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 regulated markets, which are dominated by regulated monopolists. Solar projects in restructured markets are 23 percent less likely to adopt frontier technology. We also find small negative effects for wind projects. 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 regulated 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 regulated 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: 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 the adoption of larger wind turbines. 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.

Our measure of market structure corresponds to state-level decisions to restructure their electricity markets. This decision typically involves introducing competition into both retail

[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.

and wholesale markets. Regulated markets by this definition can overlap with competitive wholesale markets, and we control for being located in the footprint of a competitive wholesale market in estimation. While our state-level measure of market structure was not randomly assigned, it was determined a decade before our sample. States that restructured are observably different than regulated states, and we use rich data on wind and solar resource quality to control for the geographic determinants of technology choice. We also control directly for likely confounders, such as land prices and ordinances restricting renewable development.

We first estimate models of axis-tracking adoption as a function of market structure for the solar power industry. Our data include all utility-scale solar projects built in the United States from 2001-2020. We derive the model we estimate from solar developers' profit maximization problem. The channels above imply that market structure can affect developers' valuation for future revenues. We use detailed meteorological and price data to construct a project-specific measure of the expected revenue from each technology, and we allow the weight a developer places on this measure in its indirect utility function to vary with market structure.

We also estimate models of wind turbine size as a function of market structure for the wind power industry. Our data include all wind projects over 5 MW built in the United States from 2001-2020. Because size is a feature of the chosen turbine rather than the choice itself, we do not estimate a choice model for this industry. We instead regress the rotor diameter of the chosen turbine on market structure and flexibly control for meteorological factors that can affect this choice. Our preferred specification uses the double selection approach in Belloni, Chernozhukov and Hansen (2014*b*) to select from high-dimensional wind resource controls while allowing for correct inference. We also describe whether, all else equal, wind projects that sign long-term contracts to sell electricity are more likely to adopt larger turbines.

We find that competition is associated with lower technology adoption. Solar projects in restructured markets are 8.4 percentage points, or 23 percent, less likely to adopt tracking panels than projects in regulated markets. Similarly, wind projects in restructured markets use turbines with rotor diameters that are 3.2 meters, or 3 percent, smaller than projects in regulated markets. We also find that signing a long-term contract is positively correlated with using larger turbines.

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 if 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).

The results in this paper imply that competition does not increase the probability of adopting frontier technology in this context. Arizona considered restructuring its electricity market in 2018 (Wincher, 2018), and Nevada voters rejected a 2018 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 that 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. Macher, Miller and Osborne (2021) 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. 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 exceptions have found mixed evidence of restructuring's success: restructuring led to firms choosing less capital-intensive environmental compliance options (Fowlie, 2010), an "overinvestment" in natural gas generation (Hill, 2021), a faster transition from coal to natural gas for electricity generation (Gowrisankaran, Langer and Reguant, 2024), and an increase in utility invest-

[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).

[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.

ment in transmission and distribution (Cicala, 2022*b*). 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 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.[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 provides evidence for financing costs as a potential mechanism. Section 7 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: regulated 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 regulated 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 states might have

[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.

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

There are also competitive wholesale markets in regulated states, but we do not focus on this dimension of competition. State-level electricity restructuring typically had three pieces: retail competition, a competitive wholesale market operated by an independent system operator, and divestiture of generation by the incumbent utility. Individual power control areas could also opt to join competitive wholesale markets (Cicala, 2022*a*), so some projects in regulated states are located in the footprint of competitive wholesale markets. Our state-level definition of restructuring classifies these projects as regulated, though we control for their ability to participate in competitive wholesale markets in estimation.

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 regulated 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 regulated electricity markets, this is not the case for either wind or solar generation. In both restructured and regulated 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 regulated 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 regulated 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 larger turbine models. 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 regulated 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 our measure of technology adoption is whether a project used this technology. Figure 1a shows that the use of tracking has increased steadily in both market types.

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,

[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 regulated 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 regulated 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, regulated 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.

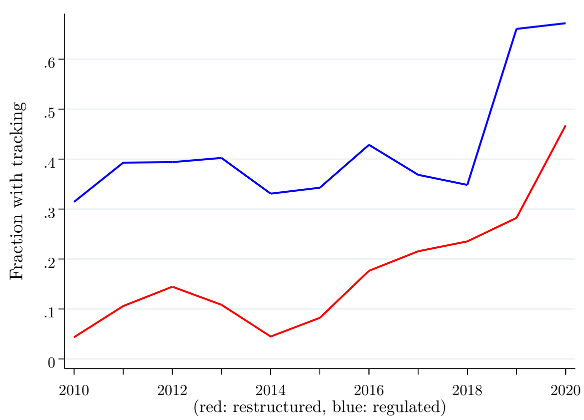
[7] Technology adoption in solar can also involve choice of using panels with newer materials apart from using tracking. This includes using panels with higher efficiency silicon-cells or the recently developed perovskite-cells. Over 99 percent of the projects in our data use silicon cells, and we do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

or steep sites (grades greater than 5-6 percent) may preclude the use of tracking (Kiewit, n.d.).

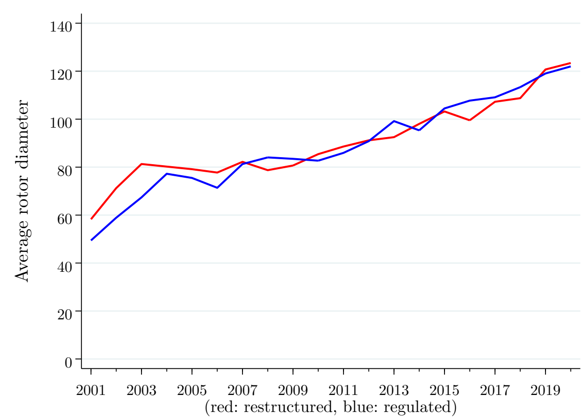
2.2.2 Wind: Larger turbines

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 in both restructured and regulated states.[8] Thus, our measure of technology adoption is whether projects use larger wind turbines, as a function of market structure.

