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

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Abstract

This paper investigates the dynamic efficiency of policy uncertainty in the US wind energy industry. Policy expiration embedded in the Production Tax Credit induced uncertainty among wind farm investors and expedited investment. I compile a comprehensive data set of the investment, production, and long-term contracts on the US wind energy market. I find significant bunching in the number of new wind farms at the expiration dates of the short policy windows and a large mismatch among wind farm investment timing, continuously improving upstream turbine technology, and evolving demand for wind energy. I then develop an empirical model featuring the bilateral bargaining of long-term contracts, endogenous buyer matching, and dynamic wind farm investment under policy uncertainty. Model estimates reveal that a lapse in policy extension reduced the perceived likelihood of policy renewal to 30%, and counterfactual simulations demonstrate that removing policy uncertainty postpones 53% of the 2011 cohort of wind farms by 3.5 years. The net social benefits increase by 5.9 billion dollars and 28.9% after removing policy uncertainty. Moreover, removing policy uncertainty could save fiscal expenditure without sacrificing social welfare.

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1 Introduction

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

This paper explores the dynamic efficiency of policy uncertainty, using the US wind energy industry as the empirical setting. Wind energy grew from a marginal share in 2000 to the biggest renewable energy source in 2019. This industry is featured by a huge irreversible investment cost, and the boom of wind energy has been heavily supported by federal tax incentives, known as the Production Tax Credit (PTC) in a form similar to long-term output subsidies. The PTC has been active since 1992, but when implemented, it was segmented into a series of shorter policy windows with expiration dates.[1] A lack of government commitment combined with occasional lapses between expiration and renewal caused policy uncertainty among wind farm investors about the future extension.[2] Under policy uncertainty, investors expedited their investment and bunched investment timing near the expiration time. Consequently, it leads to two opposing forces shaping social welfare. On the one hand, the expedited investment reaps environmental benefits earlier. On the other hand, the bunching of investment approaching policy expiration creates a mismatch among wind farm investment timing, continuously improving upstream turbine technology, and the evolving demand for wind energy. The overall welfare effect is ex-ante ambiguous.

I compile a comprehensive data set of the investment, production, and long-term contracts on the US wind energy market and document three key stylized facts. First, I find significant bunching of the investment timing for wind farms at the expiration dates of the short policy windows, especially in 2012, mainly due to a lapse between expiration and renewal. Second, while the investment was bunched at expiration dates in earlier years, the upstream wind turbine technology is quickly improving and becoming cheaper. It creates a large mismatch between the timings of investment and technological advancement. Third, utilities, an important group of buyers of wind capacity, have a shrinking unfulfilled demand as they procure more wind energy over time and meet state-level regulations. Consequently, expedited entry of wind farms that are equipped with old technology preempt utilities of a larger unfulfilled demand, while more recent entrants with better technology sell wind capacity to utilities of a smaller unfulfilled demand, suggesting a matching

[1]As noted in Bistline et al. (2023), the continual expiration and extension of 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.

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

efficiency loss between utilities and wind farms due to policy uncertainty.

Motivated by the stylized facts and institutional details, I next develop a structural model of the wind energy market in the US. The structural model consists of a dynamic part and a static part. In the dynamic part, the wind farm investors form beliefs about the probability of the future renewal of PTC. Given the turbine technology and turbine procurement cost exogenously evolving, those investors decide whether to invest in the current period or wait until the next period. If they decide to invest in this period, there are two channels to sell wind capacity, and the discounted sum of flow profits from selling wind energy is determined in the static part of the model. The first channel is for wind farms to sell capacity to utilities over a long-term Power Purchase Agreement, while the second channel is for wind farms to sell their capacity to other non-utility buyers such as corporations or sign financial contracts.

In the static part of the model, wind farms first choose which type of buyer to sell wind capacity to. If they decide to sell to utilities, they choose which utility to match with, weighing the profit from a potential negotiation against the pairwise matching cost. Wind farms then negotiate with the matched utility over the power purchase prices, total procured capacity, and whether to choose an output-based tax credit or a cash grant as the subsidy type. Alternatively, for those wind farms that sell capacity to non-utility buyers, I model a linear demand curve, combining information for both the corporate buyers and merchant/hedge contracts. For the bilateral bargaining, I model the detailed profit functions for both utilities (the buyer) and wind farms (the seller). Utilities obtain profits with procured wind energy from both selling electricity and obtaining renewable credits, net the costs they pay to wind farms as negotiated in the Power Purchase Agreement, while the profits for wind farms combine the revenues generated from the Power Purchase Agreement and total government subsidies, net total turbine expenditures. The optimal procured wind capacity and the subsidy type choice maximize the joint profit, while the negotiated price splits the total surplus between the two parties.

I estimate the static model in three steps. First, I estimate the bilateral bargaining model, combining the optimality conditions for the power purchase prices, total capacity, and subsidy type choice. I recover parameters governing utility willingness to pay and wind farm turbine costs, conditional on a rich set of controls of unobserved demand shocks. I estimate a bargaining weight parameter, which is identified by the relative path-through ratio 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 especially if they are further away from the state-level standard, and they have two-thirds of the bargaining weight relative to wind farms. Wind farms have a convex cost function with respect to the total capacity, and they value one-dollar tax credit as only 83.9 cents of cash grants. Using the parameter estimates, I find that around 22.4% of wind farms will negotiate a negative capacity or earn a negative profit without the Production Tax Credit. Even conditional on positive profits, the average profit without PTC is 47.0% smaller than the average profit with PTC. This result highlights the potential cost of missing deadlines and losing the qualification of PTC and explains the rushed entry when there is a lower belief for PTC renewal.

Second, I estimate a linear demand curve for non-utility buyers and I 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 -1.59. Third, I estimate the buyer type choice and the utility matching problem. I find that the mean likelihood of selling capacity to a non-utility buyer is around 24.2%. The matching cost between a wind farm and a utility is much larger if they are located in different states, which also increases with their geographical distances.

The static model quantifies the profit for wind farms if they enter the market, and captures rich forces underlying the profit function. In the dynamic part of the model, potential entrants make entry decisions comparing the expected profit from the investment net the entry cost, and the option value of waiting. The option value of waiting subsumes the perceived likelihood of policy extension. I treat the perceived likelihood of policy extension as the parameter in the model and allow it to vary over time, and thus the dynamic problem is non-stationary. I impose two assumptions on the belief structure to make the estimation feasible. First, I assume that if the policy is eliminated, wind farm investors will hold the belief that the policy will be terminated forever. Second, the perceived likelihood of a one-year policy extension will carry over for future years in expectation. Under these two assumptions, the policy belief parameter acts as a weight between two boundaries of the optional value of waiting. The lower bound is the continuation value when the subsidy is terminated forever, while the upper bound is the continuation value when the subsidy is renewed according to the perceived likelihood of policy extension in the next year.

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

I estimate the dynamic part of the model in two steps. First, to tackle the aforementioned identification challenge, I focus on a recent policy window when the policy was announced to cover a relatively long period. I assume the problem to be stationary for the policy window, solve the dynamic model using functional approximation and estimate the entry cost parameters by matching model-predicted entry rates with data. Second, I use the estimated cost parameters to solve the dynamic model in earlier years with policy uncertainty. I solve the perceived likelihood of policy extension year by year while allowing the belief of endogenous state variables to be determined in the equilibrium.

I estimate the mean realized entry cost to be 17.94-19.19 million dollars. Moreover, I find a higher land price exacerbates the entry cost. More importantly, there was enormous uncertainty with respect to the policy renewal especially for the 2011 cohort. The average perceived probability of policy renewal is around 0.3 due to the pessimism about the policy extension as well as the delayed renewal action, which largely explains the investment spike that year.

With estimated model primitives, I implement four counterfactual analyses. In the first counterfactual exercise, I simulate the investment decision when the policy uncertainty is eliminated and calculate the welfare consequences of policy uncertainty by comparing the simulated case without policy uncertainty and the baseline scenario. Removing policy uncertainty reduces the number of new wind projects in 2011 by 52.7% and increases the number of new wind projects in 2012-2018 by 24.1% on average annually. Those delayed wind farms would postpone their entry by 3.56 years.

Overall, the numbers of total wind projects are roughly the same, suggesting that removing policy uncertainty mainly changes the entry timing but keeps the total number of entrants constant over an 11-year horizon. However, the total wind capacity increases by 6.3% once policy uncertainty is removed and the total output increases by 8.7%, as more wind farms enter when turbine technology is more advanced. I evaluate the benefits of wind energy following Callaway et al. (2018) and estimate the average marginal operating emissions rate (MOER) of coal- or gas-fueled power plants in each state and year, which measures the saved carbon emissions due to more renewable energy. I calculate the total social surplus of wind energy from the twenty-year operations of those wind farms. It is defined as the sum of reducing carbon social costs, avoiding fossil input costs, and adding capacity values to the system, minus the turbine costs and entry costs paid by wind farm investors. Overall, removing policy uncertainty delays the entry of wind farms as well as the total benefits of wind energy, but the negative effect can be completely offset by a better timing alignment among investment, technology, and wind demand. I find the total social surplus increases by 6.8 billion dollars and 18.4% after eliminating policy uncertainty. The net social surplus, which is the total social surplus further subtracted by the government subsidies, increases by 5.9 billion dollars and by 28.9% from the baseline scenario.

In the second counterfactual exercise, I investigate how the 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 without sacrificing social welfare, which demonstrates the fiscal burden brought by policy uncertainty. In the third counterfactual exercise, I quantify the welfare effects when policy uncertainty is resolved early. Following the same intuition as in Gowrisankaran et al. (2023), I find that resolving policy uncertainty before wind farms make their entry decision will reduce the rushed entry and alleviate the negative impact of policy uncertainty, even holding the mean likelihood of policy extension constant. In the last counterfactual exercise, I find that if turbine technology or utility demand is held constant, removing policy uncertainty still improves social welfare but the effect shrinks to less than 30% of the full dynamic results, which indicates that the dynamic market environment greatly exacerbates the efficiency loss from policy uncertainty.

This paper contributes to the following three strands of literature. First, this paper contributes to the literature on the measurement and evaluation of policy uncertainty. Policy uncertainty is pervasive and broadly studied in both macroeconomics and microeconomics, and 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). Compared to earlier literature, this paper focuses on the US wind industry as a specific empirical setting and studies the consequences of policy uncertainty with micro evidence. 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). My paper structurally quantifies the extent of policy uncertainty and evaluates the dynamic consequences of policy uncertainty 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 a different setting and exploits a different strategy to identify policy 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., 2022), spatial misallocation (Callaway et al., 2018; Sexton et al., 2021), values of wind energy (Cullen, 2013; Novan, 2015), upstream innovation (Covert and Sweeney, 2022; Gerarden, 2023), storage technology (Butters et al., 2021), transmission congestion (Fell et al., 2021), carbon taxes (Elliott, 2022), contract risks (Ryan, 2021), interconnections (Gonzales et al., 2023; Johnston et al., 2023), Renewable Portfolio Standards (Hollingsworth and Rudik, 2019; Abito et al., 2022), and renewable subsidies (De Groote and Verboven, 2019; Kay and Ricks, 2023; Bistline et al., 2023). My paper offers 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 industry, there are recent papers about the timing of subsidies (Langer and Lemoine, 2018; Armitage, 2021), subsidy design (Barwick et al., 2022), and subsidy types (Johnston, 2019; Aldy et al., 2023). Different from the previous papers, I focus 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.

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

2 Wind Industry and Government Policies in the US

2.1 Wind Industry in the US

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

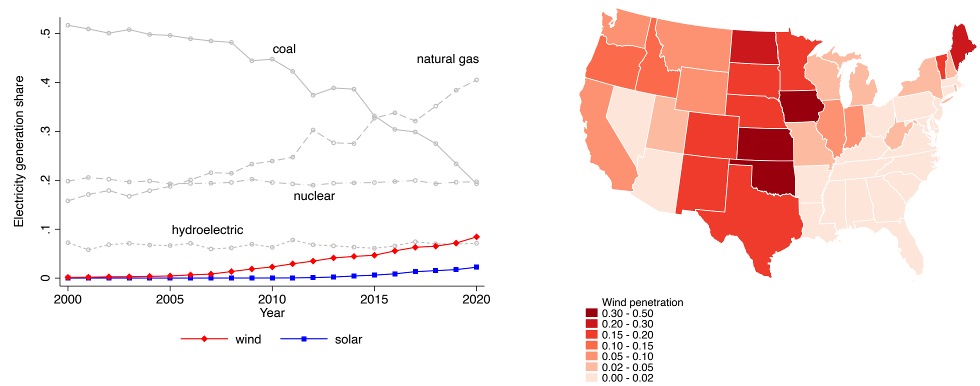
A wind farm requires enormous investment upfront. Investors had to spend more than 100 million dollars to construct an average-sized wind farm in 2019 just for the turbine procurement, leaving alone the transportation cost of wind turbines, the construction cost of the wind farm, the land lease cost,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

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

turbine manufacturers for equipment procurement, negotiate with utilities or corporations to sell outputs, and seek financing for the projects. Finally, with contracts secured, investors could start the construction process. The typical wind development process takes a total of 3-4 years, and the construction process alone takes around 6-9 months. Once the wind farm starts operation, it could be in service for around 30 years. Large sunk costs, together with a long time to build, indicate the importance of dynamic incentives in wind investment.

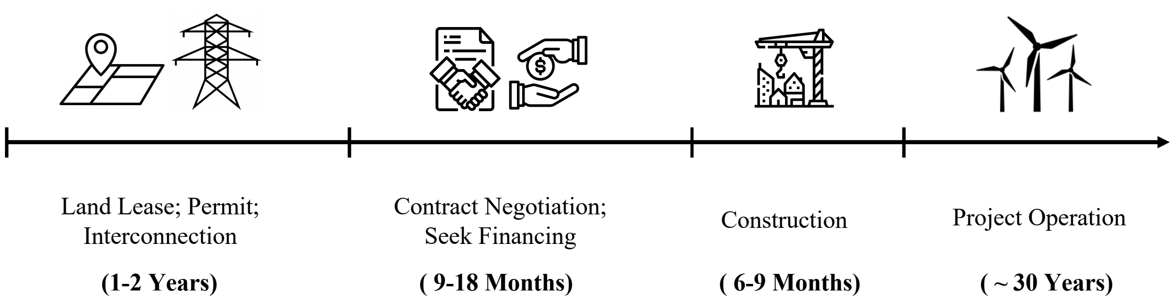
Figure 1: Share and Penetration Rate of Wind Energy

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



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

Figure 2: Timeline of Building a Wind Farm



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

There are two types of investors on the market, independent power producers and utilities, and they together own over 99% of wind energy. On the one hand, the wind farms owned by independent power producers take up around 80% of the total capacity. They typically sign a long-term wind procurement contract with utilities or non-utility buyers (for example, 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 includes the price term, the procured capacity, and the time length of the agreement, among other details. Moreover, wind energy owned by independent power producers could also sign merchant or hedge contracts.[4] As shown in Appendix Figure A.1, utility PPAs are the most common channel to sell wind power, while more non-utility PPAs emerged in the market after 2015.

On the other hand, wind capacity directly owned by utilities is around 20% of the total capacity, and they will supply electricity to the wholesale market (in restructured states) or the consumers (in regulated states). This paper focuses mainly on wind farms invested by independent power producers due to their dominant market shares. As utilities could either own wind farms or procure wind energy from independent power producers, endogenizing wind capacity under direct utility ownership requires a model of make-or-buy choices of utilities, which is beyond the scope of this paper.

2.2 Government Policies

The wind power industry in the US crucially relies on the tax credit from the federal government, upon numerous state-level policies. The most influential and long-standing tax credit is the production tax credit (PTC), which was initially established in 1992. It provided qualified wind farms with a 10-year inflation-adjusted tax credit for wind power generation and stood at $24/MWh in 2018. Although PTC has been in effect for most of the time since 1992, the incentives provided by PTC were segmented into smaller policy windows, with an explicit expiration date at the end of each time window. The essential condition to quality for PTC is tied to these expiration dates: before 2012, a wind farm was required to start operation before policy expiration, while after 2013, a wind farm is required to demonstrate that five percent or more of the total cost of the project has been incurred before policy expiration with a two-year (four-year after 2016) safe harbor to start operation.[5] As shown in Figure 3, the PTC is enforced by different acts during different sample periods. For example, from February 2009 to December 2012, the PTC was enacted in the American Recovery and Reinvestment Act. Subsequently, the PTC was enacted in the American Taxpayer Relief Act (2013), the Tax Increase Prevention Act (2014), and the Consolidated Appropriations Act (after 2015).

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

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

Since 2005, there have been seven different acts enacting PTC sequentially, which segments the policy into windows of 1-5 years. Before 2009, the renewal of PTC in the next act was announced several months before its expiration. However, at the end of 2012, 2013, and 2014, the renewal of PTC was announced after the deadline passed. Although the lapse between policy expiration and renewal could be as short as two days at the beginning of 2013, it still disturbed the market incentives and created policy discontinuities. With a lack of government commitment, wind investors were faced with policy uncertainty before policy expiration about whether the PTC would be extended or not. The delay in policy action from Congress as well as political debates about renewable subsidies exacerbated the uncertainty in the market.[6] [7]

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 renewal of the PTC, 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..."

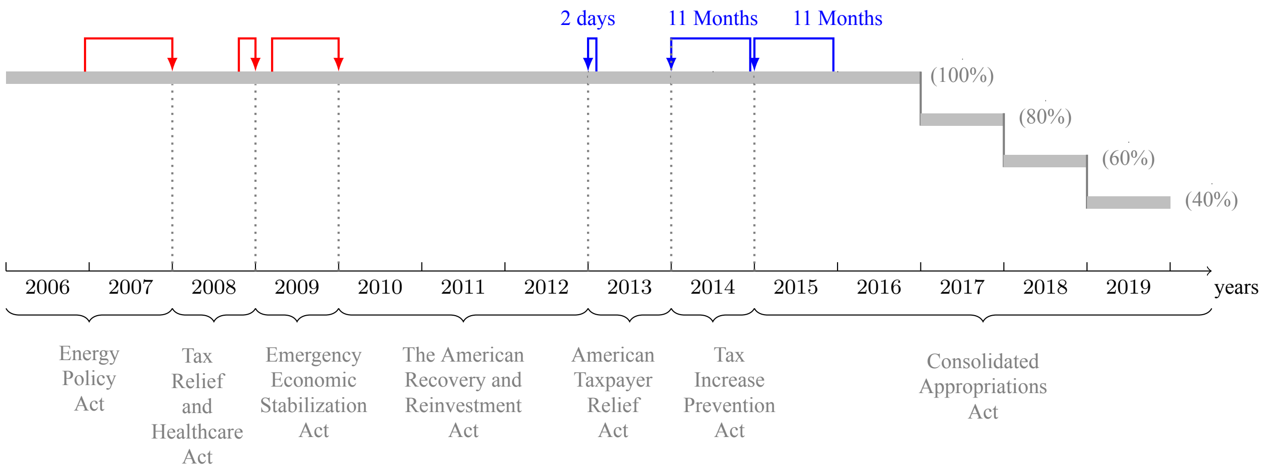
The concerns about the expired PTC were ex-post proven to be unnecessary, as only 2 days after the expiration of the PTC, it was extended again in the American Taxpayer Relief Act and the subsidy was retroactive. Similar things happened again in 2014 and 2015, although the lapses were much longer, and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

Along with the production tax credit, there was also the Section 1603 Grant, which provided an upfront investment subsidy equal to 30 percent of the investment costs. Between 2009-2012, investors could opt in for either PTC or Section 1603 Grant. Unlike PTC, the Section 1603 Grant was announced to expire for sure after 2012. Johnston (2019) and Aldy et al. (2023) study the selection and efficiency consequences of having both production tax credits and investment subsidies on the market. Since there were many wind farms under either subsidy, I assume that these two policies provided similar incentives to new wind farms on average and study the uncertainty and discontinuity under this federal policy bundle.

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

[7] 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).

Figure 3: Timeline of Production Tax Credit



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

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

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

3 Data and Stylized Facts

3.1 Data

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

One key piece of information missing from USWTDB and EIA-860 is the time of investment for wind farms. Both USWTDB and EIA-860 record the month when a wind farm starts to supply electricity, however, as illustrated in Figure 2, there is a lag between finalizing the investment decision and starting operation, including a construction period of 6-9 months. I follow Johnston and Yang (2019) to use the information from the Federal Aviation Administration (FAA) Obstruction Evaluation/Airport Airspace Analysis (OE/AAA) database. The FAA data reports the scheduled dates of starting construction. I match the FAA data with EIA-860 and measure the time of investment as the time when a wind farm starts construction.[8]

The second data set is the detailed 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 the amount of capacity, negotiated price, term length, and buyer and seller information. The data is at the contract level and covers the universe of wind capacity as compared with EIA Form-860 data. The modal contract length of Power Purchase Agreements is 20 years. For more detailed data processing, please refer to Appendix Section B.

