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

Luming Chen*

January 2025

Click here for the latest version.

Abstract

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

Keywords: Wind energy, policy uncertainty, dynamic model, firm belief

*Chen: University of Michigan. Email: lumingch@umich.edu. I am deeply indebted to my committee members Panle Jia Barwick, Kenneth Hendricks, Jean-François Houde, and Shanjun Li for their invaluable support and guidance. I thank Hunt Allcott, Tom Eisenberg, Natalia Fabra, Todd Gerarden, Sarah Johnston, Karam Kang, Hyuk-soo Kwon, Ashley Langer, Jaepil Lee, Lorenzo Magnolfi, Martin O'Connell, Michael Ricks, Ivan Rudik, Christopher Sullivan, Ashley Swanson, Richard Sweeney, Jeff Thurk, Christopher Timmins, Jingyuan Wang, Tianli Xia, Nahim Bin Zahur, and participants at UW-Madison, Arizona, Cornell, Michigan, PKU, TSE, UGA, UNC, UT Dallas, UVA Batten, Vanderbilt, AERE, AMES, ASSA, BSE Summer Forum, Camp Resources, EARIE, ES-DSE, Harvard Climate Economics Pipeline Workshop, IIOC, NASMES, NBER Summer Institute, Northeast Workshop on Energy Policy and Environmental Economics, Stanford SITE, SEA, and SED for their helpful comments. All errors are my own.

1 Introduction

Government policies are frequently implemented to foster the growth of infant industries. However, given limited government resources and political cycles, many policies start off by committing to a short period with expiration dates, which might get renewed later. This common implementation pattern of "enactment – expiration – renewal" segments the policy into short time windows, induces policy uncertainty at the expiration time, and steers investors to near-term incentives who should otherwise plan for a longer horizon.

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

I first provide data evidence for this welfare trade-off. I compile a comprehensive data set of investment, production, and long-term contracts in the US wind energy market from 2003 to 2018 and document three key stylized facts. First, I find significant bunching of wind farm investment at the expiration dates of short policy windows, especially in 2012, mainly due to a lapse between expiration and renewal. Second, while the investment bunched at expiration dates in earlier years, the wind turbine technology is quickly

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

improving and becoming cheaper. This creates a large misalignment between the timings of investment and technological advancement. Third, utilities, an important group of buyers of wind capacity, have shrinking unfulfilled demand as they procure more wind energy over time and meet state-level regulations. Consequently, policy uncertainty expedited the entry of wind farms with older technology, which matched with utilities having larger unfulfilled demand. In contrast, more recent entrants with better technology sell wind capacity to utilities with smaller unfulfilled demand, indicating a loss in matching efficiency between utilities and wind farms due to policy uncertainty.

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

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

Conditional on entry, wind farms choose whom to supply, with two primary channels to sell wind capacity. The first channel is to sell capacity to utilities over a long-term Power Purchase Agreement, while the second channel involves selling the capacity to other non-

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

utility buyers such as corporations, or through merchant hedge contracts. I model demand from non-utility buyers using a linear demand curve, combining turbine technology, turbine price, contract types, and a set of demand shifters. Alternatively, if wind farms sell to utilities, they choose which utility to supply, weighing the profit from a potential negotiation against the pairwise matching cost that depends on the locations of the two parties. The wind farm and the matched utility engage in Nash bargaining to determine the capacity of wind farms and the procurement price.

The model estimation involves three steps. First, I estimate the bilateral bargaining model, in which the bargaining weight parameter is identified by the pass-through of utilities' willingness to pay as well as wind farms' turbine cost to the negotiated price. I find that utilities capture two thirds of the gains from trade when bargaining. Moreover, 22.4% of wind farms will earn zero or negative profits without the PTC. Even conditional on positive profits, the average profit without the PTC is 47.0% lower. This result highlights the potential cost of missing deadlines and losing the qualification of the PTC. It also explains the rushed entry when there is perception of a lower probability for the PTC renewal.

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

Last, I estimate the parameters in the dynamic entry problem. There is a key identification challenge on how to disentangle the policy belief parameters from the entry cost distribution parameters. My identification argument hinges on the temporal structure of the policy. I leverage the fact that the government announced in 2015 to cover the subsidy from 2015 to 2019. The government further imposed a safe harbor period: wind farms could qualify for the PTC if more than five percent of their total investment costs were incurred before policy expiration, with a two-year grace period to begin operation (extended to four years after 2016). I rely on this more recent policy window to identify parameters of entry cost distribution, assuming the perceived likelihood of policy renewal to be one. Moreover, the bunching of investment in earlier deadline years pins down the perceived likelihood of policy extension, conditional on entry costs, turbine technology, and utility demand. I estimate the mean realized entry cost to be approximately 35 million dollars, and the mean entry cost increases with the land price. More importantly, there was enormous uncertainty towards policy renewal especially for the 2011 cohort. The average perceived probability of policy renewal is about 30% due to the pessimism about the policy renewal as well as the delayed extension, which largely explains the investment spike that year.

With estimated model primitives, I implement three counterfactual analyses. In the first counterfactual exercise, I simulate the investment decision when the perceived likelihood of policy renewal is one such that there is no uncertainty in policy renewal. Removing renewal uncertainty reduces the number of new wind projects in 2011 by 52.7% and increases the number of new wind projects between 2012 and 2018 by 24.1% on average annually.[3] Those delayed wind farms would postpone their entry by 3.6 years. Overall, the total wind capacity increases by 6.3% once policy uncertainty is removed and the total output increases by 8.7%, as wind farms enter later when the turbine technology is more advanced. I follow Callaway, Fowlie, and McCormick (2018) to estimate the total benefits of wind energy, and calculate social surplus from wind energy as total benefits minus turbine costs and entry costs borne by wind farm investors, as well as the total subsidy. I find that the social surplus increases by 5.9 billion dollars and 28.9% after eliminating policy uncertainty. This result demonstrates that although the entry of wind farms is delayed, this negative effect is completely offset by a better timing alignment among investment, technology, and wind demand.

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

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

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

This paper contributes to the following strands of literature. First, this paper adds to the literature on the measurement and evaluation of policy uncertainty.[4] Policy uncertainty is pervasive and broadly studied in both macroeconomics and microeconomics. Examples include uncertainty in economic policy (Baker, Bloom, and Davis, 2016), trade policy (Handley and Limão, 2017), and environmental policy (Dorsey, 2019; Gowrisankaran, Langer, and Zhang, 2024).[5] Gowrisankaran, Langer, and Zhang (2024) 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 the existing literature, my paper focuses on the uncertainty in the subsidy renewal, which is a common but understudied cause of policy uncertainty. My paper exploits the temporal variation in the policy design to identify firm belief, and estimates a novel empirical model to quantify policy uncertainty from the bunching of investment timing. 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, Reynolds, and Samano, 2016; Petersen, Reguant, and Segura, 2024), values of wind energy (Cullen, 2013; Novan, 2015), upstream innovation (Covert and Sweeney, 2022; Gerarden, 2023), and renewable subsidies (De Groote and Verboven, 2019; Kay and Ricks, 2023; Mu, 2023; Bradt, 2024), among others.[6] My paper develops a new 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.

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

[5] Policy uncertainty in the Production Tax Credit in the US wind industry has also been recognized by earlier work such as Barradale (2010) and Johnston and Yang (2019).

[6] Other related topics include transmission congestion (Fell, Kaffine, and Novan, 2021), carbon taxes (Elliott, 2022), contract risks (Ryan, 2021; Fabra and Llobet, 2025), risk sharing (Hara, 2023), and interconnections (Gonzales, Ito, and Reguant, 2023; Johnston, Liu, and Yang, 2023).

Third, this paper directly speaks to the empirical literature about industrial policy implementation. Specific to the power and clean energy sector, there are recent papers about the timing of subsidies (Langer and Lemoine, 2022; Armitage, 2021), subsidy design (Barwick, Kwon, and Li, 2023), and subsidy types (Johnston, 2019; Aldy, Gerarden, and Sweeney, 2023). Different from the previous papers, my paper focuses on policy continuity and demonstrate the potential welfare loss from the "on-again/off-again" renewal pattern of subsidies, especially when the market environment is dynamic. Last, this paper also contributes to the literature on the dynamic model and firm beliefs (Doraszelski, Lewis, and Pakes, 2018; Jeon, 2022). I develop a tractable industrial dynamic model with evolving policy beliefs under policy uncertainty. Moreover, I recover investors' belief parameters with a novel strategy, utilizing both the temporal structure in the policy design and the bunching of investment timing.

2 Wind Industry and Government Policies in the US

2.1 Wind Industry in the US

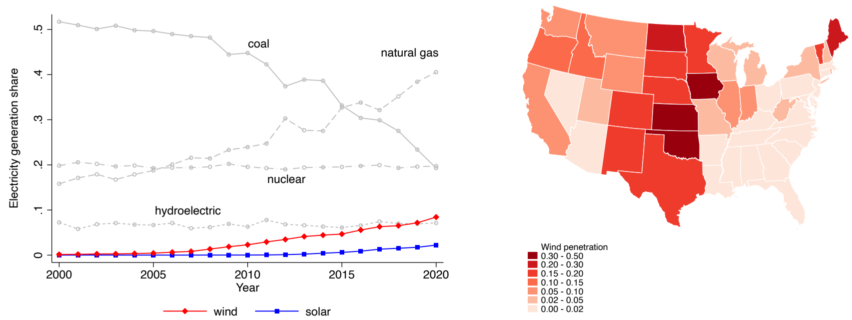
Wind energy has become America's largest renewable energy source. It provided 8.3% of total electricity generation and 42% of new power plant installation in 2020 (Wiser and Bolinger, 2021). As shown in Figure 1, wind energy grew from a very marginal share of total electricity generation in 2000 to the fourth most important energy source in the US in 2020. Geographically, wind energy is concentrated in Texas, the Midwest, and the Plains. Texas enjoyed the largest wind generation, taking up 28% of total wind power generation nationwide in 2019.

A wind farm requires enormous upfront investment. For example, investors had to spend more than 100 million dollars to construct an average-sized wind farm in 2019 just for turbine procurement, not to mention the additional costs for turbine transportation, wind farm construction, land lease, permits, and grid access.[7] It also takes a long time to plan and construct a wind farm as summarized in Appendix Figure A1. First, investors need to sign a land lease, acquire government permits, and apply for interconnection agreement after lengthy waiting in the interconnection queue. Next, investors negotiate with upstream turbine manufacturers for equipment procurement, negotiate with utilities or corporations

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

Figure 1: Shares and Penetration Rates of Wind Energy

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



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

to sell outputs, and seek financing from banks. Finally, with contracts secured, investors can start the construction process. A typical wind development process takes three to four years in total, and the construction process alone takes six to nine months. Once a wind farm starts operation, it will typically be in service for about 30 years. Large sunk costs, coupled a long time to build, highlight the importance of dynamic incentives in wind investment.

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

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

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

2.2 Government Policies

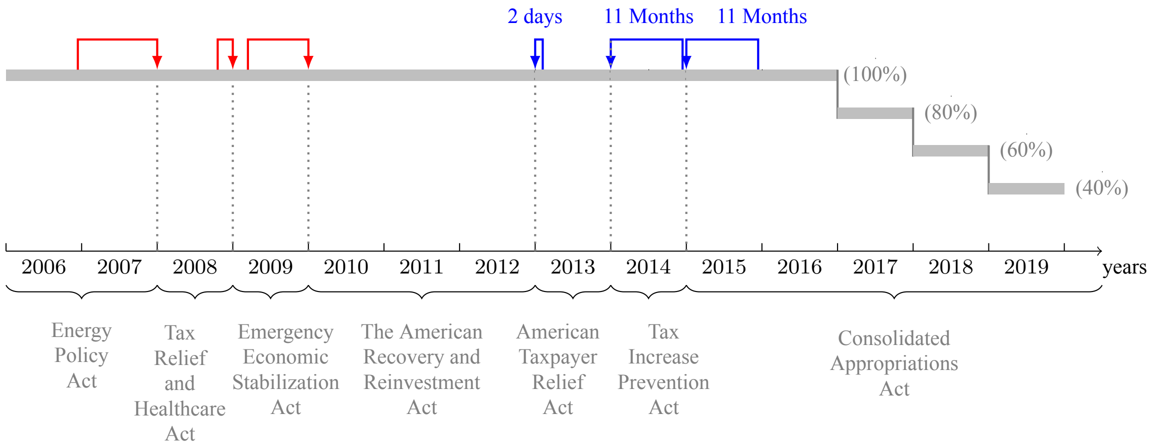
The wind industry in the US crucially relies on federal supports, as well as numerous state-level policies. The most important federal policy is the Production Tax Credit (PTC), which provided qualified wind farms with a 10-year inflation-adjusted tax credit for wind power generation and stood at $24/MWh in 2018. Although the PTC has been in effect since 1992, incentives provided by the PTC were segmented into smaller policy windows with set expiration dates. Conditions to qualify for the PTC are tied to these expiration dates: before 2012, a wind farm was required to start operation before the policy expiration, while after 2013, a wind farm is required to demonstrate that five percent or more of its total investment cost has been incurred before the policy expiration, with a two-year safe harbor to start operation (extended to four years after 2016).[9] As shown in Figure 2, the PTC is enforced by different acts across sample periods. For example, from January 2010 to December 2012, the PTC was enacted in the American Recovery and Reinvestment Act. Subsequently, the PTC was enacted in the American Taxpayer Relief Act (2013), the Tax Increase Prevention Act (2014), and the Consolidated Appropriations Act (after 2015).

Since 2005, there have been seven different acts implementing the PTC sequentially, which segments the policy into windows of one to five years. Before 2009, PTC renewals in the next act were announced several months before expiration. However, at the end of 2012, 2013, and 2014, PTC renewals were announced after the deadlines had passed. Although the lapse between policy expiration and renewal could be as short as two days at the beginning of 2013, it still disturbed market incentives and created policy discontinuities. With a lack of government commitment, wind investors were faced with policy uncertainty before expiration about whether the PTC would be extended or not. The delayed policy action from Congress and political debates about renewable subsidies exacerbated the uncertainty

[9] A more recent change in the safe harbor rule can be referenced at National Law Review.

in the market.[10] [11]

Figure 2: Timeline of the Production Tax Credit



Notes: This figure shows timing of the Production Tax Credit. Starting points of arrows indicate announcement time of policy renewal in the next act, while endpoints represent start time of the new act. There were 2-day, 11-month, and 11-month lapses between expiration of the previous act and announcement of the next act at the end of 2012, 2013, and 2014, respectively, though the policy was retroactive.

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

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

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

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

harbor period. Starting in 2015, incentives provided by the PTC were stabilized, despite the decreasing amount of the tax credit.

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

Apart from federal policies, there are also various state-level policies. One important state-level policy is the Renewable Portfolio Standards (RPS). RPS stipulates the minimum share of electricity generation using qualified renewable energy for utilities. If utilities fail to satisfy the requirement, they have to buy renewable credit from the credit market. Otherwise, they can also sell credits for profits. RPS provides important incentives to utilities to procure wind energy.[13] States could also have corporate/sales tax incentives, property tax incentives, feed-in tariffs, bond/loan programs, and other industry recruitment policies for wind farms. As shown in Appendix Figure A3, states with RPS are also more likely to have other different kinds of state-level incentives for wind energy.

3 Data and Stylized Facts

3.1 Data

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

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

[13] Abito, Flores-Golfin, van Benthem, Vasey, and Velichkov (2022) studies the consequences of cross-state trading restrictions and state-specific interim annual targets under RPS.