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 and market structure. Figure 1b plots the average (across wind projects) turbine rotor diameter in meters by year of operation. Red line indicates the statistic for restructured states and blue line indicates the statistic for regulated state.

[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).

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 regulated 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 regulated 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 regulated 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

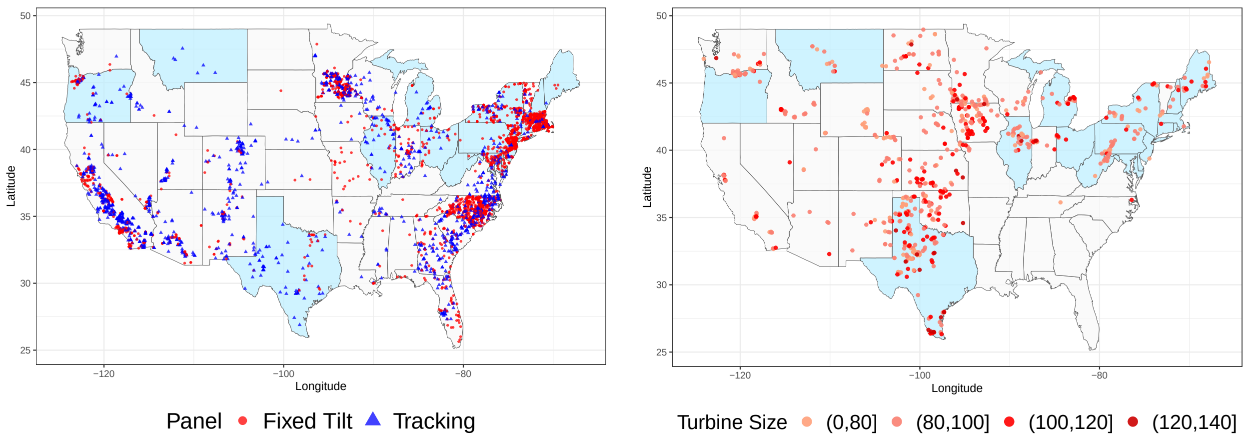
We use data on all utility-scale solar and wind generators that began operation in 2001-2020. These data come from U.S. Energy Information Administration (EIA) Form 860. All generators that are at least 1 MW in size and connected to the power grid submit Form 860 each year.

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. Using turbine-level data from the American Clean Power Association, we verify that most projects use only one turbine model, and we use the rotor diameter for the predominant turbine model in estimation. Figure 2a and 2b show the spatial distribution of wind and solar projects, as well as their technology choices.[9]

We use data from the National Renewable Energy Laboratory (NREL) to construct counterfactual electricity production under tracking v.s. fixed panel for solar projects. This

[9]We classify states as restructured using the list in Kleit and Rose (2016). These restructured states are highlighted in light blue in Figure 2. Oregon and Montana are de facto more similar to regulated states, and results are similar if we reclassify them as regulated rather than restructured: the negative impact of restructuring on adoption is similar in magnitude for both solar and wind industries. Appendix A provides more detail on the geographic distribution of our sample of solar projects.

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.

measure is a function of site specific solar 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 site specific hourly data on averages and standard deviations of wind speeds and wind directions from NREL's Wind Integration National Dataset (WIND) Toolkit.[11]

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

[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. 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 air pressure and precipitation, but we do not use these in our specifications.

National Laboratory. Appendix B provides more detail. A key assumption is that the price the project receives does not depend on its technology choice.

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 regulated 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×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.

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.[12]

[12] We report summary statistics by restructuring status for solar industry in Table D1 and for wind industry in Table D2 in Appendix D.

Table 1: Summary statistics

	Solar		Wind	
	Mean	Std. Dev.	Mean	Std. Dev.
Size (MW)	11.01	25.35	108.23	81.93
Restructured (0/1)	0.33	0.47	0.36	0.48
Utility (0/1)	0.07	0.26	0.16	0.37
Realized price ($/MWh)	104.31	51.36	49.21	29.39
Expected REC price ($/MWh)	5.60	11.22	4.35	8.21
Expected Revenue ($100,000)	1.88	0.99	-	-
Tracking (0/1)	0.37	0.48	-	-
Wind speed (m/s)	-	-	8.01	0.75
Turbine Rotor Diameter (m)	-	-	91.05	16.41
Long-term contract (0/1)	-	-	0.70	0.46

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. Expected Revenue is the difference in revenue from a tracking panel v.s. fixed panel of size 5 MW. 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. 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 (705 projects) for this statistic. Each observation is a solar or wind project in our sample. N=4,086 for solar; N=842 for wind.

4 Technology adoption in the solar power industry

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

We estimate models of axis-tracking adoption for solar projects. Appendix C microfounds the following Logit model from a solar developer's profit maximization problem:

$$\Pr(tracking_i = 1) = \alpha \cdot \Delta revenue_i + \beta \cdot \Delta revenue_i \times restructured_i + \gamma + \epsilon_i \qquad (1)$$

where $tracking_i$ is an indicator for whether project i used tracking panels. $\Delta revenue$ is the difference in annual revenue between tracking and fixed tilt panels for a 5 MW project in the location of project i.[13] 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.

We allow for the coefficient on the difference in expected revenue to vary with market structure. The model in Appendix C shows that the expected utility from future revenues decreases with the discount rate, and discount rates may be lower in regulated markets. Alternatively, deviations from profit maximization in regulated markets may result in a lower weight on expected revenues in the choice problem. Our specification accounts for the net effect of these channels.

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 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 specification controls for price directly, alleviating this concern. Controlling for price affects our interpretation of the effect of market structure on adoption, something we return to later in this section.

