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 21 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 papers have found mixed results (Gilbert, 2006; Goettler and Gordon, 2011), 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.

Should policymakers with the aim of speeding the energy transition restructure their electricity markets to promote competition? 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.

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: solar axis tracking. The fraction of new solar projects adopting this technology grew from under 20 percent in 2010 to over 55 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 includes all utility-scale solar and wind projects built in the U.S. from 2001-2020. When they build a new project, firms choose its technology to maximize their expected profits. This decision is sensitive to geography, and we use detailed data on resource quality 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. Finally, we describe whether, all else equal, wind projects that have signed long-term contracts to sell electricity are more likely to adopt these technologies.

We find that solar projects within restructured markets are 21 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 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 to sell a project's power 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. 81 percent of projects built by non-utilities). The quality of these contracts is also lower. We find that long-term contracts in restructured markets are for shorter terms on average (17.7 vs. 20.7 years) and tend to be with less creditworthy buyers (58 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. 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, 20 percent of solar projects would use axis tracking compared to the realized 25 percent. Full restructuring also decreases producer surplus by $61 million and leads to an additional $37 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).[1] While there are undoubtedly other factors in this decision, our results suggest another wave of states restructuring their electricity markets would not speed the transition to a low-carbon electricity grid.

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 competitors produce more in equilibrium, spreading the fixed cost of new technology over more units. In our setting, the returns to new technology do not necessarily increase with output. Instead, we find the higher financing costs associated with competition outweigh any positive effects it has on adoption.

[1]This 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).

This paper also contributes to the literature on the effects of electricity market restructuring by considering its impact on firm investment decisions. This contrasts with much of the literature which has focused on shorter-term outcomes. 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), 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. Fowlie (2010) finds it led firms to choose less capital-intensive environmental compliance options, Hill (2021) an "overinvestment" in natural gas generation, and Cicala (2022) an increase in utility investment in transmission and distribution. In the context of renewable energy, we find that restructuring reduces adoption of frontier generation technologies.

Finally, this paper adds to recent work suggesting 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 innovate. 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.[2]

[2]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.

The rest of this paper is organized as follows. Section 2 provides 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: restructured markets and traditional markets. Historically, generation, transmission, distribution, and retailing were thought of as natural monopolies, and one highly regulated firm would provide all four. 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 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 explanation suggests regulated utilities would build renewable projects in traditional markets but not restructured markets, the reality is more complicated. Two types of firms build 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 utilities 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 non-restructured electricity 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 U.S. 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 non-restructured 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.[3,4]

[3]These projects are called "merchant" generators. We only observe this status for wind projects, and 84 percent wind projects in our sample are merchant generators. We do see a few merchant generators in traditional markets because they may still be located within the footprint independent system operator allowing them to participate in wholesale markets; 75 percent of wind projects in traditional markets are merchant compared to 94 in restructured markets.

[4]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

2.2 Technological innovations

We next describe the technological innovations we study, both of which increase production in return for high upfront costs. For solar, this is the adoption of solar panels that track the sun. 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.[5]

2.2.1 Solar: Axis-tracking technology

Whereas traditional fixed-tilt panels are set permanently at one angle, solar axis-tracking panels rotate to maximize time spent perpendicular to the sun. While 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 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

treatment (FERC, n.d.). Regulated utilities usually sign long-term contracts with these qualifying facilities to purchase renewable power. While the exact terms for rate setting of the contracts varies by individual states, those in traditional markets 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.). PURPA has been especially influential in promoting the development of solar projects: about half of the solar projects in our data are qualifying facilities.

[5]Technology adoption in solar can also involve choice of using panels with newer materials apart from using tracking. However, because we do not observe the material used in solar panels for all projects we restrict our classification to tracking vs. fixed tilt.

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.[6]

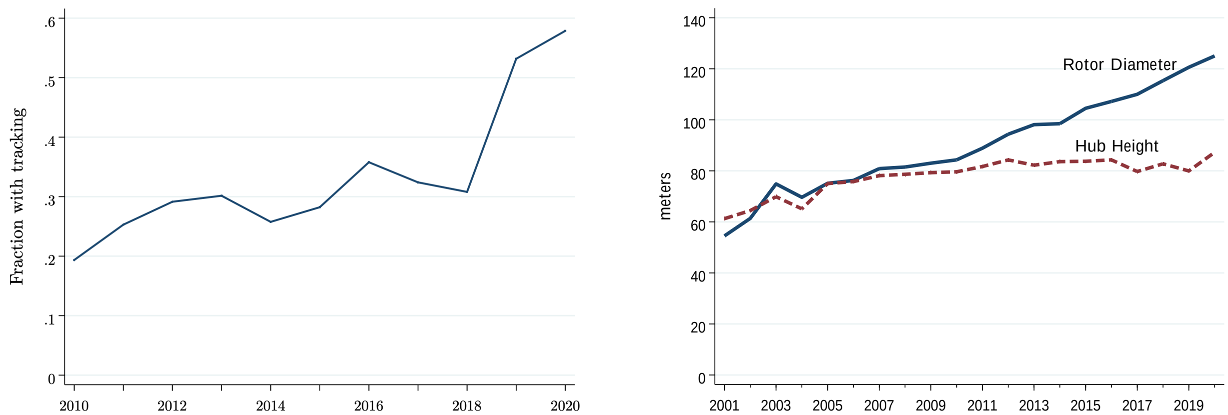
Our measure of technology adoption is whether the project uses a turbine model that advances the technological frontier, i.e., a model that is both new and substantially better than the previous model. We first define which models are new. The industry releases seven models a year on average, with the largest manufacturer, GE, averaging one new release a year.[7] 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.

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

[6] A recent trend in wind industry is 'repowering' of older projects. Repowering generally involves replacing part of a wind project with larger wind turbines. While we do not observe which projects were repowered, it is sometimes reported as a separate project phase in our data.

[7] We also observe several GE turbine models being used by different wind projects constructed in the same year. Figure B4 in Appendix illustrates this point.

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 technical 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.



(a) Solar: Axis tracking

(b) Wind: Larger turbines

Figure 1: Technology adoption over time

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 simultaneously 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, the same size (in MW) solar project will need more land if it is going to use tracking technology. 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. Regulated utilities 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 restructured markets are more 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 a contract with a longer 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 high 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 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 US electricity market restructuring increased prices.[8] Thus, this channel has an ambiguous effect on adoption, and based on what others have found, we should expect it led to more adoption in restructured markets.

3 Data

We use data on all utility-scale solar and wind generators and 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. For the wind analysis, we use data for all wind projects that are at least 5 MW in size and began operation in 2001 - 2020[9].

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 they include the predominant wind turbine used for each project, along with the average rotor diameter, rating, and hub height.[10] Figure 2a and 2b show the spatial distribution of wind and solar projects, as well as their technology choices. Restructured states are highlighted in light blue.

