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

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Abstract

This paper examines the dynamic efficiency of policy uncertainty in the US wind energy industry. Policy expiration induced uncertainty for wind farm investors and expedited investment. I document timing misalignment among wind farm investment, turbine technology advancement, and evolving demand for wind energy. I then develop a dynamic entry model under policy uncertainty that incorporates long-term contract negotiation and buyer choice. Model estimates reveal that a policy lapse reduced the perceived likelihood of renewal to 30%. Eliminating policy uncertainty increases the social surplus by 5.9 billion dollars and could reduce fiscal expenditure without compromising social welfare.

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1 Introduction

Government policies are frequently implemented to foster the growth of infant industries. However, given limited government resources and political cycles, many policies start off by committing to a short period with expiration dates, which 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 a longer horizon.

This paper explores the dynamic efficiency of policy uncertainty, using the US wind energy industry as an empirical setting. Wind energy expanded from a small portion of total electricity generation in 2000 to become the largest renewable energy source in 2019. This industry is characterized by significant irreversible investment costs and has been heavily supported by federal tax incentives, known as the Production Tax Credit (PTC). The PTC provides inflation-adjusted tax credits for each unit of output over a ten-year period, and the qualification hinges on wind farms starting production before policy expiration. Although the PTC has been in place since 1992, it has been implemented in a series of shorter policy windows with set expiration dates.[1] A lack of government commitment, coupled with occasional lapses between expiration and renewal, caused policy uncertainty among wind farm investors about future extension. Consequently, investors expedited their investment under policy uncertainty and often bunched investment timing near the expiration time. It leads to two opposing forces shaping social welfare. On the one hand, the expedited investment delivers environmental benefits earlier. On the other hand, the bunching of the investment timing creates a misalignment with the improving upstream turbine technology and the evolving demand for wind energy. The overall welfare effect is ambiguous *ex ante*.

I first provide data evidence for this welfare trade-off. I compile a comprehensive data set of investment, production, and long-term contracts in the US wind energy market from 2003 to 2018 and document three key stylized facts. First, I find significant bunching of wind farm investment at the expiration dates of short policy windows, especially in 2012, mainly due to a lapse between expiration and renewal. Second, while the investment bunched at expiration dates in earlier years, the wind turbine technology is quickly improving and becoming cheaper. This creates a large misalignment between the timings of investment and technological advancement. Third, utilities, an important group of buyers of wind capacity, have shrinking unfulfilled demand as they procure more wind energy over time and meet state-level regulations. Consequently, policy uncertainty expedited the entry of wind farms with older technology, which matched with utilities having larger unfulfilled demand. In contrast, more recent entrants with better technology sell wind capacity to utilities with smaller unfulfilled demand, indicating a loss in matching efficiency between utilities

[1] As noted in Bistline et al. (2023), the continual expiration and extension of the PTC in the wind industry created an "on-again/off-again" status of the policy and resulted in a boom-bust cycle of wind development. The industry calls for "strong long-term policy support" according to the Union of Concerned Scientists.

and wind farms due to policy uncertainty.

Building on the stylized facts and institutional details, I develop a dynamic model of wind farms' entry problem.[2] The set of potential entrants in each market consists of wind farm investors who have obtained interconnection agreements with grid operators and have not yet entered. Each investor needs to decide whether to enter or wait. The incentive to enter lies in securing the PTC for the next ten years and matching with a buyer of larger unfilled demand. Conversely, the incentive to wait lies in the prospect of accessing future turbines with higher productivity and lower prices. This trade-off depends crucially on the investor's belief about the likelihood of the PTC renewal. If the probability of extending the PTC is low, the expected payoff from entering is likely to exceed the continuation value of waiting and, as a result, wind investors will rush into the market.

Specifically, potential entrants make entry decisions comparing the option value of waiting and the expected profit from investment net of entry cost. I incorporate the time-varying perceived likelihood of policy renewal as parameters subsumed in the option value of waiting, which introduces non-stationarity to the dynamic problem. As the belief structure will be of infinite dimension without restrictions, I impose two assumptions to make the estimation feasible. First, if the policy is paused, wind farm investors will hold the belief that the policy will be terminated forever. Second, the perceived likelihood of a one-year policy extension remains constant for future years within each cohort but varies between cohorts. Under these two assumptions, the non-stationary dynamic problem is transformed into a sequence of cohort-specific stationary problems.

Conditional on entry, wind farms choose whom to supply, with two primary channels to sell wind capacity. The first channel is to sell capacity to utilities over a long-term Power Purchase Agreement, while the second channel involves selling the capacity to other non-utility buyers such as corporations, or through merchant hedge contracts. I model demand from non-utility buyers using a linear demand curve, combining turbine technology, turbine price, contract types, and a set of demand shifters.

Alternatively, if wind farms sell to utilities, they choose which utility to supply, weighing the profit from a potential negotiation against the pairwise matching cost that depends on the locations of the two parties. The wind farm and the matched utility engage in Nash bargaining to determine the terms of the long-term contract. The wind farm's capacity and the choice of subsidy types are set to maximize the gains from trade when bargaining, and the procurement price divides the gains between the wind farm and the utility.[3] For the bilateral bargaining, I model the detailed profit functions for both utilities and wind farms. On the demand hand, utilities earn profits with procured wind energy from both selling electricity and obtaining renewable credits, net of the costs they pay

[2] "Investment" and "entry" are used interchangeably and defined as the decision to start building a wind farm. During the sample period, the frequency of retrofitting was low.

[3] The Section 1603 Grant provided an upfront investment subsidy equal to 30 percent of the investment costs. Between 2009 and 2012, investors could opt in for either the PTC or the Section 1603 Grant. I explain details of this alternative subsidy option in later sections.

to wind farms as negotiated in the Power Purchase Agreement. Their willingness to pay depends on retail electricity price, renewable credit price, and the gap between the state-level Renewable Portfolio Standard and their current renewable output shares. On the supply side, wind farms earn profits from the Power Purchase Agreement and government subsidies net of total turbine cost.

The estimation of the structural model involves four steps. First, I estimate the bilateral bargaining model. I recover parameters governing utility willingness to pay and wind farm turbine costs, conditional on a rich set of controls for unobserved demand shocks. Moreover, I estimate a bargaining weight parameter, identified by the pass-through of utilities' willingness to pay as well as wind farms' turbine cost to the negotiated price. Overall, I find that utilities value wind energy more if they are further below the state-level Renewable Portfolio Standard. They also capture two thirds of the gains from trade when bargaining. Using the parameter estimates, I find that 22.4% of wind farms will earn zero or negative profits without the PTC. Even conditional on positive profits, the average profit without the PTC is 47.0% lower than the average profit with the PTC. This result highlights the potential cost of missing deadlines and losing the qualification of the PTC. It also explains the rushed entry when there is perception of a lower probability for the PTC renewal.

Second, I estimate a linear demand curve for non-utility buyers and instrument the wind energy price with supply-side shifters as well as state policies to identify the price coefficient. The estimated average elasticity is around -1.6. Third, I estimate the buyer type choice and the utility matching model. I find that the mean likelihood of selling capacity to a non-utility buyer is 24.2%. The matching cost between a wind farm and a utility increases with their geographical distances.

Last, I estimate the parameters in the dynamic entry problem. There is a key identification challenge on how to disentangle the policy belief parameters from the entry cost distribution parameters. My identification argument hinges on the temporal structure of the policy. I leverage the fact that the government announced in 2015 to cover the subsidy from 2015 to 2019. The government further imposed safe harbor period: wind farms could qualify for the PTC if more than five percent of their total investment costs were incurred before policy expiration, with a two-year grace period to begin operation (extended to four years after 2016). I rely on this more recent policy window to identify parameters of entry cost distribution, assuming the perceived likelihood of policy renewal to be one. Moreover, the bunching of investment in earlier deadline years conditional on entry costs pins down the perceived likelihood of policy extension.

Following the identification strategy, I first focus on the more recent policy window, solve the stationary dynamic model using functional approximation, and estimate the entry cost parameters by matching model-predicted entry rates with data. Next, I use the estimated cost parameters to solve the dynamic model in earlier years with policy uncertainty, and estimate the perceived likelihood of policy extension year by year. I estimate the mean realized entry cost to be approximately 35 million dollars, and the mean entry cost increases with the land price. More importantly, there was enormous uncertainty towards policy renewal especially for the 2011 cohort. The average perceived probability of policy renewal is about 30% due to the pessimism about the policy renewal as well as the delayed extension, which largely explains the investment spike that year.

With estimated model primitives, I implement three counterfactual analyses. In the first counterfactual exercise, I simulate the investment decision when the perceived likelihood of policy renewal is one such that there is no policy renewal uncertainty. Removing policy renewal uncertainty reduces the number of new wind projects in 2011 by 52.7% and increases the number of new wind projects between 2012 and 2018 by 24.1% on average annually.[4] Those delayed wind farms would postpone their entry by 3.6 years.

Overall, the numbers of total wind projects are roughly the same, suggesting that removing policy uncertainty mainly shifts the entry timing without changing the total number of entrants over an 11-year period. However, the total wind capacity increases by 6.3% once policy uncertainty is removed and the total output increases by 8.7%, as wind farms enter later when the turbine technology is more advanced. I assume wind farms operate for twenty years and calculate the gains in social surplus in the absence of policy uncertainty. Wind energy substitutes the production of coal- or gas-fueled power plants and brings three social benefits: 1) it reduces carbon emissions; 2) it saves fossil fuel costs; and 3) it brings new capacity and reduces the amount of new investment required to keep the electricity grid reliable and safe. I follow 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, which measures the saved carbon emissions due to renewable energy. The social surplus from wind energy is calculated as total benefits minus turbine costs and entry costs borne by wind farm investors, as well as the total subsidy. I find that the social surplus increases by 5.9 billion dollars and 28.9% after eliminating policy uncertainty. This result demonstrates that although the entry of wind farms is delayed, this negative effect is completely offset by a better timing alignment among investment, technology, and wind demand.

In the second counterfactual exercise, I investigate how welfare effects of policy uncertainty change under different subsidy levels. I find that if policy uncertainty is fully removed, the subsidy level could be reduced by \$2/MWh (around 9%) without compromising social welfare, which demonstrates the fiscal burden brought by policy uncertainty. In the third counterfactual exercise, I evaluate the welfare effects of resolving policy uncertainty early. I simulate a scenario where the government announces the policy extension status before wind farms make their entry decisions. The policy status follows a Bernoulli distribution with a mean equal to the estimated likelihood of policy extension. This scenario maintains the level of policy uncertainty and thus the expected subsidy level as observed in reality, but eliminates *ex-ante* uncertainty by changing the timing of policy uncertainty resolution. I find that early resolution reduces rushed entries and mitigates the negative effects of policy uncertainty. It captures 14.0% of the welfare gain achieved by fully eliminating policy uncertainty. Therefore, keeping the expected value of subsidy the same but reducing

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

the variance of realized policy status can recover 14.0% of welfare loss, while the rest 86.0% of welfare loss is due to a lower expected value of subsidy. Although the subsidy is in place on the market at all times, *ex-ante* policy uncertainty alters the expectations of investors and undermines the benefits of the subsidy.

This paper contributes to the following four strands of literature. First, this paper adds to the literature on the measurement and evaluation of policy uncertainty. Policy uncertainty is pervasive and broadly studied in both macroeconomics and microeconomics. Examples include uncertainty in economic policy (Baker et al., 2016), fiscal policy (Fernández-Villaverde et al., 2015), trade policy (Handley and Limão, 2017), and environmental policy (Gowrisankaran et al., 2023; Dorsey, 2019).[5] Policy uncertainty in the Production Tax Credit in the US wind industry has also been recognized by earlier work such as Barradale (2010) and Johnston and Yang (2019). Compared to the existing literature, my paper quantifies the extent of policy uncertainty from the bunching of investment timing. Moreover, my paper evaluates the dynamic efficiency as well as the underlying channels through the lens of a structural model.

Gowrisankaran et al. (2023) is most closely related to my paper and studies the welfare consequences of policy uncertainty in the Air Toxics Standards on the coal power industry. Compared to Gowrisankaran et al. (2023), my paper focuses on the uncertainty in the subsidy renewal and exploits the temporal variation in the policy design to identify belief parameters. Moreover, my paper highlights two new channels through which policy uncertainty shapes social welfare: the misalignment between the timings of investment and technology, as well as the matching efficiency between buyers and sellers.

Second, this paper relates to the literature on the renewable energy market. Recent work has covered a wide range of topics, including intermittency (Gowrisankaran et al., 2016; Petersen et al., 2024), values of wind energy (Cullen, 2013; Novan, 2015), upstream innovation (Covert and Sweeney, 2022; Gerarden, 2023), storage technology (Butters et al., 2021), and renewable subsidies (De Groote and Verboven, 2019; Kay and Ricks, 2023; Mu, 2023; Bradt, 2024), among others.[6] My paper develops a new empirical structural model for the wind energy market in the US, which features the bilateral bargaining of Power Purchase Agreements, the matching between utilities and wind farms, as well as dynamic entry of wind farms under policy uncertainty, incorporating rich heterogeneity motivated by policies and a set of endogenous choices of wind farms.

Third, this paper directly speaks to the empirical literature about industrial policy implementation. Specific to the power and clean energy sector, there are recent papers about the timing of

[5] More broadly, this paper is also related to the real options theory and empirical applications (Dixit and Pindyck, 1994; Collard-Wexler, 2013; Kellogg, 2014).

[6] Other related topics include spatial misallocation (Callaway et al., 2018; Sexton et al., 2021), transmission congestion (Fell et al., 2021), carbon taxes (Elliott, 2022), contract risks (Ryan, 2021; Fabra and Llobet, 2025), risk sharing (Hara, 2023), interconnections (Gonzales et al., 2023; Johnston et al., 2023), and the Renewable Portfolio Standards (Hollingsworth and Rudik, 2019; Abito et al., 2022).

subsidies (Langer and Lemoine, 2022; Armitage, 2021), subsidy design (Barwick et al., 2023), and subsidy types (Johnston, 2019; Aldy et al., 2023). Different from the previous papers, my paper focuses on policy continuity and demonstrate the potential welfare loss from the "on-again/off-again" renewal pattern of subsidies, especially when the market environment is dynamic.

Last, this paper also contributes to the literature on the dynamic model and firm beliefs (Doraszelski et al., 2018; Jeon, 2022; Gowrisankaran et al., 2023). I develop a tractable industrial dynamic model with evolving policy beliefs under policy uncertainty and I empirically estimate investors' belief parameters utilizing the temporal structure in the policy design.

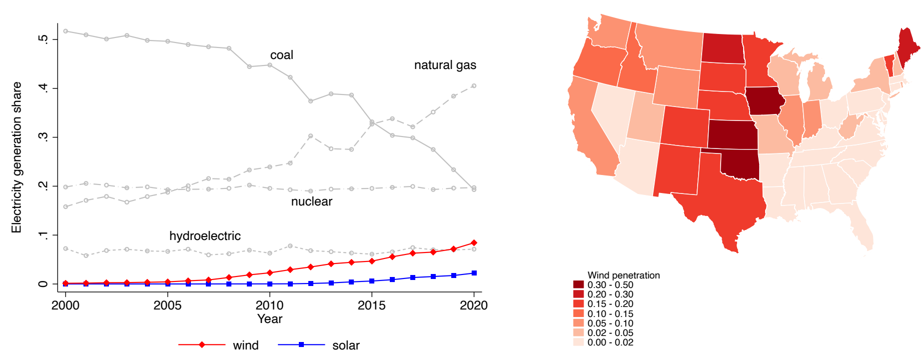
2 Wind Industry and Government Policies in the US

2.1 Wind Industry in the US

Wind energy has become America's largest renewable energy source. It provided 8.3% of 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 of total electricity generation in 2000 to the fourth most important energy source in the US in 2020. Geographically, wind energy is concentrated in Texas, the Midwest, and the Plains. Texas enjoyed the largest wind generation, taking up 28% of total wind power generation nationwide in 2019.

Figure 1: Shares and Penetration Rates of Wind Energy

(a) Wind Shares **(b)** Wind Penetration Rates



Notes: This figure shows electricity generation shares and penetration rates of wind energy. Panel (a) presents shares of electricity generation between 2000 and 2020 by different energy sources based on data from EIA-906, EIA-920, and EIA-923. Red diamonds denote shares of electricity generation from wind farms, while blue squares denote shares using solar energy. Panel (b) presents wind penetration rates in 2019 for each contiguous state. Wind penetration rate is defined as the fraction of electricity produced by wind compared to total generation.

A wind farm requires enormous upfront investment. For example, investors had to spend more than 100 million dollars to construct an average-sized wind farm in 2019 just for turbine procurement, not to mention the additional costs for turbine transportation, wind farm construction, land lease, permits, and grid access.[7] It also takes a long time to plan and construct a wind farm as summarized in Appendix Figure A1. First, investors need to sign a land lease, acquire government permits, and apply for interconnection agreement after lengthy waiting in the interconnection queue. Next, investors negotiate with upstream turbine manufacturers for equipment procurement, negotiate with utilities or corporations to sell outputs, and seek financing from banks. Finally, with contracts secured, investors can start the construction process. A typical wind development process takes three to four years in total, and the construction process alone takes six to nine months. Once a wind farm starts operation, it will typically be in service for about 30 years. Large sunk costs, coupled a long time to build, highlight the importance of dynamic incentives in wind investment.

There are two types of investors in the market: independent power producers and utilities, and they together own over 99% of wind energy. On the one hand, independent power producers own approximately 80% of total capacity. They typically sign a long-term wind procurement contract with utilities or non-utility buyers (e.g., corporations). These contracts are known as the Power Purchase Agreements (PPA). Negotiating and signing a PPA is critical for project financing as it secures a long-term revenue stream. A typical PPA specifies the procurement price, procured capacity, duration of the agreement, and other details. Moreover, independent power producers could also sign merchant hedge contracts.[8] As shown in Appendix Figure A2, utility PPAs are the most common channel to sell wind power, while more non-utility PPAs emerged after 2015.

On the other hand, utilities directly own the rest 20% of wind capacity. As they can either own wind farms or procure wind energy from independent power producers, endogenizing wind capacity under direct utility ownership requires modeling their make-or-buy choices and is beyond the scope of this paper. Instead, this paper focuses on wind farms invested by independent power producers due to their dominant market shares.

2.2 Government Policies

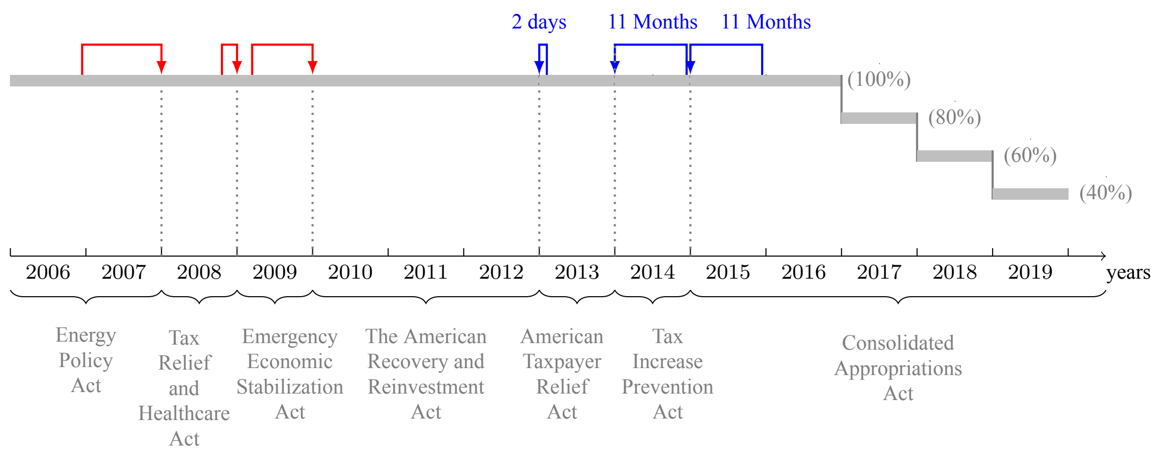
The wind industry in the US crucially relies on tax credit from the federal government, as well as numerous state-level policies. The most important tax credit is the Production Tax Credit (PTC), which provided qualified wind farms with a 10-year inflation-adjusted tax credit for wind power generation and stood at $24/MWh in 2018. Although the PTC has been in effect since 1992, incentives provided by the PTC were segmented into smaller policy windows with set expiration dates. Conditions to qualify for the PTC are tied to these expiration dates: before 2012, a wind farm was

[7] 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.

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

required to start operation before the policy expiration, while after 2013, a wind farm is required to demonstrate that five percent or more of its total investment cost has been incurred before the policy expiration, with a two-year safe harbor to start operation (extended to four years after 2016).[9] As shown in Figure 2, the PTC is enforced by different acts across sample periods. For example, from January 2010 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 2: Timeline of the Production Tax Credit



Notes: This figure shows timing of the Production Tax Credit. Starting points of arrows indicate announcement time of policy renewal in the next act, while endpoints represent start time of the new act. There were 2-day, 11-month, and 11-month lapses between expiration of the previous act and 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 implementing the PTC sequentially, which segments the policy into windows of one to five years. Before 2009, PTC renewals in the next act were announced several months before expiration. However, at the end of 2012, 2013, and 2014, PTC renewals were announced after the deadlines had passed. Although the lapse between policy expiration and renewal could be as short as two days at the beginning of 2013, it still disturbed market incentives and created policy discontinuities. With a lack of government commitment, wind investors were faced with policy uncertainty before expiration about whether the PTC would be extended or not. The delayed policy action from Congress and political debates about renewable subsidies exacerbated the uncertainty in the market.[10] [11]

[9] More recent change in the safe harbor can be found here.

[10] For example, Republican US presidential candidate Mitt Romney declared that he would let wind power tax credits expire (see The Guardian).

[11] American Taxpayer Relief Act of 2012 was introduced in the House on July 24, 2012, as a partial resolution to the US fiscal cliff. The passing of the bill involved days of negotiations between Senate leaders and the Obama administration (see Star Tribune).

The 2011 Wind Technologies Market Report (Wiser and Bolinger, 2012), published by the Department of Energy in August 2012, suggested that investors were uncertain about the PTC renewal, and tended to rush into the market in order to qualify for the tax credit. According to the report, "...the wind energy sector is currently experiencing serious federal policy uncertainty, and therefore rushing to complete projects by the end of the year. Moreover, 2011 saw another year pass without any concrete Congressional action on what are seemingly the wind power industry's two highest priorities – a longer-term extension of federal tax (or cash) incentives and passage of a federal renewable or clean energy portfolio standard..."

Concerns about the expired PTC were ultimately proven to be unnecessary, as it was extended again only 2 days after expiration through the American Taxpayer Relief Act with the tax credit applied retroactively. Similar events occurred again in 2014 and 2015. Although the latter two lapses were much longer, wind farms only needed to incur five percent of its total investment cost before deadlines to qualify for the PTC thanks to the safe harbor period. Starting in 2015, incentives provided by the PTC were stabilized, despite the decreasing amount of the tax credit.

Along with the PTC, there was also the Section 1603 Grant, which provided an upfront investment subsidy covering 30 percent of total investment cost. Between 2009 and 2012, investors could choose either the PTC or the Section 1603 Grant. The Section 1603 Grant was announced to expire after 2012 and has been terminated ever since.[12]

Apart from federal policies, there are also various state-level policies. One important state-level policy is the Renewable Portfolio Standards (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.[13] 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 A3, states with RPS are also more likely to have other different kinds of state-level incentives for wind energy.

3 Data and Stylized Facts

3.1 Data

I compile several data sets in the US wind industry. The first two data sets come from the United States Wind Turbine Database (USWTDB) maintained by the United States Geological Survey (USGS) and the EIA-860 maintained by the Department of Energy's Energy Information Admin-

[12] Johnston (2019) and Aldy et al. (2023) study the selection and efficiency consequences of having both production tax credits and investment subsidies in the market.

[13] Abito et al. (2022) studies the consequences of cross-state trading restrictions and state-specific interim annual targets under RPS.

istration, respectively. These two data sets provide universal information about investment and characteristics of the utility-scale wind farms that were online between 2003 and 2019. USWTDB has more comprehensive coverage and detailed wind turbine characteristics, while EIA-860 also includes information about the owners of wind farms and rich data for other energy sources. Moreover, I supplement these two data sets with EIA-923, which covers the monthly electricity generation and enables me to measure production efficiency of wind projects.

Both USWTDB and EIA-860 record the month when a wind farm starts to supply electricity, however, as illustrated in Appendix Figure A1, there is a lag between finalizing investment decision and starting operation, including a construction period of six to nine 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.[14]

The second data set is the Power Purchase Agreement (PPA) data from the American Clean Power Association (formerly American Wind Energy Association). The PPA data includes long-term contract information such as names of the wind farms and buyers, the amount of capacity, negotiated price, and contract duration.

Moreover, I collect interconnection queue data from the ISO/RTO websites and obtain renewable credit price data from a financial service platform Marex. I also use retail electricity price data from EIA-861, agricultural land price data from the USDA National Agricultural Statistics Service, and the annual turbine price from Lawrence Berkeley National Laboratory. The the state-level policies including Renewable Portfolio Standards were hand-collected from Database of State Incentives for Renewables & Efficiency (DSIRE). For more detailed data processing, please refer to the Online Data Appendix.