Apart from these main data sets, I collect the interconnection queue data from the websites of ISOs/RTOs. I use the 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 procurement price from Lawrence Berkeley National Laboratory. I hand-collected the state-level policies including RPS from DSIRE.

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

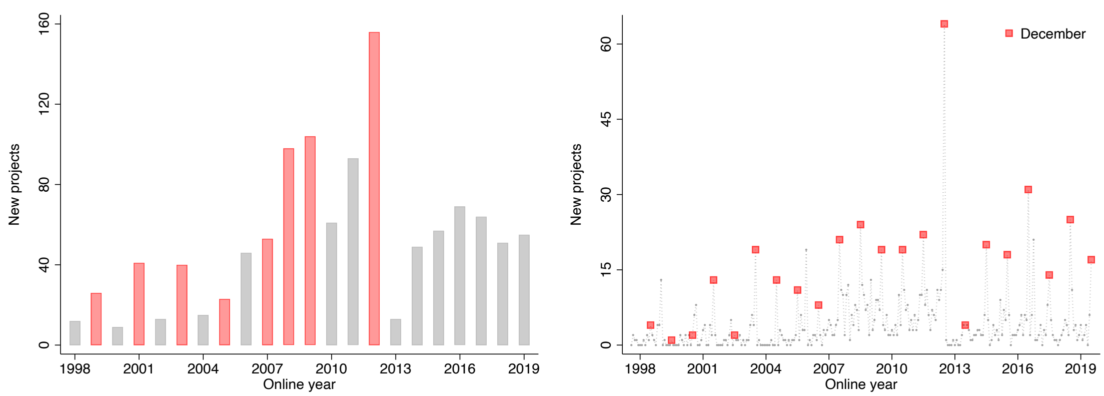
3.2 Stylized Facts

3.2.1 The Timing of Investment

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

Figure 4: Time Trend for Wind Projects Newly Online

(a) Annual Trend **(b)** Monthly Trend



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

This time pattern aligns well with the timing of policy implementation as well as the time to build required in the wind industry. As shown in Figure 3, the Emergency Economic Stabilization Act and the American Recovery and Reinvestment Act were enacted in October 2008 and February 2009 respectively. During the 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 time period. By the end of 2012, it was clear that the Section 1603 Grant would be discontinued, but there was enormous uncertainty about whether the Production Tax Credit would be extended or not due to the time lapse in renewal. Consequently, there was a rushed inflow of new wind projects before policy expiration to secure a flow of subsidies for the next 10 years of operation, as we observe the bunching in the number of projects newly online in 2012. This distortion owing to the subsidy expiration is more obvious when we examine the monthly trend of new wind projects. As shown in Panel (b) of Figure 4, the bunching in 2012 was mainly driven by a massive entry in December of 2012, which was ten times as large as the average monthly investment from January 2001 to November 2012.[9]

Although the Production Tax Credit was renewed shortly after its expiration in 2013, the investment flow didn't recover immediately. The main reason is that it takes a relatively long time to build new wind farms. After 2015, the PTC was planned for relatively longer terms, and the incentives provided by the PTC were also stabilized. Therefore, there has been a steady time trend of new wind projects since 2015. I plot the time trend of new wind capacity in Appendix Figure A.4, and find the bunching pattern robust for the aggregate capacity as well. The average capacity per wind farm was stable in 2012 and displays an increasing trend over time.

There could be different channels for the bunching in the online timing. First, wind farms might expedite the construction process to meet the expiration dates of PTC, which was tied to the online time of wind projects before 2012. However, as shown in Panel (a) of Appendix Figure A.5, the average construction time remains stable at around 9 months across different online years. Panel (b) further plots the average construction time across years when wind farms start construction. There was suggestive evidence that wind projects starting construction in 2012 were more likely 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 in the bunching.

Alternatively, the massive entry in 2012 might reflect the expedited waiting process in the interconnection queue. However, as shown in Panel (a) of Appendix Figure A.6, 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 Mismatch

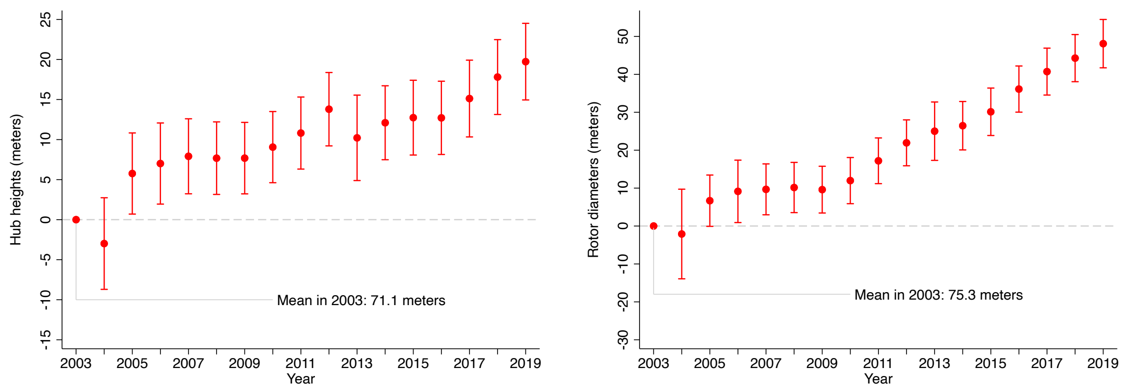
In contrast to the bunched timing of investment, the technology of wind turbines is continuously improving over time. There are three key components of a typical horizontal-axis wind turbine, a tower, a nacelle, and three rotor blades. The potential of wind power generation crucially depends on the height of the tower and the length of the rotor blades. Taller towers enable the turbine to access better wind resources up in the air, while longer rotor blades lead to larger swept areas and

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

capture more wind energy inputs (Covert and Sweeney, 2022). I present the time trend of average tower heights and rotor diameters of new wind farms in Figure 5. As is evident from Panels (a) and (b), the hub heights and rotor diameters are getting larger, and almost follow linear trends after 2009. The average hub height for newly invested wind farms in 2008-2013 was 80.13 meters, while the average hub height for newly invested wind farms in 2014-2019 increased by 6.5% to 85.30 meters. Similarly, the average rotor diameter for newly invested wind farms in 2008-2013 was 88.04 meters, while the average rotor diameter for newly invested wind farms in 2014-2019 increased by 24.6% to 109.69 meters.

Figure 5: Time Trend of Wind Turbine Technology

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



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

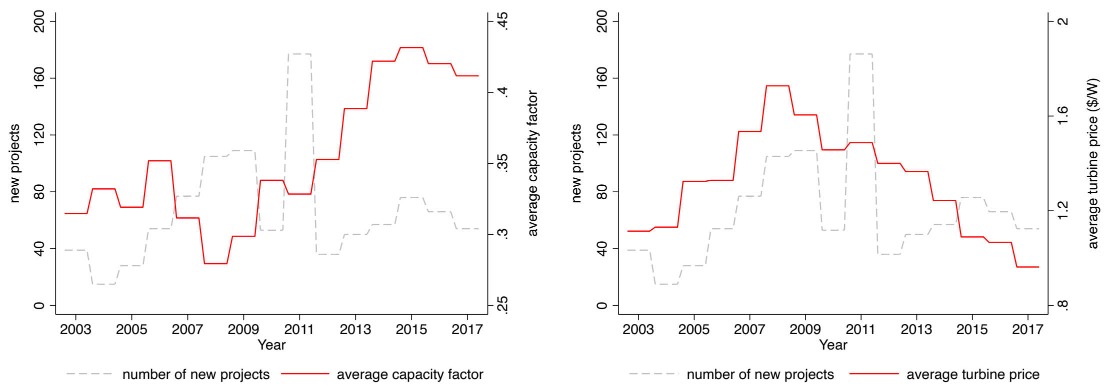
Bunched investment timing and improving turbine technology lead to a mismatch between the timings of investment and technology. Panel (a) of Figure 6 plots the contrast of these time trends. I plot the number of new wind farms according to their construction start years as well as the technological efficiency of each cohort. I measure the technological efficiency with the capacity factor (the ratio of average power output and maximum power production) at the age of one.[10] Newly invested wind farms in 2008-2013 had an average capacity factor of 0.32, while that number in 2014-2018 rose to 0.41, increasing by 27.2%. While the investment bunched in earlier years, the upstream wind turbine technology is continuously and quickly improving, thus there were many wind farms equipped with less productive turbines as a result of policy uncertainty.[11]

[10] 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."

[11] One concern is that the average productivity of a wind farm is also affected by the wind resources of its location,

Figure 6: Mismatch between Investment and Turbine Technology

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



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

Moreover, the average turbine prices are also decreasing over time. As shown in Panel (b), since peaking in 2008-2009 at around 1,700 dollars per kilowatt, the average turbine price has been declining. On average, the turbine price fell below 1,000 dollars per kilowatt after 2015. Therefore, early investment in 2008-2011 largely foregoes later cheaper technology. Decreasing turbine procurement prices and increasing turbine production efficiency together indicate a substantial option value of delaying entering the market for better and cheaper technology. However, policy uncertainty expedited wind farm entry, foregoing the benefits of technological improvement and leading to inefficiency in the 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 key incentive for them to procure wind capacity is to satisfy state-level Renewable Portfolio Standards (RPS), 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 Renewable Portfolio Standards. It measures the unfulfilled demand of each utility for renewable energy in order to meet the RPS. The details of how this variable is constructed and

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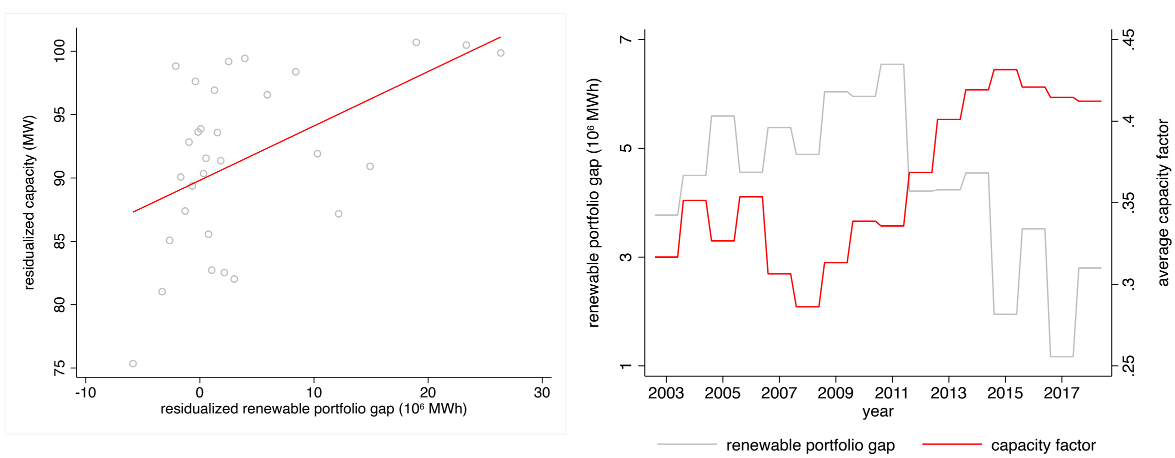
and later entrants might be faced with locations with worse wind resources. However, as shown in Appendix Figure A.7, the average wind speed for each cohort is generally stable over time. The wind resources are more stable for later entrants, as the standard deviation of the daily average wind speed is lower.

estimated can be found in Section 4 and Appendix Section C.3.

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 7. This relationship is robust conditioning on a set of controls including electricity prices, turbine productivity, and time 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 more wind energy online, the average unfulfilled demand for utilities has decreased sharply since 2011, which contrasts with increasing 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 and matched with utilities of larger unfulfilled demand. Those utilities require a larger amount of wind capacity but match with wind farms using turbines of lower productivity. For more recently entered wind farms, although the turbine technology has been much better, they could only sell capacity to utilities which have a smaller unfulfilled demand. It results in the overall matching efficiency loss between the utilities and wind farms.

Figure 7: Matching Efficiency between Utilities and Wind Farms

(a) Capacity and RPG **(b)** RPG and Capacity Factor



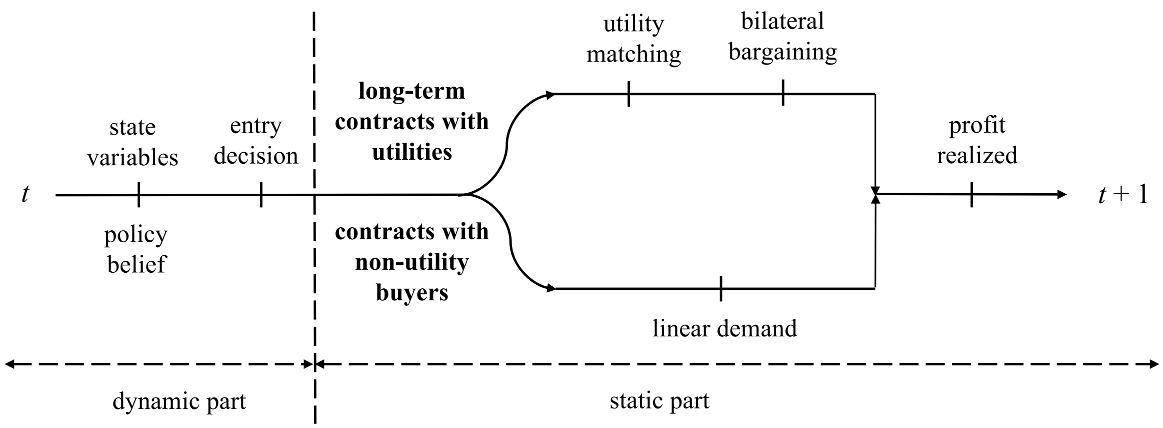
Notes: This figure provides descriptive evidence about the matching efficiency between utilities and wind farms. Panel (a) shows the binned scatter plot of wind capacity to the Renewable Portfolio Gaps (RPG) of utilities. Renewable Portfolio Gap measures the unfulfilled demand of each utility for renewable energy in order to meet the RPS. 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.

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

4 Model

The structural model consists of a dynamic part and a static part as shown in Figure 8. Wind farm investors form beliefs about the future probability of federal subsidy renewals in the dynamic part. They incur a random entry cost drawn from a common distribution at the beginning of each period. Wind farm investors will enter the market if the discounted sum of flow profits from investment net the entry cost exceeds the option value of waiting, and will choose to wait otherwise. Under policy uncertainty, wind farm investors secure a flow of future federal subsidies if they enter before the subsidy expires, but they forego better and cheaper technology in the future.

Figure 8: Overview of Structural Model



Notes: This figure provides an overview of the structural model.

The discounted sum of flow profits from investment is determined in the static part of the model. There are two different channels for wind farms to sell their capacity. First, a wind farm could negotiate with a utility about a long-term power purchase agreement, in which the wind farm and the utility jointly decide three endogenous objects simultaneously: the power purchase price, the procured capacity, and which type of subsidies to select. Second, wind farms could also sell capacity to buyers other than utilities such as corporations, or sign financial agreements such as hedge and merchant contracts.

I assume time t is discrete at the yearly level. I denote a wind farm as i and a utility as j. Wind farm investors make the dynamic decision about when to enter the market, while utilities procure capacity from wind farms through long-term power purchase agreements.

4.1 Static Part

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

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

Suppose utility j begins a power purchase agreement with wind farm i in year t for a length of T years at the negotiated price of p_{ij}.[12] The profit function for utility j from this contract is

$$\pi^U_t(p_{ij}, k^w_{ij}) = \sum_{s=t+1}^{t+T} E_t \beta^{s-t} \{ \underbrace{r_s Q_{js} - p_{ij}\alpha_{is}k^w_{ij} - c(Q^f_{js}, Q^{or}_{js}, Q^o_{js})}_{\text{profit from electricity generation}} + \underbrace{\lambda_s(\alpha_{is}k^w_{ij} + Q^{or}_{js} - z_s Q_{js}) - h_{js}}_{\text{profit from renewable credits}} \}. \tag{1}$$

Profit flow starts from year $t+1$ as it takes one year on average between the finalization of the investment decision and the beginning of service of wind farms. I assume the production 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 the data well as shown in Appendix Figure A.9. I define $c(\cdot)$ as the annual cost function for using the rest three types of fuel sources. Another feature I add to the profit function is the hassle cost h_{jt}, which captures the frictions on the renewable credit market as well as the dynamic incentives of credit banking that I abstract from. The hassle cost is higher for utilities that are further away from the Renewable Portfolio Standards requirement and thus need to transact a larger number of renewable credits. If a utility doesn't have any newly procured wind energy, the hassle cost h_{jt} is assumed to be a quadratic function of the gap between the current renewable energy generation and the state requirement for utility j in year t. Moreover, procuring wind capacity saves the hassle cost, especially when the utility is further away from the state-level goal. Therefore, incorporating

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

h_{jt} fits the data pattern that utilities that are further away from the Renewable Portfolio Standards goals tend to procure more wind capacity.

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

Profit Function for Wind Farms The profit that the wind farm i receives equals the sum of the total revenues from the power purchase agreements and the total subsidies from the government, minus the turbine cost it has to pay. Wind farms receive flow revenues from the power purchase agreements for the contract length of T years. The total subsidies TS_{ijt} depends on the subsidy type choice which I denote as $\mathcal{D}_{ij}$. $\mathcal{D}_{ij}$ equals 1 for PTC and 0 for Section 1603 Grant since both two options were available during 2009-2012. The wind farm receives the production tax credit for the first 10 years of its production under PTC, while 30% of the total upfront investment cost would be subsidized under Section 1603 Grant in the form of cash grants. As the grant amount is approximately linear with respect to the total capacity, I assume that the investment subsidy is a linear function of total capacity ηk_{ij}^w, where η denotes the unit investment cost.

Wind farms might value PTC and grant less than their face values. On the one hand, wind farms usually partner with large investors who finance part of the investment cost of the wind farm in exchange for tax credits received by it. Consequently, wind farms typically discount the values of tax credits compared to the cash subsidies due to the transaction cost and asymmetric information problem that occurred in the partnership process as well as the market power of those large investors as tax equity providers (Johnston, 2019). On the other hand, wind farms could deduct the investment cost from their tax liability, but receiving the grant reduces the tax deduction they could have obtained. Following Johnston (2019), the overall schedule of the total subsidy TS_{ijt} can be defined as follows.

$$TS_{ijt}(k_{ij}^w, \mathcal{D}_{ij}) = \mathcal{D}_{ij} \times \tau \times d_t \times (\sum_{s=t+1}^{t+10} E_t \beta^{s-t} \alpha_{is} k_{ij}^w) + (1 - \mathcal{D}_{ij}) \times (30\% - \tau C_1) \times \eta k_{ij}^w$$

d_t denotes the amount of tax credit per unit of wind energy generation under PTC. τ represents the value discount of tax credits compared with an equal dollar amount of grants. C_1 is a constant term to calculate the depreciation deductions combining the marginal tax rates, the discount factor, as well as the depreciation deduction rule.

The profit of the wind farm i, given the power purchase agreement price p_{ij}, the total subsidy schedule TS_{ijt}, and the turbine cost per capacity c_{it}, can be expressed as the follows.

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

I allow for the turbine cost per unit of capacity c_{it} to depend on a set of turbine cost shifters $\boldsymbol{X_{it}}$ including the average annual turbine price and turbine brands, and ξ_{it} denotes the unobserved cost shocks. Moreover, I allow the convexity of the total turbine cost, and thus c_{it} will also be a function of k_{ij}^w. If $\gamma_2 > 0$, the total turbine cost is convex in capacity.

$$c_{it} = \boldsymbol{\gamma_1 X_{it}} + \frac{k_{ij}^w}{2\gamma_2} + \xi_{it}. \tag{3}$$

Bilateral Bargaining Wind farm i and utility j participate in the bilateral bargaining process to negotiate simultaneously over the procured capacity k_{ij}^w, the contracted price p_{ij}, and which subsidy type to take $\mathcal{D}_{ij}$. Under the assumption of Nash bargaining, the optimal capacity k_{ij}^w and the policy choice $\mathcal{D}_{ij}$ maximize the joint surplus, and the optimal price p_{ij} divides the joint surplus between two parties (Chipty and Snyder, 1999). If the negotiation fails, I assume that wind farms would earn a payoff from waiting for another year to enter the market, while utilities would generate electricity with their current energy production portfolios. The optimization problem can be formulated as follows.

$$\{\mathcal{D}_{ij}^*, k_{ij}^{w*}\} = \text{argmax } [\pi_t^U(p_{ij}, k_{ij}^w) + \pi_t^W(p_{ij}, k_{ij}^w, \mathcal{D}_{ij})] + \sigma_1\epsilon_{it}^{\mathcal{D}}$$

$\epsilon_{it}^{\mathcal{D}}$ follows the extreme value type-I distribution and σ_1 is the standard deviation of the random shock. $\epsilon_{it}^{\mathcal{D}}$ captures the random shock unrelated to the payoff, such as the tax liability of investors that finance wind farm construction and the credit constraints faced by the wind farm investor. Meanwhile, the negotiated price p_{ij}^* will maximize the Nash product of their surpluses from contracting such that

$$p_{ij}^* = \text{argmax } [\pi_t^U(p_{ij}, k_{ij}^w) - \pi_t^U(p_{ij} = \infty)]^\rho \times [\pi_t^W(p_{ij}, k_{ij}^w, \mathcal{D}_{ij}) - \pi_t^W(p_{ij} = \infty)]^{1-\rho}.$$

ρ denotes the bargaining weight of utilities. $\pi_t^U(p_{ij} = \infty)$ and $\pi_t^W(p_{ij} = \infty)$ denote the threat points for utilities and wind farms respectively.