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

[13]We set the panel size to 5 MW across all projects rather than using actual size because size may also be affected by market structure and thus a bad control. Appendix Table Table F7 shows results are robust to controlling for project size.

[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.

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. 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 of adoption. The elasticity of adoption with respect to revenue has the expected positive sign only for the control function specifications. On average, a percent increase in revenue leads to 1.8 percent increase in probability of adopting a tracking panel (Column 4).

For our preferred specification in Column (4), the average marginal effect of restructuring on adoption is a decrease of 8.4 percentage points. This difference is statistically significant at the 1 percent level. The mean probability of using tracking is 0.37, implying that, at the mean, projects in restructured states are 23 percent less likely to adopt axis-tracking technology.

Another way to interpret the magnitude of the estimated effect is to quantify the difference in financing costs across the two markets that would rationalize it. Appendix C shows the ratio of the coefficients on the difference in revenue across market types is a function of the discount rate. Suppose that project developers in regulated markets use a discount rate of 5 percent for these investment decisions. If the entire difference in adoption across market types is explained by differences in financing costs, our estimates would be consistent with developers in restructured markets using a discount rate of 7.5 percent for these decisions.[15]

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 F3 shows that

[15]We find that the ratio of coefficients in regulated to restructured markets is 1.507. Assuming solar projects last 25 years, this ratio corresponds to $\frac{r_{\text{restructured}}(1-1/(1+r_{\text{regulated}})^{25})}{r_{\text{regulated}}(1-1/(1+r_{\text{restructured}})^{25})}$. If we assume $r_{\text{regulated}}$ is 5, then $r_{\text{restructured}}$ is 7.5.

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

	Uncorrected		Control Function	
	(1)	(2)	(3)	(4)
Δ Revenue ($100,000)	0.018**	0.013	0.364***	0.288***
	(0.009)	(0.009)	(0.021)	(0.023)
Δ Revenue × Restructured	-0.125***	-0.105***	-0.047***	-0.045***
	(0.009)	(0.009)	(0.011)	(0.011)
Revenue Elasticity	-0.205	-0.203	2.268	1.816
Observations	4,086	4,086	4,086	4,086
ISO	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Terrain Ruggedness		✓		✓
Farm Size & Value		✓		✓
Log Likelihood	-2435	-2319	-2261	-2210

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 2001-2020. Δ Revenue is the difference in expected revenue from using tracking versus not. Restructured is one if the project is located in a restructured state. Revenue elasticity is the average elasticity of revenue across all projects. All specifications include fixed effects for operating year and a binary indicator for being located in the footprint of a competitive wholesale market (ISO). Terrain ruggedness is the standard deviation of terrain elevation. 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: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

our estimates of the negative impact of restructuring on adoption are similar in magnitude to our estimates in Table 2 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 F4). The negative impact of restructured on adoption is moderately larger for projects that qualify for PURPA.

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 regulated 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 F5).

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 (Averch and Johnson, 1962). Utilities account for only 7 percent of the solar projects in our sample, and we confirm that our results are not sensitive to including these projects (Appendix Table F6).

4.3 Accounting for price effects

The results in Table 2 estimate 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.[16]

We re-estimate the logit model of the choice to use tracking 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. Appendix Table F8 reports estimates from logit models that include expected production rather than revenue. We still find a negative and statistically significant relationship between restructuring and technology adoption. These estimates are similar in magnitude to the baseline estimates in Table 2. Thus, allowing for price effects would not change our conclusions.

5 Technology adoption in the wind power industry

We next estimate a model of turbine rotor diameter as a function of market structure. Developers typically choose a wind turbine model to use for each project from a set of available choices.

We model the rotor diameter of the chosen turbine for project i as follows:

$$turbine\ size_i = \beta \cdot restructured_i + \mathbf{X}'\Lambda + \gamma + u_i \tag{2}$$

[16] 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. In our data, we see that solar (but not wind) projects located in restructured markets receive higher prices on average. The technologies we study increase production, so a higher market price increases the returns to adoption.

where *turbine size*$_i$ is the rotor diameter (in meters) of the turbine model used in project i and *restructured*$_i$ is a binary indicator for market structure. The returns to using different models vary with site-specific wind resource quality. We flexibly control for wind resources at the project site, summarized by the vector $\mathbf{X}$. We use hourly averages of wind speeds, hourly standard deviations of wind speeds, and hourly averages of wind direction at 80 and 100 meters. The market for wind turbines is global, and we control for turbine costs using operating year fixed effects (γ).

5.1 Results

Table 3 reports the coefficient estimates from Equation 2. Column (1) shows a small positive and statistically insignificant effect of restructuring. However, this effect vanishes after accounting for wind quality at the project site. Column (2) shows that projects in restructured markets on average use 3 meters smaller wind turbines than the ones in regulated markets. This effect translates to about 3.29 percent smaller wind turbines in restructured states. One concern with this specification is overfitting due to the number of wind controls (about 144 terms). To address this concern, we use Lasso to select the optimal number of wind controls. Column (3) shows the coefficient estimate from this post selection procedure, *Naive Lasso* is similar to Column (2).

However, inference using post-model-selection method like Lasso is problematic. These methods generally suffer from omitted variable bias since they tend to drop variables correlated with the predictors of interest (Belloni, Chernozhukov and Hansen, 2014*a*). Further with limited data, this procedure can introduce sample variability issues in variable selection.

We use Double Selection or Double Lasso approach in Belloni, Chernozhukov and Hansen (2014*b*) to address these issues in inference using Lasso for model selection. Double selection is a two step procedure, wherein the first step involves selecting controls (using Lasso) that are predictors of the outcome variable followed by a second step which is aimed at selecting variables that are predictors of the treatment. The coefficient of interest is then estimated using OLS of the outcome on the treatment and the union of controls selected in the first two steps. This process corrects the variable selection issues (and thus, omitted variable bias) in using Naive Lasso for inference (Belloni, Chernozhukov and Hansen, 2014*a*).