3.2 Stylized Facts

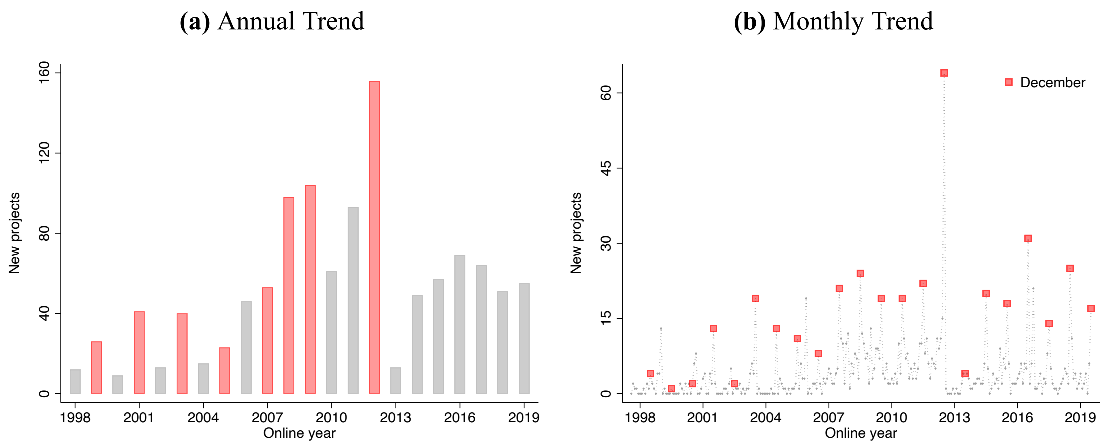
3.2.1 The Timing of Investment

I first investigate the time trend of wind farm investment. Figure 3 presents the annual and monthly numbers of wind farms that are newly online. Significant bunching in wind farm investment occurred whenever the policy was scheduled to expire. A substantial number of wind farms started operation between 2008 and 2012, especially in 2012. Following the large investment spike in 2012, new investment dropped significantly in 2013. It was only after 2015 that the annual level of investment recovered, and the time trend stayed stable afterward. I plot the time trend of the

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

total new wind capacity in Appendix Figure A4, and find a similar bunching pattern. Moreover, the sizes of wind farms were stable in 2012 and have shown an increasing trend over time.

Figure 3: Time Trend for Wind Projects Newly Online



Notes: This figure shows the annual and monthly numbers of wind projects that are newly online. I construct the annual and monthly time trends based on the data from EIA-860. Red bars in Panel (a) represent years with policy expiration, while red squares in Panel (b) represent the new projects that are online in December.

This time pattern aligns well with the timing of policy implementation. During the years between 2009 and 2012, in addition to the Production Tax Credit, there was also the Section 1603 Grant, which provided extra funding flexibility to investors and partly explained the surge of wind projects during this period. By the end of 2012, there was significant uncertainty about the PTC extension due to the time lapse in renewal. Consequently, there was a rushed inflow of new wind projects before the policy expiration, as wind farm investors hoped to secure subsidies for next ten years of operation, resulting in the bunching of new investment in 2012. The impacts of the PTC expiration is more pronounced when examining the monthly trend of new wind projects. As shown in Panel (b), the bunching in 2012 was mainly driven by a massive entry in December 2012, which was the exact month of expiration of the PTC. Although the PTC was renewed shortly after its expiration in 2013, the investment flow didn't recover immediately, as it takes a relatively long time to build new wind farms. After 2015, the PTC was promised for a longer window, resulting in a steady time trend of new wind projects between 2015 and 2019.

There are alternative explanations for the bunching in the online timing. First, wind farms might shorten the construction process to meet the expiration dates of the PTC. However, as shown in Panel (a) of Appendix Figure A5, the average construction time remains stable at around nine 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 to have a shorter construction period to meet the end-of-year expiration date. However, this difference is relatively small in magnitude, and thus the rushed construction is unlikely to be the main driver of 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 A6, the total years spent between entering into the interconnection queue and starting construction are also stable across 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 time or the interconnection approval time.

3.2.2 Timing Misalignment

In contrast to the bunched investment timing, 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). As shown in Appendix Figure A7, the hub heights and rotor diameters of new wind farms are getting larger, almost following linear trends after 2009. The average hub heights and rotor diameters of wind farms invested between 2014 and 2019 are 6.5% and 24.6% larger compared to those invested between 2008 and 2013.

Policy uncertainty induces a misalignment between the timing of investment and technological advancement. Panel (a) of Figure 4 presents the contrast between the bunched investment timing and improving turbine technology. I plot the number of new wind farms according to their construction start years. Moreover, I measure the technological efficiency using capacity factor at the age of one, defined as the ratio of average power output and maximum power capability.[15] Newly invested wind farms between 2008 and 2013 had an average capacity factor of 0.32, while that number between 2014 and 2018 rose to 0.41, increasing by 27.2%. While the investment bunched in earlier years, the turbine technology is continuously and quickly improving, and thus there were many wind farms equipped with less productive turbines as a result of policy uncertainty.[16]

Moreover, the average turbine prices are also decreasing over time. As shown in Panel (b), since peaking at around 1,700 dollars per kilowatt between 2008 and 2009, the average turbine

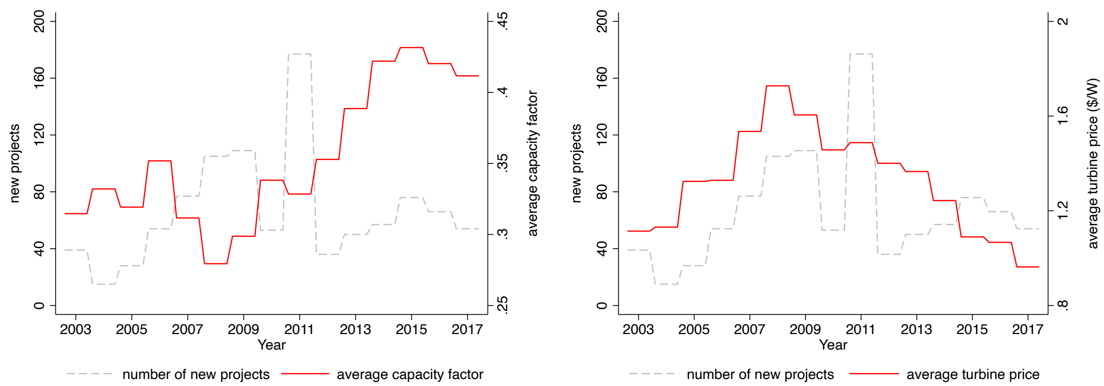
[15] According to EIA, capacity factor is defined as "the ratio of the electrical energy produced by a generating unit for the period of time considered to the electrical energy that could have been produced at continuous full-power operation during the same period." A detailed description of capacity factors can be found in Appendix Section B.

[16] 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 A8, the average wind speed for each cohort is generally stable over time. The wind resources are less volatile for later entrants, as the standard deviation of daily average wind speed is lower.

Figure 4: Investment, Turbine Technology, and Turbine Price

(a) Capacity Factor

(b) Turbine Price



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

price has been declining and fallen below 1,000 dollars per kilowatt since 2015. Therefore, early investment between 2008 and 2011 largely foregoes later cheaper turbines.

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 wind farm entry but partially missed the benefits of technological improvement and potentially led to inefficient investment timing.

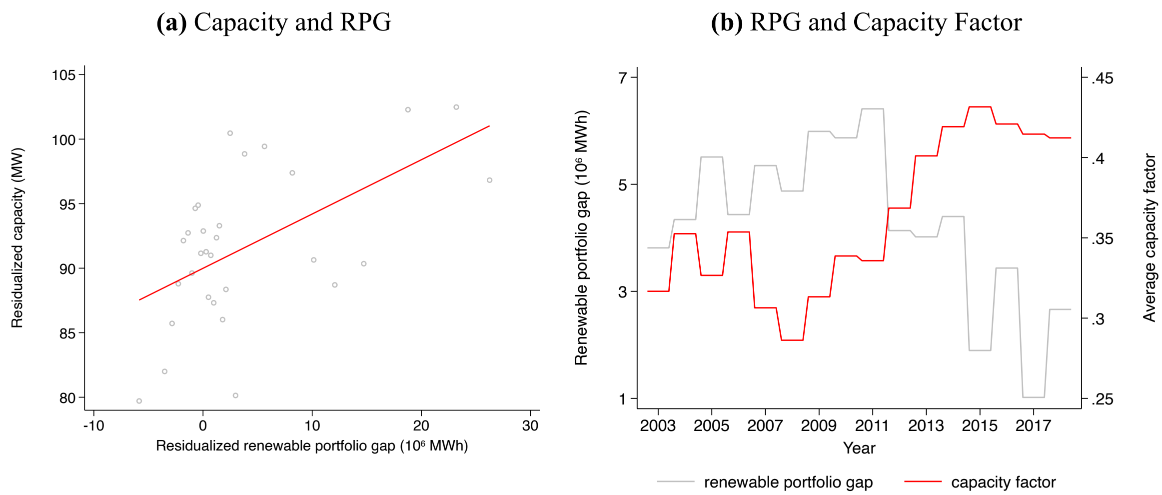
3.2.3 Matching Efficiency between Wind Farms and Utilities

Utilities are important buyers of wind power, as they procure wind capacity through long-term contracts from wind farms. One crucial incentive for them to procure wind capacity is to meet the state-level Renewable Portfolio Standards, which require utilities to have a certain share of total electricity generation from renewable energy. I construct a variable, renewable portfolio gap (RPG), which is defined as the difference between renewable energy generation and the amount stipulated by the Renewable Portfolio Standards. It measures the unfulfilled demand of each utility for renewable energy in order to meet the Renewable Portfolio Standards.[17]

I find that utilities with a larger renewable portfolio gap, and thus more unfulfilled demand, are more likely to procure a larger amount of wind capacity through long-term contracts as shown in Panel (a) of Figure 5. This relationship is robust conditioning on a set of controls including elec-

[17] The details of how this variable is constructed and estimated can be found in Section 4 and Appendix Section B.

Figure 5: Matching Efficiency between Utilities and Wind Farms



Notes: This figure provides descriptive evidence about the matching efficiency between utilities and wind farms. Panel (a) shows the binned scatter plot of wind capacity to the renewable portfolio gap (RPG) of utilities. Renewable portfolio gap measures the unfulfilled demand of each utility for renewable energy in order to meet the Renewable Portfolio Standards. I control electricity prices, turbine productivity, and time trends. Panel (b) shows the time trend of the average RPG of utilities that procured wind capacity each year, as well as the mean turbine capacity factor for each new cohort of wind farms.

tricity prices, turbine productivity, and linear yearly trends. I further plot the time trend for average renewable portfolio gaps of utilities in Panel (b). The average renewable portfolio gaps of utilities increased before 2011 as more states implemented Renewable Portfolio Standards. However, with the addition of more wind capacity, the average unfulfilled demand for utilities has decreased sharply since 2011, in contrast to the ongoing increase in turbine productivity over time. Consequently, a mass of wind farms rushed into the market due to policy uncertainty in the early years of the industry, equipped with turbines of lower productivity but matched with utilities of larger unfulfilled demand. For more recently entered wind farms, although the turbine technology has improved significantly, they could only sell capacity to utilities with smaller unfulfilled demand. This misalignment leads to a loss in matching efficiency between the utilities and wind farms.

Motivated by industry background and stylized facts, I build an empirical model of wind farm dynamic entry decision under evolving technology, demand, and policy uncertainty. I explore the key determinants of wind farm profits, and how policy beliefs held by investors evolve over time.

4 Model

I develop a dynamic model of wind farms' entry problem. Wind farm investors form beliefs about the PTC renewal probability and decide whether to enter or wait. Under the policy uncertainty, wind farm investors secure a flow of future federal subsidies if they enter before the PTC expires, but they forego better and cheaper technology in the future. Upon entry, there are two channels for wind farms to sell their capacity. The first channel is to negotiate a long-term power purchase agreement with a utility, in which they jointly decide the power purchase price, the procured capacity, and which type of subsidies to select. The second channel is to sell capacity to buyers other than utilities such as corporations, or sign financial agreements such as merchant hedge contracts.

I assume time t is discrete at a yearly level, and denote a wind farm as i and a utility as j. For the illustration of the model, its identification and estimation, and the results, I divide the model into three modules: bilateral bargaining with utilities, demand from non-utility buyers and buyer choice, and dynamic entry under policy uncertainty. I present each component in parallel.

4.1 Bilateral Bargaining with Utilities

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.[18] The total electricity generation Q_{jt} can be expressed as $Q_{jt} = Q_{jt}^w + Q_{jt}^f + Q_{jt}^{or} + Q_{jt}^o$.

By procuring wind capacity, utility j earn revenues from electricity generation and obtain renewable energy credits, and it pays procurement cost at the price in the power purchase agreement to wind farms. I define state as the geographical market m and assume both electricity market and renewable credit market to be competitive. Therefore, utility j is faced with retail electricity price r_{mt}, renewable credit price λ_{mt}, and the Renewable Portfolio Standards requirement z_{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 to fulfill the requirement; otherwise, they could sell renewable credits to earn revenues. I suppress 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 duration of T years.[19] The profit function for utility j from this contract is

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

$$h_{jt} = \delta \times (Q_{jt}^{gap} - \alpha_{it} k_{ij}^w) \times Q_{jt}^{gap}, \quad Q_{jt}^{gap} = z_s(Q_{jt}^f + Q_{jt}^{or} + Q_{jt}^o) - Q_{jt}^{or}.$$

Profit flow starts from year $t+1$ as it takes one year on average between the finalization of investment decision and the beginning of production for wind farms. I assume the production

[18] I endogenize procured wind capacity k_{jt}^w in the model but leave capacity of the other three types of fuel sources exogenous, since the output share of wind energy is less than 9% at the end of the sample window.

[19] t denotes the year when negotiation happens, which I assume to be determined in the dynamic entry decision. Consequently, for each pair of bargaining, t is predetermined.

function for wind farm i as $Q^w_{ijt} = \alpha_{it} k^w_{ij}$, where α_{it} is the annualized capacity factor. The linear functional form fits data well as shown in Appendix Figure A9. I define c_{js} as the annual cost function for using energy sources other than wind.

h_{jt} represents the hassle cost which captures frictions in the renewable credit market as well as dynamic credit banking incentives that I abstract from. This hassle cost is a quadratic function of Q^{gap}_{jt}, which measures the demand for extra renewable credits and is calculated as the gap between renewable energy generation required by the state and existing renewable energy generation. The quadratic functional form fits the data pattern that utilities further away from the state-level goal tend to procure more wind capacity as illustrated in Panel (a) of Figure 5. Moreover, the hassle cost is attenuated by procuring wind capacity k^w_{ij}, and the marginal cost saving is larger if the utility is further away from the state-level requirement.

Profit function for wind farms The profit that wind farm i receives equals the sum of total revenues from power purchase agreements and total subsidies from the government, minus turbine costs. The total subsidies depend on the chosen subsidy types. If the PTC is chosen, the wind farm receives tax credit for the first ten years of its production. If the Section 1603 Grant is selected, which was available between 2009 and 2012, 30% of total upfront investment cost would be subsidized in the form of cash grants.

Wind farms might value both tax credits and grants less than their face values as discussed by Johnston (2019). On the one hand, wind farms usually partner with large investors who finance part of the investment cost in exchange for tax credits. This partnership process involves transaction cost, asymmetric information problem, and market power issues, which discount values of tax credits. On the other hand, wind farms also discount values of the grant because it directly subsidizes on investment and reduces tax deduction for investment-related expenses that wind farms could have earned. The overall schedule of total subsidy TS_{ijt} can be defined as follows.

$$TS_{ijt}(k^w_{ij}, D_{ij}) = S_{it}(D_{ij}) \times k^w_{ij}.$$

$$S_{it}(D_{ij}) = D_{ij} \times \tau \times d_t \times (\sum_{s=t+1}^{t+10} E_t \beta^{s-t} \alpha_{is}) + (1 - D_{ij}) \times (30\% - \tau C_1) \times \eta.$$

D_{ij} denotes the subsidy type choice, which equals 1 for the PTC and 0 for the Section 1603 Grant, and $S_{it}(D_{ij})$ represents the subsidy per unit of capacity. Under the PTC, the amount of tax credit per unit of wind energy generation is denoted by d_t, but the value of one tax credit is discount at $\tau < 1$. Under the Section 1603 Grant, the investment subsidy a linear function of total capacity and η denotes the unit investment cost. C_1 is the missed tax deduction calculated using marginal tax rates, the discount factor, as well as the depreciation deduction rule (Johnston, 2019).

The profit of wind farm i, given power purchase agreement price p_{ij}, total subsidy schedule

TS_{ijt}, and turbine cost per capacity c_{it}, can be expressed as the follows.

$$\pi_t^W(p_{ij}, k_{ij}^w, D_{ij}) = \sum_{s=t+1}^{t+T} E_t \beta^{s-t} p_{ij} \alpha_{is} k_{ij}^w + TS_{ijt}(k_{ij}^w, D_{ij}) - c_{it} k_{ij}^w + \sigma \epsilon_{it}^D. \tag{2}$$

$$c_{it} = \boldsymbol{\gamma_1 X_{it}} + \frac{k_{ij}^w}{2\gamma_2} + \xi_{it}.$$

I allow for the turbine cost per unit of capacity c_{it} to depend on a set of shifters $\boldsymbol{X_{it}}$ including average turbine prices and turbine brand dummies, and ξ_{it} denotes unobserved cost shocks. Moreover, I allow flexible convexity γ_2 of total turbine cost with respect to the capacity. ϵ_{it}^D follows the extreme value type-I distribution and captures random shocks specific to either subsidy type, such as tax liability and credit constraints of investors. σ_1 is the standard deviation of the random shock.

Bilateral bargaining Wind farm i and utility j participate in the bilateral bargaining process to negotiate over the procured capacity k_{ij}^w, the contracted price p_{ij}, as well as which subsidy type to take D_{ij} simultaneously. The optimization problem can be formulated as follows.

$$\max_{k_{ij}^w, p_{ij}, D_{ij}} [\pi_t^U(p_{ij}, k_{ij}^w) - \pi_t^U(p_{ij} = \infty)]^\rho \times [\pi_t^W(p_{ij}, k_{ij}^w, D_{ij}) - \pi_t^W(p_{ij} = \infty)]^{1-\rho}.$$

ρ denotes the bargaining weight of utilities. $\pi_t^U(p_{ij} = \infty)$ represents the profits that utilities would obtain with their current energy portfolios if the negotiation fails, and $\pi_t^W(p_{ij} = \infty)$ represents the payoffs that wind farms would earn from waiting for another year to enter. Under the assumption of Nash bargaining, the optimal capacity k_{ij}^w and the policy choice D_{ij} maximize the joint surplus, and the optimal price p_{ij} divides the joint surplus between two parties (Chipty and Snyder, 1999).

The optimal capacity follows the condition in equation (3). I use Θ_{jt} to represent the discounted sum of the effective market price, combining the retail electricity price and renewable credit price. Moreover, I denote the utility's total renewable portfolio gap as Φ_{jt}. If wind energy is more valuable due to either higher electricity prices or higher renewable credit prices, or if the utilities have relatively lower shares of renewable capacity compared with the state-level Renewable Portfolio Standards requirement, utilities are willing to pay more for additional wind capacity. The optimal wind capacity equalizes the marginal benefit from the willingness to pay for utilities and the marginal cost of wind capacity net of the subsidy. $\tilde{\xi}_{ijt}$ is a random shock that subsumes the measurement errors in Θ_{jt} and Φ_{jt}, as well as the unobserved turbine cost shifters ξ_{it}.

$$\underbrace{(\Theta_{jt} + \delta\Phi_{jt})}_{\text{willingness to pay}} \alpha_i = \underbrace{\boldsymbol{\gamma_1 X_{it}} + \frac{k_{ij}^{w*}}{\gamma_2}}_{\text{turbine cost}} - \underbrace{S_{it}(D_{ij})}_{\text{subsidy}} + \tilde{\xi}_{ijt}. \tag{3}$$

$$\Theta_{jt} = \sum_{s=t+1}^{t+T} E_t \beta^{s-t}[r_s + \lambda_s(1-z_s)]. \quad \Phi_{jt} = \sum_{s=t+1}^{t+T} E_t \beta^{s-t} Q_{js}^{gap}. \tag{4}$$

Moreover, the optimal price follows the condition in equation (5). If the utility has a larger bargaining power ρ, the negotiated price will be low enough to only cover turbine costs net government subsidies. 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 $\pi_t^W(p_{ij} = \infty)$ gives wind farms better bargaining positions and increases the negotiated price.

$$\frac{\beta(1-\beta^T)}{1-\beta} p_{ij}^* = (1-\rho)(\underbrace{\Theta_{jt} + \delta\Phi_{jt}}_{\text{willingness to pay}}) + \rho[\underbrace{\frac{c_{it}}{\alpha_i}}_{\text{turbine cost}} - \underbrace{\frac{S_{it}(D_{ij})}{\alpha_i}}_{\text{subsidy}} + \underbrace{\frac{\pi_t^W(p_{ij} = \infty)}{\alpha_i k_{ij}^{w*}}}_{\text{bargaining leverage}}]. \tag{5}$$

Finally, I could derive the optimal choice probability of the subsidy type $P_{ij}^{\text{subsidy}}(D_{ij}^* = 1)$ as follows. I abbreviate profit functions of utilities and wind farms as $\pi_{ij}^U(D_{ij})$ and $\pi_{ij}^W(D_{ij})$.

$$P_{ij}^{\text{subsidy}}(D_{ij}^* = 1) = \frac{\exp[\frac{\pi_{ij}^U(1) + \pi_{ij}^W(1)}{\sigma_1}]}{\sum_{D_{ij}=\{0,1\}} \exp[\frac{\pi_{ij}^U(D_{ij}) + \pi_{ij}^W(D_{ij})}{\sigma_1}]}. \tag{6}$$

4.2 Demand of Non-Utility Buyers and Buyer Choice

Demand of non-utility buyers An alternative channel for selling wind capacity is to sell to non-utility buyers such as corporations or to sign merchant hedge 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. I assume non-utility buyers demand capacity k_i^{nu} at wind energy price p_i^{nu} from wind farm i. The demand function is

$$k_i^{nu} = -\zeta_1 p_i^{nu} + \zeta_2 \alpha_i + \boldsymbol{\zeta_3 X_i} + \boldsymbol{\zeta_4 Z_i^{nu}} + \upsilon_i. \tag{7}$$

Similar to equation (3), $\boldsymbol{X_i}$ includes average turbine prices and turbine brand dummies. $\boldsymbol{Z_i^{nu}}$ denotes a set of demand shifters including dummies for balancing authorities and different contract types (long-term contracts with corporate buyers, hedge contracts, or merchant contracts). υ_i represents unobserved demand shifters. The profit function of wind farms that sell capacity to non-utility buyers is denoted as $\pi_t^{nu}(k_i^{nu}, p_i^{nu})$.

Buyer type choice and utility matching Wind farms choose which channel to sell wind capacity, and if they decide to sell capacity via utility power purchase agreements, which utility to be matched with. I model the choice of whether to sell capacity to non-utility buyers as a random variable following a binary distribution with mean μ_m that varies across markets. If the realized value of this random variable equals zero, which indicates that wind farm i chooses to negotiate a utility power purchase agreement, it will choose which utility to be matched with. I define the potential buyers $\mathcal{J}_{it}$ as those utilities that had signed agreements before 2019 and are within 400 miles from the focal wind farm i. Those potential buyers differ in the renewable portfolio gaps and the distances from the wind farm, and some of them might even be located in a different state from the focal wind farm. The choice of the matched utility is formulated as follows.

$$\max_{j \in \mathcal{J}_{it}} \pi_t^W(p_{ij}^*, k_{ij}^{w*}, D_{ij}^*) - \underbrace{(\gamma_3 \mathbb{1}\{m_i \neq m_j\} + \gamma_4 Dist_{ij})}_{\text{matching cost}} + \sigma_2 \epsilon_{ij}. \tag{8}$$

I use $\pi_t^W(p_{ij}^*, k_{ij}^{w*}, D_{ij}^*)$ to denote the profit for wind farm i with each potential buyer j via bilateral bargaining. Moreover, I use m_i and m_j to represent the state of wind farm i and utility j respectively, and $Dist_{ij}$ the distance between them. I assume the matching cost depends on whether wind farm i and utility j are in the same state and how far away they are geographically. ϵ_{ij} denotes the i.i.d. random shock following the extreme value type I distribution. The standard deviation of the error term is σ_2. Consequently, the optimal probability of choosing j^* can be defined as follows.

$$P_{it}^{\text{buyer}}(j = j^*) = (1 - \mu_m) \times \frac{\exp[\frac{\pi_t^W(p_{ij^*}^*, k_{ij^*}^{w*}, D_{ij^*}^*) - \gamma_3 \mathbb{1}\{m_i \neq m_{j^*}\} - \gamma_4 Dist_{ij^*}}{\sigma_2}]}{\sum_{j \in \mathcal{J}_{it}} \exp[\frac{\pi_t^W(p_{ij}^*, k_{ij}^{w*}, D_{ij}^*) - \gamma_3 \mathbb{1}\{m_i \neq m_j\} - \gamma_4 Dist_{ij}}{\sigma_2}]}. \tag{9}$$

The *ex-ante* profit function π_{it} of wind farm i, if it enters the market in year t, would be defined as follows, where $\varkappa$ represents Euler's constant.

$$\begin{aligned} \pi_{it} = & \mu_m \times \pi_t^{nu}(k_i^{nu}, p_i^{nu}) + (1 - \mu_m) \times \sigma_2 \times \\ & \{\log[\sum_{j \in \mathcal{J}_{it}} \exp(\frac{\pi_t^W(p_{ij}^*, k_{ij}^{w*}, D_{ij}^*) - \gamma_3 \mathbb{1}\{m_i \neq m_j\} - \gamma_4 Dist_{ij}}{\sigma_2})] + \varkappa\}. \end{aligned} \tag{10}$$

4.3 Dynamic Entry under Policy Uncertainty

Potential entrant i decides whether to enter in year t or wait until later. If it decides to enter, the expected total profit will be the gross profit π_{it} in equation (10) from the static model, net the entry cost ψ_{it}. I assume that

$$\psi_{it} = \kappa W_{it} + \nu_{it}, \text{ where } \nu_{it} \sim F(\nu) = 1 - e^{-\frac{\nu_{it}}{\phi}}.$$

W_{jt} denotes the observed entry cost shifter. ν_{it} is the i.i.d. entry cost shock, which follows an exponential distribution with a mean parameter ϕ. I define the net profit for wind farm i if it decides to enter in year t as $\Pi(\boldsymbol{s}_{it}, \omega_t) = \pi_{it} - \kappa W_{it}$.