Solving the first-order condition to maximize the joint surplus $\pi_t^U(p_{ij}, k_{ij}^w) + \pi_t^W(p_{ij}, k_{ij}^w, \mathcal{D}_{ij})$ with respect to the capacity k_{ij}^w yields an equation about the optimal capacity function as follows.

$$\sum_{s=t+1}^{t+T} E_t\beta^{s-t}[r_s + \lambda_s(1 - z_s) + \delta Q_{js}^{gap}]\alpha_{is} + \frac{TS_{ijt}}{k_{ij}^{w*}} - \boldsymbol{\gamma_1 X_{it}} - \frac{k_{ij}^{w*}}{\gamma_2} - \xi_{it} = 0. \tag{4}$$

I leverage the fact that capacity factors vary by the cohort of wind projects, but remain stable with respect to the ages of projects even 10 years after entry. Therefore, I use the capacity factor upon entry to measure turbine productivity α_i and assume it to be constant as the turbine ages (see Appendix Section C for detailed discussion). I summarize the government subsidy per unit of capacity as Ω_{it}.

$$\Omega_{it} = \mathcal{D}_{ij} \times \frac{\beta(1-\beta^{10})}{1-\beta}\tau d_t \alpha_i + (1-\mathcal{D}_{ij}) \times (0.3 - \tau C_1)\eta. \tag{5}$$

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

$$\Theta_{jt} = \sum_{s=t+1}^{t+T} E_t \beta^{s-t}[r_s + \lambda_s(1-z_s)]. \quad \Phi_{jt} = \sum_{s=t+1}^{t+T} E_t \beta^{s-t} Q_{js}^{gap}. \tag{6}$$

Both Θ_{jt} and Φ_{jt} are important shifters of utilities' willingness to pay for procured wind energy. 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. As the Renewable Portfolio Standards are typically announced for a long period with interim targets, I also assume utilities have perfect foresight of the future state-level requirements.

Combining Equations (4), (5), and (6), we could derive Equation (7) which has intuitive economic interpretations. The marginal benefit of wind capacity comes from the willingness to pay for utilities as well as the federal subsidy. However, the marginal benefit needs to be balanced with the marginal cost of wind capacity. $\tilde{\xi}_{ijt}$ is a random shock that includes the measurement errors in Θ_{jt} and Φ_{jt}, as well as the unobserved turbine cost shifters ξ_{it}.

$$\underbrace{(\Theta_{jt} + \delta\Phi_{jt})\,\alpha_i}_{\text{willingness to pay}} + \underbrace{\Omega_{it}}_{\text{subsidy}} = \underbrace{\boldsymbol{\gamma_1 X_{it}} + \frac{k_{ij}^{w*}}{\gamma_2}}_{\text{turbine cost}} + \tilde{\xi}_{ijt}. \tag{7}$$

Equation (7) yields the optimal capacity k_{ij}^{w*} as a function of the subsidy choice $\mathcal{D}_{ij}$ since $\mathcal{D}_{ij}$ is embedded in Ω_{it}. We could derive the optimal choice probability of the subsidy type $P_{ij}^{\text{subsidy}}(\mathcal{D}_{ij}^* = 1)$ as follows. I abbreviate the profit function of the utility as $\pi_{ij}^U(\mathcal{D}_{ij})$ and the profit function of the wind farm as $\pi_{ij}^W(\mathcal{D}_{ij})$.

$$P_{ij}^{\text{subsidy}}(\mathcal{D}_{ij}^* = 1) = \frac{\exp\{[\pi_{ij}^U(1) + \pi_{ij}^W(1)]/\sigma_1\}}{\sum_{\mathcal{D}_{ij}=\{0,1\}} \exp\{[\pi_{ij}^U(\mathcal{D}_{ij}) + \pi_{ij}^W(\mathcal{D}_{ij})]/\sigma_1\}}. \tag{8}$$

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

$$\frac{\beta(1-\beta^T)}{1-\beta} p_{ij}^* = (1-\rho)(\Theta_{jt} + \delta\Phi_{jt}) + \rho[\frac{c_{it}}{\alpha_i} - \frac{\Omega_{it}}{\alpha_i} + \frac{\pi_t^W(p_{ij}=\infty)}{\alpha_i k_{ij}^{w*}}]. \tag{9}$$

The optimal pricing equation (9) has intuitive interpretations. If the utility has a larger bargaining power, the negotiated price will be low enough to only cover the rescaled turbine cost net government 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 such that the negotiated price will be larger.

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 hedge and merchant contracts. Due to a lack of data on the characteristics of both corporate buyers and these financial contracts, I model this second channel using a linear demand curve. I assume non-utility buyers demand capacity k_i^{nu} at the wind energy price of p_i^{nu} from the wind farm i. The demand function is

$$k_i^{nu} = -\zeta_1 p_i^{nu} + \zeta_2 \alpha_i + \boldsymbol{\zeta_3 X_i} + \boldsymbol{\zeta_4 Z_i^{nu}} + \upsilon_i. \tag{10}$$

Similar to Equation (7), $\boldsymbol{X_i}$ includes average turbine prices as well as dummies for turbine brands. $\boldsymbol{Z_i^{nu}}$ denotes a set of demand shifters including dummies for different balanced authorities and different types of contracts (long-term contracts with corporate buyers, hedge contracts, or merchant contracts). υ_i represents unobserved demand shifters. I define the profit of wind farms that sell capacity to non-utility buyers 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 a utility Power Purchase Agreement to sell its capacity, it will have a discrete choice of which utility to be matched with. I denote the matched utility as j^*. I define the potential buyers $\mathcal{J}_{it}$ as those utilities that had signed wind PPA before 2019 and are within 400 miles from the focal wind farm i. They have different renewable portfolio gaps and are located at different distances from the wind farm. Some utilities in the potential buyer pool might even be located in a different state from the focal wind farm. The choice of the matched utility can be formalized as the following problem.

$$\max_{j \in \mathcal{J}_{it}} \pi_t^W(p_{ij}^*, k_{ij}^{w*}, \mathcal{D}_{ij}^*) - \underbrace{(\gamma_3 \mathbb{1}\{m_i \neq m_j\} + \gamma_4 Dist_{ij})}_{\text{matching cost}} + \sigma_2 \epsilon_{ij} \tag{11}$$

I use $\pi_t^W(p_{ij}^*, k_{ij}^{w*}, \mathcal{D}_{ij}^*)$ 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 from 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.

$$P_{it}^{\text{buyer}}(j = j^*) = (1 - \mu_m) \times \frac{\exp\{[\pi_t^W(p_{ij^*}^*, k_{ij^*}^{w*}, \mathcal{D}_{ij^*}^*) - \gamma_3 \mathbb{1}\{m_i \neq m_{j^*}\} - \gamma_4 Dist_{ij^*}]/\sigma_2\}}{\sum\limits_{j \in \mathcal{J}_{it}} \exp\{[\pi_t^W(p_{ij}^*, k_{ij}^{w*}, \mathcal{D}_{ij}^*) - \gamma_3 \mathbb{1}\{m_i \neq m_j\} - \gamma_4 Dist_{ij}]/\sigma_2\}}. \tag{12}$$

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.

$$\begin{aligned} \pi_{it} = &\mu_m \times \pi_t^{nu}(k_i^{nu}, p_i^{nu}) + \\ &(1 - \mu_m) \times \sigma_2 \times \{\log[\sum_{j \in \mathcal{J}_{it}} \exp(\frac{\pi_t^W(p_{ij}^*, k_{ij}^{w*}, \mathcal{D}_{ij}^*) - \gamma_3 \mathbb{1}\{m_i \neq m_j\} - \gamma_4 Dist_{ij}}{\sigma_2})] + \varkappa\}. \end{aligned} \tag{13}$$

Summary of the Static Part and Discussion The static part of the model can be summarized by five equations. The capacity function (7), subsidy choice function (8), and pricing function (9) together define the optimal solution to the bargaining problem. The demand of non-utility buyers is defined in (10), and the choice of the buyer is given by (12). The static part of the model yields a measure of profit if the wind farm i decides to enter in year t given by (13), which is a key input to the dynamic model.

However, there are caveats to the model. First, I only endogenize the capacity of procured wind energy but abstract away the responses of other fuel sources. The wind penetration rate was low during my sample period in most states, and the massive exit of coal power plants in the later period of my sample was mainly due to cheaper gas prices instead of wind investment. 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 utilities' dynamic decisions away. I assume utilities are myopic and their choices of when to procure wind capacity are exogenous in my model. As utilities could sign contracts with multiple wind farms and a wind farm is faced with many buyers in their choice set, search friction might not be a primary concern and one-sided decisions could capture the matching pattern well. Moreover, since wind turbine productivity and unfulfilled demand of utility are complements in generating total profit, a one-sided discrete choice based on profits from each potential pair of matching is sufficient to capture the complementarities, without complicating the model by introducing utilities' dynamic problem.

4.2 Dynamic Part

Dynamic Decision of Potential Entrants 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} as illustrated in the Equation (13) from the static model, net the entry cost ψ_{it}. I assume that

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

where 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 denote the state variables potential entrant i condition for the dynamic decision as $\boldsymbol{s}_{it}$. The state variables $\boldsymbol{s}_{it}$ include the 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 status of the policy ω_t. ω_t is a dummy variable representing the policy status in year t. $\omega_t = 1$ indicates that the federal subsidy is enacted in year t, while $\omega_t = 0$ indicates that the federal subsidy is absent in year t. ω_t is always 1 *ex-post* in the wind industry as the PTC was always extended. The wind procurement price p_{ij}, the wind capacity k^w_{ij}, and the subsidy choice D_{ij} all depend on both state variables $\boldsymbol{s}_{it}$ as well as the policy status ω_t. Therefore, the net profit for wind farm i if it decides to enter in year t is defined as

$$\Pi(\boldsymbol{s}_{it}, \omega_t) = \pi_{it} - \kappa W_{it}.$$

The dynamic optimization problem is as follows.

$$V_t(\boldsymbol{s}_{it},\omega_t,\nu_{it}) = \max\{\Pi(\boldsymbol{s}_{it},\omega_t) - \nu_{it}, \beta E_t[V_{t+1}(\boldsymbol{s}_{it+1},\omega_{t+1},\nu_{it+1})|\boldsymbol{s}_{it},\omega_t]\}. \tag{14}$$

$V_t(\boldsymbol{s}_{it},\omega_t,\nu_{it})$ 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 $\beta E_t[V_{t+1}(\boldsymbol{s}_{it+1},\omega_{t+1},\nu_{it+1})|\boldsymbol{s}_{it},\omega_t]$, the 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 policy uncertainty, denoted by $b_t(\omega_{t+1}|\omega_t)$. I allow $b_t(\omega_{t+1}|\omega_t)$ to 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. $b_t(\omega_{t+1}|\omega_t)$ is the source of the non-stationarity of this dynamic problem. Therefore, the option value of waiting can be expressed as follows.

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

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

$b_t(\omega_{t+1}|\omega_t)$ allows flexible beliefs about future policy evolution but also imposes identification challenges if arbitrary policy belief is permitted, as multiple streams of policy beliefs could rationalize one single investment decision. Moreover, with T years there could be 2^T different policy paths with subsidies switching on and off, making the policy belief parameters $b_t(\omega_{t+1}|\omega_t)$ under-identified given the infinite horizon of the dynamic problem here. In light of the identification challenges, I impose the following two assumptions to discipline policy belief $b_t(\omega_{t+1}|\omega_t)$ and make the problem feasible for estimation.

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

Assumption 1 indicates that the policy status is absorbing once terminated. If the policy is eliminated in year t, wind farm investors will hold the belief that the policy is terminated forever. This assumption is consistent with the reality that 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 follows.

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

As $\omega_t = 0$ is the 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.

$$V_t(\boldsymbol{s}_{it}, \omega_t = 0, \nu_{it}) = V^0(\boldsymbol{s}_{it}, \nu_{it}) = \max\{\Pi^0(\boldsymbol{s}_{it}) - \nu_{it}, \beta E[V^0(\boldsymbol{s}_{it+1}, \nu_{it+1})|\boldsymbol{s}_{it}]\}. \tag{15}$$

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

Assumption 2 indicates that the perceived likelihood of a one-year policy extension will be constant for future years. As I only allow the policy to be extended year by year, this assumption precludes the possibility that wind investors have more information about future policy extensions beyond next year. However, I allow the expectation to change across the years and I allow the investors to revise their beliefs according to the new information. Consequently, $b_t(\omega_{t+s+1} = 1 \mid \omega_{t+s} = 1)$ and $b_{t+s}(\omega_{t+s+1} = 1 \mid \omega_{t+s} = 1)$ 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.[13] Instead of imposing Assumption 2, the belief evolution could be parameterized as a first-order Markov process, but a longer time series will be required to make the estimation feasible. An alternative model with the policy belief will be to use a mixture distribution as described in the Appendix Section D.1. However, without underlying time-varying beliefs, this model cannot rationalize the bunches in the investment time trend; with underlying time-varying beliefs, this alternative model is essentially isomorphic to the baseline model.

Under Assumption 2, we construct $E_t[V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1}, \nu_{it+1})|\omega_t = 1]$ as follows.

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

I define $\Pi(\boldsymbol{s}_{it}, \omega_t = 1)$ as $\Pi^1(\boldsymbol{s}_{it})$ and $V_t(\boldsymbol{s}_{it}, \omega_t = 1, \nu_{it})$ as $V^1(\boldsymbol{s}_{it}, \nu_{it}; b_t)$, and $V^1(\boldsymbol{s}_{it}, \nu_{it}; b_t)$

[13] An intuitive alternative of Assumption 2 is that $b_t(\omega_{t+s+1} = 1 \mid \omega_{t+s} = 1) = b_t(\omega_{t+1} = 1 \mid \omega_t = 1) \times q^s, \forall s \geqslant 0$. Therefore, the perceived likelihood of a one-year policy extension will be exponentially discounted with the decay parameter q. However, this assumption will yield a model isomorphic to the baseline model with a discount factor βq.

can be solved from the following equation.

$$V^1(\boldsymbol{s}_{it}, \nu_{it}; b_t) = \max\{\Pi^1(\boldsymbol{s}_{it}) - \nu_{it}, \beta\{E_t[V^1(\boldsymbol{s}_{it+1}, \nu_{it+1}; b_t)|\boldsymbol{s}_{it}] \times b_t \\ + E[V^0(\boldsymbol{s}_{it+1}, \nu_{it+1})|\boldsymbol{s}_{it}] \times (1 - b_t)\}\} \tag{16}$$

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 the source of non-stationarity.

$$V(\boldsymbol{s}_{it}, \omega_t, \nu_{it}; b_t) = \max\{\Pi(\boldsymbol{s}_{it}, \omega_t) - \nu_{it}, \oint_{\boldsymbol{s}_{it+1}, \nu_{it+1}} \beta E_t[V^1(\boldsymbol{s}_{it+1}, \nu_{it+1}; b_t) \times b_t \\ + V^0(\boldsymbol{s}_{it+1}, \nu_{it+1}) \times (1 - b_t)] dG(\boldsymbol{s}_{it+1}|\boldsymbol{s}_{it}) dF(\nu_{it+1})\} \tag{17}$$

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

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

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

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

As PTC shifts up firm value 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, as well as policy belief parameters b_t, are key primitives I want to identify and estimate in the dynamic model.

5 Identification and Estimation

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

5.1 Static Part

Bilateral Bargaining There are three key equations from the bilateral bargaining problem: the optimal capacity function (7), the optimal subsidy type choice (8), and the optimal pricing function (9). In the optimal capacity function, $\tilde{\xi}_{ijt}$ mainly captures the measurement errors in the willingness to pay, as well as the unobserved turbine cost shifters, both of which are assumed exogenous to the observables. I rewrite Equation (7) as follows for estimation.

$$\begin{aligned} k_{ij}^{w*} =& \beta_1(\Theta_{jt} + \delta\Phi_{jt}) + \beta_2(\Theta_{jt} + \delta\Phi_{jt}) \times \alpha_i + \gamma_2\Omega_{it} + \\ & (\beta_3 + \beta_{31}\text{GE}_i + \beta_{32}\text{Siemens}_i + \beta_{33}\text{Others}_i) \times \text{TP}_t^{\text{Vestas}} + \boldsymbol{\beta_4 Z_{jt}^U} + \xi_{1,ijt} \end{aligned} \tag{18}$$

Compared to Equation (7), I include both utilities' willingness to pay $(\Theta_{jt} + \delta\Phi_{jt})$ and its interaction with turbine capacity factor $(\Theta_{jt} + \delta\Phi_{jt}) \times \alpha_i$ to the estimation equation to deal with the colinearity issue, as the government subsidy per unit of capacity Ω_{it} is also a function of turbine capacity factor α_i. The cost convexity γ_2 is identified by the effect of the unit subsidy on the negotiated capacity. A more generous subsidy brings a higher marginal benefit to wind capacity, which will be balanced by a larger marginal cost. If the total turbine cost is steeper in capacity, utilities and wind farms will negotiate a smaller wind farm size in response to a higher subsidy. 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 the main shifter of the turbine cost, and I allow the effect to vary across different turbine brands, including 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 fixed effects of the states of the utility, the utility type (cooperative, investor-owned, or others), as well as term lengths (less than 15 years, 15-20 years, or more than 20 years). The total turbine cost can be backed out as

$$\hat{c}_{it} = -\frac{(\hat{\beta}_3 + \hat{\beta}_{31}\text{GE}_i + \hat{\beta}_{32}\text{Siemens}_i + \hat{\beta}_{33}\text{Others}_i) \times \text{TP}_t^{\text{Vestas}}}{\hat{\gamma}_2} + \frac{k_{ij}^{w*}}{2\hat{\gamma}_2}.$$

The subsidy choice function (8) also incorporates the optimal capacity function (7), which in turn depends on the subsidy choice through Ω_{it}. Therefore, the total surplus from the subsidy choice $\mathcal{D}_{ij}$ can be expressed as follows.

$$\pi_{ij}^U(\mathcal{D}_{ij}) + \pi_{ij}^W(\mathcal{D}_{ij}) = (\Theta_{jt} + \delta\Phi_{jt})\alpha_i k_{ij}^{w*}(\mathcal{D}_{ij}) + \Omega_{it}(\mathcal{D}_{ij})k_{ij}^{w*}(\mathcal{D}_{ij}) - c_{it}(\mathcal{D}_{ij})k_{ij}^{w*}(\mathcal{D}_{ij})$$

However, as discussed in detail in Appendix Section C.4, a back-of-envelope calculation suggests that Section 1603 Awardees on average were better off by selecting the grant, while many wind farms that opted into Production Tax Credit 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 Production Tax Credit 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 ς likelihood that the wind farm investors would take the default option regardless of the payoffs, while for a probability of $1 - \varsigma$ the 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 follows.

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

I use the sample in 2008-2012 to form the likelihood function.[14] 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 Production Tax Credit when the grant was more profitable.[15]

In the optimal pricing function, I assumed $\pi^W_t(p_{ij} = \infty)$ 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 (9), 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 $\bar{\Phi}_{it}$, as shown in Panels (a) and (b) of Appendix Figure A.8. This data pattern is intuitive as $\pi^W_t(p_{ij} = \infty)$ increases with the average willingness to pay for nearby alternative utilities. Panel (c) also displays a large variation of average p_{ij} across time. Motivated by the data fact, I rewrite Equation (9) for estimation as follows, where $\pi^W_t(p_{ij} = \infty)$ is expressed as a flexible control function $f(\cdot)$ with quadratic bases and year fixed effects.

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

The key parameter in the optimal pricing function (9) 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 $(\frac{\hat{c}_{it} - \Omega_{it}}{\alpha_i})$ on the negotiated price. If the utility has a larger bargain-

[14] Some wind projects that selected the Section 1603 Grant started construction in 2008.