Both USWTDB and EIA-860 record the month when a wind farm starts to supply electricity, however, as illustrated in Appendix Figure A1, there is a lag between finalizing investment decision and starting operation, including a construction period of six to nine months. I follow Johnston and Yang (2019) to use the information from the Federal Aviation Administration (FAA) Obstruction Evaluation/Airport Airspace Analysis (OE/AAA) database. The FAA data reports the scheduled dates of starting construction. I match the FAA data with EIA-860 and measure the time of investment as the time when a wind farm starts construction.[14]

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

Moreover, I collect interconnection queue data from the ISO/RTO websites and obtain renewable credit price data from a financial service platform Marex. I also use retail electricity price data from EIA-861, agricultural land price data from the USDA National Agricultural Statistics Service, and the annual turbine price from Lawrence Berkeley National Laboratory. The the state-level policies including Renewable Portfolio Standards were hand-collected from Database of State Incentives for Renewables & Efficiency (DSIRE).[15]

3.2 Stylized Facts

3.2.1 The Timing of Investment

I first investigate the time trend of wind farm investment. Figure 3 presents the annual and monthly numbers of wind farms that are newly online. Significant bunching in wind farm investment occurred whenever the policy was scheduled to expire. A substantial number of wind farms started operation between 2008 and 2012, especially in 2012. Following the large investment spike in 2012, new investment dropped significantly in 2013. It was only after 2015 that the annual level of investment recovered, and the time trend stayed stable afterward. I plot the time trend of the total new wind capacity in Appendix Figure A4, and

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

[15] For more detailed data processing, please refer to the Online Supplemental Appendix.

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

Figure 3: Time Trend for Wind Projects Newly Online

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

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

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

There are alternative explanations for the bunching in the online timing. First, wind farms might shorten the construction process to meet the expiration dates of the PTC. However, as shown in Panel (a) of Appendix Figure A5, the average construction time remains stable at around nine months across different online years. There was suggestive evidence in Panel (b) 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. Second, the massive entry in 2012 might reflect the expedited waiting process in the interconnection queue. However, as shown in Panel (a) of Appendix Figure A6, the total years spent between entering into the interconnection queue and starting construction are also stable across years when wind farms start construction. Moreover, Panel (b) shows that many projects that started construction in 2011 entered the interconnection queue as early as before 2006. Therefore, the bunching in the online years is achieved mainly through the expedited investment decision, instead of merely reflecting the shortened construction time or the interconnection approval time.

3.2.2 Timing Misalignment

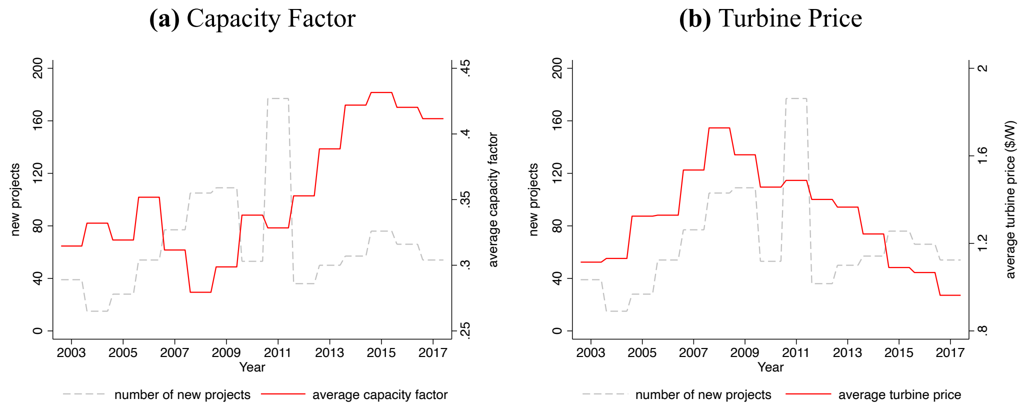
In contrast to the bunched investment timing, the technology of wind turbines is continuously improving over time. There are three key components of a typical horizontal-axis wind turbine: a tower, a nacelle, and three rotor blades. The potential of wind power generation crucially depends on the height of the tower and the length of the rotor blades. Taller towers enable the turbine to access better wind resources up in the air, while longer rotor blades lead to larger swept areas and capture more wind energy inputs. As shown in Appendix Figure A7, the hub heights and rotor diameters of new wind farms are getting larger, almost following linear trends after 2009. The average hub heights and rotor diameters of wind farms invested between 2014 and 2019 are 6.5% and 24.6% larger compared to those invested between 2008 and 2013.

Policy uncertainty induces a misalignment between the timing of investment and technological advancement. Panel (a) of Figure 4 presents the contrast between the bunched investment timing and improving turbine technology. I plot the number of new wind farms according to their construction start years. Moreover, I measure the technological efficiency using capacity factor at the age of one, defined as the ratio of average power output and maximum power capability.[16] Newly invested wind farms between 2008 and 2013 had

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

an average capacity factor of 0.32, while that number between 2014 and 2018 rose to 0.41, increasing by 27.2%. While the investment bunched in earlier years, the turbine technology is continuously and quickly improving, and thus there were many wind farms equipped with less productive turbines as a result of policy uncertainty.[17]

Figure 4: Investment, Turbine Technology, and Turbine Price



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

Moreover, the average turbine prices are also decreasing over time. As shown in Panel (b), since peaking at around 1,700 dollars per kilowatt between 2008 and 2009, the average turbine price has been declining and fallen below 1,000 dollars per kilowatt since 2015. Therefore, early investment between 2008 and 2011 largely foregoes later cheaper turbines.

Decreasing turbine procurement prices and increasing turbine production efficiency together indicate a substantial option value of delaying entering the market for better and cheaper technology. However, policy uncertainty expedited wind farm entry but partially missed the benefits of technological improvement and potentially led to inefficient investment timing.

[17] One concern is that the average productivity of a wind farm is also affected by the wind resources of its location, and later entrants might be faced with locations with worse wind resources. However, as shown in Appendix Figure A8, the average wind speed for each cohort is generally stable over time. The wind resources are less volatile for later entrants, as the standard deviation of daily average wind speed is lower.

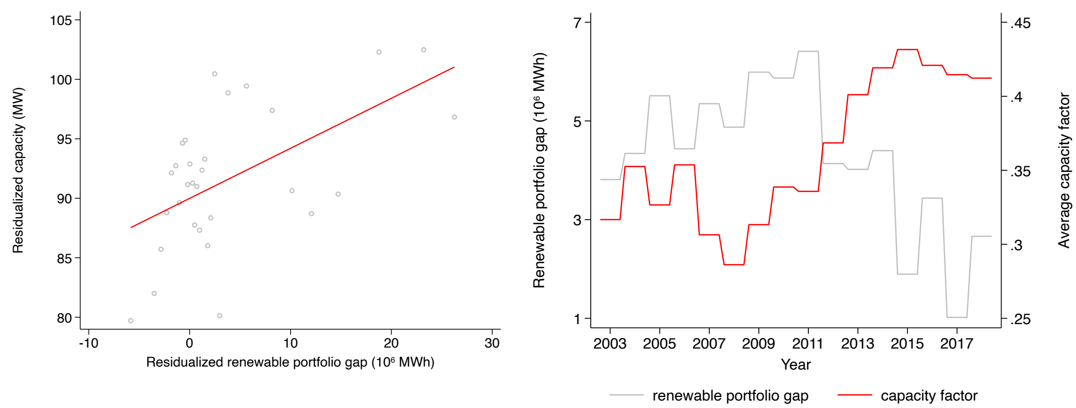
3.2.3 Matching Efficiency between Wind Farms and Utilities

Utilities are important buyers of wind power, as they procure wind capacity through long-term contracts from wind farms. One crucial incentive for them to procure wind capacity is to meet the state-level Renewable Portfolio Standards, which require utilities to have a certain share of total electricity generation from renewable energy. I construct a variable, renewable portfolio gap (RPG), which is defined as the difference between renewable energy generation and the amount stipulated by the Renewable Portfolio Standards. It measures the unfulfilled demand of each utility for renewable energy in order to meet the Renewable Portfolio Standards.[18]

Figure 5: 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 gap (RPG) of utilities. Renewable portfolio gap measures the unfulfilled demand of each utility for renewable energy in order to meet the Renewable Portfolio Standards. I control electricity prices, turbine productivity, and time trends. Panel (b) shows the time trend of the average RPG of utilities that procured wind capacity each year, as well as the mean turbine capacity factor for each new cohort of wind farms.

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

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

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

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

4 Model

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

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

4.1 Bilateral Bargaining with Utilities

Profit function for utilities By procuring wind capacity k_{ij} from wind farm i, utility j earn revenues from electricity generation and obtain renewable energy credits, and it pays procurement cost at the price p_{ij} in the power purchase agreement to the wind farm. I define state as the geographical market m and assume both electricity market and renewable credit market to be competitive. Therefore, utility j is faced with retail electricity price r_{mt}, renewable credit price λ_{mt}, and the Renewable Portfolio Standards requirement z_{mt}. If the share of electricity generation using renewable energy falls short of z_{mt}, utilities need to buy renewable credits to fulfill the requirement; otherwise, they could sell renewable credits to earn revenues. I suppress subscript m for the remainder of the section.

Suppose utility j begins a power purchase agreement with wind farm i in year t for a duration of T years.[19] The profit function for utility j from this contract is

$$\pi_t^U(p_{ij}, k_{ij}) = \sum_{s=t+1}^{t+T} \mathbb{E}_t \beta^{s-t} \{ \underbrace{(r_s - p_{ij})\alpha_i k_{ij}}_{\text{profit from elec. gen.}} + \underbrace{\lambda_s(\alpha_i k_{ij} - Q_{jt}^{gap}) - h_{js}}_{\text{profit from renewable credits}} \}.$$

Profit flow starts from year $t+1$ as it takes one year on average between finalizing investment decision and starting production for wind farms. I assume the production function for wind farm i as $\alpha_i k_{ij}$, where α_i is the annualized capacity factor.[20] Moreover, Q_{jt}^{gap} is calculated as the difference between renewable energy generation required by the state ($z_{mt}\times$ utility j's total output) and existing renewable energy generation, which measures the demand for extra renewable credits. I assume utilities have perfect foresight of the state-level Renewable Portfolio Standards z_t, and they hold rational expectations with respect to the transition dynamics of electricity price r_t and renewable credit price λ_t.

h_{jt} represents the hassle cost which captures frictions in the renewable credit market as well as dynamic credit banking incentives. This hassle cost is a quadratic function of Q_{jt}^{gap} such that $h_{jt} = \delta \times (Q_{jt}^{gap} - \alpha_i k_{ij}) \times Q_{jt}^{gap}$. The quadratic functional form fits the data pattern that utilities further away from the state-level goal tend to procure more wind capacity as illustrated in Panel (a) of Figure 5. Moreover, the hassle cost is attenuated by procuring wind capacity k_{ij}, which reduces h_{jt} more especially if the utility is further away from the state-level requirement.

Profit function for wind farms The profit that wind farm i receives equals the sum of

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

[20] The linear functional form fits data well as shown in Appendix Figure A9. Moreover, I find that capacity factors evolve systematically with the cohort, but display limited variation with respect to the age of wind farms. Therefore, I treat the annualized capacity factor to be constant as a wind farm ages and calculate it at the age of one for the best data coverage. More detailed discussion is in Appendix Section B.1.

total revenues from power purchase agreements and total subsidies from the government, minus turbine costs.

$$\pi_t^W(p_{ij}, k_{ij}) = \underbrace{\frac{\beta(1-\beta^T)}{1-\beta} p_{ij}\alpha_i k_{ij}}_{\text{revenue from PPA}} + \underbrace{\frac{\beta(1-\beta^{10})}{1-\beta} d_t \alpha_i k_{ij}}_{\text{PTC}} - \underbrace{c_{it} k_{ij}}_{\text{turbine cost}}.$$

Wind farm i receives tax credit for the first ten years of its production and the amount of tax credit per unit of wind energy generation is denoted by d_t.[21] Moreover, I parameterize the turbine cost per unit of capacity c_{it} such that $c_{it} = \boldsymbol{\gamma_1 X_{it}} + \frac{k_{ij}}{2\gamma_2}$. I allow c_{it} to depend on a set of shifters $\boldsymbol{X_{it}}$ including average turbine prices and turbine brand dummies. I also allow flexible convexity γ_2 of total turbine cost with respect to the capacity.

Bilateral bargaining Wind farm i and utility j participate in the bilateral bargaining process to negotiate over the procured capacity k_{ij} and the contracted price p_{ij} simultaneously. The optimization problem can be formulated as follows.

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

ρ denotes the bargaining weight of utilities. $\pi_t^U(p_{ij} = \infty)$ represents the profits that utilities would obtain with their current energy portfolios if the negotiation fails, and $\pi_t^W(p_{ij} = \infty)$ represents the payoffs that wind farms would earn from waiting for another year to enter. Under the assumption of Nash bargaining, the optimal capacity maximizes the gains from trade, while the optimal price divides the gains between two parties.

The optimal capacity follows equation (1). If wind energy is more valuable due to either higher electricity prices (r_s) or renewable credit prices (λ_s), or lower shares of existing renewable capacity compared with the state-level Renewable Portfolio Standards requirement (Q_{js}^{gap}), utilities are willing to pay more for additional wind capacity. The optimal wind capacity equalizes the marginal benefit from utilities' willingness to pay and the marginal cost of wind capacity net of the PTC. ξ_{ijt} denotes unobserved demand and cost shocks.

[21] My model also considers the availability of the Section 1603 Grant between 2009 and 2012 and assumes the subsidy choice is exogenous, since the profit variation under either subsidy type is an order of magnitude smaller than the variation across different wind farms. Moreover, I incorporate an 85% value discount for a one-dollar tax credit compared to a one-dollar cash grant following Johnston (2019), which accounts for transaction costs, asymmetric information problems, and market power issues.

$$\underbrace{(\sum_{s=t+1}^{t+T} \mathbb{E}_t \beta^{s-t}[r_s + \lambda_s(1-z_s) + \delta Q_{js}^{gap}])\,\alpha_i}_{\text{willingness to pay}} = \underbrace{\boldsymbol{\gamma_1 X_{it}} + \frac{k_{ij}^*}{\gamma_2}}_{\text{turbine cost}} - \underbrace{\frac{\beta(1-\beta^{10})}{1-\beta} d_t \alpha_i}_{\text{PTC}} + \xi_{ijt}. \tag{1}$$

Moreover, the optimal price follows equation (2). If the utility has a larger bargaining power ρ, the negotiated price will be low enough to only cover turbine costs net of government subsidies. If the wind farm has a bigger bargaining power, the negotiated price will be closer to the willingness to pay for utilities. Higher outside option $\pi_t^W(p_{ij} = \infty)$ gives wind farms better bargaining positions and increases the negotiated price.

$$\begin{aligned} \frac{\beta(1-\beta^T)}{1-\beta} p_{ij}^* = (1-\rho) \times & \underbrace{\sum_{s=t+1}^{t+T} \mathbb{E}_t \beta^{s-t}[r_s + \lambda_s(1-z_s) + \delta Q_{js}^{gap}]}_{\text{willingness to pay}} \\ & + \rho \times [\underbrace{\frac{c_{it}}{\alpha_i} - \frac{\beta(1-\beta^{10})}{1-\beta} d_t}_{\text{turbine cost net of PTC}} + \underbrace{\frac{\pi_t^W(p_{ij}=\infty)}{\alpha_i k_{ij}^*}}_{\text{bargaining leverage}}]. \end{aligned} \tag{2}$$

4.2 Demand of Non-Utility Buyers and Buyer Choice

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

$$k_i^{nu} = -\zeta_1 p_i^{nu} + \zeta_2 \alpha_i + \boldsymbol{\zeta_3 X_i} + \boldsymbol{\zeta_4 Z_i^{nu}} + \upsilon_i. \tag{3}$$

Similar to equation (1), $\boldsymbol{X_i}$ includes average turbine prices and turbine brand dummies. $\boldsymbol{Z_i^{nu}}$ denotes a set of demand shifters including dummies for balancing authorities and contract types (long-term contracts with corporate buyers or merchant hedge contracts). υ_i represents unobserved demand shifters. The profit function of wind farms that sell capacity to non-utility buyers is denoted as $\pi_t^{nu}(k_i^{nu}, p_i^{nu})$.