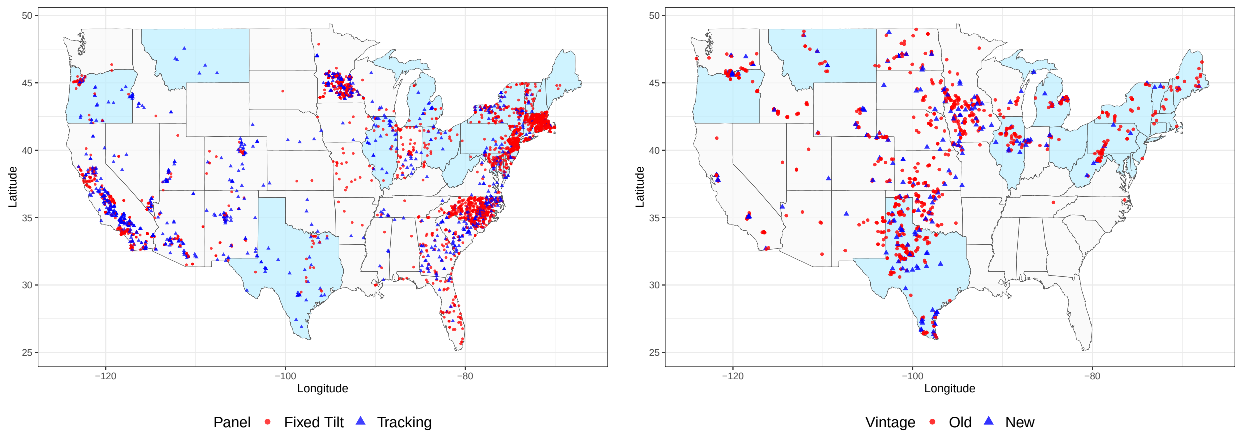
We use data from NREL to construct counterfactual electricity production, as a function of site specific solar and wind resources, under all possible technology choices. For each solar project, we construct a measure of total electricity production (GWh) for

[8]It is also true that states with high prices initially were more likely to restructure, and we discuss this in Section 2.3.

[9]We exclude wind projects smaller than 5 MW in size as they are more likely to have missing information for characteristics we use in estimation. Projects under 5 MW account for about 1 percent of total wind project capacity of our data. Solar projects under 5 MW are also more likely to have missing data, but projects from 1-5 MW account for a substantial share of solar capacity.

[10]We also observe turbine-level data for each wind project from the American Wind Energy Association (AWEA), and, using these data, we verify that most wind projects use only one turbine model.

Figure 2: Spatial distribution of Solar and Wind Projects



(a) Solar projects: 2010 - 2020

(b) Wind projects: 2001 - 2020

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

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).[11] For wind, we use hourly data on wind speeds from The Wind Integration National Dataset (WIND) Toolkit from NREL.[12] We combine these data with the power curve data from The Wind Power to compute counterfactual annual energy production for each turbine model at each location.

To compute revenues 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. For wind projects, we follow Aldy, Gerarden and Sweeney (2021) and construct this price at the project level using resale price data from EIA Form 861M, PPA prices from AWEA, and Renewable Energy Credit (REC) prices from the Lawrence Berkeley Lab. For solar, we use resale

[11]PVWatts uses the hourly Typical Month Year (TMY) data on solar radiation for the calculation. TMY data are derived from a series of multiyear data set to provide solar radiation and meteorological data that best represent the median condition for a "typical" year.

[12]The WIND Toolkit data includes meteorological conditions in the US for the years 2007-2013 at 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.

price data at the project level and assign state level averages in cases with missing values in the EIA Form 861M data.

Table 1 reports the summary statistics for key variables for the solar and wind sectors. A striking difference across the two sectors is the difference in project size. The average capacity of a solar project is 8.5 MW whereas the average capacity of a wind project is 108 MW. A slightly smaller proportion of solar projects are located in restructured states than wind projects: 0.36 vs. 0.42. Seven percent of solar projects are developed by utilities, compared to sixteen percent of wind projects.

Table 1: Summary statistics

	Solar		Wind	
	Mean	Std. Dev.	Mean	Std. Dev.
Size (MW)	8.54	19.29	108.00	81.89
Restructured (0/1)	0.36	0.48	0.42	0.49
Utility (0/1)	0.07	0.26	0.16	0.37
Long-term contract (0/1)	-	-	0.59	0.49
Frontier technology (0/1)	0.29	0.45	0.15	0.36
Realized prices ($/MWh)	90.58	44.10	47.70	31.33

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 was built by a utility. Frontier technology is using tracking panels for solar; a new vintage turbine model for wind. Each observation is a solar or wind project in our sample. N=3,573 for solar; N=1,033 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.

$$\Pr(\mathit{tracking}_i = 1) = \beta \cdot \mathit{restructured}_i + \alpha \cdot \Delta \mathit{revenue}_i + \delta_t + \epsilon_i \tag{1}$$

where $\mathit{restructured}_i$ is an indicator for whether project i is in a restructured state. $\Delta \mathit{revenue}$ is the difference in annual revenue between tracking and fixed tilt panels for a 5 MW project in the location of project i.[13] Because there are only two choices, including the difference in revenue corresponds to a utility function where revenue enters directly.[14] Including revenue in the model allows us to condition 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 (δ_t) 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.

[13] We set the panel size to 5 MW across all projects rather than using actual size because size may be a bad control.

[14] 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,

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

For a binary logit model this reduces to,

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

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, $\partial U_j / \partial R_j = \alpha,\ j \in \{0, 1\}$

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. We use a 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.[15] Our measure of energy production from a 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 prices. These high prices usually resulted from signing expensive long-term contracts for and investment 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. 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

[15]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.

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 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 6.6 percentage point decline in the probability of using axis-tracking panels. The mean probability of using tracking is 0.29, so this is a 21 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.

We conduct robustness checks to 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 D1 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 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 also estimate the model separately for projects that do and do not qualify for PURPA (see Appendix Table D2). 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, and this could bias our results if these major de-

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

	Uncorrected		Control Function	
	(1)	(2)	(3)	(4)
Restructured	-0.184***	-0.143***	-0.092***	-0.066***
	(0.036)	(0.016)	(0.017)	(0.020)
Δ Revenue ($100,000)	0.011	0.007	0.260***	0.217***
	(0.018)	(0.009)	(0.019)	(0.025)
Revenue Elasticity	0.069	0.044	1.713	1.482
Observations	3,564	3,564	3,564	3,564
Year FE	X	X	X	X
Terrain Ruggedness		X		X
Farm Size & Value		X		X
Log Likelihood	-2004	-1899	-1886	-1831

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 for using tracking versus not from the PVWatts calculator. 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: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

velopers tend to locate in traditional markets.[16] We include an indicator for projects that are developed by one of the larger solar developers. Coefficient estimates in Appendix Table D3 are quantitatively similar to the baseline estimates in Table 2, ruling out this concern.

