Capital versus Output Subsidies: Implications of Alternative Incentives for Wind Investment

Joseph E. Aldy, Todd D. Gerarden, and Richard L. Sweeney*

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Abstract

We examine the choice between using capital and output subsidies to promote wind energy in the United States. In this sector, some subsidies support upfront investment while others reward output. We exploit a natural experiment in which wind farm developers were unexpectedly given the opportunity to choose between these two options in order to estimate the differential impact of these subsidies on project productivity. We then use these estimates to evaluate the public economics of U.S. wind energy subsidies. Using matching and fuzzy regression discontinuity designs, we find that wind farms choosing the capital subsidy produce 11 to 12 percent less electricity per unit of capacity than wind farms selecting the output subsidy and that this effect is driven by incentives generated by these subsidies rather than selection. The Federal government expends about 25 percent more per kilowatt-hour of power produced under the capital subsidy than it does under the output subsidy.

Keywords: energy subsidies, instrument choice

JEL Codes: H23, Q42, Q48

*Aldy: Harvard Kennedy School, Resources for the Future, National Bureau of Economic Research, and Center for Strategic and International Studies; joseph_aldy@hks.harvard.edu. Gerarden: Harvard Kennedy School; gerarden@fas.harvard.edu; Sweeney: Boston College; sweeneri@bc.edu. Jeff Bryant, Napat Jatusripitak, Michael O'Brien, Carlos Paez, Jun Shepard, and Howard Zhang provided excellent research assistance. Thanks to Jud Jaffe for assistance with the 1603 grant program data; Scott Walker, Gabe Chan and Jörn Hünteler for assistance with wind speed data; and Curtis Carlson, John Horowitz, and Adam Looney for assistance with historical tax policy information. This work has been supported by the Alfred P. Sloan Foundation (grant 2015-13862) and the Harvard University Center for the Environment. Todd Gerarden acknowledges support from U.S. EPA STAR Fellowship Assistance Agreement no. FP-91769401-0. This paper has not been formally reviewed by the EPA. The views expressed in this paper are solely those of the authors, and EPA does not endorse any products or commercial services mentioned in this paper. We have benefited from feedback provided by seminar participants at the AERE Summer Conference, Columbia, Duke, EAERE Summer School, Harvard, and Yale, as well as from Alberto Abadie, Kelsey Jack, Joel Landry, Jeff Liebman, Paul Goldsmith-Pinkham, and Jim Stock.

1 Introduction

Having decided it is desirable to increase the supply of a particular good, policymakers face a choice between subsidizing inputs to the production of that good or subsidizing its provision directly. For example, governments can subsidize water or support crop prices; provide cheap financing for low income housing construction or supplement rents paid to landloards accepting low income tennants. Which approach garners more supply for a given ammount of public expenditure? Answering this question empirically is challenging because both subsidy types are rarely available at the same time or in the same industry. In this paper, we focus on wind energy in the United States, where some subsidies support capital investment while others reward the production of electricity. Exploiting a natural experiment in which wind farm developers could choose between investment and output subsidies, we estimate the impact of this choice on project productivity, and then use these estimates to evaluate the public economics of U.S. wind energy subsidies.

Between 2004 and 2014 wind power capacity in the United States increased tenfold, driven by an array of implicit and explicit federal and state renewable energy subsidies. Historically, the primary Federal subsidy program has been the production tax credit (PTC), which provided eligible owners with approximately 2 cents for each kilowatt hour (kWh) of output produced during the first ten years of operation. In 2009, an alternative Federal subsidy, the 1603 grant, was introduced, and its election provided developers with an up-front cash payment equal to 30 percent of investment costs in lieu of the PTC. In reality, there was a third option, the investment tax credit (ITC). In practice, firms chose between the PTC and the section 1603 grant, since the latter yielded equivalent nominal value to the ITC but did not require tax liability for monetization. Designed to address the unprecedented challenges of monetizing tax credits during the financial crisis, the section 1603 grant was a truly unique and, importantly, unexpected policy innovation.

We use this unexpected temporal discontinuity in 1603 grant eligibility to implement two complementary empirical strategies: a matched difference-in-differences (MDD) analysis and a fuzzy regression discontinuity (RD) research design. Our matching strategy exploits a panel of electricity generation for wind projects placed into service between 2002 and 2012. We estimate a propensity score model for subsidy selection using data from the period during which both the PTC and 1603 grant were available and use these estimates to infer counterfactual treatment status for projects that entered before the 1603 grant was available. We then use these estimates in a model akin to difference-in-differences to separate the policy effect from the selection effect and any effects generated by contemporaneous changes in the environment (e.g., changes in technology or site quality).

In the regression discontinuity analysis, we restrict our sample to wind farms coming online within 12 months of the January 1, 2009 policy innovation. As we discuss below, the long lead time of wind project development ensures that 1603 grant recipients in this window would have been well underway before the grant was even created. We instrument for 1603 cash grant recipient status with a binary indicator for exogenous grant eligibility. This allows us to isolate the local average treatment effect of cash grant receipt on subsequent electricity generation outcomes, isolating this causal effect from the effect of selection by firms. We assess the sensitivity of these results using alternative bandwidths.

In our baseline ordinary least squares model using the full sample, we find that 1603-recipient wind farms produce approximately 9 percent less power than PTC recipients. Our matching analysis produces an estimated policy effect of approximately 12 percent. In our fuzzy RD estimates using the restricted sample, we also find that 1603 grant receipt results in an 11 percent less power generation than PTC receipt. All three models provide estimates of similar magnitude, suggesting that the potential for selection in this setting may be small after conditioning on observable characteristics.

These findings suggest the form of subsidy available to wind investors has important implications for the social benefits of investment. The primary motivation for Federal wind power subsidies is reducing damages due to environmental externalities created by conventional sources of electricity generation. Our findings suggest the 1603 cash grant induces less electricity generation than the PTC, even for otherwise equivalent projects.

We also investigate the expected fiscal outlay per MWh of production to wind farms claiming the PTC and the 1603 grant. We forecast generation for PTC- and 1603-recipient wind farms out 10 years, and compare the average PTC outlay per MWh to the average 1603 outlay per MWh. We find that the Federal government will pay more per MWh of production for about three-quarters of 1603 recipients than it would have under the production tax credit. The average outlay per MWh for a 1603 recipient is \$29, about one-quarter greater than the PTC of \$23.

1.1 Related Literature

A number of papers have studied the impact of subsidies on renewable energy. Hitaj (2013) analyzes the drivers of wind power development in the United States and finds that the Federal PTC plays an important role in promoting wind power. Metcalf (2010) shows how the PTC affects the user cost of capital and illustrates the adverse impact of lapses in the PTC on wind capacity investment. Using data on hourly outputs and prices for twenty-five wind and nine solar generating plants, Schmalensee (2013) evaluates the impacts of subsidies on the value of these plants' outputs, the variability of output at plant and regional levels, and the variation in performance among plants and regions. Our paper represents the first attempt to distinguish the impacts of alternative subsidy types.

Despite extensive research on both optimal taxation and instrument choice, there is little research on the relative performance of input and output subsidies. Parish and McLaren (1982) compare input and output subsidies financed by distortionary taxation in a general theoretical model. They conclude the relative efficiency of these subsidies is context-dependent. Two key factors determine which subsidy is more efficient. First, the shape of the production function matters: with decreasing returns, an input subsidy can achieve a given increase in output at less cost than an output subsidy. Second, input intensities matter: subsidizing one input can be more cost-effective than a uniform input subsidy if that input is used more intensively at the margin than on average. In the special case of a decreasing returns production function, subsidizing an input that is used more intensively on the margin than on average and is not substitutable with other inputs is more efficient than subsidizing output. In other situations, the output subsidy can dominate a non-uniform input subsidy.

