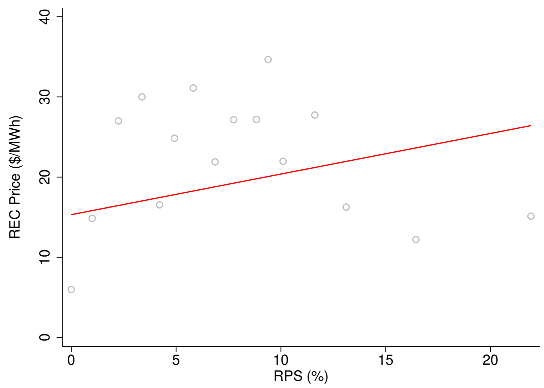
Figure A.12: Time Trend of Aggregate Electricity Price



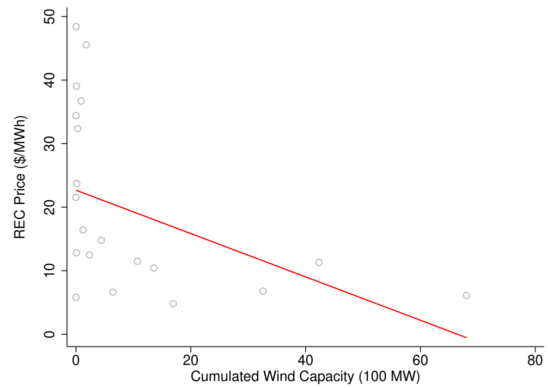
Notes: This figure shows the time trend of average electricity price. I measure the average electricity price with the state-level annual retail electricity price from EIA 861, weighted by the state-level annual electricity sales and adjusted by inflation.

