Market Structure and Technology Adoption in Renewable Energy

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Abstract

We study the effect of market structure on technology adoption in the U.S. solar and wind power industries. We compare adoption across two market types: restructured markets, which are designed to promote competition, and traditional markets, which are dominated by regulated monopolists. Solar projects in restructured markets are 24 percent less likely to adopt frontier technology, while the effect for wind projects is negative but statistically insignificant. We provide evidence this negative relationship between competition and adoption is explained by differences in financing costs across the two market types.

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1 Introduction

Does competition increase innovation? The relationship is theoretically ambiguous (Schumpeter, 1934, 1942; Arrow, 1962) and endogenous market structure complicates empirical analysis. Existing empirical papers have found mixed results (Gilbert, 2006),[1] suggesting the effect of competition on innovation is context dependent. Similar challenges apply to studying how competition affects technology adoption, a key driver of innovation (Macher, Miller and Osborne, 2021).

Electricity markets are an interesting context to study how competition affects technology adoption for two reasons. First, the electricity sector is expected to undergo massive changes in response to global climate change. These changes will involve adopting new, cleaner ways of generating electricity. Second, the level of competition is these markets is largely a policy choice: policymakers make numerous regulatory decisions that directly affect the level of competition. The starkest of these decisions is whether to have a traditional market, where a regulated monopoly produces and sells electricity, or a restructured market, where firms compete to supply electricity generation and retail it to consumers.

The competition induced by electricity market restructuring may affect technology adoption through a few channels. Product market selection may force firms in restructured markets to adopt technologies that maximize expected profits. Alternatively, the stability provided by traditional markets may lead to lower financing costs and thus higher levels of adoption. Market structure may also affect the price of electricity, which, in turn, affects the returns to adoption.

[1]Recent papers have more consistently found that competition decreases innovation. A negative relationship has been found for the microprocessor industry (Goettler and Gordon, 2011), Chilean manufacturing (Cusolito, Garcia-Marin and Maloney, 2023), U.S. manufacturing (Autor et al., 2020), and among firms that were prosecuted for collusion (Kang, 2023). Yet, Bloom, Draca and Reenan (2016) find competition increases innovation in European manufacturing, and Igami (2017) and Igami and Uetake (2020) find competition spurs innovation in the hard disk drive industry, at least when there are few firms.

As a step toward understanding this relationship, we study the effect of electricity market structure on technology adoption in the solar and wind power industries. For solar, we study the adoption of one innovation: panels that move to track the sun. The fraction of new solar projects adopting solar axis tracking grew from about 20 percent in 2010 to nearly 60 percent in 2020. For wind, we study what drives the adoption of frontier wind turbine technologies. Wind turbines have steadily grown in size and efficiency over the last twenty years with new models coming out each year. Both technologies increase production in return for a greater upfront cost.

We estimate discrete choice models of technology adoption as a function of market structure. Our data include all utility-scale solar and wind projects built in the United States from 2001-2020. When they build a new project, firms choose the project's technology to maximize their expected profits. This decision is sensitive to resource quality, and we use detailed data on solar irradiance and wind speeds to control for its effect on these choices. While market structure was not randomly assigned, it was determined a decade before our sample, and our results are robust to controlling for likely confounders. We also describe whether, all else equal, wind projects that sign long-term contracts to sell electricity are more likely to adopt frontier turbine technology.

We find that competition reduces adoption: solar projects within restructured markets are 24 percent less likely to use tracking technology than projects in traditional markets. Wind developers in restructured markets are also less likely to adopt the newest turbine technology, though this effect is imprecisely estimated and not statistically significant. Instead, we find that signing a long-term contract to sell a project's power is the best predictor of using a frontier wind turbine model.

Lower adoption in restructured markets is likely explained by higher financing costs. Financing is done at the project-level in these industries, and long-term contracts lower financing costs by reducing the probability of default. While we do not observe whether solar developers sign a long-term contract for each project, we do observe this information for wind projects. Wind projects in restructured markets are less likely to sign long-term contracts (58 vs. 83 percent). The quality of these contracts is also lower. We find that long-term contracts in restructured markets are for shorter terms on average (18.3 vs. 20.9 years) and tend to be with less creditworthy buyers (59 vs. 84 percent are signed with a utility buyer).

To provide context for these estimates, we simulate counterfactual adoption of solar axis tracking if all states had restructured their electricity markets. We focus only on technology choices; we do not endogenize developers' entry decisions or model the effect of restructuring on market prices. We find that if all states had restructured, by 2020, 19 percent of solar projects would use axis tracking compared to the realized 28 percent. Full restructuring also decreases solar industry producer surplus by $91 million and leads to an additional $47 million in external costs from CO_2 emissions. If this mechanism whereby competition reduces adoption generalizes to entirely new generation technologies, the potential welfare effects are much larger.

The results in this paper imply that competition does not speed technology adoption in this context, and it may hinder adoption by increasing financing costs. In 2018, Arizona considered restructuring its electricity market (Wincher, 2018) and Nevada voters rejected a ballot initiative that would have introduced retail competition and dissolved the state's regulated monopoly (Akers, 2018).[2] While there are undoubtedly other factors in this decision, our results suggest another wave of states restructuring their electricity markets would not speed the adoption of low-carbon generation technologies.

This paper contributes to the limited empirical evidence on the relationship between competition and technology adoption. The most similar paper is Macher, Miller and Osborne (2021) which finds that, holding demand fixed, competition decreases technology adoption in the Portland cement industry. The likely mechanism is that firms with fewer

[2]This 2018 rejection was after Nevada voters approved the same initiative in 2016. Because it was a constitutional amendment, voters had to approve the initiative twice for it to take effect. The 2018 campaign was the most expensive ballot initiative in Nevada history, with the incumbent utility, NV Energy, spending $63 million to defeat the measure (Snyder and Rindels, 2018).

competitors produce more in equilibrium, spreading the fixed cost of new technology over more units. While we find a similar result, the mechanism is different. In our setting, producing more requires buying more solar panels or wind turbines, so the fixed cost of the new technology roughly scales with output. Instead, higher financing costs likely explain our finding that competition reduces adoption.[3]

This paper also contributes to the literature on the effects of electricity market restructuring by considering its impact on firm investment decisions. Restructuring has been found to cause generator-side efficiency gains in input use (Bushnell and Wolfram, 2005; Fabrizio, Rose and Wolfram, 2007; Craig and Savage, 2013; Cicala, 2015; Chan et al., 2017), fewer outages and enhanced safety at nuclear plants (Davis and Wolfram, 2012; Hausman, 2014), and higher markups and prices (MacKay and Mercadal, 2021). A major goal of restructuring was to give firms an incentive to innovate and invest in cost-cutting technologies, yet its success at achieving these longer-term goals has received less attention. The few exceptions focus on the early 2000s and find mixed evidence on restructuring's success. These papers find restructuring led to firms choosing less capital-intensive environmental compliance options (Fowlie, 2010), an "overinvestment" in natural gas generation (Hill, 2021), and an increase in utility investment in transmission and distribution (Cicala, 2022). In the context of renewable energy, we find that restructuring reduces adoption of frontier generation technologies.

Finally, this paper relates to recent work suggesting that the link between adoption and innovation may justify large consumer subsidies for renewable energy. Gerarden (2022) finds that consumer subsidies for purchasing solar spur adoption which, in turn, induces innovation. This innovation by international firms then increases long-run solar adoption in other countries. Covert and Sweeney (2022) find learning by doing exists in wind turbine manufacturing and has important effects on firm incentives to inno-

[3]Both this paper and Macher, Miller and Osborne (2021) study the effect of competition on technology adoption. In contrast, Fioretti et al. (2022) shows that technology adoption can also affect competition in the context of the upstream oil and gas sector.

vate. Both papers imply innovation decisions in these industries are affected by firms' willingness to adopt new technology at a global scale. We find that electricity market competition likely decreases this willingness to adopt new technologies.[4]

The rest of this paper is organized as follows. Section 2 provides an overview of the electricity market and describes the technological advances we study. Section 3 discusses the data sources and main variables used in the analysis. Section 4 and Section 5 describe the model of technology adoption, empirical strategy, and results for the solar and wind power industries respectively. Section 6 discusses how accounting for the effect of market structure on prices would affect the results, and Section 7 provides evidence for financing costs as a potential mechanism. Section 8 evaluates policy counterfactuals for the solar industry, and Section 9 concludes.

2 Market structure and technological innovations

2.1 Market structure, participants, and pricing

2.1.1 Two market types

To a first approximation, there are two types of electricity markets: traditional markets and restructured markets. Historically, generation, transmission, distribution, and retailing were thought of as natural monopolies, and one highly regulated firm would provide all four. We refer to this structure as a traditional market. Over time, the minimum efficient scale for generation fell, and states began restructuring their markets to allow for competition in generation and retailing. In the late 1990s, all fifty states had hearings on whether they should restructure their electricity markets, with nineteen states eventually restructuring (Fowlie, 2010). If not for California's electricity crisis in 2000, many more

[4]These papers highlight the importance of spillovers from adoption. While the mechanisms whereby competition affects adoption are likely similar worldwide, we expect the spillovers from the specific sub national policy we study to be small. These spillovers would also bias us toward finding smaller effects of competition on adoption.

states might have restructured. No states have restructured their electricity markets since the initial wave in the late 1990s.

2.1.2 The same firms build wind and solar projects in both market types

While this description of the two market types suggests that regulated utilities would build renewable projects in traditional markets but not in restructured markets, the reality is more complicated. Two types of firms build most utility-scale wind and solar projects: independent power producers (IPPs) and investor-owned utilities (IOUs). The IPPs building renewables can be large or small firms, and they often specialize in renewable energy projects. Investor-owned utilities, on the other hand, are vertically integrated monopolies which are regulated by state public utility commissions. While utilities own most fossil fuel generation in traditional electricity markets, this is not the case for either wind or solar generation. In both restructured and traditional markets, most renewable generation is constructed and owned by IPPs, and the most active IPPs build projects nationwide.

2.1.3 Price-setting differs across the two market types

While the same firms compete in both types of markets, the way power is sold differs across the two. Most wind and solar generated electricity in the United States is sold through long-term contracts called power purchase agreements (PPAs). These PPAs are signed prior to construction and are usually necessary to secure financing for the project. In traditional markets, the utility that acts as a regulated monopolist issues a request for proposals to build utility-scale wind or solar generation. It will then sign a power purchase agreement with whichever firm submits the most attractive bid. In restructured markets, requests for proposals are sometimes used, but independent power producers may also sign PPAs with power retailers or private firms. As a result, prices in restructured markets are often set by a process where sellers match to buyers while prices in traditional markets are set by a mechanism similar to a procurement auction. Renewable energy projects in restructured markets also have the option to enter without signing a PPA and instead sell their output at the wholesale market price.[5][6]

2.2 Technological innovations

We next describe the technological innovations we study, both of which increase production in return for higher upfront costs. For solar, this is the adoption of solar panels that track the sun.[7] For wind, this is the adoption of new vintage turbine models; because new models are released each year, a model that is 'new' in 2008 will no longer be new in 2011. Adoption decisions are made at the time of project construction and cannot be changed after a project is built.

2.2.1 Solar: Axis-tracking technology

Whereas traditional fixed-tilt panels are set permanently in one direction, solar axis-tracking panels rotate from east to west over the course of the day to track the sun. Although the technology is developed, tracking systems tend to have higher maintenance costs, and there is still some uncertainty about their long-term durability (Bolinger, Seel and LaCommare, 2017). Tracking technology did not change much over our sample, and

[5]These projects are called "merchant" generators. We only observe this status for wind projects, and 15 percent of wind projects in our sample are merchant generators. There are a few merchant generators in traditional markets. These projects are located within the footprint of an independent system operator and thus able to participate in wholesale markets; 5 percent of wind projects in traditional markets are merchant compared to 29 percent in restructured markets.

[6]Another channel through which renewable power is sold is through the implementation of the 1978 Public Utilities Regulatory Policies Act (PURPA). One of the objectives of PURPA was to promote renewable generation by offering eligible IPPs, referred to as "qualifying facilities", special rate and regulatory treatment (FERC, n.d.). Regulated utilities usually sign long-term contracts with these qualifying facilities to purchase renewable power. While how contract rates are set varies by state, traditional states typically use a competitive bidding process or an avoided cost formula determined by the utility. On the other hand, restructured states are more likely to opt for market-based prices (National Regulatory Research Institute, n.d.). Solar projects are much more likely than wind projects to be compensated under PURPA, and about half of the solar projects in our data are qualifying facilities.

[7]Technology adoption in solar can also involve choice of using panels with newer materials apart from using tracking. This includes using panels with higher efficiency silicon-cells or the recently developed perovskite-cells. Over 99 percent of the projects in our data use silicon cells, and we do not observe information about the types of silicon cells. Thus, we restrict our classification to tracking vs. fixed tilt.

our measure of technology adoption is whether a project used this technology. Figure 1a shows that the use of tracking has increased steadily.