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

$$\max_{j \in \mathcal{J}_{it}} \underbrace{\pi_t^W(p_{ij}^*, k_{ij}^*)}_{\text{profits from bargaining}} - \underbrace{(\gamma_3 \mathbb{1}\{m_i \neq m_j\} + \gamma_4 Dist_{ij})}_{\text{matching cost}} + \sigma \epsilon_{ij}. \tag{4}$$

I use $\pi_t^W(p_{ij}^*, k_{ij}^*)$ to denote the profit for wind farm i with each potential buyer j via bilateral bargaining. I assume the matching cost depends on whether wind farm i and utility j are in the same state and how far away they are. 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. Consequently, the optimal probability of choosing j^* can be defined as follows.

$$P_{it}^{\text{buyer}}(j = j^*) = (1 - \mu_m) \times \frac{\exp[\frac{\pi_t^W(p_{ij*}^*, k_{ij*}^*) - \gamma_3 \mathbb{1}\{m_i \neq m_{j*}\} - \gamma_4 Dist_{ij*}}{\sigma}]}{\sum_{j \in \mathcal{J}_{it}} \exp[\frac{\pi_t^W(p_{ij}^*, k_{ij}^*) - \gamma_3 \mathbb{1}\{m_i \neq m_j\} - \gamma_4 Dist_{ij}}{\sigma}]}. \tag{5}$$

The *ex-ante* profit function π_{it} of wind farm i, if it enters the market in year t, would be defined as equation (6), where $\varkappa$ represents Euler's constant.

$$\begin{aligned} \pi_{it} = &\mu_m \times \pi_t^{nu}(k_i^{nu}, p_i^{nu}) + (1 - \mu_m) \times \sigma \times \\ &\{\log[\sum_{j \in \mathcal{J}_{it}} \exp(\frac{\pi_t^W(p_{ij}^*, k_{ij}^*) - \gamma_3 \mathbb{1}\{m_i \neq m_j\} - \gamma_4 Dist_{ij}}{\sigma})] + \varkappa\}. \end{aligned} \tag{6}$$

4.3 Dynamic Entry under Policy Uncertainty

4.3.1 Potential Entrants and Dynamic Entry Decision

Wind farm investors need to enter the interconnection queue, get approved by several studies, and sign interconnection agreements before they are eligible to enter the market.[22]

[22] 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

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 entry decisions.[23]

At the beginning of year t, potential entrant i incurs entry cost ψ_{it}, where $\psi_{it} = \kappa W_{it} + \nu_{it}$. W_{jt} denotes the observed entry cost shifter. ν_{it} is an i.i.d. entry cost shock, which follows an exponential distribution $F(\nu_{it}) = 1 - e^{-\frac{\nu_{it}}{\phi}}$ with a mean parameter ϕ. If potential entrant i decides to enter, I define the net profit of entry as $\Pi_{it} = \pi_{it} - \kappa W_{it}$.

Potential entrant i conditions on a vector of state variables $\boldsymbol{s}_{it}$ for the dynamic decision, including shifters for buyers' willingness to pay, turbine technology, turbine cost, subsidy level, and entry cost shifter W_{jt}. Another important state variable is the policy status ω_t, which is a dummy variable that equals one if the federal subsidy is present in year t, and zero if the federal subsidy is absent in year t. ω_t is always one ex post as the PTC was always extended, and it shifts all the contract terms as well as the profit of wind farms Π_{it}. I denote $V_t(\boldsymbol{s}_{it}, \omega_t, \nu_{it})$ as the value function of wind farm i in year t, defined as follows.

$$V_t(\boldsymbol{s}_{it}, \omega_t, \nu_{it}) = \max\{ \underbrace{\Pi(\boldsymbol{s}_{it}, \omega_t) - \nu_{it},}_{\text{net profit of entering today}} \underbrace{\beta \mathbb{E}_t[V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1}, \nu_{it+1}) | \boldsymbol{s}_{it}, \omega_t]}_{\text{option value of waiting}} \}. \tag{7}$$

If the net profit of entry in year t exceeds the option value of waiting, potential entrant i will choose to enter the market in year t. Otherwise, it will wait for one more year and face the same decision again next year. The option value of waiting depends on the distribution of unobserved entry cost shock $F(\nu_{it})$ and the transition dynamics of state variables $G(\boldsymbol{s}_{it+1} | \boldsymbol{s}_{it})$ such that

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

Moreover, the option value of waiting depends crucially on an *ex-ante* belief for the policy evolution, denoted by $b_t(\omega_{t+1} | \omega_t) \in [0, 1]$. I allow the policy to be extended only year by year, and $b_t(\omega_{t+1} | \omega_t)$ can vary by time to capture that wind farm investors form different policy beliefs depending on the actions taken by the government as well as other

stopping problem, like the one studied in this paper.

[23] 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 2.3 and 2.5 years respectively in 2010, according to the PJM website. Anecdotes suggest that a typical project completed in 2008 spent fewer than two years in the queue for interconnection approval compared to three years in 2015, according to the news from Utility Dive.

political and economic shocks.[24] The option value of waiting can be further expanded as follows, and $b_t(\omega_{t+1}|\omega_t)$ is the source of non-stationarity in this dynamic problem.

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

I denote the entry decision as a dummy variable E_{it} and the entry probability as $P_t^E(\boldsymbol{s}_{it}, \omega_t)$. Since the PTC shifts up firm values such that $V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1} = 1, \nu_{it+1}) > V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1} = 0, \nu_{it+1})$, 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 this year.

$$P_t^E(\boldsymbol{s}_{it}, \omega_t) = Pr(E_{it} = 1) = 1 - exp(-\frac{\Pi(\boldsymbol{s}_{it}, \omega_{it}) - \beta\mathbb{E}_t[V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1}, \nu_{it+1})|\boldsymbol{s}_{it}, \omega_t]}{\phi}). \tag{8}$$

4.3.2 Belief Structure

Since the dynamic problem extends over an infinite horizon, potential entrants need to form beliefs about the entire sequence of future policy status $\{b_t(\omega_{t+s+1}|\omega_{t+s})\}_{s\geqslant 0}^{\infty}$. Moreover, if policy belief is permitted to be fully flexible, including examples such that perceived future subsidies switching between on and off, infinite streams of policy beliefs could rationalize one single investment decision. Therefore, I impose two assumptions to discipline policy beliefs and make the problem feasible for estimation.

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

Assumption 1 indicates that the policy is perceived as terminated once paused. If the policy is absent in year t, wind farm investors will hold the belief that the policy is terminated forever. This assumption is consistent with the reality that the Section 1603 Grant was discontinued after 2012 and hasn't been rebooted ever since. Under this assumption, $\mathbb{E}_t[V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1}, \nu_{it+1})|\omega_t = 0] = V_{t+1}(\boldsymbol{s}_{it+1}, \omega_{t+1} = 0, \nu_{it+1})$. Consequently, the value function $V_t(\boldsymbol{s}_{it}, \omega_t = 0, \nu_{it})$ doesn't depend on time-varying 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 Bellman equation.

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

$$V_t(\boldsymbol{s}_{it}, \omega_t = 0, \nu_{it}) = V^0(\boldsymbol{s}_{it}, \nu_{it}) = \max\{\Pi^0(\boldsymbol{s}_{it}) - \nu_{it}, \beta\mathbb{E}[V^0(\boldsymbol{s}_{it+1}, \nu_{it+1})|\boldsymbol{s}_{it}]\}. \quad (9)$$

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

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

I denote $\Pi(\boldsymbol{s}_{it}, \omega_t = 1)$ as $\Pi^1(\boldsymbol{s}_{it})$ and $V_t(\boldsymbol{s}_{it}, \omega_t = 1, \nu_{it})$ as $V^1(\boldsymbol{s}_{it}, \nu_{it}; b_t)$. Under Assumption 2, $V^1(\boldsymbol{s}_{it}, \nu_{it}; b_t)$ solves the following Bellman equation (10), which nests $V^0(\boldsymbol{s}_{it}, \nu_{it})$ solved from Bellman equation (9).

$$\begin{aligned} V^1(\boldsymbol{s}_{it}, \nu_{it}; b_t) = \max\{\Pi^1(\boldsymbol{s}_{it}) - \nu_{it}, \beta\{\mathbb{E}_t[V^1(\boldsymbol{s}_{it+1}, \nu_{it+1}; b_t)|\boldsymbol{s}_{it}] \times b_t + \\ \mathbb{E}[V^0(\boldsymbol{s}_{it+1}, \nu_{it+1})|\boldsymbol{s}_{it}] \times (1 - b_t)\}\}. \end{aligned} \quad (10)$$

4.3.3 State Space, Transition, and Equilibrium

I include three sets of variables in the state space $\boldsymbol{s}_{it}$ to capture the rich interactions among government policies, turbine technology, and utility demand in determining the profit of entry as well as the option values of waiting. The first set of state variables are time-varying and exogenous, including the annual average productivity of wind turbines $\bar{\alpha}_t$, the average turbine prices $\text{TP}_t^{\text{Vestas}}$, the subsidy levels d_t, and the prevailing market price r_t and λ_t.[25] I assume potential entrants' beliefs about these state variable transitions as AR(1) models.

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

The second set of state variables are time-invariant and exogenous. I construct a predicted utility demand using time-invariant shifters in equation (1), and predicted matching cost shifters from equation (4). I project p_i^{nu} on $\boldsymbol{Z_i^{nu}}$ as in equation (3) to construct another time-invariant state variable for the demand of non-utility buyers.

The third set of state variables are time-varying and endogenous, which measure the changing renewable portfolio gaps of utilities in the buyer pool. As each wind farm has 18 buyers on average in its choice set, keeping track of the renewable portfolio gap for each individual utility is computationally challenging. Motivated by Gowrisankaran and Rysman (2012) and Hendel and Nevo (2013), I use inclusive values for wind farms that can be attributed to the changing renewable portfolio gaps for buyers, denoted by Φ_{it}.

$$\Phi_{it} = \pi_{it}(\{Q_{jt}^{gap}\}_{j\in\mathcal{J}_{it}}) - \pi_{it}(\{Q_{jt}^{gap} = 0\}_{j\in\mathcal{J}_{it}}).$$

The inclusive values Φ_{it} is the difference in the *ex-ante* profit functions from equation (6) with and without the realized renewable portfolio gap for each utility. The transition of Φ_{it} is endogenous in the model because the renewable portfolio gaps of utilities shrink after they procure additional new wind capacity. Therefore, more entries of wind farms today will reduce future values of Φ_{it}. I model the transition process of it as an AR(1) process with the amount of the one-year lagged new wind capacity online K_{mt} in the state m as an endogenous shifter.[26] 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 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 moments of the industry states.[27] This equilibrium concept is widely used in recent empirical papers (Barwick, Kalouptsidi, and Zahur, 2021; Jeon, 2022; Vreugdenhil, 2023). The entry decision satisfies equation (8) under the policy beliefs $b_t(\omega_{t+1}|\omega_t)$ and the transition dynamics of state variables $G(\boldsymbol{s}_{it+1}|\boldsymbol{s}_{it})$, while wind farms employ the equilibrium entry decisions to form expectations about Φ_{it} and K_{mt}.

[26] The one-year lag captures the gap between the entry of a wind farm and the start of its production.

[27] I assume that each wind farm is atomic and the impact of its action on the aggregate state variable is negligible due to a low level of market concentration.

4.4 Model Discussion

I close the section with brief discussions of the model assumptions. First, I only endogenize the capacity of procured wind energy but abstract away responses of other fuel sources. The wind penetration rate was low during my sample period in most states, and I assume the responses of other fuel sources as exogenous to keep the model tractable. However, my model still captures increasing gas power capacity, decreasing coal power capacity, and decreasing gas prices, mainly through utilities' willingness to pay for wind capacity which subsumes the evolution of electricity prices and renewable portfolio gaps.

Second, I assume that policy uncertainty does not directly influence bargaining terms. I find little evidence of discontinuity in the average capacity (Appendix Figure A4) or negotiated prices (Appendix Figure A10) for wind farms that began construction in 2011. This suggests that the impact of policy uncertainty on profits from investment is relatively minor compared to its effect on entry timing decisions.

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

Fourth, I assume that turbine technology and price are exogenous to investment in the U.S. wind industry. The cumulative wind power capacity in the U.S. represents 16% of the global wind power fleet, and there is no observed trend break in either turbine technological advancements or turbine prices following the surge of U.S. investments (Figure 4). I conduct a robustness check in Section 7.1 to quantify potential bias from ignoring the learning-by-doing effects, following Covert and Sweeney (2022).

5 Identification and Estimation

I discuss how data variations identify the model and how estimation procedures recover model parameters in this section. I start with key primitives including the turbine cost function, utilities' bargaining power parameter, the demand function for non-utility buyers, as well as the matching cost in utility choices. I then discuss how to identify and estimate model primitives in the dynamic part, including parameters governing the entry cost distribution and the policy beliefs.

5.1 Bilateral Bargaining with Utilities

There are two key equations from the bilateral bargaining problem: optimal capacity function (1) and optimal pricing function (2), which I jointly estimate via non-linear least squares.[28] In the optimal capacity function, I include the average turbine price of Vestas, $\text{TP}_t^{\text{Vestas}}$ and its interactions with turbine brand dummies (GE, Vestas, Siemens Gamesa, and others) in $\boldsymbol{X_{it}}$ as main shifters in the turbine cost function. I further control a set of demand shifters, including dummies of the states of the utility, utility types, as well as contract duration intervals.[29] Conditional on this rich set of controls, ξ_{ijt} mainly captures measurement errors in the willingness to pay and turbine costs, and is assumed exogenous to the observables. The cost convexity γ_2 is identified by the effect of the unit subsidy on the negotiated capacity. If total turbine cost is steeper in capacity, utilities and wind farms will negotiate a smaller wind farm size in response to a subsidy increase. Moreover, the hassle cost coefficient δ is identified from the relative importance of renewable portfolio gaps Q_{js}^{gap} to market prices.

In the optimal pricing function, I assume $\pi_t^W(p_{ij} = \infty)$ as the payoff that wind farms would have earned from waiting for another year to enter and selling capacity to a utility from the rest of the potential buyer pool. I find that conditional on all other observables in equation (2), the residual variation in negotiated prices is positively correlated with the average willingness to pay from nearby alternative utilities, which gives a better bargaining position for the wind farm (Panels (a) and (b) of Appendix Figure A10). Moreover, the average p_{ij}^* displays a large variation across cohorts (Panel (c)). Motivated by these data facts, I express $\pi_t^W(p_{ij} = \infty)$ as a flexible control function with quadratic bases of the average willingness to pay from nearby alternative utilities as well as year fixed effects.