[15] 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 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 difference alone.

ing power ρ, the negotiated price tends to be low and co-moves closer to the time trend of the net turbine cost, conditioning on a flexible control for the bargaining leverage.

I jointly estimate the optimal capacity function (7), the optimal subsidy type choice (8), and the optimal pricing function (9) by optimizing the following problem

$$\min E(\xi_{1,ijt}^2) + E(\xi_{2,ijt}^2) - E(llf_{1,ij}).$$

Demand for Non-Utility Buyers I estimate the linear demand function for non-utility buyers (10) with instruments. As υ_i captures unobserved demand shifters, it's correlated with the price p_i^{nu}, which introduces bias to the 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 be correlated with demand shifters for non-utility buyers. 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 wind power recruitment policies, property tax incentives, or sales tax incentives in the wind industry. These policies are implemented by the state government to boost renewable energy. As wind energy is only part of the renewable energy mix, and non-utility buyers demand no more than 30% of the total wind capacity, these supply-side policies are unlikely to be correlated with the unobserved demand shifters of non-utility buyers.

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 (12). 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 follows, where I denote the choice $\mathbb{1}(j^* = 0)$ as selling capacity to non-utility buyers.

$$llf_2 = \sum_{it}\{\sum_{l\in\mathcal{J}_{it}} \mathbb{1}(j^*=l)\log\{(1-\mu_m)\times \frac{\exp\{[\pi^W(p_{il}^*, k_{il}^{w*}, \mathcal{D}_{il}^*) - \gamma_3\mathbb{1}\{m_i \neq m_l\} - \gamma_4 Dist_{il}]/\sigma_2\}}{\sum_{j\in\mathcal{J}_{it}} \exp\{[\pi^W(p_{ij}^*, k_{ij}^{w*}, \mathcal{D}_{ij}^*) - \gamma_3\mathbb{1}\{m_i \neq m_j\} - \gamma_4 Dist_{ij}]/\sigma_2\}}\} + \mathbb{1}(j^*=0)\log(\mu_m)\}. \tag{19}$$

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 magnitudes of the gradient of matching likelihood with respect to the shifters. The mean parameters of the buyer type choice μ_m are pinned down by the frequency of non-utility contracts observed across markets.

5.2 Dynamic Part

The key identification challenge in the dynamic part of the model is how to separately identify the parameters of the entry cost distribution (κ and ϕ) and the policy belief parameters b_t. The main identification strategy is to exploit the temporal structure of the policy. There are years when the policy extension was certain, which helps identify parameters of entry cost distribution κ and ϕ given $b_t = 1$. Moreover, any deviation in those deadline years from the "smooth" trend of wind investment predicted by the model would be rationalized by b_t. The key identification assumption for the policy belief parameters is that conditional on observables, the entry cost distribution moves smoothly in the deadline years of the policy windows.

Following the 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 data. Second, I use the estimated entry cost parameters to solve the dynamic programming problem and focus on policy windows with policy expiration to estimate the policy belief parameters. As policy uncertainty leads to the non-stationarity of the dynamic problem, I solve the dynamic model year by year.

Definition of Potential Entrants 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. The identities of potential entrants are observed as wind farm investors need to enter the interconnection queue, get approved by all studies, and sign the interconnection agreements before they are eligible to enter the market. Therefore, I define projects that have been in the interconnection queue for two or more years as the set of potential entrants and model their optimal investment decisions.[16] For more details about

[16]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. As I explained in detail in Appendix Section B.3, 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

the interconnection queue data and how I construct the measure of potential entrants, please refer to Appendix Section B.3.

Equilibrium and State Space 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 state. 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.[17] I use the annual average productivity of wind turbines $\bar{\alpha}_t$ instead of the realized productivity for each individual wind farm to ease the concern of the selection issue. The 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 (18) to control for time-invariant variations in the utility demand. I project p_i^{nu} on $\boldsymbol{Z_i^{nu}}$ as in Equation (10) 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 the utilities in the buyer pool. Each wind farm has on average 18 buyers 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 the inclusive value for wind farms that can be attributed to the changing renewable portfolio gaps for buyers. I construct the inclusive values according to Equation (13) with the realized renewable portfolio gap for each utility, simulate the 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 follows.

$$\text{IV}_{it}(\boldsymbol{\Phi}_{it}) = \pi_{it}(\boldsymbol{\Phi}_{it}) - \pi_{it}(\boldsymbol{\Phi}_{it}), \boldsymbol{\Phi}_{it} = \{\Phi_{jt}\}_{j \in \mathcal{J}_{it}}.$$

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

by year. Johnston et al. (2023) provide a thorough overview of the interconnection queue and the congestion issues in PJM.

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

wind farms today will reduce the future value of $\text{IV}_{it}(\mathbf{\Phi}_{it})$. I approximate the transition process of $\text{IV}_{it}(\mathbf{\Phi}_{it})$ 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.

$$\text{IV}_{it}(\mathbf{\Phi}_{it}) = \rho_1^{\Phi}\text{IV}_{it-1}(\mathbf{\Phi}_{it-1}) + \rho_2^{\Phi}\text{NewCap}_{mt-1} + \xi_i^{\Phi} + \epsilon_{it}^{\Phi} \tag{20}$$

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 follows.

$$\text{NewCap}_{mt} = \rho_1^{nc}\text{NewCap}_{mt-1} + \rho_0^{nc} + \epsilon_{mt}^{nc} \tag{21}$$

Estimation Step 1: Entry Cost Parameters I focus on the policy windows in which there was no policy uncertainty such that $b_t = 1$. As the main source of non-stationarity is policy uncertainty, I exploit the feature that the Consolidated Appropriations Act was announced at the end of 2015 to cover through at least 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 4, in contrast to the jumping trend in earlier years, provides another piece of supporting evidence that the policy environment was largely stationary in this period.

The stationary dynamic problem can be formulated as follows.

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

$$E[V(\boldsymbol{s}_{it+1}, \nu_{it+1})|\boldsymbol{s}_{it}] = \oint_{\boldsymbol{s}_{it+1}, \nu_{it+1}} V(\boldsymbol{s}_{it+1}, \nu_{it+1}) dG(\boldsymbol{s}_{it+1}|\boldsymbol{s}_{it}) dF(\nu_{it+1}).$$

I use the policy window between 2014 and 2018 to estimate the stationary dynamic problem and use the policy window between 2013 and 2018 as a robustness check. Since the amount of new wind capacity was stable over time in 2013-2018 and the dynamic problem is stationary, I estimate Equations (20) and (21) directly from the data as a first step. 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 $\{u_l(\boldsymbol{s}_{it})\}_{l=1}^{L}$ following Gowrisankaran et al. (2023) 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, 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. Since I assume the random entry cost shock follows an exponential distribution, solving the dynamic programming problem is equivalent to estimating the 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.

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

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 the continuation value, which can be approximated as $V^0(\boldsymbol{s}_{it}) = \sum_{l=1}^{L} \gamma_l^{v_0} u_l(\boldsymbol{s}_{it})$. I solve $\{\gamma_l^{v_0}\}_{l=1}^L$ from Equation (15) and the firm profit Π_{it}^0 when the PTC is absent is constructed using static model estimates. For the upper bound of the continuation value, 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 (16).

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 low b_t induces a large amount of new wind capacity online and reduces the future renewable portfolio gaps of utilities more drastically. Therefore, solving the value function $V^0(\boldsymbol{s}_{it})$ and $V^1(\boldsymbol{s}_{it}, b_t)$ involves solving 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.[18]

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

The policy belief b_t is the solution to the following optimization problem.

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

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}.

4. Solve for new ρ_0^{nc} and ρ_1^{nc} and update the belief.

5. Repeat steps 2-4 until the values of ρ_0^{nc} and ρ_1^{nc} converge.

6. 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.

7. Iterate on b_t until the sum of squared errors is minimized.

For more details of the dynamic estimation, please refer to the Appendix Section D.

6 Results

6.1 Static Parameters

I first estimate turbine productivity α_i, utilities' effective market price Θ_{jt}, and total renewable portfolio gap Φ_{jt} directly from the data. I find that capacity factors evolve systematically with the cohort but display limited variation with respect to the age of wind farms (in Panels (a) and (b) of Appendix Figure A.9), and that the annual total output on average is linearly increasing with the nameplate capacity (in Panel (c) of Appendix Figure A.9). Therefore, I treat the annualized

[18] 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.

capacity factor as constant and calculate it at the age of one for each wind farm for the best data coverage. I take the inflation-adjusted Production Tax Credit as $22/MWh for its 2011 value. The unit government subsidy Ω_{it} is then calculated according to Equation (5) and the discount factor β is assumed as 0.95. Moreover, for utilities' effective market price Θ_{jt} and total renewable portfolio gap Φ_{jt}, I assume utilities to hold rational expectations with respect to the transition dynamics of electricity price, renewable credit price, and their energy source composition, and utilities have perfect foresight of the state-level Renewable Portfolio Standards. I estimate the transition dynamics of each component using AR(1) models with trend breaks as well as heterogeneous time trends across states and then aggregate them according to Equation (6). I defer a detailed discussion of the estimation of α_i, Θ_{jt}, and Φ_{jt} to Appendix Section C.

I proceed to estimate the static model using these estimated shifters. Table 1 presents the estimation results of the bilateral bargaining model. I estimate the optimal capacity Equation (7), the optimal subsidy type choice (8), and the optimal pricing Equation (9) simultaneously. I control for a rich set of fixed effects Z_{jt} in Equation (7), including state effects, contract term length fixed effects, as well as the utility type fixed effects.[19] I incorporate these rich fixed effects to control for unobserved demand shifters. Moreover, as I explained in Section 5.1, I include a saturated quadratic function of the average effective market prices of nearby alternative utilities $\bar{\Theta}_{-jt}$ and their average renewable portfolio gaps $\bar{\Phi}_{-jt}$ as well as year fixed effects in Equation (9) as controls for $\pi_t^W(p_{ij} = \infty)$. I assume away the choice-specific random shock in the subsidy type decision in columns (1)-(3) and let 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 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 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 ($\Theta_{jt} + \kappa\Phi_{jt}$) 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 more productive wind farm will be more effective in filling their renewable portfolio gaps.

For cost parameters, γ_2 is estimated to be positive, which indicates that the total capacity cost is convex in the total amount of procured capacity. 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

[19] I categorize the contract lengths into three groups: shorter than 15 years, between 15-20 years, and longer than 20 years. I also group utilities into three types: investor-owned, cooperatives, and others (such as municipal, etc).

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 (7), (8) and (9)). Columns (1)-(3) estimate Equations (7) and (9) jointly under the calibrated τ and then estimate Equation (8), while columns (4)-(5) estimate Equations (7), (8) and (9) 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 (9) as controls for $\pi_t^W(p_{ij} = \infty)$. Standard errors are in parentheses.

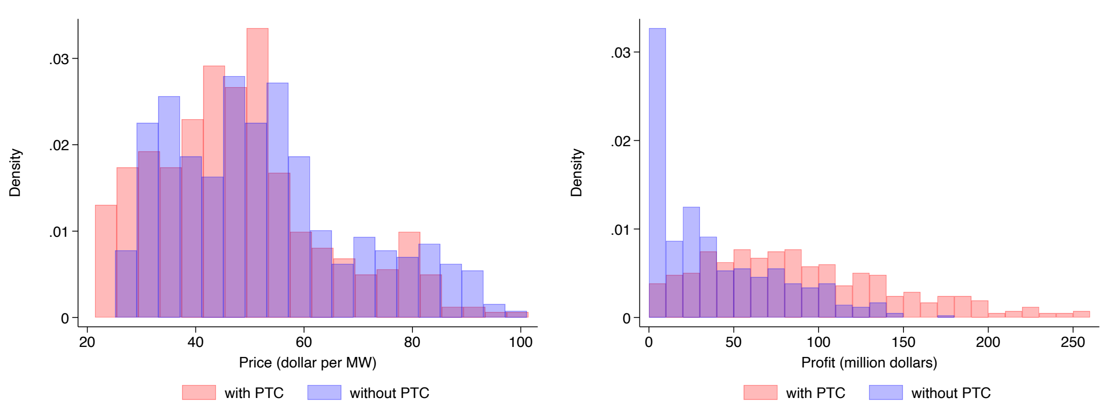
prices significantly reduce the optimal negotiated capacity. Although GE and Siemens-Gemasa seem to share similar turbine prices with Vestas, the unit capacity cost is significantly higher for other smaller brands, conditional on the turbine efficiency.

I estimate the bargaining weight of utilities ρ to be around 0.67. Therefore, utilities have two-thirds of the bargaining power compared with wind farms. ρ is also significantly different from 1, thus the change in PTC will not be perfectly passed through on the negotiated price, and assuming a take-it-or-leave-it model and imposing full rent extraction by utilities will underestimate the importance of 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 parameter estimate decreases by around 10%, but the estimation results are stable, which illustrates the robustness of the estimation results with respect to the assumptions on the threat points.

I allow for the choice-specific random shock in the policy-type decision in columns (4)-(5) as in Equation (8). The standard deviation of the random shock is estimated to be large, which is roughly the same magnitude as the average subsidy received by the 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 C.4. I further estimate the discount on tax credit τ in column (5) instead of calibrating the value. However, I find that wind farms perceive one dollar of the tax credit as 83.9 cents of cash transfer, which is close to the estimate by 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.

Figure 9: Estimated Profit and Price w/o PTC

(a) Price **(b)** Profit



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

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 $\pi_{ij}^W(d_t = 0)$ when PTC is absent. The distributions are shown in Figure 9. The discounted sum of profit π_{ij}^W is 89.6 million dollars on average, 124.5 million dollars at the 75th percentile, and 172.1 million dollars at the 90th percentile. Only 1.9% of wind farms earn a negative profit. When PTC is removed, bilateral bargaining will yield a lower negotiated capacity, but a higher negotiated price. The negotiated price without PTC $p_{ij}^*(d_t = 0)$ is 9.0% higher compared with p_{ij}^*. I assume that a negative negotiated capacity will lead to the failure of the project such that $k_{ij}^{w*} = 0$. Around 22.4% of wind farms will fail or earn a negative profit (I normalize as zero profit) without PTC, which further corroborates the importance of this federal incentive in supporting the industry. Even conditional on positive profits, $\pi_{ij}^W(d_t = 0)$ on average is 47.0% smaller than π_{ij}^W. This result highlights the potential cost of missing deadlines and losing the qualification of PTC and explains the rushed entry when there is a lower perceived likelihood for PTC extension.

I also simulate the profits under only PTC or Section 1603 Grant as shown in Panel (a) of Table A.10. The variation for a given wind farm under either subsidy type is one-order magnitude smaller compared to the variation across wind farms. I present the aggregate time trend for the profit when both subsidies are available, when only PTC is available, and when both subsidies are removed in Panel (b). The profits are increasing over time as a consequence of improving turbine technology. As the PTC phased out after 2016, the gap between profits with or without subsidies also got closer. During 2008-2012, the availability of both subsidies increased the profit by around 8.8%.

The estimation results of the demand function for non-utility buyers are shown in Table 2. I control for the balancing authority fixed effects as well as the contract type fixed effects as X_i in Equation (10).[20] Column (1) presents the OLS estimates. The price coefficient ζ_1 is around -0.769. 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 whether a state implemented wind power recruitment policies, property tax incentives, or sales tax incentives. I present the IV estimate using only the renewable credit price for utility as the baseline and discuss the results using different combinations of instruments in Appendix Section C.6. The IV estimate of the price coefficient is larger in magnitude than the OLS result by around 20%. I further regress log capacity on log price, and the estimated average elasticity is around -1.59. 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).

[20] I categorize all balancing authorities into four groups: ERCOT (37%), PJM (17%), SPP (15%), and the rest (31%). I also group the contract type into four groups: merchant contracts (44%), Power Purchase Agreements with non-utilities (27%), hedge contracts (10%), and the rest (19%).

Table 2: Demand Function for Non-Utility Buyers

	Capacity		log(Capacity)	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Price	-0.769	-0.922		
	(0.108)	(0.239)		
log(Price)			-1.181	-1.590
			(0.132)	(0.266)
Productivity (α_i)	-12.124	-13.513	0.003	-0.052
	(10.316)	(10.246)	(0.170)	(0.180)
GE	11.738	12.673	-0.097	-0.102
	(13.765)	(13.394)	(0.220)	(0.222)
Siemens	-6.636	-6.465	-0.016	-0.053
	(13.786)	(13.721)	(0.219)	(0.230)
Other Brands	-40.355	-38.247	-1.002	-0.942
	(14.947)	(15.347)	(0.273)	(0.282)
Turbine Price	-4.789	-4.831	0.011	0.023
	(1.999)	(2.019)	(0.034)	(0.035)
Observations	309	309	309	309
R^2	0.387	0.151	0.585	0.336
F Stat. for Exc. IV		60.340		87.427
Balance-Authority Dummies	✓	✓	✓	✓
Contract-Type Dummies	✓	✓	✓	✓

Notes: This table shows the estimation results of the linear demand curve for non-utility buyers (Equation (10)). Column (1) shows the OLS estimates, while column (2) shows the IV estimates. I use the renewable credit price for utilities as the instrument for the wind price faced by non-utility buyers. Robust standard errors are in parentheses.

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 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 around 24.2%. However, this probability is much larger in Texas, Illinois, and New York, as these markets are where the hedge and merchant contracts concentrated geographically.

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 (12)). Standard errors are in parentheses.

6.2 Dynamic Parameters

I present the estimation results for dynamic parameters in Table 4. I use the policy window between 2013 and 2018 to estimate entry cost parameters in column (1), and use the policy window between 2014 and 2018 to estimate entry cost parameters in column (2). I use column (2) as the baseline result. The mean parameter ϕ of the entry cost distribution is estimated to be around 290.87, and thus the mean entry cost conditional on entry is simulated to be 17.94-19.19 million dollars. Moreover, I include the average state-level annual agricultural land price as W_{it} after subtracting the sample mean. The coefficient μ is estimated to be positive, which indicates that higher land price exacerbates the entry cost for new wind farms. The mean land cost accounts for 53.2%-70% of the total entry cost.

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 around 0.3 for the 2011 cohort due to the pessimism about the policy extension as well as the delayed renewal action. 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 a larger extrapolation error when estimating belief parameters in this early stage using entry cost parameters estimated from a much later sample period.

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.

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 A.11. 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 counterfactual exercise is to answer the key research question of how policy uncertainty affects dynamic market efficiency and social welfare. I simulate the investment decision when the policy uncertainty is eliminated. I calculate the welfare consequences of policy uncertainty by comparing the baseline scenario with policy uncertainty and the simulated case without policy uncertainty. I decompose the welfare consequences of policy uncertainty to different channels and explore effect heterogeneity across states. The second counterfactual exercise is to adjust subsidy generosity. As the Production Tax Credit was at a fixed value after adjusting for inflation throughout its history until 2016, I investigate how the welfare effects of policy uncertainty change under different levels of subsidies and explore the interactions between subsidy generosity and policy uncertainty. The third counterfactual exercise is to explore the welfare effects under early resolution of policy uncertainty. I simulate the investment decision when policy uncertainty is resolved before and after wind farm investors make entry decisions and compare the welfare effects between these two scenarios. The last counterfactual exercise is to evaluate the welfare effects of policy uncertainty in a more static market environment. I compare the impacts of investment trajectory and social surplus of policy uncertainty when the wind turbine technology is constant or the characteristics of the buyer pool are fixed.

7.1 Effects of Policy Uncertainty on Investment and Welfare

I simulate the baseline scenario when policy uncertainty is in place with the estimated belief parameters in Table 4 and a counterfactual case when policy uncertainty is completely removed such that $b_t = 1$. 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 a wind farm decides to wait, it will go back to the potential entrant pool and be faced with the same dynamic problem next year. The details of counterfactual simulations can be found in Appendix Section D.

This counterfactual exercise is to quantify the impacts of policy uncertainty on wind farm investment and social surplus. Removing policy uncertainty completely is an extreme policy scenario, but maintaining a long-term policy is the new direction of policy design. For example, the Inflation Reduction Act of 2022 extended the Production Tax Credit until 2025 and 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.[21] Moreover, containing policy uncertainty can also be

[21]For the Inflation Reduction Act of 2022, please see a summary from the White House and from the EPA.

achieved by rolling policy windows with a longer gap between the announcement and the implementation of the renewal.