Tracking systems are more suitable in some locations than others. Tracking increases production more in sunny areas than in cloudy areas because cloud cover diffuses solar radiation (U.S. Energy Information Administration, 2017). Its advantage relative to fixed-tilt panels is highest in the morning and evening, as both types of system operate at the same angle around solar noon (Bushong, 2015). Finally, high wind speeds, poor soil quality, or steep sites (grades greater than 5-6 percent) may preclude the use of tracking (Kiewit, n.d.).

2.2.2 Wind: Larger turbines

A wind project is a collection of wind turbines, and these turbines are where most technological progress occurs. Advancements in turbine technology have led to steadily larger turbines. Power generation is proportional to the area swept by the rotor, so larger turbines generate more energy in the same wind conditions (Covert and Sweeney, 2022). The choice of turbine model is affected by meteorological factors like wind speed, wind direction, and atmospheric pressure, as well as geographic factors like land availability. Other considerations include the cost of the turbine and expected maintenance costs (Windustry, 2007). Because turbines last for over 20 years, technological progress diffuses through the industry via new wind projects choosing new, more advanced turbine models. The long-term increase in rotor diameter shown in Figure 1b is due to projects adopting these new, larger models.[8]

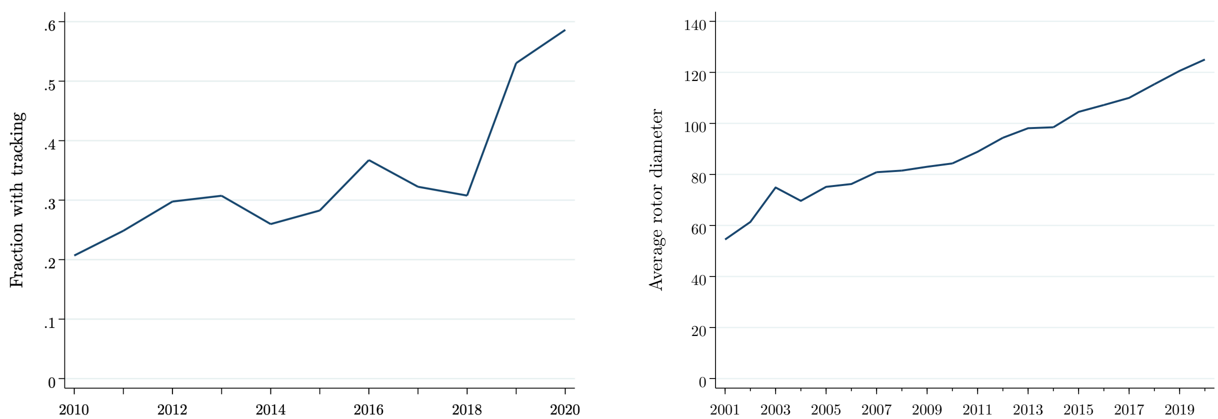
Our measure of technology adoption is whether the project uses a turbine model that advances the technological frontier, i.e., a model that is both new and substantially better than the previous model. We first define which models are new. The industry releases

[8]It is possible for wind developers to "re-power" projects by upgrading their turbines. While re-powering is becoming more common, it is still rare in the United States. This is partly because the U.S. stock of wind turbines is relatively new, and re-powering tends to happen once turbines are at least ten years old (Fitzgerald and Giberson, 2021).

seven models a year on average, with the largest manufacturer, GE, averaging one new release a year. We classify a model as new for the first 4 quarters after it is released. Because we do not observe release dates, we assume the release date is one quarter before a turbine model is used by a project in our data. Appendix Figure D4 shows that both new and significantly older models by the same manufacturer are chosen simultaneously.

We use turbine size to classify whether a newly introduced model is a technological advancement. Some of the newly introduced models are minor iterations on previous versions rather than true advancements. For example, we see GE introduce the 1.5-91.5 model two years after it introduces the 1.5-90 model. We categorize a model as a technological advancement if its rotor diameter is at least 5 meters greater than the largest existing turbine model by that manufacturer. Under this classification, 75 percent of the new turbine models introduced over our sample are technological advancements.

Figure 1: Technology adoption over time



(a) Solar: Axis tracking (b) Wind: Larger turbines

Notes: Figure 1a plots the fraction of solar projects using tracking by year of operation. Figure 1b plots the average (across wind projects) turbine rotor diameter in meters by year of operation.

2.2.3 Technology is chosen at entry

Renewable energy projects take years to develop, and these technologies are chosen after site selection but before construction. The first step in building a renewable energy project is leasing land for the project. Next, the developer applies for permitting and interconnection to the transmission system. It then tries to secure a long-term contract to sell the power, at which point it secures financing and purchases the solar panels or wind turbines for the project (AWEA, 2019). While sites are chosen at least a year before a project commits to a technology, it is possible the desired technology affects sight selection. For example, solar axis-tracking requires more land for the same size (in MW) solar project, though it also leads to higher production per MW of capacity. We abstract from this possibility by taking locations as given when estimating models of technology choice.

2.3 Relationship between market structure and technology adoption

We hypothesize that there are three channels through which market structure may affect adoption: competition, financing, and prices. The first is that more competition may induce firms to adopt new technologies. While utilities rarely build wind and solar projects in traditional markets, they still have considerable sway over the types of generation constructed. These regulated monopolists have little incentive to favor adopting new technology, and may even exhibit regulatory induced risk aversion (Jha, 2022). This hypothesis would imply that projects in traditional markets are less likely to adopt new technologies.

Market structure may also affect adoption though its effect on financing costs. Financing is typically done at the project-level for wind and solar projects, with developers setting up project-specific LLCs (Johnston, 2019). Naturally, a long-term contract to sell the power will lead to lower financing costs, as will, among projects with long-term contracts, a longer contract term. Financing costs also vary with the creditworthiness of the firm buying the power (International Finance Corporation, 2015), so projects that sign long-term contracts with regulated utilities may have lower financing costs. Lower financing costs should translate into lower discount rates when making investment decisions, and thus a higher probability of adopting these technologies. Thus, this hypothesis would imply more adoption in traditional markets.

Finally, market structure should directly affect technology adoption through its effect on the market price. Because these technologies increase production in return for higher upfront costs, higher output prices increase the probability of adoption. The impetus for restructuring was that introducing competition would result in lower prices by encouraging the firms supplying electricity to innovate and cut costs. Despite this aim, the effect of restructuring on market prices is ambiguous: restructuring gives firms an incentive to cut costs but allows them to exercise market power. MacKay and Mercadal (2021) find this second effect dominates, and electricity market restructuring increased prices. Thus, this channel has an ambiguous effect on adoption, and based on what others have found, we might expect it led to more adoption in restructured markets.

Market structure may also affect adoption by affecting appropriability, but we do not expect this channel to be important here. Unless there are strong intellectual property rights, competition can result in too little innovation because firms appropriate only a fraction of the benefits (Gilbert, 2006). Similarly, if there is uncertainty about the quality of a new technology, early adopters bear the risks of adoption without capturing all of the benefits. For the technologies we study, most of the uncertainty is about the durability of the technology and will not be resolved for many years. Thus, developers that wait to adopt cannot learn much from the experiences of early adopters.

3 Data

We use data on all utility-scale solar and wind generators that began operation in 2001-2020. These data come from U.S. Energy Information Administration (EIA) Form 860. All generators that are at least 1 MW in size and connected to the power grid submit

Form 860 each year. Because few solar generators began operation before 2010, the solar analysis uses data from 2010 - 2020.

The EIA data also include the technology choice for each project. For solar projects, they include whether the panels are fixed tilt, single-axis tracking, or dual-axis tracking. Very few generators use dual-axis tracking (<2 percent), so we combine both single- and dual-axis tracking into one indicator for tracking technology. For wind projects, these data include the predominant wind turbine model used for each project, along with its rotor diameter, capacity (rating), and hub height.[9] Figure 2a and 2b show the spatial distribution of wind and solar projects, as well as their technology choices. Appendix A provides more detail on the geographic distribution of our sample of solar projects.

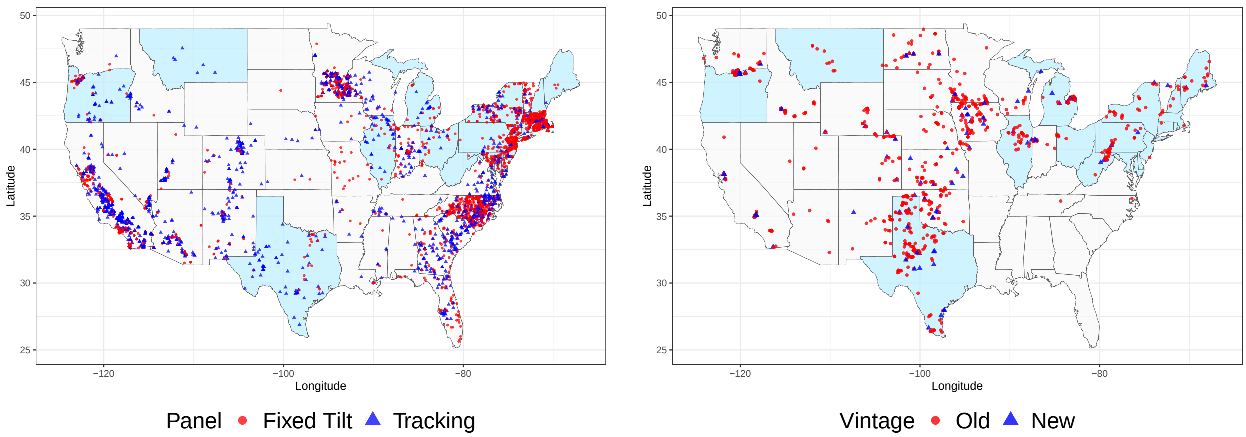
We classify states as restructured using the list in Kleit and Rose (2016). These restructured states (CT, DE, IL, MA, MD, MI, MT, NH, NY, OH, OR, PA, RI, TX, and WV) are highlighted in light blue in Figure 2. Oregon and Montana are de facto more similar to traditional states, and results are similar if we reclassify them as traditional rather than restructured: the negative impact of restructuring on adoption is slightly larger in magnitude for solar and very similar for wind.

We use data from the National Renewable Energy Laboratory (NREL) to construct counterfactual electricity production under all possible technology choices. This measure is a function of site specific solar and wind resources. For each solar project, we construct a measure of total electricity production (GWh) for single-axis tracking and fixed tilt panels using PVWatts Version 6 from NREL. The algorithm uses solar resource data at the project site to calculate the total electricity produced over a single year under each technology (Dobos, 2014).[10] For wind, we use hourly data on wind speeds from NREL's

[9]We use turbine-level data from the American Clean Power Association to verify that most projects use only one turbine model.

[10]PVWatts uses the hourly Typical Month Year (TMY) data on solar radiation for the calculation. TMY data are derived from many years of data; they provide solar radiation and meteorological data that best represent the median condition for a "typical" year. PVWatts combines these solar resource data with the array type (fixed tilt/tracking), tilt angle, azimuth angle, and module type (standard, thin film, or premium) to predict annual energy production. We observe these panel characteristics in the EIA data.

Figure 2: Spatial distribution of Solar and Wind Projects



(a) Solar projects: 2010 - 2020

(b) Wind projects: 2001 - 2020

Notes: Solar projects $\geq$ 1 MW, wind projects $\geq$ 5 MW; restructured states highlighted in light blue.

Wind Integration National Dataset (WIND) Toolkit.[11] We combine these data with power curve data from The Wind Power to compute counterfactual annual energy production for each turbine model at each location.

To construct the revenue from different technologies, we combine our measure of counterfactual production with an estimate of the price the project would receive for its electricity. This estimate is based on the realized price the project received. We follow Aldy, Gerarden and Sweeney (2022) and construct this price at the project level using resale revenue and quantity data from the EIA Form 923, retail prices from Form 861M, and Renewable Energy Credit (REC) prices from S&P Global Market Intelligence and Lawrence Berkeley National Laboratory. Appendix C provides more detail. A key assumption is that the price the project receives does not depend on its technology choice.

About 550 projects (14 percent of projects) have missing information on tilt or azimuth angles. For these projects, we use the values suggested in the PVWatts manual (Dobos, 2014).

[11]The WIND Toolkit data includes meteorological conditions in the United States for the years 2007-2013 for 2 kilometers by 2 kilometers grid cells. It also includes data on wind direction, air pressure, and precipitation, but we do not use these in our calculation.

Our data on long term contracts for the wind power industry come from the American Clean Power Association (formerly the American Wind Power Association). These data are proprietary and at the wind project phase level. For wind projects with multiple phases, each phase generally corresponds to one generator in the EIA data. We match these data using the EIA plant code, operating date, project name, and location. We group traditional and virtual power purchase agreements into one indicator for signing a long term contract. For projects missing these data, we collect these data by hand from publicly available sources.