[16]We classify following developers as large developers: Strata Solar, First Solar, Cypress Creek Renewables, NextEra Energy Resources, SunPower, Sempra Energy, Recurrent Energy, and SunEdison. However, we only observe developers for 30 percent of the projects in our data. Out of these, 36 percent are developed by a large developer.

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 B3 shows how the number 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 cost, as well as whether it is new technology. We construct site-specific measure of expected revenues for each turbine model. The market for turbines is global, and, while we do not observe turbine prices, 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 in quarter t is

$$\begin{aligned} U_{ijt} = \beta \cdot \textit{new vintage}_{jt} + \beta_m \cdot \textit{new vintage}_{jt} \times \textit{restructured}_i \\ + \alpha \cdot \textit{revenue}_{ij} + \mathrm{X}_{ijt} + \delta_j + \epsilon_{ijt} \end{aligned} \tag{2}$$

where $\textit{new vintage}_{jt}$ is an indicator for if turbine model j is at the technological frontier in quarter t. To allow the utility for choosing a frontier model to vary with market structure, we also include $\textit{new vintage}_{jt} \times \textit{restructured}_i$ where $\textit{restructured}_i$ is an indicator for whether project i is located in a restructured electricity market. $\textit{revenue}_{ij}$ 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_{ijt} includes turbine model age and its square, as well as an indicator for whether a site's wind speed distribution lies outside the turbine'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 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 observe whether a project developer signs a long-term contract to sell the project's power. We also estimate specifications allowing the utility of a new vintage model to depend on this variable.

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 in 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 1.5 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	-0.149	-0.530**	-0.479*	-0.181	-0.539**	-0.505*
	(0.188)	(0.232)	(0.253)	(0.188)	(0.251)	(0.275)
New Vintage × Restructured	-0.135		-0.114	-0.099		-0.075
	(0.229)		(0.230)	(0.246)		(0.257)
New Vintage × Long-term contract		0.403**	0.497**		0.489*	0.485*
		(0.242)	(0.242)		(0.265)	(0.256)
Revenue ($100,000)	0.384***	0.374***	0.374***	1.789***	1.771***	1.766***
	(0.075)	(0.075)	(0.075)	(0.419)	(0.420)	(0.417)
Revenue Elasticity	1.476	1.436	1.435	6.869	6.800	6.780
Observations	17,234	17,234	17,234	17,234	17,234	17,234
Turbine Model FE	X	X	X	X	X	X
Turbine age and age^2	X	X	X	X	X	X
Site/Turbine Class Mismatch	X	X	X	X	X	X
# 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 of conditional logit model uncorrected for revenue endogeneity. Columns (4) - (6) include residuals from 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 estimated revenue obtained from the turbine model, New Vintage specifies whether the chosen turbine is a frontier model, Restructured is a dummy variable indicating if the project is in a restructured state. Turbine age and age^2 control for the number of years since turbine's introduction. Site/Turbine Class Mismatch is a binary variable specifying if there is a mismatch between site wind class and turbine wind class. Bootstrap standard errors with 1000 replications reported in parenthesis 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 the market structure in 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.

Similar to the solar industry, we address the concern that larger wind developers could be more likely to use frontier wind turbines than smaller developers.[17] We re-estimate the model including the interaction between the new vintage turbine indicator and an indicator for a large developer. Coefficient estimates in Table E4 in Appendix are quantitatively similar to the baseline estimates in Table 3.

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. Would our conclusions differ if we allowed for these price effects?

Higher prices in restructured markets could cause the total effect of restructuring on adoption to be positive. We expect higher market prices to increase adoption and we expect prices to be higher in restructured markets.[18] States with higher prices restructured, 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. But MacKay and Mercadal (2021) find that restructuring also caused higher prices.

We next re-estimate models of the choice to use frontier without controlling for price. 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 production rather than revenue. We find a statistically significant negative effect of restructuring on adoption for solar and a

[17]We classify following developers as large developers: NextEra Energy Resources, Avangrid Renewables, Invenergy LLC, EDP Renewables North America LLC, and EDF Renewables. These developers represent about 30 percent of total wind projects in our data.

[18]At last unconditionally, the project-level prices in our data are slightly higher in traditional markets. Mean resale prices for solar are 90.8 $/MWh in traditional markets vs. 90.1 $/MWh in restructured markets. For wind, they are 49.4 $/MWh in traditional markets vs. 45.4 $/MWh in restructured markets.

Table 4: Relationship without conditioning on price

	Solar		Wind		
	(1)	(2)	(3)	(4)	(5)
Restructured	-0.090***	-0.064***			
	(0.017)	(0.018)			
Production (GWh)	0.272***	0.226***	0.585***	0.577***	0.576***
	(0.018)	(0.021)	(0.127)	(0.127)	(0.127)
New Vintage Turbine Model			-0.182	-0.584**	-0.543**
			(0.188)	(0.232)	(0.254)
New Vintage × Restructured			-0.126		-0.089
			(0.228)		(0.230)
New Vintage × Long-term contract				0.544**	0.537**
				(0.241)	(0.242)
Production Elasticity	1.875	1.623	4.351	4.295	4.284
Observations	3,564	3,564	17,234	17,234	17,234
Log Likelihood	-1905	-1843	-2192	-2189	-2189

Notes: Columns (1) and (2) show average marginal effects from 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, farm size and value. Columns (3) to (5) show coefficient estimates of conditional logit model for wind turbine choice. Sample is all wind projects that began operation post 2001 with at least 5 MW in size. 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.

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 restructured markets are less likely to adopt frontier technology. This difference is not explained by differences in input or 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 done at the project level, long-term contracts result in lower financing costs. These contracts are more common in traditional markets: 81 percent of wind projects in traditional markets signed long-term contracts compared to 58 percent in restructured markets.[19] Yet, Table 3 shows that the negative point estimate for the effect of restructuring, while diminished, does not disappear when we control for signing 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 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.

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

[19] To calculate this statistic, we limit our sample to non-utility 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.

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	-0.221***	-0.214***	-2.970***	-2.787***
	(0.056)	(0.044)	(0.815)	(0.772)
Mean utility share	0.746	0.746		
Mean contract length (years)			19.69	19.69
Observations	603	603	367	367
R^2	0.206	0.258	0.131	0.169
Operating Year FE	X	X	X	X
Project Characteristics		X		X

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 that began operation post 2001 with at least 5 MW in size and that signed a long-term contract. Excludes projects with missing values for contract off taker (N=11) and contract length (N=247). Project characteristics include capacity in MW, manufacturer fixed effect, and an indicator specifying whether the project developer is amongst the top five developers. Robust standard errors clustered at the state level reported in parenthesis. Significance: ***p<0.01;**p<0.05;*p< 0.1

solar industry where we more precisely estimate the relationship between market structure and adoption.

We consider counterfactuals of full restructuring (all states are restructured) and no restructuring (no states are restructured or 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.