Although capital and output subsidies are used interchangeably in many settings, few have been studied empirically. In the context of afforable housing, where some policies support inputs (housing units) while others support outputs (housing services), "the empirical literature is unanimous in finding that tenant-based housing certificates and vouchers provide housing of any quality at a much lower total cost... than each major program of project-based assistance" (Olsen, 2000). In the case of education, randomized trials providing financial incentives to students suggest that subsidizing inputs, such as offering incentives for reading books, has a greater impact on student achievement than output-based incentives (Fryer, 2011). While the mechanisms behind each result are idiosyncratic, this highlights the potential importance of context-dependent factors in determining whether input or output subsidies are preferable.

The rest of this paper proceed as follows. Section 2 provides a brief introduction to the economics of wind energy, the policy environment, and the available data. Section 3 discusses our empirical strategy. Section 4 reports the results and sections 5 and 6 discuss policy implications and conclude.

2 Background

2.1 The Economics of Wind Power

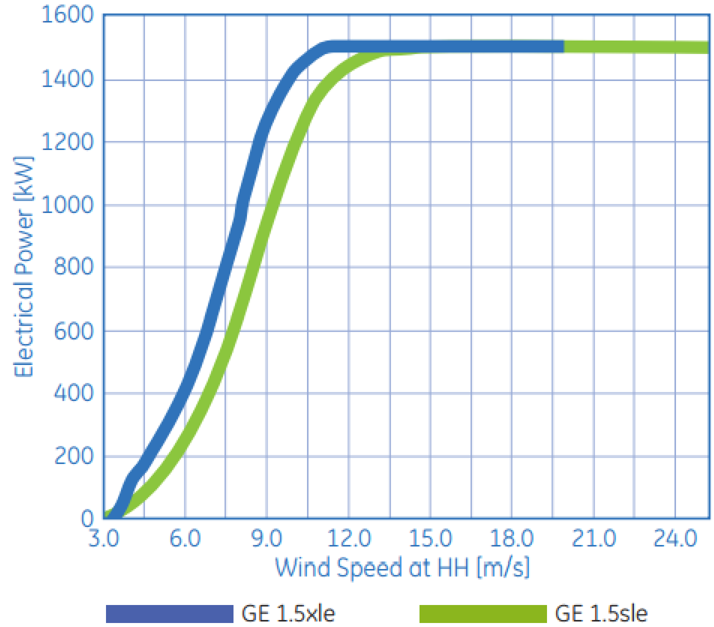
A wind turbine consists of a rotor with three long blades connected to a gearbox and generator atop a large tower. As wind passes through the blades, the rotor spins a drive shaft connected through a series of gears to a generator that converts this kinetic energy to electrical energy. The amount of power generated by a wind turbine is determined primarily by the design of the turbine, the velocity of the wind, and the direction of the wind relative to the orientation of the turbine. Nameplate capacity, denominated in megawatts (MW), is the maximum rated output of a turbine operating in ideal conditions. While no power is generated if the wind isn't blowing fast enough to spin the turbine, if the wind is blowing too fast it will damage the turbine. Wind turbines typically operate at rated capacity at wind speeds of 33 miles per hour (15 meters/second), and shut down when the wind speed exceeds 45-55 miles per hour (20-25 meters/second). Figure 1 presents the marketed power curves for two common General Electric wind turbine models, demonstrating the nonlinear relationship between windspeed and output.

Building a wind farm involves large up-front costs. During the time period we study, average project costs were $2 million per MW for projects ranging from 20 MW to over 200 MW (Wiser and Bolinger, 2014). Developers have to first survey and secure access to land that is both sufficiently windy and close to existing transmission lines. They then have to obtain financing and siting permits, as well as negotiate any power purchase agreements. Turbines are ordered up to 24 months before ground is broken, and, at that point, the size and location of a project is fairly fixed.[1] All told, it takes 9 to 12 months to complete construction of a wind project (Brown and Sherlock, 2011), with site permitting and turbine lead times often double that. Wind farms coming online in 2009 in the Midcontinent Independent System Operator (MISO) footprint spent an average of 3.5 years in the interconnection queue. In 2010, the average time in the queue was 2.7 years.[2]

[1] Turbine lead times approached two years during the peak demand period in the first half of 2008 (Lantz et al., 2012). Market fundamentals have since changed, and lead times have dropped significantly. Nevertheless, there is a natural lag between turbine contract and power purchase agreement signing and project commissioning such that turbines ordered in early 2008 were employed in projects that were completed in 2010.

[2] Authors' estimate based on MISO data.

Figure 1: Reported Power Curves for 1.5 MW General Electric Turbines



Although wind turbines do not incur fuel costs, there are a number of variable costs associated with running a wind farm efficiently once it is installed. Turbines need to be monitored and serviced regularly in order to operate at peak efficiency. Placing more emphasis on routine maintenance can reduce the probability of failure, and, conditional on failure, service arrangements and crane availability induce variation in turnaround times across operators. The gearbox, in particular, contains a complicated set of parts that, if not serviced, can reduce the fraction of wind power harnessed or cause the unit to be taken offline entirely. In 2013, operations and maintenance costs at U.S. wind farms were typically on the order of \$5 to \$20 per MWh, with a few plants with O&M costs in excess of \$60/MWh (Wiser and Bolinger, 2014).

The following equation summarizes the realized output y_{it} generated by a wind turbine at a given point in time t,

$$y_{it} = a_{it} e_i(w_{it}, m_{it}) k_i$$

where $a \in \{0, 1\}$ is an indicator for whether the turbine is available for operation that period and k_i is the nameplate capacity of the turbine. The turbine's efficiency $e_i \leq 1$ is a turbine-specific function of the wind speed and quality that period (w_{it}) and the turbine's state of maintenance (m_{it}).The above reference power curves can thus be seen as the production frontier where $a = 1$ and m is at its maximum.

2.2 Policy Background

The United States has implemented many policies – at Federal, state, and even local levels – to promote investment in wind power. Since 1992, the leading Federal subsidy for wind farm developers has been the production tax credit (PTC). The PTC is a per-kilowatt-hour tax credit for electricity generated by qualified energy resources and sold by the operator to an unrelated party during the taxable year. Congress initially set the PTC at 1.5 cents/kWh, but automatic inflation adjustments made it worth 2.3 cents/kWh for qualifying generation in 2014. A qualifying generation source can claim the PTC for only the first ten years of generation after the facility is placed into service. Prior to the 2008 financial crisis, wind farm developers typically monetized tax credits by partnering with a financial firm in the tax equity market.[3] During the financial crisis, more than half of the suppliers of tax equity departed the market, which introduced financing challenges for wind farm developers that did not have (nor anticipate to have) sufficient tax liability to monetize the tax credits on their own (U.S. PREF, 2010).

In this financial context, wind farm developers sought new ways to realize the value of the PTC. During the 2008-2009 Presidential Transition, representatives of the wind industry advocated for making the PTC refundable and/or to create long carry-back provisions to the Presidential Transition Team and Congressional staffers, but these ideas were not acceptable to the bill writers.[4] In early January 2009, Congressional and Presidential Transition Team members discussed for the first time the idea of availing the investment tax

[3]For example, in 2007, Lehman Brothers, AIG, Merrill Lynch, among others, provided equity to wind developers and in return these financial firms claimed the projects' production tax credit (and accelerated depreciation benefits) in their respective tax filings.