Finally, we construct control variables for land characteristics. These include county-level average farm size and farm value per acre from the USDA Agricultural Census for the years 2002, 2007, 2012, and 2017. We linearly interpolate these data to construct annual measures. We also construct a measure of terrain ruggedness using data from the National Elevation Database. Specifically, we calculate the standard deviation of terrain elevation within the 30m$\times$30m grid that contains the latitude and longitude for the project.

The samples we use in estimation drop projects with missing characteristics. We drop solar projects with missing data on either their choice of tracking or the variables we use to construct expected revenue (2.2 percent of projects, 1.3 percent of capacity). For wind, we first drop projects smaller than 5 MW. These small projects are much more likely to have missing characteristics and account for less than 1 percent of total capacity. Of the remaining projects, we drop those that are missing the power curve data we use to construct expected revenue (18 percent of projects, 20 percent of capacity).

Table 1 reports summary statistics for key variables for the solar and wind sectors. A striking difference is that solar projects are smaller than wind projects. The average capacity of a solar project is 11 MW whereas the average capacity of a wind project is 109 MW. A smaller proportion of solar projects are located in restructured states than wind projects: 0.33 vs. 0.41. Finally, 7 percent of solar projects are owned by utilities, compared to 16 percent of wind projects.

Table 1: Summary statistics

	Solar		Wind	
	Mean	Std. Dev.	Mean	Std. Dev.
Size (MW)	11.11	25.49	108.70	81.87
Restructured (0/1)	0.33	0.47	0.41	0.49
Utility (0/1)	0.08	0.26	0.16	0.37
Long-term contract (0/1)	-	-	0.70	0.46
Frontier technology (0/1)	0.37	0.48	0.12	0.33
Realized price ($/MWh)	103.72	50.94	49.30	29.39
Expected REC price ($/MWh)	5.60	11.22	4.39	8.24

Notes: Size is nameplate capacity. Restructured is an indicator for being located in a state with a restructured electricity market. Utility is an indicator for if the project is classified as a utility project in the EIA data. Long-term contract is an indicator for whether the project signed a power purchase agreement to sell its power. We restrict the sample to non-utilities (694 projects) for this statistic. Frontier technology is using tracking panels for solar; a new vintage turbine model for wind. Realized price is a measure of the price the project received for its power. Expected REC price is the average price for renewable electricity credits at the project's location. We use the sum of these prices as our price measure. Each observation is a solar or wind project in our sample. N=4,035 for solar; N=831 for wind.

4 Technology adoption in the solar power industry

4.1 A model of the choice to use axis-tracking panels

We estimate logit models of the probability of choosing tracking technology as a function of market structure, as well as expected revenue differences.

$$\Pr(tracking_i = 1) = \beta \cdot restructured_i + \alpha \cdot \Delta revenue_i + \gamma + \epsilon_i \tag{1}$$

where $tracking_i$ is an indicator for whether project i used tracking panels. $restructured_i$ is an indicator for whether project i is in a restructured state. $\Delta revenue$ is the difference in annual revenue between tracking and fixed tilt panels for a 5 MW project in the location of project i. We set the panel size to 5 MW across all projects rather than using actual size because size may be a bad control.[12] Because there are only two choices, including the difference in revenue corresponds to a utility function where revenue enters directly.[13].

Including revenue in the model allows us to condition on two important factors that affect this choice: solar resource quality and prices. The intensity and angle of solar irradiance affect the production benefits of tracking, while the value of this additional production depends on the price. We include operating year fixed effects (γ) to control for time shocks common to all the projects, namely the cost difference between the two panel types. The market for solar panels is global, with most panels produced in China (Gerarden, 2022), so we expect projects in different locations to face similar prices.

Our preferred specifications use a control function to address the endogeneity of revenue. We construct our revenue measure using project-specific realized prices. These prices are likely correlated with the error term; for example, a project with low financing costs may be more likely to use tracking and also willing to supply power at a lower price. To address this endogeneity, we use a control function approach.[14] We use a

[12]Appendix Table E5 shows our results are robust to controlling flexibly for project size.

[13]Let the utility of panel type j ($j = 0$ for fixed tilt and $j = 1$ for tracking) for a project be $U_j = \alpha R_j + \epsilon_j$, where R_j is the annual revenue from panel j. The probability of choosing tracking,

$$\Pr(tracking = 1) = Prob(U_1 > U_0) = Prob(\epsilon_0 - \epsilon_1 < \alpha(R_1 - R_0))$$

For a binary logit model this reduces to,

$$\Pr(tracking = 1) = \frac{1}{1 + e^{\alpha(R_1 - R_0)}} = \frac{1}{1 + e^{\alpha \Delta R}}$$

Equation 1 estimates the expression above, and includes an indicator for restructuring and operating year fixed effects (the coefficients of these variables are normalized to zero for $j = 0$) along with the revenue difference. The parameter α measures the marginal utility of revenue, $\partial U_j / \partial R_j = \alpha,\ j \in \{0, 1\}$

[14]Specifically, we regress the difference in revenues on the difference in production to recover the residuals ($\hat{\mu}_i$). We then estimate the logit regression with the predicted residuals ($\hat{\mu}_i$) as a control variable in the second step. The key assumption for the validity of this approach is that the errors in the first and the second step are uncorrelated (Train, 2009; Petrin and Train, 2010). Therefore, conditional on μ_i, $revenue_i$ is independent of ϵ_i in Equation 1.

control function rather than the instrumental variables estimator because the model is non-linear, but our approach is akin to instrumenting for revenue with production. Our measure of energy production from a solar panel depends only on resource quality at the project site.

After conditioning on price, restructuring is arguably exogenous. While restructuring was not randomly assigned, many of the factors that determined which states restructured in the late 1990s are unlikely to affect renewable energy developers' technology adoption decisions today. An exception is prices: states with the high retail electricity prices were more likely to restructure their electricity markets. These high prices usually resulted from expensive investments in nuclear power (Borenstein and Bushnell, 2000). Our main specifications control for price directly, alleviating this concern. Controlling for price affects our interpretation of the effect of market structure on adoption, something we return to in Section 6.

While restructuring was pre-determined, states that restructured are observably different than states that did not, and we control for likely confounders directly. Many of the states that restructured are coastal states. We include county-level farmland value to control for how these states likely have higher land prices. These states also tend to be northern states, and we control for the impact of latitude on the choice of tracking via our measure of expected production. Restructured states may also have more rugged terrain, and we control for ruggedness using a measure of elevation changes. Finally, restructured states may be more supportive of renewable energy and thus more likely to have renewable portfolio standards. These standards affect adoption via their effect on the price of renewable energy, which we control for by including expected REC prices in the revenue measure.

4.2 Results

Across all specifications, we find that being located in a restructured market decreases the probability of using tracking. Table 2 reports the marginal effects and their corresponding standard errors. From our preferred specification in Column (4), restructuring is associated with a statistically significant 9 percentage point decline in the probability of using axis-tracking panels. The mean probability of using tracking is 0.37, so this is a 24 percent decline. After we correct for the endogeneity of prices, an increase in the expected revenue from tracking (relative to no tracking) leads to a statistically significant increase in the probability it is adopted.

Table 2: Effect of market structure on choice to use tracking panels

	Uncorrected		Control Function	
	(1)	(2)	(3)	(4)
Restructured	-0.233***	-0.199***	-0.094***	-0.090***
	(0.014)	(0.015)	(0.018)	(0.018)
Δ Revenue ($100,000)	-0.017**	-0.014*	0.444***	0.373***
	(0.008)	(0.008)	(0.025)	(0.030)
Revenue Elasticity	-0.104	-0.0922	2.924	2.521
Observations	4,035	4,035	4,035	4,035
Year FE	✓	✓	✓	✓
Terrain Ruggedness		✓		✓
Farm Size & Value		✓		✓
Log Likelihood	-2427	-2297	-2228	-2179

Notes: Average marginal effects from logit model of tracking (0/1). Standard logit model in columns (1) and (2). Control function in columns (3) and (4). Sample is all solar projects at least 1 MW in size that began operation in 2010-2020. Δ Revenue is the difference in expected revenue from using tracking versus not. Restructured is if the project is located in a restructured state. Terrain ruggedness is the standard deviation of terrain elevation and its square. Farm Size & Value are county level average farm size and value per acre. Bootstrap standard errors with 1000 replications in parentheses for columns (3) and (4). Significance: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

We conduct several robustness checks. First, we address the concern that these results are driven by North Carolina. Despite not being particularly sunny, North Carolina is the state with the largest number of solar projects after California. Appendix Table E1 shows that our estimates of the negative impact of restructuring on adoption are even larger in magnitude when we control for being located in North Carolina. High solar investment in North Carolina was likely due to state-level policies incentivizing solar, one of which was favorable compensation for solar projects under the Public Utilities Regulatory Policies Act (PURPA).

To test whether our results are instead due to differences in how PURPA was implemented across states, we estimate the model separately for projects that do and do not qualify for PURPA (see Appendix Table E2). The negative impact of restructured on adoption is moderately larger for projects that qualify for PURPA, but this difference is not statistically significant.

Another concern is that larger, more established solar developers may be more likely to use tracking than smaller developers. This firm-level heterogeneity could bias our estimates if large developers are also more likely to develop projects in traditional markets. We observe the solar developer for a subset of larger projects, and results are quantitatively similar when we include an indicator for having a large developer (Appendix Table E3).

Finally, we show our results are not driven by utility projects. Most regulated utilities are subject to rate-of-return regulation, which gives them a financial incentive to choose capital-intensive technologies. Utilities account for only 8 percent of the solar projects in our sample, and we confirm that our results are not sensitive to including these projects (Appendix Table E4).

5 Technology adoption in the wind power industry

5.1 A model of wind turbine choice

We next estimate a model of wind turbine choice as a function of market structure. We do not observe the date a new turbine model is introduced or the date a wind developer signs the contract to purchase turbines. Instead, we assume a turbine model is available from a quarter ahead of the first quarter-year it appears in the data until 4 quarters past the last observed quarter-year. A project can choose a turbine if the project's operation date falls within the availability range of that turbine. Appendix Figure D3 shows how the number of models in the choice set varies over our sample. Because projects are choosing from more than two options, we use a conditional logit model rather than the logit model we used for the solar industry.

The utility from a given turbine model depends on its expected revenue less its cost, as well as whether it is new technology. We construct a site-specific measure of expected revenues for each turbine model. We do not observe turbine prices, so we instead use fixed effects to control for the cost of turbines. Like the market for solar panels, the market for wind turbines is global. The analogous specification to the one for solar would be to include turbine model by operating year fixed effects, but this is too demanding of the data. Instead, we proxy for cost using turbine model fixed effects and the age of the turbine. Because the price of turbines falls over time, including the turbine's age (years since it was introduced) captures some of the time-varying cost. We also allow this utility to depend on whether the turbine model is a technological advancement and its interaction with market structure.

The utility from turbine model j for project i is

$$U_{ij} = \beta \cdot new\ vintage_{ij} + \beta_m \cdot new\ vintage_{ij} \times restructured_i \qquad (2)$$
$$+ \alpha \cdot revenue_{ij} + X_{ij} + \delta_j + \epsilon_{ij}$$

where $new\ vintage_{ij}$ is an indicator for if turbine model j is at the technological frontier in the quarter that project i began operation. To allow the utility for choosing a frontier model to vary with market structure, we also include $new\ vintage_{ij} \times restructured_i$ where $restructured_i$ is an indicator for whether project i is located in a restructured electricity market. $revenue_{ij}$ is the expected annual revenue from one turbine of model j for project i and depends on the distribution of wind speed at project i's location. X_{ij} includes turbine model age and its square, as well as an indicator for whether the wind speed distribution at the location of project i lies outside turbine j's recommended range. Finally, δ_j are turbine model fixed effects.

Developers may have a dis-utility from adopting newer, untested turbines. This effect would result in a negative β, though this parameter is sensitive to our choice of when new turbine models appear in the choice set. Analogously to the solar industry, we allow the utility of adopting a new turbine model to differ across market types. For the wind industry, we also observe whether a project developer signs a long-term contract to sell the project's power, and we estimate specifications allowing a long term contract to affect the utility of a new turbine model.

As with the analysis of solar industry, we use a control function approach to account for the endogeneity of revenue. We include residuals from the regression of revenue on turbine production as the control function when we estimate the conditional logit specification in Equation 2.

5.2 Results

Table 3 reports estimates from the conditional logit model. As expected, the coefficient on annual revenue is positive and statistically significant. It is larger in magnitude when we use a control function. For our preferred specification in Column (6), our estimates imply that a one percent increase in revenue from a turbine increases its probability of adoption by 6.8 percent. This elasticity compares to a revenue elasticity of 2.5 for solar. More elastic demand is intuitive because there are many close substitutes for each wind turbine model, whereas there are only two choices for solar.