The key parameter in the optimal pricing function (2) is the bargaining parameter ρ. The identification of ρ comes from the relative pass-through ratios of utility willingness to pay and net turbine cost per unit on the negotiated price. If the utility has a larger bargaining power ρ, the negotiated price tends to be low and co-moves closer to the net turbine cost, after flexibly controlling for bargaining leverages.

[28] A more detailed description of the estimation can be found in Appendix Section B.

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

5.2 Demand of Non-Utility Buyers and Buyer Choice

Demand for non-utility buyers I estimate the linear demand function for non-utility buyers (3) with instruments. As υ_i captures unobserved demand shifters, it's correlated with price p_i^{nu}, which introduces bias to price coefficient ζ_1. I use three sets of instruments to tackle the identification challenge. The first instrument is the renewable credit price in each state. As renewable credit is a product of the Renewable Portfolio Standards which targets utilities, its price is less likely to be correlated with demand shifters for non-utility buyers who constitute a smaller segment of the total demand. The second instrument is the average land price. As the locations of wind farms are exogenously given in the model, land prices are orthogonal to the demand shifters for non-utility buyers, but might be incorporated into the wind energy price for wind farm investors to break even. The third set of instruments are dummy variables indicating whether a state implemented property tax incentives, sales tax incentives, or other wind power recruitment policies. These policies are implemented by the state government to boost renewable energy. As non-utility buyers demand no more than 30% of total wind capacity, these supply-side policies are unlikely to be correlated with their unobserved demand shocks.

Buyer type choice and utility matching I back out matching cost coefficients γ_3 and γ_4, the scale parameter σ, and the mean parameters of the buyer type choice μ_m from estimating the buyer choice problem (5) via MLE. 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. The standard deviation of the error term σ is identified as the magnitude of the residual variation in the utility choice that cannot be explained by the profit gap between choosing the matched utility j^* and an alternative utility. The matching cost coefficients γ_3 and γ_4 are identified by the gradients of matching likelihood with respect to the matching cost shifters. The mean parameters of the buyer type choice μ_m are pinned down by the frequency of non-utility contracts observed across markets.

5.3 Dynamic Entry under Policy Uncertainty

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

Following the identification strategy, I take two steps to estimate the dynamic model. First, I focus on the time period between 2014 and 2018 when there was no policy uncertainty with $b_t = 1$ to estimate entry cost parameters by matching model-predicted entry rates with the data. I use the time period between 2013 and 2018 as a robustness check. The stationary dynamic programming problem can be formulated as follows.

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

I approximate the profit surface as a function of the quadratic basis of the state space $u_l(\boldsymbol{s}_{it})$ following Gowrisankaran, Langer, and Zhang (2024). I solve the dynamic programming problem via value function approximation $V(\boldsymbol{s}_{it}) = \sum_{l=1}^{L} \gamma_l^v u_l(\boldsymbol{s}_{it})$, similar to Sweeting (2013) and Barwick and Pathak (2015). Moreover, I include the annual state-level land price as the entry cost shifter W_{it} to capture the time trend in the entry cost. 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 number of entrants in state m and year t from the data.

$$\{\kappa, \phi\} = \text{argmin} \sum_{mt} (\hat{P}^E_{mt} - P^E_{mt})^2, \quad \text{where} \quad \hat{P}^E_{mt} = [\sum_{i=1}^{N_{mt}} \hat{P}^E_t(\boldsymbol{s}_{it}, \kappa, \phi)]/N_{mt}.$$

Second, I focus on policy windows with expiration to estimate policy belief parameters. I use the estimated entry cost parameters to solve the upper bound and lower bound of the continuation value. The value function when the PTC is *certain* to be terminated is the lower bound of continuation values, approximated as $V^0(\boldsymbol{s}_{it}, b_t) = \sum_{l=1}^{L} \gamma_l^{v_0}(b_t) u_l(\boldsymbol{s}_{it})$

following equation (9).[30] For the upper bound of continuation values, I approximate it as $V^1(\boldsymbol{s}_{it}, b_t) = \sum_{l=1}^{L} \gamma_l^{v_1}(b_t) u_l(\boldsymbol{s}_{it})$. For each given guess of policy belief parameter b_t, I solve $\{\gamma_l^{v_1}\}_{l=1}^{L}$ from equation (10). I allow the belief of the transition dynamics for endogenous state variable K_{mt} and Φ_{it} to adjust in the equilibrium according to the policy belief b_t. A lower b_t induces a substantial amount of new wind capacity online, thereby reducing utilities' future renewable portfolio gaps more sharply. 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.

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

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

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

6 Results

6.1 Bilateral Bargaining with Utilities

Panel A of Table 1 presents the estimation results of the bilateral bargaining model. 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. For cost parameters, the total capacity cost is convex in the procured capacity as γ_2 is estimated to be positive. Therefore, it would be disproportionately more costly to construct a larger wind farm, since the challenges to transport, install, operate, and maintain wind turbines escalate with taller towers and longer blades. Moreover, I find higher turbine prices significantly reduce the negotiated capacity.

I estimate the bargaining weight ρ of utilities to be approximately 0.67. Therefore, utilities capture two thirds of the gains from trade when bargaining. ρ is also significantly different from 1, suggesting that the change in the PTC will not be perfectly passed through

[30]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 the transition dynamics of K_{mt} and Φ_{it} solved in the equilibrium.

to the negotiated price. Moreover, assuming a take-it-or-leave-it model and imposing full rent extraction by utilities will underestimate the importance of the PTC to the industry. I leave out the controls for $\pi^W(p_{ij} = \infty)$ in the robustness check, which essentially assumes that the threat point is zero for all wind farms. The bargaining weight estimate decreases by about 10% and the rest of the estimation results are stable, which illustrates the robustness with respect to the assumptions about the threat points.

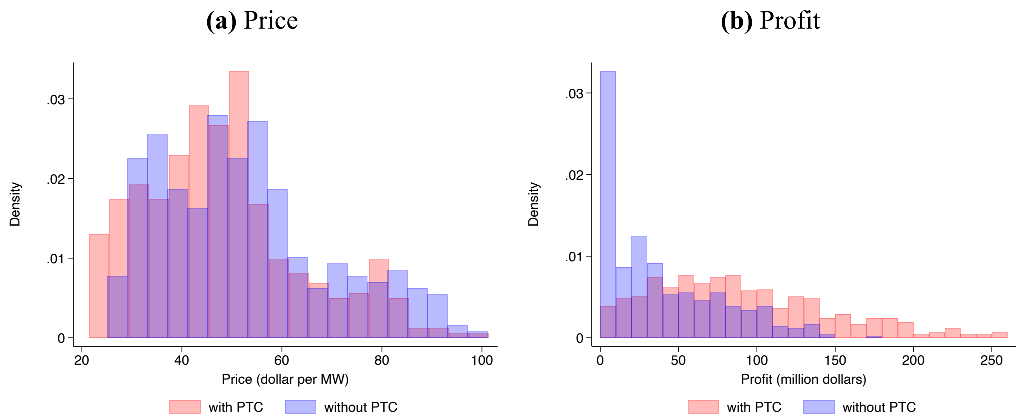
Table 1: Parameter Estimates for Bargaining, Non-utility Demand, and Buyer Choice

Coefficient	Parameter	Estimate	S.E.
Panel A: Parameters of Bilateral Bargaining			
Hassle Cost	δ	5.502	(2.557)
Turbine Price	γ_1	-0.071	(0.008)
Unit Capacity Cost Convexity	γ_2	0.116	(0.012)
Bargaining Weight	ρ	0.671	(0.023)
Panel B: Parameters of Demand for Non-Utility Buyers			
Price Coefficient, OLS	ζ_1	-0.770	(0.107)
Price Coefficient, IV	ζ_1	-0.923	(0.238)
Panel C: Parameters of Utility Matching and Buyer Type Choice			
Matching Cost, Different States	μ_1	0.087	(0.010)
Matching Cost, Distance	μ_2	0.186	(0.032)
Scale of ϵ_{ijt}	σ	0.042	(0.004)
Non-utility Probability	ζ_3	0.243	(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 bilateral bargaining model (equations (1) and (2)), the linear demand curve for non-utility buyers (equation (3)), and the utility matching and buyer type choice (equation (5)). Standard errors are in parentheses.

I calculate the discounted sum of profit π_{ij}^W for each wind farm and construct the counterfactual negotiated price $p_{ij}^*(d_t = 0)$ and the discounted sum of profit $\pi_{ij}^W(d_t = 0)$ in the absence of the subsidy, as shown in Figure 6. The discounted sum of profit π_{ij}^W is 89.6 million dollars on average, 124.5 million dollars at the 75$^{\text{th}}$ percentile, and 172.1 million dollars at the 90$^{\text{th}}$ percentile. Only 1.9% of wind farms earn a negative profit. When the PTC is removed, bilateral bargaining yields a lower negotiated capacity, but a higher negotiated

Figure 6: Estimated Profit and Price w/o PTC



Notes: This figure shows the distributions of profits and negotiated prices w/o the PTC being present.

price. The negotiated price without the PTC $p^*_{ij}(d_t = 0)$ is 9.0% higher compared with p^*_{ij}. I assume that a negative negotiated capacity will lead to the failure of the bargaining. About 22.4% of wind farms will fail or earn a negative profit (I normalize as zero profit) without the PTC, underscoring the critical role of this federal incentive in supporting the industry. Even for wind farms earning positive profits, $\pi^W_{ij}(d_t = 0)$ on average is 47.0% smaller than π^W_{ij}. This result highlights the significant cost of missing deadlines and losing PTC eligibility, explaining the rushed entry given low perceived likelihood of the PTC extension.

6.2 Demand of Non-Utility Buyers and Buyer Choice

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

I further estimate the utility matching model and the buyer type choice model as shown in Panel C of Table 1. The matching cost between a wind farm and a utility is much larger if they are located in different states. The matching cost also increases with their geographical distance. Being in different states is equivalent to increasing the distance by 470 miles on average in raising the matching cost. The estimated scale of choice-specific random shock is 0.042, which is equivalent to 54.7% of the average profit from bilateral bargaining. The mean likelihood of selling capacity to a non-utility buyer is approximately 24.3%. However, this probability is much larger in Texas, Illinois, and New York, as these markets are where the merchant hedge contracts concentrated geographically.

6.3 Dynamic Entry under Policy Uncertainty

I present the estimation results for dynamic parameters in Table 2. Column (1) uses the policy window between 2013 and 2018 to estimate entry cost parameters, and column (2) use the policy window between 2014 and 2018, which I use as the baseline result. The mean parameter ϕ of the entry cost distribution is estimated to be 290.9, and thus the mean entry cost conditional on entry is simulated to be approximately 35 million dollars. The total investment cost net of turbine cost averages 42 million reported by a group of wind farms between 2009 and 2012, aligning closely with my estimate.[31] Moreover, I include the average demeaned state-level annual agricultural land price as W_{it}. The coefficient μ is estimated to be positive. Therefore, higher land price exacerbates the entry cost for new wind farms, which accounts for 53%-70% of the total entry cost.

Next, I use the estimated cost parameters to solve the dynamic programming problem during the policy windows when there is policy uncertainty and estimate the policy belief parameters. The results are presented in Panel B. The average perceived probability of policy renewal is about 0.3 for the 2011 cohort due to the pessimism about the policy extension as well as the delayed policy renewal. The low estimate is also consistent with the investment spike observed in the raw data. The average perceived probability of policy renewal for the 2012 cohort recovers to 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,

[31] This is calculated from the Section 1603 Grant award record in which the award amount is 30% of the total investment cost.

Table 2: Parameter Estimates for Dynamic Model

Coefficient	Parameter	(1) Estimate	(1) S.E.	(2) Estmate	(2) S.E.
Panel A: Entry Cost Parameters					
Mean Entry Cost	ϕ	324.201	(73.383)	290.865	(53.120)
Land Price	κ	57.119	(26.900)	67.424	(28.676)
Panel B: Belief Parameters					
Policy Belief 2006	b_{2006}	0.540	(0.030)	0.583	(0.040)
Policy Belief 2007	b_{2007}	0.731	(0.151)	0.758	(0.033)
Policy Belief 2008	b_{2008}	0.995	(0.276)	0.999	(0.281)
Policy Belief 2009	b_{2009}	0.852	(0.114)	0.930	(0.230)
Policy Belief 2010	b_{2010}	0.920	(0.067)	0.925	(0.167)
Policy Belief 2011	b_{2011}	0.230	(0.140)	0.322	(0.121)
Policy Belief 2012	b_{2012}	0.768	(0.099)	0.843	(0.360)
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 50 times.

which might be due to more sparse investment as well as a larger extrapolation error when estimating belief parameters in this early stage using entry cost parameters estimated from a much later sample period.

I test the model fit by drawing the entry cost shocks randomly 100 times and simulating the entry decision of wind farms, as shown in Appendix Figure A11. The model fits the overall investment time trend and captures the investment spikes and dips well, although it over-predicts entry in the early years. This is likely due to the lumpy nature of the wind farm entry in specific markets while I impose a relatively restrictive entry cost structure in the model.

7 Counterfactual Analysis

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

7.1 Effects of Policy Uncertainty on Investment and Welfare

I simulate the baseline scenario with the policy uncertainty, using the estimated belief parameters from Table 2, and a counterfactual scenario when there is no renewal uncertainty, setting $b_t = 1$. This counterfactual is policy-relevant, as maintaining a long-term policy is the new direction in subsidy design (Bistline, Mehrotra, and Wolfram, 2023).[32] Even under rolling policy windows, announcing the policy renewal in advance of expiration can largely mitigate the policy uncertainty, as the estimation results reveal limited policy uncertainty in deadline years when there were no policy lapses.

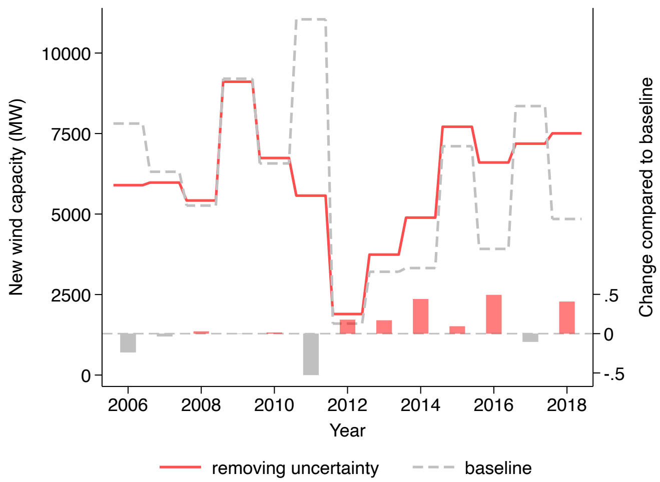
I simulate the model between 2006 and 2018 and wind farm investors endogenously adjust their expectations of the state variables. At the beginning of each year, a wind farm draws a random entry cost from the estimated common distribution and decides whether to enter in the current year. If a wind farm decides to wait, it returns to the pool of potential entrants and faces the same dynamic problem next year. The details of counterfactual simulations can be found in Appendix Section E.