[4]One of the authors served as one of two staff representing the Obama Presidential Transition Team who negotiated the energy provisions of the Recovery Act. He regularly met with representatives of the renewable industry, including staff to trade associations (including the American Wind Energy Association, the Solar Energy Industries Association, the Geothermal Energy Association, and the American Council on Renewable Energy), staff of wind power firms (including Vestas, GE, and Iberdrola), and staff to various firms that finance wind power projects (including Chadbourne and Parke, GE Capital, Morgan Stanley, and the U.S. Partnership for Renewable Energy Finance). He met regularly with staff to the House Ways and Means and Senate Finance Committees in December 2008 and January 2009, as well as with career Treasury staff in the Office of Tax Policy. In January 2009, upon agreement with Congressional negotiators of what became the section 1603 cash grant in the Recovery Act, the author briefed a large meeting of the renewables industry at the Presidential Transition Team offices where the unexpected, novel nature of this policy was evident in the meeting participants' reactions.

credit (ITC) to all renewable power sources (at that time, the ITC primarily benefited solar). Moreover, the bill negotiators agreed to provide an option for project developers to select a cash grant of equal value to the ITC in lieu of the ITC or PTC. When the bill became law the following month, Congress agreed to make the ITC and section 1603 cash grant options available retroactively to projects placed into service on or after January 1, 2009.[5]

The Recovery Act thus provided wind power developers with a new, mutually exclusive subsidy choice: (1) they could claim the production tax credit (PTC) or (2) they could claim the section 1603 cash grant in lieu of tax credits.[6] This policy approach was novel and unexpected along two dimensions. First, wind power had never been supported by an investment subsidy and the policy proposals discussed by wind industry advocates focused on modifying the existing production tax credit. Second, providing a taxpayer with the option of a tax credit or a cash payment in lieu of the tax credit had never been pursued before the Recovery Act in any tax policy context (John Horowitz, Office of Tax Policy, U.S. Treasury, 2015).[7] The 1603 grant program expired in 2012, with projects having to have completed "significant" construction by October 1, 2012 in order to be eligible for the program. In total the Treasury made about 400 section 1603 grant awards to wind farms, disbursing over $12 billion.

These subsidies exist in a complicated energy and environmental policy space characterized by multiple, overlapping regulatory and fiscal policy instruments focused on wind power development (Aldy, 2013; Metcalf, 2010; Schmalensee, 2012). Since the major tax reform of 1986, wind project developers could employ the modified accelerated cost recovery system that effectively permits a developer to depreciate all costs over five years, instead of the norm of twenty years for power generating capital investments. Since 2005, the Department of Energy loan guarantee program provided a mechanism for wind power

[5]Wind projects were already eligible for the PTC under current law at the time.

[6] While the ARRA also provided developers with the option of taking an Investment Tax Credit (ITC), in practice, the choice came down between the PTC and the section 1603 grant, since the latter yields equivalent value to the ITC, processed in a matter of four to six weeks instead of on an annual tax reporting basis, and did not require tax liability for monetization.

[7]The Fall 2008 debate over a one-year extension of the wind PTC further illustrates the novelty of the cash grant policy. At that time, the PTC had been authorized by a 2006 tax law that established a December 31, 2008 sunset. On October 2, 2008, as a part of the Troubled Asset Relief Program (TARP) Bill, Congress extended the PTC sunset provision to December 31, 2009. Despite the obvious salience of the financial crisis in writing the PTC extension into the TARP Bill, Congress did not provide the investment tax credit or the cash grant option in the law. Put simply, the legislative action on the TARP Bill preceded the idea of giving wind developers options over their choice of subsidy.

developers to secure a Federal guarantee on project debt that could significantly lower the cost of financing the project. Many states also have renewable portfolio standards which mandate that a minimum share of the states consumption come from qualified renewable sources. As Schmalensee (2012) notes, transparency into renewable energy credit markets is heterogeneous around the country and, in many states, quite poor. Nonetheless, in some years for some states, wind power generation has earned more than $50/MWh, or more than twice the value of the production tax credit. States also provide subsidies through state tax credits and property tax exemptions.

For purposes of the statistical analyses below, it is important to recognize that these policy instruments generally did not change contemporaneously with the policy innovation of the section 1603 grants. For example, the Department of Energy loan guarantee program did not issue any loan guarantees to wind projects before 2010. The state renewable portfolio standards experienced only very modest changes in 2008 and 2009, with the exception of Kansas establishing a new RPS in May 2009, California increasing its 2020 RPS goal in September 2009, and Nevada adding post-2015 compliance schedule in June 2009. Given the development lead times necessary for wind farm investment, we do not believe that these changes in RPS policies would impact any wind capacity decisions in 2008 and 2009.

2.3 Data

The primary data sources for this paper are two publicly available Energy Information Administration (EIA) surveys covering all utility-scale wind farms in the United States. Form EIA-860, which is collected annually, contains the following variables: first date of commercial operation, nameplate capacity in megawatts, number of turbines, operator name, location, and regulatory status. This annual plant level information is combined with monthly generation data from survey EIA-923.

We then supplement this EIA data with exact turbine latitude and longitude for every wind farm from the American Wind Energy Association (AWEA). We merged these location data with wind speed data from 3TIER. 3TIER uses global wind and weather monitor data to interpolate half-hourly wind speed and direction data for the entire continental United States. For each facility in the EIA data, we fed these predicted hourly wind speeds into a reference 1.5 MW wind turbine power curve from Carrillo et al. 2009. We then used this predicted power output to get an engineering estimate of the potential

Table 1: Summary Statistics by Entry Date

Entry Year	Wind Farms	1603	Nameplate	No. Turbines	Wind Speed	Regulated	Capacity Factor
2002	20	0	53.81	65.89	7.24	0.05	0.27
2003	24	0	67.11	74.16	7.25	0.00	0.31
2004	19	0	25.34	39.56	7.30	0.11	0.24
2005	30	0	65.61	45.76	7.50	0.03	0.35
2006	43	0	44.20	27.75	7.25	0.12	0.32
2007	39	0	123.73	76.64	7.36	0.08	0.33
2008	90	0	93.51	54.44	7.29	0.11	0.33
2009	88	51	85.96	52.51	7.16	0.15	0.30
2010	60	50	87.59	50.65	7.07	0.07	0.32
2011	78	56	72.82	38.82	6.69	0.05	0.30
2012	117	61	98.96	48.61	7.04	0.13	0.33

output attainable for each plant each month.

The final data set comes from the U.S. Department of Treasury. These data contain information on every recipient of a 1603 cash grant, including the amount awarded (equal to 30 percent of project investment costs), the date of the award, and the date placed in service. Based on the guidance provided by staff at the American Wind Energy Association, we have assumed that all developers of non-1603 recipient wind farms claimed the PTC. We have confirmed that no corporation claimed the ITC for PTC-eligible projects (i.e., wind) in 2009, 2010, and 2011 in the annual Internal Revenue Service Estimated Data Line Counts reports for corporation tax returns. We do not have tax data on the PTC claims, although we observe all power related data for presumed PTC-claimants through the EIA data described above.

The EIA data spans 2002 to 2014. We remove plants which came online prior to 2002 before generation data are available. We also remove facilities that came on-line after 2012 in order to ensure that we observe at least 24 months of production for each plant. Finally, we remove plants that are publicly owned (for example municipal power plants and cooperatives). These plants are not eligible for the production tax credit, and therefore fall outside the scope of this paper looking at the tradeoffs between capital and output subsidies. Table 1 presents an annual summary of these data for this restricted sample.

Table 2 compares projects entering after the 1603 program was introduced by subsidy type. These projects differ on a number of observable dimensions. Although the overall size of the projects are comparable, 1603 projects use larger turbines and are located in areas with lower wind quality. The share of regulated firms is lower for 1603 recipients than PTC recipients. Finally, projects selecting the 1603 grant have lower capacity factors by 4 percentage points. The capacity factor is the ratio of observed output (MWh) to the maximum attainable output of a plant if it had constantly produced at its nameplate capacity.[8] In the next section, we describe our strategy for decomposing this observed difference in productivity across subsidy types into a selection and treatment effect.

Table 2: Comparison of 2009-2012 Projects by Policy Choice

	PTC	1603	Difference	(p-value)
Nameplate Capacity	91.72	85.37	6.35	0.47
# Turbine	50.05	46.41	3.64	0.46
Turbine Size	1.80	1.94	-0.14	0.02
Mean Wind Speed	7.30	6.83	0.47	0.00
Regulated	0.23	0.03	0.20	0.00
Capacity Factor	0.34	0.30	0.04	0.00
New Wind Farms	125	218		

3 Empirical Strategy

3.1 Model

In order to estimate whether shifting subsidies from the intensive to the extensive margin reduced wind farm productivity, we assume the following model for electricity generation outcomes as a function of subsidy regime and wind farm characteristics:

$$y_{it} = \alpha D_i + \beta X_{it} + \nu_t + \epsilon_{it} \tag{1}$$

where y is a production outcome variable of interest (electricity generation or capacity factor), D is an indicator for whether the wind farm took the 1603 grant and X is a vector

[8] Capacity factors are a commonly used metric of profitability and operational activity in the electric power sector.

of controls (e.g., wind farm capacity, wind quality, regulatory regime, presence of a power purchase agreement, location, etc.). The coefficient of interest, α, is the effect of the 1603 grant on production outcomes. For example, if wind farms were less productive under the 1603 grant, we would expect α to be negative.