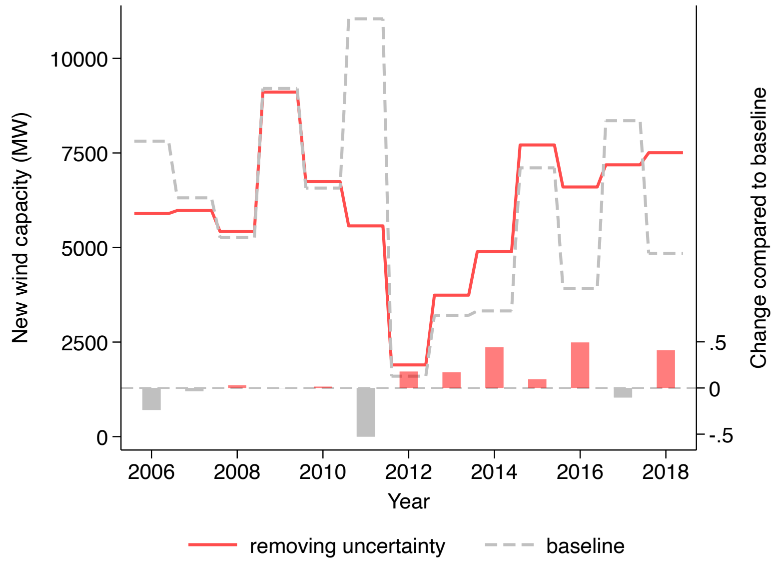
Investment Trajectory The baseline and counterfactual investment trajectories are shown in Figure 10. Removing policy uncertainty greatly delays the entry of wind farms. The number of new wind projects in 2011 is reduced by 52.7% and the total new capacity decreases by 5500 MW. The wind projects delay their entry to later years and I find that the number of new wind projects in 2012-2018 increases by 24.1% on average annually. Those delayed wind farms postpone their entry by 3.56 years and the average entry year of all new projects between 2011-2018 is delayed by 0.72 years.

Social Welfare I calculate the welfare change brought by policy uncertainty for the policy window in 2008-2018. Policy uncertainty induces earlier entry of wind farms and expedites the environmental benefits of reducing carbon emissions. However, policy uncertainty creates a mismatch among investment timing, technological improvement, as well as demand evolution, which leads to efficiency loss. I first compare outputs under two scenarios. As shown in Panel A of Table 5, the numbers of total wind projects are roughly the same, suggesting that removing policy uncertainty mainly changes the entry timing but keeps the total number of entrants constant over an 11-year horizon. However, the total capacity increases by 6.3% once policy uncertainty is removed. Moreover, the total output increases by 8.7%. As more investment takes place during the policy window when the turbine productivity is higher and the turbine price is lower, investment timing aligns better with technology. Utilities with unfulfilled demand also procure more wind capacity when there is better technology. Consequently, the total capacity and output both increase despite similar numbers of wind projects, as illustrated in Appendix Figure A.12.

I calculate the profit of wind farms on the market in Panel B of Table 5. Though 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 peak of 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 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

Figure 10: 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.

more renewable energy.[22] I assume the social cost of carbon to be \$80 per ton.[23] The statistics of the avoided operating costs and capacity values are taken directly from Callaway et al. (2018). I abstract away electricity demand responses as they are outside of my model. The social surplus from wind energy could then be calculated as total benefits, including avoiding carbon emissions, reducing fossil fuel costs, and increasing capacity values, minus the turbine costs and entry costs paid by the wind farm investors.

The cost and benefit analysis of policy uncertainty is presented in Panel (c) of Table 5. Total benefits increase by 5.8 billion dollars in total, 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 waiting cost. 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 such as \$50 per ton,

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

[23] 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.

the total benefits increase by 4.6 billion dollars compared to the baseline.

The social surplus of wind energy, after taking the decreasing turbine costs and entry costs into consideration, increases by 6.8 billion dollars and 18.4% from the baseline. The total subsidy increases by 5.2% as the PTC is based on total output.[24] The total profit on the market cannot fully justify subsidies as the net profit is negative, but removing policy uncertainty reduces this deficit by 0.2 billion dollars. However, the net social surplus increases by 5.9 billion dollars in total, a 28.9% increase from the baseline.

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%
Social Surplus	TB-TC-EC	37.0	43.8	6.8	18.4%
Subsidy	S	16.5	17.3	0.9	5.2%
Net Profit	TP-S	-1.6	-1.5	0.2	
Net 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.

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 underlying this total improvement: the delayed environmental benefits, the improvement of timing alignment between investment and technology, as well as the matching efficiency gain between utilities and

[24] 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.

wind farms. Removing policy uncertainty reduces total benefits from wind energy through the first channel, but improves total benefits through the latter two channels. 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 of 1 MWh wind energy generation for 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, assuming that each wind farm operates for twenty years.

$$\text{TB} = \sum_{mt} \frac{1-\beta^{20}}{1-\beta} \alpha_t k_{mt}(\mathbf{\Phi}_{mt}) b_m N_{mt} \beta^t.$$

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.

$$\begin{aligned}\tilde{\text{TB}} - \text{TB} = \frac{1-\beta^{20}}{1-\beta} [& \underbrace{\sum_{mt} \bar{\alpha} k_{mt}(\Phi_{mt}) b_m (\tilde{N}_{mt} - N_{mt}) \beta^t}_{\text{delayed environmental benefits}} + \\ & \underbrace{(\alpha_t - \bar{\alpha}) k_{mt}(\Phi_{mt}) b_m (\tilde{N}_{mt} - N_{mt}) \beta^t}_{\text{timing alignment}} + \\ & \underbrace{\alpha_t (\tilde{k}_{mt}(\tilde{\Phi}_{mt}) - k_{mt}(\Phi_{mt})) b_m \tilde{N}_{mt} \beta^t}_{\text{matching efficiency gain}}]\end{aligned} \tag{22}$$

The decomposition results are shown in Appendix Figure A.13. 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 net social surplus increases more especially in states with larger wind demand or more generous state-level supports. As shown in Appendix Figure A.14, the improvement in the net social surplus by removing policy uncertainty is larger for states with larger unfulfilled demand for utilities (Φ_{jt}) or demand shifters ($\boldsymbol{\beta_4 Z^U_{jt}}$). Moreover, the change in the net social surplus from removing policy uncertainty is also larger if a state implements more stringent 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 where state subsidies are also provided, as state policies make it easier for wind projects to expedite their entry to qualify for the PTC.

7.2 Effects of Policy Uncertainty under Various Subsidy Levels

I investigate how the welfare effects of policy uncertainty change under different subsidy levels. The Production Tax Credit was at a fixed value after adjusting for inflation throughout its history until 2016. Therefore, until 2016, the government set policy windows and decided when to renew the subsidy, but held the generosity of subsidies constant. However, an alternative level of subsidy might yield better social surplus under policy uncertainty. I keep the belief parameters as they are for other years, but 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. I calculate the social surplus and the net social surplus of wind energy for each case, and the results are summarized in Figure 11.

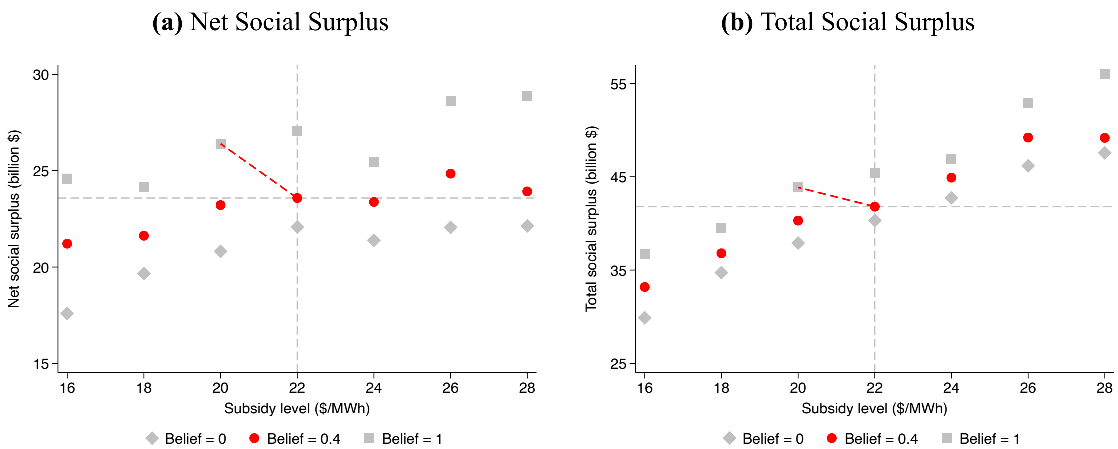
Overall, the social surplus of wind energy increases with the level of subsidy but decreases with the extent of policy uncertainty in 2011. The baseline level of net social surplus with a subsidy level of $22/MWh and policy belief parameter in 2011 as 0.4 is lower than the net social surplus with a subsidy level of $18/MWh but with full policy certainty in 2011. Similarly, the baseline level of social surplus with a subsidy level of $22/MWh and policy belief in 2011 as 0.4 is lower than the social surplus with a subsidy level of $20/MWh but with policy certainty in 2011. Therefore, we could reduce the level of subsidy without sacrificing social welfare if we could contain policy uncertainty.

A similar exercise is to compare social welfare under the baseline level of policy uncertainty and when policy uncertainty is maximized. As shown in Figure 11, if the policy uncertainty is further exacerbated such that the policy belief parameter is 0 in 2011, the net social surplus of wind energy is lower than that when the subsidy level is $20/MWh under the current level of policy uncertainty. The same pattern also holds true for total social surplus. Therefore, if we adjust policy uncertainty to its maximum in 2011, the social welfare can be sustained by decreasing the subsidy level by $2-$3/MWh even under the current level of policy uncertainty. This exercise shows the fiscal cost of policy uncertainty. Removing policy uncertainty could save fiscal expenditure for the government without sacrificing 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

Figure 11: 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.

two scenarios. First, policy uncertainty was resolved at the beginning of the year 2011 such that the government had a random draw of whether to extend subsidies from a binary distribution with a mean of 0.4 and announced the policy extension status to the wind industry. Wind farm investors would know the future policy status promised by the government before they make the entry decision. This is the early resolution of policy uncertainty. Second, policy uncertainty was resolved after the wind farm investors made the investment decision and the mean probability is 0.4, which is similar to 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).

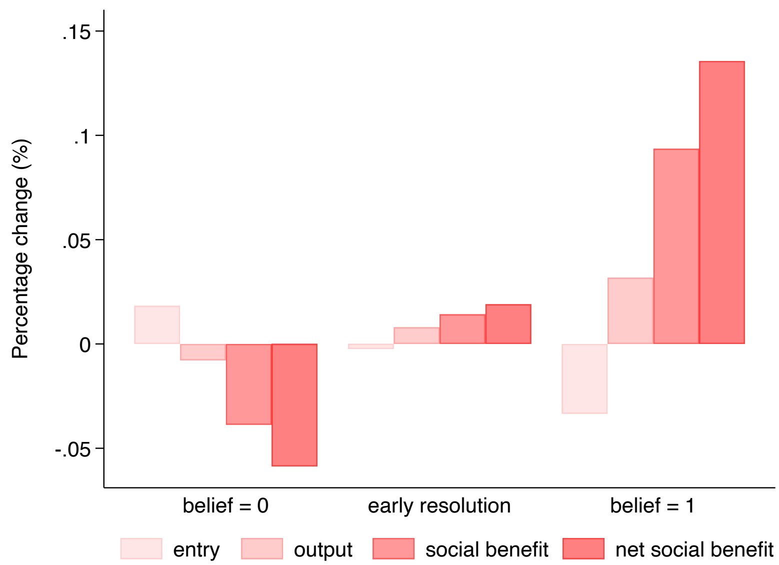
The results are shown in Figure 12. I plot the percentage change in the number of new projects, total outputs, social surplus, and net social surplus compared to the baseline scenario. I find that when the policy uncertainty is resolved early, the number of new wind projects will be smaller. This is 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.[25] Overall, the welfare effect of policy uncertainty under early resolution is positive compared with the baseline scenario. The total and net social surplus of wind energy increase by 1.4% and 1.9%.

Early resolution of policy uncertainty captures 10.4%-15.2% of the welfare gain under full removal of policy uncertainty depending on the welfare measures. Despite that the Production Tax

[25] 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.

Credit is always renewed *ex post*, the *ex-ante* uncertainty faced 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 15% of welfare loss, while the rest 85% of welfare loss is due to a lower expected value of subsidy from *ex-ante* uncertainty. Although the subsidy is in effect on the market at all times, *ex-ante* policy uncertainty undermines the role of the subsidy by shifting the expectations of investors and leads to welfare loss.

Figure 12: 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, social surplus, and net social surplus when policy belief is 0, when policy belief is 1, and when policy uncertainty is resolved early compared to the baseline scenario.

7.4 Effects of Policy Uncertainty without Dynamic Environment

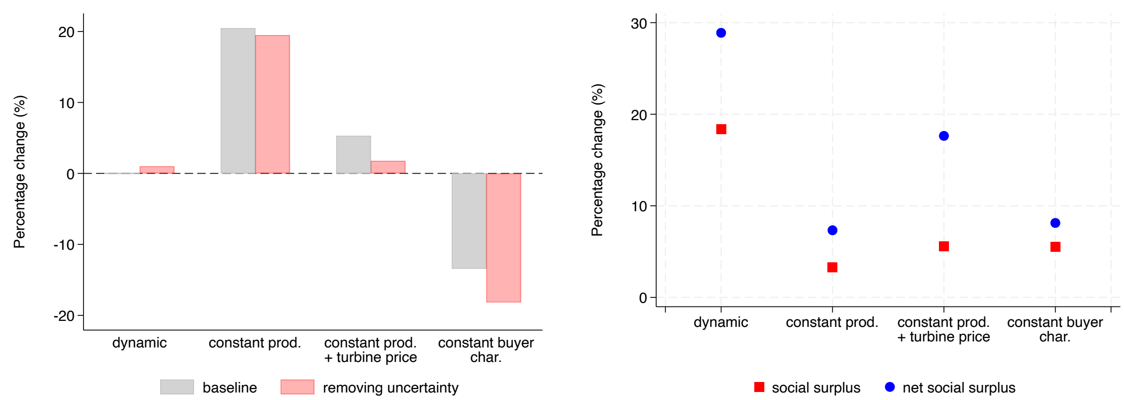
I explore the welfare consequences of policy uncertainty in a more static market environment. I consider three scenarios: 1) the turbine productivity is constant at the 2011 level; 2) both the turbine productivity and price are constant at the 2011 level, and thus the technology is fixed at the 2011 level; 3) the renewable portfolio gap is fixed for each utility at its 2011 level. I simulate the investment decision with and without policy uncertainty and compare the total number of wind projects, total output, social surplus, and net social surplus in 2008-2018.

The results are shown in Figure 13. Panel (a) presents the number of wind farms. The first scenario is the baseline full dynamic case where turbine productivity, turbine price, and buyer characteristics are all changing over time. I set the full dynamic scenario with policy uncertainty as the benchmark and calculate the percentage change in other cases. I find that keeping turbine technology constant will increase the entry of new wind farms, as the incentive to wait for better technology is eliminated. On the contrary, keeping the renewable portfolio gaps constant for every buyer will eliminate the preemption incentive of wind farms and there will be fewer wind farms operating on the market.

Figure 13: Outcomes without Dynamic Environment

(a) Number of Wind Farms

(b) Social Surplus



Notes: This figure shows the market outcomes when the market environment is more static. There are four scenarios: 1) the baseline full dynamics where turbine productivity, turbine price, and buyer characteristics are all changing over time; 2) the turbine productivity is constant at the 2011 level; 3) both the turbine productivity and price are constant at the 2011 level; 4) the renewable portfolio gap is fixed for each utility at its 2011 level. I plot the number of wind farms, the total outputs, the social surplus, and the net social surplus in 2008-2018.

When market primitives are constant, removing policy uncertainty will reduce the number of wind farms to various extents for different reasons. If the technology is constant, postponed wind farms will find it difficult to enter later as they need a longer waiting time to have a favorable entry cost draw to justify their investment decision with continuously low productivity or high turbine prices. If the buyer pool is constant, postponed wind farms have incentives to further delay with a lack of preemption incentives.

I then calculate the change in the social surplus and net social surplus from wind energy by removing policy uncertainty. As I discussed in Table 5, the social surplus and net social surplus increase by 18.4% and 28.9%, respectively. When the market environment is more static, the welfare gain from removing uncertainty will also be smaller. If there is no turbine productivity change, the social benefits and net social benefits increase by 3.3% and 7.3% respectively, around 1/5 to 1/4 of the full dynamic results. If there is no buyer characteristics change, the social benefits and net social benefits increase will also shrink to 30% of the full dynamic results. In the absence of technological change or demand evolution, removing policy uncertainty still improves social welfare to reduce entry timing distortion, but the welfare gain will be much smaller. The dynamic market environment greatly exacerbates the efficiency loss from policy uncertainty.

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, endogenous buyer matching, 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 net social benefits 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 sacrificing social welfare if the government can manage to contain policy uncertainty. I also find that the dynamic market environment exacerbates the efficiency loss from policy uncertainty and early resolution of the policy uncertainty could capture more than 10% 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 these nascent industries. After decades of ‘on-again/off-again’ policy status, the Inflation Reduction Act of 2022 extended the Production Tax Credit until 2025 and 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.

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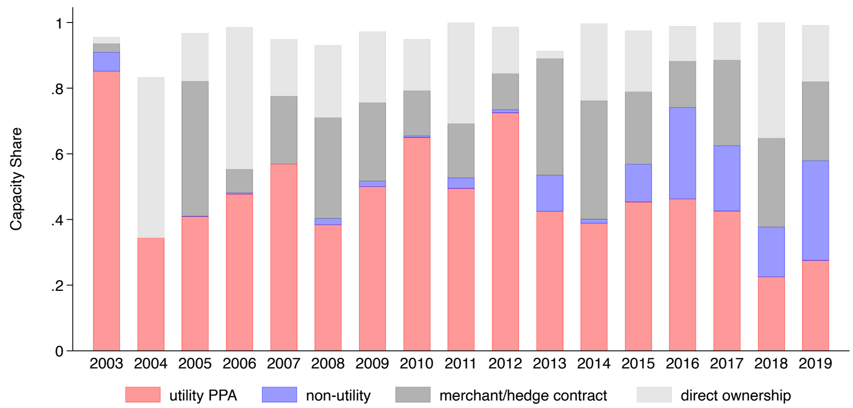
Online Appendix (Not for Publication)

Table of Contents

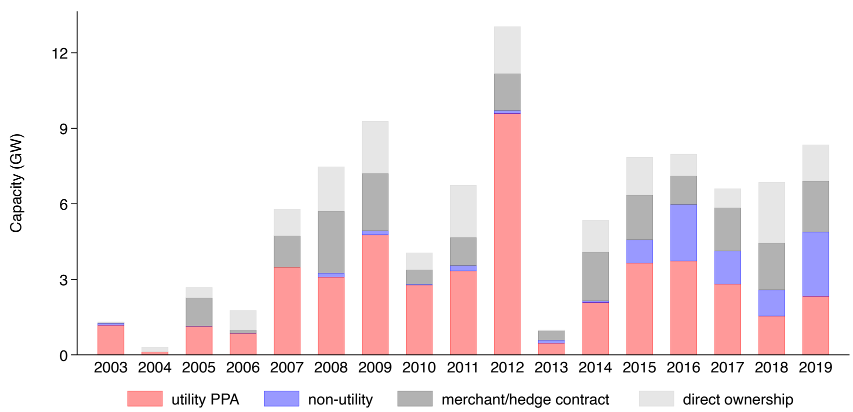
A Additional Figures and Tables

Figure A.1: Capacity by Offtake Types

(a) Capacity Share



(b) Capacity Volume

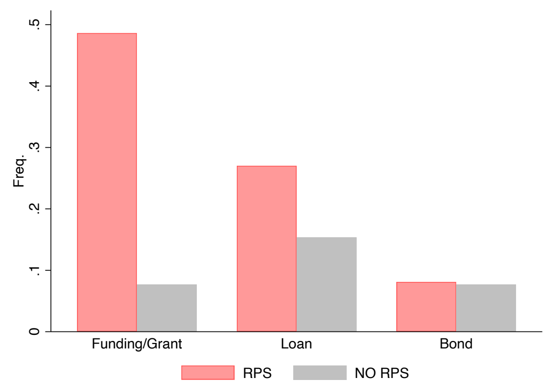


Notes: This figure shows the capacity distribution by offtake types across years. There are four offtake types: utility PPA, non-utility offtaker, merchant/hedge contracts, and direct ownership. Panel (a) describes the share of capacity, while Panel (b) shows the volumes.