Investment Trajectory The baseline and counterfactual investment trajectories are shown in Figure 7. Eliminating policy renewal uncertainty significantly delays the entry of wind farms. The number of new wind projects in 2011 is reduced by 52.7% and the total new

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

capacity decreases by 5500 MW. Wind projects shift their entry to later years and the number of new wind projects between 2012 and 2018 increases by 24.1% on average annually. Those delayed wind farms postpone their entry by 3.6 years and the average entry year of all new projects between 2011 and 2018 is delayed by 0.7 years.[33]

Figure 7: Investment Trajectory with and without Policy Uncertainty



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

Social Welfare I calculate the welfare impacts of policy uncertainty between 2008 and 2018. Policy uncertainty prompts earlier entry of wind farms and expedites the environmental benefits of reducing carbon emissions. However, policy uncertainty induces misalignment among investment timing, technological advancement, as well as demand evolution, which leads to efficiency loss. As shown in Panel A of Table 3, the numbers of total wind projects are approximately the same, suggesting that removing policy uncertainty mainly shifts the entry timing without changing the total number of entrants over an 11-year period. However, the total capacity increases by 6.3% when policy uncertainty is removed and the total output increases by 8.7%. As more investment occurs during the period with higher turbine productivity and lower turbine price, investment timing aligns better with techno-

[33] The investment trajectory without policy uncertainty still displays a dip in 2012 mainly due to project withdrawals from the queue in that year. It's empirically challenging to further incorporate queue withdrawal decision in the current structural model and the welfare conclusion is likely to be conservative.

logical advancement. Moreover, utilities with unfulfilled demand are able to procure more wind capacity under better technology. Consequently, the total capacity and output both increase despite similar numbers of wind projects, as illustrated in Appendix Figure A12.

I calculate the profit of wind farms on the market in Panel B of Table 3. Although there is more wind capacity, the total turbine cost increases only slightly by 1.5% because the new entry timing takes better advantage of the decreasing turbine price. The entry cost is also lower mainly due to a shift of the entry timing away from the peak average land price in 2011. Total profit, calculated as the difference between the static profit Π_{it} and the entry cost, increases by 7.1%.

I evaluate the benefits of wind energy following Callaway, Fowlie, and McCormick (2018). I assume wind farms operate for 20 years and calculate the discounted sum of benefits. Wind energy substitutes fossil fuels in generating electricity and lead to three sources of benefits on the grid: reducing carbon emissions, avoiding fossil input costs, and adding capacity values to the system. I estimate the average marginal operating emissions rate (MOER) of coal- or gas-fueled power plants in each state and year, which is defined as the marginal response in system-wide emissions with respect to total production change from generators due to more renewable energy.[34] I assume the social cost of carbon to be $80 per ton.[35] The statistics of the avoided operating costs and capacity values are from Callaway, Fowlie, and McCormick (2018).[36]

The cost and benefit analysis of policy uncertainty is presented in Panel (c) of Table 3. Total benefits increase by 5.8 billion dollars, a 5.2% increase compared to the baseline. Although the benefit could only be harvested later due to the delayed entry, a rise in total output dominates the cost of waiting. Among 5.8 billion dollars in total benefit gain, 60% are from the reduced carbon emission. If I take a more conservative estimate of the social cost of carbon as $50 per ton, the total benefits increase by 4.6 billion dollars compared to the baseline. The total subsidy increases by 5.2% as the PTC is based on total output.[37]

[34] Callaway, Fowlie, and McCormick (2018) find that regional average MOERs offer a useful means of "calibrating regional policy incentives to compensate for external emissions benefits."

[35] 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, Fowlie, and Sallee (2021) use both $50 per ton and $100 per ton.

[36] More details can be found in the Online Supplemental Appendix.

[37] 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.

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

Table 3: Outputs, Benefits and Costs with and without Policy Uncertainty

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

Notes: This table shows the outputs, benefits, and costs in the wind industry between 2008 and 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.

A potential concern regarding the welfare effect is the assumption that turbine technology is exogenous as discussed in Section 4.4. However, removing policy renewal uncertainty delays the average entry year of new projects from 2011 to 2018 by only 0.7 years. Combined with the fact that the turbine market is global and the U.S. held a 16% share of cumulative capacity in 2019, the impact of the learning-by-doing channel is likely secondary in the welfare calculation. A back-of-the-envelope calculation using the *upper-bound* estimate of the learning parameter from Covert and Sweeney (2022) indicates that, even accounting for slower technology improvement, the social surplus effect would decrease by less than 10%, leaving all the qualitative results unchanged.

Effect Decomposition The total benefit from removing policy uncertainty increases by 5.8 billion dollars as well as 5.2% compared to the baseline. There are three channels shaping this outcome: the delayed environmental benefits reduces the total benefit, which is counteracted by the improvement of timing alignment between investment and technology, as well as the matching efficiency gain between utilities and wind farms. The decomposition results are shown in Appendix Figure A13. Removing policy uncertainty delays the entry of wind farms as well as the total benefits of wind energy. However, the negative effect can be completely offset by a better timing alignment between investment and technology. Moreover, the matching efficiency gain between utilities and wind farms contributes roughly 30% compared to the welfare effect from timing alignment.

Effect Heterogeneity I explore the heterogeneity in the welfare consequences across states and find some suggestive evidence that the social surplus increases more in states with larger wind demand or more generous state-level supports. As shown in Appendix Figure A14, the improvement in social surplus from removing policy uncertainty is more pronounced in states with greater unfulfilled demand for utilities (Q_{jt}^{gap}) or demand shifters ($\boldsymbol{\beta_4 Z_{jt}^U}$). Moreover, the change in the social surplus from removing policy uncertainty is also larger in states with stricter Renewable Portfolio Standards or more generous state-level subsidies. One interpretation is that state subsidies are complements to federal tax incentives. Wind energy will benefit more from stable federal subsidies in those states that also provide state subsidies, as state policies make it easier for wind farms to expedite entry and thus they are more responsive to federal policy uncertainty.

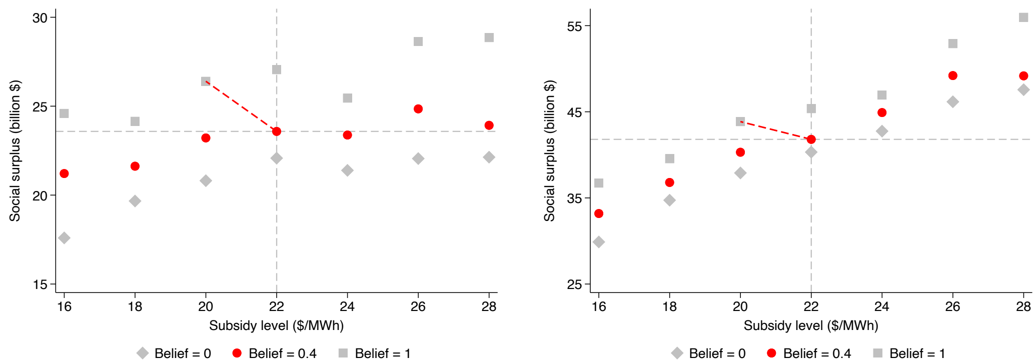
7.2 Effects of Policy Uncertainty under Various Subsidy Levels

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

Overall, the social surplus of wind energy increases with the level of subsidy but de-

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

(a) Social Surplus **(b)** Social Surplus + Total Subsidy



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.

creases with the extent of policy uncertainty in 2011. In the baseline scenario, with a subsidy level of \$22/MWh and a 2011 policy belief parameter of 0.4, the social surplus is lower than what could be achieved with a subsidy level of \$18/MWh under full policy certainty in 2011. Without accounting for the subsidy itself, the social surplus in the baseline scenario would still be lower than what could be achieved with a subsidy level of \$20/MWh under full policy certainty in 2011. Therefore, the subsidy level could be reduced by at least 9% without reducing social welfare if policy uncertainty were minimized.

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

7.3 Effects of Early Resolution of Policy Uncertainty

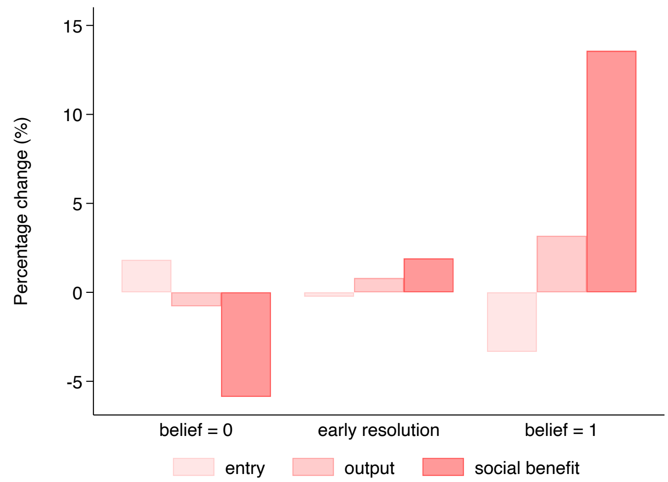
The third counterfactual exercise is to quantify the welfare effects when policy uncertainty is resolved early. I focus on the policy uncertainty in 2011 and simulate the investment decision under two scenarios. In the first scenario, policy uncertainty was resolved at the beginning of 2011 with the government drawing a random outcome from a binary distribution (mean of 0.4) and announcing the policy extension status to investors. This is the early resolution of policy uncertainty and wind farm investors would know the future policy status promised by the government before they make the entry decision. In the second scenario, policy uncertainty was resolved after the wind farm investors made the investment decision and the mean probability of policy renewal is 0.4, mirroring the baseline scenario. Both two scenarios have the same mean likelihood of policy extension, and the only difference is the timing of policy uncertainty resolution. This exercise is in the same spirit as in Gowrisankaran, Langer, and Zhang (2024) and also similar to the mean-risk decomposition exercise in the trade policy uncertainty literature (Handley and Limão, 2017).

The results are shown in Figure 9. I plot the percentage change in the number of new projects, total outputs, and social surplus compared to the baseline scenario. I find that when the policy uncertainty is resolved early, the number of new wind projects will be smaller. This is consistent with the intuition that early resolution of the policy uncertainty will reduce the rushed entry of wind farms and alleviate the negative impact of policy uncertainty.[38] Overall, the welfare effect of policy uncertainty under early resolution is positive compared with the baseline scenario, and the social surplus of wind energy increases by 1.9%.

Early resolution of policy uncertainty captures 14.0% of the welfare gain under full elimination of policy uncertainty. Despite that the PTC is always renewed ex post, the *ex-ante* uncertainty faced by wind farm investors results in both a lower expected value of subsidy and a larger variance of realized policy status. Keeping the expected value of subsidy the same but reducing the variance of realized policy status can recover 14% of welfare loss, while the rest 86% of welfare loss is due to a lower expected value of subsidy from *ex-ante* uncertainty. Although the subsidy was in effect on the market at all times, *ex-ante* policy uncertainty undermined the role of the subsidy by shifting the expectations of investors and led to welfare loss.

[38] 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.

Figure 9: Welfare Effects of Early Resolution of Policy Uncertainty



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

8 Conclusion

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

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

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

References

Jose Miguel Abito, Felipe Flores-Golfin, Arthur A. van Benthem, Gabrielle Vasey, and Kamen Velichkov. Designing more cost-effective trading markets for renewable energy. 2022.

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

Sarah Armitage. Technology transitions and timing of environmental policy: Evidence from efficient lighting. 2021.

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

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

Jay Bartlett. Reducing risk in merchant wind and solar projects through financial hedges. 2019.

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

Panle Jia Barwick, Myrto Kalouptsidi, and Nahim Bin Zahur. Industrial policy implementation: Empirical evidence from china's shipbuilding industry. 2021.

Panle Jia Barwick, Hyuksoo Kwon, and Shanjun Li. Attribute-based subsidies and market power: An application to electric vehicles. 2023.

John ET Bistline, Neil R Mehrotra, and Catherine Wolfram. Economic implications of the climate provisions of the inflation reduction act. *Brookings Papers on Economic Activity*, 2023(1):77–182, 2023.

Severin Borenstein, Meredith Fowlie, and James Sallee. Designing electricity rates for an equitable energy transition. 2021.

Jacob Bradt. A policy by any other name: Unconventional industrial policy in the us residential solar industry. 2024.

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

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

Thomas Covert and Richard Sweeney. Winds of change: Estimating learning by doing without cost or input data. 2022.

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

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

Avinash K Dixit and Robert S Pindyck. *Investment under uncertainty*. Princeton university press, 1994.

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

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

Jonathan T Elliott. Investment, emissions, and reliability in electricity markets. 2022.

Natalia Fabra and Gerard Llobet. The costs of counterparty risk in long-term contracts. 2025.

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

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

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

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

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

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

Gautam Gowrisankaran, Ashley Langer, and Wendan Zhang. Quantifying environmental policy uncertainty: The case of air toxics standards. 2024.

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

Konan Hara. Encouraging renewable investment: Risk sharing using auctions. 2023.

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

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

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

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

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

Sarah Johnston and Chenyu Yang. Policy uncertainty and investment in wind energy. 2019.

Sarah Johnston, Yifei Liu, and Chenyu Yang. An empirical analysis of the us generator interconnection policy. 2023.

Owen Kay and Michael Ricks. Time-limited subsidies: Optimal taxation with implications for renewable energy subsidies. 2023.

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

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

Tianshi Mu. The dynamic effects of renewable subsidies in the green energy transition. 2023.

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

Claire Petersen, Mar Reguant, and Lola Segura. Measuring the impact of wind power and intermittency. *Energy Economics*, 129:107200, 2024.

Nicholas Ryan. Holding up green energy: Counterparty risk in the indian solar power market. 2021.

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

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

Ryan Wiser and Mark Bolinger. 2011 Wind Technologies Market Report. 2012.

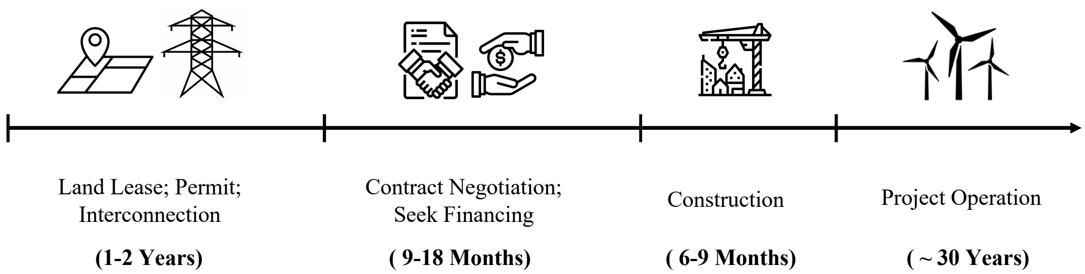
Ryan Wiser and Mark Bolinger. 2020 Wind Technologies Market Report. 2021.

Nahim Bin Zahur. Long-term contracts and efficiency in the liquefied natural gas industry. 2022.

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

A Additional Figures

Figure A1: Timeline of Building a Wind Farm

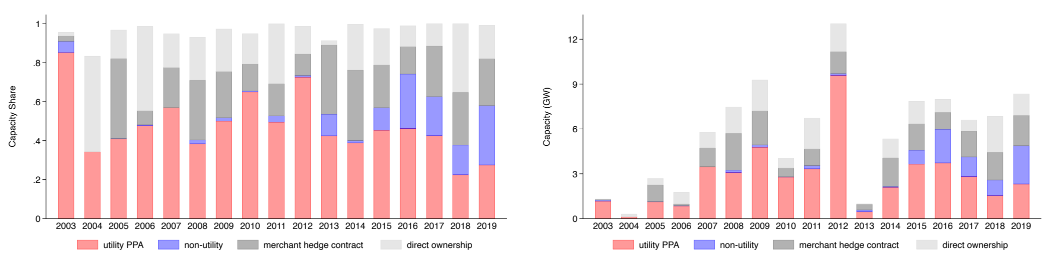


Notes: The main source of the time statistics is the Wind Powers America Annual Report 2019 by AWEA.