Column (4) in Table 3 reports the coefficient estimate of market structure using the double-selection procedure. The estimate suggests a 3.18 meter smaller wind turbines in restructured markets, which translates to a 3.5 percent effect. Coefficient estimates in Column (5) suggests that projects that sign long-term contracts are more likely to adopt larger turbines. This effect of a long-term contract is statistically significant at the five 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.

Table 3: Effect of market structure on turbine rotor diameter (m)

	Dependent variable: Rotor Diameter (m)				
	OLS		Naive Lasso	Double Selection	
	(1)	(2)	(3)	(4)	(5)
Restructured	0.331	-2.997**	-2.268**	-3.185**	-2.571*
	(0.742)	(1.520)	(1.038)	(1.436)	(1.487)
Long-term contract					1.522**
					(0.739)
R^2	0.678	0.763	0.715	-	-
Mean Rotor Diameter (m)	91.05	91.05	91.05	91.05	91.05
Observations	842	842	842	842	842
Year FE	✓	✓	✓	✓	✓
ISO	✓	✓	✓	✓	✓
Wind Controls		✓	✓	✓	✓

Notes: Columns (1) and (2) are the coefficient estimates of the OLS regression with rotor diameter as the dependent variable. Column (3) shows coefficient estimate from using Lasso to select wind controls, and Columns (4) and (5) uses double selection to correct for omitted variable bias in Naive Lasso. The penalty term (λ) for Lasso in double selection and 'Naive Lasso' is selected using 10 fold Cross Validation. Sample is all wind projects at least 5 MW in nameplate capacity that began operating in 2001-2020. Restructured is a dummy variable for if the project is in a restructured state. Long-term contract is a dummy variable if the project signed a long-term contract to see its power. All specifications include fixed effects for operating year, binary indicator for ISO, and for the presence of wind ordinance at the project location. Wind controls include hourly average wind speeds and wind direction at 80m and 100m, and standard deviation of wind speeds at 80m and 100m. Robust standard errors reported in parenthesis. Significance: *** p<0.01, ** p<0.05, *** p<0.1.

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 larger wind turbines than smaller developers and also more likely to build projects in one type of market. We re-estimate the model including an indicator for large developer, and by including an interaction between market structure and large developer. The resulting estimates are quantitatively similar (Appendix Table G10).

We also estimate specifications controlling for project specific realized prices to see if some of these effects are driven by price differences across markets.[17] We treat these results as descriptive since prices could be endogenous to factors other than the ones included in our regressions. Coefficient estimates in Appendix Table G12 are similar to the baseline estimates, ruling out this concern.

6 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 regulated markets: 83 percent of wind projects in regulated markets signed long-term contracts compared to 58 percent in restructured markets.[18] 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 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 regulated markets are more desirable. Column (1) of Table 4 shows that, of projects that sign long-term contracts, those in regulated markets are more likely to sign them with utilities. Similarly, in column (3) we find that

[17]Contrary to solar, wind projects located in restructured markets receive lower prices on average. Expected REC prices follow a similar pattern.

[18]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.

long-term contracts in regulated 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 regulated markets leading to lower financing costs for wind and solar developers.

Table 4: 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

7 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 likely 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.

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Appendix

A Additional detail on the sample of solar projects

The sample for the solar analysis includes 4,086 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 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.

C A model of technology choice for solar projects

This section microfounds our model of axis tracking adoption. Starting from the full choice problem, we make several approximations to derive the utility specification we take to data. We start with a model of expected profit maximization but then discuss how market structure could affect developers' objective function.

Solar developers choose whether to use axis tracking panels to maximize the expected present value of profits. In each year of operation t, static profits from using technology $j \in \{\text{fixed}, \text{tracking}\}$ for site i are

$$\pi_{ijt} = p_{it} Q_{ijt} - OM_{ijt} \tag{3}$$

where p_{it} is the per MWh price of wind power at site i in year t, Q_{ijt} is annual production from technology j at site i in year t, and OM_{ijt} is operations and maintenance costs for technology j at site i in year t.[19]

At the time of the technology decision y, the present value of expected profits for using technology j at site i is

$$\Pi_{ijy} = -F_{ijy} + \sum_{t=1}^{T} \left(\frac{1}{1+r}\right)^{t} \mathbb{E}_y \left[p_{it} Q_{ijt} - OM_{ijt}]) \right] \tag{4}$$

where F_{ijy} is the installation cost of the solar project with technology j in site i in year y, r is the relevant annual interest rate for this investment decision, t is the year of operation, and T is the life of the project. The expectation operator is denoted $\mathbb{E}_y$ to emphasize that this is the expectation at the time of the technology decision y, before the project begins operation. The current formulation assumes the technology is chosen one year before the project earns the revenue for the first year of operation.

To a first approximation, a developer's expectation of static profits does not vary based on the year of operation. Although there is variation in year-on-year production due to variation in weather, these deviations from the average are not predictable. While prices can vary over time, they are usually fixed via a power purchase agreement, and it is common for contracts to specify a fixed price per MWh with pre-specified escalations to account for inflation. Even for projects exposed to market prices, electricity prices are closely tied to natural gas prices which, at the annual level, roughly follow a random walk. Finally, operations and maintenance costs increase with years in service, but the increase is gradual

[19] This formulation where assumes a constant per MWh price, which is consistent with many long term contracts, rather than a price that varies by hour of the day.

until the second half of the project's lifespan, years which contribute little to expected profits. This approximation allows us to drop the t subscripts in the expectation and simplify

$$\Pi_{ijy} = -F_{ijy} + \underbrace{\frac{1}{r}\left(1 - \frac{1}{(1+r)^T}\right)}_{\kappa(r)} \mathbb{E}_y\left[p_i Q_{ij} - OM_{ij}\right] \tag{5}$$