Potential entrant i conditions on a vector of state variables $\boldsymbol{s}_{it}$ for the dynamic decision, including shifters for buyers' willingness to pay, turbine technology, turbine cost, subsidy level, and entry cost shifter W_{jt}. Another important state variable besides $\boldsymbol{s}_{it}$ is the policy status ω_t. ω_t is a dummy variable that equals one if the federal subsidy is present in year t, and zero the federal subsidy is absent in year t. Its value is always one *ex-post* as the PTC was always extended. Whether the subsidy is present or not shifts all the contract terms as well as the profit of wind farms π_{it}.

The dynamic optimization problem is as follows.

$$V_t(\boldsymbol{s}_{it}, \omega_t, \nu_{it}) = \max\{\Pi(\boldsymbol{s}_{it}, \omega_t) - \nu_{it}, \beta E_t[V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1}, \nu_{it+1})|\boldsymbol{s}_{it}, \omega_t]\}. \tag{11}$$

$V_t(\boldsymbol{s}_{it}, \omega_t, \nu_{it})$ is the value function of wind farm i in year t conditional on state variables $\boldsymbol{s}_{it}$, policy status ω_t, as well as the i.i.d. entry cost shock ν_{it}. $E_t[V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1}, \nu_{it+1})|\boldsymbol{s}_{it}, \omega_t]$ is the option value of waiting in year t. If the net profit of entry in year t, $\Pi(\boldsymbol{s}_{it}, \omega_t) - \nu_{it}$, exceeds the discounted option value of waiting $\beta E_t[V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1}, \nu_{it+1})|\boldsymbol{s}_{it}, \omega_t]$, potential entrant i will choose to enter the market in year t. Otherwise, potential entrant i will wait for one more year and face the same decision again next year.

The option value of waiting $E_t[V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1}, \nu_{it+1})|\boldsymbol{s}_{it}, \omega_t]$ depends on the distribution of unobserved entry cost shock $F(\nu_{it})$ and the transition dynamics of state variables $G(\boldsymbol{s}_{it+1}|\boldsymbol{s}_{it})$. Moreover, it depends crucially on an *ex-ante* belief for the policy evolution due to the policy uncertainty, denoted by $b_t(\omega_{t+1}|\omega_t)$. I allow the policy to be extended only year by year, and $b_t(\omega_{t+1}|\omega_t)$ can vary by time to capture the fact that wind farm investors form different policy beliefs depending on the actions taken by the government as well as other political and economic shocks.[20] $b_t(\omega_{t+1}|\omega_t)$ is the source of the non-stationarity of this dynamic problem. Therefore, the option value of waiting can be expressed as follows.

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

$$\begin{aligned} E_t[V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1}, \nu_{it+1})|\omega_t] = {} & V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1} = 1, \nu_{it+1}) \times b_t(\omega_{t+1} = 1|\omega_t) \\ & + V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1} = 0, \nu_{it+1}) \times b_t(\omega_{t+1} = 0|\omega_t). \end{aligned}$$

I allow flexible beliefs about future policy evolution, but solving an infinite-horizon dynamic problem requires regularities on $\{b_t(\omega_{t+s}|\omega_t)\}_{s>1}^{\infty}$. Otherwise, if arbitrary policy belief is permitted, including examples such that perceived future subsidies switching between on and off, infinite streams of policy beliefs could rationalize one single investment decision. Therefore, I impose two assumptions to discipline policy belief and make the problem feasible for estimation.

[20] In reality, the PTC could be announced with a window longer than one year, such as between 2010 and 2012. However, considering different lengths of policy windows introduces another layer of uncertainty and further complicates the model. Therefore, I allow the policy to be extended only year by year for simplicity.

Assumption 1 (absorbing state) $b(\omega_{t+1} = 0|\omega_t = 0) = 1$.

Assumption 1 indicates that the policy is perceived as terminated once paused. If the policy is absent in year t, wind farm investors will hold the belief that the policy is terminated forever. This assumption is consistent with the reality that the Section 1603 Grant was discontinued after 2012 and hasn't been rebooted ever since. Consequently, the continuation values when $\omega_t = 0$ can be simplified as $E_t[V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1}, \nu_{it+1})|\omega_t = 0] = V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1} = 0, \nu_{it+1})$.

As $\omega_t = 0$ is an absorbing state, the continuation value doesn't depend on time-varying policy beliefs and can be simplified as a stationary function $V^0(\boldsymbol{s}_{it}, \nu_{it})$. I further denote $\Pi(\boldsymbol{s}_{it}, \omega_t = 0)$ as $\Pi^0(\boldsymbol{s}_{it})$, which leads to the following equation.

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

Assumption 2 (simple forecast) $b_t(\omega_{t+s+1} = 1|\omega_{t+s} = 1) = b_t(\omega_{t+1} = 1|\omega_t = 1) = b_t, s \geqslant 0$.

Assumption 2 indicates that the perceived likelihood of a one-year policy extension will be perceived to apply to future years, which precludes the cases that wind investors have more information about future policy extensions beyond the next year. However, I allow the expectation to change across years and I allow the investors to revise their beliefs according to new information. Consequently, $b_t(\omega_{t+s+1} = 1|\omega_{t+s} = 1)$ and $b_{t+s}(\omega_{t+s+1} = 1|\omega_{t+s} = 1)$ could be different to reflect unanticipated shock realized in year $t + s$. $b_t(\omega_{t+1}|\omega_t)$ is henceforth an index that summarizes the policy uncertainty faced by wind farm investors in year t. Instead of imposing Assumption 2, the belief evolution could be parameterized as a first-order Markov process, but a relatively short time series prohibits such endeavor. An alternative policy belief model will use a mixture distribution as described in the Appendix Section C. However, without underlying time-varying beliefs, this model cannot rationalize the jumping bunching patterns in the investment time trend; with underlying time-varying beliefs, this alternative model is essentially isomorphic to the baseline model.

I denote $\Pi(\boldsymbol{s}_{it}, \omega_t = 1)$ as $\Pi^1(\boldsymbol{s}_{it})$ and $V_t(\boldsymbol{s}_{it}, \omega_t = 1, \nu_{it})$ as $V^1(\boldsymbol{s}_{it}, \nu_{it}; b_t)$. Under Assumption 2, $V^1(\boldsymbol{s}_{it}, \nu_{it}; b_t)$ solves the following equation.

$$\begin{aligned} V^1(\boldsymbol{s}_{it}, \nu_{it}; b_t) = \max\{\Pi^1(\boldsymbol{s}_{it}) - \nu_{it}, \beta\{E_t[V^1(\boldsymbol{s}_{it+1}, \nu_{it+1}; b_t)|\boldsymbol{s}_{it}] \times b_t \\ + E[V^0(\boldsymbol{s}_{it+1}, \nu_{it+1})|\boldsymbol{s}_{it}] \times (1 - b_t)\}\}. \end{aligned} \tag{13}$$

Therefore, the dynamic model could be expressed as follows where I rewrite $V_t(\boldsymbol{s}_{it}, \omega_t, \nu_{it})$ as $V(\boldsymbol{s}_{it}, \omega_t, \nu_{it}; b_t)$ to emphasize sources of non-stationarity.

$$\begin{aligned} V(\boldsymbol{s}_{it}, \omega_t, \nu_{it}; b_t) = \max\{\Pi(\boldsymbol{s}_{it}, \omega_t) - \nu_{it}, \oint_{\boldsymbol{s}_{it+1}, \nu_{it+1}} \beta E_t[V^1(\boldsymbol{s}_{it+1}, \nu_{it+1}; b_t) \times b_t \\ + V^0(\boldsymbol{s}_{it+1}, \nu_{it+1}) \times (1 - b_t)] dG(\boldsymbol{s}_{it+1}|\boldsymbol{s}_{it}) dF(\nu_{it+1})\}. \end{aligned} \tag{14}$$

I denote the entry decision as a dummy variable E_{it} and the entry probability is $P_t^E(\boldsymbol{s}_{it}, \omega_t)$ as below. Since the PTC shifts up firm values such that $V^1(\boldsymbol{s}_{it}, \nu_{it}; b_t) > V^0(\boldsymbol{s}_{it}, \nu_{it})$, if potential entrants believe there is a low possibility of policy renewal, 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 κ and ϕ, and policy belief parameters b_t, are key primitives in the dynamic model.

$$P_t^E(\boldsymbol{s}_{it}, \omega_t) = Pr(E_{it} = 1) = 1 - exp(-\frac{\Pi(\boldsymbol{s}_{it}, \omega_{it}) - \beta E_t[V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1}, \nu_{it+1})|\boldsymbol{s}_{it}, \omega_t]}{\phi}).$$

4.4 Model Discussion

There are several caveats to the model. First, I only endogenize the capacity of procured wind energy but abstract away responses of other fuel sources. The wind penetration rate was low during my sample period in most states. Since the main purpose of the static model is to construct a measure of profit if wind farms enter the market and capture the interactions among technological improvement, government subsidies, and buyer characteristics, I assume the responses of other fuel sources as exogenous to keep the model tractable.

Second, I model the matching between wind farms and utilities as a discrete choice of buyers for wind farms, but abstract away utilities' decisions. I assume utilities are myopic and their choices of when to procure wind capacity are exogenous. Since wind turbine productivity and unfulfilled demand of utilities are complements in generating total profit, a one-sided discrete choice based on profits from each potential pair of matching is sufficient to capture these complementarities.

Third, I assume that turbine technology is exogenous to investment in the U.S. wind industry. The cumulative wind power capacity in the U.S. represents 16% of the global wind power fleet, and there is no observed trend break in turbine technological advancements following the surge of U.S. investments. I conduct a robustness check in Section 7.1 to quantify potential bias from ignoring the learning-by-doing effects, following Covert and Sweeney (2022).

5 Identification and Estimation

I discuss how data variations identify the model and how estimation procedures recover model parameters in this section. I start with key primitives including the turbine cost function, utilities' bargaining power parameter, the demand function for non-utility buyers, as well as the matching cost in utility choices. 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 Bilateral Bargaining with Utilities

There are three key equations from the bilateral bargaining problem: the optimal capacity function (3), the optimal pricing function (5), and the optimal subsidy type choice (6). In the optimal capacity function, $\tilde{\xi}_{ijt}$ mainly captures measurement errors in the willingness to pay, as well as unobserved turbine cost shifters, both of which are assumed exogenous to the observables. I rewrite equation (3) as follows for estimation.[21]

$$\begin{aligned} k_{ij}^{w*} =& \beta_1(\Theta_{jt} + \delta\Phi_{jt}) + \beta_2(\Theta_{jt} + \delta\Phi_{jt}) \times \alpha_i + \gamma_2 S_{it} + \\ & (\beta_3 + \beta_{31}\text{GE}_i + \beta_{32}\text{Siemens}_i + \beta_{33}\text{Others}_i) \times \text{TP}_t^{\text{Vestas}} + \boldsymbol{\beta_4 Z_{jt}^U} + \xi_{1,ijt}. \end{aligned} \tag{15}$$

The cost convexity γ_2 is identified by the effect of the unit subsidy on the negotiated capacity. If total turbine cost is steeper in capacity, utilities and wind farms will negotiate a smaller wind farm size in response to a subsidy increase. Moreover, the hassle cost coefficient δ is identified from the relative importance of the renewable portfolio gap Φ_{jt} to the effective market price Θ_{jt}. I include the average turbine price of Vestas, $\text{TP}_t^{\text{Vestas}}$, as a main shifter of turbine cost, and allow its effect to vary across turbine brands: GE, Vestas, Siemens Gamesa, and others. I further control a set of demand shifters $\boldsymbol{Z_{jt}^U}$ to identify the cost parameters, including the dummies of the states of the utility, utility types, as well as contract duration intervals.[22]

In the optimal pricing function, I assume $\pi_t^W(p_{ij} = \infty)$ as the payoff that wind farms would have earned from waiting for another year to enter and selling capacity to a utility from the rest of the potential buyer pool. I find that conditional on all other observables in equation (5), the residual variation in negotiated prices is positively correlated with the average effective market prices of the potential buyer pool $\bar{\Theta}_{it}$ and their average renewable energy gap $\bar{\Phi}_{it}$, since a higher average willingness to pay from nearby alternative utilities gives a better bargaining position for the wind farm (Panels (a) and (b) of Appendix Figure A10). Moreover, the average p_{ij}^* displays a large variation across time (Panel (c)). Motivated by these data facts, I rewrite equation (5) and express $\pi_t^W(p_{ij} = \infty)$ as a flexible control function $f(\cdot)$ with quadratic bases and year fixed effects.

$$\frac{\beta(1-\beta^T)}{1-\beta} p_{ij}^* = (1-\rho)(\Theta_{jt} + \delta\Phi_{jt}) + \rho\{\frac{\hat{c}_{it}}{\alpha_i} - \frac{S_{it}}{\alpha_i} + \frac{f[\bar{\Phi}_{it}, \bar{\Theta}_{it}, \alpha_i, \text{TP}_t^{\text{Vestas}}, \mathbb{1}(t)]}{\alpha_i k_{ij}^{w*}}\} + \xi_{2,ijt}.$$

The key parameter in the optimal pricing function (5) is the bargaining parameter ρ. The identification of ρ comes from the relative pass-through ratios of utility willingness to pay $(\Theta_{jt} + \delta\Phi_{jt})$ and net turbine cost per unit $(\frac{\hat{c}_{it} - S_{it}}{\alpha_i})$ on the negotiated price. If the utility has a larger bargain-

[21] Compared to equation (3), I include both utilities' willingness to pay $(\Theta_{jt} + \delta\Phi_{jt})$ and its interaction with turbine capacity factor in the estimation equation to deal with the colinearity issue, as the government subsidy per unit of capacity S_{it} is also a function of turbine capacity factor α_i.

[22] The utility types include cooperative, investor-owned, or others. The term length intervals include three groups: less than 15 years, 15-20 years, or more than 20 years.

ing power ρ, the negotiated price tends to be low and co-moves closer to the net turbine cost after flexibly controlling for bargaining leverages.

The subsidy choice function (6) also incorporates the optimal capacity function (3), which in turn depends on the subsidy choice through S_{it}. However, as discussed in detail in Appendix Section B, while Section 1603 Awardees on average were better off by selecting the grant, many wind farms that opted into the PTC could have earned more if they had adopted the grant. This data pattern suggests a challenge in explaining the policy choice only through the subsidy payoffs. The fact that wind farms selected the PTC despite the availability of a more profitable alternative might be due to unobserved benefits to tax equity providers or behavioral inertia to stick to the default option. Therefore, I assume there is a probability ς that wind farm investors would take the default option regardless of payoffs, while with a probability of $1-\varsigma$ wind farm investors would make a discrete choice of the subsidy according to the total surplus and the i.i.d. preference shock.

As I assume the choice-specific random shock to follow the extreme value type-I distribution, the log-likelihood function can be expressed as below.[23]

$$llf_{1,ij} = \sum_{D_{ij}=\{0,1\}} D_{ij} \log\{\varsigma \times D_{ij} + (1-\varsigma) \times \frac{\exp[\frac{\pi^U_{ij}(D_{ij})+\pi^W_{ij}(D_{ij})}{\sigma_1}]}{\sum\limits_{D_{ij}=\{0,1\}} exp[\frac{\pi^U_{ij}(D_{ij})+\pi^W_{ij}(D_{ij})}{\sigma_1}]}\}.$$

The key parameter σ_1 is identified as the magnitude of the residual variation in the subsidy choice that cannot be explained by the total surplus gap between choosing Section 1603 Grant and the PTC, while ς is identified by the share of wind projects that opted into the PTC when the grant was more profitable.[24]

I jointly estimate the optimal capacity function (3), the optimal pricing function (5), and the optimal subsidy type choice (6) by optimizing the problem: min $E(\xi^2_{1,ijt}) + E(\xi^2_{2,ijt}) - E(llf_{1,ij})$.

5.2 Demand of Non-Utility Buyers and Buyer Choice

Demand for non-utility buyers I estimate the linear demand function for non-utility buyers (7) with instruments. As υ_i captures unobserved demand shifters, it's correlated with price p^{nu}_i, which introduces bias to price coefficient ζ_1. I use three sets of instruments to tackle the identification challenge. The first instrument is the renewable credit price in each state. As renewable credit is a product of the Renewable Portfolio Standards which targets utilities, its price is less likely to

[23] I use the sample between 2008 and 2012 to form the likelihood function as some wind projects that selected the Section 1603 Grant started construction in 2008.

[24] When σ_1 is large, the choice predicted by the logit model is close to a random choice guided by a coin flip, and ς is identified by how much the choice probability of the PTC is above 50%. When σ_1 is small, the choice predicted by the logit model is close to the choice by simply picking a more profitable option, and ς is identified by how much the choice probability is above the share predicted by the profit gap alone.

be correlated with demand shifters for non-utility buyers who constitute a smaller segment of the total demand. The second 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 third set of instruments are dummy variables indicating whether a state implemented property tax incentives, sales tax incentives, or other wind power recruitment policies. These policies are implemented by the state government to boost renewable energy. As non-utility buyers demand no more than 30% of total wind capacity, these supply-side policies are unlikely to be correlated with their unobserved demand shocks.

Buyer type choice and utility matching I back out matching cost coefficients γ_3 and γ_4, the scale parameter σ_2, and the mean parameters of the buyer type choice μ_m from the buyer choice problem (9). I allow μ_m to vary across Texas, Illinois, New York, and the rest of the states, as the former three states are major markets where non-utility contracts prevail. I construct the profit from matching with each potential buyer from the buyer pool $\mathcal{J}_{it}$ using estimates from the bilateral bargaining model. I formulate the log-likelihood function as below, where I denote the choice $\mathbb{1}(j^* = 0)$ as selling capacity to non-utility buyers. The standard deviation of the error term σ_2 is identified as the magnitude of the residual variation in the utility choice that cannot be explained by the profit gap between choosing the matched utility j^* and an alternative utility. The matching cost coefficients γ_3 and γ_4 are identified by the gradients of matching likelihood with respect to the matching cost shifters. The mean parameters of the buyer type choice μ_m are pinned down by the frequency of non-utility contracts observed across markets.

$$\begin{aligned} llf_2 = \sum_{it} \{ \sum_{l \in \mathcal{J}_{it}} & \mathbb{1}(j^* = 0) \log(\mu_m) + \mathbb{1}(j^* = l) \log\{(1 - \mu_m) \times \\ & \frac{\exp\{[\pi^W(p^*_{il}, k^{w*}_{il}, \mathcal{D}^*_{il}) - \gamma_3 \mathbb{1}\{m_i \neq m_l\} - \gamma_4 Dist_{il}]/\sigma_2\}}{\sum\limits_{j \in \mathcal{J}_{it}} \exp\{[\pi^W(p^*_{ij}, k^{w*}_{ij}, \mathcal{D}^*_{ij}) - \gamma_3 \mathbb{1}\{m_i \neq m_j\} - \gamma_4 Dist_{ij}]/\sigma_2\}} \} \}. \end{aligned} \tag{16}$$

5.3 Dynamic Entry under Policy Uncertainty

The primary identification challenge in the dynamic component of the model is to separate the parameters of the entry cost distribution (κ and ϕ) from the policy belief parameters b_t. The main identification strategy is to exploit the temporal structure of the policy. I leverage the fact that the Consolidated Appropriations Act was announced to cover from 2015 to 2019. Moreover, the government also included a two-year safe harbor window in 2013 and extended that to four years in 2016, which effectively softened the requirements from subsidy expiration dates and reduced the incentives for wind farms to rush into the market. The stable investment trend between 2013 and 2018 as shown in Figure 3, contrasts the jumping trend in earlier years, providing further support that the policy environment was largely stable in this period. Therefore, I assume that there is no policy uncertainty in the later period of the sample, and the entry rates pin down the parameters of entry cost distribution κ and ϕ given $b_t = 1$. Additionally, the bunching of investment in those deadline years conditional on the transition process of state variables and entry costs would help pin down belief parameters b_t.

Following the identification strategy, I take two steps to estimate the dynamic model. First, I focus on policy windows when there is no policy uncertainty, and estimate entry cost parameters by matching model-predicted entry rates with the data. Second, I use the estimated entry cost parameters to solve the dynamic programming problem and focus on policy windows with expiration to estimate policy belief parameters. Since policy uncertainty introduced non-stationarity to the dynamic problem, I solve the dynamic model year by year.

Definition of potential entrants The identities of potential entrants are observed as wind farm investors need to enter the interconnection queue, get approved by several studies, and sign interconnection agreements before they are eligible to enter the market.[25] 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 decisions.[26]

Equilibrium, state space, and transition dynamics I adopt an equilibrium concept similar to the moment-based Markov Equilibrium (Ifrach and Weintraub, 2017) and assume that each wind farm keeps track of its own states and some moments of the industry states. This equilibrium concept is widely used in recent empirical papers such as Barwick et al. (2021), Jeon (2022), and Vreugdenhil (2023). Note that the equilibrium concept I adopt is different from the Approximate Belief Oligopoly Equilibrium (ABOE) introduced in Gowrisankaran et al. (2023), as I assume that each wind farm is atomic and the impact of its action on the aggregate state variable is negligible. I define a set of state variables, including the annual average productivity of wind turbines $\bar{\alpha}_t$, the average turbine prices $\text{TP}_t^{\text{Vestas}}$, the effective market price Θ_{it}, and the subsidy levels d_t.[27] [28] The

[25] 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 the optimal stopping problem.

[26] 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 in 2010, according to the PJM website. Anecdotes suggest that a typical project completed in 2008 spent fewer than two years in the queue for interconnection approval compared to three years in 2015, according to the news from Utility Dive. As I explained in detail in Online Data Appendix, although the backlog and congestion issues are salient in recent years, two-year waiting time might be a reasonable assumption because it is roughly a median in my sample period (2003-2018). Assuming increasing waiting time across years is challenging as it introduces large jumps in the number of potential entrants year by year. Johnston et al. (2023) provide a thorough overview of the interconnection queue and the congestion issues in PJM.

[27] I use the annual average productivity of wind turbines $\bar{\alpha}_t$ instead of realized productivity for each individual wind farm to ease concerns of the selection issue.

[28] I use the effective market price for the state where the wind farm i is located. Given that most of the utilities

transition processes of these four time-varying state variables are exogenous in the model, and I recover $G(\boldsymbol{s}_{it+1}|\boldsymbol{s}_{it})$ from the data with AR(1) models following Barwick et al. (2021). I further construct a linear combination $\boldsymbol{\beta_4 Z_{jt}^U}$ as in equation (15) to control for time-invariant variations in the utility demand. I project p_i^{nu} on $\boldsymbol{Z_i^{nu}}$ as in equation (7) to construct another time-invariant state variable for the demand of non-utility buyers.

Moreover, I construct a proxy to measure the changing renewable portfolio gap of utilities in the buyer pool. Each wind farm has 18 buyers on average in its choice set, and keeping track of the renewable portfolio gap for each individual utility is computationally challenging. Motivated by Gowrisankaran and Rysman (2012) and Hendel and Nevo (2013), I use inclusive values for wind farms that can be attributed to the changing renewable portfolio gaps for buyers. I construct inclusive values according to equation (10) with the realized renewable portfolio gap for each utility, simulate inclusive values again but set all renewable portfolio gaps to be zeros, and then take the difference between these two. The inclusive value that can be attributed to the changing buyer characteristics is defined as $\text{IV}_{it}(\boldsymbol{\Phi}_{it}) = \pi_{it}(\boldsymbol{\Phi}_{it}) - \pi_{it}(\boldsymbol{\Phi}_{it} = \boldsymbol{0}), \boldsymbol{\Phi}_{it} = \{\Phi_{jt}\}_{j \in \mathcal{J}_{it}}$.