Figure A.13: Renewable Energy Credit Prices

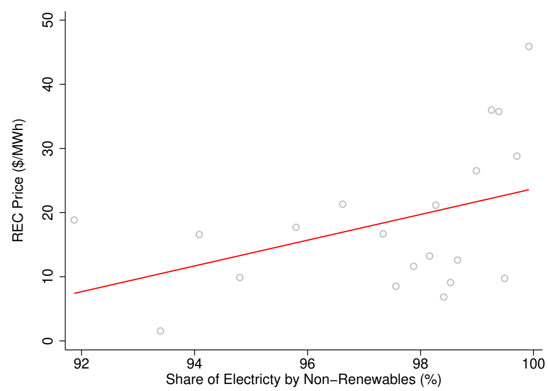
(a) Renewable Portfolio Standards



(b) Cumulative Wind Capacity



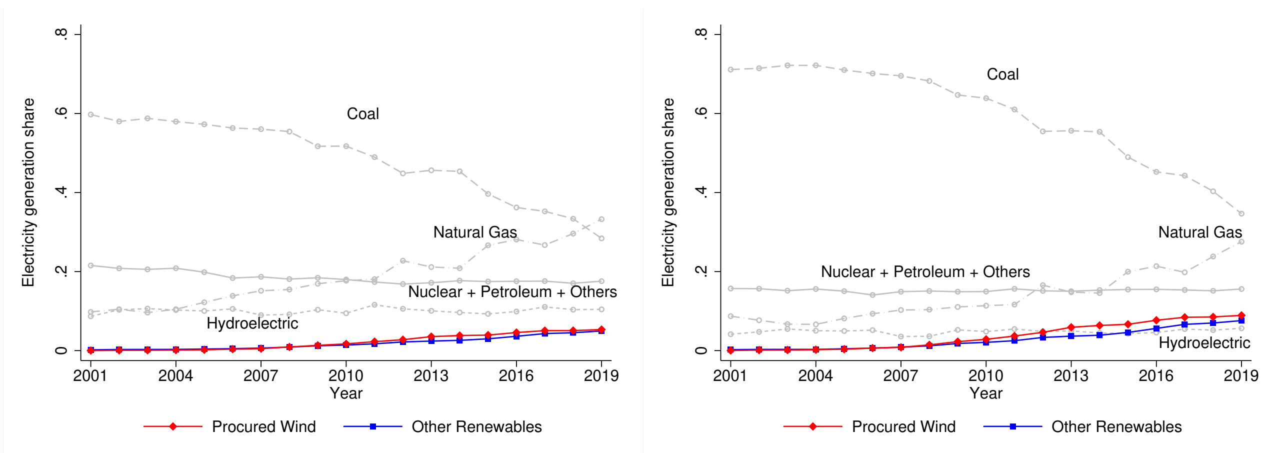
(c) Electricity Share by Non-Renewables



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

Figure A.14: Time Trend of Output Share by Energy Source

(a) All Utilities **(b)** PPA Sample



Notes: This figure shows the time trend of the shares of electricity generated by different energy sources. Panel (a) displays the time trend for all utilities, while Panel (b) shows the time trend for utilities from the PPA sample.

Additional Tables

Table A.1: Electricity Price Process

	Electricity Price		
	(1)	(2)	(3)
Lagged Electricity Price	0.989***	0.706***	
	(0.003)	(0.057)	
Time Trend		-0.057	
		(0.087)	
Lagged Electricity Price $\times 1(\text{Year} \leqslant 2009)$			0.688***
			(0.096)
Lagged Electricity Price $\times 1(\text{Year} > 2009)$			0.678***
			(0.045)
Time Trend $\times 1(\text{Year} \leqslant 2009)$			0.934***
			(0.297)
Time Trend $\times 1(\text{Year} > 2009)$			-0.138
			(0.176)
$1(\text{Year} > 2009)$			6.252**
			(2.749)
Observations	765	765	765
Adjusted R^2	0.955	0.962	0.963
State Dummies		✓	✓

Notes: This table shows the transition dynamics of electricity prices at the city and yearly levels. The empirical model is specified in Equation (16). Standard errors are clustered at the state level. *p < 0.10; **p<0.05; ***p<0.01.

Table A.2: REC Prices

	REC Price	
	(1)	(2)
Renewable Portfolio Standards	0.347*	0.693***
	(0.177)	(0.191)
Cumulated Wind Capacity (100 MW)	-0.149***	-0.086
	(0.043)	(0.062)
Share of Electricty by Non-Renewables (%)	0.019	-0.003
	(0.082)	(0.081)
Observations	152	152
Adjusted R^2	0.089	0.141
Year Dummies		✓

Notes: This table shows the relationship between state-level annual renewable energy credit (REC) prices and state Renewable Portfolio Standards (RPS), cumulative wind capacity, and the share of electricity generated by non-renewable sources including fossil fuels and nuclear energy. Robust standard errors are reported. *p < 0.10; **p<0.05; ***p<0.01.

Table A.3: Energy Mix Process

	Net Generation			
Panel A: Coal and Natural Gas				
	Coal		Natural Gas	
	(1)	(2)	(3)	(4)
Lagged Variable $\times 1(\text{Year} \leqslant 2009)$	0.976***	0.964***	1.052***	1.053***
	(0.009)	(0.013)	(0.024)	(0.023)
Lagged Variable $\times 1(\text{Year} > 2009)$	0.939***	0.944***	1.038***	1.035***
	(0.012)	(0.014)	(0.004)	(0.004)
Time Trend $\times 1(\text{Year} \leqslant 2009)$	-0.152***		0.006	
	(0.032)		(0.005)	
Time Trend $\times 1(\text{Year} > 2009)$	-0.065***		0.001	
	(0.021)		(0.004)	
$1(\text{Year} > 2009)$	0.248	0.670***	0.055	0.021
	(0.250)	(0.174)	(0.058)	(0.023)
Observations	2460	2460	7491	7491
Adjusted R^2	0.969	0.969	0.976	0.976
State Dummies	✓		✓	
State Dummies $\times$ Time Trend		✓		✓