Estimating this equation using OLS is problematic due to the fact that D_i was chosen. The PTC pays the project approximately $23 for every MWh generated (and this amount will be adjusted higher for inflation over time), while the section 1603 grant reimburses developers for 30 percent of there up-front investment costs. Intuitively, plants that expect to have high output relative to their investment costs would prefer the PTC, while plants with relatively high investment costs per unit of expected output would prefer the section 1603 grant. Thus, OLS estimates would confound any reduced marginal effort due to the section 1603 grant program with the fact that less productive plants are likely to have selected into it. We employ two empirical approaches to identify the causal effect of the section 1603 grant on wind farm output: a matched difference-in-differences estimator and a fuzzy regression discontinuity estimator.

3.2 Matched Difference-in-Differences

Our first empirical strategy conceptually combines propensity score matching and difference-in-differences. To isolate the effect of marginal incentives from selection, we first use a matching analysis to identify which firms ineligible for the 1603 cash grant (due to coming on-line before 2009) would have taken it, had it been available. We then use difference-in-differences based on this predicted treatment in order to look for differential changes in productivity across two groups, those plants likely to select the 1603 grant when it is available and those likely to prefer the PTC. Specifically, we use the following steps:

1. **Estimate a propensity score regression:** We estimate a probit model on firms that began generating electricity while the 1603 grant was available to determine the selection rule for these firms. Selection is based on a spline in nameplate capacity, a quadratic function of wind speed, potential capacity factor output, and state dummies. The results are presented in appendix table A.1.

2. **Predict selection in the pre-period:** We use these results to predict the propensity score for firms that began generating electricity before the 1603 grant was available.

3. **Match pre and post 1603 observations on estimated propensity score.** This step recovers an estimate of each wind farm's counterfactual treatment status (i.e., latent type). Appendix figure A.1 presents the predicted propensity scores for plants entering before and after the 1603 program became available. The distributions are not identical. In order to create a balanced comparison group, we match each pre-period plant to the post-period plant with the closest propensity score, and then assign this pre-period plant its matched counterpart's observed assignment. Let $\hat{D}$ be this new matched assignment.

4. **Estimate the treatment effect:** Finally we regress electricity generation outcomes on the constructed assignment variable $\hat{D}$ interacted with an indicator for whether the plant entered before or after the 1603 became available:

$$y_{it} = \eta\hat{D}_i + \zeta 1\left\{1603 \text{ eligible}\right\}_i + \alpha\hat{D}_i \cdot 1\left\{1603 \text{ eligible}\right\}_i + \beta X_{it} + \nu_t + \epsilon_{it}$$

   In this difference-in-differences specification, η captures the effect of selection on generation outcomes, ζ captures common changes in outcomes for pre- and post-period entrants, and α captures the effect of the 1603 cash grant (and the associated change in marginal incentives) on generation outcomes. In practice, we use cohort fixed effects, allowing ζ to vary with time.

3.2.1 Identification

This matching strategy hinges on three key assumptions. First, there must be overlap (common support) in key project covariates. We test this using the data and find the assumption holds for the characteristics we include. However, even though this assumption holds for each characteristic on its own, the matching analysis is potentially susceptible to the curse of dimensionality as we condition on more wind farm characteristics simultaneously with a fixed sample (making the data more sparse).

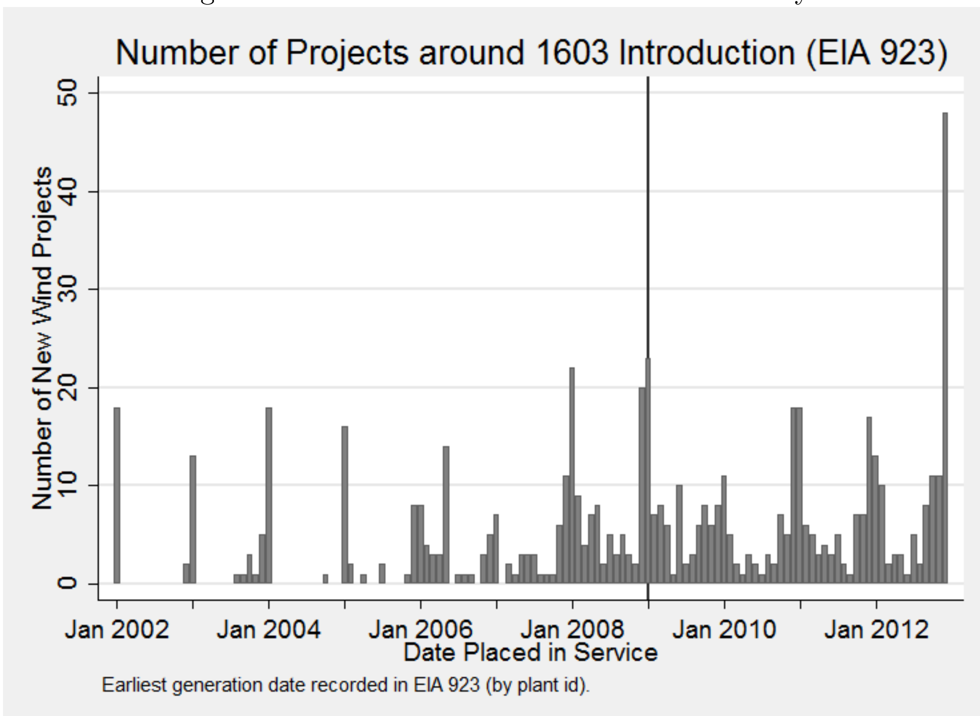
Second, the analysis assumes away latent characteristics that affect both production decisions and subsidy choice (i.e., unconfoundedness). We ameliorate this concern by including a rich set of wind farm characteristics in our analysis. This approach would fail if there are other covariates that we cannot condition on due to either a lack of data or a lack of common support among the treated and untreated samples.

Finally, the covariates used for matching must be unaffected by the treatment. While we cannot directly assess this assumption in equilibrium, the long development timeline of wind farms reduces concern over any response of project covariates to treatment. We also use a narrow time window around the policy change in our RD analysis to address this concern.

3.3 Regression Discontinuity Design

While the section 1603 cash grant was not randomly assigned, its creation came as a plausibly exogenous shock to the industry. This suggests that the timing of the Recovery Act might provide a source of identification. Data on wind project entry dates provides evidence on the exogeneity of the 1603 cash grant program. We plot the number of new projects coming online each month using EIA Form 923 data and highlight the January 1, 2009 date when wind power developers gained access to the the policy choice described above (Figure 2). This plot highlights the seasonal variation in projects coming online. On the whole, projects are more likely to come online in the first and last months of the year than in other months. In some years, such as 2004, this variation is driven by uncertainty around the expiration of the PTC. The frequency of project entry around the introduction of the 1603 cash grant policy in the last months of 2008 and the first months of 2009 are not statistically different from entry rates in the same months (or same quarters) in other years dating to 2001. Thus, project developers did not appear to adjust the timing in entry to the policy innovation.

Figure 2: Evidence of Seasonal Variation in Entry



We analyze the effect of investment and output subsidies on electricity generation outcomes using an instrumental variables research design, harnessing the natural experiment created by the 1603 cash grant program. We use the exogenous change in eligibility of wind projects for 1603 cash grant, which depends on the date of initial electricity generation. We implement a fuzzy regression discontinuity research design, using a binary indicator for initial date of electricity generation to instrument for cash grant recipient status,

$$D_i = \gamma \cdot 1\left\{1603 \text{ eligible}\right\}_i + \delta X_{it} + \nu_i \tag{2}$$

where $1\left\{1603 \text{ eligible}\right\}_i$ is an indicator for 1603 program eligibility based on the date of initial electricity generation. We then use the predicted values from this first stage, $\hat{D}$, to estimate α using our main estimating equation in a two-stage least squares (2SLS) framework.