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 the years for the two counterfactuals. For example, 27 percent of total projects in 2020 are predicted to use tracking when all states are traditional markets. In contrast, full restructuring would lead to just over 20 percent of projects using tracking in 2020.

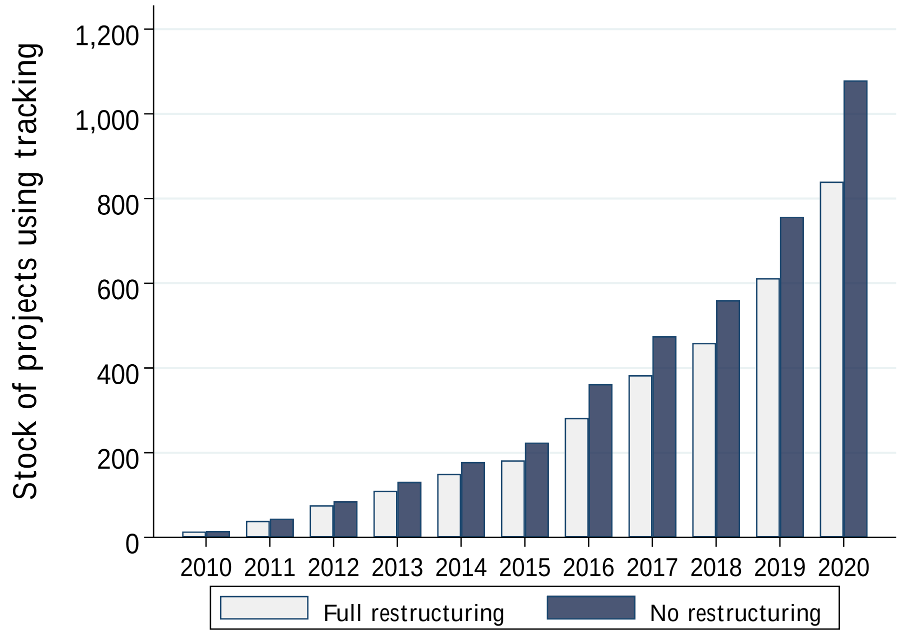


Figure 3: Solar projects predicted to use tracking panels
Note: This figure compares the predicted stock of projects using tracking technology under the following counterfactuals scenarios:
Full restructuring: All states are restructured
No restructuring: No states are restructured.

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.

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 policy counterfactual (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 in year t is

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

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

We find that all states restructuring would have reduced welfare by about 100 million dollars per year. Table 6 shows the that, relative to the status quo, the loss in solar developer producer surplus from all states restructuring is $61 million per year, while the gain from no restructuring is $14 million per year. When tracking is adopted, increased electricity production from solar offsets electricity production from fossil fuel generators. Thus, adoption reduces greenhouse gas emissions. By reducing axis-tracking adoption, all states restructuring would have increased carbon emissions by 0.718 million metric tons per year at a social cost of 37 million per year.[20]

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	−60.7	−0.718	−36.64
No states are restructured	13.8	0.260	13.28

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

[20]We convert the surplus values for each project to MWh by diving them by realized project prices. 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.

We repeat this exercise for the wind industry, and find the overall surplus loss from all states restructuring is about a fifth of the loss for the solar industry (see Appendix F). A major caveat is that the wind results are based on point estimates with large confidence intervals.

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. We show evidence this result is due to higher financing costs in restructured markets.

While the welfare effects we quantify are modest, there are reasons to think the effects are much larger. We find that all states restructuring would lead to an annual surplus loss of 100 million dollars in the solar industry. If the mechanism of higher financing costs muting adoption generalizes to entirely new generating technologies, the effects could be much larger. 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 effects 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, we focus on the relationship between competition and technology adoption, contributing to the limited empirical work in this area.

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Appendix

A Trends in solar technology adoption

A.1 Geographic trends in solar industry

Our sample includes 3,573 projects, 34 percent of which have tracking technology. The size distribution is positively skewed, with about 75 percent less than or equal to 5 MW and a few projects over 100 MW in size. California and North Carolina account for about 50 percent of projects over 5 MW with 383 and 314 projects respectively. No other state has more than 75 projects. Solar projects are primarily located in the southern half of the U.S.

Many projects are located in the southwest U.S. where the solar resource quality is highest. The use of axis-tracking is also more common in the Southwest. This pattern is likely because the benefits of tracking are highest in areas with fewer clouds and thus higher levels of direct normal irradiance (DNI). North Carolina is a large outlier with 16 percent of the solar projects. North Carolina has a renewable portfolio standard with a solar-specific target and a 35 percent state renewable energy tax credit (Rocky Mountain Institute, 2015).

B Trends in wind technology adoption

B.1 Wind turbine advancement classification algorithm

The following example further illustrates our algorithm on classifying a turbine model as a technical advancement: Take the case Gamesa G97-2.0. It is a turbine model with a rotor diameter of 97m and turbine rating 2.0 MW appearing first in our data in 2011Q4. We classify it as an advancement in rotor diameter since it is 7m bigger than Gamesa's last biggest turbine model (G90-2.0) within the 2.0 rating group. However, it is not considered an improvement in turbine rating as it does not exceed the highest rated model made by Gamesa, G126-2.5 which first appears in our data in 2003Q4.

We run this algorithm for all the 137 turbine models in our data from 2001 through 2019. As per our definition, we classify 110 models as an advancement in rotor diameter and 65 models as an advancement in turbine rating. Figure B1 shows the result of this classification for our sample. This figure plots the total number of turbine models that were either an advancement in rotor diameter, turbine rating, or both over 2001 - 2019. We see that size advancements are more frequent than rating advancements with at least one turbine model being classified as a size advancement each year.

To further explore how usage of turbine models that are advancements differs from non-advancements, we look at the average duration of models by manufacturers. We define duration as the number of years a turbine model is seen in our data, i.e. it is simply the number of years between the dates of first project and the last project using that turbine model. Figure B2 plots the average duration of turbine models from various manufacturers. For both the panels in Figure B2, we restrict to models that are used in at least 3 projects.