We can construct the expected quantity of production Q_{ij} from the data on solar resource quality at the site. If we pair this with an expected price, we can constructed expected annual revenue which we denote as $\tilde{R}_{ij}$.

$$\Pi_{ijy} = -F_{ijy} + \kappa(r)\tilde{R}_{ijy} - \kappa(r)OM_{ijy} \tag{6}$$

Assume that installation costs, F_{ijy}, are additively separable in site-specific characteristics and the cost of the panels. In this case, the site-specific characteristics (e.g. permitting, grading, construction costs) drop out of the choice problem. Further assume that the per-unit cost of each technology is the same for all developers, so it can be captured by a year-by-technology FE, δ_{jy}, multiplied by the project's capacity. Finally, we abstract from the operations and maintenance term because we do not observe these costs in the data. The installation year-by-technology fixed effect likely captures most of the relevant variation in these expected costs. The utility function can now be written as

$$U_{ijy} = \delta_{jy} \times size_i + \kappa(r)\tilde{R}_{ijy} + \tilde{\epsilon}_{ijy} \tag{7}$$

where $size_i$ is the project's capacity. Dividing through by capacity gives

$$U_{ijy} = \delta_{jy} + \kappa(r)R_{ijy} + \epsilon_{ijy} \tag{8}$$

where R is revenue per MW of capacity. As discussed in section 2 the coefficient on revenue may vary with market structure. It depends on the interest rate, and the relevant capital costs may be lower in regulated markets. Alternatively, if utilities in regulated markets are procuring power based on objectives other than cost minimization, e.g., if these utilities have a bias for status quo technology, observed technology choices by developers could reflect these utilities lower valuations for revenues. To allow for these possibilities, we replace $\kappa(r)$ with β_m where $m \in \{\text{regulated, restructured}\}$.

$$U_{ijy} = \delta_{jy} + \beta_m R_{ijy} + \epsilon_{ijy} \tag{9}$$

To take this model to data, we assume the error term follows a type I extreme value distribution and that developers choose the technology that maximizes their utility. The probability of choosing solar axis tracking for site i in year y is

$$\begin{aligned}
\Pr(tracking = 1) &= \Pr(U_{\text{tracking},y} > U_{\text{fixed},y}) \\
&= \Pr\left(\epsilon_{\text{fixed},y} - \epsilon_{\text{tracking},y} < \beta_m(R_{\text{tracking},y} - R_{\text{fixed},y}) + \delta_{\text{tracking},y} - \delta_{\text{fixed},y}\right)
\end{aligned}$$

For a binary logit model this reduces to,

$$\Pr(tracking = 1) = \frac{1}{1 + \exp(\beta_{m,\text{tracking}}(R_{\text{tracking},y} - R_{\text{fixed},y}) + \delta_{\text{tracking},y})} = \frac{1}{1 + \exp(\beta_m \Delta R + \delta_y)}$$

which is the model in Equation Equation 1.[20]

[20] Note that we normalize the operating year fixed effects coefficients for fixed tilt panel to be zero.

D Supplementary Tables

D.1 Descriptive Statistics by Restructuring Status

Table D1: Summary statistics by Restructuring Status for Solar Industry

	Restructured (N = 1335)		Regulated (N=2751)		Difference (1)-(3)
	Mean	Std Dev	Mean	Std Dev	
	(1)	(2)	(3)	(4)	(5)
Tracking (0/1)	0.23	0.42	0.44	0.50	-0.219***
Nameplate Capacity (MW)	6.79	22.99	13.06	26.18	-6.273***
Utility (0/1)	0.04	0.21	0.09	0.29	-0.046***
Realized Price ($/MWh)	122.36	59.18	95.55	44.55	26.813***
Elevation (std dev)	40.44	34.64	45.22	63.23	-4.786***
Farm value per acre ($ 1000s)	13.20	18.64	6.91	7.72	6.297***
Farm size per acre	302.91	1069.69	416.18	625.56	-113.275***
Δ Production (MWh)	1578.65	215.56	1929.48	431.44	-350.831***
Δ Revenue (100,000 $)	1.91	0.93	1.87	1.02	0.048

Notes: This table reports descriptive statistics of dependent and key explanatory variables used in the solar logit analysis, broken down by restructuring status. Sample is all solar projects at least 1 MW in size that began operation in 2001-2020. Total number of solar projects in restructured states is 1335 and those in regulated states is 2751. Column (5) reports the difference in mean. Significance: *** p<0.01, ** p<0.05, *** p<0.1.

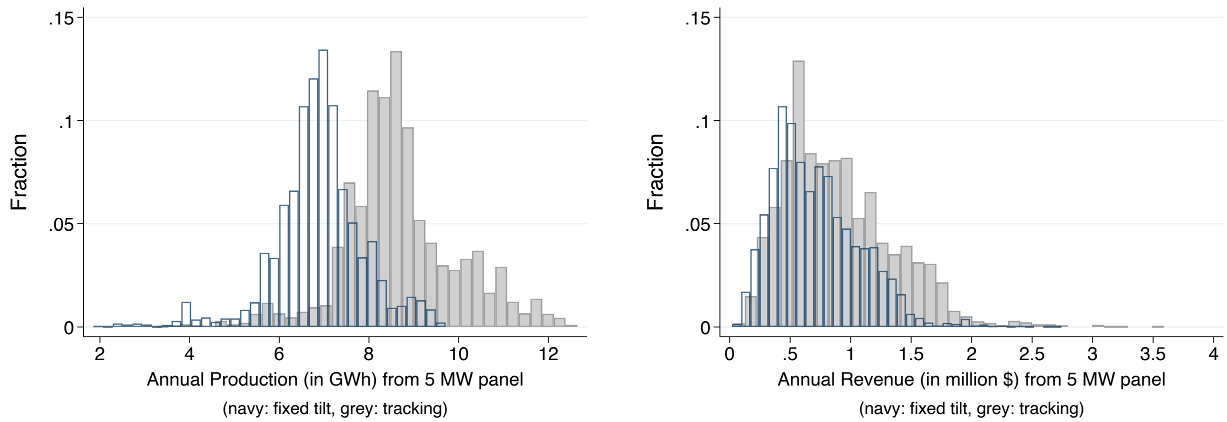
Table D2: Summary statistics by Restructuring Status for Wind Industry