Figure A2: Capacity by Offtake Types

(a) Capacity Share

(b) Capacity Volume

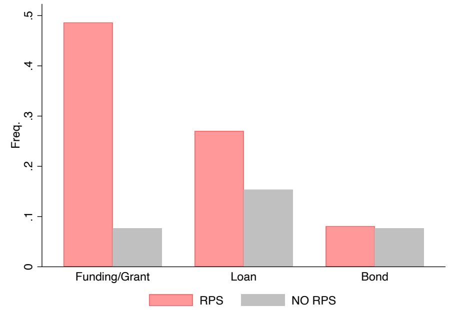


Notes: This figure shows the capacity distribution by offtake types across years. There are four offtake types: utility PPA, non-utility offtaker, merchant hedge contracts, and direct ownership. Panel (a) describes the share of capacity, while Panel (b) shows the volumes.

Figure A3: State-level Policies

(a) Tax Policies

(b) Financing Policies

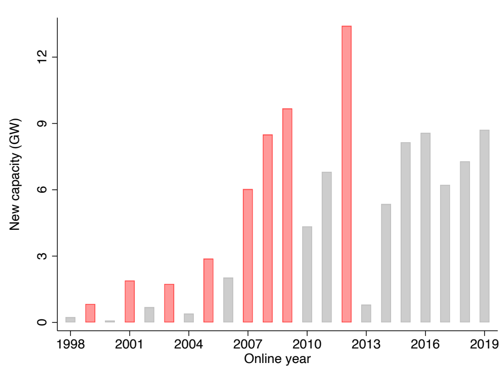


(c) Other Policies

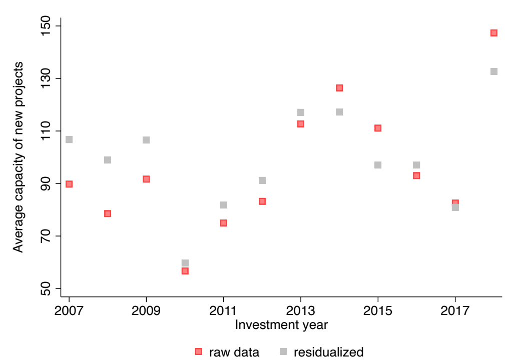
Notes: This figure shows the frequencies of different types of state policies for states with or without the RPS. State policies, including the RPS, are hand-collected by the author from DSIRE (https://www.dsireusa.org).

Figure A4: Time Trend for Investment: Capacity

(a) Total Capacity



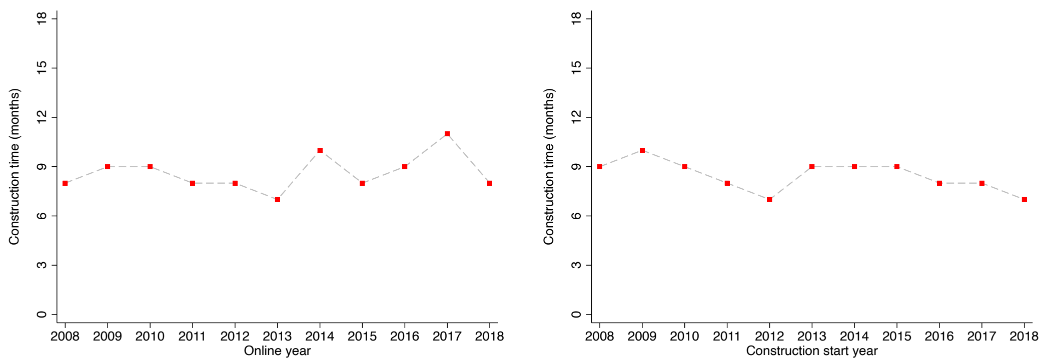
(b) Average Capacity



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

Figure A5: Construction Time

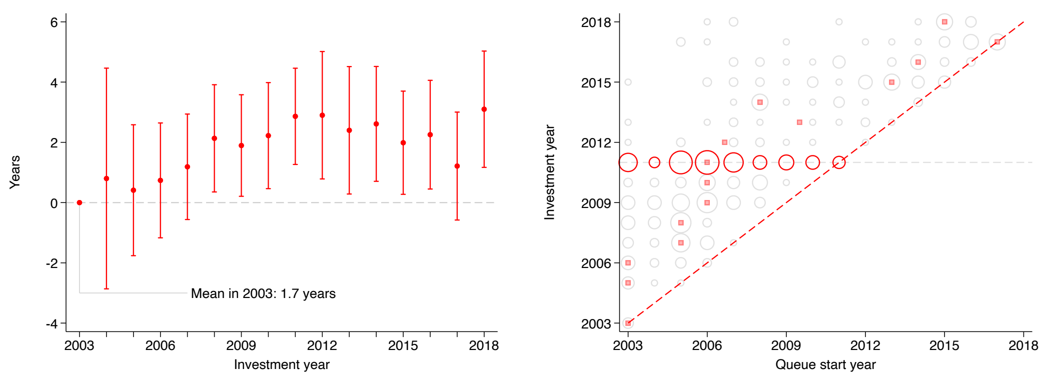
(a) by Online Years **(b)** by Construction Start Years



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

Figure A6: Interconnection Queues

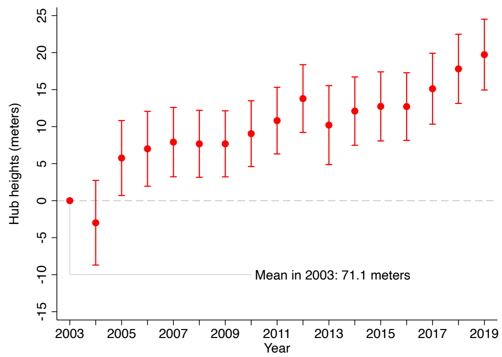
(a) Average Time **(b)** Distribution of Queue Start Years



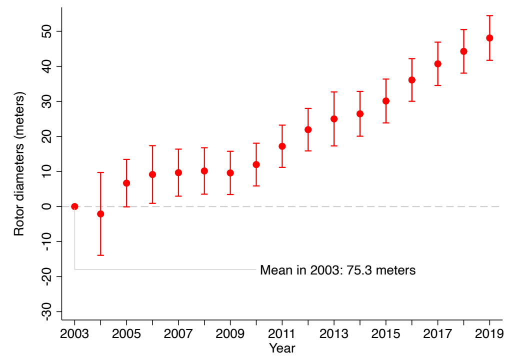
Notes: This figure shows the descriptive evidence for the interconnection queues. Panel (a) plots the average time spent between entering the interconnection queues and starting wind farm construction. Panel (b) plots the distribution of years to start construction and years to enter the queues, where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

Figure A7: Time Trend of Wind Turbine Technology

(a) Hub Heights



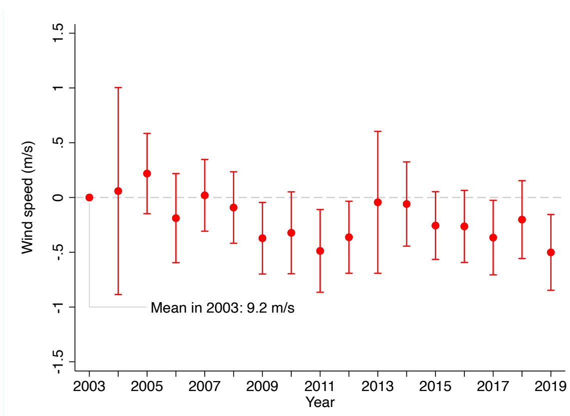
(b) Rotor Diameters



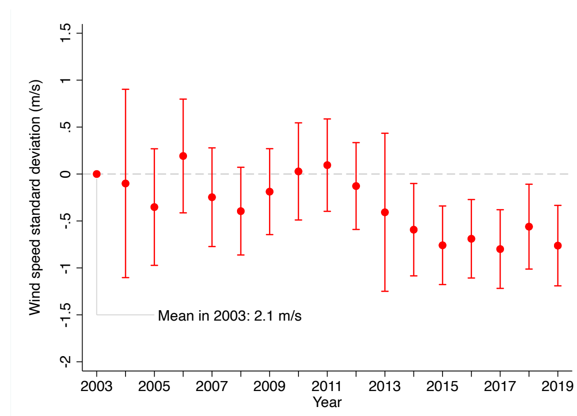
Notes: This figure shows the annual time trends of turbine technologies for new wind projects. I construct the annual time trends of hub heights and rotor diameters from the U.S. Wind Turbine Database (USWTDB) published by USGS.

Figure A8: Time Trend of Wind Speeds

(a) Mean



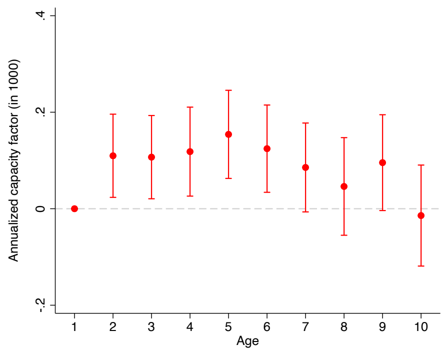
(b) Standard Deviation within Locations



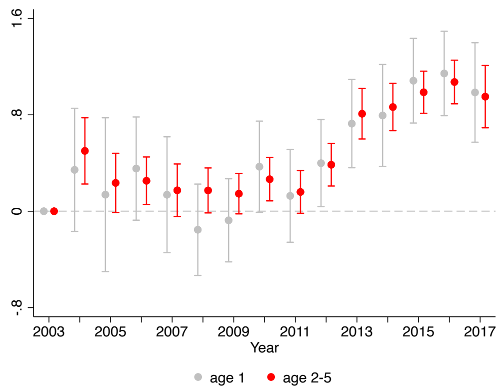
Notes: This figure shows the annual time trends of wind speed at locations of new wind projects. The wind speed is measured at 80 meters at sites nearest to the wind project location based on the Wind Toolkit Data from National Renewable Energy Laboratory (NREL). The mean and standard deviation for each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

Figure A9: Description of Annualized Capacity Factor

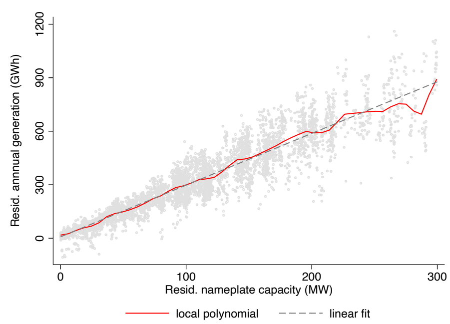
(a) Capacity Factor and Age



(b) Capacity Factor, Age, and Cohort



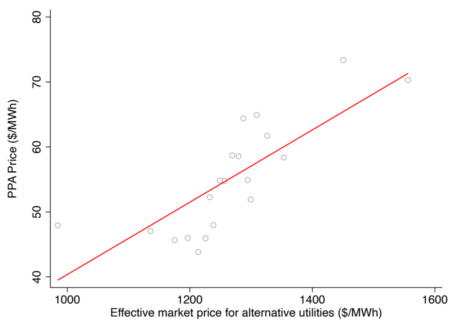
(c) Annual Output and Nameplate Capacity



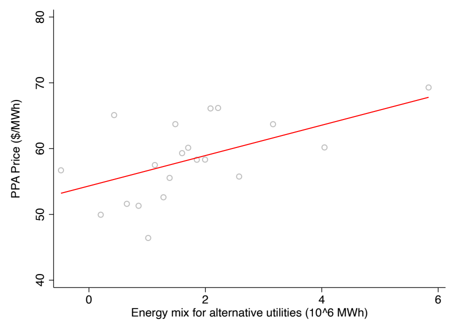
Notes: This figure presents the descriptive data patterns of the annualized capacity factor of wind farms. Panels (a) and (b) explore the relationship among the capacity factors, ages, and cohorts of wind farms. I rescale the annualized capacity factor and divide it by 1000. The average annualized capacity factor is 2.82×10^3 at the wind farm and year level. Panel (a) plots the coefficient estimates of β_a in equation (11), controlling for the entry cohort dummies. Panel (b) plots the coefficient estimates of β_c in equation (11), 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 solid line is the local polynomial approximation, while the gray dashed line is the linear fit between these two variables.

Figure A10: PPA Price and WTP of Alternative Utilities

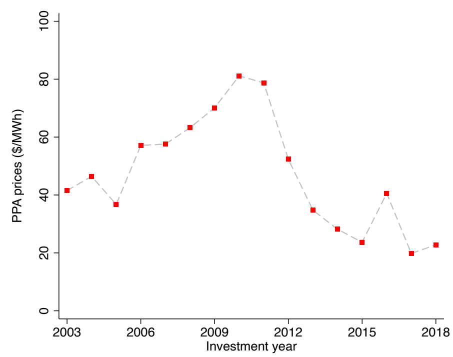
(a) Effective Price



(b) Renewable Portfolio Gaps



(c) Time Trend of PPA Prices

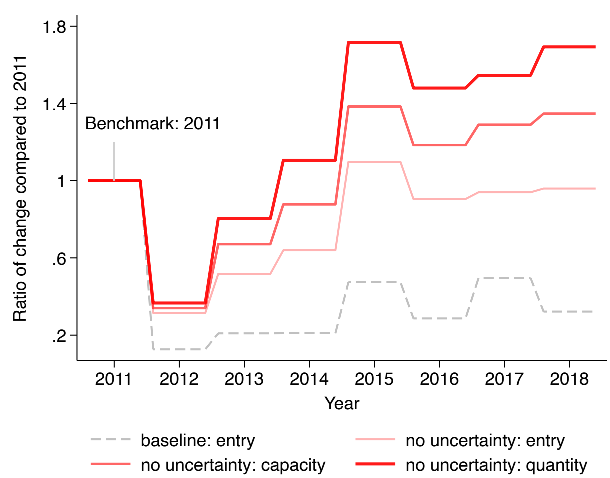


Notes: This figure describes the basic pattern of the Power Purchase Agreement (PPA) prices. Panels (a) and (b) show the conditional relationship between PPA prices and willingness to pay shifters for the alternative utilities within 400 miles. Panel (a) shows the relationship between PPA prices and the average effective prices (retail electricity prices and renewable credit 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 renewable portfolio gaps of the focal utility in the bargaining pair, effective market price, estimated unit capacity price, turbine cost, as well as the total capacity for the wind farm and the utility participating in the bilateral negotiation. Panel (c) plots the average time trend of the PPA prices.

Figure A11: Dynamic Model Fit

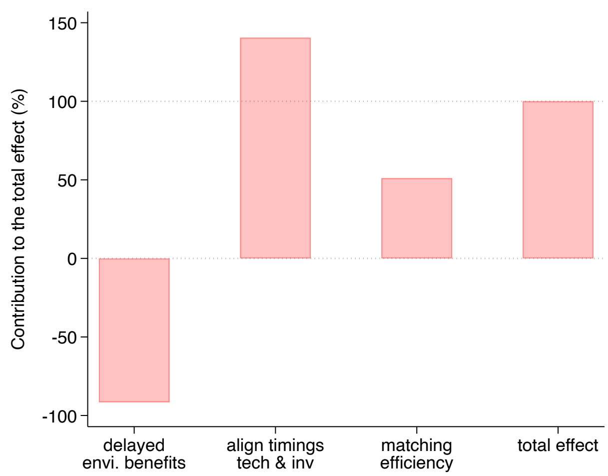
Notes: This figure shows the dynamic model fit. The red line denotes the model-predicted number of wind projects, while the gray dashed line denotes the number of wind projects in the raw data.