3.3.1 Identification

The key assumption that identifies α and allows interpretation as a local average treatment effect is the exclusion restriction.[9] The exclusion restrict requires that subsidy eligibility (the instrument) only affects outcomes through its effect on subsidy choice (the endogenous variable). This assumption is not testable. To assess the importance of time-varying shocks that generate persistent differences in electricity generation outcomes, we plot trends of key variables over the period 2002 to 2012 in the appendix (Figure A.2). The figure includes investment size and average wind speed (pre-treatment variables) and capacity factor (an outcome). The small sample size and significant cross-sectional heterogeneity provide only suggestive evidence, at best, in favor of the exclusion restriction. Therefore, we also address possible violations of the exclusion restriction through a sensitivity analysis using alternative bandwidths (see Section 4.2).

Once the policy is established, it is possible that wind farm developers will make changes in how they develop and site future projects, which could violate the exclusion restriction. Our main RD specification therefore uses a bandwidth of one year on either side of the start date of the policy, relying only on a comparison of projects that came online in 2008 and 2009. This has two main advantages. First, long-run trends in wind turbine technology and electricity markets are less likely to influence our results. Second, projects that came online in early 2009 were planned and began construction in 2008, which implies that these facilities were originally designed for the PTC (Bolinger et al., 2010). This helps mitigate concern that 1603 grant recipients are fundamentally different, as may be the case in later periods. Table 3 presents t-tests for key project characteristics, comparing projects coming online in 2008 with those coming online in 2009. The means of all pre-treatment characteristics – capacity, number of turbines, wind speeds, and regulatory status – are statistically indistinguishable. The capacity factor, an outcome variable, is lower (and statistically distinguishable) for projects coming online in 2009 than for projects coming online in 2008.

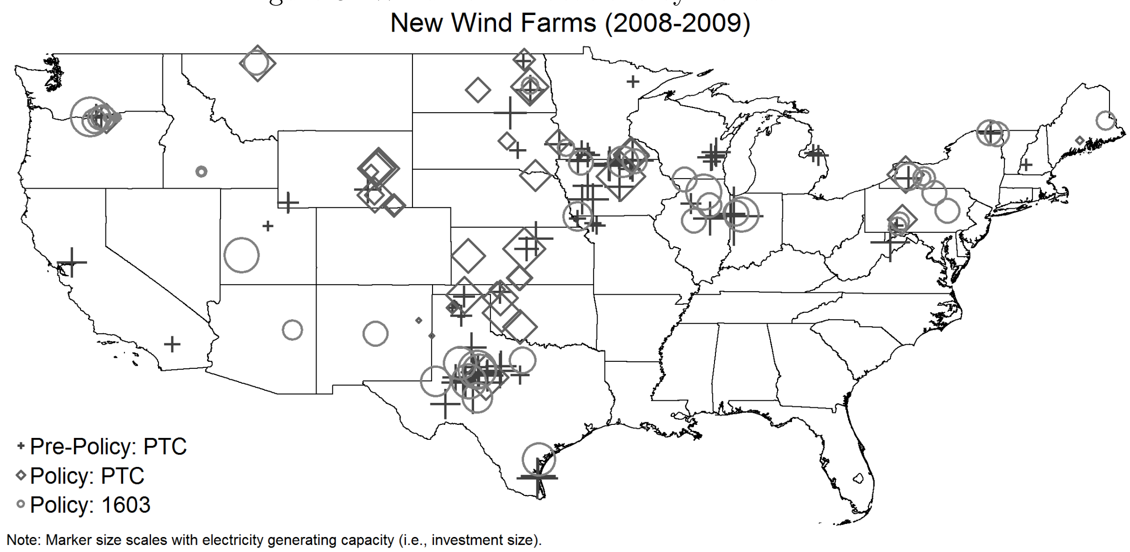
[9] We also rely on three other restrictions/assumptions. First, we know from data that the first stage is non-zero. Second, the monotonicity assumption holds by virtue of the policy environment: firms cannot "defy" treatment assignment because the 1603 grant is only available from the Federal government. Finally, we assume homogeneous treatment effects.

Table 3: Comparison of projects entering one year before and after the policy

	2008	2009	Difference	p-value
Nameplate Capacity	93.51	85.96	7.55	0.57
# Turbine	54.44	52.51	1.93	0.82
Turbine Size	1.85	1.73	0.12	0.07
Mean Wind Speed	7.29	7.16	0.13	0.33
Regulated	0.11	0.15	-0.04	0.47
Capacity Factor	0.33	0.30	0.02	0.01
New Wind Farms	90	88		
1603 Recipients	0	51		

As a final piece of descriptive evidence, we map the location of new wind farms in 2008 and 2009 in Figure 3. We distinguish between projects that came online in 2008 and 2009. For those that came online in 2009, we further distinguish between PTC and 1603 recipients. This map suggests there are regional factors that affect subsidy choice. Wind farms electing to receive the PTC tend to be located in certain regions and states, while 1603 recipients are located in other areas. This selection is not surprising and does not undermine our empirical strategy, as our RD compares firms entering in the policy period (2009) to similar firms entering in the pre-policy period (2008). Most projects completed in 2009, the policy period, are located near a facility built in 2008.

Figure 3: Wind Farm Locations by Period



In sum, these descriptive results suggest that wind farms built just before and after the January 2009 policy change are broadly similar in cross-sectional characteristics, and yet the average capacity factor of the projects coming online in 2009 is lower than that of the projects coming online in 2008. This provides support for our research design and is suggestive of a causal effect of the 1603 cash grant policy on electricity generation.

4 Results

4.1 Matched Difference-in-Differences

Table 4 reports the main results. The dependent variable in each regression is the log of monthly net generation (Appendix Table A.2 reports the results using capacity factor as the dependent variable). The table contains three pairs of results, each with and without state fixed effects. Models (1) and (2) contain the OLS results using the full sample. Models (3) and (4) also contains OLS results, where the the sample is restricted to all pre-1603 projects and their post-1603 matches. The final two models implement our combined matching and difference-in-differences approach. The sample is an unbalanced panel of monthly generation from 2002 to 2014. All models contain time fixed effects (i.e., indicators for each year and month combination), cohort fixed effects, indicators for contract relationship status, and quadratic age terms to account for changes in productivity over the lifetime of wind turbines.

The primary coefficient of interest (α) appears in the fifth row of the table, on the variable 1603 Recipient. Coefficients are reported in log points. In the first two columns, using the full sample, 1603 projects are 8 percent less productive than their PTC counterparts. Restricting the post-1603 cohorts to plants with similar propensity scores a the pre-2009 cohorts yields estimates of an 11 to 13 percent decline in productivity. The matched difference-in-differences estimates in the final two columns are not statistically different from their matched OLS counterparts. Our preferred specification, with state fixed effects (column 6), generates a treatment affect of roughly 12 percent productivity loss associated with the 1603 program.