Table 3: Market structure and wind turbine choice

	Uncorrected			Control Function		
	(1)	(2)	(3)	(4)	(5)	(6)
New Vintage Turbine Model	-0.140	-0.530**	-0.470*	-0.172	-0.539**	-0.495*
	(0.187)	(0.232)	(0.252)	(0.205)	(0.250)	(0.266)
New Vintage × Restructured	-0.158		-0.138	-0.122		-0.098
	(0.230)		(0.231)	(0.263)		(0.255)
New Vintage × Long-term contract		0.503**	0.496**		0.489*	0.484*
		(0.242)	(0.242)		(0.276)	(0.260)
Revenue ($100,000)	0.384***	0.374***	0.373***	1.787***	1.771***	1.764***
	(0.075)	(0.075)	(0.075)	(0.414)	(0.426)	(0.412)
Revenue Elasticity	1.476	1.436	1.435	6.862	6.800	6.773
Observations	17,234	17,234	17,234	17,234	17,234	17,234
Turbine Model FE	✓	✓	✓	✓	✓	✓
Turbine age and age^2	✓	✓	✓	✓	✓	✓
Site/Turbine Class Mismatch	✓	✓	✓	✓	✓	✓
# Projects	831	831	831	831	831	831
# Turbine Models	51	51	51	51	51	51
Log Likelihood	-2189	-2187	-2187	-2182	-2180	-2180

Notes: Columns (1) - (3) show coefficient estimates from a conditional logit model uncorrected for revenue endogeneity. Columns (4) - (6) include residuals from an OLS regression of revenue on annual production as the control function in the conditional logit specification. Sample is all wind projects that began operation post 2001 with at least 5 MW in size. Revenue is the annual expected revenue from the turbine model, New Vintage specifies whether the chosen turbine is a frontier model, Restructured is a dummy variable for if the project is in a restructured state. Turbine age and age^2 control for the number of years since the turbine's introduction. Site/Turbine Class Mismatch is a binary variable for if there is a mismatch between site wind class and turbine wind class. Bootstrap standard errors with 1000 replications in parentheses for columns (4) - (6). Significance: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

Projects in restructured states are less likely to adopt new vintage turbines, but this effect is statistically indistinguishable from zero. Coefficient estimates in Columns (5) suggest that projects that sign long-term contracts are more likely to adopt new turbines. This effect is similar after conditioning on market structure (Column (6)). This effect of a long-term contract on adoption is statistically significant at the ten percent level. We do not interpret this estimate as causal because project developers select into signing long-term contracts, but a causal effect would be consistent with economic theory. Long-term contracts reduce financing costs, thereby increasing the returns to technology adoption.

Controlling for the type of firms building these projects yields similar estimates. We first address the concern that larger wind developers could be more likely to use frontier wind turbines than smaller developers and also more likely to build projects in one type of market. We re-estimate the model including the interaction between the new vintage turbine indicator and an indicator for a large developer. The resulting estimates are quantitatively similar (Appendix Table F6). We next confirm that results are similar if we exclude utility projects from the sample (Appendix Table F7).

6 Accounting for price effects

The previous sections estimated the effect of market structure on adoption *conditional* on output prices. Yet, market structure may also affect technology adoption via its effect on the market price. We next consider whether accounting for price effects would change our conclusions.

Higher prices in restructured markets could cause the total effect of restructuring on adoption to be positive. The evidence of the effect of restructuring on prices is inconclusive (Bushnell, Mansur and Novan, 2017), but MacKay and Mercadal (2021) find that restructuring caused prices to increase. Even if restructuring did not increase prices, we still might expect restructured states to have higher prices. States with higher prices were more likely to restructure, and some factors that led to relatively high prices in the 1990s, such as a lack of hydro power resources, should also lead to high prices today. In our data, we see that solar (but not wind) projects located in restructured markets receive higher prices on average.[15] The technologies we study increase production, so a higher market price increases the returns to adoption.

We next re-estimate models of the choice to use frontier technology without controlling for prices. We consider this a conservative test for whether accounting for price effects would change our conclusions. It is conservative because we do not expect the entire difference in prices across the market types to be caused by restructuring.

We still find a negative relationship between restructuring and technology adoption. Table 4 reports estimates from models that include expected production rather than revenue. Recall, our production variable only depends on wind and solar resource quality at the project location. We again find a statistically significant negative effect of restructuring on adoption for solar and a negative point estimate for this effect for wind. Thus, allowing for price effects would not change our conclusions.

7 Financing costs as a mechanism

We find that projects in more competitive markets are less likely to adopt frontier technology. This difference is not explained by differences in output prices across the two market types. This section provides descriptive evidence that it is instead due to differences in financing costs.

Because renewable energy financing is typically done at the project level, long-term contracts result in lower financing costs. These contracts are more common in traditional

[15] Unconditionally, the project-level prices in our data are higher in restructured states for solar but not for wind. Mean resale prices for solar are \$94.9/MWh in traditional markets vs. \$122/MWh in restructured markets. For wind, they are \$50.8/MWh in traditional markets vs. \$47.1/MWh in restructured markets. Expected REC prices follow the similar pattern. Mean REC prices for solar are \$1.8/MWh in traditional markets vs. \$13.4/MWh in restructured markets. For wind, mean REC prices are the similar across the two market types, about \$4/MWh in traditional markets vs. \$5/MWh in restructured markets.

Table 4: Relationship without conditioning on price

	Solar		Wind		
	(1)	(2)	(3)	(4)	(5)
Restructured	-0.128***	-0.110***			
	(0.017)	(0.017)			
Production (GWh)	0.309***	0.259***	0.584***	0.577***	0.575***
	(0.017)	(0.019)	(0.127)	(0.127)	(0.127)
New Vintage Turbine Model			-0.170	-0.584**	-0.529**
			(0.187)	(0.232)	(0.254)
New Vintage × Restructured			-0.157		-0.121
			(0.229)		(0.231)
New Vintage × Long-term contract				0.544**	0.535**
				(0.241)	(0.242)
Production Elasticity	1.751	1.525	4.347	4.295	4.279
Observations	4,035	4,035	17,234	17,234	17,234
Log Likelihood	-2285	-2214	-2192	-2189	-2189

Notes: Columns (1) and (2) show average marginal effects from a logit model of tracking (0/1). Sample is all solar projects at least 1 MW in size that began operation in 2010-2020. Column (1) controls for year fixed effects and Column (2) controls for year fixed effects, terrain ruggedness, and farm size and value. Columns (3) to (5) show coefficient estimates from a conditional logit model of wind turbine choice. Sample is all wind projects at least 5 MW in size that began operation in 2001-2020. All wind specifications control for turbine model fixed effects, turbine age and age^2, and site/turbine class mismatch. Significance: *** p<0.01, ** p<0.05, *** p<0.1.

markets: 83 percent of wind projects in traditional markets signed long-term contracts compared to 58 percent in restructured markets.[16] Yet, Table 3 shows that the negative point estimate for the effect of restructuring, while diminished, does not disappear when we control for signing a long-term contract. We next explore how other aspects of these contracts vary with market structure.

The two aspects we focus on are who the contract is with (utility vs. non-utility) and the length of the contract. We expect both contracts with utilities and contracts for longer

[16] To calculate this statistic, we limit our sample to non-utility projects (84 percent of projects). Regulated utilities are usually vertically integrated: the utility building the project is the same utility selling power to households. Thus, these projects have a reliable buyer for their power without needing to sign a long-term contract.

terms to be more secure, and thus result in lower financing costs for the project that signs them. A contract with a utility is more secure because regulated utilities are unlikely to go bankrupt and default on the contract. They are regulated natural monopolies that can pass costs through to a captive base of ratepayers. Similarly, contracts for longer terms have a longer period before the project is exposed to output price risk.

For both of these measures, contracts in traditional markets are more desirable. Column (1) of Table 5 shows that, of projects that sign long-term contracts, those in traditional markets are more likely to sign them with utilities. Similarly, in column (3) we find that long-term contracts in traditional markets tend to be for longer terms. Columns (2) and (4) show that these estimates are robust to controlling for project characteristics. This pattern is consistent with the way power is sold in traditional markets leading to lower financing costs for wind and solar developers.

Table 5: Regressions of power purchaser type and contract length on market structure

	Dependent variable:			
	Contract buyer: Utility (0/1)		Contract length (years)	
	(1)	(2)	(3)	(4)
Restructured	-0.222***	-0.212***	-3.086***	-2.894***
	(0.056)	(0.045)	(0.814)	(0.774)
Mean utility share	0.744	0.744		
Mean contract length (years)			19.69	19.69
Observations	597	597	364	364
R^2	0.205	0.259	0.135	0.174
Operating Year FE	✓	✓	✓	✓
Project Characteristics		✓		✓

Notes: Columns (1) and (2) are results of linear probability models with dependent variable as a dummy variable indicating whether the power purchaser is a utility. Columns (3) and (4) are regressions of contract length on market structure. Sample is all wind projects at least 5 MW in size that began operation in 2001-2020 and signed a long term contract. Projects with missing values for contract off taker (n=11) and contract length (n=247) are excluded. Project characteristics include capacity in MW, a turbine manufacturer fixed effect, and an indicator for whether the project developer is amongst the top five developers. Robust standard errors in parentheses, clustered by state. Significance: ***p<0.01;**p<0.05;*p< 0.1

8 Counterfactual adoption under different policies

To provide context for our estimates, we next quantify the implied differences in adoption timing and welfare under different levels of market competition. We focus on the solar industry where we more precisely estimate the relationship between market structure and adoption.[17]

We consider counterfactuals of full restructuring (all states are restructured) and no restructuring (all states are traditional). Note that these counterfactuals focus specifically on the technology choices; we do not endogenize developers' entry decisions or model the effect of restructuring on market prices. Recall that the logit analysis fixes the panel size at 5 MW. We assume constant returns to scale while scaling the results of the counterfactual analysis to the realized project size. Another assumption underlying this calculation is that project size in unaffected by either market structure or the choice to use tracking.

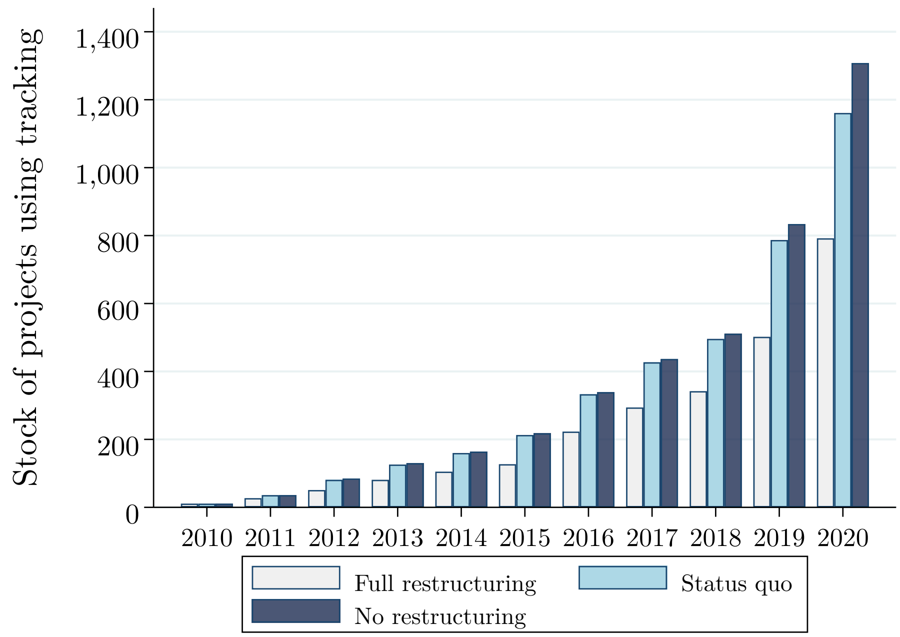
Compared to no restructuring, full restructuring slows down the adoption of tracking panels (Figure 3). We notice a diverging pattern in the stock of projects predicted to use tracking over time for the two counterfactuals. For example, 32 percent of solar projects in 2020 are predicted to use tracking when all states are traditional markets. In contrast, full restructuring would lead to just over 19 percent of projects using tracking in 2020.

8.1 Welfare effects

We next translate these estimates to changes in welfare under alternative policies. Our measure of welfare is solar developer producer surplus plus the value of avoided carbon dioxide emissions. We do not account for fossil fuel generator producer surplus or local emissions.

[17] Appendix G reports the analogous analysis for the wind industry.

Figure 3: Solar projects predicted to use tracking panels



Notes: This figure compares the predicted stock of projects using tracking technology under two counterfactual scenarios - Full restructuring, where all states are restructured, and No restructuring, where all states are traditional. For comparison, we also present the predicted stock of projects under the status quo of partial restructuring.