Figure B2a shows the average number of years a model that is not a technical advancement stays in the market. We notice that on an average turbine models from ma-

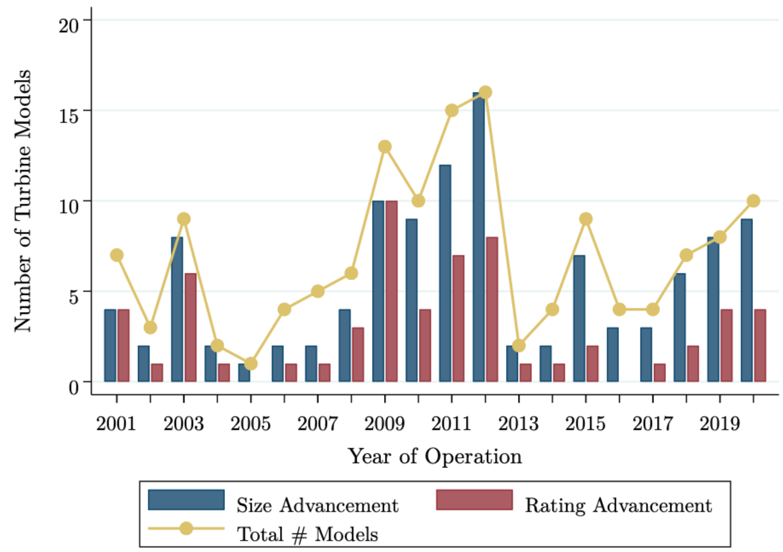
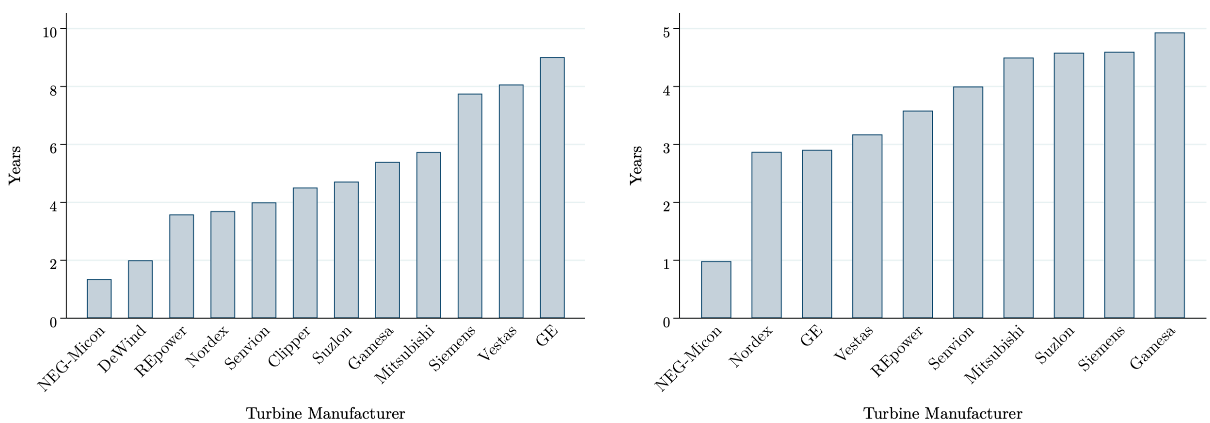


Figure B1: Introduction of new turbine models over time by wind manufacturers



(a) Average duration of turbine models that are not advancements

(b) Average duration of models that are advancements

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

jor manufacturers like GE, Siemens, Vestas, and Gamesa stay in the market for much longer than models from smaller manufacturers. This could be an indication of brand loyalty towards bigger manufacturers and a willingness to use already established turbine models. For example, five models from GE have a duration of more than 10 years whereas there is only one model from a manufacturer other than GE, Siemens, Vestas, and Gamesa with a duration of more than 10 years. In contrast to Figure B2a, the pattern in Figure B2b shows that models that are technical advancements tend to stay in the market for a shorter duration and there is no noticeable difference in the average duration across manufacturers. This suggests that developers tend to show a dis-utility for newer models without any preference for specific manufacturers.

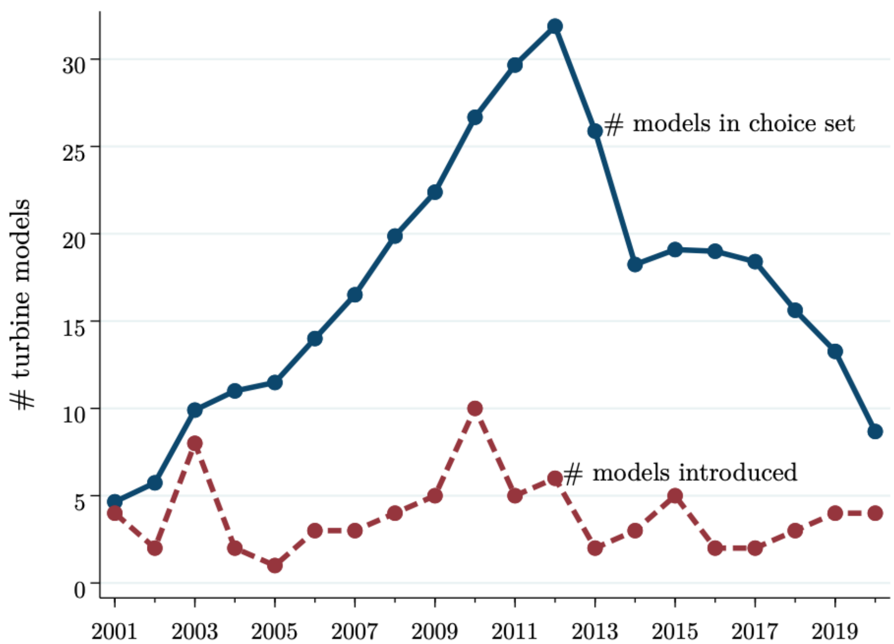


Figure B3: Wind turbine introduction and choice set

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.