Table 4: Matched DD Results - Log Generation

	(1)	(2)	(3)	(4)	(5)	(6)
log(Capacity)	1.015***	1.042***	1.015***	1.040***	1.015***	1.039***
	(0.0115)	(0.0141)	(0.0134)	(0.0184)	(0.0133)	(0.0180)
Max Capacity Factor	0.161	0.0998	0.00729	-0.0279	0.00689	-0.0269
	(0.117)	(0.112)	(0.137)	(0.142)	(0.136)	(0.140)
Wind Speed (m/s)	0.387***	0.447***	0.471***	0.552***	0.472***	0.552***
	(0.0449)	(0.0466)	(0.0523)	(0.0516)	(0.0524)	(0.0517)
Wind Speed Sq.	-0.0149***	-0.0179***	-0.0187***	-0.0225***	-0.0188***	-0.0225***
	(0.00252)	(0.00253)	(0.00290)	(0.00279)	(0.00294)	(0.00278)
1603 Recipient	-0.0811**	-0.0873***	-0.133**	-0.114**	-0.127*	-0.123**
	(0.0362)	(0.0334)	(0.0521)	(0.0490)	(0.0663)	(0.0609)
Regulated	0.0261	-0.0497	0.0829	0.0911	0.0819	0.0930
	(0.110)	(0.105)	(0.154)	(0.110)	(0.154)	(0.109)
Est. 1603 Recipient					-0.00637	0.0107
					(0.0429)	(0.0415)
Regression Type	OLS	OLS	OLS	OLS	MDD	MDD
State FE	N	Y	N	Y	N	Y
Adjusted R-sq.	0.925	0.931	0.923	0.928	0.923	0.928
Observations	39521	39521	28649	28649	28649	28649

Data include an unbalanced panel of monthly observations from 2002 to 2014.
All models contain time dummies, cohort dummies, and dummies for contract types.
Standard errors clustered by wind farm reported in parentheses.
MDD standard errors are not corrected for uncertainty in first-stage matching.

4.2 Regression Discontinuity Design

Table 5 reports the main results. All models are run on the restricted sample of wind farms that came online in 2008 or 2009. The dependent variable in each regression is the log of monthly net generation (Appendix Table A.3 reports the results using capacity factor as the dependent variable). The first three models present OLS results and the last three re-estimate the same second stage specification instrumenting for 1603 status with an indicator for whether the wind farm was eligible for the 1603 program. The sample is a balanced panel of monthly generation from 2010 to 2014 and all models contain time fixed effects (i.e., indicators for each year and month combination).

The primary coefficient of interest (α) appears in the fifth row of the table, on the variable 1603 Recipient. Coefficients are reported in log points. Conditioning on only nameplate capacity, output predictions, and wind speed data, 1603 projects are 7 percent less productive than their PTC counterparts. Adding additional covariates (regulatory status and contract type) increases the effect size slightly, although adding state fixed effects produce estimates a lower, much noisier estimate of 4. The IV estimates in the next three columns using identical second-stage specifications are higher than their OLS counterparts, although they are not statistically different. Again, adding state fixed effects produces noisier results, which is not surprising, given the small sample. Our preferred specification, without state fixed effects but with additional covariates (column 5), generates a treatment effect of approximately 11 percent productivity loss associated with the section 1603 grant program.

Table 5: RDD Results - Log Generation

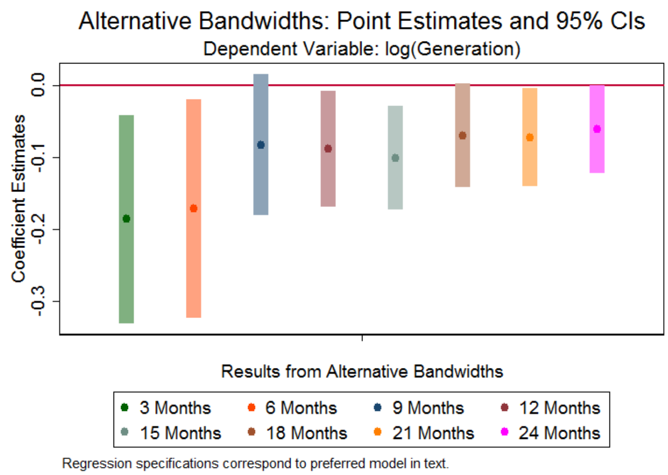
	(1)	(2)	(3)	(4)	(5)	(6)
log(Capacity)	0.961***	0.965***	0.992***	0.963***	0.966***	0.994***
	(0.00817)	(0.00784)	(0.00704)	(0.00861)	(0.00829)	(0.00730)
Wind Speed (m/s)	0.265***	0.243***	0.320***	0.257***	0.234***	0.321***
	(0.0522)	(0.0507)	(0.0436)	(0.0528)	(0.0515)	(0.0430)
Wind Speed Sq.	-0.00698**	-0.00753***	-0.0102***	-0.00675**	-0.00729***	-0.0104***
	(0.00283)	(0.00277)	(0.00228)	(0.00286)	(0.00279)	(0.00226)
Max Capacity Factor	0.266**	0.178*	0.117	0.279***	0.186**	0.122
	(0.105)	(0.0925)	(0.103)	(0.0990)	(0.0868)	(0.101)
1603 Recipient	-0.0695**	-0.0747**	-0.0410	-0.115**	-0.112**	-0.0736*
	(0.0328)	(0.0333)	(0.0315)	(0.0477)	(0.0473)	(0.0428)
Regulated		0.0908**	-0.0729*		0.0763*	-0.0748**
		(0.0423)	(0.0380)		(0.0457)	(0.0381)
PPA (AWEA)		0.0618*	-0.0563*		0.0532	-0.0572*
		(0.0346)	(0.0311)		(0.0363)	(0.0310)
Regression Type	OLS	OLS	OLS	2SLS	2SLS	2SLS
State FE	N	N	Y	N	N	Y
Adjusted R-sq.	0.955	0.959	0.967	0.955	0.959	0.967
Observations	10679	10679	10679	10679	10679	10679
F-stat				128	125	89

Data include a balanced panel of monthly observations from 2010 to 2014 for all wind farms.
All models contain time dummies. Standard errors clustered by wind farm reported in parentheses.

Alternative Bandwidths One concern with this research design is the possibility that firms respond quickly to the policy by designing wind farms specifically for the 1603 cash grant, rather than simply opting for the grant given their pre-existing design. In this case, our empirical analysis would not be able to isolate the causal effect of the investment subsidy on intensive outcomes from producer responses on the extensive margin. We address this concern by varying the temporal bandwidth in our fuzzy regression discontinuity design.

To the extent that investors cannot respond immediately to the introduction of the 1603 grant program due to binding constraints (e.g., turbine contracts, permitting, etc.), smaller bandwidths are more representative of the true intensive margin effect of the investment subsidy. However, smaller bandwidths generate smaller samples, lessening statistical precision and generating possible concern over weak instruments. We present coefficients in graphical form for estimates of the effect of 1603 receipt on generation and capacity factor using alternative bandwidths ranging from three months to 24 months (Figures 4 and A.3). The results are consistent and reinforce our baseline findings: all specifications suggest receipt of the 1603 grant (investment subsidy) leads firms to produce less electricity than if they received the production subsidy.

Figure 4: Alternative Bandwidths: Generation

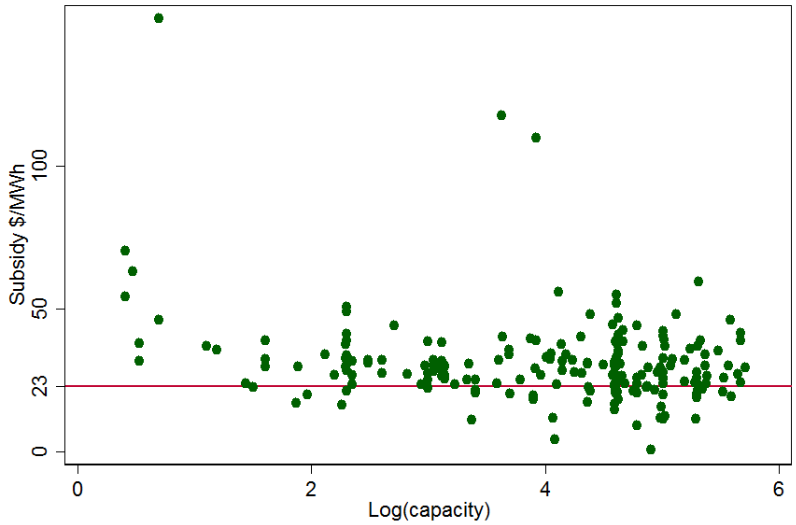


5 Discussion

5.1 Policy Implications

If the policy goal is to remedy externalities from conventional power sources, a Pigovian approach, which set taxes on fossil fuel plants equal to their marginal damages would be first-best. However, this policy has been politically difficult to implement. An equivalent alternative would be to construct a two-part instrument combining an optimal subsidy to clean electricity generation with a tax on all electricity generation (Fullerton, 1997). This policy is technologically and politically difficult to implement. Instead, the Federal government has chosen to reduce emissions from the electric power sector by offering subsidies to renewable energy, resulting in a cleaner average generatior mix. Although these subsidies generate efficiency losses due to their indirect (Parry, 1998) and blunt (Wibulpolprasert, 2013) nature, their widespread use means that there is still value in understanding how to implement this second best approach as cost-effectively as possible.