The transition of $\text{IV}_{it}(\boldsymbol{\Phi}_{it})$ is endogenous in the model because the renewable portfolio gaps of utilities shrink after they procure additional new wind capacity. Therefore, more entries of wind farms today will reduce future values of $\text{IV}_{it}(\boldsymbol{\Phi}_{it})$. I approximate the transition process of $\text{IV}_{it}(\boldsymbol{\Phi}_{it})$ as an AR(1) model with the amount of new wind capacity online NewCap_{mt-1} in the state m and year $t-1$ as an endogenous shifter (equation (17)). I further allow the constant term in the AR(1) model to vary across wind farms. The amount of new wind capacity online NewCap_{mt} in the state m and year t is thus another endogenous state variable in the dynamic problem. It captures a preemptive incentive of wind farms such that they would like to enter early to access buyers with a higher willingness to pay, counteracting incentives to delay their entry for better and cheaper technology. I assume NewCap_{mt} to follow another AR(1) process as equation (18).

$$\text{IV}_{it}(\boldsymbol{\Phi}_{it}) = \rho_1^{\Phi}\text{IV}_{it-1}(\boldsymbol{\Phi}_{it-1}) + \rho_2^{\Phi}\text{NewCap}_{mt-1} + \xi_i^{\Phi} + \epsilon_{it}^{\Phi}. \tag{17}$$

$$\text{NewCap}_{mt} = \rho_1^{nc}\text{NewCap}_{mt-1} + \rho_0^{nc} + \epsilon_{mt}^{nc}. \tag{18}$$

Estimation step 1: entry cost parameters I first focus on the policy windows between 2014 and 2018 when there was no policy uncertainty with $b_t = 1$ to estimate the stationary dynamic problem. I use the policy window between 2013 and 2018 as a robustness check. The stationary

are in the same state as the focal wind farm, Θ_{it} is a close approximation for the average effective market price of the buyer pool.

dynamic programming problem can be formulated as follows.

$$V(\boldsymbol{s}_{it},\nu_{it}) = \max\{\Pi(\boldsymbol{s}_{it}) - \nu_{it}, \oint_{\boldsymbol{s}_{it+1},\nu_{it+1}} \beta V(\boldsymbol{s}_{it+1},\nu_{it+1}) dG(\boldsymbol{s}_{it+1}|\boldsymbol{s}_{it}) dF(\nu_{it+1})\}.$$

I approximate the profit surface as a function of the quadratic basis of the state space $u_l(\boldsymbol{s}_{it})$ following Gowrisankaran et al. (2023). I solve the dynamic programming problem via value function approximation $E[V(\boldsymbol{s}_{it},\nu_{it})] = \sum_{l=1}^{L} \gamma_l^v u_l(\boldsymbol{s}_{it})$, similar to Sweeting (2013) and Barwick and Pathak (2015). Moreover, I include the annual state-level land price as the entry cost shifter W_{it} to capture the time trend in the entry cost. Solving the dynamic problem is equivalent to estimating coefficients $\{\gamma_l^v\}_{l=1}^L$ as follows.

$$\{\gamma_l^v\}_{l=1}^L = \text{argmin} \sum_{it} \{\sum_{l=1}^{L} \gamma_l^v u_l(\boldsymbol{s}_{it}) - [\hat{\Pi}(\boldsymbol{s}_{it}) - \kappa W_{it} - \phi \times \hat{P}_t^E(\boldsymbol{s}_{it})]\}^2$$

$$\text{where} \quad \hat{P}_t^E(\boldsymbol{s}_{it}) = 1 - \exp\{-\frac{\hat{\Pi}(\boldsymbol{s}_{it}) - \kappa W_{it} - \beta \sum_{l=1}^{L} \gamma_l^v E[u_l(\boldsymbol{s}_{it+1})|\boldsymbol{s}_{it}]}{\phi}\}.$$

I solve entry cost parameters κ and ϕ by matching the model-predicted state-level entry rate with the data where N_{mt} is the observed number of entrants in state m and year t from the data.

$$\{\kappa,\phi\} = \text{argmin} \sum_{mt} (\hat{P}_{mt}^E - P_{mt}^E)^2, \quad \text{where} \;\; \hat{P}_{mt}^E = \frac{\sum_{i=1}^{N_{mt}} \hat{P}_t^E(\boldsymbol{s}_{it},\kappa,\phi)}{N_{mt}}.$$

Estimation step 2: policy belief parameters I use the estimated cost parameters to solve the upper bound and lower bound of the continuation value. The value function when the PTC is *certain* to be terminated is the lower bound of continuation values, approximated as $V^0(\boldsymbol{s}_{it}) = \sum_{l=1}^{L} \gamma_l^{v_0} u_l(\boldsymbol{s}_{it})$ following equation (12). For the upper bound of continuation values, I approximate it as $V^1(\boldsymbol{s}_{it}, b_t) = \sum_{l=1}^{L} \gamma_l^{v_1}(b_t) u_l(\boldsymbol{s}_{it})$. For each given guess of policy belief parameter b_t, I solve $\{\gamma_l^{v_1}\}_{l=1}^L$ from equation (13). I allow the belief of the transition dynamics for NewCap_{mt} to endogenously adjust according to the perceived likelihood of policy extension b_t. A lower b_t induces a substantial amount of new wind capacity online, thereby reducing utilities' future renewable portfolio gaps more sharply. Consequently, solving the value functions $V^0(\boldsymbol{s}_{it})$ and $V^1(\boldsymbol{s}_{it}, b_t)$ involves finding the correct belief of ρ_0^{nc} and ρ_1^{nc} in the equilibrium. I solve for b_t year by year to match the model-predicted state-level entry rate with the data. The model-predicted entry rate is as follows.[29]

$$\hat{P}_t^E(\boldsymbol{s}_{it}) = 1 - \exp\{-\frac{\hat{\Pi}(\boldsymbol{s}_{it}) - \hat{\kappa} W_{it} - \beta[\hat{V}^1(\boldsymbol{s}_{it}, b_t) \times b_t + \hat{V}^0(\boldsymbol{s}_{it}, b_t) \times (1 - b_t)]}{\hat{\phi}}\}.$$

The policy belief b_t is the solution to the following optimization problem. For more details of the dynamic estimation, please refer to the Appendix Section E.

$$b_t = \text{argmin} \sum_m (\hat{P}_{mt}^E - P_{mt}^E)^2, \quad \text{where} \quad \hat{P}_{mt}^E = \frac{\sum_{i=1}^{N_{mt}} \hat{P}_t^E(\boldsymbol{s}_{it}, b_t)}{N_{mt}}.$$

6 Results

6.1 Bilateral Bargaining with Utilities

I recover turbine productivity α_i, utilities' effective market price Θ_{jt}, and total renewable portfolio gap Φ_{jt} from the data. As capacity factors evolve systematically with cohorts but exhibit limited variation across ages of wind farms, I calculate α_i as the annualized capacity factor at the age of one for each wind farm. Moreover, for utilities' effective market price Θ_{jt} and total renewable portfolio gap Φ_{jt}, I assume utilities have perfect foresight of the state-level Renewable Portfolio Standards, and they hold rational expectations with respect to the transition dynamics of electricity price, renewable credit price, and their energy source composition. I take the inflation-adjusted Production Tax Credit as \$22/MWh for its 2011 value and assume the discount factor to be 0.95. A detailed discussion of the estimation of α_i, Θ_{jt}, and Φ_{jt} is in Appendix Section B.

Table 1 presents the estimation results of the bilateral bargaining model. Columns (1)-(3) assume away the choice-specific random shock in the subsidy type decision and the bargaining pair pick the subsidy type that gives a higher total surplus if the wind farm investor is the non-default type. I calibrate the value discount on tax credit τ as 0.85 according to Johnston (2019). The estimated coefficient β_1 of utilities' willingness to pay is positive, as utilities with a higher willingness to pay for wind energy will demand a larger capacity. The estimated hassle cost parameter δ is also 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. Columns (2) and (3) include the interactions between utilities' willingness to pay ($\Theta_{jt} + \delta\Phi_{jt}$) and the annualized capacity factor (α_i) in the capacity function. I find that utilities with a higher willingness to pay tend to procure a smaller wind farm if the wind farm is very productive, as a wind farm with higher productivity will be more effective in filling their renewable portfolio gaps.

[29] For a given guess of b_t, the lower bound $\hat{V}^0(\boldsymbol{s}_{it}, b_t)$ will also depend on b_t through ρ_0^{nc} and ρ_1^{nc} solved in the equilibrium.

For cost parameters, the total capacity cost is convex in the procured capacity as γ_2 is estimated to be positive. 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 find higher turbine prices significantly reduce the negotiated capacity. GE and Siemens-Gemasa seem to share similar cost functions with Vestas, while the unit capacity cost is significantly higher for other smaller brands, conditional on the turbine efficiency.

I estimate the bargaining weight ρ of utilities to be approximately 0.67. Therefore, utilities capture two thirds of the gains from trade when bargaining. ρ is also significantly different from 1, suggesting that the change in the PTC will not be perfectly passed through to the negotiated price. Moreover, assuming a take-it-or-leave-it model and imposing full rent extraction by utilities will underestimate the importance of the PTC to the industry. Column (3) leaves out the controls for $\pi^W(p_{ij} = \infty)$, which essentially assumes that the threat point is zero for all wind farms. The bargaining weight estimate decreases by around 10% and the rest of the estimation results are stable, which illustrates the robustness with respect to the assumptions about the threat points.

I allow for the choice-specific random shock in the subsidy type decision in columns (4)-(5) as in equation (6). The standard deviation of the random shock is estimated to be large, which is roughly the same magnitude as the average subsidy received by a wind farm. This is consistent with the fact that many wind farms that chose the PTC could have obtained a larger amount of federal subsidy if they had opted into the Section 1603 Grant as discussed in Appendix Section B.4. I further estimate the discount on tax credit τ in column (5) instead of calibrating the value, and find that wind farms perceive one dollar of the tax credit as 83.9 cents of cash transfer, which is close to the estimate in the literature (Johnston, 2019). As a consequence of the large standard deviation of the random shock in the subsidy choice problem, I use parameter estimates in column (2) as the baseline for the subsequent model simulation.

I calculate the discounted sum of profit π_{ij}^W for each wind farm and construct the counterfactual negotiated price $p_{ij}^*(d_t = 0)$ and the discounted sum of profit $\pi_{ij}^W(d_t = 0)$ in the absence of the subsidy, as shown in Figure 6. The discounted sum of profit π_{ij}^W is 89.6 million dollars on average, 124.5 million dollars at the 75$^{\text{th}}$ percentile, and 172.1 million dollars at the 90$^{\text{th}}$ percentile. Only 1.9% of wind farms earn a negative profit. When the PTC is removed, bilateral bargaining yields a lower negotiated capacity, but a higher negotiated price. The negotiated price without the PTC $p_{ij}^*(d_t = 0)$ is 9.0% higher compared with p_{ij}^*. I assume that a negative negotiated capacity will lead to the failure of the bargaining. Around 22.4% of wind farms will fail or earn a negative profit (I normalize as zero profit) without the PTC, underscoring the critical role of this federal incentive in supporting the industry. Even for wind farms earning positive profits, $\pi_{ij}^W(d_t = 0)$ on average is 47.0% smaller than π_{ij}^W. This result highlights the significant cost of missing deadlines and losing PTC eligibility, explaining the rushed entry given low perceived likelihood of the PTC extension.

I also explore the time trends of the average profits under both the PTC and the Section 1603

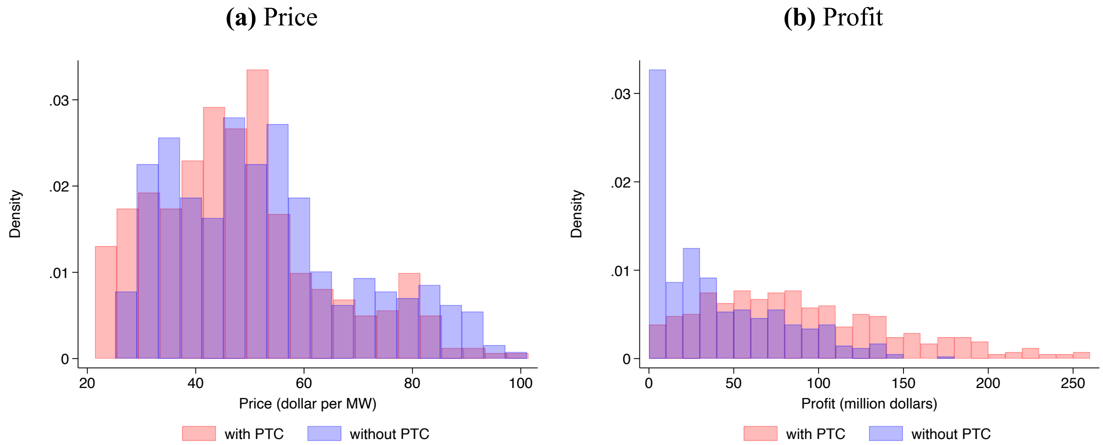
Table 1: Parameter Estimates for Bilateral Bargaining

	(1)	(2)	(3)	(4)	(5)
Panel A: Utility Willingness to Pay					
Hassle Cost, δ	6.288	5.510	4.789	6.198	6.459
	(2.581)	(2.550)	(2.605)	(2.519)	(2.545)
Willingness to Pay, β_1	0.094	0.109	0.103	0.109	0.106
	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)
Interaction: WTP and Capacity Factor, β_2		-0.004	-0.004	-0.004	-0.003
		(0.002)	(0.002)	(0.002)	(0.002)
Panel B: Wind Farm Cost					
Unit Capacity Cost Convexity, γ_2	0.109	0.115	0.127	0.114	0.114
	(0.012)	(0.012)	(0.014)	(0.011)	(0.012)
Turbine Price, β_3	-0.064	-0.072	-0.069	-0.072	-0.069
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
GE, β_{31}	0.000	0.002	0.002	0.001	0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Siemens, β_{32}	-0.009	-0.008	-0.008	-0.008	-0.008
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Others, β_{33}	-0.018	-0.018	-0.018	-0.019	-0.020
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Panel C: Bargaining and Policy Choice					
Bargaining Weight, ρ_1	0.673	0.672	0.617	0.678	0.675
	(0.023)	(0.023)	(0.025)	(0.023)	(0.024)
Default Probability, ς	0.385	0.385	0.385	0.113	0.136
	(0.058)	(0.058)	(0.058)	(0.054)	(0.108)
Policy Choice, σ_1				0.057	0.054
				(0.016)	(0.021)
Credit Valuation, τ					0.839
					(0.047)
Observations	416	416	416	416	416
Calibrated τ	0.850	0.850	0.850	0.850	-
Control for $\pi^W(p_{ij} = \infty)$	✓	✓		✓	✓
Utility-State, Term-Length, Utility-Type FE	✓	✓	✓	✓	✓

Notes: This table shows the estimation results of the bilateral bargaining model (equations(3), (5), and (6)). Columns (1)-(3) estimate equations(3) and (5) jointly under the calibrated τ and then estimate equation (6), while columns (4)-(5) estimate equations(3), (5), and (6) jointly. As discussed 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 renewable portfolio gaps $\bar{\Phi}_{-jt}$ as well as year fixed effects in equation (5) as controls for $\pi_t^W(p_{ij} = \infty)$. Standard errors are in parentheses.

Grant, under only the PTC, and without either subsidy, as shown in Appendix Figure A11. For a given wind farm, the profit variation under either subsidy type is an order of magnitude smaller than the variation across different wind farms. As the PTC phased out after 2016, the gap between profits with or without subsidies gradually decreased. During 2008-2012, the availability of both subsidies increased the profit by about 8.8%.

Figure 6: 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.

6.2 Demand of Non-Utility Buyers and Buyer Choice

The estimation results of the demand function for non-utility buyers are shown in Table 2. Column (1) presents the OLS estimates and the price coefficient ζ_1 is around -0.770. Conditional on wind energy prices, the average turbine price is negatively correlated to the procured wind capacity. I use three sets of instruments to deal with the endogeneity issues associated with the wind price: the renewable credit price in each state, the annual agricultural land price at the state level, dummy variables indicating the presence of state tax incentives. I present the IV estimate using only the renewable credit price for utilities as the baseline and discuss the results using different combinations of instruments in Appendix Section D.1. The IV estimate of the price coefficient is larger in magnitude than the OLS result by approximately 20%. I further regress log capacity on log price, and the estimated average elasticity is around -1.6. There is a sparse reference for the demand elasticity in the wind capacity, but the magnitude roughly aligns with the previous estimates in the liquefied natural gas industry (Zahur, 2022) and solar panel industry (Gerarden, 2023).

I further estimate the utility matching model and the buyer type choice model as shown in Table 3. The matching cost between a wind farm and a utility is much larger if they are located in different states. The matching cost also increases with their geographical distance. Being in different states is equivalent to increasing the distance by 470 miles on average in raising the matching cost. The estimated scale of choice-specific random shock is 0.049, which is equivalent to 54.7% of the average profit from bilateral bargaining. The mean likelihood of selling capacity to a non-utility buyer is approximately 24.2%. However, this probability is much larger in Texas, Illinois, and New York, as these markets are where the merchant hedge contracts concentrated geographically.

Table 2: Demand Function for Non-Utility Buyers

	Capacity		log(Capacity)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Price	-0.770	-0.923		
	(0.107)	(0.238)		
log(Price)			-1.183	-1.600
			(0.132)	(0.266)
Observations	310	310	310	310
R^2	0.387	0.151	0.580	0.331
F Stat. for Exc. IV		60.527		87.539
Control Variables	✓	✓	✓	✓
Balance-Authority Dummies	✓	✓	✓	✓
Contract-Type Dummies	✓	✓	✓	✓

Notes: This table shows the estimation results of the linear demand curve for non-utility buyers (equation (7)). Columns (1) and (3) show the OLS estimates, while columns (2) and (4) show the IV estimates. I use the renewable credit price for utilities as the instrument for the wind price faced by non-utility buyers. I add turbine prices, capacity factor, and turbine brand dummies as control variables. Robust standard errors are in parentheses.

Table 3: Parameter Estimates for Utility Matching and Buyer Type Choice

Coefficients	Parameters	Estimates
Matching Cost, Different States	μ_1	0.101
		(0.013)
Matching Cost, Distance	μ_2	0.215
		(0.039)
Scale of ϵ_{ijt}	σ_2	0.049
		(0.006)
Non-utility Probability	ζ_3	0.242
		(0.019)
Non-utility Probability, Texas	$\zeta_{3,TX}$	0.795
		(0.033)
Non-utility Probability, Illinois	$\zeta_{3,IL}$	0.541
		(0.082)
Non-utility Probability, New York	$\zeta_{3,NY}$	0.950
		(0.049)

Notes: This table shows the estimation results of the utility matching and buyer type choice (equation (9)). Standard errors are in parentheses.

6.3 Dynamic Entry under Policy Uncertainty

I present the estimation results for dynamic parameters in Table 4. Column (1) uses the policy window between 2013 and 2018 to estimate entry cost parameters, and column (2) use the policy window between 2014 and 2018, which I use as the baseline result. The mean parameter ϕ of the entry cost distribution is estimated to be 290.9, and thus the mean entry cost conditional on entry is simulated to be approximately 35 million dollars. The total investment cost, derived from the Section 1603 Grant award after accounting for turbine costs, averages 42 million, aligning closely with my estimate. Moreover, I include the average demeaned state-level annual agricultural land price as W_{it}. The coefficient μ is estimated to be positive. Therefore, higher land price exacerbates the entry cost for new wind farms, which accounts for 53%-70% of the total entry cost.

Table 4: Parameter Estimates for Dynamic Model

	(1)	(2)
Panel A: Entry Cost Parameters		
Mean Entry Cost, ϕ	324.201	290.865
	(99.301)	(105.841)
Land Price, κ	57.119	67.424
	(30.245)	(34.713)
Panel B: Belief Parameters		
Policy Belief 2006, b_{2006}	0.540	0.583
	(0.193)	(0.147)
Policy Belief 2007, b_{2007}	0.731	0.758
	(0.302)	(0.220)
Policy Belief 2008, b_{2008}	0.995	0.999
	(0.111)	(0.013)
Policy Belief 2009, b_{2009}	0.852	0.930
	(0.273)	(0.306)
Policy Belief 2010, b_{2010}	0.920	0.925
	(0.158)	(0.150)
Policy Belief 2011, b_{2011}	0.230	0.322
	(0.092)	(0.230)
Policy Belief 2012, b_{2012}	0.768	0.843
	(0.470)	(0.363)
Years without Uncertainty	2013-2018	2014-2018

Notes: This table shows the estimation results of the dynamic model. Column (1) estimates entry cost parameters using the sample window between 2013 and 2018, while column (2) estimates entry cost parameters using the sample window between 2014 and 2018. Standard errors for entry cost parameters are block-bootstrapped 500 times, while standard errors for belief parameters are block-bootstrapped 20 times.

Next, I use the estimated cost parameters to solve the dynamic programming problem during the policy windows when there is policy uncertainty and estimate the policy belief parameters. The results are presented in Panel (b). The average perceived probability of policy renewal is about 0.3 for the 2011 cohort due to the pessimism about the policy extension as well as the delayed policy renewal. The low estimate is also consistent with the investment spike observed in the raw data. The average perceived probability of policy renewal for the 2012 cohort recovers to around 0.843 as policy uncertainty still hovered. The belief parameters in other years are estimated to be close to 1, with the exception of 2006-2007, which might be due to more sparse investment as well as a larger extrapolation error when estimating belief parameters in this early stage using entry cost parameters estimated from a much later sample period.

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 Appendix Figure A12. The model fits the overall investment time trend and captures the investment spikes and dips well, although I over-predicted entry in the early years. This is likely due to the lumpy nature of the wind farm entry in specific markets while I impose a relatively restrictive entry cost structure in the model.

7 Counterfactual Analysis

I present results for three sets of counterfactual exercises. The first exercise addresses the main research question of how policy uncertainty affects dynamic market efficiency and social welfare. Given that the PTC was consistently renewed ex post, I simulate the investment decisions under the scenario of certain policy renewal. I then compare the welfare changes between the baseline scenario and the scenario without renewal uncertainty, decompose the welfare consequences of policy uncertainty into various channels, and analyze effect heterogeneity across states. The second counterfactual exercise involves further adjusting the generosity of the PTC. As the PTC remained fixed in value (adjusted for inflation) until 2016, I investigate how the welfare effects of policy uncertainty change under different subsidy levels. The third counterfactual exercise explores the welfare effects of early resolution of policy uncertainty. I simulate the investment decision when policy uncertainty is resolved before and after wind farm investors make entry decisions, comparing the welfare effects between these two scenarios while keeping the expected subsidy constant.

7.1 Effects of Policy Uncertainty on Investment and Welfare

I simulate the baseline scenario with the policy uncertainty, using the estimated belief parameters from Table 4, and a counterfactual scenario when there is no renewal uncertainty, setting $b_t = 1$. This counterfactual is policy-relevant, as maintaining a long-term policy is the new direction in subsidy design (Bistline et al., 2023).[30] Even under rolling policy windows, announcing the policy renewal in advance of expiration can largely mitigate the policy uncertainty, as the estimation results reveal limited policy uncertainty in deadline years when there were no policy lapses.

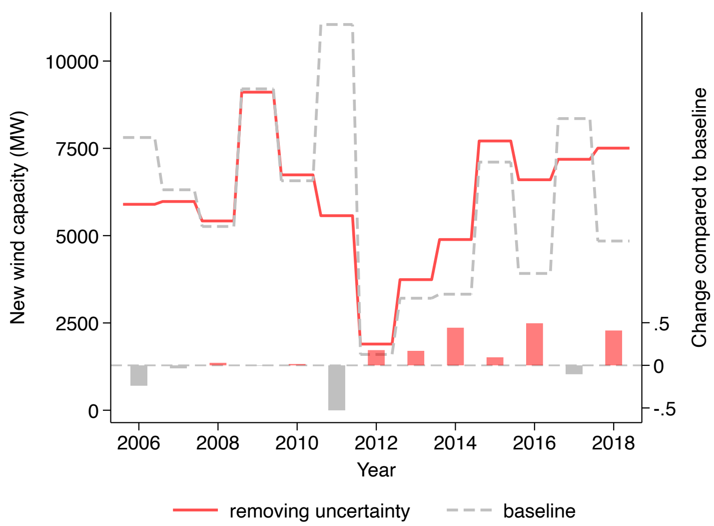
I simulate the model between 2006 and 2018 and wind farm investors endogenously adjust their expectations of the state variables. At the beginning of each year, a wind farm draws a random entry cost from the estimated common distribution and decides whether to enter in the current year. If

[30] For example, the Inflation Reduction Act of 2022 extended the Production Tax Credit until 2025 and committed to replace it with the Clean Electricity Production Tax Credit after 2025. More importantly, the Clean Electricity Production Tax Credit will remain in place until at least 2032, or until U.S. greenhouse gas emissions from electricity fall to 25% of the 2022 levels. For the Inflation Reduction Act of 2022, please see a summary from the White House and from the EPA.

a wind farm decides to wait, it returns to the pool of potential entrants and faces the same dynamic problem next year. The details of counterfactual simulations can be found in Appendix Section E.

Investment Trajectory The baseline and counterfactual investment trajectories are shown in Figure 7. Eliminating policy renewal uncertainty significantly delays the entry of wind farms. The number of new wind projects in 2011 is reduced by 52.7% and the total new capacity decreases by 5500 MW. Wind projects shift their entry to later years and the number of new wind projects between 2012 and 2018 increases by 24.1% on average annually. Those delayed wind farms postpone their entry by 3.6 years and the average entry year of all new projects between 2011 and 2018 is delayed by 0.7 years.

Figure 7: Investment Trajectory with and without Policy Uncertainty



Notes: This figure shows the investment trajectory with and without policy uncertainty. The gray dashed line denotes the model-predicted new capacity under baseline policy uncertainty, while the red solid line denotes the new capacity without policy uncertainty. The bottom panel shows the percentage change in the number of new projects when policy uncertainty is removed compared to the baseline scenario.

Social Welfare I calculate the welfare impacts of policy uncertainty between 2008 and 2018. Policy uncertainty prompts earlier entry of wind farms and expedites the environmental benefits of reducing carbon emissions. However, policy uncertainty induces misalignment among investment timing, technological advancement, as well as demand evolution, which leads to efficiency loss. As shown in Panel A of Table 5, the numbers of total wind projects are approximately the same, suggesting that removing policy uncertainty mainly shifts the entry timing without changing the total number of entrants over an 11-year period. However, the total capacity increases by 6.3% when policy uncertainty is removed and the total output increases by 8.7%. As more investment occurs during the period with higher turbine productivity and lower turbine price, investment timing aligns better with technological advancement. Moreover, utilities with unfulfilled demand are able to procure more wind capacity under better technology. Consequently, the total capacity and output both increase despite similar numbers of wind projects, as illustrated in Appendix Figure A13.

I calculate the profit of wind farms on the market in Panel B of Table 5. Although there is more wind capacity, the total turbine cost increases only slightly by 1.5% because the new entry timing takes better advantage of the decreasing turbine price. The entry cost is also lower mainly due to a shift of the entry timing away from the peak average land price in 2011. Total profit, calculated as the difference between the static profit Π_{it} and the entry cost, increases by 7.1%.

I evaluate the benefits of wind energy following Callaway et al. (2018). I assume wind farms operate for 20 years and calculate the discounted sum of benefits. Wind energy substitutes fossil fuels in generating electricity and lead to three sources of benefits on the grid: reducing carbon emissions, avoiding fossil input costs, and adding capacity values to the system. I estimate the average marginal operating emissions rate (MOER) of coal- or gas-fueled power plants in each state and year, which is defined as the marginal response in system-wide emissions with respect to total production change from generators due to more renewable energy.[31] I assume the social cost of carbon to be \$80 per ton.[32] The statistics of the avoided operating costs and capacity values are taken directly from Callaway et al. (2018).[33]

The cost and benefit analysis of policy uncertainty is presented in Panel (c) of Table 5. Total benefits increase by 5.8 billion dollars, a 5.2% increase compared to the baseline. Although the benefit could only be harvested later due to the delayed entry, a rise in total output dominates the cost of waiting. Among 5.8 billion dollars in total benefit gain, 60% are from the reduced carbon emission. If I take a more conservative estimate of the social cost of carbon as \$50 per ton, the total benefits increase by 4.6 billion dollars compared to the baseline.

The total subsidy increases by 5.2% as the PTC is based on total output.[34] The total profit in the market cannot fully justify subsidies as the net profit is negative, but removing policy uncertainty reduces this deficit by 0.2 billion dollars. Moreover, the social surplus from wind energy—calculated as total benefits minus turbine costs and entry costs borne by wind farm investors, as well as the total subsidy—increases by 5.9 billion dollars and 28.9% from the baseline.