Producer surplus is the utility in dollar terms that a project developer receives from its technology choice from the available set of alternatives. We compute the change in surplus received by solar developers under a counterfactual policy (c) compared to the baseline (b). Under the assumption of i.i.d. type 1 extreme value errors, the change in surplus for solar project i is

$$\Delta S_i = \frac{1}{\alpha}\left[\ln\Big(\exp\left(\alpha\Delta revenue + \beta \cdot restructured^c + \gamma\right) + 1\Big) - \ln\Big(\exp\left(\alpha\Delta revenue + \beta \cdot restructured^b + \gamma\right) + 1\Big)\right] \quad (3)$$

where α is the marginal utility of revenue, Δrevenue is the difference in revenue from tracking versus a fixed tilt panel, and γ is the operating year fixed effect (Small and Rosen, 1981).

We find that all states restructuring would have reduced welfare by about 138 million dollars per year. Table 6 shows that, relative to the status quo, the loss in solar developer producer surplus from all states restructuring is \$91 million per year, while the gain from no restructuring is \$25 million per year. When tracking is adopted, increased electricity production from solar offsets electricity production from fossil fuel generators (under the assumption that project size is unaffected). Thus, adoption reduces greenhouse gas emissions. By reducing axis-tracking adoption, all states restructuring would have increased carbon emissions by 0.92 million metric tons per year at a social cost of \$47 million per year.[18]

Table 6: Change in producer surplus and avoided CO_2 under counterfactual policies

Counterfactual	Δ Surplus	Avoided CO_2	
	Million \$	MMT	Million \$
All states are restructured	−91.07	−0.92	−46.78
No states are restructured	25.58	0.11	5.91

Notes: Total change in solar developer producer surplus and avoided carbon emissions per year in real 2018 dollars. We use a Social Cost of Carbon of \$51/ton to convert the value of CO_2 in million metric tons (MMT) to million \$. A negative sign indicates a loss in producer surplus or an increase in emissions. Sample is all solar projects at least 1 MW in size that began operation in 2010-2020.

These simulations compare two steady states and abstract from the transition between them. The U.S. states that restructured did so well before our sample starts in 2010. If a state restructured its electricity market today, there would be a transition to the new market structure. We would expect uncertainty to be high during this transition, likely depressing investment and technology adoption. In this case, accounting for

[18]We estimate counterfactual production using the predicted probability of adoption from the logit model. We then use avoided emissions rate from EPA's AVERT (EPA, 2021) to compute the avoided CO_2. We use a Social Cost of Carbon of \$51/metric ton (US Interagency Working Group on Social Cost of Carbon, 2021) to calculate the dollar value of avoided carbon emissions.

the transition would reinforce our finding that another wave of states restructuring is unlikely to speed the adoption of low-carbon generation technologies.

9 Conclusion

Electricity markets are expected to decarbonize in response to global climate change. Regulatory policies can either slow or increase the speed of this transition to a low-carbon electricity grid. One such policy is restructuring, which introduces competition into electricity generation. In this paper, we study on how restructuring affects the probability renewable energy projects use frontier generation technologies. We find that renewable projects located in restructured markets are less likely to use these technologies and present evidence this result is due to higher financing costs in restructured markets.

While the welfare effects of slower adoption are modest for the technologies we study, the effects of slower adoption for all technologies may be much larger. We would expect larger effects if the mechanism of higher financing costs muting adoption generalizes to entirely new generating technologies. Electricity generation accounted for 32 percent of U.S. carbon emissions in 2021 (U.S. Energy Information Administration, 2022), so the aggregate external benefits from a faster transition could be substantial. A willingness to adopt new technology can also induce innovation by upstream manufacturers (Popp, 2019). This innovation is key to achieving climate goals because, absent it, developing countries are projected to have large increases in carbon emissions.

The results in this paper are informative about how competition affects innovation specifically; they do not address the question of how market structure affects overall investment. We take the level of investment in renewable energy as given and compare technology choices. While it may be interesting to study these decisions jointly, unobserved factors that affect entry are more likely to be correlated with market structure than factors that affect technology choice, and we leave this question to future work.

Instead, this paper contributes to the limited empirical evidence on the relationship between competition and technology adoption. Many new technologies require substantial upfront investments for benefits over a long time horizon. Their adoption is thus sensitive to financing costs. We consider one such example, and find that the overall effect of competition on adoption is negative.

References

Akers, Mick. 2018. “Nevada ballot questions: Voters reject breaking up NV Energy, pass Marsy’s Law.” *Las Vegas Sun*.

Aldy, Joseph E., Todd D. Gerarden, and Richard L. Sweeney. 2022. “Investment versus Output Subsidies: Implications of Alternative Incentives for Wind Energy.” Working Paper.

Arrow, Kenneth. 1962. “Economic welfare and the allocation of resources for invention.” In *The rate and direction of inventive activity: Economic and social factors*. 609–626. Princeton University Press.

Autor, David, Davod Dorn, Gordon H. Hanson, Gary Pisano, and Pian Shu. 2020. “Foreign Competition and Domestic Innovation: Evidence from US Patents.” *AER: Insights*, 2(3): 357–374.

AWEA. 2019. “Wind Powers America Annual Report 2019.” https://www.awea.org/resources/publications-and-reports/market-reports.

Bloom, Nicholas, Mirko Draca, and John Van Reenan. 2016. “Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity.” *Review of Economics Studies*, 83: 87–117.

Bolinger, Mark, Joachim Seel, and Kristina Hamachi LaCommare. 2017. “Utility-Scale Solar 2016: An Empirical Analysis of Project Cost, Performance, and Pricing Trends in the United States.” https://emp.lbl.gov/publications/utility-scale-solar-2016-empirical.

Borenstein, Severin, and James Bushnell. 2000. “Electricity Restructuring: Deregulation or Reregulation?” *Regulation*, 23(2): 46–52.

Bushnell, James, and Catherine Wolfram. 2005. "Ownership Change, Incentives and Plant Efficiency: The Divestiture of U.S. Electric Generation Plants." UC Berkeley: Center for the Study of Energy Markets.

Bushnell, James, Erin T. Mansur, and Kevin Novan. 2017. "Review of the Economics Literature on US Electricity Restructuring." Working Paper.

Bushong, Steven. 2015. "Why solar tracking is a key technology for unlocking the potential of utility-scale PV." *Solar Power World*.

Chan, Ron H., Harrison Fell, Ian Lange, and Shanjun Li. 2017. "Efficiency and environmental impacts of electricity restructuring on coal-fired power plants." *Journal of Environmental Economics and Management*, 81: 1–18.

Cicala, Steve. 2015. "When Does Regulation Distort Costs? Lessons from Fuel Procurement in US Electricity Generation." *American Economic Review*, 105(1): 411–444.

Cicala, Steve. 2022. "Restructuring the Rate Base." Working Paper.

Covert, Thomas R, and Richard L Sweeney. 2022. "Winds of Change: Estimating Learning by Doing without Cost or Input Data." Working paper.

Craig, J Dean, and Scott J Savage. 2013. "Market restructuring, competition and the efficiency of electricity generation: Plant-level evidence from the United States 1996 to 2006." *The Energy Journal*, 34(1).

Cusolito, Ana Paula, Alvavaro Garcia-Marin, and William F. Maloney. 2023. "Proximity to the Frontier, Markups, and the Response of Innovation to Foreign Competition: Evidence from Matched Production- Innovation Surveys in Chile." *American Economic Review*, 5(1): 3554.

Davis, Lucas W., and Catherine Wolfram. 2012. "Deregulation, Consolidation, and Efficiency: Evidence from US Nuclear Power." *American Economic Journal: Applied Economics 2012*, 4(4): 194–225.

Dobos, Aron P. 2014. "PVWatts Version 5 Manual." National Renewable Energy Lab.(NREL), Golden, CO (United States). https://www.nrel.gov/docs/fy14osti/62641.pdf.

EPA. 2021. "Avoided emissions and generation tool (AVERT)." U.S. Environmental Protection Agency (EPA) Office of Air and Radiation Climate Protection Partnerships Division, Washington D.C. Data retrieved from: https://www.epa.gov/avert/download-avert/.

Fabrizio, Kira R., Nancy L. Rose, and Catherine D. Wolfram. 2007. "Do Markets Reduce Costs? Assessing the Impact of Regulatory Restructuring on US Electric Generation Efficiency." *American Economic Review*, 97(4): 1250–1277.

FERC. n.d.. "PURPA Qualifying Facilities." https://www.ferc.gov/qf.

Fioretti, Michele, Alessandro Iaria, Aljoscha Janssen, Clément Mazet-Sonilhac, and Robert K. Perrons. 2022. "Innovation Begets Innovation and Concentration: The Case of Upstream Oil & Gas in the North Sea." Working Paper.

Fitzgerald, Timothy, and Michael Giberson. 2021. "Wind project performance with age: Policy, technology, markets, and the maturing wind power industry." *Electricity Journal*, 34(107047).

Fowlie, Meredith. 2010. "Emissions Trading, Electricity Industry Restructuring, and Investment in Pollution Control." *American Economic Review*, 100(3): 837–883.

Gerarden, Todd. 2022. "Demanding innovation: The impact of consumer subsidies on solar panel production costs." Working paper.

Gilbert, Richard. 2006. "Looking for Mr. Schumpeter: Where Are We in the Competition-Innovation Debate?" *Innovation Policy and the Economy*, 6: 159–215.

Goettler, Ronald L., and Brett R. Gordon. 2011. "Does AMD Spur Intel to Innovate More?" *Journal of Political Economy*, 119(6): 1141–1200.

Hausman, Catherine. 2014. "Corporate incentives and nuclear safety." *American Economic Journal: Economic Policy*, 6(3): 178–206.

Hill, Alexander. 2021. "Excessive entry and investment in deregulated markets: Evidence from the electricity sector." *Journal of Environmental Economics and Management*, 110(102543).

Igami, Mitsuru. 2017. "Estimating the Innovators Dilemma: Structural Analysis of Creative Destruction in the Hard Disk Drive Industry, 19811998." *Journal of Political Economy*, 125(3): 798–847.

Igami, Mitsuru, and Kosuke Uetake. 2020. "Mergers, Innovation, and Entry-Exit Dynamics: Consolidation of the Hard Disk Drive Industry, 19962016." *Review of Economic Studies*, 87: 2672–2702.

International Finance Corporation. 2015. "Utility-Scale Solar Photovoltaic Power Plants: A Project Developer's Guide." https://www.ifc.org/wps/wcm/connect/topics_ext_content/ifc_external_corporate_site/sustainability-at-ifc/publications/publications_utility-scale+solar+photovoltaic+power+plants.

Jha, Akshaya. 2022. "Regulatory Induced Risk Aversion in Coal Contracting at US Power Plants: Implications for Environmental Policy." *Journal of the Association of Environmental and Resource Economists*, 9(1): 51–78.

Johnston, Sarah. 2019. "Nonrefundable Tax Credits versus Grants: The Impact of Subsidy Form on the Effectiveness of Subsidies for Renewable Energy." *Journal for the Association of Environmental and Resource Economists*, 6(3): 433–460.

Kang, Hyo. 2023. "How Does Price Competition Affect Innovation? Evidence from US Antitrust Cases." Working Paper.

Kiewit. n.d.. "Fixed-Tilt vs. Axis Tracker Solar Panels." *KED Plant Insider*. https://www.kiewit.com/plant-insider/current-issue/fixed-tilt-vs-axis-tracker-solar-panels/.

Kleit, Andrew N., and Kenneth Rose. 2016. "Is It Time to Deregulate All Electric Utilities?" *The Wall Street Journal*. https://www.wsj.com/articles/is-it-time-to-deregulate-all-electric-utilities-1479092461.

Macher, Jeffrey T, Nathan H Miller, and Matthew Osborne. 2021. "Finding Mr. Schumpeter: technology adoption in the cement industry." *The RAND Journal of Economics*, 52(1): 78–99.

MacKay, Alexander, and Ignacia Mercadal. 2021. "Deregulation, Market Power, and Prices: Evidence from the Electricity Sector." Working Paper.

National Regulatory Research Institute. n.d.. "PURPA Tracker." https://www.naruc.org/nrri/nrri-activities/purpa-tracker/.

Petrin, Amil, and Kenneth Train. 2010. "A control function approach to endogeneity in consumer choice models." *Journal of Marketing Research*, 47(1): 3–13.

Popp, David. 2019. "Environmental policy and innovation: a decade of research." National Bureau of Economic Research Working Paper No. 25631.

Rocky Mountain Institute. 2015. "5 Reasons for North Carolina's Rapid Emergence as a Solar Energy Leader."

Schumpeter, Joseph A. 1934. *The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle.* Cambridge, MA:Harvard University Press.

Schumpeter, Joseph A. 1942. *Capitalism, Socialism, and Democracy.* Harper & Brothers.

Small, Kenneth A, and Harvey S Rosen. 1981. "Applied welfare economics with discrete choice models." *Econometrica*, 49(1): 105–130.

Snyder, Riley, and Michelle Rindels. 2018. "Voters reject energy choice ballot question, as other initiatives advance on comfortable margins." *The Nevada Independent*.