	Restructured (N=303)		Regulated (N=539)		Difference
	Mean	Std Dev	Mean	Std Dev	
	(1)	(2)	(3)	(4)	(1)-(3)
Rotor Diameter (m)	91.67	17.24	90.69	15.93	0.979
Nameplate Capacity (MW)	115.98	80.55	103.87	82.46	12.113**
Utility (0/1)	0.05	0.21	0.23	0.42	-0.182***
Realized Price ($/MWh)	44.46	32.60	51.88	26.90	-7.419***
Expected REC Price ($/MWh)	5.41	10.11	3.79	6.94	1.620*
Wind Speed (m/s)	8.03	0.66	8.00	0.79	0.033
Wind Ordinance (0/1)	0.10	0.29	0.19	0.39	-0.094***

Notes: This table reports descriptive statistics of dependent and key explanatory variables used in the turbine size analysis for the wind industry, broken down by restructuring status. Sample is all wind projects at least 5 MW in size that began operation in 2001-2020. Total number of wind projects in restructured states is 303 and those in regulated states is 539. Column (5) reports the difference in mean. Significance: *** p<0.01, ** p<0.05, *** p<0.1.

E Supplementary Figures

Figure E1: Annual energy production and revenue for solar projects

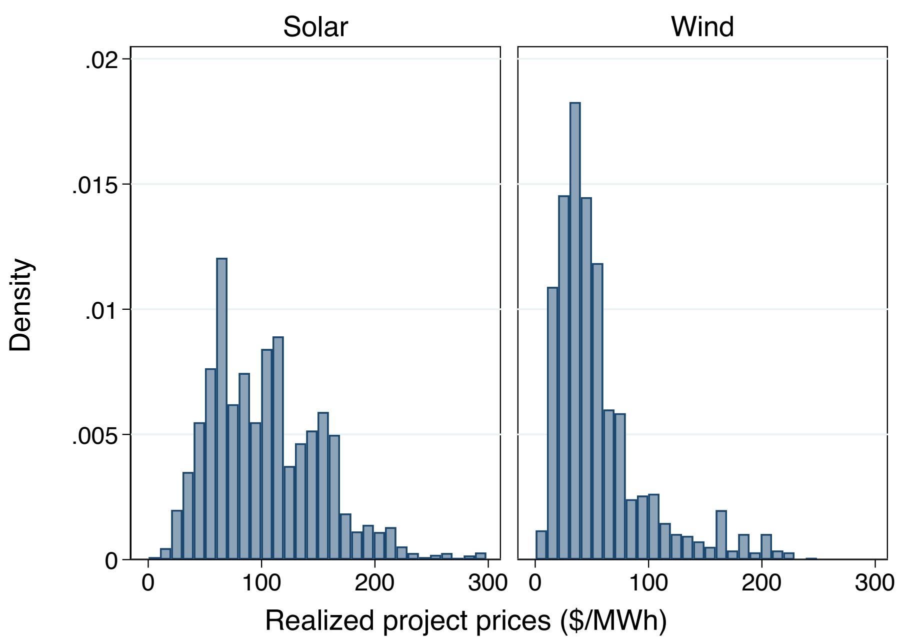


(a) Annual energy production (GWh)

(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 2001-2020.

Figure E2: 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 2001 - 2020, and all wind projects of at least 5 MW in size that began operation in 2001-2020.

F Robustness checks for solar results

F.1 Results controlling for projects in North Carolina

Table F3: Effect of market structure on choice to use tracking panels

	Uncorrected		Control Function	
	(1)	(2)	(3)	(4)
Δ Revenue ($100,000)	-0.012	-0.012	0.352***	0.273***
	(0.009)	(0.009)	(0.025)	(0.026)
Δ Revenue $\times$ Restructured	-0.124***	-0.106***	-0.054***	-0.050***
	(0.008)	(0.009)	(0.011)	(0.012)
North Carolina	-0.318***	-0.283***	0.013	-0.049
	(0.018)	(0.020)	(0.053)	(0.048)
Revenue Elasticity	-0.399	-0.368	2.212	1.735
Observations	4,086	4,086	4,086	4,086
ISO	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Terrain Ruggedness		✓		✓
Farm Size & Value		✓		✓
Log Likelihood	-2367	-2269	-2223	-2175

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 2001-2020. Δ Revenue is the difference in expected revenue from using tracking versus not. Restructured is one if the project is located in a restructured state. Revenue elasticity is the average elasticity of revenue across all projects. North Carolina is an indicator for projects in North Carolina. All specifications include fixed effects for operating year and a binary indicator for ISO. Terrain ruggedness is the standard deviation of terrain elevation. 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: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

F.2 Results by projects qualifying for PURPA rates

Table F4: Logit regression of tracking on market structure

	Uncorrected		Control Function	
Sample	Not QF	QF	Not QF	QF
	(1)	(2)	(3)	(4)
Δ Revenue (\$100,000)	-0.036***	0.071***	0.322***	0.291***
	(0.012)	(0.013)	(0.034)	(0.035)
Δ Revenue $\times$ Restructured	-0.078***	-0.146***	-0.006	-0.104***
	(0.012)	(0.013)	(0.014)	(0.017)
Revenue Elasticity	-0.424	0.0272	2.404	1.584
Observations	2,085	1,977	2,085	1,977
ISO	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Terrain Ruggedness	✓	✓	✓	✓
Farm Size & Value	✓	✓	✓	✓
Log Likelihood	-1200	-1029	-1121	-998.9