Figure 5: Subsidy per MWh for 1603 Recipients



Of the 205 facilities which took the 1603, 159 had implicit subsidies higher than the current 23$/MWh production tax credit.

It is is against this backdrop that this paper has sought to estimate productivity gains from incentivizing wind on the margin rather than through investment subsidies. In order to provide some context for the results above, it is thus useful to compare the effective subsidy recieved by each section 1603 grant recipeint to what they would have received under the PTC. Figure 5 plots the implied subsidy per megawatt hour under the first ten years of generation for each 1603 grant recipient. We predict post-2014 data for the 1603 recipient wind farms using the observed temporal decay rate in power generation for all wind farms in our data set, which represents virtually all utility-scale wind farms that have come online in the United States since the 1980s. The average implied subsidy is \$29/MWh. For comparison purposes, the current production tax credit is \$23/MWh for the first ten years of generation. About 75 percent of 1603 recipients appear to fare better under this capital subsidy, which is not surprising, given that they selected into it.

5.2 Negative Electricity Prices and Wind Power Generation

Beyond the question of targeting the subsidy to the externality, there is the issue of whether the additional power generated by PTC-claiming wind farms has social value in power markets. Power markets occassionally have power generated from inflexible suppliers (e.g., nuclear power plants) that exceeds demand (e.g., the middle of the night). Some critics of wind subsidies claim that the PTC encourages wind farms to produce power even when the social value of that incremental power is negative: a wind farm would be willing to pay to send its power to the grid because these losses would be more than compensated by the production tax credit.

To investigate whether the difference in power generation reflects this perverse incentive to sell during negative price periods, we have compiled at least four years of hourly nodal prices for each of three markets: the Midcontinent ISO, the PJM Interconnection, and ISO New England. For each market, we have approximately 8-11 million annual observations of hour-by-node electricity prices. MISO has the largest fraction of negative price hours among these three markets, with 1.8\% of hourly nodal prices falling below zero in 2008, and increasing to an annual range of 2.8\% to 3.7\% negative prices over 2009-2011. About 1/3 of these negative prices are of sufficiently large magnitude that the PTC alone could not justify a profit-maximizing wind farm producing power. In evaluating the monthly frequency of negative prices, we find that September and June have negative prices nearly 5\% of the time, while January and February have the lowest frequency of negative prices of 1.0\% and 1.6\% of the time, respectively. The PJM Interconnection follows a similar pattern, but with a lower frequency of negative prices ranging between 0.66\% and 0.82\% of the time on an annual basis over 2009-2012. Like MISO, January and February have the fewest negative price observations among any month, averaging less than 0.3\% of the time. ISO New England has very, very few negative prices (no month-year has negative prices more than 1/100 of 1\% of the time). The frequency of negative prices in these markets suggests that the generation differences are larger than the availability of negative price hours could explain.

We have further explored the seasonality of wind power generation depending on the wind farms' subsidy choice to assess how it compares with the seasonality of negative electricity prices. We have estimated our preferred specification for the fuzzy regression discontinuity estimator on a monthly basis. We find that the largest (and statistically significant) reductions in power generation for section 1603 grant claimants relative to PTC claimants are for January, February, and March. The September and June impacts are much smaller in magnitude (less than one-third) and not statistically different from zero. If one thought that PTC wind farms generate more power because they generate when prices are negative – a time when 1603 plants may not generate – then we would expect to see larger magnitude 1603 grant effects for those months characterized by higher frequency of negative price hours. Thus, this assessment suggests that the phenomenon observed in our primary empirical analyses is not a function of differential incentives across facilities (due to their subsidy choice) to produce power during times when society places no value (indeed negative value) on incremental power generation.

6 Conclusion

We have exploited an unprecedented natural experiment in tax policy implemented through the 2009 Recovery Act, which provided the taxpayer a choice of subsidy type. This facilitates analysis of the impacts of the choice of a capital or a production subsidy on power generation from a zero-carbon power source, wind power. We find that wind projects choosing the capital subsidy had an 11 to 12 percent lower power generation per unit of capacity than those projects choosing the output subsidy. For these projects, the Federal government will spend about 25 percent more per MWh of generation for wind farms claiming the 1603 grant than if they claimed the production tax credit.

This research provides evidence on the trade-offs between investment subsidies and output subsidies that is relevant to many areas of public finance. Investment and output subsidies are likely to generate different outcomes in other circumstances. In contexts where output determines (or proxies for) the social benefits of a policy, therefore, output subsidies may outperform investment subsidies. This highlights the importance of targeting policy to encourage activities that maximize social surplus directly rather than rewarding related activities that may only be loosely correlated with social surplus.

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A Appendix

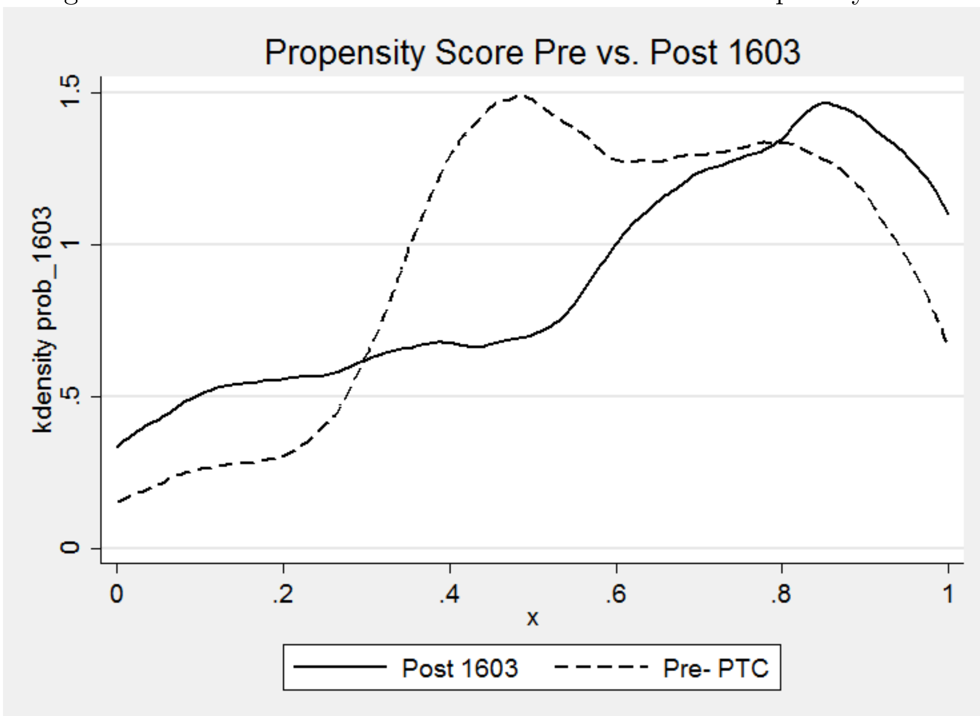
A.1 Result from first stage of MDD design

Table A.1: Log Generation Regressions

	1603 Recipient
1603 Recipient	
spline_1	0.111***
	(0.0285)
spline_2	-0.0177*
	(0.00946)
spline_3	0.00413
	(0.00645)
spline_4	-0.000280
	(0.00287)
Max Capacity Factor	1.091
	(0.899)
Wind Speed (m/s)	0.429
	(0.951)
Wind Speed Sq.	-0.0295
	(0.0598)
Regulated	-1.351***
	(0.330)
Constant	2.065
	(193.0)
Observations	321
Pseudo R^2	0.327

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.1: Distributions of Estimated and Predicted Propensity Scores