Train, Kenneth E. 2009. *Discrete choice methods with simulation.* Cambridge university press.

U.S. Energy Information Administration. 2017. "More than half of utility-scale solar photovoltaic systems track the sun through the day." https://www.eia.gov/todayinenergy/detail.php?id=30912.

U.S. Energy Information Administration. 2022. "Monthly Energy Review, December 2022." https://www.eia.gov/totalenergy/data/monthly/pdf/mer.pdf.

US Interagency Working Group on Social Cost of Carbon. 2021. "Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide: Interim Estimates under Executive Order 13990." American Council for an Energy Efficient Economy, Washington, DC.

Wincher, David. 2018. "State regulators revisit allowing customers to choose competitive power providers." *Arizona Daily Star*.

Windustry. 2007. "Community Wind Toolbox Chapter 15: Turbine Selection and Purchase." http://www.windustry.org/community_wind_toolbox_15_turbine_selection_and_purchase.

Appendix

A Additional detail on the sample of solar projects

The sample for the solar analysis includes 4,035 projects, 37 percent of which have tracking technology. The size distribution is positively skewed: 75 percent of projects are less than or equal to 5 MW, and a few projects are over 100 MW. Larger projects are more likely to use tracking. About 28 percent of projects less than or equal to 5 MW in size use tracking compared to 52 percent for projects over 5 MW.

Many solar projects are located in the Southwest (27 percent) and Southeast (25 percent) where the solar resource quality is highest. Yet, 24 percent of projects in our sample are located in the Northeast. The use of axis-tracking is more common in the Southwest because the benefits of tracking are highest in areas with few clouds. Two states account for a large share of the solar projects in our sample: California, with 17 percent, and North Carolina, with 16 percent. North Carolina is a large outlier relative to its size and solar resource quality. In addition to favorable rates under PURPA, North Carolina had a renewable portfolio standard with a solar-specific target and a 35 percent state renewable energy tax credit (Rocky Mountain Institute, 2015).

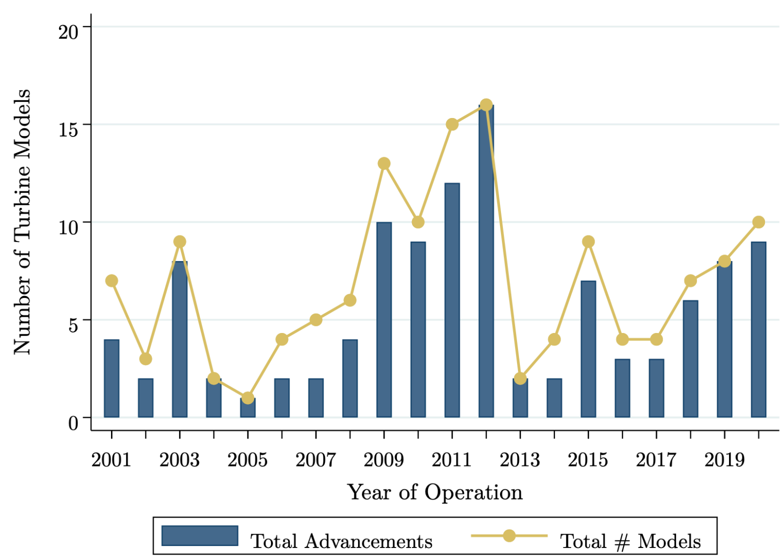
B Wind turbine advancement classification algorithm

The following example illustrates our algorithm for classifying a turbine model as a technological advancement. Consider the Gamesa G97-2.0 turbine model, which has a rotor diameter of 97 meters and a turbine rating of 2.0 MW. It first appears in our data in the fourth quarter of 2011. We classify it as a technological advancement because, with a rotor diameter of 97 meters, its rotor diameter is more than 5 meters larger than

Gamesa's largest existing turbine model within the 2.0 rating group (G90-2.0), which has a rotor diameter of 90 meters.

We run this algorithm for all 137 turbine models in our data from 2001 through 2020. We classify 110 models as technological advancements. Figure B1 plots the total number of turbine models that were advancements from 2001-2020. At least one new turbine model is classified as a technological advancement in each year.

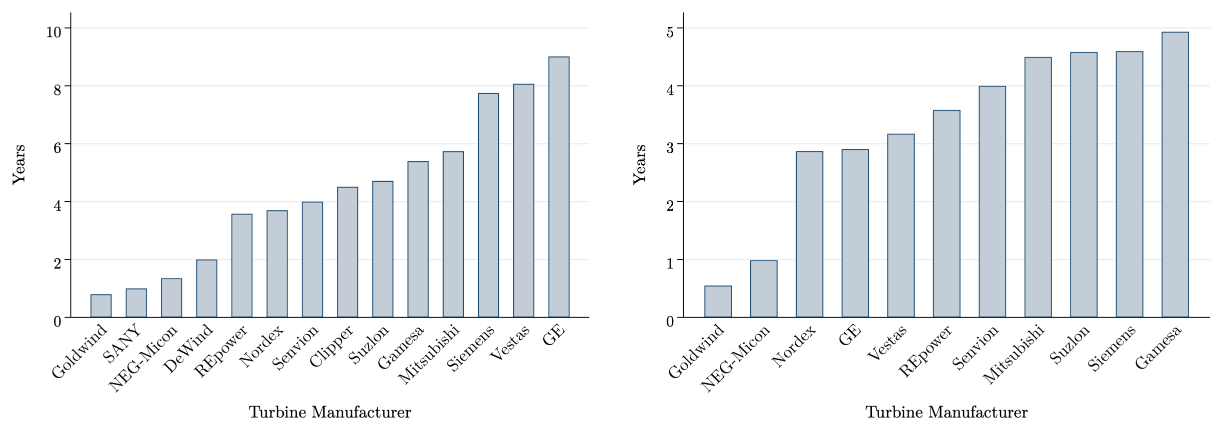
Figure B1: Introduction of new turbine models over time by wind manufacturers



Notes: Vertical bar denotes the total number of turbine models identified as technological advancements by our algorithm. Yellow line denotes the total number of turbine models introduced in a year. We restrict to turbine models that are used in at least 3 projects.

To explore how usage differs between advancements and non-advancements, we look at the average duration of models by manufacturer for each group. We define duration as the number of years a turbine model appears in our data. Specifically, it is the time between the quarter of operation for the first project using that model and the quarter of operation for the last project using that model. Figure B2 shows that models that are technological advancements tend to have shorter durations.

Figure B2: Average duration of turbine models (years) for different manufacturers



(a) Not Advancements

(b) Advancements

Notes: We restrict to turbine models that are used in at least 3 projects for both panels (a). and (b). Advancements refers to turbine models classified as technological advancements.

C Constructing project specific prices

As discussed in Section 3, we construct project specific prices from resale data from EIA Form 923, retail prices from EIA Form 861M, and Renewable Energy Credit (REC) price data from S&P Global Market Intelligence and the Lawrence Berkeley National Laboratory.

We first compute an average price for each project. Our primary data source is resale price data from the EIA. These data are called resale because they are the revenue from the sale of electricity to a purchasing entity which then resells it to end-use consumers. The EIA began collecting these plant-level data in 2011. For each year, we divide annual resale revenue by resale quantity to get an average price. We then take the median of these prices across years the project was in operation and adjust it to 2018 dollars. We assign the ISO level average for the projects with missing resale prices.

Some projects also report retail sales in addition to sales for resale. For these projects, we follow Aldy, Gerarden and Sweeney (2022) and use a weighted average of the resale price and the retail price, where the weight on the resale price is the fraction of sales for resale (mean 0.79 for solar, 0.98 for wind). Our measure of the retail price is the state level annual average retail price from EIA Form 861M.

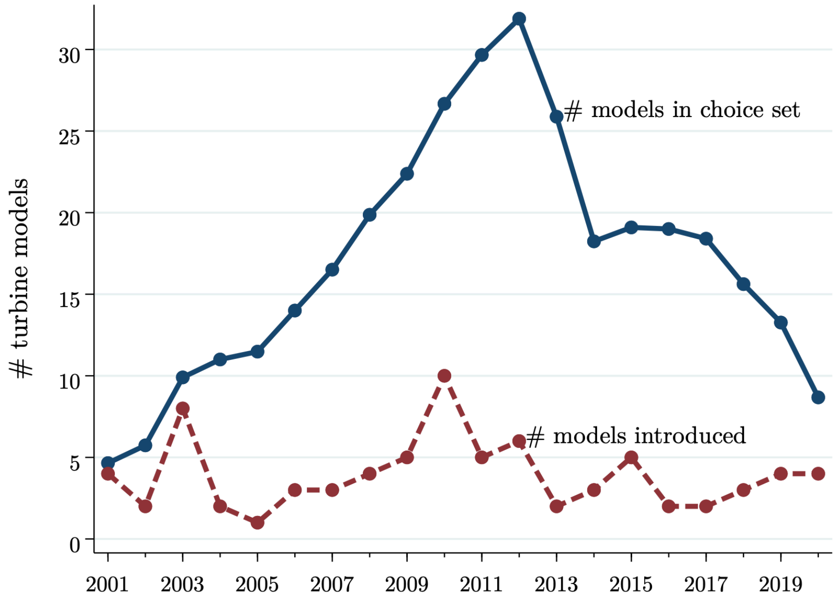
Next, we account for marginal revenue from sales of Renewable Energy Credits (RECs). Many states have Renewable Portfolio Standards (RPS) which require firms that retail electricity to procure a set amount of electricity from renewable sources. To operationalize this policy, states require these firms to retire RECs each year. Solar and wind projects generate a REC for each unit of production, and can sell these RECs to firms subject to the RPS. We combine state level REC prices from Lawrence Berkeley National Laboratory and S&P Global Market Intelligence. Because some states allow non-renewable entities to obtain RECs from qualifying renewable generators outside the state, we combine the REC prices with cross-state REC compliance data from Lawrence

Berkeley National Laboratory. Finally, we add these expected REC prices to the project-level prices.

This procedure largely follows the one used in Aldy, Gerarden and Sweeney (2022) to construct project-level prices for wind projects. There are two key differences. First, their measure of the output price is the maximum of prices derived from resale data from the EIA and PPA prices from the American Wind Energy Association and Bloomberg New Energy Finance. Second, they use REC data from Marex Spectron, whereas we use REC data from S&P Global Market Intelligence.