Figure A12: 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.

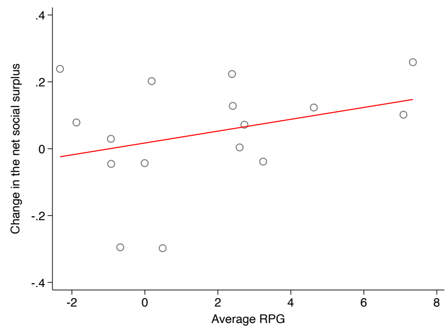
Figure A13: Welfare Decomposition



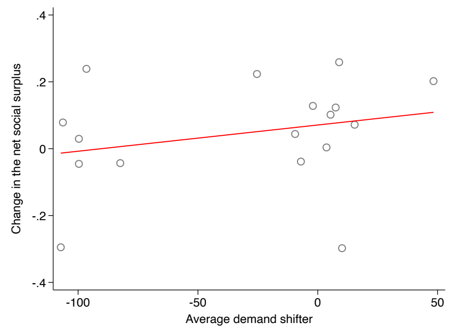
Notes: This figure shows the welfare decomposition. The change in the total benefits from wind energy can be decomposed into three channels: the delayed environmental benefits, the improvement of timing alignment between investment and technology, as well as the matching efficiency gain between utilities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

Figure A14: Welfare Heterogeneity from Removing Policy Uncertainty

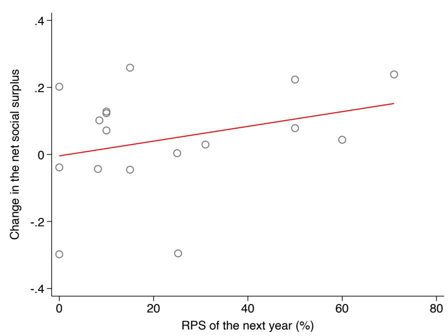
(a) Average RPG



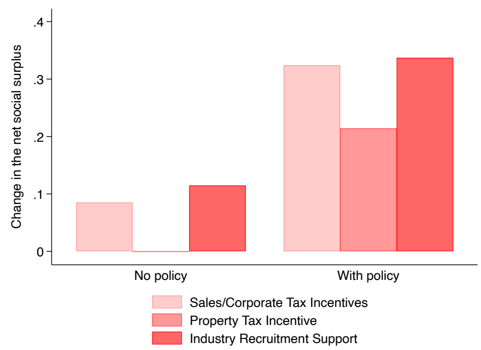
(b) Utility Demand Shifter



(c) Renewable Portfolio Standards



(d) State Subsidies



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

B Estimation Details for Bilateral Bargaining

B.1 Annualized Capacity Factor α_{it}

I parameterize wind power generation Q^w_{ijt} as a linear function of procured capacity k_{ij}, as I find that the annual total output on average is linearly increasing with nameplate capacity. I residualize both the annual total generation and the nameplate capacity on entry cohort dummies and age dummies and then plot the linear fit and local polynomial approximation between these two variables. As shown in Appendix Figure A9, the non-parametric relationship is very close to the linear fit, and the linear function has explanatory power as high as 0.83. Under the assumption of the linear production function, I define the annualized capacity factor $\alpha_{it} = \frac{Q^w_{ijt}}{k_{ij}}$.

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

$$\alpha_{it} = \sum_{a=2}^{10} \beta_a \times \mathbb{1}(\text{age}_{it} = a) + \sum_{c=2004}^{2018} \beta_c \times \mathbb{1}(\text{cohort}_i = c) + \epsilon_{it}. \tag{11}$$

I plot the age effects β_a in Panel (a) of Appendix Figure A9. The overall average capacity factor is relatively stable even for ten years after entry. The capacity factor peaks at age 5. However, the difference is only around 5% compared to the level of the baseline group. Moreover, I divide the sample into two groups: wind farms of age 1 and wind farms of age 2-5. I estimate the equation (11) without age dummies and plot β_c for two age groups in Panel (b). I find that capacity factors evolve systematically with the cohort, but display limited variation with respect to the age of wind farms. This is further supported by the fact that the cohort dummies alone explain 84.3% of the variations of the average capacity factor at the cohort-age level, while the age dummies alone explain 5.5% only. Therefore, I treat the annualized capacity factor to be constant as a wind farm ages and calculate it at the age of one for the best data coverage such that $\alpha_i = \alpha_{it}$ when $\text{age}_{it} = 1$.

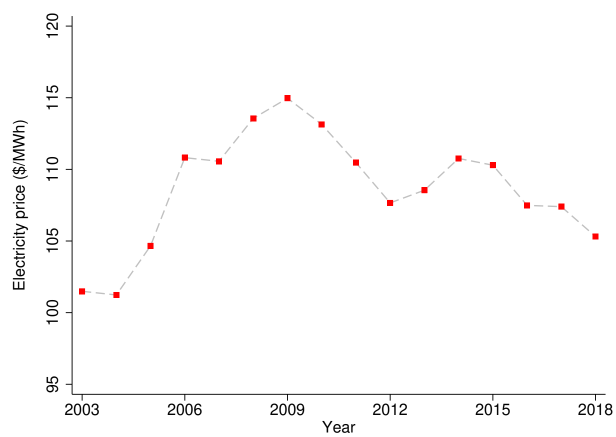
B.2 Transition Dynamics of Market Prices

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

$$\begin{aligned} r_{mt} &= \gamma_1 r_{mt-1} \times \mathbb{1}(t \leqslant 2009) + \gamma_2 r_{mt-1} \times \mathbb{1}(t > 2009) + \gamma_3 t \times \mathbb{1}(t \leqslant 2009) \\ &\quad + \gamma_4 t \times \mathbb{1}(t > 2009) + \gamma_5 \mathbb{1}(t > 2009) + \xi_m + \epsilon_{mt}. \end{aligned} \tag{12}$$

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

Figure B1: Time Trend of Aggregate Electricity Price



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

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

Table B1: Transition Dynamics of Electricity Prices

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

Notes: This table shows the transition dynamics of electricity prices at the state and yearly levels. The empirical model is specified in equation (12). Standard errors are clustered at the state level. *p < 0.10; **p<0.05; ***p<0.01.

prices and have perfect foresight with respect to the Renewable Portfolio Standards z_{mt}.

Table B2: Transition Dynamics of Renewable Energy Credit Prices

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

Notes: This table shows the transition dynamics of renewable energy credit (REC) prices at the state and yearly levels. The empirical model is specified in equation (12). Robust standard errors are reported. *p < 0.10; **p<0.05; ***p<0.01.

B.3 Transition Dynamics of Renewable Portfolio Gaps

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}. The total electricity generation Q_{jt} can be expressed as $Q_{jt} = Q^w_{jt} + Q^f_{jt} + Q^{or}_{jt} + Q^o_{jt}$. Utilities are faced with the Renewable Portfolio Standards requirement z_{mt} in state m and year t. I define renewable portfolio gap Q^{gap}_{jt} as follows.

$$Q^{gap}_{jt} = z_s(Q^f_{jt} + Q^{or}_{jt} + Q^o_{jt}) - Q^{or}_{jt}.$$

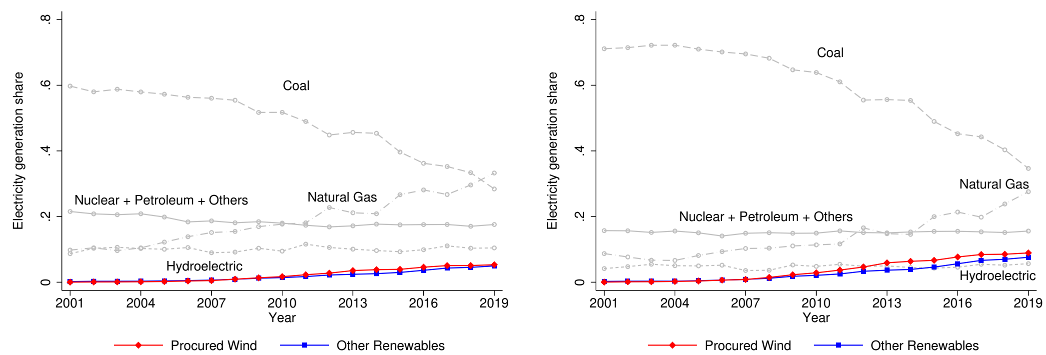
I first describe the overall time trend of electricity generation by energy source, separately for all the utilities and utilities in the Power Purchase Agreement (PPA) sample. The share of coal-fired electricity is decreasing over time, while the share of gas-fired electricity is increasing at the national level as shown in Appendix Figure B2. Despite limited volumes, procured wind and other renewables (including solar, biomass, geothermal, and utility-owned wind) are both increasing. Meanwhile, total generations from nuclear, petroleum, hydroelectric, and other energy sources are mostly stable. Compared to the entire sample of utilities, those in the Power Purchase Agreement sample have a much larger coal power share compared to the national average and a smaller natural gas power share.

I next estimate the transition process of electricity output portfolios at the utility level. I categorize different energy sources into four types: coal, natural gas, other non-renewables (including nuclear, petroleum, and others), and other renewables (including solar, biomass, geothermal, and wind directly owned by utilities). I exclude hydroelectric power following Hollingsworth and Rudik (2019), as many Renewable Portfolio Standards excluded hydroelectric power built before the implementation. I use the AR(1) model to capture the evolution process of net generations from these four different energy sources. As the capacity investment is lumpy, I exclude utilities that have never used a certain fuel type from the regression. I take the coefficient estimates from the AR(1) model with utility dummies and a time trend. The results are shown in Appendix Table B3.

I assume utilities have rational expectations with respect to the evolution of their own electricity generation from each type of fuel source, and they have perfect foresight with respect to the Renewable Portfolio Standards. If a utility has never used a certain fuel type during the sample period, I assume that its expectation of future usage remains zero.

Figure B2: Time Trend of Output Share by Energy Source

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



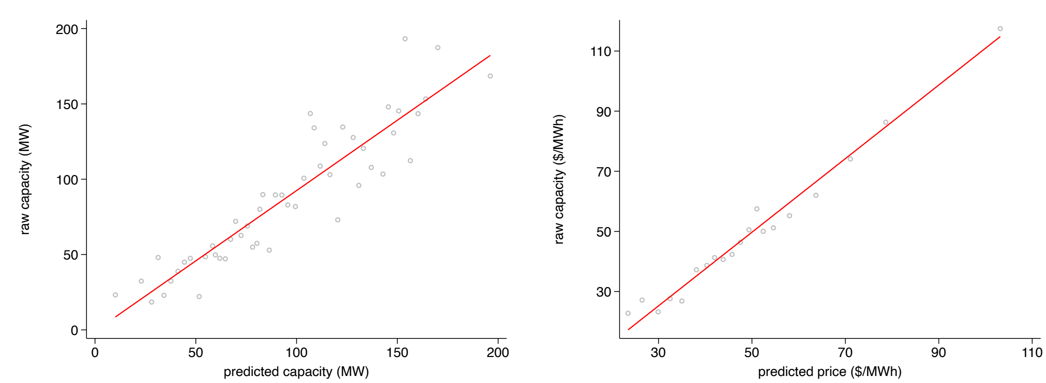
Notes: This figure shows the time trend of the shares of electricity generated by different energy sources. Panel (a) displays the time trend for all utilities, while Panel (b) shows the time trend for utilities from the Power Purchase Agreement sample. Other renewables include solar, biomass, geothermal, and utility-owned wind.

B.4 Model Fit

I check the model fit of the bargaining model using estimates from Panel A of Table 1. The binned scatter plots of the raw and predicted capacity and price according to equation (1) and (2) are shown in Appendix Figure B3. The model explains around 42% of the data variation for capacity, and 67% of the data variation for price.

Figure B3: Model Fit for the Bilateral Bargaining Model

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



Notes: This figure shows the static model fit for the capacity function (1) and the negotiated price equation (2).

Table B3: Transition Dynamics of Electricity Generation by Sources

	Net Generation			
Panel A: Coal and Natural Gas				
	Coal		Natural Gas	
	(1)	(2)	(3)	(4)
Lagged Variable	0.868***	0.955***	0.936***	1.039***
	(0.067)	(0.011)	(0.020)	(0.007)
Time Trend	-0.067***		0.011***	
	(0.013)		(0.003)	
Observations	2459	2460	7488	7491
Adjusted R^2	0.969	0.969	0.977	0.976
Utility Dummies	✓		✓	
State Dummies $\times$ 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 $\times$ Time Trend		✓		✓

Notes: This table shows the transition dynamics of net electricity generation using coal, natural gas, other non-renewable sources (including nuclear, petroleum, and others), and other renewable sources (including solar, biomass, geothermal, and wind directly owned by utilities) at the state and yearly levels. The empirical model is similar to equation (12). Standard errors are clustered at the state level. *p < 0.10; **p<0.05; ***p<0.01.

C An Alternative Dynamic Model

There is an alternative dynamic model for the evolving policy beliefs, which preserves the stationarity of the problem.[39] The notations are the same as in Section 4.3. ω_t represents the policy status in year t, which could take three values: (1) $\omega_t = H$, which indicates that the federal subsidy is enacted in year t and the probability of policy renewal is 1; (2) $\omega_t = L$, which indicates that the federal subsidy is enacted in year t, but the probability of policy renewal is only $b < 1$; (3) $\omega_t = 0$, which indicates that the federal subsidy is terminated. In

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

each period, the *ex-ante* likelihood of $\omega_t = H$ conditional on policy renewal is equal to ρ_H.

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

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

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

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.

D Estimation Details for Demand of Non-Utility Buyers and Buyer Choice

D.1 Demand of Non-Utility Buyers

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

Table D1: 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			✓	✓

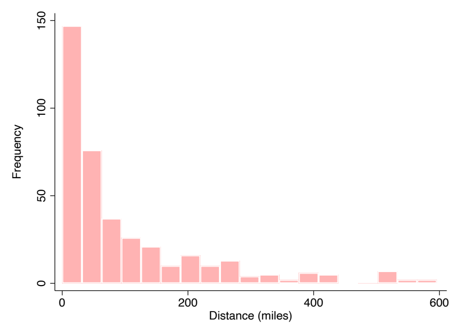
Notes: This table shows the estimation results of the linear demand curve for non-utility buyers (equation (3)). I use a combination of three instruments for the price: the renewable credit price for utilities, the annual agricultural land price at the state level, and whether the state offers subsidy policies to wind farms. State policies include sales tax incentives, property tax incentives, and industry recruitment support for the wind industry. Column (1) uses the same instrument as in Panel B of Table 1. Robust standard errors are in parentheses.