A potential concern regarding the welfare effect is the assumption that turbine technology is exogenous as discussed in Section 4.4. However, removing policy renewal uncertainty delays the

[31] Callaway et al. (2018) find that regional average MOERs offer a useful means of "calibrating regional policy incentives to compensate for external emissions benefits."

[32] According to Brookings, the Obama administration estimated the social cost of carbon at \$43 per ton globally, while the Trump administration only considered the effects of carbon emissions within the United States, estimating the number to be between \$3 and \$5 per ton. The Biden administration estimated the social cost of carbon to be \$51 per ton, but the EPA proposed a nearly fourfold increase to \$190 in November 2022. Borenstein et al. (2021) use both \$50 per ton and \$100 per ton.

[33] More details can be found in Appendix Section F.

[34] Note that the total subsidy increase is smaller in percentage than the output. This is because all the dollar values are discounted to 2008, while the total quantity is a simple sum.

Table 5: Outputs, Benefits and Costs with and without Policy Uncertainty

		Baseline	No Uncertainty	Difference	Percentage
Panel A: Output					
Number of Projects		464.1	468.8	4.7	1.0%
Total Capacity (MW)		40191.3	42718.7	2527.5	6.3%
Total Output (10^6 MWh)		1598.5	1738.3	139.8	8.7%
Panel B: Profit (Billion USD)					
Turbine Cost	TC	43.4	44.1	0.6	1.5%
Entry Cost	EC	32.6	31.0	-1.6	-4.9%
Total Profit	TP	14.8	15.9	1.0	7.1%
Panel C: Benefit and Cost (Billion USD)					
Total Benefit	TB	113.1	119.0	5.8	5.2%
Environmental Benefit		68.4	71.9	3.5	5.1%
Others		44.7	47.1	2.4	5.3%
Subsidy	S	16.5	17.3	0.9	5.2%
Net Profit	TP-S	-1.6	-1.5	0.2	
Social Surplus	TB-TC-EC-S	20.6	26.5	5.9	28.9%

Notes: This table shows the outputs, benefits, and costs in the wind industry in 2008-2018 comparing the scenario when the policy uncertainty is removed and the baseline scenario. All the dollar values are discounted to 2008 with a discount factor of 0.95.

average entry year of new projects from 2011 to 2018 by only 0.7 years. Combined with the fact that the turbine market is global and the U.S. held a 16% share of cumulative capacity in 2019, the impact of the learning-by-doing channel is likely secondary in the welfare calculation. A back-of-the-envelope calculation using the *upper-bound* estimate of the learning parameter from Covert and Sweeney (2022) indicates that, even accounting for slower technology improvement, the social surplus effect would decrease by less than 10%, leaving all the qualitative results unchanged.

Effect Decomposition The total benefit from removing policy uncertainty increases by 5.8 billion dollars as well as 5.2% compared to the baseline. There are three channels shaping this outcome: the delayed environmental benefits reduces the total benefit, which is counteracted by the improvement of timing alignment between investment and technology, as well as the matching efficiency gain between utilities and wind farms. I use N_{mt} to denote the number of new wind farms in state m and year t, and the average capacity as k_{mt}, which is a function of average unfulfilled demand for buyers $\mathbf{\Phi}_{mt}$. I also use b_m to represent the benefit per MWh wind energy generation in state m, for which I take a sample mean at the state level. α_t is the average annualized capacity factor of wind turbines. TB represents the total benefit such that TB $= \sum_{mt} \frac{1-\beta^{20}}{1-\beta} \alpha_t k_{mt}(\mathbf{\Phi}_{mt}) b_m N_{mt} \beta^t$, assuming that each wind farm operates for twenty years.

I use $\tilde{X}$ to represent the value in the counterfactual scenario for every variable X under baseline. $\bar{\alpha}$ is the average turbine capacity factor in the sample. Consequently, the change in the total benefits of wind energy can be decomposed into the following three channels.

$$\begin{aligned}\tilde{\text{TB}} - \text{TB} = \frac{1-\beta^{20}}{1-\beta}\sum_{mt}\beta^t b_m[&\underbrace{\bar{\alpha}k_{mt}(\boldsymbol{\Phi}_{mt})(\tilde{N}_{mt}-N_{mt})}_{\text{delayed environmental benefits}} + \underbrace{(\alpha_t-\bar{\alpha})k_{mt}(\boldsymbol{\Phi}_{mt})(\tilde{N}_{mt}-N_{mt})}_{\text{timing alignment}} \\ &+ \underbrace{\alpha_t(\tilde{k}_{mt}(\tilde{\boldsymbol{\Phi}}_{mt})-k_{mt}(\boldsymbol{\Phi}_{mt}))\tilde{N}_{mt}}_{\text{matching efficiency gain}}].\end{aligned} \tag{19}$$

The decomposition results are shown in Appendix Figure A14. Removing policy uncertainty delays the entry of wind farms as well as the total benefits of wind energy. However, the negative effect can be completely offset by a better timing alignment between investment and technology. Moreover, the matching efficiency gain between utilities and wind farms contributes roughly 30% compared to the welfare effect from timing alignment.

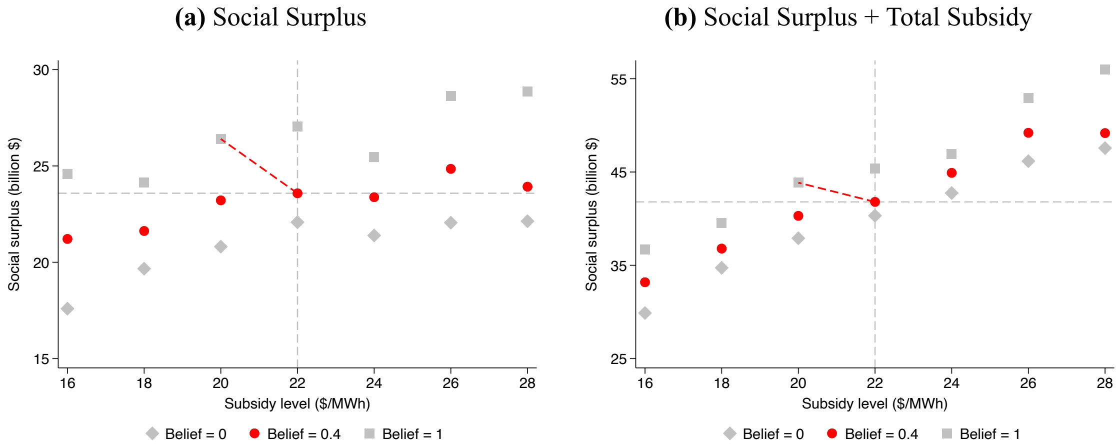
Effect Heterogeneity I explore the heterogeneity in the welfare consequences across states and find some suggestive evidence that the social surplus increases more in states with larger wind demand or more generous state-level supports. As shown in Appendix Figure A15, the improvement in social surplus from removing policy uncertainty is more pronounced in states with greater unfulfilled demand for utilities (Φ_{jt}) or demand shifters ($\boldsymbol{\beta_4 Z_{jt}^U}$). Moreover, the change in the social surplus from removing policy uncertainty is also larger in states with stricter Renewable Portfolio Standards or more generous state-level subsidies. One interpretation is that state subsidies are complements to federal tax incentives. Wind energy will benefit more from stable federal subsidies in those states that also provide state subsidies, as state policies make it easier for wind farms to expedite entry and thus they are more responsive to federal policy uncertainty.

7.2 Effects of Policy Uncertainty under Various Subsidy Levels

I investigate how the welfare effects of policy uncertainty vary under different subsidy levels. The government set policy windows of the PTC and decided when to renew the subsidy, but held the generosity of the PTC constant until 2016. However, alternative subsidy levels might yield better social surplus under policy uncertainty. Keeping the belief parameters as they are for other years, I simulate market outcomes by setting the belief parameter in 2011 to 0 (most uncertain about renewal), 0.4 (baseline), and 1(most certain about renewal) while varying the subsidy levels from \$16/MWh to \$28/MWh. I calculate the social surplus of wind energy in each scenario, and the results are summarized in Figure 8.

Overall, the social surplus of wind energy increases with the level of subsidy but decreases with the extent of policy uncertainty in 2011. In the baseline scenario, with a subsidy level of \$22/MWh

Figure 8: Welfare Effects of Policy Uncertainty under Various Subsidy Levels



Notes: This figure shows the welfare effects of policy uncertainty under various subsidy levels. I keep the belief parameter as it is for other years, and simulate the market outcomes by setting the belief parameter in 2011 to 0 (most uncertain), 0.4 (baseline), and 1(most certain) when the subsidy levels vary from \$16/MWh to \$28/MWh.

and a 2011 policy belief parameter of 0.4, the social surplus is lower than what could be achieved with a subsidy level of \$18/MWh under full policy certainty in 2011. Without accounting for the subsidy itself, the social surplus in the baseline scenario would still be lower than what could be achieved with a subsidy level of \$20/MWh under full policy certainty in 2011. Therefore, we could reduce the subsidy level by at least 9% without compromising social welfare if policy uncertainty were minimized.

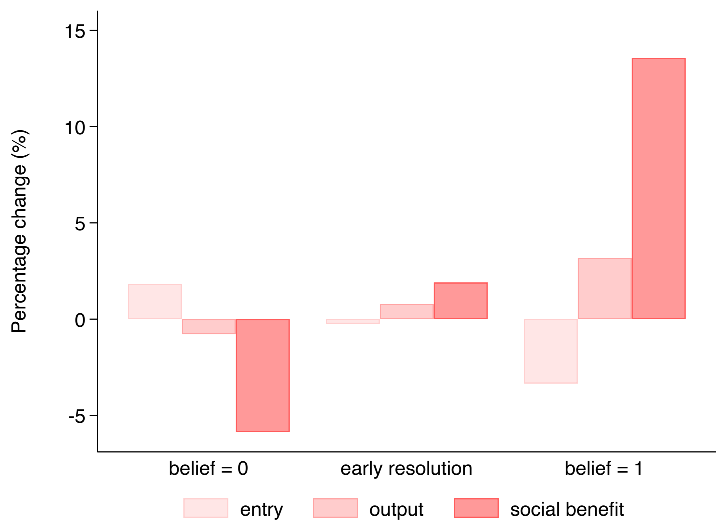
A similar exercise compares social welfare under the baseline level of policy uncertainty to a scenario with maximized policy renewal uncertainty. As shown in Figure 8, if the policy uncertainty is further exacerbated such that the policy renewal completely surprises investors (policy belief parameter = 0 in 2011), the social surplus of wind energy with a subsidy level of \$22/MWh is lower than that the social surplus achieved with \$20/MWh under the current level of policy uncertainty. This exercise illustrates the fiscal cost of policy uncertainty: removing policy uncertainty could save fiscal expenditure for the government without compromising social welfare.

7.3 Effects of Early Resolution of Policy Uncertainty

The third counterfactual exercise is to quantify the welfare effects when policy uncertainty is resolved early. I focus on the policy uncertainty in 2011 and simulate the investment decision under two scenarios. In the first scenario, policy uncertainty was resolved at the beginning of 2011 with the government drawing a random outcome from a binary distribution (mean of 0.4) and announcing the policy extension status to the wind industry. This is the early resolution of policy uncertainty and wind farm investors would know the future policy status promised by the government before they make the entry decision. In the second scenario, policy uncertainty was resolved after the wind farm investors made the investment decision and the mean probability of policy renewal is 0.4, mirroring the baseline scenario. Both two scenarios have the same mean likelihood of policy extension, and the only difference is the timing of policy uncertainty resolution. This exercise is in the same spirit as in Gowrisankaran et al. (2023) and also similar to the mean-risk decomposition exercise in the trade policy uncertainty literature (Handley and Limão, 2017).

The results are shown in Figure 9. I plot the percentage change in the number of new projects, total outputs, and social surplus compared to the baseline scenario. I find that when the policy uncertainty is resolved early, the number of new wind projects will be smaller. This is consistent with the intuition that early resolution of the policy uncertainty will reduce the rushed entry of wind farms and alleviate the negative impact of policy uncertainty.[35] Overall, the welfare effect of policy uncertainty under early resolution is positive compared with the baseline scenario, and the social surplus of wind energy increase by 1.9%.

Figure 9: Welfare Effects of Early Resolution of Policy Uncertainty



Notes: This figure shows the welfare effects of policy uncertainty under early policy uncertainty. I keep the belief parameter as it is for other years, and simulate the market outcomes with the belief parameter in 2011 as 0.4. I simulate the model when the policy uncertainty is resolved before wind farm investors make the entry decision (early resolution) and after (baseline). I calculate the change in the number of new projects, total outputs, and social surplus when policy belief is 0, when policy belief is 1, and when policy uncertainty is resolved early compared to the baseline scenario.

Early resolution of policy uncertainty captures 14.0% of the welfare gain under full elimination of policy uncertainty. Despite that the PTC is always renewed ex post, the *ex-ante* uncertainty faced

[35] Mathematically, the key is that entry probability is a concave function of the difference between profits if entry in the current period and the option values from waiting.

by wind farm investors results in both a lower expected value of subsidy and a larger variance of realized policy status. Keeping the expected value of subsidy the same but reducing the variance of realized policy status can recover 14% of welfare loss, while the rest 86% of welfare loss is due to a lower expected value of subsidy from *ex-ante* uncertainty. Although the subsidy was in effect on the market at all times, *ex-ante* policy uncertainty undermined the role of the subsidy by shifting the expectations of investors and led to welfare loss.

8 Conclusion

I evaluate the dynamic consequences of policy uncertainty in the US wind industry. Policy uncertainty in the Production Tax Credit, induced by continual expiration and extension, expedited wind farm investment and created a bunching of the investment timing at those policy expiration dates. However, it also caused a large mismatch among wind farm investment timing, continuously improving upstream turbine technology, and the evolving demand for wind energy.

To evaluate whether expedited environmental benefits from wind energy outweigh the efficiency loss from distorted investment timing, I develop an empirical model featuring the bilateral bargaining of long-term contracts, buyer choice, and dynamic wind farm investment under policy uncertainty. I find that a lapse in policy extension reduced the perceived likelihood of policy renewal to 30%. I implement counterfactual simulations and find that removing policy uncertainty postpones the entry of 53% of the 2011 wind farm cohort by 3.5 years. The social surplus increase by 5.9 billion dollars and 28.9% after removing policy uncertainty. Moreover, policy uncertainty also imposes fiscal burdens on the government, as the total subsidies can be partially saved without compromising social welfare if the government can manage to contain policy uncertainty. I also find that early resolution of policy uncertainty could capture 14% of the welfare gain under full removal of policy uncertainty.

Overall, this paper highlights the importance of containing policy uncertainty under a dynamic market environment, which is often the case for those nascent industries. After decades of "on-again/off-again" policy status, the Inflation Reduction Act of 2022 extended the Production Tax Credit until 2025. Moreover, it was announced that the Clean Electricity Production Tax Credit will replace the traditional Production Tax Credit after 2025 which will not be phased out until 2032, or when U.S. greenhouse gas emissions from electricity are 25% of 2022 emissions or lower. Strong long-term industrial support eliminates interim policy uncertainty and will further boost the development of wind energy and improve allocative efficiency.

References

Abito, J. M., Flores-Golfin, F., van Benthem, A. A., Vasey, G., and Velichkov, K. (2022). Designing more cost-effective trading markets for renewable energy.

Aldy, J. E., Gerarden, T. D., and Sweeney, R. L. (2023). Investment versus output subsidies: Implications of alternative incentives for wind energy. *Journal of the Association of Environmental and Resource Economists*, 10(4):981–1018.

Armitage, S. (2021). Technology transitions and timing of environmental policy: Evidence from efficient lighting.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636.

Barradale, M. J. (2010). Impact of public policy uncertainty on renewable energy investment: Wind power and the production tax credit. *Energy Policy*, 38(12):7698–7709.

Bartlett, J. (2019). Reducing risk in merchant wind and solar projects through financial hedges.

Barwick, P. J., Kalouptsidi, M., and Zahur, N. B. (2021). Industrial policy implementation: Empirical evidence from china's shipbuilding industry.

Barwick, P. J., Kwon, H., and Li, S. (2023). Attribute-based subsidies and market power: An application to electric vehicles.

Barwick, P. J. and Pathak, P. A. (2015). The costs of free entry: an empirical study of real estate agents in greater boston. *The RAND Journal of Economics*, 46(1):103–145.

Bistline, J. E., Mehrotra, N. R., and Wolfram, C. (2023). Economic implications of the climate provisions of the inflation reduction act. *Brookings Papers on Economic Activity*, 2023(1):77–182.

Borenstein, S., Fowlie, M., and Sallee, J. (2021). Designing electricity rates for an equitable energy transition.

Bradt, J. (2024). A policy by any other name: Unconventional industrial policy in the us residential solar industry.

Butters, R. A., Dorsey, J., and Gowrisankaran, G. (2021). Soaking up the sun: Battery investment, renewable energy, and market equilibrium.

Callaway, D. S., Fowlie, M., and McCormick, G. (2018). Location, location, location: The variable value of renewable energy and demand-side efficiency resources. *Journal of the Association of Environmental and Resource Economists*, 5(1):39–75.

Chipty, T. and Snyder, C. M. (1999). The role of firm size in bilateral bargaining: A study of the cable television industry. *Review of Economics and Statistics*, 81(2):326–340.

Collard-Wexler, A. (2013). Demand fluctuations in the ready-mix concrete industry. *Econometrica*, 81(3):1003–1037.

Covert, T. and Sweeney, R. (2022). Winds of change: Estimating learning by doing without cost or input data.

Cullen, J. (2013). Measuring the environmental benefits of wind-generated electricity. *American Economic Journal: Economic Policy*, 5(4):107–33.

De Groote, O. and Verboven, F. (2019). Subsidies and time discounting in new technology adoption: Evidence from solar photovoltaic systems. *American Economic Review*, 109(6):2137–72.

Dixit, A. K. and Pindyck, R. S. (1994). *Investment under uncertainty*. Princeton university press.

Doraszelski, U., Lewis, G., and Pakes, A. (2018). Just starting out: Learning and equilibrium in a new market. *American Economic Review*, 108(3):565–615.

Dorsey, J. (2019). Waiting for the courts: Effects of policy uncertainty on pollution and investment. *Environmental and Resource Economics*, 74(4):1453–1496.

Elliott, J. T. (2022). Investment, emissions, and reliability in electricity markets.

Fabra, N. and Llobet, G. (2025). The costs of counterparty risk in long-term contracts.

Fan, Y. and Xiao, M. (2015). Competition and subsidies in the deregulated us local telephone industry. *The RAND Journal of Economics*, 46(4):751–776.

Fell, H., Kaffine, D. T., and Novan, K. (2021). Emissions, transmission, and the environmental value of renewable energy. *American Economic Journal: Economic Policy*, 13(2):241–72.

Fernández-Villaverde, J., Guerrón-Quintana, P., Kuester, K., and Rubio-Ramírez, J. (2015). Fiscal volatility shocks and economic activity. *American Economic Review*, 105(11):3352–3384.

Gerarden, T. D. (2023). Demanding innovation: The impact of consumer subsidies on solar panel production costs. *Management Science*, 69(12):7799–7820.

Gonzales, L. E., Ito, K., and Reguant, M. (2023). The investment effects of market integration: Evidence from renewable energy expansion in chile. *Econometrica*, 91(5):1659–1693.

Gowrisankaran, G., Langer, A., and Zhang, W. (2023). Quantifying environmental policy uncertainty: The case of air toxics standards.

Gowrisankaran, G., Reynolds, S. S., and Samano, M. (2016). Intermittency and the value of renewable energy. *Journal of Political Economy*, 124(4):1187–1234.

Gowrisankaran, G. and Rysman, M. (2012). Dynamics of consumer demand for new durable goods. *Journal of Political Economy*, 120(6):1173–1219.

Handley, K. and Limão, N. (2017). Policy uncertainty, trade, and welfare: Theory and evidence for china and the united states. *American Economic Review*, 107(9):2731–2783.

Hara, K. (2023). Encouraging renewable investment: Risk sharing using auctions.

Hendel, I. and Nevo, A. (2013). Intertemporal price discrimination in storable goods markets. *American Economic Review*, 103(7):2722–2751.

Hollingsworth, A. and Rudik, I. (2019). External impacts of local energy policy: The case of renewable portfolio standards. *Journal of the Association of Environmental and Resource Economists*, 6(1):187–213.

Ifrach, B. and Weintraub, G. Y. (2017). A framework for dynamic oligopoly in concentrated industries. *The Review of Economic Studies*, 84(3):1106–1150.

Jeon, J. (2022). Learning and investment under demand uncertainty in container shipping. *The RAND Journal of Economics*, 53(1):226–259.

Johnston, S. (2019). Nonrefundable tax credits versus grants: the impact of subsidy form on the effectiveness of subsidies for renewable energy. *Journal of the Association of Environmental and Resource Economists*, 6(3):433–460.

Johnston, S., Liu, Y., and Yang, C. (2023). An empirical analysis of the us generator interconnection policy.

Johnston, S. and Yang, C. (2019). Policy uncertainty and investment in wind energy.

Kay, O. and Ricks, M. (2023). Time-limited subsidies: Optimal taxation with implications for renewable energy subsidies.

Kellogg, R. (2014). The effect of uncertainty on investment: Evidence from texas oil drilling. *American Economic Review*, 104(6):1698–1734.

Langer, A. and Lemoine, D. (2022). Designing dynamic subsidies to spur adoption of new technologies. *Journal of the Association of Environmental and Resource Economists*, 9(6):1197–1234.

Mu, T. (2023). The dynamic effects of renewable subsidies in the green energy transition.

Novan, K. (2015). Valuing the wind: renewable energy policies and air pollution avoided. *American Economic Journal: Economic Policy*, 7(3):291–326.

Petersen, C., Reguant, M., and Segura, L. (2024). Measuring the impact of wind power and intermittency. *Energy Economics*, 129:107200.

Ryan, N. (2021). Holding up green energy: Counterparty risk in the indian solar power market.

Sexton, S., Kirkpatrick, A. J., Harris, R. I., and Muller, N. Z. (2021). Heterogeneous solar capacity benefits, appropriability, and the costs of suboptimal siting. *Journal of the Association of Environmental and Resource Economists*, 8(6):1209–1244.

Sweeting, A. (2013). Dynamic product positioning in differentiated product markets: The effect of fees for musical performance rights on the commercial radio industry. *Econometrica*, 81(5):1763–1803.

Vreugdenhil, N. (2023). Booms, busts, and mismatch in capital markets: Evidence from the offshore oil and gas industry.

Wiser, R. and Bolinger, M. (2012). 2011 Wind Technologies Market Report. Annual Report.

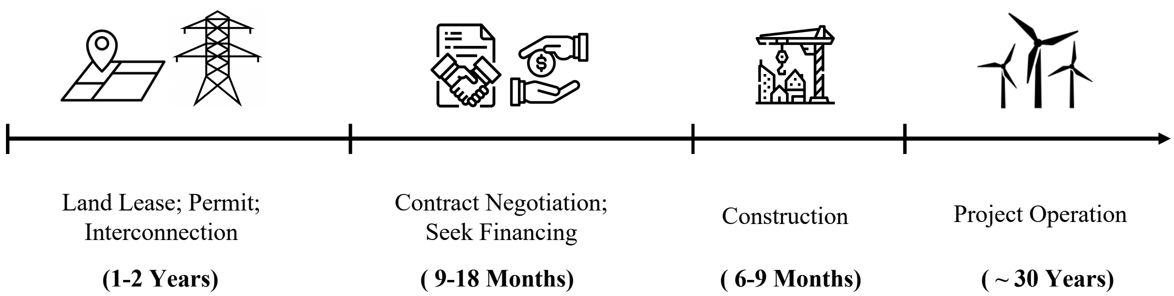
Wiser, R. and Bolinger, M. (2021). 2020 Wind Technologies Market Report. Annual Report.

Zahur, N. B. (2022). Long-term contracts and efficiency in the liquefied natural gas industry.

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

A Additional Figures

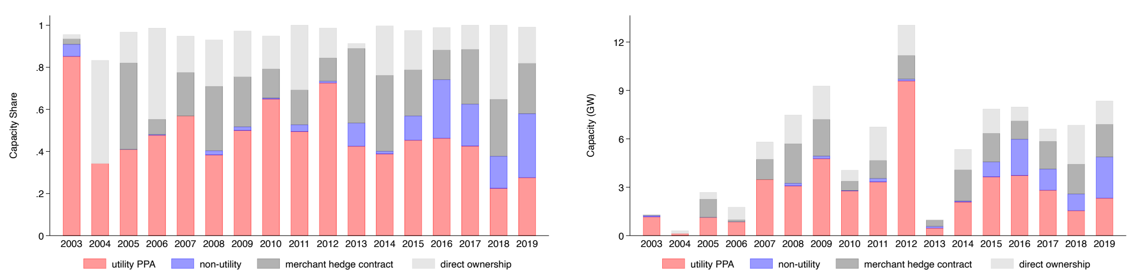
Figure A1: Timeline of Building a Wind Farm



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

Figure A2: Capacity by Offtake Types

(a) Capacity Share **(b)** Capacity Volume

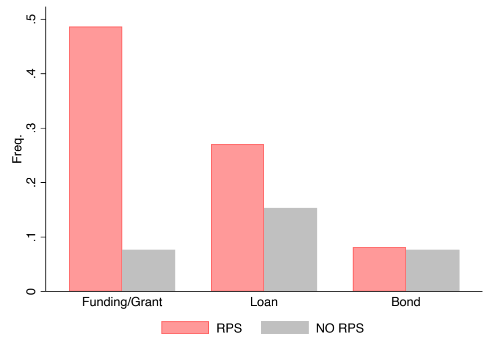


Notes: This figure shows the capacity distribution by offtake types across years. There are four offtake types: utility PPA, non-utility offtaker, merchant hedge contracts, and direct ownership. Panel (a) describes the share of capacity, while Panel (b) shows the volumes.