Figure A.2: State-level Policies

(a) Tax Policies

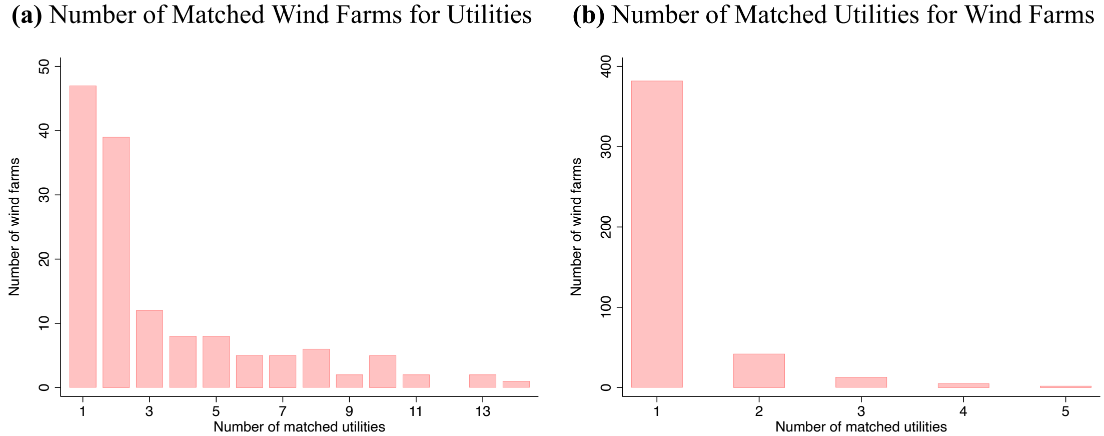
(b) Financing Policies



(c) Other Policies

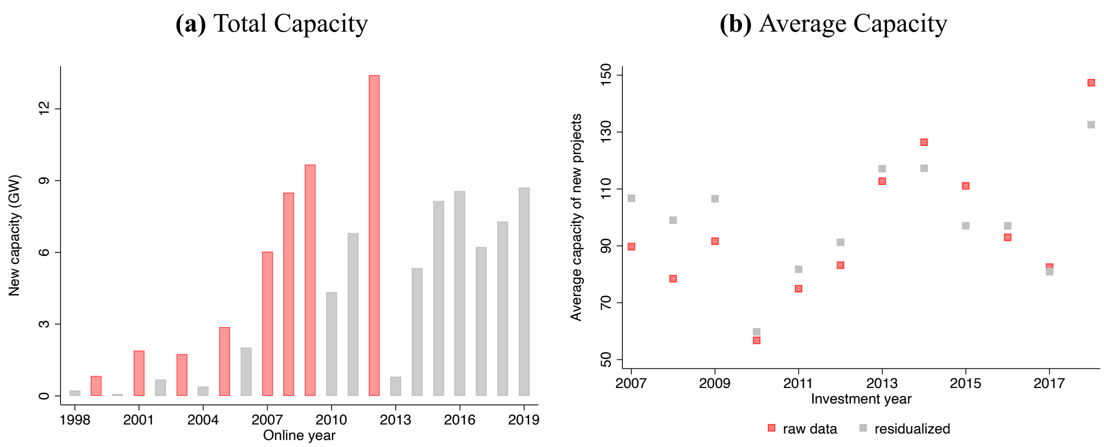
Notes: This figure shows the frequencies of different types of state policies for states with or without RPS. State policies, including RPS, are hand collected by the author from DSIRE (`https://www.dsireusa.org/`).

Figure A.3: Matching between Utilities and Wind Farms



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

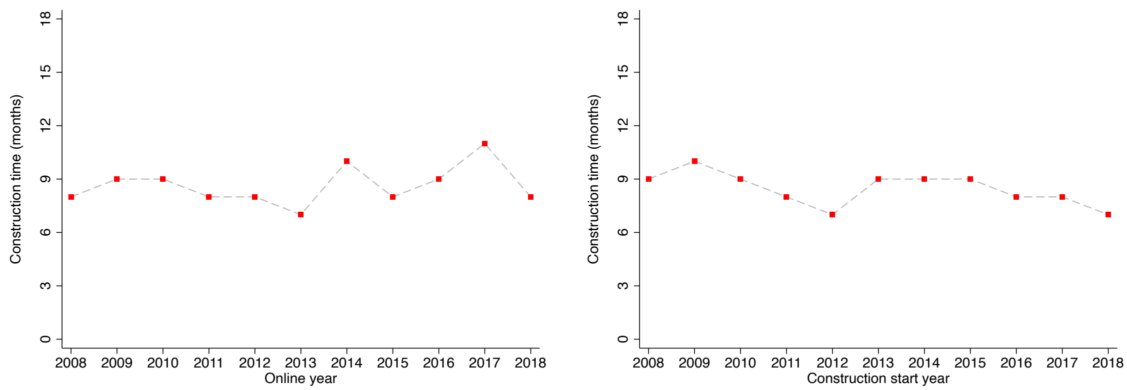
Figure A.4: Time Trend for Investment: Capacity



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

Figure A.5: Construction Time

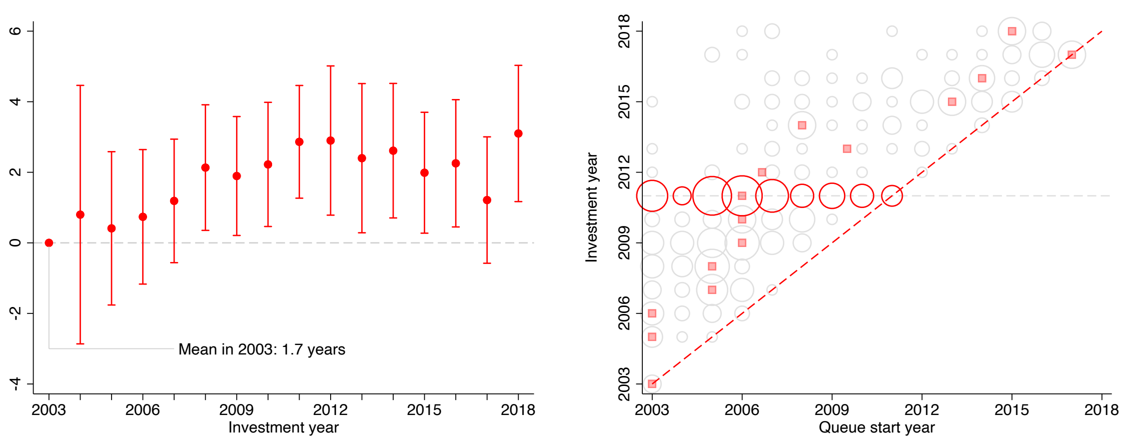
(a) by Online Years **(b)** by Construction Start Years



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

Figure A.6: Interconnection Queues

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

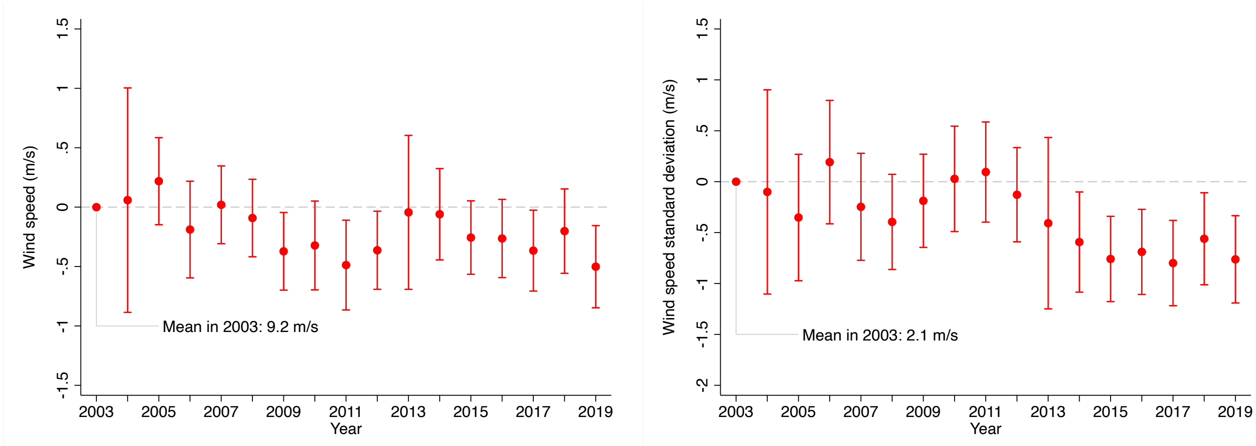


Notes: This figure shows the descriptive evidence for the interconnection queues. Panel (a) plots the average time spent between entering into the interconnection queues and starting construction. Panel (b) plots the distribution of years to start construction and start the queues, where the size of 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 A.7: Time Trend of Wind Speeds

(a) Mean

(b) Standard Deviation within Locations



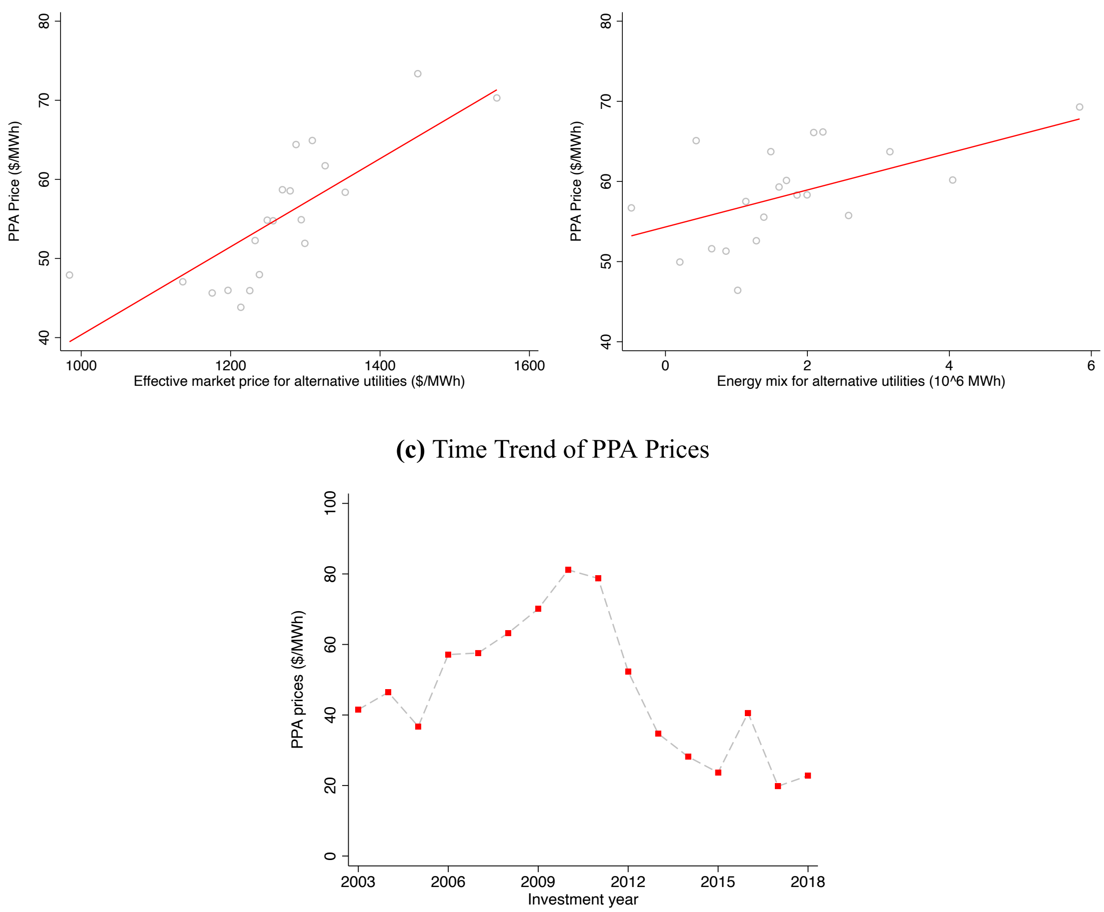
Notes: This figure shows the annual time trends of wind speed at locations of new wind projects. The wind speed is measured at 80 meters at sites nearest to the wind project location based on the Wind Toolkit Data from National Renewable Energy Laboratory (NREL). The mean and standard deviation for each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

Figure A.8: PPA Price and WTP of Alternative Utilities

(a) Effective Price for Alt Util

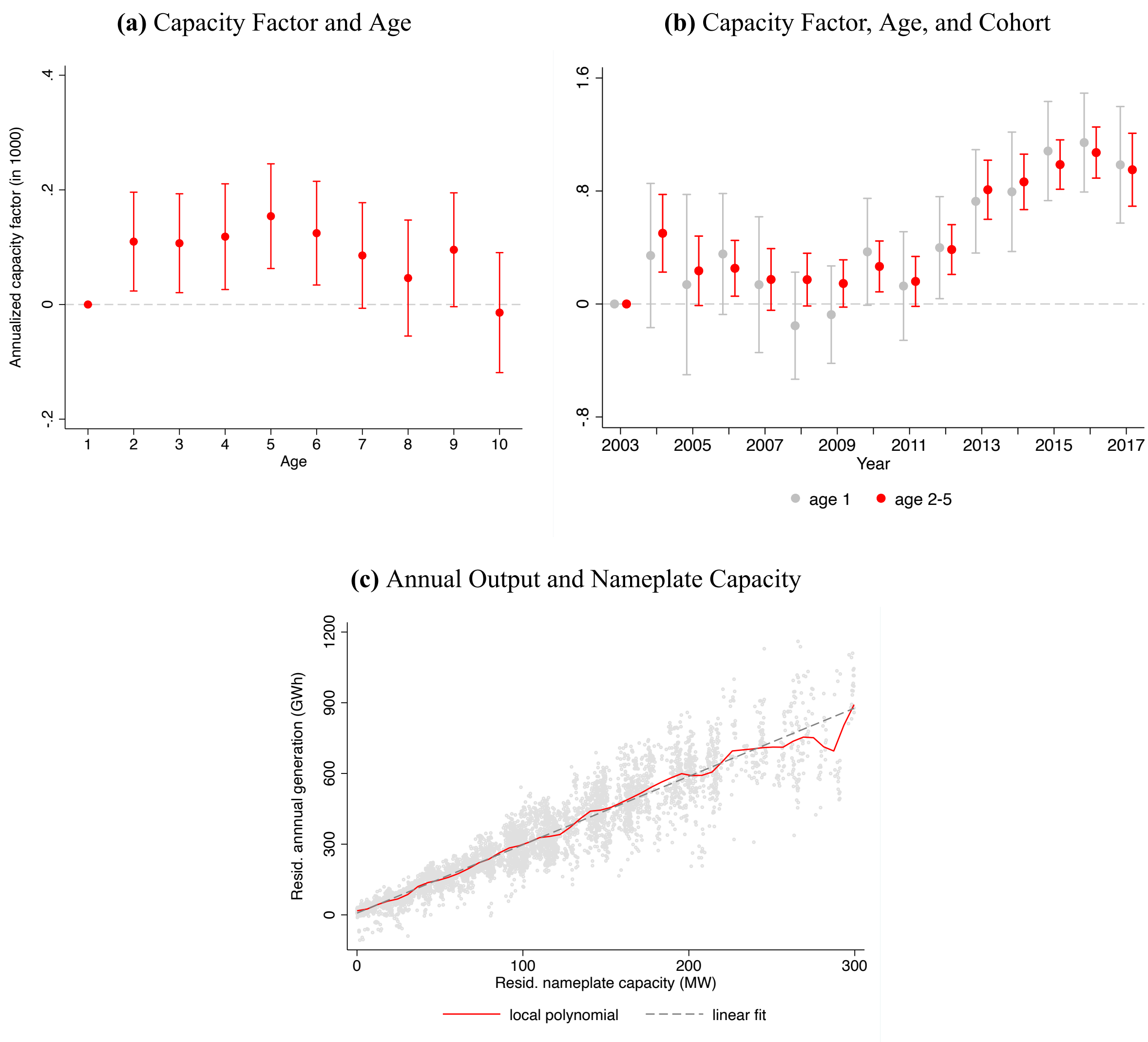
(b) Energy Composition for Alt Util

(c) Time Trend of PPA Prices



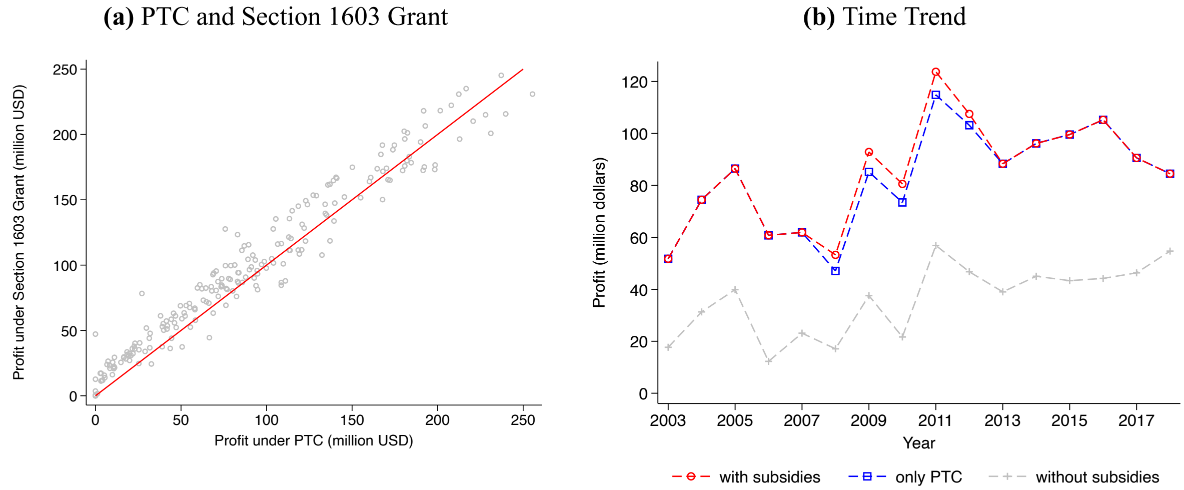
Notes: This figure describes the basic pattern of the Power Purchase Agreement (PPA) prices. Panels (a) and (b) show the conditional relationship between PPA prices and two willingness to pay shifters for the alternative utilities within 400 miles. Panel (a) shows the relationship between PPA prices 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 A.9: Description of Annualized Capacity Factor



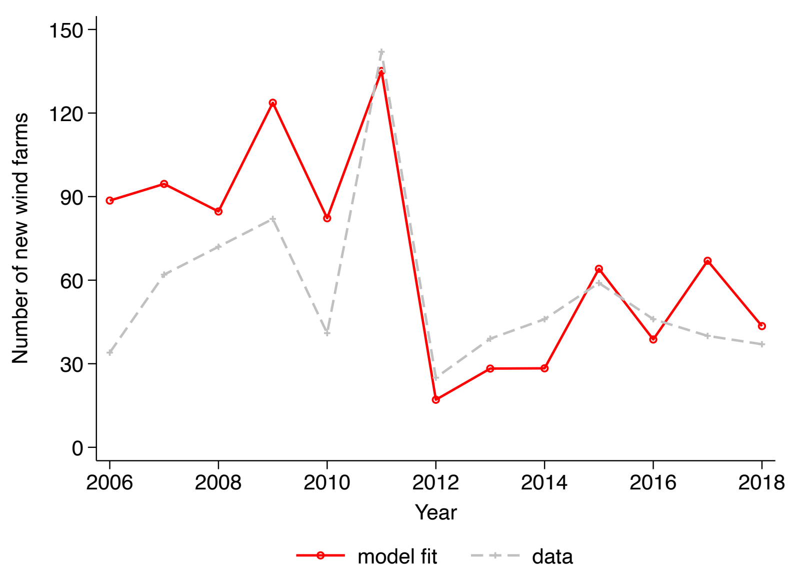
Notes: This figure presents the descriptive data patterns of the annualized capacity factor of wind farms. Panels (a) and (b) explore the relationship among the capacity factors, ages, and cohorts of wind farms. I rescale the annualized capacity factor and divide it by 1000. The average annualized capacity factor is 2.82×10^3 at the wind farm and year level. Panel (a) plots the coefficient estimates of β_a in Equation (23), controlling for the entry cohort dummies. Panel (b) plots the coefficient estimates of β_c in Equation (23), for the groups of wind farms of age 1 and age 2-5 separately. For both Panels (a) and (b), the 95% confidence intervals are constructed from the robust standard errors. Panel (c) shows the relationship between the annual output and the nameplate capacity of wind farms. I residualize both the annual output and the nameplate capacity on entry cohort dummies and age dummies. The scatter plot is at the wind farm and year level. The red dashed line is the local polynomial approximation, while the blue solid line is the linear fit between these two variables.