D.2 Buyer Choice

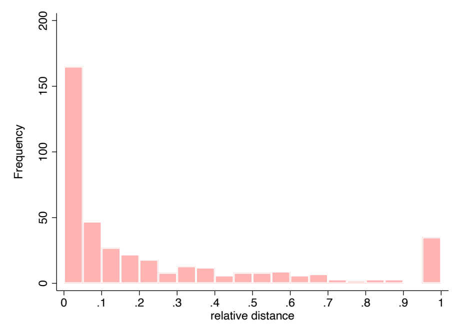
I match each wind farm in the sample with utilities that were active in the EIA-860 data when that wind farm started construction. The geographical distance between each wind farm and utility pair is calculated using the coordinates of the wind farm and the closest power plant owned by the utility. I first summarize the matching patterns between utilities and wind farms in Appendix Figure D1. 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 pairs of a wind farm and its unmatched utility are from the same state. Panel (d) presents a similar pattern for whether a utility and wind farm pair is in the same balancing authority. Overall, a wind farm is more likely to be matched to a utility that is geographically closer and within its own state or balancing authority.

Figure D1: Matching Patterns between Utilities and Wind Farms

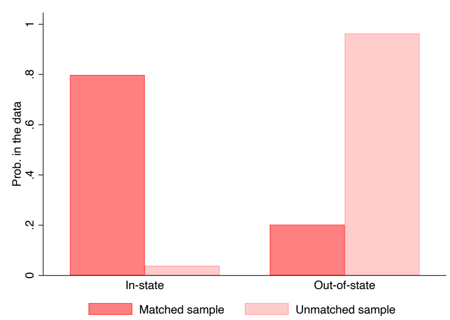
(a) Distance



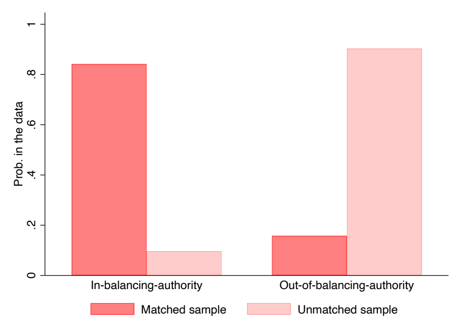
(b) Relative Distance



(c) State



(d) Balancing Authority



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

Motivated by the empirical pattern, I restrict the buyer set to those utilities that are within 400 miles of the focal wind farm.[40] I next explore the determinants of buyer choice

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

as shown in Appendix Table D2. The dependent variable $\mathbb{1}(\text{Match})$ is a dummy variable that takes the value one if the utility is the chosen buyer for the wind farm. I find that utilities with a larger renewable portfolio gap (larger unfulfilled demand) are more likely to be matched. Moreover, utilities that are in the same state as the focal wind farm, or that are closer, are more likely to be chosen.

Table D2: Determinants of the Utility Matching Choice

	$\mathbb{1}(\text{Match})$		
	(1)	(2)	(3)
Renewable Portfolio Gap (10^9 MWh)	1.516***	1.545***	1.589***
	(0.191)	(0.211)	(0.219)
$\mathbb{1}(\text{Same States})$	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 $\mathbb{1}(\text{Match})$ is a dummy variable that takes the value one if the utility is the chosen buyer for the wind farm. Dummies for utility types include whether a utility is investor-owned, a cooperative, or of other types (such as municipal, etc.). Standard errors are clustered at the wind farm level. *p < 0.10; **p<0.05; ***p<0.01.

E Estimation and Simulations Details for Dynamic Model

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

State Space and Basis Function I define a set of state variables as follows.

(1) the annual average productivity of wind turbines $\bar{\alpha}_t$,

(2) average turbine prices $\text{TP}_t^{\text{Vestas}}$,

(3) market prices combining both electricity prices r_{mt} and renewable credit prices λ_{mt},

(4) inclusive value that can be attributed to the changing renewable portfolio gaps for buyers Φ_{it},

(5) a predicted utility demand using time-invariant shifters in equation (1),

(6) non-utility demand shifter as a projection of p_i^{nu} on $\boldsymbol{Z_i^{nu}}$ similar to equation (3),

(7) predicted matching cost, defined as the mean of $(\hat{\gamma_3}\mathbb{1}\{m_i \neq m_j\} + \hat{\gamma_4}Dist_{ij})$ from equation (4),

(8) one-year lagged amount of new wind capacity online K_{mt} in the state m and year t

(9) the subsidy level d_t,

(10) a dummy variable defining whether i is before 2013,

(11) and state-level land prices W_{mt}.

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

Transition Dynamics of State Variables There are six time-varying exogenous state variables in my model. The subsidy level d_t and the dummy variable defining whether i is before 2013 evolve deterministically. The rest four variables, including annual average productivity of wind turbines, the average turbine prices, the effective market price, and the state-level land prices are exogenous in the model, and I recover their transition dynamics from the data with AR(1) models.

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

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

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

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

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

I define the effective market price Θ_{it} as a combination of future retail electricity prices and renewable energy credit (REC) prices. This captures part of utility willingness to pay as in equation (1). The transition dynamics of electricity prices r_t and renewable credit prices λ_t are explored in Appendix Section B.

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

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 (12) for the static estimation in Appendix Section B. I estimate the transition dynamics of Θ_{jt} using the empirical model below and results are shown as follows. The total number of observations is 800 and the adjusted R-square is 0.996. The standard error is in parentheses and clustered at the state level.

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

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

$$\Phi_{it} = \underset{0.591\ (0.020)}{\rho_1^{\Phi}}\Phi_{it-1} + \underset{-0.240\ (0.023)}{\rho_2^{\Phi}}K_{mt} + \xi_i^{\Phi} + \epsilon_{it}^{\Phi}.$$

The amount of one-year lagged new wind capacity online K_{mt} in the state m and year t is thus another endogenous state variable in the dynamic problem. I assume K_{mt} to follow another AR(1) process as in equation (13). When estimating entry cost parameters using the more recent policy window, as stationarity is assumed, I directly estimate equation (13) using data from 2015 to 2018, and the results are presented below the equation. Results using data from 2014 to 2018 are very similar. When estimating the policy belief parameters and implementing counterfactual simulations, I endogenously solve ρ_1^{nc} and ρ_0^{nc} in the equilibrium.

$$K_{mt} = \underset{0.791(0.047)}{\rho_1^{nc}}K_{mt-1} + \underset{0.032\ (0.022)}{\rho_0^{nc}} + \epsilon_{mt}^{nc}. \tag{13}$$

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

E.2 Simulation Details of the Dynamic Model

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

1. For year t, I simulate a sample of potential entrants in state m and year t of the size of 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 $V^0(\boldsymbol{s}_{it}, b_t)$ and $V^1(\boldsymbol{s}_{it}, b_t)$.
3. Simulate the trajectory of K_{mt}, solve for new ρ_0^{nc} and ρ_1^{nc}, and update the belief.
4. Repeat steps 2-3 until the values of ρ_0^{nc} and ρ_1^{nc} converge.
5. Solve the value functions $V^0(\boldsymbol{s}_{it}, b_t)$ and $V^1(\boldsymbol{s}_{it}, b_t)$.
6. Draw entry cost ν_{it} 100 times and each potential entrant makes optimal entry timing decision according to equation (7). Sum over the entry decision of each potential entrant and calculate the total number of entrants Entry$_{mt}$.
7. Update the PotentialEntrants$_{mt+1}$ to add the number of delayed entrants from year t. Repeat the steps (1)-(6) for year $t+1$.

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

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

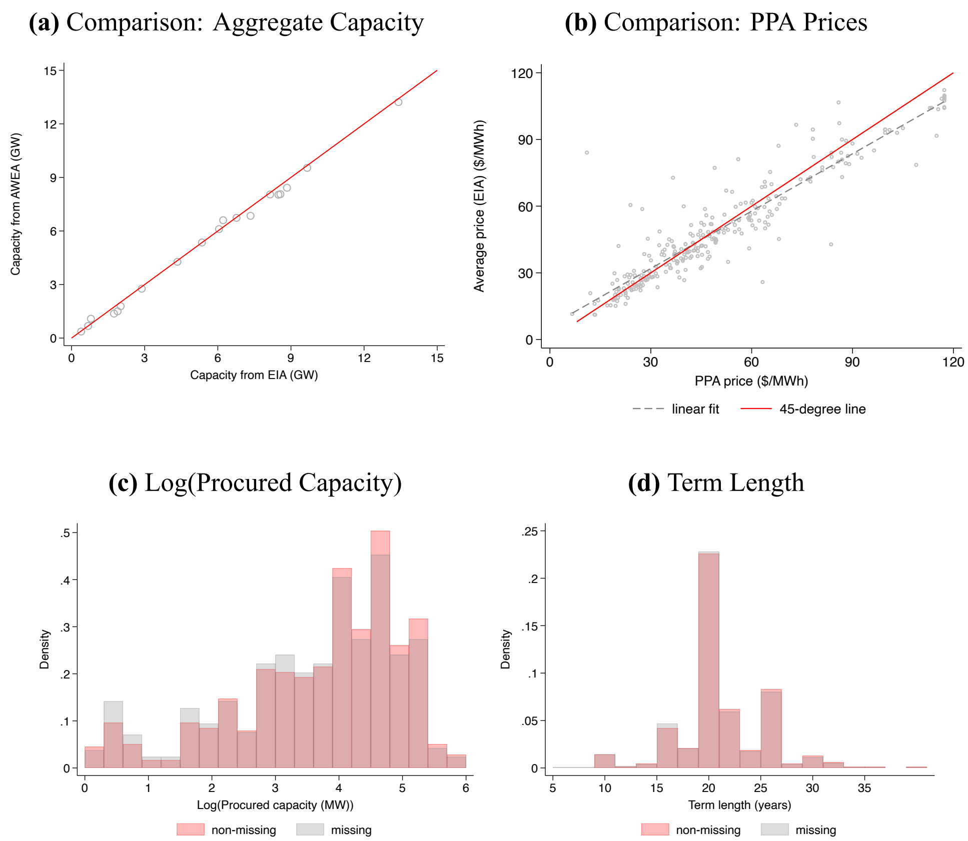
A PPA Data

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

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

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

Figure OA1: Data Description of the PPA Sample



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

B REC Price Data

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

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

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

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

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

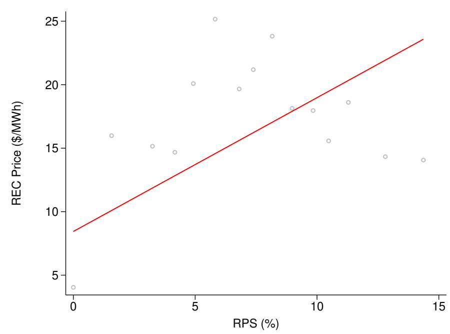
Moreover, the trading of the RECs is fragmented into different markets such that the credits are registered to be traded only in the corresponding tracking systems, as shown in Appendix Table OA1 based on Table 1 in Abito, Flores-Golfin, van Benthem, Vasey, and Velichkov (2022). The tracking system fixed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

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

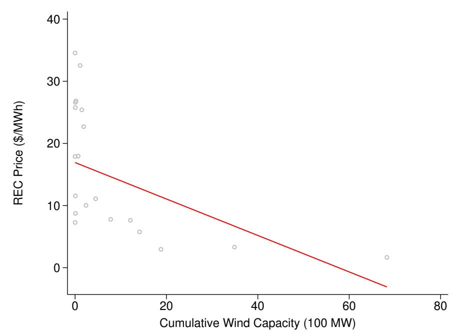
y_{mt} denotes the REC prices in state m and year t. $\boldsymbol{X_{mt}}$ includes the RPS in year t, the cumulative wind capacity in state m and year t, as well as the share of electricity generated out of non-renewable sources. The corresponding tracking system of state m is denoted by k, and γ_{kt}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

Figure OA2: Renewable Energy Credit Prices and Other Market Outcomes

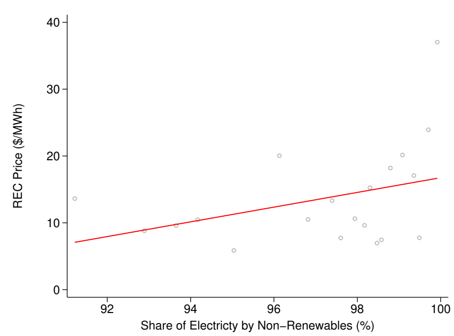
(a) Renewable Portfolio Standards



(b) Cumulative Wind Capacity



(c) Electricity Share by Fossil and Nuclear Power



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

Table OA1: REC Tracking System and Price Imputation

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

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

C Interconnection Queue Data

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

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

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

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

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

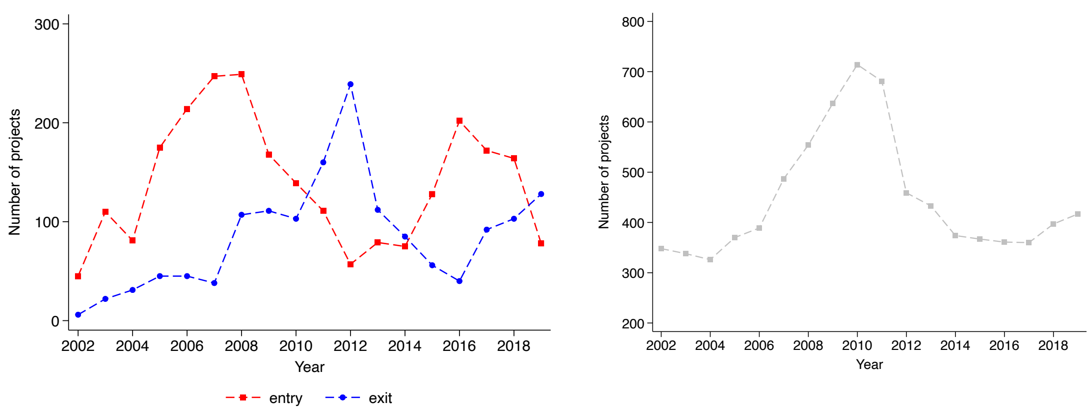
[1] MISO interconnection queue is accessed on Oct 31st, 2022. CAISO interconnection queue is accessed on Oct 31st, 2022. PJM interconnection queue is accessed on Nov 1st, 2022. ISO-NE interconnection queue is accessed on Nov 2nd, 2022. NYISO interconnection queue is accessed on Nov 2nd, 2022. SPP interconnection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

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

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

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

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

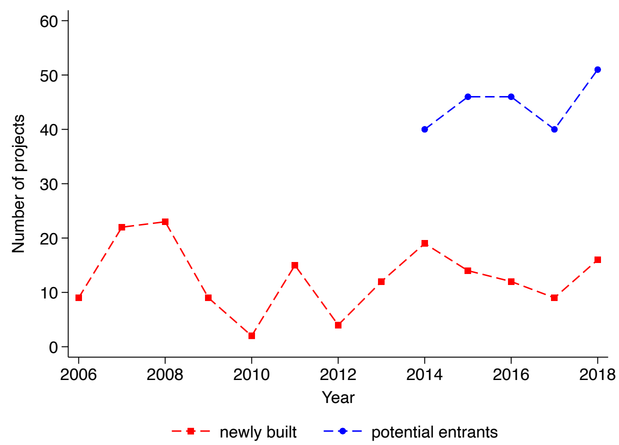


Notes: This figure shows the aggregate time trend for the interconnection queue in MISO, CAISO, PJM, ISO-NE, NYISO, and SPP. "Entry" denotes the number of projects that entered the queue, and "exit" denotes the number of projects that withdrew from the queue. The number of potential entrants for the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

D Calculation of Social Benefits of Wind Energy

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

Figure OA4: Newly Built Projects and Potential Entrants in ERCOT



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

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

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

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

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

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

References

Jose Miguel Abito, Felipe Flores-Golfin, Arthur A. van Benthem, Gabrielle Vasey, and Kamen Velichkov. Designing more cost-effective trading markets for renewable energy. 2022.

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

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