Figure A3: State-level Policies

(a) Tax Policies

(b) Financing Policies

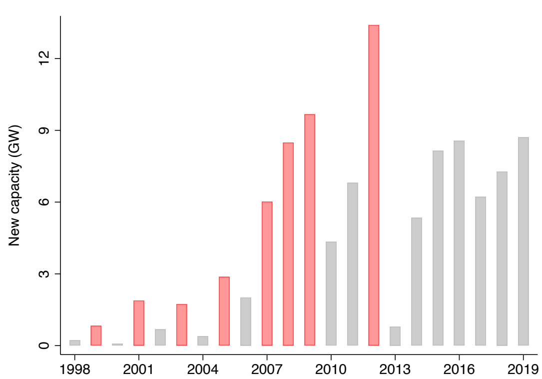


(c) Other Policies

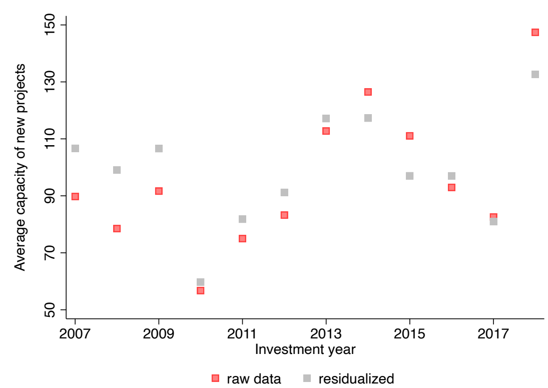
Notes: This figure shows the frequencies of different types of state policies for states with or without the RPS. State policies, including the RPS, are hand-collected by the author from DSIRE (https://www.dsireusa.org).

Figure A4: Time Trend for Investment: Capacity

(a) Total Capacity



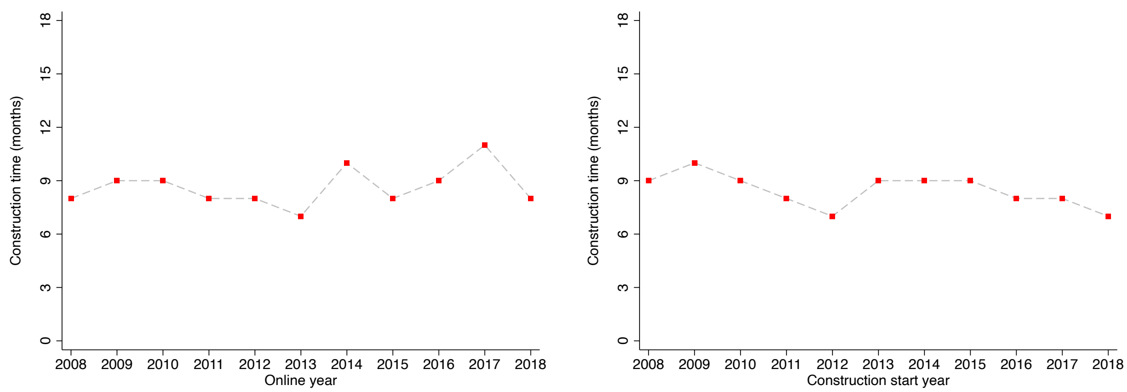
(b) Average Capacity



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

Figure A5: Construction Time

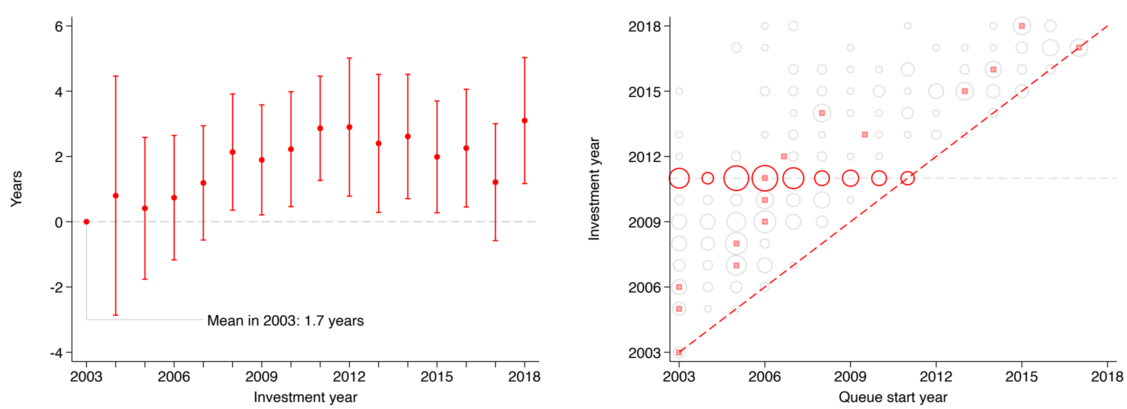
(a) by Online Years **(b)** by Construction Start Years



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)). I construct the annual time trends of the average construction time from FAA data and EIA-860.

Figure A6: Interconnection Queues

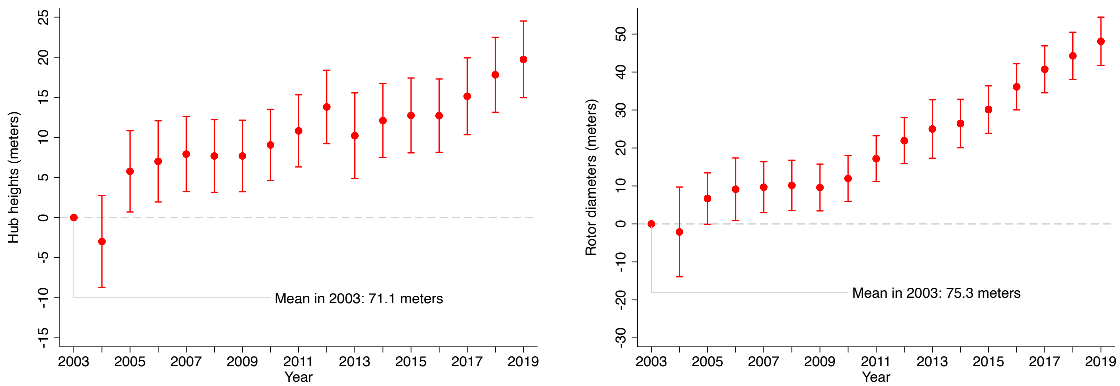
(a) Average Time **(b)** Distribution of Queue Start Years



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 A7: Time Trend of Wind Turbine Technology

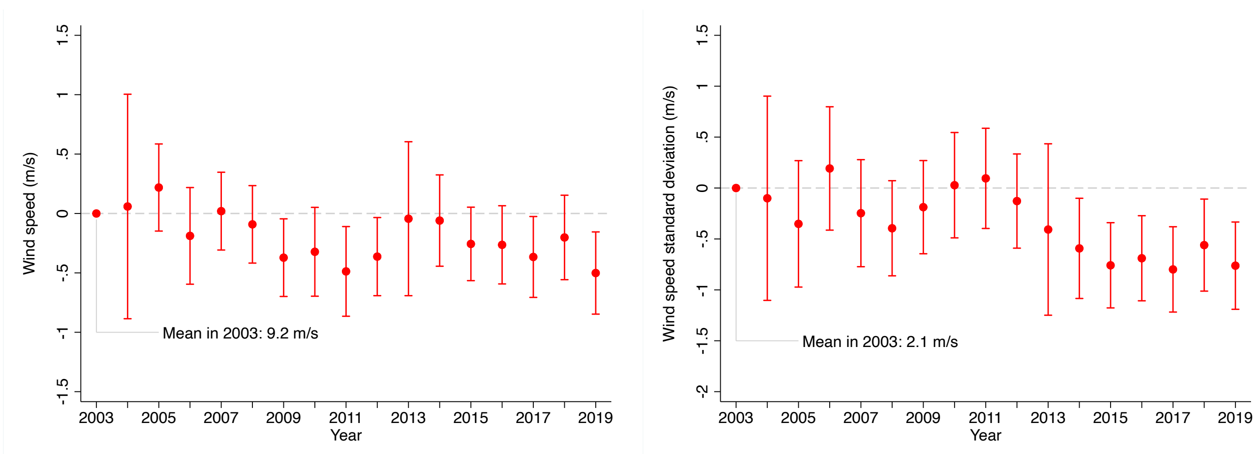
(a) Hub Heights **(b)** Rotor Diameters



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

Figure A8: Time Trend of Wind Speeds

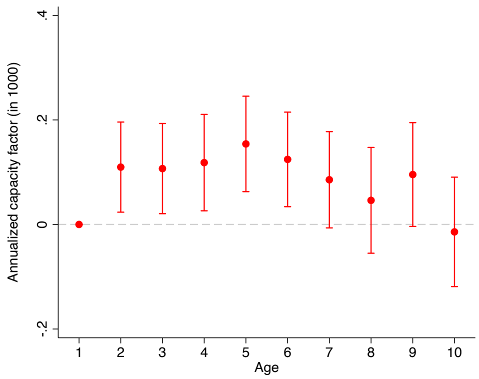
(a) Mean **(b)** Standard Deviation within Locations



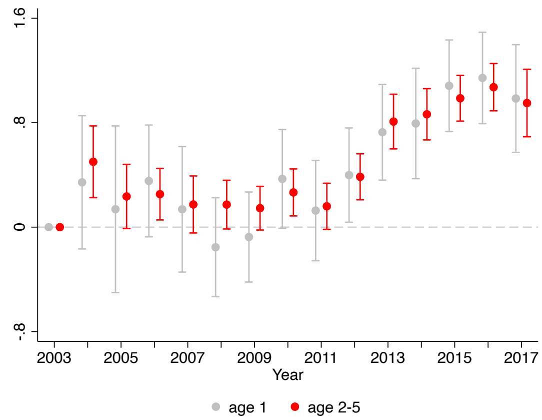
Notes: This figure shows the annual time trends of wind speed at locations of new wind projects. The wind speed is measured at 80 meters at sites nearest to the wind project location based on the Wind Toolkit Data from National Renewable Energy Laboratory (NREL). The mean and standard deviation for each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

Figure A9: Description of Annualized Capacity Factor

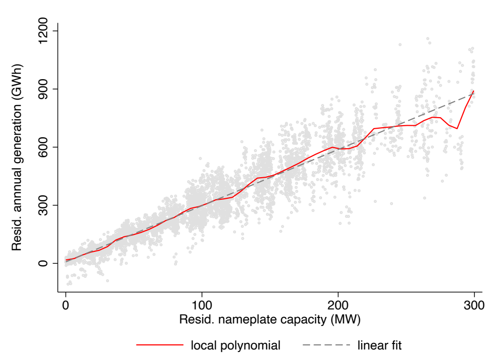
(a) Capacity Factor and Age



(b) Capacity Factor, Age, and Cohort



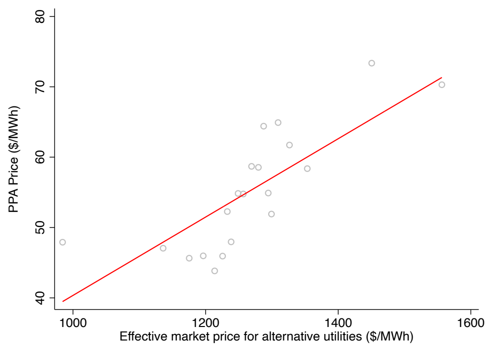
(c) Annual Output and Nameplate Capacity



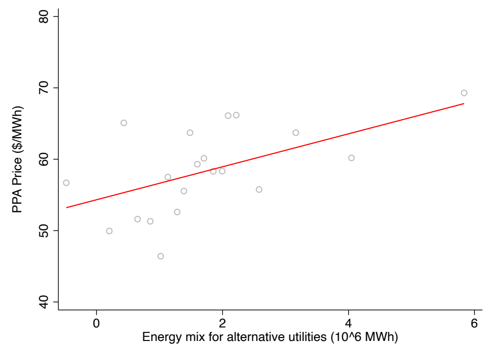
Notes: This figure presents the descriptive data patterns of the annualized capacity factor of wind farms. Panels (a) and (b) explore the relationship among the capacity factors, ages, and cohorts of wind farms. I rescale the annualized capacity factor and divide it by 1000. The average annualized capacity factor is 2.82×10^3 at the wind farm and year level. Panel (a) plots the coefficient estimates of β_a in equation (20), controlling for the entry cohort dummies. Panel (b) plots the coefficient estimates of β_c in equation (20), 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 A10: PPA Price and WTP of Alternative Utilities

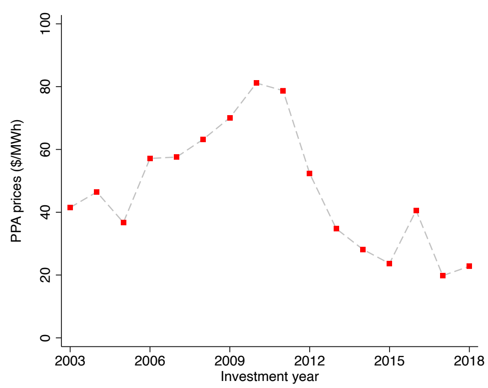
(a) Effective Price for Alt Util



(b) Energy Composition for Alt Util



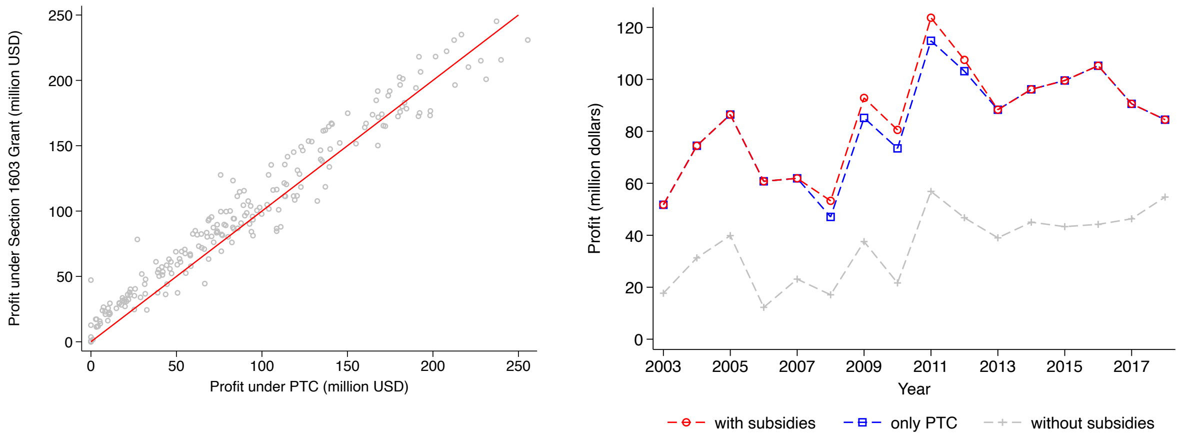
(c) Time Trend of PPA Prices



Notes: This figure describes the basic pattern of the Power Purchase Agreement (PPA) prices. Panels (a) and (b) show the conditional relationship between PPA prices and two willingness to pay shifters for the alternative utilities within 400 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 renewable portfolio gaps for alternative utilities. 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. Panel (c) plots the average time trend of the PPA prices.

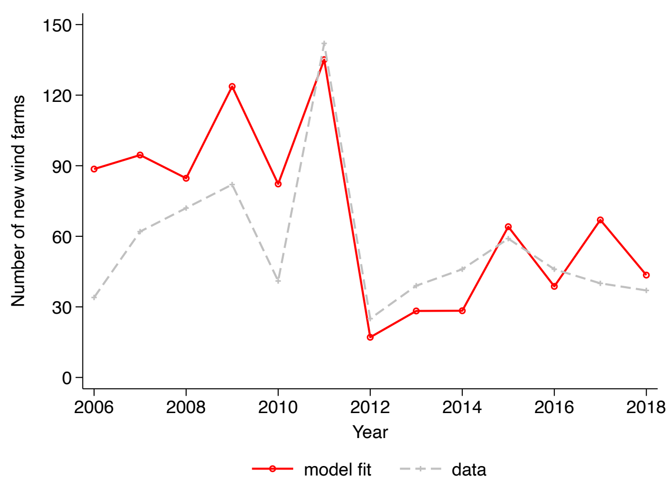
Figure A11: Summary of Simulated Static Profits

(a) PTC and Section 1603 Grant **(b)** Time Trend



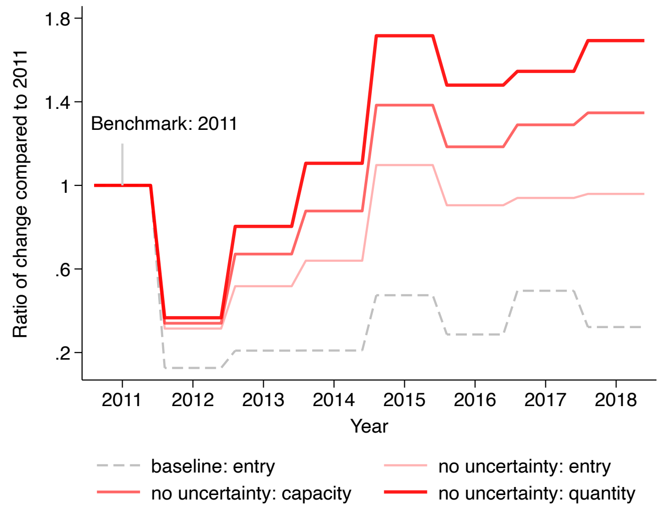
Notes: This figure summarizes the basic patterns of the simulated profit from bilateral bargaining. Panel (a) presents simulated profits under either the PTC or the Section 1603 Grant. Each circle represents one wind farm, and the red solid line is the 45-degree line. Panel (b) plots the average profits with both subsidies, with only the PTC, and without subsidies over time.

Figure A12: Dynamic Model Fit



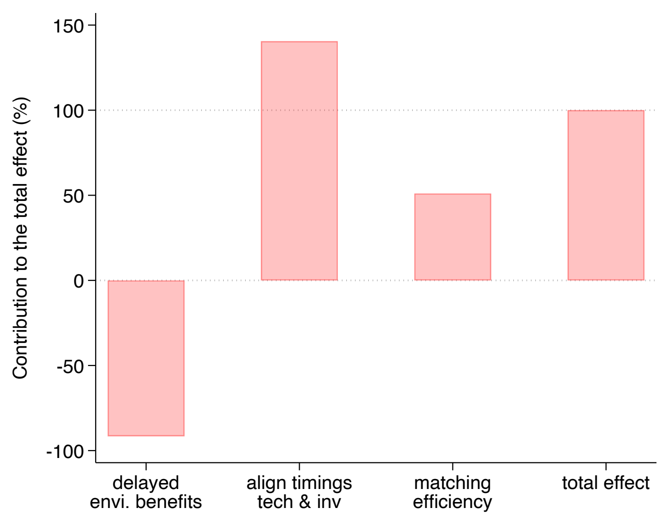
Notes: This figure shows the dynamic model fit. The red line denotes the model-predicted number of wind projects, while the gray dashed line denotes the number of wind projects in the raw data.

Figure A13: New Projects, Capacity, and Output with and without Policy Uncertainty



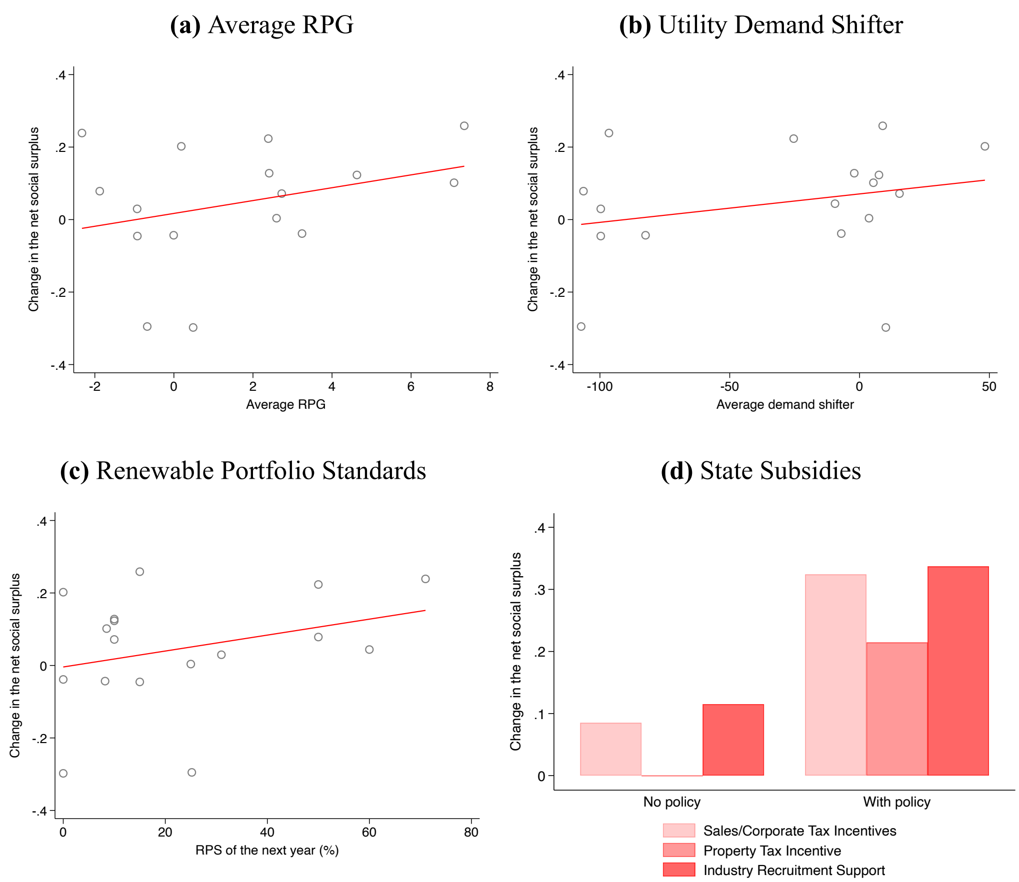
Notes: This figure shows the number of new projects, the amount of new capacity, and the total outputs generated by the new cohort under the baseline scenario and when the policy uncertainty is removed. I set the level in 2011 as the benchmark and calculate the percentage change in later years.

Figure A14: Welfare Decomposition



Notes: This figure shows the welfare decomposition according to equation (19). The change in the total benefits from wind energy can be decomposed into three channels: the delayed environmental benefits, the improvement of timing alignment between investment and technology, as well as the matching efficiency gain between utilities and wind farms.

Figure A15: Welfare Heterogeneity from Removing Policy Uncertainty



Notes: This figure shows the welfare effects when policy uncertainty is removed across states with different characteristics and state-level policies. Panel (a) plots the net social benefit change against the average renewable portfolio gap. Panel (b) plots the net social benefit change against the average utility demand shifters. Panel (c) plots the net social benefit change against the renewable portfolio standards in each state in 2012. Panel (d) plots the mean net social benefit change among states with or without certain state-level subsidies, including sales tax incentives, property tax incentives, and industry recruitment supports.

B Estimation Details for Bilateral Bargaining with Utilities

B.1 Estimation of Annualized Capacity Factor α_{it}

I parameterize wind power generation Q^w_{ijt} as a linear function of procured capacity k^w_{ij}, as I find that the annual total output on average is linearly increasing with nameplate capacity. I residualize both the annual total generation and the nameplate capacity on entry cohort dummies and age dummies and then plot the linear fit and local polynomial approximation between these two variables. As shown in Appendix Figure A9, 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 $\alpha_{it} = \frac{Q^w_{ijt}}{k^w_{ij}}$.

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

$$\alpha_{it} = \sum_{a=2}^{10} \beta_a \times \mathbb{1}(\text{age}_{it} = a) + \sum_{c=2004}^{2018} \beta_c \times \mathbb{1}(\text{cohort}_i = c) + \epsilon_{it}. \tag{20}$$

I plot the age effects β_a in Panel (a) of Appendix Figure A9. The overall average capacity factor is relatively stable even for ten years after entry. The capacity factor peaks 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 (20) without age dummies and plot β_c for two age groups in Panel (b). I find that capacity factors evolve systematically with the cohort, but display limited variation with respect to the age of wind farms. This is further supported 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 explain 5.5% only. Therefore, I treat the annualized capacity factor to be constant as a wind farm ages and calculate it at the age of one for the best data coverage such that $\alpha_i = \alpha_{it}$ when $\text{age}_{it} = 1$.

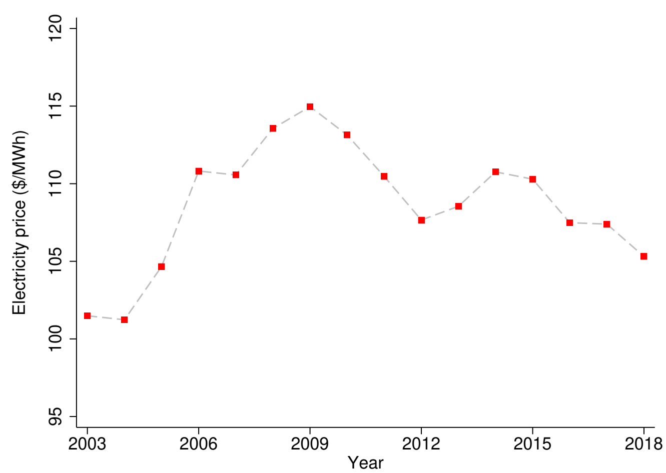
B.2 Estimation of Effective Market Price Θ_{jt}

I denote the effective market price as Θ_{jt}, which is a combination of retail electricity prices and renewable energy credit (REC) prices. I assume that utilities have a rational expectation of the future evolution of both retail electricity prices and renewable energy credit (REC) prices. I use the annual average retail electricity price r_{mt} at each state m. As shown in Appendix Figure B1, the average inflation-adjusted electricity price, weighted by the annual sales in each state, increased before 2009 but has declined since then due to plummeting natural gas prices. I model the evolution of electricity prices using an AR(1) process, and allow the AR(1) coefficient and the time trend to differ before and after 2009. I assume that utilities have rational expectations with respect to the evolution of retail electricity prices but for two separate periods, and the trend break in 2009 wasn't anticipated. ξ_m is the state dummy.

$$\begin{aligned} r_{mt} = {} & \gamma_1 r_{mt-1} \times \mathbb{1}(t \leqslant 2009) + \gamma_2 r_{mt-1} \times \mathbb{1}(t > 2009) + \gamma_3 t \times \mathbb{1}(t \leqslant 2009) \\ & + \gamma_4 t \times \mathbb{1}(t > 2009) + \gamma_5 \mathbb{1}(t > 2009) + \xi_m + \epsilon_{mt}. \end{aligned} \tag{21}$$

The estimation results are shown in Appendix Table B1. The time trend of electricity prices varies sharply before and after 2009, and the R^2 of the regression is as high as 0.963.