Figure A.10: Summary of Simulated Static Profits



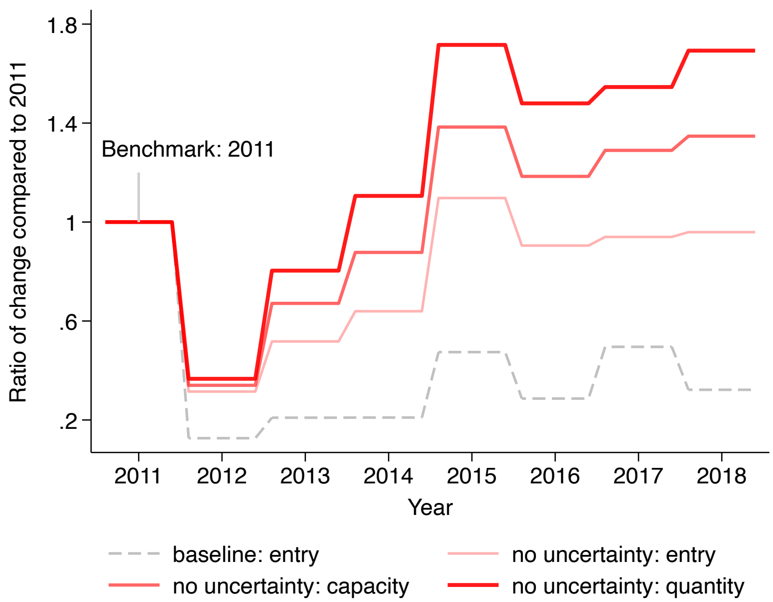
Notes: This figure summarizes the basic patterns of the simulated profit from bilateral bargaining. Panel (a) presents simulated profits under either PTC or Section 1603 Grant. Each circle represents one wind farm, and the red solid line is the 45-degree line. Panel (b) plots the average profits with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

Figure A.11: Dynamic Model Fit



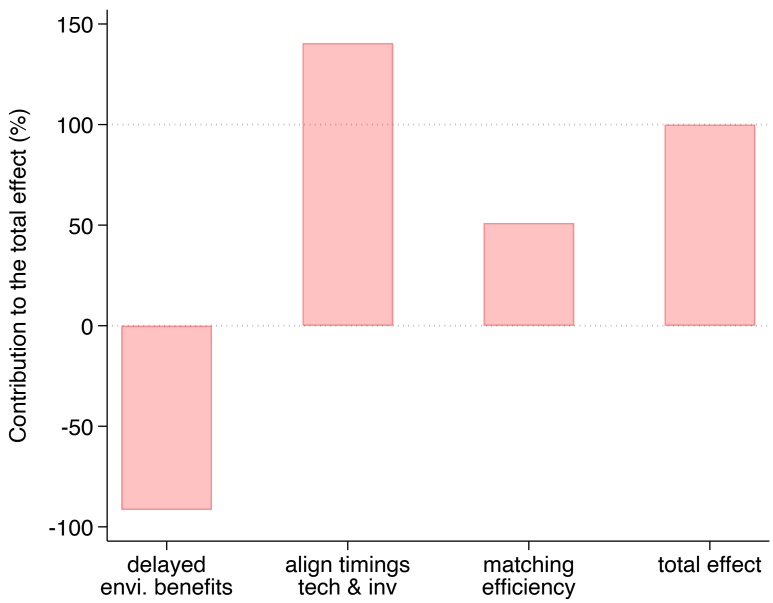
Notes: This figure shows the dynamic model fit. The red line denotes the model-predicted number of wind projects, while the gray dashed line denotes the number of wind projects in the raw data.

Figure A.12: New Projects, Capacity, and Output with and without Policy Uncertainty



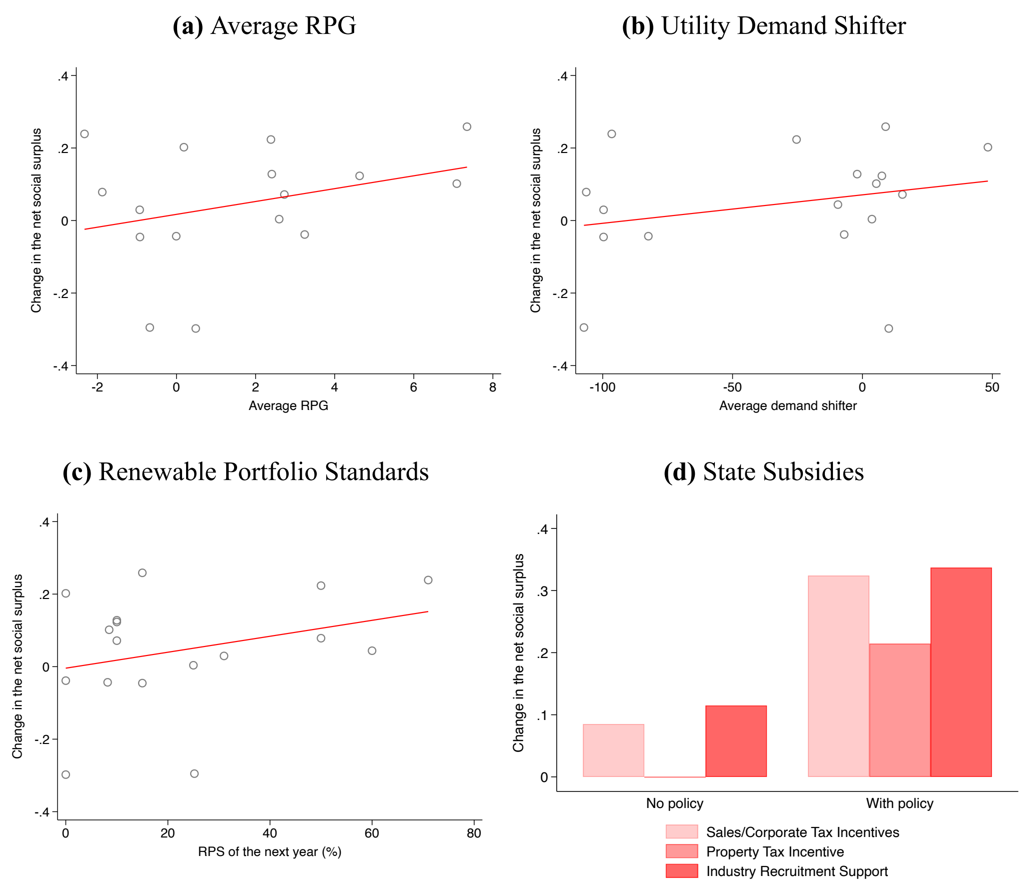
Notes: This figure shows the number of new projects, the amount of new capacity, and the total outputs generated by the new cohort under the baseline scenario and when the policy uncertainty is removed. I set the level in 2011 as the benchmark and calculate the percentage change in later years.

Figure A.13: Welfare Decomposition



Notes: This figure shows the welfare decomposition according to Equation (22). 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 A.14: 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 Data Cleaning

B.1 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 B.1).

I keep the PPA data with utilities being 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 seems quite 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 B.1, 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. My strategy of imputation for PPA prices follows that of Aldy et al. (2023). I back out the 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 B.1, I find they align well with each other.

B.2 REC Price Data

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

$$y_{mt} = \beta_m \times \mathbb{1}(\text{state} = m) \times t + \xi_m + \epsilon_{mt}$$

I use y_{mt} to denote the REC prices in state m and year t. I extrapolate the missing REC prices from the estimated state-specific time trends.

Second, I extrapolate the REC prices in other active REC states. State-level Renewable Portfolio Standards (RPS) typically stipulate a minimum share of renewable-sourced electricity out of the total generation for each utility, and utilities need to purchase additional Renewable Energy Credits if they fall short of the standards. The demand for renewable energy credit is shifted by the stringency of RPS as well as the volume of electricity generated by non-renewable sources, while the supply of renewable energy credit comes from new wind capacity addition and other renewable sources. As shown in Appendix Figure B.2, I find REC prices to be positively correlated with the RPS, as more stringent Renewable Portfolio Standards boost the demand for renewable energy credits. Meanwhile, REC prices are negatively correlated with existing wind capacity, because existing wind capacity expands the supply of renewable energy credits. Moreover, REC prices are also positively correlated with the share of electricity generated from non-renewable sources such as fossil fuels and nuclear energy. A higher non-renewable share of electricity generation shifts the demand curve of renewable energy credits outwards.

Moreover, the trading of renewable credits is fragmented into different markets, and the credits are registered to be traded in different tracking systems as shown in Table B.1 based on Table 1 in Abito et al. (2022). The variation in the tracking systems could explain around 60% of the data variation in the REC prices. Therefore, I estimate the following regression model and predict the REC prices in the rest of the active REC states (with a slight abuse of the notations).

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

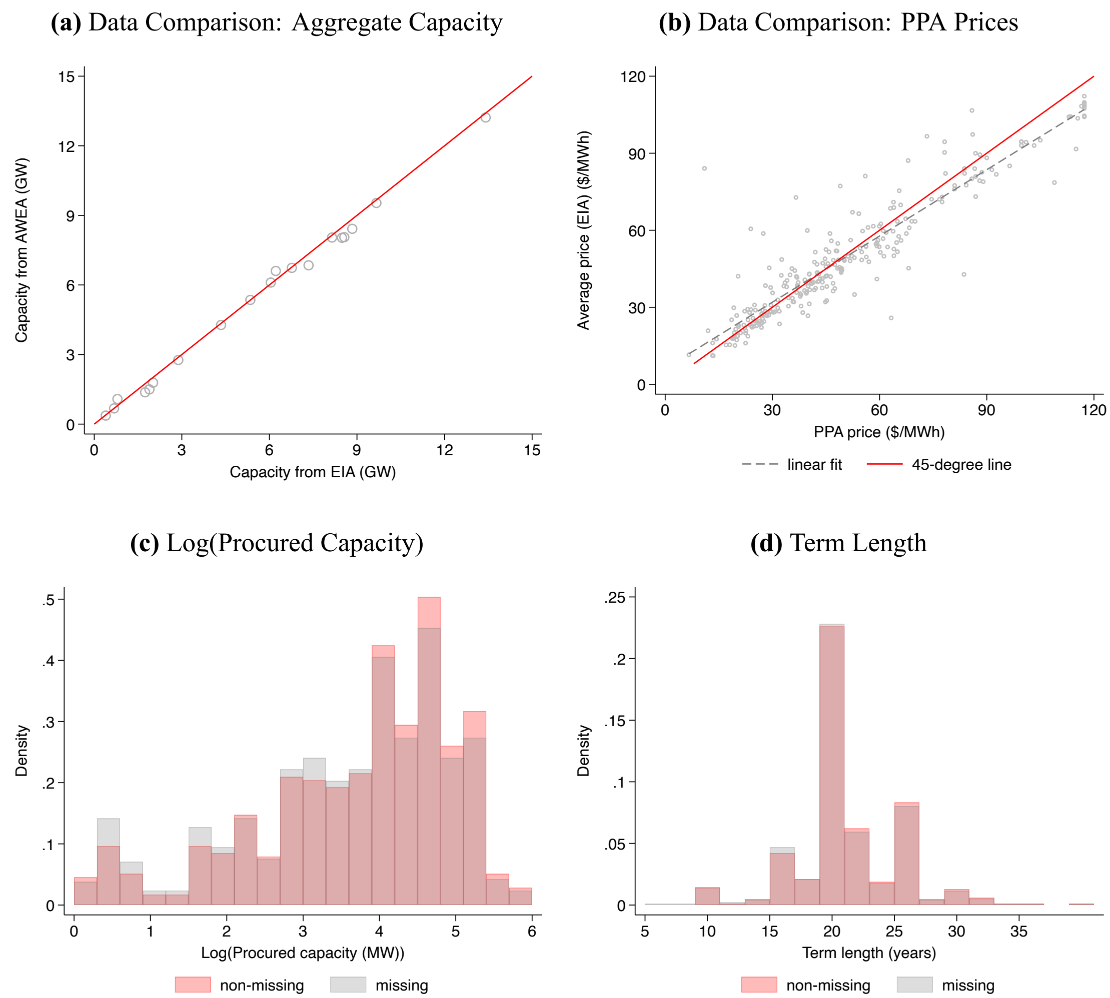
I use y_{mt} to denote the REC prices in state m and year t. The tracking system of state m is denoted by k, and $\boldsymbol{X_{mt}}$ includes the RPS in year t, the cumulative wind capacity in state m and year t, as well as the share of electricity generated out of non-renewable sources. Therefore, I extrapolate the REC prices based on observables as well as 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 one order of magnitude larger than the rest of the markets.

Table B.1: REC Tracking System and Price Imputation (Table 1 from Abito et al. (2022))

State	Established year	Tracking system	Imputation
Arizona	2006	None	national average
California	2002	WREGIS	No
Colorado	2004	WREGIS	WREGIS
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	M-RETS
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	M-RETS
Missouri	2007	NAR	national average
Montana	2005	M-RETS, WREGIS	M-RETS
Nevada	1997	NVTREC, WREGIS	M-RETS
New Hampshire	2007	NEPOOL-GIS	No
New Jersey	1991	PJM-GATS	No
New Mexico	2002	WREGIS	WREGIS
New York	2004	NYGATS	national average
North Carolina	2007	NC-RETS	national average
North Dakota	2007	M-RETS	M-RETS
Ohio	2008	M-RETS, PJM-GATS	No
Oklahoma	2010	None	national average
Oregon	2007	WREGIS	WREGIS
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	WREGIS
Vermont	2015	NEPOOL-GIS	NEPOOL-GIS
Washington	2006	WREGIS	WREGIS
Wisconsin	1998	M-RETS	M-RETS

Notes: This table records the establishment year as well as the tracking system of the Renewable Energy Credit market in relevant states based on Table 1 from Abito et al. (2022). The column "Imputation" indicates how I impute missing REC prices in those states. Generally, I impute REC prices using observables including the Renewable Portfolio Standards, cumulative wind capacity, and the share of electricity generated by non-renewable resources, 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 because no price in the corresponding tracking system is available, while "No" indicates that the data is not missing and no imputation is required.

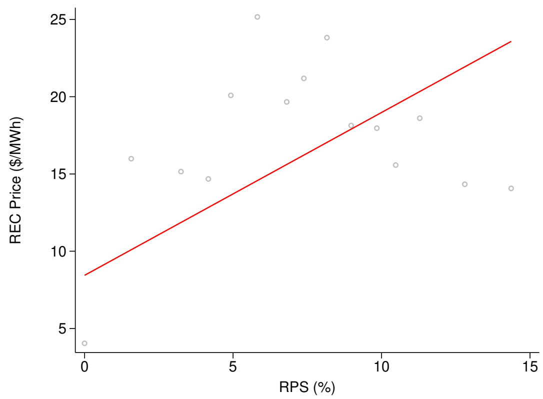
Figure B.1: Data Description of the PPA Sample



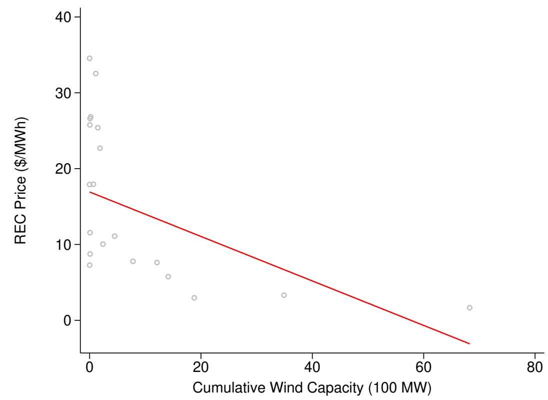
Notes: This figure presents the results of the data description for the PPA sample. Panels (a) and (b) show the results of the data quality cross-check between AWEA and EIA. Panel (a) plots the annual aggregate new capacity from EIA and AWEA. The red solid line denotes the 45-degree line. Panel (b) plots 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 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" sub-sample denotes the one that matches both utility IDs and wind farm IDs with EIA, and the "missing" sub-sample denotes the one with either unmatched utility IDs or unmatched wind farm IDs.

Figure B.2: Renewable Energy Credit Prices and Other Market Outcomes

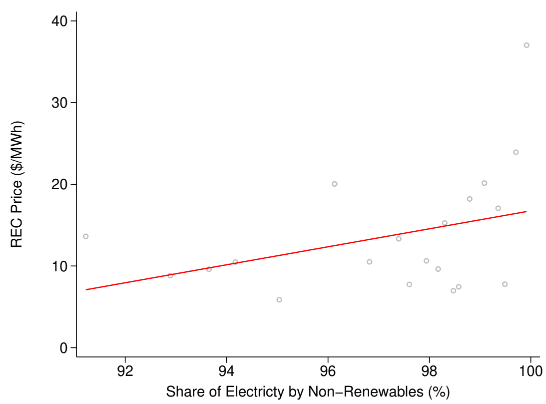
(a) Renewable Portfolio Standards



(b) Cumulative Wind Capacity



(c) Electricity Share by Non-Renewables



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

B.3 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.[26] 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.[27] Another way to leave the queue is to successfully build a wind farm, which I back out using the EIA data.

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

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

I define $\text{PotentialEntrants}_{m,2002}$ as twice as large as the maximum of NewBuilt_{mt} in the state m, serving as an initial value. I adjust $\text{PotentialEntrants}_{mt}$ to be equal to NewBuilt_{mt} if the former falls below the latter. I describe the time trend for Entry_{mt}, Exit_{mt}, and $\text{PotentialEntrants}_{mt}$ in Appendix Figure B.3. 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 B.4, the number of newly built wind farms is stable

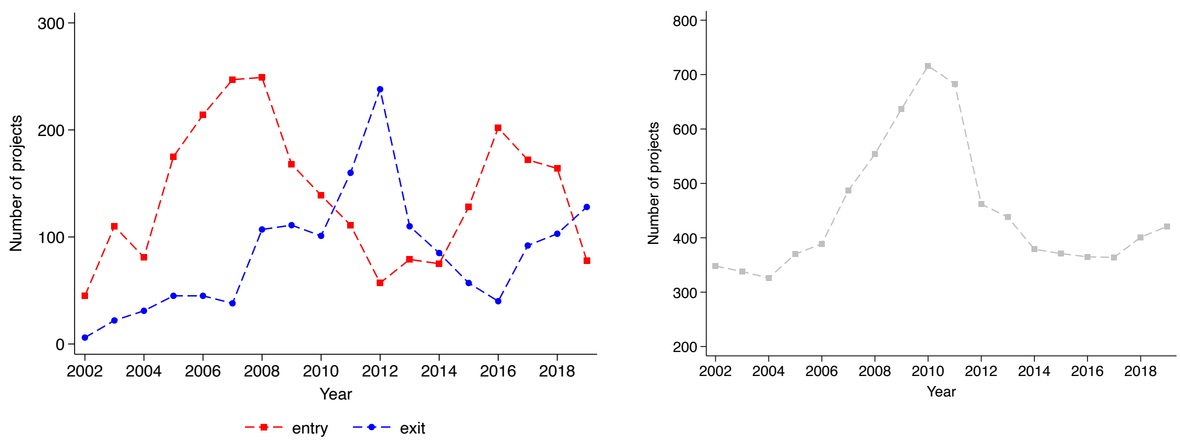
[26] MISO interconnection queue is accessed at this link on Oct 31st, 2022. CAISO interconnection queue is accessed at this link on Oct 31st, 2022. PJM interconnection queue is accessed at this link on Nov 1st, 2022. ISO-NE interconnection queue is accessed at this link on Nov 2nd, 2022. NYISO interconnection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

[27] 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).

compared to the rest of the US, and the number of potential entrants in 2014-2018 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.

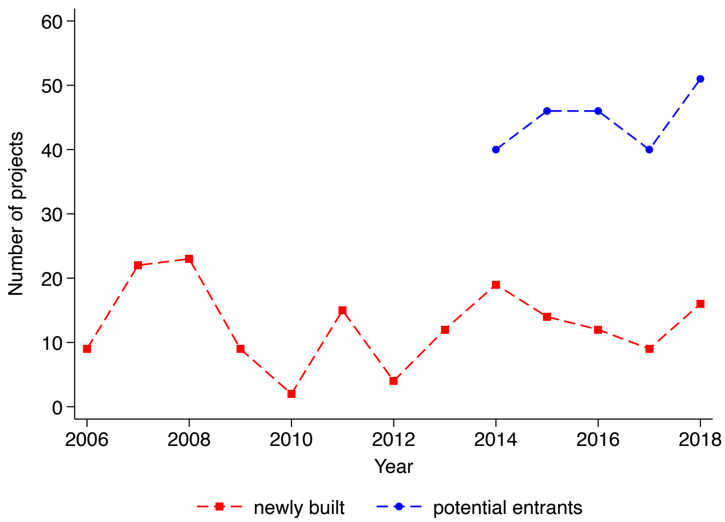
Figure B.3: Entry, Exit, and Potential Entrants in Queues

(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 B.4: 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.