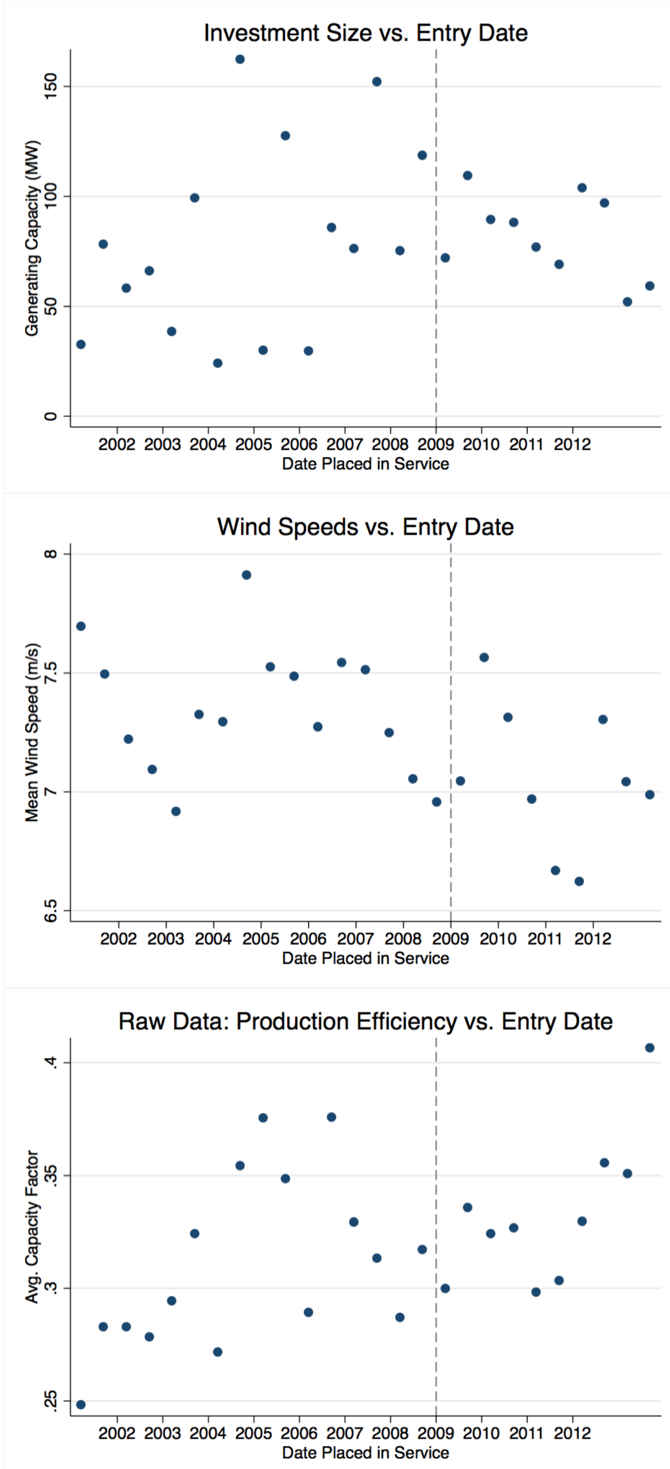


A.2 Additional discussion of RD design

We plot the trends of key variables over the period 2002 to 2012 to assess the exclusion restriction in Figure A.2. In each plot, the vertical dashed line represents the time when the 1603 cash grant policy became available to new wind farms. The first chart plots the average nameplate capacity (i.e., size) of new wind farms over time. There is no clear trend in average capacity over this period, although the variance does appear to be decreasing over time. Wind speeds appear to be trending downward over time. This could be a result of the best sites having been taken in previous periods or improvements in technology that allow economic investments at lower wind speeds. This trend highlights the importance of including time-varying observable characteristics in our model. It also suggests caution in interpreting results given the possibility of other, unobservable covariates that we cannot include in our model. We use various bandwidths to further assess the strength of the exclusion restriction (see Section 4).

We also test for evidence of a break in electricity generation outcomes in the raw data to support our RD design. We compute capacity factor using electricity generation outcomes from 2013-2014 and plot this variable by entry date over time in the final panel of Figure A.2. This plot shows heterogeneity over time in capacity factor with no clear trend. There is a drop in capacity factor from 2008 to 2009 as would be expected in an RD, but it is difficult to tell whether this is driven by the 1603 grant policy or just an anomaly given the variation in the data.

Figure A.2: Trends



A.3 Capacity Factor Results

Table A.2: Matched DD - Capacity Factor Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Max Capacity Factor	0.0558^{**}	0.0636^{**}	0.0238	0.0356	0.0232	0.0353
	(0.0261)	(0.0247)	(0.0301)	(0.0294)	(0.0299)	(0.0292)
Wind Speed (m/s)	0.0762^{***}	0.0904^{***}	0.0972^{***}	0.117^{***}	0.0975^{***}	0.117^{***}
	(0.0104)	(0.0106)	(0.0119)	(0.0113)	(0.0118)	(0.0113)
Wind Speed Sq.	-0.00239^{***}	-0.00317^{***}	-0.00337^{***}	-0.00435^{***}	-0.00340^{***}	-0.00434^{***}
	(0.000594)	(0.000586)	(0.000676)	(0.000632)	(0.000674)	(0.000630)
1603 Recipient	-0.0276^{***}	-0.0228^{***}	-0.0349^{**}	-0.0291^{**}	-0.0259^{*}	-0.0236^{*}
	(0.00844)	(0.00787)	(0.0135)	(0.0125)	(0.0154)	(0.0142)
Regulated	0.0194	0.0151	0.0295	0.0358	0.0281	0.0349
	(0.0244)	(0.0221)	(0.0379)	(0.0280)	(0.0388)	(0.0288)
Est. 1603 Recipient					-0.00984	-0.00655
					(0.00815)	(0.00810)
Regression Type	OLS	OLS	OLS	OLS	MDD	MDD
State FE	N	Y	N	Y	N	Y
Adjusted R-sq.	0.410	0.462	0.414	0.460	0.415	0.460
Observations	39602	39602	28694	28694	28694	28694

Data include an unbalanced panel of monthly observations from 2002 to 2014.
All models contain time dummies, cohort dummies, and dummies for contract types.
Standard errors clustered by wind farm reported in parentheses.
MDD standard errors are not corrected for uncertainty in first-stage matching.

Table A.3: RDD - Capacity Factor Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Wind Speed (m/s)	0.0353**	0.0327**	0.0613***	0.0324**	0.0303**	0.0621***
	(0.0158)	(0.0152)	(0.0123)	(0.0159)	(0.0152)	(0.0121)
Wind Speed Sq.	0.000607	0.000127	-0.000925	0.000674	0.000184	-0.000987
	(0.000854)	(0.000828)	(0.000655)	(0.000865)	(0.000834)	(0.000648)
Max Capacity Factor	0.0605*	0.0333	0.0210	0.0659**	0.0367	0.0233
	(0.0346)	(0.0306)	(0.0305)	(0.0325)	(0.0288)	(0.0297)
1603 Recipient	-0.0230**	-0.0260***	-0.0136	-0.0406***	-0.0381***	-0.0252**
	(0.00961)	(0.00945)	(0.00898)	(0.0138)	(0.0135)	(0.0123)
Regulated		0.0175	-0.0258**		0.0131	-0.0262**
		(0.0122)	(0.0116)		(0.0134)	(0.0116)
PPA (AWEA)		0.0202**	-0.0165*		0.0174*	-0.0167*
		(0.00979)	(0.00924)		(0.0104)	(0.00923)
Regression Type	OLS	OLS	OLS	2SLS	2SLS	2SLS
State FE	N	N	Y	N	N	Y
Adjusted R-sq.	0.450	0.508	0.620	0.445	0.506	0.618
Observations	10680	10680	10680	10680	10680	10680
F-stat				128	124	89

Data include a balanced panel of monthly observations from 2010 to 2014 for all wind farms.
All models contain time dummies. Standard errors clustered by wind farm reported in parentheses.

Figure A.3: Alternative Bandwidths: Capacity Factor