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 2001-2020. We do not observe qualifying facility status for 24 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. All specifications include fixed effects for operating year and a binary indicator for ISO. 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: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

F.3 Results controlling for developer size

Table F5: Logit regression of tracking on market structure

	Uncorrected		Control Function	
	(1)	(2)	(3)	(4)
Δ Revenue ($100,000)	0.016*	0.013	0.339***	0.272***
	(0.010)	(0.009)	(0.021)	(0.022)
Δ Revenue × Restructured	-0.109***	-0.103***	-0.047***	-0.044***
	(0.019)	(0.009)	(0.011)	(0.011)
Large Developer	0.089***	0.060***	0.153***	0.102***
	(0.023)	(0.023)	(0.023)	(0.023)
Revenue Elasticity	-0.179	-0.194	2.098	1.709
Observations	4,086	4,086	4,086	4,086
ISO	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Terrain Ruggedness		✓		✓
Farm Size & Value		✓		✓
Log Likelihood	-2427	-2316	-2261	-2210

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 2001-2020. Δ Revenue is the difference in expected revenue from using tracking versus not. Restructured is if the project is located in a restructured state. All specifications include fixed effects for operating year and a binary indicator for ISO. 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: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

F.4 Results excluding utilities

Table F6: Logit regression of tracking on market structure

	Uncorrected		Control Function	
	(1)	(2)	(3)	(4)
Δ Revenue (\$100,000)	0.019**	0.012	0.401***	0.148***
	(0.009)	(0.009)	(0.022)	(0.018)
Δ Revenue $\times$ Restructured	-0.121***	-0.098***	-0.038***	-0.084***
	(0.009)	(0.009)	(0.011)	(0.010)
Revenue Elasticity	-0.187	-0.187	2.565	0.744
Observations	3,780	3,780	3,780	3,780
ISO	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Terrain Ruggedness		✓		✓
Farm Size & Value		✓		✓
Log Likelihood	-2257	-2129	-2078	-2081

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 2001-2020 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. All specifications include fixed effects for operating year and a binary indicator for ISO. 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: *** $p<0.01$, ** $p<0.05$, *** $p<0.1$.

F.5 Results controlling for project size

Table F7: Effect of market structure on choice to use tracking panels

	Uncorrected		Control Function	
	(1)	(2)	(3)	(4)
Δ Revenue (\$100,000)	0.027***	0.019**	0.256***	0.217***
	(0.008)	(0.009)	(0.019)	(0.021)
Δ Revenue $\times$ Restructured	-0.104***	-0.091***	-0.048***	-0.045***
	(0.008)	(0.009)	(0.010)	(0.011)
Nameplate Capacity (MW)	0.005***	0.004***	0.006***	0.005***
	(0.000)	(0.000)	(0.001)	(0.001)
Revenue Elasticity	-0.104	-0.126	1.590	1.367
Observations	4,086	4,086	4,086	4,086
ISO	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Terrain Ruggedness		✓		✓
Farm Size & Value		✓		✓
Log Likelihood	-2321	-2247	-2215	-2176

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 2001-2020. Δ Revenue is the difference in expected revenue from using tracking versus not. Restructured is one if the project is located in a restructured state. Revenue elasticity is the average elasticity of revenue across all projects. All specifications include fixed effects for operating year and a binary indicator for ISO. Terrain ruggedness is the standard deviation of terrain elevation. 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.

F.6 Results without conditioning on prices

Table F8: Logit regression of tracking on market structure without conditioning on prices

	Logit	
	(1)	(2)
Δ Production (GWh)	0.318***	0.264***
	(0.018)	(0.022)
Δ Production $\times$ Restructured	-0.059***	-0.060***
	(0.011)	(0.012)
Observations	4,086	4,086
ISO	✓	✓
Year FE	✓	✓
Terrain Ruggedness		✓
Farm Size & Value		✓
Production Elasticity	1.663	1.412
Log Likelihood	-2317	-2244

Notes: 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 2001-2020. Δ Production is the difference in expected production from using tracking versus not. Restructured is one if the project is located in a restructured state. All specifications include fixed effects for operating year and a binary indicator for ISO. 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.

F.7 Results comparing different measures of market structure

Table F9: Logit regression of tracking on market structure

	State-level Restructuring	Competitive Wholesale Market	Either
	(1)	(2)	(3)
Δ Revenue ($100,000)	0.325***	0.368***	0.368***
	(0.026)	(0.023)	(0.023)
Δ Revenue × Market Structure	-0.043***	0.008	0.011
	(0.011)	(0.008)	(0.010)
Observations	4,086	4,086	4,086
Year FE	✓	✓	✓
Terrain Ruggedness	✓	✓	✓
Farm Size & Value	✓	✓	✓
Revenue Elasticity	2.075	2.516	2.532
Log Likelihood	-2210	-2220	-2220

Notes: 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 2001-2020. Δ Revenue is the difference in expected revenue from using tracking versus not. All specifications are corrected for revenue endogeneity using a control function approach. State-level restructuring is a dummy variable for if the project is in a restructured state. Competitive Wholesale Market is an indicator for being located in the footprint of a competitive wholesale market. Either is the union of the two. All specifications include fixed effects for operating year. 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.