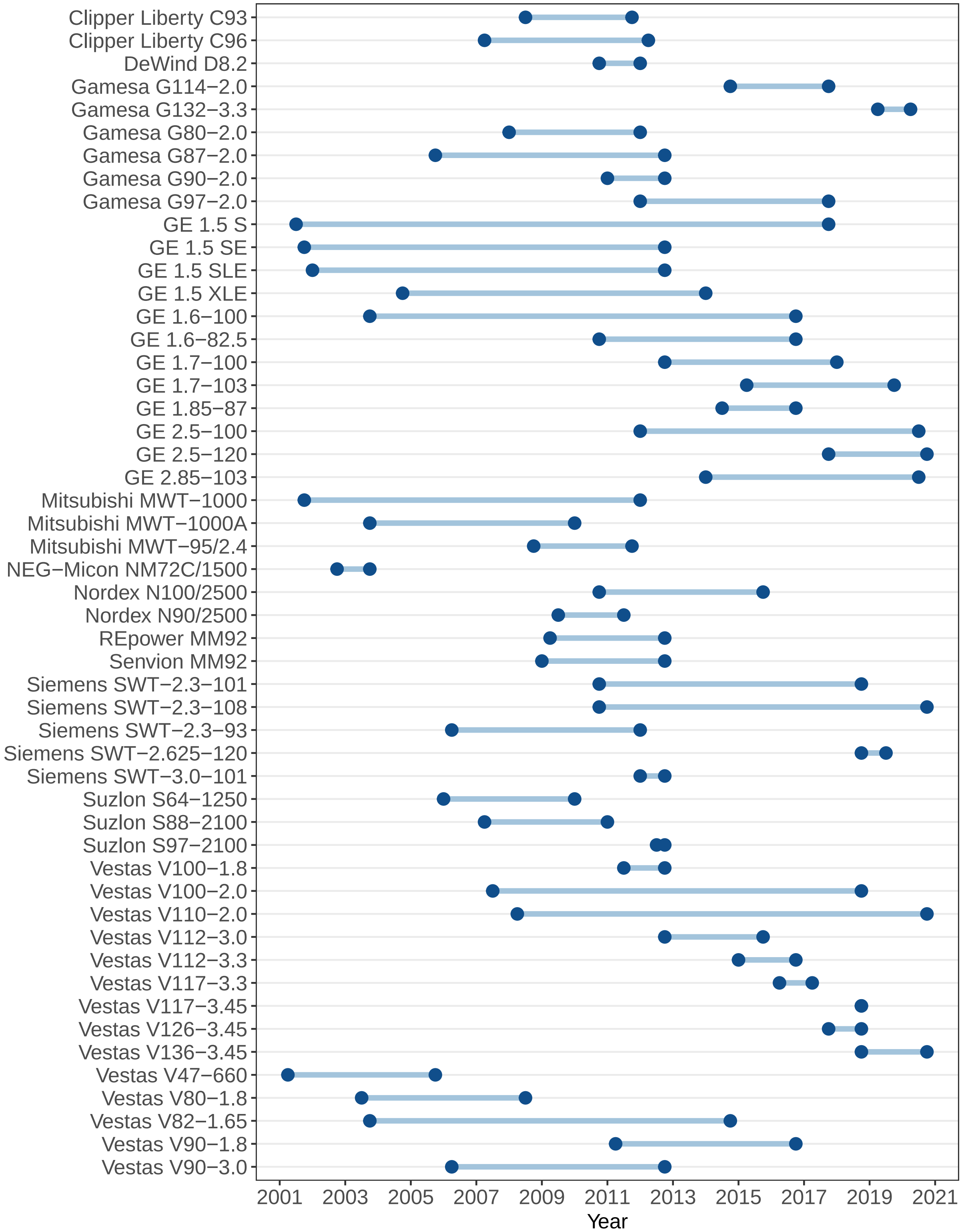
D Supplementary Figures

Figure D3: Wind turbine introduction and choice set



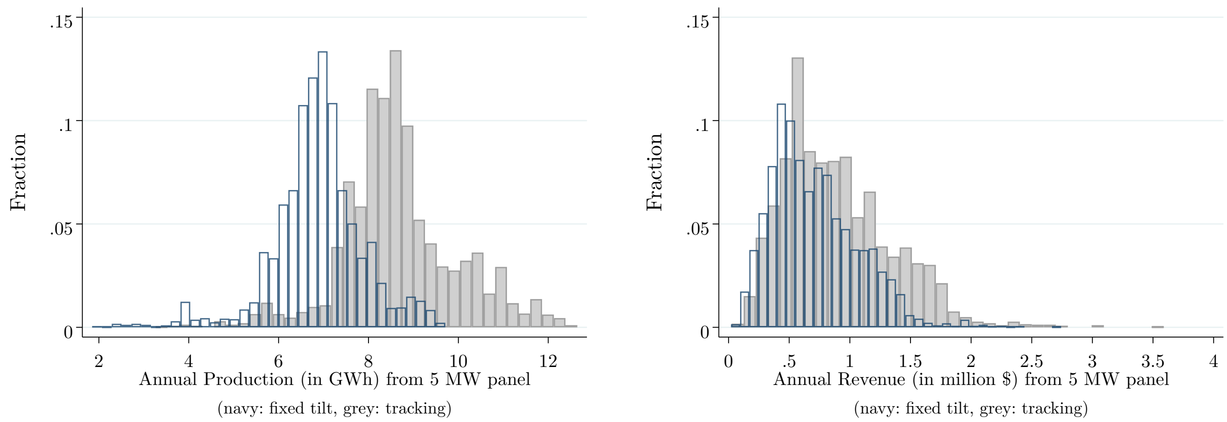
Notes: Solid blue line denotes the number of turbine models in project choice set averaged over the months in a year. Dashed red line denotes the total number of turbine models introduced in a year.

Figure D4: Observed duration for each wind turbine model



Notes: Ranges constructed based on the earliest and latest operating year (in our data) of projects using the turbine model.

Figure D5: Annual energy production and revenue for solar projects

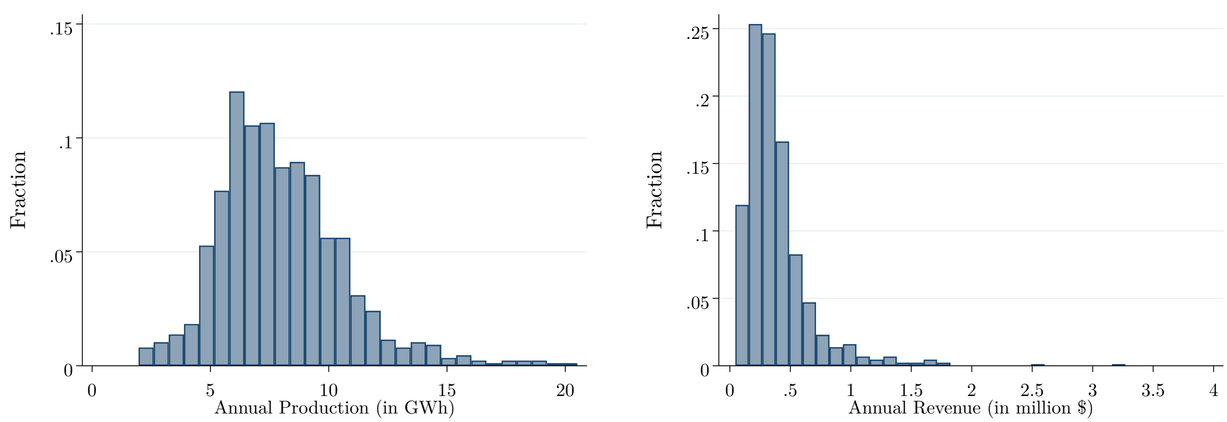


(a) Annual energy production (GWh)

(b) Annual revenue (million $)

Notes: Annual energy production (in GWh) and revenue (million $) from a 5 MW fixed tilt and tracking panel for all U.S. solar projects at least 1 MW in size that began operation in 2010-2020.

Figure D6: Annual energy production and revenue for wind projects

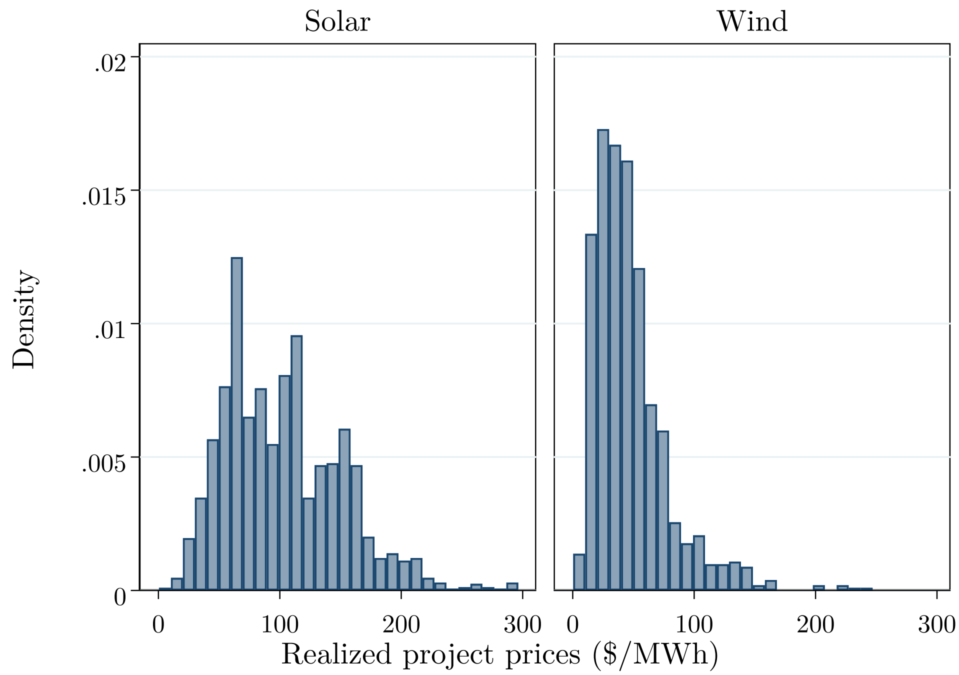


(a) Annual energy production (GWh)

(b) Annual revenue (million $)

Notes: Annual energy production (in GWh) and revenue (million $) from the predominant turbine used for all U.S. wind projects at least 5 MW in size that began operation in 2001-2020.

Figure D7: Histogram of realized prices for wind and solar projects



Notes: Sample is all solar projects at least 1 MW in size that began operation in 2010 - 2020, and all wind projects of at least 5 MW in size that began operation in 2001-2020.

E Robustness checks for solar results

E.1 Results controlling for projects in North Carolina

Table E1: Logit regression of tracking on market structure

	Uncorrected		Control Function	
	(1)	(2)	(3)	(4)
Restructured	-0.255***	-0.218***	-0.123***	-0.114***
	(0.014)	(0.015)	(0.017)	(0.019)
North Carolina	-0.322***	-0.291***	-0.268***	-0.259***
	(0.017)	(0.019)	(0.025)	(0.024)
Δ Revenue ($100,000)	-0.053***	-0.045***	0.370***	0.311***
	(0.009)	(0.009)	(0.026)	(0.029)
Revenue Elasticity	-0.335	-0.298	2.494	2.151
Observations	4,035	4,035	4,035	4,035
Year FE	✓	✓	✓	✓
Terrain Ruggedness		✓		✓
Farm Size & Value		✓		✓
Log Likelihood	-2354	-2241	-2186	-2139

Notes: Average marginal effects from logit model of tracking (0/1). Standard logit model in columns (1) and (2). Control function in columns (3) and (4). Sample is all solar projects at least 1 MW in size that began operation in 2010-2020, excluding utilities. Δ Revenue is the difference in expected revenue from using tracking versus not. Restructured is if the project is located in a restructured state. North Carolina is an indicator for projects in North Carolina. Terrain ruggedness is the standard deviation of terrain elevation and its square. Farm Size & Value are county level average farm size and value per acre. Bootstrap standard errors with 1000 replications in parentheses for columns (3) and (4). Significance: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

E.2 Results by projects qualifying for PURPA rates

Table E2: Logit regression of tracking on market structure

	Uncorrected		Control Function	
Sample	Not QF	QF	Not QF	QF
	(1)	(2)	(3)	(4)
Restructured	-0.179***	-0.236***	-0.047*	-0.160***
	(0.022)	(0.020)	(0.027)	(0.025)
Δ Revenue (\$100,000)	-0.059***	0.022*	0.419***	0.365***
	(0.012)	(0.012)	(0.043)	(0.048)
Revenue Elasticity	-0.375	0.153	3.137	2.331
Observations	2,053	1,962	2,053	1,962
Year FE	✓	✓	✓	✓
Terrain Ruggedness	✓	✓	✓	✓
Farm Size & Value	✓	✓	✓	✓
Log Likelihood	-1179	-1040	-1104	-999

Notes: Average marginal effects from logit model of tracking (0/1). Standard logit model in columns (1) and (2). Control function in columns (3) and (4). Columns (2) and (4) restricts sample to projects that qualify under PURPA and Columns (1) and (3) restricts sample to projects that do not qualify under PURPA. Sample is all solar projects at least 1 MW in size that began operation in 2010-2020. We do not observe qualifying facility status for 20 projects. Δ Revenue is the difference in expected revenue from using tracking versus not. Restructured is if the project is located in a restructured state. Terrain ruggedness is the standard deviation of terrain elevation and its square. Farm Size & Value are county level average farm size and value per acre. Bootstrap standard errors with 1000 replications in parentheses for columns (3) and (4). Significance: *** p<0.01, ** p<0.05, *** p<0.1.