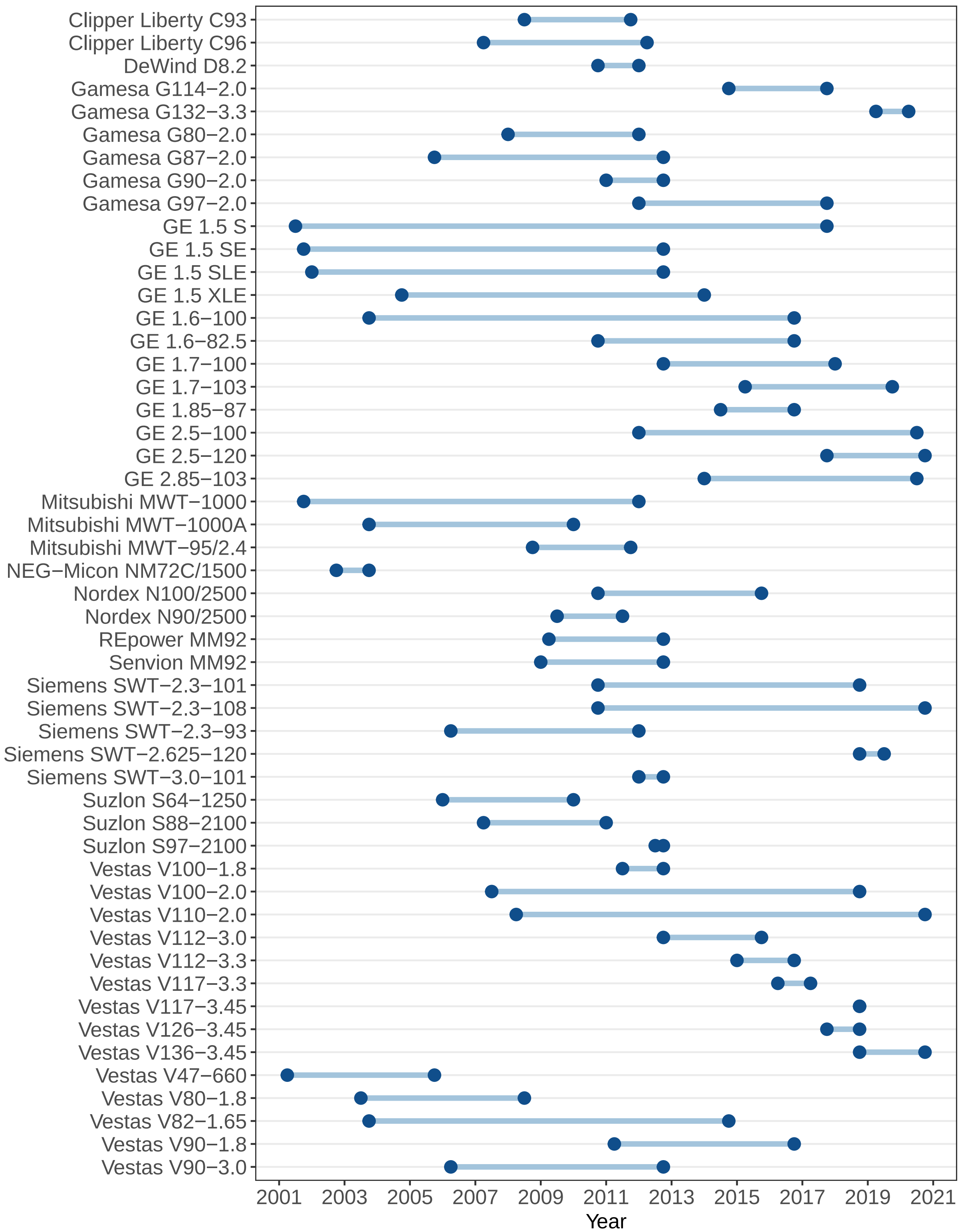
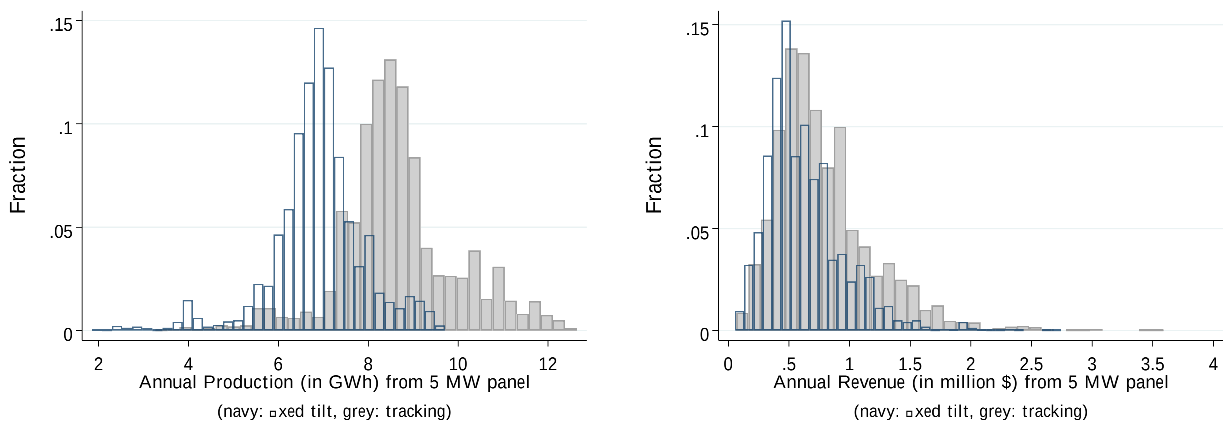


Figure B4: Observed duration of various wind turbine models in the data

C Supplementary Figures

C.1 Energy production and revenue in the solar industry

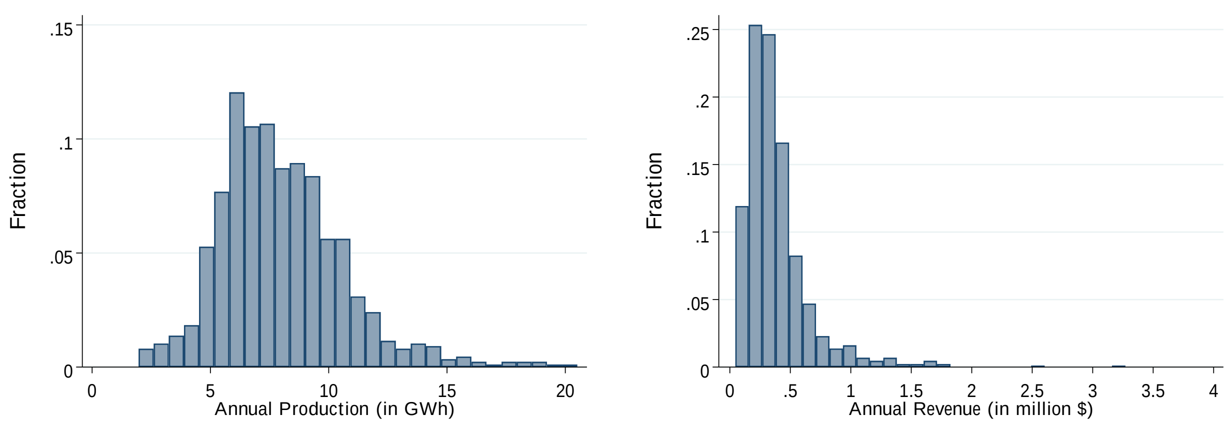


(a) Annual energy production (GWh)

(b) Annual revenue (million $)

Figure C5: Histogram of total energy production and revenue from a 5 MW tracking and fixed tilt panel for all US solar projects

C.2 Energy production and revenue in the wind industry



(a) Annual energy production (GWh)

(b) Annual revenue (million $)

Figure C6: Histogram of total energy production and revenue from wind turbines in all US wind projects