Figure B1: 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.

Similarly, I estimate an AR(1) model for the renewable energy credit prices λ_{mt} as shown in Appendix Table B2. I take the coefficient estimates from column (1) and assume utilities have rational expectations with respect to the evolution of renewable energy credit prices and have perfect foresight with respect to the Renewable Portfolio Standards z_{mt}.

The effective market price Θ_{jt} therefore can be constructed as $\Theta_{jt} = \sum_{s=t+1}^{t+T} E_t \beta^{s-t}[r_s + \lambda_s(1 - z_s)]$.

B.3 Estimation of Total Renewable Portfolio Gap Φ_{jt}

I denote the utility's total renewable portfolio gap as Φ_{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.

Table B1: Transition Dynamics of Electricity Prices

	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 $\times \mathbb{1}(\text{Year} \leqslant 2009)$			0.688***
			(0.096)
Lagged Electricity Price $\times \mathbb{1}(\text{Year} > 2009)$			0.678***
			(0.045)
Time Trend $\times \mathbb{1}(\text{Year} \leqslant 2009)$			0.934***
			(0.297)
Time Trend $\times \mathbb{1}(\text{Year} > 2009)$			-0.138
			(0.176)
$\mathbb{1}(\text{Year} > 2009)$			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 state and yearly levels. The empirical model is specified in equation (21). Standard errors are clustered at the state level. *p < 0.10; **p<0.05; ***p<0.01.

Table B2: Transition Dynamics of Renewable Energy Credit Prices

	REC Price			
	(1)	(2)	(3)	(4)
Lagged REC Price	0.886***	0.610***	0.880***	0.581***
	(0.019)	(0.044)	(0.020)	(0.051)
Time Trend			-0.170***	-0.248***
			(0.041)	(0.072)
Observations	417	417	417	417
Adjusted R^2	0.841	0.847	0.843	0.852
State Dummies		✓		✓

Notes: This table shows the transition dynamics of renewable energy credit (REC) prices at the state and yearly levels. The empirical model is specified in equation (21). Robust standard errors are reported. *p < 0.10; **p<0.05; ***p<0.01.

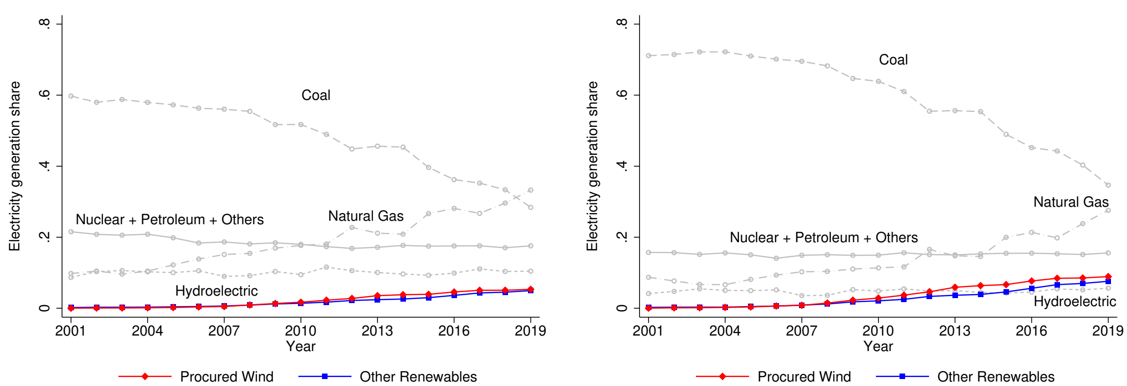
I first describe the overall time trend of electricity generation by energy source, for all the utilities and utilities in the Power Purchase Agreement (PPA) sample, respectively. The share of coal-fired electricity is decreasing over time, while the share of gas-fired electricity is increasing at the national level as shown in Appendix Figure B2. 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 mostly stable. Compared to the entire sample of utilities, those from the Power Purchase Agreement 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 electricity output portfolios 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 Renewable Portfolio Standards excluded hydroelectric power built before the implementation. I use the AR(1) model to capture the evolution process of net generations from these four different energy sources. As the capacity investment is lumpy, I exclude utilities that have never used a certain fuel type from the regression. I take the coefficient estimates from the AR(1) model with utility dummies and a time trend. The results are shown in Appendix Table B3.

I assume utilities have rational expectations with respect to the evolution of their own electricity generation from each type of fuel source, and they have perfect foresight with respect to the Renewable Portfolio Standards. If a utility has never used a certain fuel type during the sample period, I assume that its expectation of future usage remains zero. The utility's total renewable portfolio gap Φ_{jt} therefore can be constructed as $\Phi_{jt} = \sum_{s=t+1}^{t+T} E_t \beta^{s-t}[z_s(Q^f_{js} + Q^{or}_{js} + Q^o_{js}) - Q^{or}_{js}]$.

Figure B2: 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 Power Purchase Agreement sample. Other renewables include solar, biomass, geothermal, and utility-owned wind.

B.4 Subsidy Choice

The Section 1603 of the American Recovery and Reinvestment Tax Act was implemented as part of the 2009 stimulus package, providing cash grants to qualified energy properties in lieu of tax

Table B3: Transition Dynamics of Electricity Generation by Sources

	Net Generation			
Panel A: Coal and Natural Gas				
	Coal		Natural Gas	
	(1)	(2)	(3)	(4)
Lagged Variable	0.868***	0.955***	0.936***	1.039***
	(0.067)	(0.011)	(0.020)	(0.007)
Time Trend	-0.067***		0.011***	
	(0.013)		(0.003)	
Observations	2459	2460	7488	7491
Adjusted R^2	0.969	0.969	0.977	0.976
Utility Dummies	✓		✓	
State Dummies × Time Trend		✓		✓
Panel B: Other Renewable and Non-Renewable Sources				
	Other non-Renewables		Other Renewables	
	(5)	(6)	(7)	(8)
Lagged Variable	0.691***	0.994***	1.019***	1.103***
	(0.053)	(0.008)	(0.033)	(0.022)
Time Trend	0.000		0.001	
	(0.002)		(0.001)	
Observations	9602	9607	2382	2388
Adjusted R^2	0.987	0.985	0.978	0.975
Utility Dummies	✓		✓	
State Dummies × 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 state and yearly levels. The empirical model is similar to equation (21). Standard errors are clustered at the state level. *p < 0.10; **p<0.05; ***p<0.01.

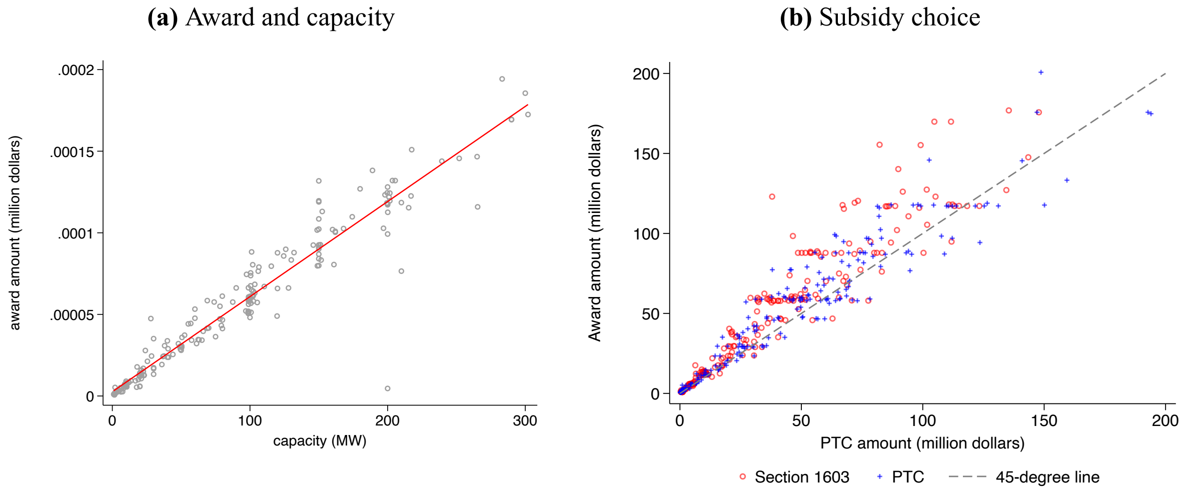
credits. According to the program guideline, qualified wind farms must be "originally placed in service between January 1, 2009, and December 31, 2011, or placed in service after 2011 and before January 1, 2013, if construction of the property begins between January 1, 2009, and December 31, 2011." [36] If wind projects selected the Section 1603 Grant instead of the Production Tax Credit, they would receive an upfront cash grant that was equal to 30% of total investment costs. I accessed the list of Section 1603 awardees from the U.S. Department of the Treasury web page and matched it with EIA data manually according to wind project names.[37] I constructed a dummy variable indicating whether a project opted into the Section 1603 Grant.

The list of Section 1603 awardees also includes the amount of the Section 1603 award. As is evident from Panel (a) of Appendix Figure B3, the amount of the award can be closely approximated as a linear function of total capacity ($R^2 = 0.932$). Consequently, I model the total grant as a linear

[36] The detailed program guideline can be found here.

[37] The detailed list of awardees can be found here.

Figure B3: Section 1603 Award and PTC



Notes: This figure shows the data patterns of the Section 1603 Grant and the subsidy choice. Panel (a) displays a scatter plot between the Section 1603 award received by each wind farm and its total capacity. The red solid line denotes the linear fit. Panel (b) shows the total subsidy under the Section 1603 Grant and the PTC for each wind farm. I split the sample into Section 1603 Awardees (red circles) and PTC recipients (blue pluses) and the dashed gray line is the 45-degree line.

function of capacity $0.3 \times \eta k_{ij}^w$. I calibrate η by running a regression of the total grant on the capacity without an intercept, and the coefficient is around 0.586 million dollars per megawatt as shown in Appendix Table B4. The heterogeneity of η across years is negligible as shown in column (2).

Another important question relevant to the modeling assumption is what determines the subsidy choice. I estimate a logit model of subsidy choice on the productivity and capacity of wind farms as shown in columns (1)-(2) in Appendix Table B5. More productive wind farms are more likely to select the output-based tax credit conditional on the size of the projects. Moreover, medium-sized wind farms are more likely to choose the Section 1603 Grant, as smaller wind farms have lower total investment costs to claim subsidies and larger wind farms might be less financially constrained and prefer tax credits for tax equity providers. Since the wind farm size is an important predictor for the subsidy choice and the wind farm size is negotiated in the bilateral bargaining, I also model the subsidy choice as a joint decision of both parties in the bilateral bargaining process.

I calculate total subsidies for each wind farm under both subsidy types. On the one hand, I impute total subsidies under the Section 1603 Grant for each wind farm i that had chosen the PTC as $TS(k_i^w \mid \text{Section 1603 Grant}) = 30\% \times \eta \times k_i^w$. On the other hand, I calculate 10-year discounted sum of total subsidy under the PTC for each wind farm i using its annualized capacity factor α_i, the amount of tax credit per unit of output d_t, and the observed capacity k_i^w, such that $TS(k_i^w \mid \text{PTC}) = \frac{\beta(1-\beta^{10})}{1-\beta} d_t \alpha_i k_i^w$. I summarize the results in Panel (b) of Appendix Figure B3. Wind farms that chose the Section 1603 Grant on average received a larger amount

Table B4: Calibration of η

	Section 1603 Award Amount	
	(1)	(2)
Capacity	0.586***	
	(0.007)	
Capacity $\times \mathbb{1}(\text{Year} == 2008)$		0.583***
		(0.017)
Capacity $\times \mathbb{1}(\text{Year} == 2009)$		0.594***
		(0.012)
Capacity $\times \mathbb{1}(\text{Year} == 2010)$		0.623***
		(0.023)
Capacity $\times \mathbb{1}(\text{Year} == 2011)$		0.574***
		(0.012)
Capacity $\times \mathbb{1}(\text{Year} == 2012)$		0.572***
		(0.026)
Observations	229	229
Adjusted R^2	0.969	0.969
Year Dummies		✓

Notes: This table shows the calibration results of η. I regress the Section 1603 Grant amount (in million dollars) on the total capacity (in MW) for each wind farm without an intercept. I further explore the heterogeneity of η across years in column (2). Standard errors are in parentheses. *p < 0.10; **p<0.05; ***p<0.01.

of federal subsidies under the Section 1603 Grant compared with the PTC. However, wind farms that chose the PTC do not seem better off, as many of them could have obtained a larger amount of federal subsidies if they had opted into the Section 1603 Grant. That wind farms selected the PTC even though there was a more profitable alternative available might be due to unobserved benefits to tax equity providers or behavioral inertia to stick to the default option. In columns (3)-(4) of Appendix Table B5, I include the difference in the total subsidies between these two choices in the logit model and find that on average, if the Section 1603 Grant yields a higher payoff, wind farms are more likely to choose it. However, the coefficient is small in magnitude, which implies the difficulty in explaining the subsidy choice merely through the payoff gaps. Therefore, as discussed in Section 5.1, I assume there is a ς probability that wind farm investors would take the default option regardless of the payoffs, while for a probability of $1-\varsigma$ wind farm investors would make a discrete choice of the subsidy according to the total surplus and the i.i.d. preference shock. This modeling approach not only allows me to partially rationalize the subsidy choice through the payoffs to two parties in the bilateral bargaining but also allows unobserved preference shocks of wind farms to explain the residual variations.

Table B5: The Determinants of the Subsidy Choices

	Whether Opt to Section 1603			
	(1)	(2)	(3)	(4)
Productivity	-0.312**	-0.421***		
	(0.137)	(0.144)		
log(Capacity)	0.585**	0.647**		
	(0.273)	(0.281)		
log(Capacity)^2	-0.086*	-0.088*		
	(0.044)	(0.045)		
Difference between Grant and PTC			0.032***	0.040***
			(0.008)	(0.008)
Observations	454	454	454	454
Pseudo R^2	0.014	0.054	0.031	0.077
Year Dummies		✓		✓

Notes: This table shows the estimation results of subsidy choices. The regression model is logit and the dependent variable is defined as a dummy, which takes the value 1 if a wind farm chooses to receive the Section 1603 Grant. I calculated the difference in total subsidies (in million dollars) between these two choices. Standard errors are in parentheses. *p < 0.10; **p<0.05; ***p<0.01.

B.5 Model Fit

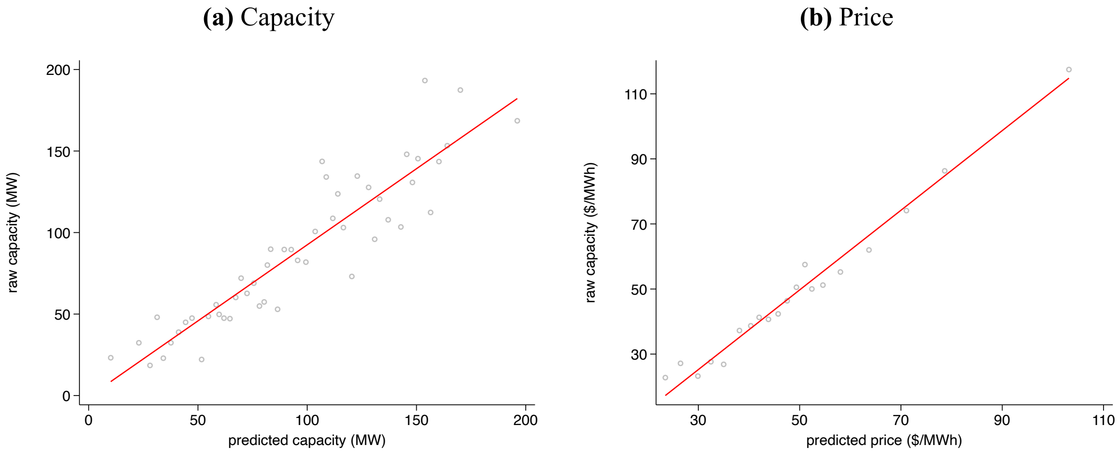
I check the model fit of the bargaining model using estimates from Table 1. The binned scatter plots of the raw and predicted capacity and price according to equation (3) and (5) are shown in Appendix Figure B4. The model explains around 42% of the data variation for capacity, and 67% of the data variation for price. I further explore the model fit for the subsidy choice as shown in Appendix Table B6. Among 301 wind projects that chose the Section 1603 Grant in the data, I predicted 79.7% correctly, while 85.2% of wind projects are correctly classified as choosing the Production Tax Credit.

Table B6: Model Fit for the Policy Choice

	Section 1603 Grant (predicted)	PTC (predicted)
Section 1603 Grant	240	61
	(0.797)	(0.203)
PTC	17	98
	(0.148)	(0.852)

Notes: This table shows the comparison of the predicted and raw policy choices. The shares of each policy type that is correctly predicted are included in parentheses.

Figure B4: Model Fit for the Bilateral Bargaining Model



Notes: This figure shows the static model fit for the capacity function (3) and the negotiated price equation (5).

C An Alternative Dynamic Model

There is an alternative dynamic model for the evolving policy beliefs, which preserves the stationarity of the problem.[38] The notations are the same as in Section 4.3. ω_t represents the policy status in year t, which could take three values: (1) $\omega_t = H$, which indicates that the federal subsidy is enacted in year t and the probability of policy renewal is 1; (2) $\omega_t = L$, which indicates that the federal subsidy is enacted in year t, but the probability of policy renewal is only $b < 1$; (3) $\omega_t = 0$, which indicates that the federal subsidy is terminated. In each period, the *ex-ante* likelihood of $\omega_t = H$ conditional on policy renewal is equal to ρ_H.

I maintain the Assumption 1 from Section 4.3 that policy elimination will be perceived as perpetual. The option value when the realized state variable is $\boldsymbol{s}_{it+1}$ and entry cost shock is ν_{it+1} conditional on different policy status ω_t can be written as follows.

$$E[V(\boldsymbol{s}_{it+1}, \omega_{t+1}, \nu_{it+1})|\omega_t = H] = V(\boldsymbol{s}_{it+1}, \omega_{t+1} = H, \nu_{it+1}) \times \rho_H + V(\boldsymbol{s}_{it+1}, \omega_{t+1} = L, \nu_{it+1}) \times (1 - \rho_H).$$

$$\begin{aligned} E[V(\boldsymbol{s}_{it+1}, \omega_{t+1}, \nu_{it+1})|\omega_t = L] = {} & V(\boldsymbol{s}_{it+1}, \omega_{t+1} = H, \nu_{it+1}) \times \rho_H \times b \\ & + V(\boldsymbol{s}_{it+1}, \omega_{t+1} = L, \nu_{it+1}) \times (1 - \rho_H) \times b \\ & + V(\boldsymbol{s}_{it+1}, \omega_{t+1} = 0, \nu_{it+1}) \times (1 - b). \end{aligned}$$

$$E[V(\boldsymbol{s}_{it+1}, \omega_{t+1}, \nu_{it+1})|\omega_t = 0] = V(\boldsymbol{s}_{it+1}, \omega_{t+1} = 0, \nu_{it+1}).$$

The advantage of this model is to preserve the stationarity of the dynamic problem and use two parameters b and ρ_H to capture evolving policy beliefs. ρ_H can be identified from the frequency of

[38] I thank Ken Hendricks and JF Houde for bringing up this modeling option and for the extensive discussion of its feasibility.

investment spikes, while b can be identified from the magnitude of investment spikes. However, the stationarity of the problem conflicts with the data pattern of jumping investment spikes across years such that the model fails to predict when the investment spikes will occur. The only solution is to index ρ_H and b by t, but the model will be isomorphic as my baseline model.

D Estimation Details for Non-Utility Demand and Buyer Choice

D.1 Demand for Non-Utility Buyers

I test the robustness of the demand function estimation for non-utility buyers. I use the renewable credit price for utilities as the instrument for the wind energy price faced by non-utility buyers, as shown in Table 2. Column (1) in Appendix Table C1 replicates column (4) in Table 2. Moreover, I further use different combinations among three sets of instruments, including the renewable credit price for utilities, the state-level subsidy dummies, and the state-level annual land prices. Overall, the estimated mean elasticity of the demand curve is between -1.7 and -1.4, and the baseline estimate (-1.6) is within this range.

Wind farms that choose to sell capacity to non-utility buyers are also involved in the subsidy type choice. I replicate Appendix Table B5 on the sub-sample that had chosen the non-utility buyers, and there is no strong empirical pattern as shown in Appendix Table C2. Therefore, I assume that wind farms simply choose the subsidy type that gives a larger total subsidy amount when I construct the profits from selling capacity to non-utility buyers.

D.2 Buyer Choice

I match each wind farm in the sample with utilities that were active in the EIA 860 data when that wind farm started construction. The geographical distance between each wind farm and utility pair is calculated using the coordinates of the wind farm and the closest power plant owned by the utility. I first summarize the matching patterns between utilities and wind farms in Appendix Figure C1. Panel (a) shows the raw distribution of the geographical distance between the matched utility and the focal wind farm. The distribution is truncated at 600 miles. The distribution displays a long tail but most of those matched pairs are within 400 miles of each other. Panel (b) shows the distribution of the relative distance of the matched utility and the focal wind farm, which measures how far away the matched utility is compared to the rest of the utilities in the buyer pool. This variable takes the value zero if the matched utility is the closest option, while it takes the value one if the furthest. Panel (b) shows that the wind farm tends to match with a utility that's closer geographically, suggesting that geographical distance might be an important shifter in the matching cost. Panel (c) explores whether a matched utility is likely to be in the same state as the focal wind

Table C1: Robustness Checks: Demand for Non-Utilities

	log(Capacity)			
	(1)	(2)	(3)	(4)
log(Price)	-1.590***	-1.389***	-1.690***	-1.423***
	(0.266)	(0.230)	(0.262)	(0.255)
Observations	309	309	309	309
R^2	0.336	0.355	0.323	0.352
Balance-Authority Dummies	✓	✓	✓	✓
Contract-Type Dummies	✓	✓	✓	✓
Instruments:				
Renewable Credit Price	✓	✓	✓	✓
Land Price		✓		✓
State Policies			✓	✓

Notes: This table shows the estimation results of the linear demand curve for non-utility buyers (equation (7)). I use a combination of three instruments for the price: the renewable credit price for utilities, the annual agricultural land price at the state level, and whether the state offers subsidy policies to wind farms. State policies include sales tax incentives, property tax incentives, and industry recruitment support for the wind industry. Column (1) replicates column (4) in Table 2. Robust standard errors are in parentheses.

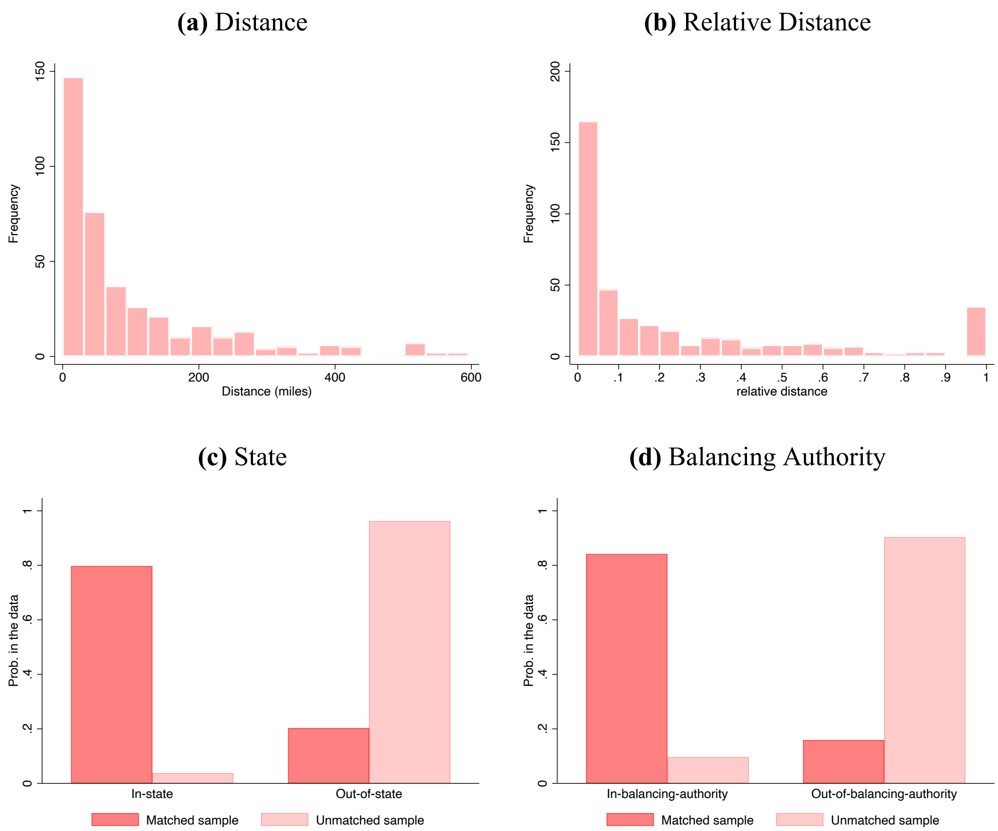
Table C2: Estimation Results: Subsidy Choice for Wind Farms Selling to Non-Utilities

	$\mathbb{1}$(Section 1603 Grant)				
	(1)	(2)	(3)	(4)	(5)
Capacity	0.005				0.003
	(0.003)				(0.004)
Price		-0.009*			-0.008
		(0.005)			(0.006)
Productivity (α_i)			0.148		0.037
			(0.257)		(0.275)
Turbine Price				-0.117	-0.229
				(0.162)	(0.174)
Observations	111	111	111	111	111
Pseudo R^2	0.016	0.022	0.002	0.003	0.037

Notes: This table shows the estimation results of subsidy choice using the sub-sample of wind farms that chose to sell capacity to non-utility buyers between 2008 and 2012. The regression model is logit and the dependent variable is defined as a dummy, which takes the value 1 if a wind farm chooses to receive the Section 1603 Grant. Standard errors are in parentheses. *p < 0.10; **p<0.05; ***p<0.01.

farm. Around 80% of the pairs of a wind farm and its matched utility are from the same state, while fewer than 5% of the pairs of a wind farm and its unmatched utility are from the same state. Panel (d) presents a similar pattern for whether a utility and wind farm pair is in the same balancing authority. Overall, a wind farm is more likely to be matched to a utility that is geographically closer and within its own state or balancing authority.