Panel B: Other Renewable and Non-Renewable Sources				
	Other non-Renewables		Other Renewables	
	(5)	(6)	(7)	(8)
Lagged Variable	0.994***	0.994***	1.098***	1.103***
	(0.008)	(0.008)	(0.024)	(0.022)
Time Trend	0.001		-0.001	
	(0.001)		(0.001)	
Observations	9607	9607	2388	2388
Adjusted R^2	0.985	0.985	0.975	0.975
State Dummies	✓		✓	
State Dummies $\times$ Time Trend		✓		✓

Notes: This table shows the transition dynamics of net electricity generation using coal, natural gas, other non-renewable sources (including nuclear, petroleum, and others), and other renewable sources (including solar, biomass, geothermal, and wind directly owned by utilities) at the city and yearly levels. The empirical model is similar to Equation (16). Standard errors are clustered at the state level. *p < 0.10; **p<0.05; ***p<0.01.

Table A.4: Profit Function

	Profit	
	PPA	Non-Util
	(1)	(2)
Productivity	2.884***	3.991***
	(0.553)	(0.473)
Linear Demand Shifters	0.512***	0.437***
	(0.115)	(0.147)
Turbine Prices	0.073***	-0.064***
	(0.017)	(0.014)
Effective Market Price	0.142***	
	(0.025)	
Energy Composition	-1.326***	
	(0.241)	
Observations	502	329
R^2	0.233	0.258

Notes: This table shows the linear profit function for wind farms under utility PPAs and non-utility buyers. Robust standard errors are reported in parentheses. *p < 0.10; **p<0.05; ***p<0.01.

Table A.5: Policy Function

	Entry Rate	
	PPA	Non-Util
	(1)	(2)
Productivity	0.011	-0.121
	(0.137)	(0.234)
Linear Demand Shifters	0.020	0.314***
	(0.020)	(0.096)
Turbine Prices	-0.004	-0.020***
	(0.004)	(0.006)
Effective Market Price	0.009**	
	(0.005)	
Energy Composition	-0.176***	
	(0.049)	
Observations	502	329
R^2	0.056	0.092

Notes: This table shows the linear policy function for wind farms under utility PPAs and non-utility buyers. The entry rate is defined as the ratio of the number of new wind farms and the total number of potential entrants. The potential entrants are those who are active in the interconnection queue. Robust standard errors are reported in parentheses. *p < 0.10; **p<0.05; ***p<0.01.

Table A.6: Transition Dynamics

Panel A	Effective Market Price	Utility Energy Mix
Lagged Variable $\times 1(\text{Year} \leqslant 2009)$	0.835***	0.961***
	(0.023)	(0.098)
Lagged Variable $\times 1(\text{Year} > 2009)$	0.817***	0.989***
	(0.018)	(0.064)
$1(\text{Year} > 2009)$	-0.172	-0.205***
	(0.106)	(0.047)
Observations	750	6829
Adjusted R^2	0.997	0.972
State Dummies	✓	
Utility Dummies		✓

Panel B	Turbine Productivity	Turbine Price
Lagged Variable $\times 1(\text{Year} \leqslant 2009)$	0.377	0.909***
	(0.384)	(0.118)
Lagged Variable $\times 1(\text{Year} > 2009)$	0.792***	0.945***
	(0.175)	(0.163)
$1(\text{Year} > 2009)$	-8.010	-2.254
	(9.728)	(2.650)
Observations	15	18
Adjusted R^2	0.699	0.843

Panel C	Land Price	Wage
Lagged Variable	0.925***	0.126***
	(0.006)	(0.033)
Observations	950	900
Adjusted R^2	0.996	0.015
State Dummies	✓	

Notes: This table shows the transition dynamics of state variables in the dynamic model. Robust standard errors are reported in parentheses. *p < 0.10; **p<0.05; ***p<0.01.