C.3 Project level (realized) prices in wind and solar industries

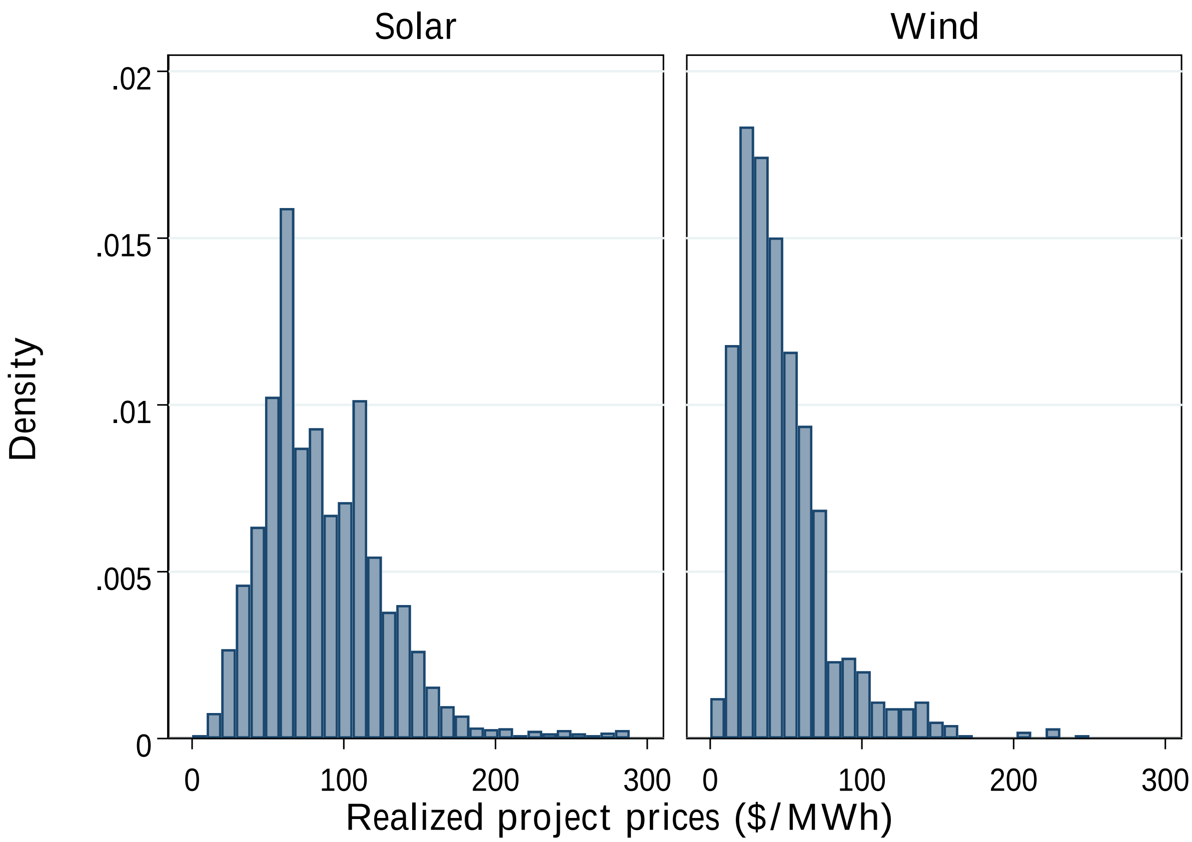


Figure C7: Histogram of realized prices ($/MWh) of wind and solar projects in the data
Notes: Sample is all wind projects of at least 5 MW of nameplate capacity that started operating from 2001 - 2020, and all solar projects that began operating in 2010 - 2020 and at least 1 MW of nameplate capacity.

D Robustness checks for Solar results

D.1 Regression results controlling for projects in North Carolina

Table D1: Logit regression of tracking on market structure

	Uncorrected		Control Function	
	(1)	(2)	(3)	(4)
Restructured	-0.215***	-0.167***	-0.125***	-0.094***
	(0.015)	(0.016)	(0.018)	(0.021)
North Carolina	-0.241***	-0.217***	-0.193***	-0.191***
	(0.017)	(0.019)	(0.023)	(0.023)
Revenue ($100,000)	-0.019**	-0.018*	0.211***	0.175***
	(0.010)	(0.009)	(0.021)	(0.025)
Revenue Elasticity	-0.119	-0.124	1.409	1.209
Observations	3,564	3,564	3,564	3,564
Year FE	X	X	X	X
Terrain Ruggedness		X		X
Farm Size & Value		X		X
Log Likelihood	-1958	-1864	-1863	-1808

Notes: This table reports the marginal effects associated with the Logit regression of probability of tracking choice (0/1) on market structure. Column (1) and (2) shows marginal effects of the Logit model uncorrected for revenue endogeneity. Columns (3) and (4) include residuals from OLS regression of revenue on annual production as the 'control function' in the Logit specification. Sample is all solar projects at least 1 MW in size that began operation in 2010-2020. Panel size is set to 5 MW for all the projects. Restructured is an indicator if the project is in a restructured state. Terrain ruggedness includes quadratic polynomial of the standard deviation of terrain elevation. Farm Size & Value include variables for county level average farm size and value per acre. NC is an indicator for projects in North Carolina. Bootstrap standard errors with 1000 replications reported in parenthesis for columns (3) and (4). Significance: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

D.2 Regression results by qualifying facility status

Table D2: Logit regression of tracking on market structure

	Uncorrected		Control Function	
Sample	Not QF	QF	Not QF	QF
	(1)	(2)	(3)	(4)
Restructured	-0.139***	-0.172***	-0.059*	-0.109***
	(0.023)	(0.020)	(0.031)	(0.027)
Revenue ($100,000)	-0.036***	0.040***	0.169***	0.270***
	(0.014)	(0.012)	(0.033)	(0.040)
Revenue Elasticity	-0.229	0.279	1.207	1.856
Observations	1,793	1,752	1,793	1,752
Year FE	X	X	X	X
Terrain Ruggedness	X	X	X	X
Farm Size & Value	X	X	X	X
Log Likelihood	-972	-864	-937	-834

Notes: This table reports the marginal effects associated with the Logit regression of probability of tracking choice (0/1) on market structure. Columns (2) and (4) restricts sample to qualifying facilities (QF) - projects that qualify under PURPA and Columns (1) and (3) restricts sample to not QF - projects that do not qualify under PURPA. Column (1) and (2) shows marginal effects of the Logit model uncorrected for revenue endogeneity. Columns (3) and (4) include residuals from OLS regression of revenue on annual production as the 'control function' in the Logit specification. All solar projects are at least 1 MW in size that began operation in 2010-2020. Panel size is set to 5 MW for all the projects. Restructured is an indicator if the project is in a restructured state. Terrain ruggedness includes quadratic polynomial of the standard deviation of terrain elevation. Farm Size & Value include variables for county level average farm size and value per acre. Bootstrap standard errors with 1000 replications reported in parenthesis for columns (3) and (4). Significance: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

D.3 Regression results controlling for developer type

Table D3: Logit regression of tracking on market structure

	Uncorrected		Control Function	
	(1)	(2)	(3)	(4)
Restructured	-0.176***	-0.139***	-0.092***	-0.067***
	(0.015)	(0.016)	(0.017)	(0.021)
Large Developer	0.088***	0.047*	-0.005	-0.020
	(0.025)	(0.025)	(0.021)	(0.022)
Revenue ($100,000)	0.012	0.007	0.261***	0.222***
	(0.009)	(0.009)	(0.020)	(0.026)
Revenue Elasticity	0.0729	0.0461	1.719	1.511
Observations	3,564	3,564	3,564	3,564
Year FE	X	X	X	X
Terrain Ruggedness		X		X
Farm Size & Value		X		X
Log Likelihood	-1998	-1897	-1886	-1831