G Robustness checks for wind results

G.1 Results controlling for developer size

Table G10: Effect of market structure on turbine rotor diameter (m)

	Dependent variable: Rotor Diameter (m)				
	OLS		Naive Lasso	Double Selection	
	(1)	(2)	(3)	(4)	(5)
Restructured	0.308	-2.921*	-2.110**	-2.707*	-2.751*
	(0.747)	(1.519)	(1.019)	(1.394)	(1.458)
Major Developer	-0.203	-1.216	-0.688	-1.109	-1.274
	(0.709)	(0.797)	(0.696)	(0.758)	(0.788)
Long-term contract					1.766**
					(0.743)
R^2	0.678	0.764	0.718	-	-
Mean Rotor Diameter (m)	91.05	91.05	91.05	91.05	91.05
Observations	842	842	842	842	842
Year FE	✓	✓	✓	✓	✓
ISO	✓	✓	✓	✓	✓
Wind Controls		✓	✓	✓	✓

Notes: Columns (1) and (2) are the coefficient estimates of the OLS regression with rotor diameter as the dependent variable. Column (3) shows coefficient estimate from using Lasso to select wind controls, and Columns (4) and (5) uses double selection to correct for omitted variable bias in Naive Lasso. Sample is all wind projects at least 5 MW in nameplate capacity that began operating in 2001-2020. Restructured is a dummy variable for if the project is in a restructured state. Major developer is an indicator for whether the project is developed by one of the top 5 developers. Long-term contract is a dummy variable if the project signed a long-term contract to see its power. All specifications include fixed effects for operating year, binary indicator for ISO, and for the presence of wind ordinance at the project location. Wind controls include hourly average wind speeds and wind direction at 80m and 100m, and standard deviation of wind speeds at 80m and 100m. Robust standard errors reported in parenthesis. Significance: *** p<0.01, ** p<0.05, *** p<0.1.

G.2 Results excluding utilities

Table G11: Effect of market structure on turbine rotor diameter (m)

	Dependent variable: Rotor Diameter (m)				
	OLS		Naive Lasso	Double Selection	
	(1)	(2)	(3)	(4)	(5)
Restructured	0.277	-2.719*	-1.432	-1.839	-2.125
	(0.813)	(1.617)	(0.976)	(1.491)	(1.534)
Long-term contract					1.480
					(0.921)
R^2	0.694	0.796	0.705	-	-
Mean Rotor Diameter (m)	91.05	91.05	91.05	91.05	91.05
Observations	705	705	705	705	705
Year FE	✓	✓	✓	✓	✓
ISO	✓	✓	✓	✓	✓
Wind Controls		✓	✓	✓	✓

Notes: Columns (1) and (2) are the coefficient estimates of the OLS regression with rotor diameter as the dependent variable. Column (3) shows coefficient estimate from using Lasso to select wind controls, and Columns (4) and (5) uses double selection to correct for omitted variable bias in Naive Lasso. Sample is all wind projects at least 5 MW in nameplate capacity that began operating in 2001-2020. Restructured is a dummy variable for if the project is in a restructured state. Long-term contract is a dummy variable if the project signed a long-term contract to see its power. All specifications include fixed effects for operating year, binary indicator for ISO, and for the presence of wind ordinance at the project location. Wind controls include hourly average wind speeds and wind direction at 80m and 100m, and standard deviation of wind speeds at 80m and 100m. Robust standard errors reported in parenthesis. Significance: *** p<0.01, ** p<0.05, *** p<0.1.

G.3 Results accounting for price effects

Table G12: Effect of market structure on turbine rotor diameter (m)

	Dependent variable: Rotor Diameter (m)				
	OLS		Naive Lasso	Double Selection	
	(1)	(2)	(3)	(4)	(5)
Restructured	0.174	-3.085**	-1.769*	-2.698*	-2.500*
	(0.756)	(1.495)	(1.028)	(1.430)	(1.443)
Realized price ($/MWh)	0.012	-0.010	0.005	-0.010	-0.014
	(0.013)	(0.018)	(0.015)	(0.018)	(0.018)
Long-term Contract					1.565**
					(0.757)
R^2	0.679	0.764	0.715		
Mean Rotor Diameter (m)	91.05	91.05	91.05	91.05	91.05
Observations	841	841	841	841	841
Year FE	✓	✓	✓	✓	✓
ISO	✓	✓	✓	✓	✓
Wind Controls		✓	✓	✓	✓

Notes: Columns (1) and (2) are the coefficient estimates of the OLS regression with rotor diameter as the dependent variable. Column (3) shows coefficient estimate from using Lasso to select wind controls, and Columns (4) and (5) uses double selection to correct for omitted variable bias in Naive Lasso. The penalty term (λ) for Lasso in double selection and 'Naive Lasso' is selected using 10 fold Cross Validation. Sample is all wind projects at least 5 MW in nameplate capacity that began operating in 2001-2020. Restructured is a dummy variable for if the project is in a restructured state. Realized price ($/MWh) is the REC adjusted resale price that a project receives. All specifications include fixed effects for operating year, binary indicator for ISO, and for the presence of wind ordinance at the project location. Wind controls include hourly average wind speeds and wind direction at 80m and 100m, and standard deviation of wind speeds at 80m and 100m. Robust standard errors reported in parenthesis. Significance: *** p<0.01, ** p<0.05, *** p<0.1.

G.4 Results comparing different measures of market structure

Table G13: Effect of market structure on turbine rotor diameter (m)

	Dependent variable: Rotor Diameter (m)		
	State-level Restructuring	Competitive Wholesale Market	Either
	(1)	(2)	(3)
Market Structure	-2.985**	-2.568	-2.832
	(1.450)	(1.813)	(1.782)
Mean Rotor Diameter (m)	91.05	91.05	91.05
Observations	842	842	842
Year FE	✓	✓	✓
Wind Controls	✓	✓	✓

Notes: All specifications show coefficient estimates from double selection model with the penalty term (λ) selected using 10 fold Cross Validation. Sample is all wind projects at least 5 MW in nameplate capacity that began operating in 2001-2020. State-level restructuring is a dummy variable for if the project is in a restructured state. Competitive Wholesale Market is an indicator for being located in the footprint of a competitive wholesale market. Either is the union of the two. All specifications include fixed effects for operating year and an indicator for the presence of wind ordinance at the project location. Wind controls include hourly average wind speeds and wind direction at 80m and 100m, and standard deviation of wind speeds at 80m and 100m. Robust standard errors reported in parenthesis. Significance: *** p<0.01, ** p<0.05, *** p<0.1.