Figure C1: Matching Patterns between Utilities and Wind Farms



Notes: This graph summarizes the matching pattern between utilities and wind farms. Panel (a) shows the raw distribution of the geographical distance between the matched utility and the focal wind farm. The distribution is truncated at 600 miles. Panel (b) shows the distribution of the relative distance of the matched utility and the focal wind farm, which measures how far away the matched utility is compared to the rest of the utilities in the buyer pool. This variable takes the value zero if the matched utility is the closest option, while it takes the value one if the furthest. Panel (c) explores whether a matched utility is likely to be in the same state as the focal wind farm and Panel (d) explores whether a utility and wind farm pair is in the same balancing authority.

Motivated by the empirical pattern, I restrict the buyer set to those utilities that are within 400 miles of the focal wind farm.[39] I next explore the determinants of buyer choice as shown in Appendix Table C3. The dependent variable $\mathbb{1}(\text{Match})$ is a dummy variable that takes the value one if the utility is the chosen buyer for the wind farm. I find that utilities with a larger renewable portfolio gap (larger unfulfilled demand) are more likely to be matched. Moreover, utilities that are in the same state as the focal wind farm, or that are closer, are more likely to be chosen.

[39]Some matched utilities fall out of this range, and I add those back to the choice set for the focal wind farm.

Table C3: Determinants of the Utility Matching Choice

	$\mathbb{1}$(Match)		
	(1)	(2)	(3)
Renewable Portfolio Gap (10^9 MWh)	1.516***	1.545***	1.589***
	(0.191)	(0.211)	(0.219)
$\mathbb{1}$(Same States)	0.063***	0.068***	0.068***
	(0.004)	(0.004)	(0.004)
Distance (10^3 Miles)	-0.123***	-0.111***	-0.112***
	(0.023)	(0.024)	(0.024)
Observations	15109	15109	15109
R^2	0.053	0.098	0.098
Wind Farm Dummies		✓	✓
Utility Type Dummies			✓

Notes: This table explores the determinants of utility choice of wind farms if they sell capacity through utility Power Purchase Agreements. The dependent variable $\mathbb{1}$(Match) is a dummy variable that takes the value one if the utility is the chosen buyer for the wind farm. Dummies for utility types include whether a utility is investor-owned, a cooperative, or of other types (such as municipal, etc.). Standard errors are clustered at the wind farm level. *p < 0.10; **p<0.05; ***p<0.01.

E Estimation and Simulations Details for Dynamic Model

E.1 Estimation Details of the Dynamic Entry under Policy Uncertainty

State Space and Basis Function I define a set of state variables, including (1) the annual average productivity of wind turbines $\bar{\alpha}_t$; (2) the average turbine prices $\text{TP}_t^{\text{Vestas}}$; (3) the effective market price Θ_{it}; (4) the inclusive value that can be attributed to the changing renewable portfolio gaps for buyers $\text{IV}_{it}(\boldsymbol{\Phi}_{it})$; (5) the utility demand shifter $\boldsymbol{\beta_4 Z_{jt}^U}$ as in equation (15); (6) the non-utility demand shifter as a projection of p_i^{nu} on $\boldsymbol{Z_i^{nu}}$ similar to equation (7); (7) the matching cost shifter MatchingCost_{it}, defined as the mean of $(\hat{\gamma}_3 \mathbb{1}\{m_i \neq m_j\} + \hat{\gamma}_4 Dist_{ij})$ from equation (8); (8) the amount of new wind capacity online NewCap_{mt} in the state m and year t; (9) the subsidy level d_t; (10) a dummy variable defining whether i is before 2013; and (11) the state-level land prices W_{mt}.

Among these 11 variables, (5), (6) and (7) are time-invariant, while others are time-varying. I solve the profit of wind farms if they enter the market as Π_{it} from the static model, and approximate the profit surface as a function of the quadratic basis of the state space $\{u_l(\boldsymbol{s}_{it})\}_{l=1}^L$ such that $\hat{\Pi}(\boldsymbol{s}_{it}) = \sum_{l=1}^{L} \hat{\gamma}_l^{\Pi} u_l(\boldsymbol{s}_{it})$. I approximate the value function as $E[V(\boldsymbol{s}_{it}, \nu_{it})] = \sum_{l=1}^{L} \gamma_l^v u_l(\boldsymbol{s}_{it})$ and solve the dynamic programming problem via value function iteration. I use the state variables (1)-(10) in $\{u_l(\boldsymbol{s}_{it})\}_{l=1}^L$ for the profit surface as land prices are only relevant for entry costs. I use (1)-(9) and (11) in $\{u_l(\boldsymbol{s}_{it})\}_{l=1}^L$ for the value function surface when estimating entry cost parameters, as I only use sample window between 2013-2018, while I use (1)-(8) and (11) in $\{u_l(\boldsymbol{s}_{it})\}_{l=1}^L$ for the value function surface when estimating belief parameters, as I estimate the model year by year and there is no variation in d_t after adjusted for inflation between 2006 and 2012. I use the fully saturated quadratic function of state variables (1)-(5), while the rest state variables are included only linearly.

Transition Dynamics of State Variables There are eight time-varying state variables in my model. The subsidy level d_t and the dummy variable defining whether i is before 2013 evolve deterministically. The annual average productivity of wind turbines $\bar{\alpha}_t$, the average turbine prices $\text{TP}_t^{\text{Vestas}}$, the effective market price Θ_{it}, and the state-level land prices W_{mt} are exogenous in the model, and I recover their transition dynamics from the data with AR(1) models.

For the effective market price Θ_{it}, I allow the AR(1) coefficient to vary before and after 2009 and I allow rich heterogeneity across states for the constant term, consistent with equation (21) for the static estimation in Appendix Section B. The estimation model and results are shown as follows. The total number of observations is 800 and the adjusted R-square is 0.996. The standard error is in parentheses and clustered at the state level.

$$\Theta_{it} = \underset{0.786\ (0.111)}{\gamma_1^{\Theta}}\Theta_{it-1} \times \mathbb{1}(t \leqslant 2009) + \underset{0.762\ (0.019)}{\gamma_2^{\Theta}}\Theta_{it-1} \times \mathbb{1}(t > 2009) + \underset{-0.166\ (0.111)}{\gamma_3^{\Theta}}\mathbb{1}(t > 2009) + \xi_m^{\Theta} + \epsilon_{it}^{\Theta}.$$

Similarly, I estimate the transition dynamics of the state-level land prices W_{mt} using the AR(1) model with rich heterogeneity across states for the constant term. The estimation model and results are shown as follows.

$$W_{mt} = \underset{0.908\ (0.021)}{\gamma_1^{W}} W_{mt-1} + \xi_m^{W} + \epsilon_{MT}^{w}.$$

For annual average productivity of wind turbines $\bar{\alpha}_t$ and the average turbine prices $\text{TP}_t^{\text{Vestas}}$, I only have the time variations of the data and I estimate AR(1) processes with trend breaks before and after 2009. The estimation model and results are shown as follows.

$$\bar{\alpha}_t = \underset{0.330\ (0.382)}{\gamma_1^{\alpha}}\bar{\alpha}_{t-1} \times \mathbb{1}(t \leqslant 2009) + \underset{0.753\ (0.210)}{\gamma_2^{\alpha}}\bar{\alpha}_{t-1} \times \mathbb{1}(t > 2009) + \underset{-1.023\ (1.270)}{\gamma_3^{\alpha}}\mathbb{1}(t > 2009) + \epsilon_{Tt}^{\alpha}.$$

$$\text{TP}_t^{\text{Vestas}} = \underset{0.909\ (0.118)}{\gamma_1^{TP}}\text{TP}_t^{\text{Vestas}} \times \mathbb{1}(t \leqslant 2009) + \underset{0.945\ (0.163)}{\gamma_2^{TP}}\text{TP}_t^{\text{Vestas}} \times \mathbb{1}(t > 2009) + \underset{-2.019\ (2.374)}{\gamma_3^{TP}}\mathbb{1}(t > 2009) + \epsilon_t^{TP}.$$

For the inclusive value that can be attributed to the changing renewable portfolio gaps for buyers $\text{IV}_{it}(\boldsymbol{\Phi}_{it})$, it's endogenously evolving in the model through NewCap_{mt}, but I assume the transition process itself is exogenously given. I approximate the transition process of $\text{IV}_{it}(\boldsymbol{\Phi}_{it})$ as an AR(1) model with the amount of new wind capacity online NewCap_{mt-1} in the state m and year $t-1$ as an endogenous shifter. I further allow the constant term in the AR(1) model to vary across wind farms. The estimation model is shown in equation (17) and the results are shown as follows.

$$\text{IV}_{it}(\boldsymbol{\Phi}_{it}) = \underset{0.591\ (0.020)}{\rho_1^{\Phi}}\text{IV}_{it-1}(\boldsymbol{\Phi}_{it-1}) + \underset{-0.240\ (0.023)}{\rho_2^{\Phi}}\text{NewCap}_{mt-1} + \xi_i^{\Phi} + \epsilon_{it}^{\Phi}.$$

The amount of new wind capacity online NewCap_{mt} in the state m and year t is thus another endogenous state variable in the dynamic problem. I assume NewCap_{mt} to follow another AR(1) process as in equation (18). When estimating entry cost parameters using the more recent policy window, as stationarity is assumed, I directly estimate equation (18) using data from 2015 to 2018. Results using data from 2014 to 2018 are very similar. When estimating the policy belief parameters and implementing counterfactual simulations, I endogenously solve ρ_1^{nc} and ρ_0^{nc} in the equilibrium.

$$\text{NewCap}_{mt} = \underset{0.791\ (0.047)}{\rho_1^{nc}}\text{NewCap}_{mt-1} + \underset{0.032\ (0.022)}{\rho_0^{nc}} + \epsilon_{mt}^{nc}.$$

A simple summary of the estimation algorithm is as follows.

1. A initial guess of b_t is given.
2. Guess ρ_0^{nc} and ρ_1^{nc}, solve the value functions $V^0(\boldsymbol{s}_{it})$ and $V^1(\boldsymbol{s}_{it}, b_t)$.
3. Simulate the trajectory of NewCap_{mt}, solve for new ρ_0^{nc}, and ρ_1^{nc} and update the belief.
4. Repeat steps 2-3 until the values of ρ_0^{nc} and ρ_1^{nc} converge.
5. Solve the value functions $V^0(\boldsymbol{s}_{it})$ and $V^1(\boldsymbol{s}_{it}, b_t)$. Predict the state-level entry rates and match them with data.
6. Iterate on b_t until the sum of squared errors is minimized.

E.2 Simulation Details of the Dynamic Model

The simulation procedures of the dynamic model mirror the estimation steps. For both the baseline and the counterfactual scenarios, I simulate the model year by year according to the following steps.

1. For year t, I simulate a sample of potential entrants in state m and year t of the size of $\text{PotentialEntrants}_{mt}$. The state variables of potential entrants follow the distribution of $\boldsymbol{s}_{it+1}$ from state m and year t observed in the data.
2. Guess ρ_0^{nc} and ρ_1^{nc}, solve the value functions $V^0(\boldsymbol{s}_{it})$ and $V^1(\boldsymbol{s}_{it}, b_t)$.
3. Simulate the trajectory of NewCap_{mt}, solve for new ρ_0^{nc} and ρ_1^{nc}, and update the belief.
4. Repeat steps 2-3 until the values of ρ_0^{nc} and ρ_1^{nc} converge.
5. Solve the value functions $V^0(\boldsymbol{s}_{it})$ and $V^1(\boldsymbol{s}_{it}, b_t)$.
6. Draw entry cost ν_{it} 100 times and each potential entrant makes optimal entry timing decision according to equation (14). Sum over the entry decision of each potential entrant and calculate the

total number of entrants Entry_{mt}.

7. Update the $\text{PotentialEntrants}_{mt+1}$ to add the number of delayed entrants from year t. Repeat the steps (1)-(6) for year $t+1$.

For policy windows between 2013 and 2018, I solve the parameters of the endogenous transition process ρ_0^{nc} and ρ_1^{nc} as well as stationary value functions $V(\boldsymbol{s}_{it})$ for years 2013 and assume the value functions are the same for the rest years. This is consistent with the estimation assumption that the dynamic problem is stationary between 2013 and 2018.

F Calculation of Social Benefits of Wind Energy

I evaluate the benefits of wind energy following Callaway et al. (2018). I assume wind farms operate for 20 years and calculate total benefits from their twenty-year operations. Wind energy substitutes fossil fuels in generating electricity and thus there are three sources of benefits from more wind energy on the grid: reducing carbon emissions, avoiding fossil input costs, and adding capacity values to the system. I estimate the average marginal operating emissions rate (MOER) of coal- or gas-fueled power plants in each state and year, which is defined as the marginal response in the system-wide emissions with respect to the total production change from generators due to more renewable energy, as Callaway et al. (2018) find that regional average MOERs offer a useful means of "calibrating regional policy incentives to compensate for external emissions benefits."

I access the data of total electricity production and carbon emission for each state at the hourly level between January 1, 2004, and December 31, 2018, from the Clean Air Markets Program Data (formerly, Continuous Emissions Monitoring Systems Database). Following Callaway et al. (2018), I first cluster hourly observations according to load profiles and peak loads using a k-means clustering algorithm. The clusters k are generated for each market r, season s, and hour-of-the-day h. I categorize all observations into eight markets according to their ISOs or RTOs, including CAISO, ERCOT, ISO-NE, MISO, PJM, SPP, NYISO, and non-ISO states. I categorize all dates into two seasons: summer/fall (May to October) and winter/spring (November to April). I generate 12 clusters of observations within each hour of the day, season, and market (such as MISO in summer/fall 10-11 a.m.). The MOER is estimated using the equation below, where E_{mkt} and G_{mkt} represent emissions and electricity generations in each hour t, cluster k, and state m.

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

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

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

A PPA Data

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

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

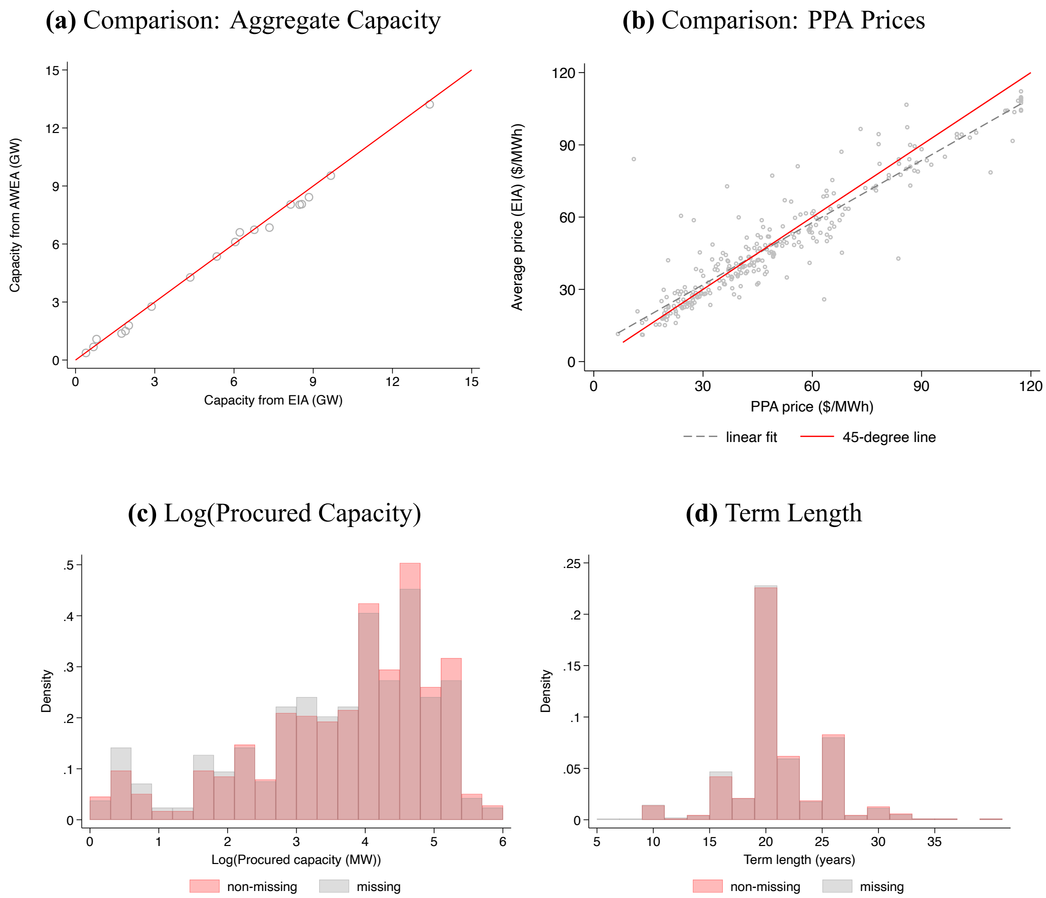
There are 36.3% contracts missing price information among all the contracts with valid utility names and wind farm IDs. I follow Aldy et al. (2023) and impute the missing PPA prices from the resale revenues and quantities reported in the EIA Form 923 from 2011 to 2019. By comparing the prices of wind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

B REC Price Data

I obtain the Renewable Energy Credit (REC) price data between 2006 and 2019 from a financial service platform Marex. I calculate the REC price estimates in a given state and year by taking the average between bids and asks from all active REC markets following Aldy et al. (2023). However, only 15 states have available information from Marex and the time coverage also varies across states. I take two steps to impute REC prices for active REC state with missing data. First, for the 15 states covered by Marex, I run the following regression to predict their REC prices in years with missing values.

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

Figure OA1: Data Description of the PPA Sample



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

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

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

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

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

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

C Interconnection Queue Data

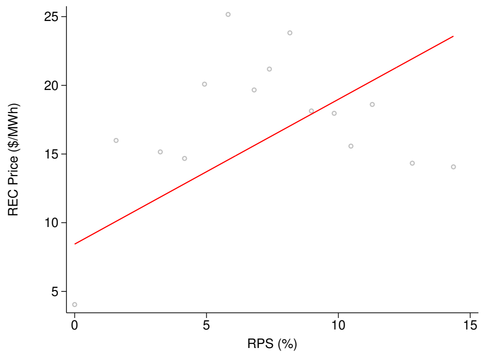
I access the interconnection queue data from different Regional Transmission Organizations (RTO) and Independent System Operators (ISO), including MISO, CAISO, PJM, ISO-NE, NYISO, and SPP.[1] Since I observe the time when a project entered the queue and withdrew from the queue, I define the former as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

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

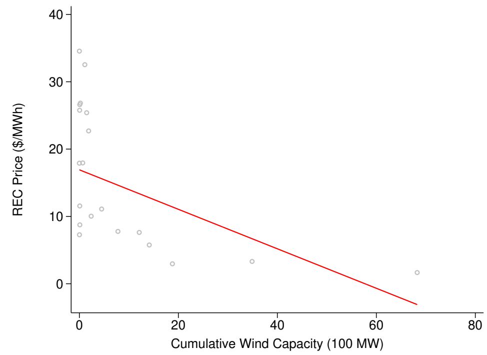
[2] Anecdotes suggest that a typical project completed in 2008 spent fewer than two years in the queue for interconnection approval compared to three years in 2015, according to the news. Although the backlog and congestion issues are salient in recent years, two-year waiting time might be a reasonable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

Figure OA2: Renewable Energy Credit Prices and Other Market Outcomes

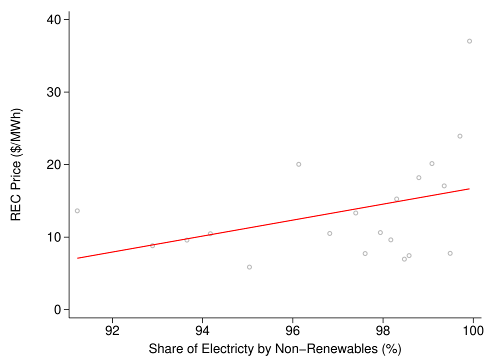
(a) Renewable Portfolio Standards



(b) Cumulative Wind Capacity



(c) Electricity Share by Fossil and Nuclear Power



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

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

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

I define $\text{PotentialEntrants}_{m,2002}$ as twice as large as the maximum of NewBuilt_{mt} in the state m, serving as an initial value. I adjust $\text{PotentialEntrants}_{mt}$ to be equal to NewBuilt_{mt} if the former falls below the latter. I describe the time trend for Entry_{mt}, Exit_{mt}, and $\text{PotentialEntrants}_{mt}$ in

Table OA1: REC Tracking System and Price Imputation

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

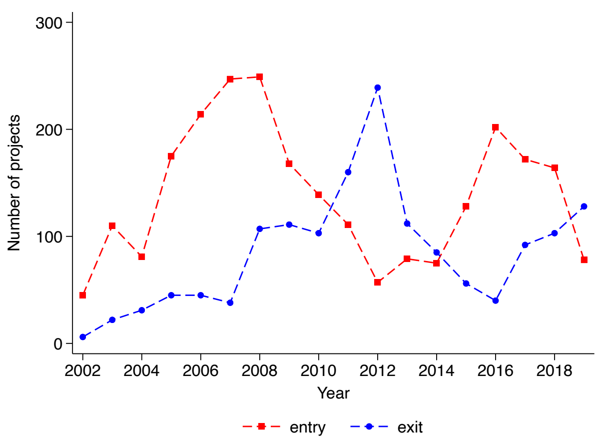
Notes: This table documents the establishment year as well as the tracking system of the Renewable Energy Credit (REC) market for relevant states based on the Table 1 from Abito et al. (2022). The column "Imputation" documents how I impute missing REC prices in the corresponding states. "Regression"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

Appendix Figure OA3. The total number of projects that entered the queue initially increased but fell between 2008 and 2012. After 2012, the trend reversed until 2016. The total number of projects that withdrew from the queue experienced a peak in 2012 and displayed a hump shape. As a consequence of the time trend for entry, exit, and successful new-built which peaked in 2011, the number of total potential entrants is also hump-shaped and peaked in 2010. The entry and withdrawal from the queue are both assumed to be exogenous to my model.

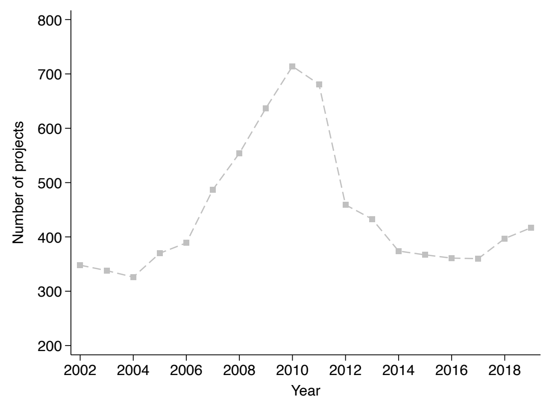
One complication is a lack of interconnection queue data for states that are not part of the ISOs or RTOs. Moreover, I only access ERCOT interconnection queue data between May 2014 and July 2018, in which the number of projects that had signed the interconnection agreement could be calculated. As shown in Appendix Figure OA4, the number of newly built wind farms is stable compared to the rest of the US, and the number of potential entrants between 2014 and 2018 was also stable within the range between 40 and 50. Therefore, I assume that the number of potential entrants is constant at 50 across years for ERCOT. For the rest of the states that lack interconnection queue data, I assume that the number of potential entrants in 2002 was twice as large as the maximum number of newly built wind farms annually in that state, which is the same as what I assume for the ISOs and RTOs. For later years, I assume the number of projects that enter the queue or withdraw from the queue follow the aggregate time trend in MISO, CAISO, PJM, ISO-NE, NYISO, and SPP, and the level is adjusted proportionally to the number of potential entrants in 2002.

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

(a) Entry and Exit

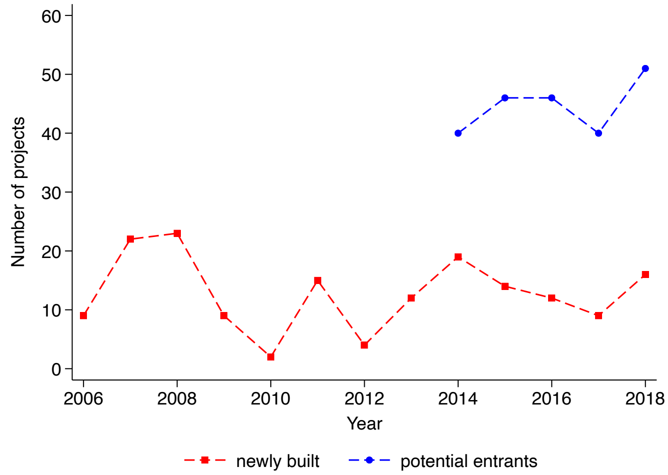


(b) Total Potential Entrants



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

Figure OA4: Newly Built Projects and Potential Entrants in ERCOT



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

References

Abito, J. M., Flores-Golfin, F., van Benthem, A. A., Vasey, G., and Velichkov, K. (2022). Designing more cost-effective trading markets for renewable energy.

Aldy, J. E., Gerarden, T. D., and Sweeney, R. L. (2023). Investment versus output subsidies: Implications of alternative incentives for wind energy. *Journal of the Association of Environmental and Resource Economists*, 10(4):981–1018.