Notes: This table reports the marginal effects associated with the Logit regression of probability of tracking choice (0/1) on market structure. Column (1) and (2) shows marginal effects of the Logit model uncorrected for revenue endogeneity. Columns (3) and (4) include residuals from OLS regression of revenue on annual production as the 'control function' in the Logit specification. Sample is all solar projects at least 1 MW in size that began operation in 2010-2020. Panel size is set to 5 MW for all the projects. Restructured is an indicator if the project is in a restructured state. Terrain ruggedness includes quadratic polynomial of the standard deviation of terrain elevation. Farm Size & Value include variables for county level average farm size and value per acre. Large Developer is an indicator for projects built by one of the larger solar developers. Bootstrap standard errors with 1000 replications reported in parenthesis for columns (3) and (4). Significance: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

E Robustness checks for Wind results

E.1 Regression results controlling for developer type

Table E4: Results of Conditional Logit model of turbine choice

	Uncorrected			Control Function		
	(1)	(2)	(3)	(4)	(5)	(6)
New Vintage Turbine Model	-0.124	-0.495**	-0.439*	-0.159	-0.506**	-0.467*
	(0.207)	(0.239)	(0.260)	(0.205)	(0.251)	(0.279)
New Vintage × Restructured	-0.139		-0.124	-0.103		-0.084
	(0.229)		(0.231)	(0.247)		(0.234)
New Vintage × Long-term Contract		0.528**	0.524**		0.512*	0.508*
		(0.245)	(0.246)		(0.270)	(0.273)
New Vintage × Large Developer	-0.066	-0.149	-0.157	-0.057	-0.139	-0.141
	(0.239)	(0.243)	(0.243)	(0.242)	(0.254)	(0.260)
Revenue ($100,000)	0.384***	0.372***	0.372***	1.787***	1.766***	1.761***
	(0.075)	(0.075)	(0.075)	(0.420)	(0.419)	(0.421)
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	X	X	X	X	X	X
Turbine age and age^2	X	X	X	X	X	X
Site/Turbine Class Mismatch	X	X	X	X	X	X
# 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 of Conditional Logit model uncorrected for revenue endogeneity. Columns (4) - (6) include residuals from 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 of nameplate capacity. Revenue is the annual estimated revenue obtained from the turbine model, New Vintage specifies whether the chosen turbine is a frontier model, Large Developer is an indicator for projects developed by one of the five large developers. Turbine age and age^2 control for the number of years since turbine's introduction. Site/Turbine Class Mismatch is a binary variable specifying if there is a mismatch between site wind class and turbine wind class. Bootstrap standard errors with 1000 replications reported in parenthesis for columns (4) - (6). Significance: *** p<0.01, ** p<0.05, *** p<0.1.

F 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 or all states are traditional), and (iii). all projects use long-term contracts (PPA).[21]

Figure F8 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. The higher rate of technology adoption is mainly from utility owned projects and projects switching from wholesale market to long-term contracts as the off-take.

F.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):

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

[21]Note that these counterfactuals focus specifically on the technology choices; we do not endogenize developers' entry decisions nor do we model the effect of restructuring on market prices.

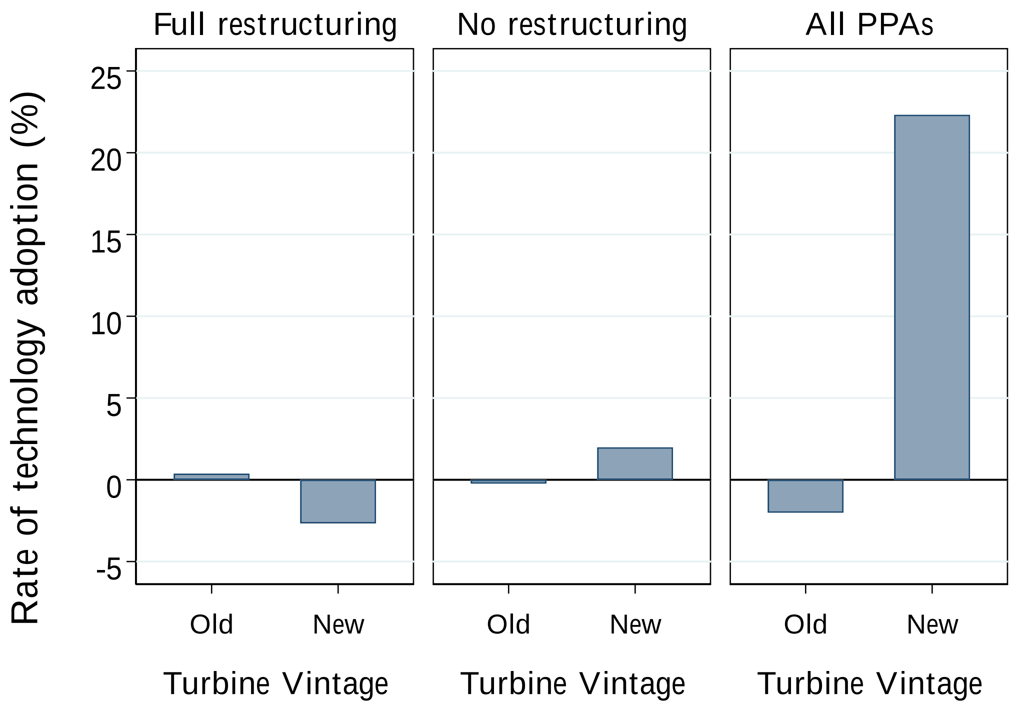


Figure F8: Rate of technology adoption in the wind industry

Note: This figure shows the percentage change in probability of adoption $\left(\frac{p_2}{p_1} - 1\right)$ of old and new vintage turbine models under the following counterfactuals:
Full restructuring: All states are restructured
No restructuring: No states are restructured
All PPAs: All projects use PPAs to sell power

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.

Table F5 shows the change in surplus, emissions avoided in each counterfactual along with the results for solar industry for reference. All states restructuring would lead to a decrease in surplus of about $20 million per year. Total annual surplus gain is about $55 million when all projects in our sample use long term contracts to sell their power.

Table F5: Total change in surplus and avoided CO_2 for the counterfactual policy scenarios

	Counterfactual	Δ Surplus	Avoided CO_2	
		Million $	MMT	Million $
A.	Solar Industry			
1.	All states are restructured	−60.7	−0.718	−36.64
2.	No states are restructured	13.8	0.260	13.28
B.	Wind Industry			
1.	All states are restructured	−10.1	−0.172	−8.75
2.	No states are restructured	7.6	0.164	8.40
3.	All projects use PPAs	54.6	1.044	53.25

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