C Estimation Details for Static Part

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

I parameterize the wind power generation Q^w_{ijt} as a linear function of the procured capacity k^w_{ij}. Though it is a simplification to assume a linear functional form, I find that the annual total output on average is linearly increasing with the nameplate capacity. I residualize both the annual total generation and the nameplate capacity on the entry cohort dummies and age dummies and then plot the linear fit and local polynomial approximation between these two variables. As shown in Appendix Figure A.9, 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 following model, 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 our baseline group, and β_a measures the differences in capacity factors between other age groups and the baseline group within an entry cohort.

$$\alpha_{it} = \sum_{a=2}^{10} \beta_a \times \mathbb{1}(\text{age}_{it} = a) + \sum_{c=2004}^{2018} \beta_c \times \mathbb{1}(\text{cohort}_i = c) + \epsilon_{it} \tag{23}$$

I plot the age effects β_a in Panel (a) of Appendix Figure A.9. The overall average capacity factor is relatively stable even for the 10 years after entry. The capacity peak arrives at age 5. However, the difference is only around 5% compared to the level of the baseline group. Moreover, I divide the sample into two groups: wind farms of age 1 and wind farms of age 2-5. I estimate the Equation (23) without age dummies and plot β_c for two age groups in Panel (b) of Appendix Figure A.9. 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 corroborated by the fact that the cohort dummies alone explain 84.3% of the variations of the average capacity factor at the cohort-age level, while the age dummies alone only explain 5.5%. Therefore, I treat the annualized capacity factor to be constant as the wind farm ages and calculate it at the age of one for each wind farm for the best data coverage such that

$$\alpha_i = \alpha_{it}, \quad \text{when age}_{it} = 1.$$

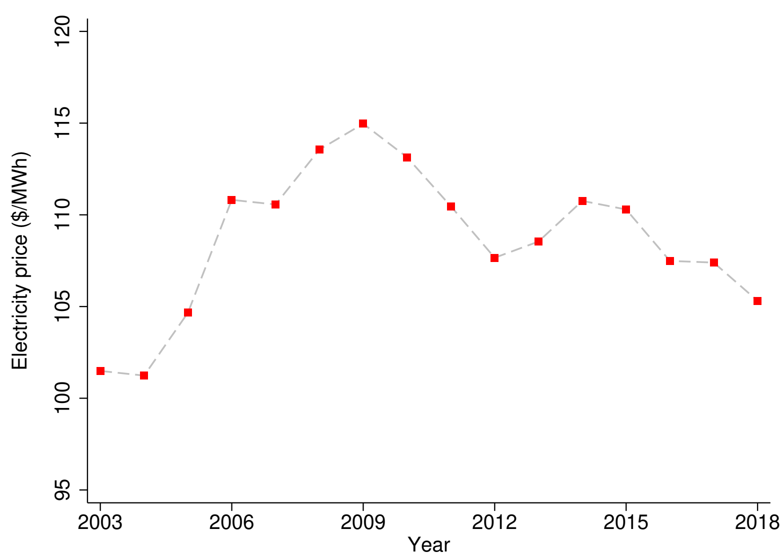
C.2 Estimation of Effective Market Price Θ_{jt}

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 at each state m to measure r_{mt}. As shown in Appendix Figure C.1, 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. In order to capture the time trend, I model the evolution of electricity prices using an AR(1) process.

$$\begin{aligned} r_{mt} = \gamma_1 r_{mt-1} \times \mathbb{1}(t \leqslant 2009) + \gamma_2 r_{mt-1} \times \mathbb{1}(t > 2009) + \gamma_3 t \times \mathbb{1}(t \leqslant 2009) \\ + \gamma_4 t \times \mathbb{1}(t > 2009) + \gamma_5 \mathbb{1}(t > 2009) + \xi_m + \epsilon_{mt} \end{aligned} \tag{24}$$

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

Figure C.1: 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 C.2. I take the coefficient estimates from column (1) and assume utilities have rational expectations with respect to the evolution of both the 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

$$\Theta_{jt} = \sum_{s=t+1}^{t+T} E_t \beta^{s-t} [r_s + \lambda_s (1 - z_s)].$$

Table C.1: 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 (24). Standard errors are clustered at the state level. *p < 0.10; **p<0.05; ***p<0.01.

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

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

I first describe the overall time trend of electricity generation by energy source, for all the utilities and utilities in the 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 C.2. Despite limited volumes, procured wind and other renewables (including solar, biomass, geothermal, and utility-owned wind) are both in-

Table C.2: 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 (24). Robust standard errors are reported. *p < 0.10; **p<0.05; ***p<0.01.

creasing. Meanwhile, total generations from nuclear, petroleum, hydroelectric, and other energy sources are mostly stable. Compared to the entire sample of utilities, those from my Power Purchase Agreement sample have a much larger coal power share compared to the national average and a smaller natural gas power share.

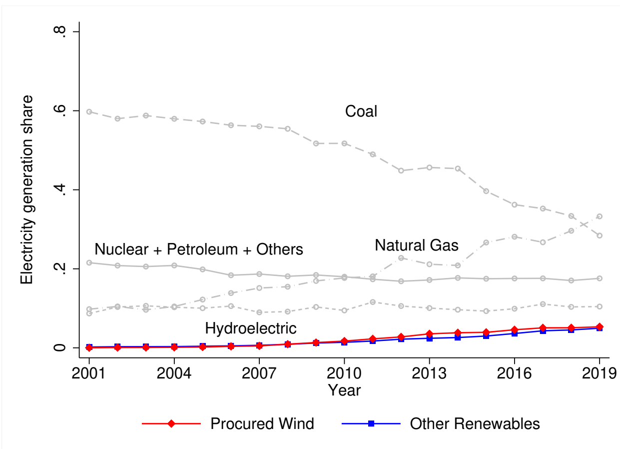
I next estimate the transition process of electricity output portfolios at the utility level. I categorize different energy sources into four types: coal, natural gas, other non-renewables (including nuclear, petroleum, and others), and other renewables (including solar, biomass, geothermal, and wind 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 corresponding 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 C.3.

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

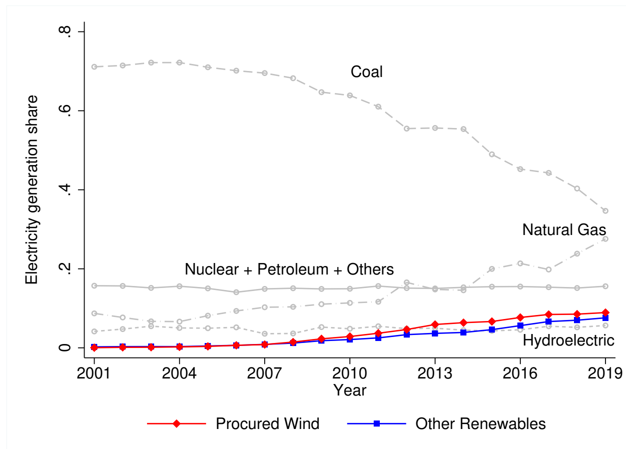
$$\Phi_{jt} = \sum_{s=t+1}^{t+T} E_t \beta^{s-t} [z_s (Q^f_{js} + Q^{or}_{js} + Q^o_{js}) - Q^{or}_{js}].$$

Figure C.2: 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.

Table C.3: 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		✓		✓

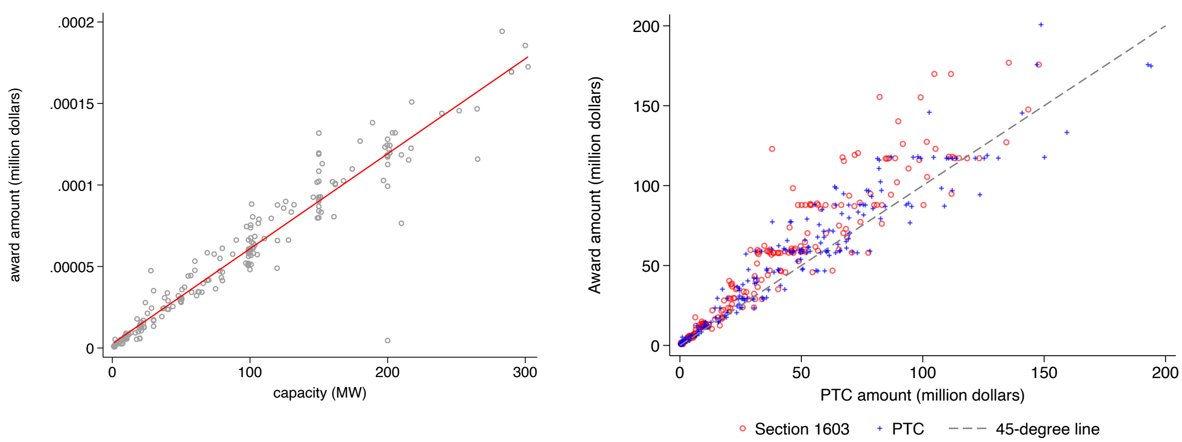
Notes: This table shows the transition dynamics of net electricity generation using coal, natural gas, other non-renewable sources (including nuclear, petroleum, and others), and other renewable sources (including solar, biomass, geothermal, and wind directly owned by utilities) at the state and yearly levels. The empirical model is similar to Equation (24). Standard errors are clustered at the state level. *p < 0.10; **p<0.05; ***p<0.01.

C.4 Subsidy Choice

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 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." [28] 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 the wind project names.[29] I constructed a dummy variable indicating whether the project opted into the Section 1603 Grant.

Figure C.3: Section 1603 Award and PTC

(a) Award and capacity **(b)** Subsidy choice



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, calculated following equations (25) and (26). 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.

The list of Section 1603 awardees also includes the amount of the Section 1603 award. As is evident from Panel (a) of Appendix Figure C.3, the amount of the award can be closely approximated as a linear function of the total capacity ($R^2 = 0.932$). Consequently, I model the total grant as a linear function of capacity $0.3 \times \eta k^w_{ij}$. I calibrate η by running a regression of the total grant on

[28] The detailed program guideline can be found here.
[29] The detailed list of awardees can be found here.

the capacity without an intercept, and the coefficient is around 0.586 million dollars per megawatt as shown in Appendix Table C.4. I further explore the heterogeneity of η across years in column (2), and I find that heterogeneity is negligible.

Another important question that is relevant to my 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 C.5. 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 the 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.

Table C.4: 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.

I calculate the total subsidies for each wind farm under both subsidy types. On the one hand, I impute the total subsidy under the Section 1603 Grant for each wind farm i that had chosen PTC, according to the calibrated η and the observed capacity as shown follows.

$$TS(k_i^w \mid \text{Section 1603 Grant}) = 30\% \times \eta \times k_i^w. \tag{25}$$

On the other hand, I calculate the 10-year discounted sum of total subsidy under 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.

$$TS(k_i^w \mid \text{PTC}) = \frac{\beta(1-\beta^{10})}{1-\beta} d_t \alpha_i k_i^w. \tag{26}$$

I summarize the results in Panel (b) of Appendix Figure C.3. Wind farms that chose the Section 1603 Grant on average received a larger amount of federal subsidies under the Section 1603 Grant compared with 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 Production Tax Credit 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), 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 relatively small, which indicates a large standard deviation of the unobserved i.i.d. shock and implies difficulty in rationalizing the subsidy choice in the model. Therefore, as discussed in Section 5.1, I assume there is a ς likelihood that the wind farm investors would take the default option regardless of the payoffs, while for a probability of $1-\varsigma$ the 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 C.5: 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		✓		✓

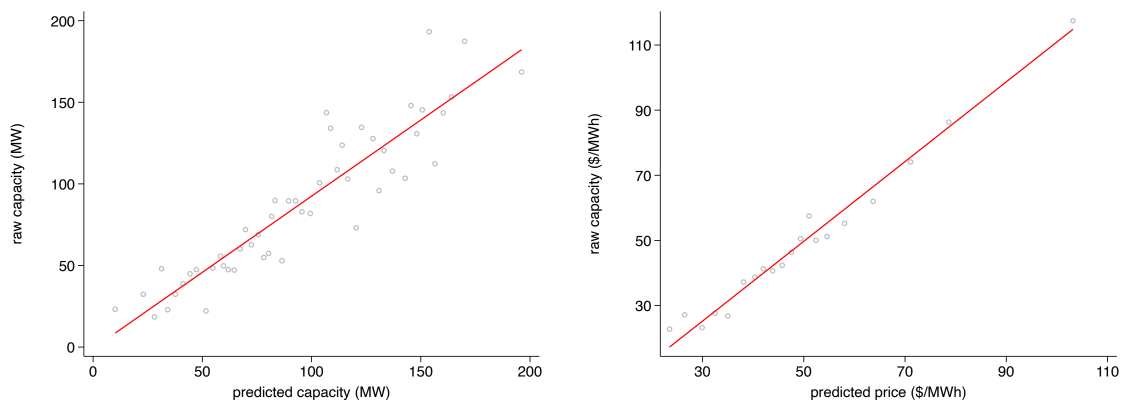
Notes: This table shows the estimation results of subsidy choices. The regression model is logit and the dependent variable is defined as a dummy, which takes the value 1 if a wind farm chooses to receive the Section 1603 Grant. I calculated the difference in total subsidies (in million dollars) between these two choices following equations (25) and (26). Standard errors are in parentheses. *p < 0.10; **p<0.05; ***p<0.01.

C.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 (7) and (9) are shown in Appendix Figure C.4. 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 C.6. 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.

Figure C.4: Model Fit for the Bilateral Bargaining Model

(a) Capacity **(b)** Price



Notes: This figure shows the static model fit for the capacity function (7) and the negotiated price equation (9).

Table C.6: 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.

C.6 Demand for Non-Utility Buyers

I test the robustness of the demand curve 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 C.7 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 -1.690 and -1.389, and the baseline estimate (-1.590) is within this range.

I estimate the wind price function for non-utility buyers as a linear projection on the utility renewable credit price, turbine productivity, turbine brand dummies, balance-authority dummies, as well as the contract-type dummies. The choice of variables is consistent with the model specification for the demand function (10). Moreover, wind farms that choose to sell capacity to non-utility buyers are also involved in the subsidy type choice. I replicate Appendix Table C.5 on the subsample that had chosen the non-utility buyers, and there is no strong empirical pattern as shown in Appendix Table C.8. 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.

Table C.7: 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 (10)). 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 C.8: 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 in 2008-2012. 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.

C.7 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 that's owned by the utility. I first summarize the matching patterns between utilities and wind farms in Appendix Figure C.5. 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 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 rest of the pairs 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.

Motivated by the empirical pattern, I restrict the buyer set to those utilities that are within 400 miles of the focal wind farm.[30] I next explore the determinants of buyer choice as shown in Appendix Table C.9. 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, defined as the difference between their current renewable generation and the state-level goal, have more unfulfilled demand and are more likely to be matched. Moreover, utilities that are in the same state as the focal wind farm, or that are closer geographically, are more likely to be chosen. Consequently, I include both a dummy indicating whether the utility and wind farm are from the same state, and the distance between the utility and wind farm in the matching cost function as shown in Equation (12).

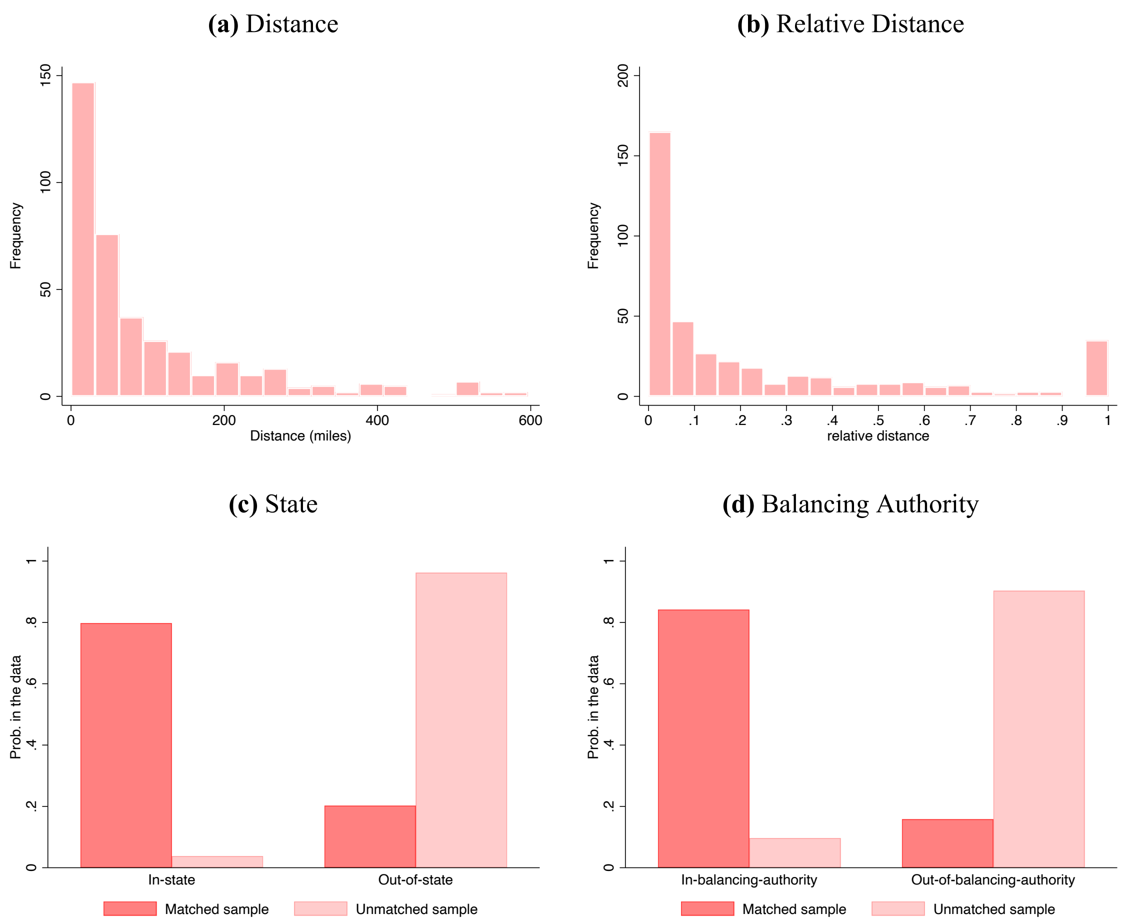
[30] Some matched utilities fall out of this range, and I add those back to the choice set for the focal wind farm.

Table C.9: 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.

Figure C.5: 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.

D Dynamic Model and Computational Details

D.1 An Alternative Dynamic Model

There is an alternative dynamic model for the evolving policy beliefs, which preserves the stationarity of the problem.[31] The notations are the same as in Section 4.2. 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. Therefore, the dynamic problem can be reformulated as follows.

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

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

I maintain the Assumption 1 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.

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

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

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

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 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.

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

D.2 Estimation Details of the Dynamic Model

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 (18); (6) the non-utility demand shifter as a projection of p_i^{nu} on $\boldsymbol{Z_i^{nu}}$ similar to Equation (10); (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 (11); (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 ten 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 (24) for the static estimation in Appendix Section C. 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.

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

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.

$$\begin{array}{l} W_{mt} = \gamma_1^W W_{mt-1} + \xi_m^W + \epsilon_{MT}^w \\ \qquad\qquad 0.908 \\ \qquad\qquad (0.021) \end{array}$$

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.

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

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

For the inclusive value that can be attributed to the changing renewable portfolio gaps for buyers $\text{IV}_{it}(\mathbf{\Phi}_{it})$, it's endogenously evolving in the model through NewCap_{mt}, but I assume its transition process is exogenously given. I approximate the transition process of $\text{IV}_{it}(\mathbf{\Phi}_{it})$ 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 (20) and the results are shown as follows.

$$\begin{array}{llll} \text{IV}_{it}(\mathbf{\Phi}_{it}) = & \rho_1^\Phi \text{IV}_{it-1}(\mathbf{\Phi}_{it-1}) + & \rho_2^\Phi \text{NewCap}_{mt-1} + & \xi_i^\Phi + \epsilon_{it}^\Phi \\ & 0.591 & -0.240 & \\ & (0.020) & (0.023) & \end{array}$$

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 follows. The estimation model is shown in Equation (21). I endogenously solve ρ_1^{nc} and ρ_0^{nc} when estimating the policy belief parameters and implementing counterfactual simulations. However, as I assume stationarity when estimating entry cost parameters, I directly estimate Equation (21) using data from 2015-2018. Estimation results using data from 2014-2018 are very similar.

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

D.3 Simulation 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 $\text{PotentialEntrants}_{mt}$. 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}.

4. Solve for new ρ_0^{nc} and ρ_1^{nc} and update the belief.

5. Repeat steps 2-4 until the values of ρ_0^{nc} and ρ_1^{nc} converge.

6. Solve the value functions $V^0(\boldsymbol{s}_{it})$ and $V^1(\boldsymbol{s}_{it}, b_t)$.

7. Draw entry cost ν_{it} 100 times and each potential entrant makes optimal entry timing decision according to Equation (17). Sum over the entry decision of each potential entrant and calculate the total number of entrants Entry_{mt}.

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

For policy windows between 2013-2018, 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.

E 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 the 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 between 10 a.m. and 11 a.m.). The MOER is estimated using the following equation, 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).[32]

[32]The detailed statistics can be found on the author's website.