E.3 Results controlling for developer size

Table E3: Logit regression of tracking on market structure

	Uncorrected		Control Function	
	(1)	(2)	(3)	(4)
Restructured	-0.224***	-0.194***	-0.094***	-0.090***
	(0.015)	(0.015)	(0.017)	(0.018)
Large Developer	0.105***	0.066***	-0.003	-0.010
	(0.024)	(0.023)	(0.021)	(0.022)
Δ Revenue ($100,000)	-0.014*	-0.013	0.445***	0.376***
	(0.008)	(0.008)	(0.027)	(0.029)
Revenue Elasticity	-0.0867	-0.0817	2.929	2.537
Observations	4,035	4,035	4,035	4,035
Year FE	✓	✓	✓	✓
Terrain Ruggedness		✓		✓
Farm Size & Value		✓		✓
Log Likelihood	-2417	-2293	-2228	-2179

Notes: Average marginal effects from logit model of tracking (0/1). Standard logit model in columns (1) and (2). Control function in columns (3) and (4). Sample is all solar projects at least 1 MW in size that began operation in 2010-2020. Δ Revenue is the difference in expected revenue from using tracking versus not. Restructured is if the project is located in a restructured state. Terrain ruggedness is the standard deviation of terrain elevation and its square. Farm Size & Value are county level average farm size and value per acre. Large Developer is an indicator for projects built by one of the larger solar developers. We the classify following developers as large developers: Strata Solar, First Solar, Cypress Creek Renewables, NextEra Energy Resources, SunPower, Sempra Energy, Recurrent Energy, and SunEdison. These data were hand collected for projects over 5 MW that began operation from 2010-2019, and we only observe developers for 30 percent of the projects in our data. Out of these, 36 percent are developed by a large developer. Bootstrap standard errors with 1000 replications in parentheses for columns (3) and (4). Significance: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

E.4 Results excluding utilities

Table E4: Logit regression of tracking on market structure

	Uncorrected		Control Function	
	(1)	(2)	(3)	(4)
Restructured	-0.230***	-0.189***	-0.084***	-0.080***
	(0.015)	(0.016)	(0.018)	(0.019)
Δ Revenue ($100,000)	-0.018**	-0.015*	0.466***	0.379***
	(0.009)	(0.008)	(0.025)	(0.030)
Revenue Elasticity	-0.107	-0.0969	3.106	2.603
Observations	3,731	3,731	3,731	3,731
Year FE	✓	✓	✓	✓
Terrain Ruggedness		✓		✓
Farm Size & Value		✓		✓
Log Likelihood	-2250	-2108	-2049	-1995

Notes: Average marginal effects from logit model of tracking (0/1). Standard logit model in columns (1) and (2). Control function in columns (3) and (4). Sample is all solar projects, excluding utilities that began operation in 2010-2020 with at least 1 MW in size. Δ Revenue is the difference in expected revenue from using tracking versus not. Restructured is if the project is located in a restructured state. Terrain ruggedness is the standard deviation of terrain elevation and its square. Farm Size & Value are county level average farm size and value per acre. Bootstrap standard errors with 1000 replications in parentheses for columns (3) and (4). Significance: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

E.5 Results controlling for project size

Table E5: Logit regression of tracking on market structure

	Uncorrected		Control Function	
	(1)	(2)	(3)	(4)
Restructured	-0.185***	-0.161***	-0.100***	-0.091***
	(0.015)	(0.015)	(0.017)	(0.018)
Δ Revenue ($100,000)	0.002	0.001	0.311***	0.266***
	(0.008)	(0.008)	(0.027)	(0.029)
Revenue Elasticity	0.0121	0.00712	2.189	1.906
Observations	4,035	4,035	4,035	4,035
Nameplate Capacity	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Terrain Ruggedness		✓		✓
Farm Size & Value		✓		✓
Log Likelihood	-2199	-2133	-2116	-2080

Notes: Average marginal effects from logit model of tracking (0/1). Standard logit model in columns (1) and (2). Control function in columns (3) and (4). Sample is all solar projects at least 1 MW in size that began operation in 2010-2020. Δ Revenue is the difference in expected revenue from using tracking versus not. Restructured is if the project is located in a restructured state. Terrain ruggedness is the standard deviation of terrain elevation and its square. Farm Size & Value are county level average farm size and value per acre. All specifications control for project nameplate capacity using a linear spine with knots at 5, 10, 15, 20, and 25 MW. Bootstrap standard errors with 1000 replications in parentheses for columns (3) and (4). Significance: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

F Robustness checks for wind results

F.1 Results controlling for developer size

Table F6: Market structure and wind turbine choice

	Uncorrected			Control Function		
	(1)	(2)	(3)	(4)	(5)	(6)
New Vintage Turbine Model	-0.115	-0.495**	-0.429*	-0.150	-0.506*	-0.457
	(0.206)	(0.239)	(0.259)	(0.208)	(0.264)	(0.288)
New Vintage × Restructured	-0.162		-0.148	-0.126		-0.107
	(0.230)		(0.232)	(0.249)		(0.244)
New Vintage × Long-term Contract		0.528**	0.523**		0.512*	0.507*
		(0.245)	(0.246)		(0.266)	(0.271)
New Vintage × Large Developer	-0.068	-0.149	-0.158	-0.059	-0.136	-0.143
	(0.239)	(0.243)	(0.243)	(0.249)	(0.253)	(0.264)
Revenue ($100,000)	0.383***	0.372***	0.371***	1.785***	1.766***	1.759***
	(0.075)	(0.075)	(0.075)	(0.401)	(0.435)	(0.433)
Revenue Elasticity	1.473	1.428	1.427	6.864	6.784	6.761
Observations	17,234	17,234	17,234	17,234	17,234	17,234
Turbine Model FE	✓	✓	✓	✓	✓	✓
Turbine age and age^2	✓	✓	✓	✓	✓	✓
Site/Turbine Class Mismatch	✓	✓	✓	✓	✓	✓
# Projects	831	831	831	831	831	831
# Turbine Models	51	51	51	51	51	51
Log Likelihood	-2189	-2187	-2186	-2182	-2180	-2180

Notes: Columns (1) - (3) show coefficient estimates from a conditional logit model uncorrected for revenue endogeneity. Columns (4) - (6) include residuals from an OLS regression of revenue on annual production as the control function in the conditional logit specification. Sample is all wind projects that began operation post 2001 with at least 5 MW in size. Revenue is the annual expected revenue from the turbine model, New Vintage specifies whether the chosen turbine is a frontier model, Restructured is a dummy variable for if the project is in a restructured state. Large Developer is an indicator for projects built by one of the larger developers. We classify following developers as large developers: NextEra Energy Resources, Avangrid Renewables, Invenergy LLC, EDP Renewables North America LLC, and EDF Renewables. These developers account for 30 percent of the wind projects in our data. Turbine age and age^2 control for the number of years since the turbine's introduction. Site/Turbine Class Mismatch is a binary variable for if there is a mismatch between site wind class and turbine wind class. Bootstrap standard errors with 1000 replications in parentheses for columns (4) - (6). Significance: *** p<0.01, ** p<0.05, *** p<0.1.

F.2 Results excluding utilities

Table F7: Market structure and wind turbine choice

	Uncorrected			Control Function		
	(1)	(2)	(3)	(4)	(5)	(6)
New Vintage Turbine Model	-0.222	-0.896***	-0.856**	-0.267	-0.926***	-0.920**
	(0.209)	(0.313)	(0.350)	(0.215)	(0.342)	(0.393)
New Vintage × Restructured	-0.186		-0.066	-0.137		-0.009
	(0.251)		(0.256)	(0.272)		(0.277)
New Vintage × Long-term contract		0.771**	0.757**		0.780**	0.777**
		(0.319)	(0.324)		(0.349)	(0.367)
Revenue ($100,000)	0.483***	0.467***	0.467***	2.064***	2.064***	2.064***
	(0.082)	(0.082)	(0.082)	(0.466)	(0.456)	(0.475)
Revenue Elasticity	1.854	1.793	1.794	7.808	7.808	7.806
Observations	14,401	14,401	14,401	14,401	14,401	14,401
Turbine Model FE	✓	✓	✓	✓	✓	✓
Turbine age and age^2	✓	✓	✓	✓	✓	✓
Site/Turbine Class Mismatch	✓	✓	✓	✓	✓	✓
# Projects	694	694	694	694	694	694
# Turbine Models	51	51	51	51	51	51
Log Likelihood	-1824	-1821	-1821	-1817	-1814	-1814

Notes: Columns (1) - (3) show coefficient estimates from a conditional logit model uncorrected for revenue endogeneity. Columns (4) - (6) include residuals from an OLS regression of revenue on annual production as the control function in the conditional logit specification. Sample is all wind projects, excluding utilities that began operation post 2001 with at least 5 MW in size. Revenue is the annual expected revenue from the turbine model, New Vintage specifies whether the chosen turbine is a frontier model, Restructured is a dummy variable for if the project is in a restructured state. Turbine age and age^2 control for the number of years since the turbine's introduction. Site/Turbine Class Mismatch is a binary variable for if there is a mismatch between site wind class and turbine wind class. Bootstrap standard errors with 1000 replications in parentheses for columns (4) - (6). Significance: *** p<0.01, ** p<0.05, *** p<0.1.

G Counterfactual adoption under different policies for the wind industry

We use the estimates from Column (6) of Table 3 to simulate the following counterfactuals for the wind industry, (i). full restructuring (all states are restructured), (ii). no restructuring (no states are restructured)(iii). all projects use long-term contracts (PPA). We include this last counterfactual for comparison; it does not correspond to a specific policy.

?? shows the percentage change in probability of adoption of old and new vintage turbine models. In contrast to the solar industry, varying extents of restructuring does not affect the rate of technology adoption in wind projects by much. Panel 3 shows that the rate of technology adoption on average increases by 22 percent when all projects use long-term contracts to sell their power. We also see a decline by about 2 percent in the usage of older models under this scenario.

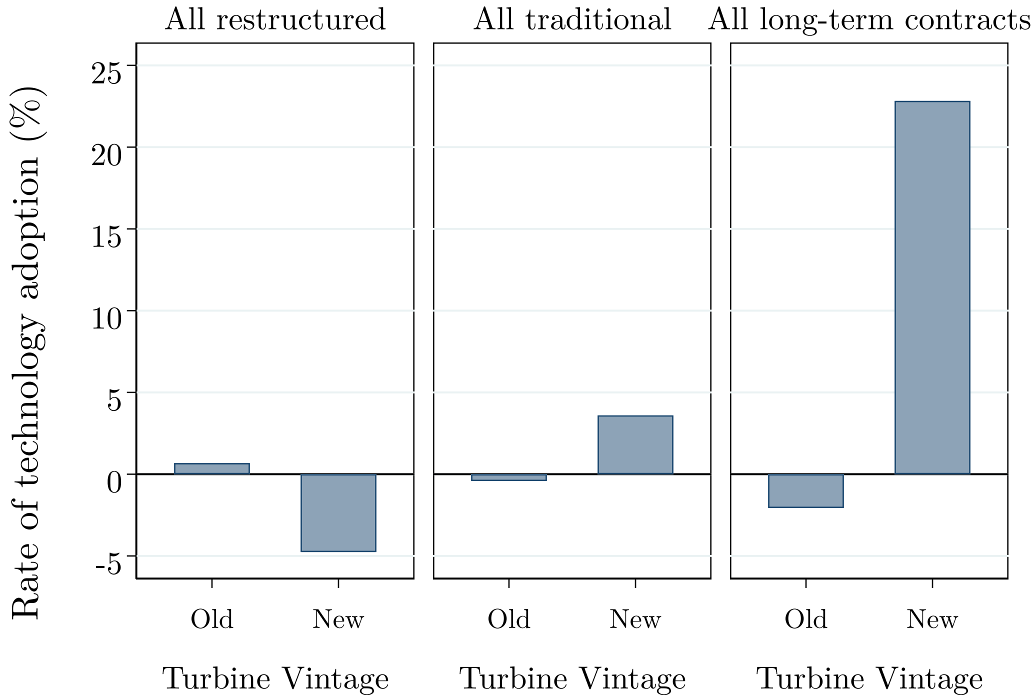
G.1 Welfare effects

We compute the welfare from technology adoption under the three counterfactual scenarios for the wind industry. Under the assumption of iid type 1 extreme value errors and linear utility, the change in surplus for a wind project i from a policy counterfactual (c) compared to the baseline (b) is given by (Small and Rosen, 1981):

$$\Delta S_i = \frac{1}{\alpha}\left[\ln\left(\sum_{j=1}^{J}\exp\left(\delta_j + \alpha R_{ij} + \beta_{ij}^{c}\right)\right) - \ln\left(\sum_{j=1}^{J}\exp\left(\delta_j + \alpha R_{ij} + \beta_{ij}^{b}\right)\right)\right] \tag{4}$$

where, α is the marginal utility of revenue, δ_j is the turbine model fixed effect, R_{ij} is the revenue from turbine model j, and β_{ij} is the parameter for restructuring. The total change in surplus is $\sum_i n_i \Delta S_i$, where n_i is the number of turbines in project i.

Figure G8: Rate of technology adoption in the wind industry



Notes: This figure shows the percentage change in probability of adoption $(p_2/p_1 - 1)$ of old and new vintage turbines under three counterfactual scenarios - All restructured, where all states are restructured, All traditional, where all states are traditional, and All long-term contracts, where all projects use long-term contracts to sell power.

Table G8 shows the change surplus and emissions avoided in each counterfactual. We also include the results for the solar industry for reference. Relative to the status quo, all states restructuring would decrease wind industry producer surplus by \$15 million per year. It would also lead to an annual increase in carbon emissions of 0.29 MMT at a social cost of \$15 million.

Table G8: Counterfactual changes in surplus and avoided CO_2

	Counterfactual	Δ Surplus	Avoided CO_2	
		Million \$	MMT	Million \$
A.	Solar Industry			
1.	All states are restructured	−91.07	−0.92	−46.78
2.	No states are restructured	25.58	0.11	5.91
B.	Wind Industry			
1.	All states are restructured	−19.48	−0.37	−18.77
2.	No states are restructured	14.77	0.29	14.77
3.	All projects use long-term contracts	59.60	1.23	62.76

Notes: Panel A. and B. show the total change in producer surplus and avoided carbon emissions from technology choice in solar and wind sectors per year in real 2018 dollars respectively. We use Social Cost of Carbon of $51/ton to convert the value of CO_2 in million metric tonnes (MMT) to million $. A negative sign indicates a loss in producer surplus or an increase in emissions. Sample in Panel A. is all solar projects at least 1 MW in size that began operation in 2010-2020. Sample in Panel B. is all wind projects that at least 5 MW in size that began operation in 2001-2020.