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

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Abstract

We examine the choice between using capital and using output subsidies to promote wind energy in the United States. We exploit a natural experiment in which wind farm developers were unexpectedly given the opportunity to choose between an upfront investment subsidy and an output subsidy in order to estimate the differential impact of these subsidies on project productivity. Using matching and instrumental variables estimators, we find that wind farms choosing the capital subsidy produce 8 to 13 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. We then use these estimates to evaluate the public economics of U.S. wind energy subsidies. Preliminary results suggest the Federal government paid 18 to 21 percent more per unit of output from wind farms receiving capital subsidies than they would have paid under the existing output subsidy.

Keywords: tax credits, energy subsidies, instrument choice
JEL Codes: H23, Q42, Q48

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1 Introduction

The Federal government uses the tax code to subsidize investment for a variety of reasons. When economic output falls well below potential output, policymakers subsidize investment to stimulate the economy. To address the public goods market failure characterizing innovation, the government subsidizes research and development spending. To spur the replacement of pollution-intensive facilities, policymakers subsidize the deployment of clean energy technologies.

In each of these cases, it's not just the capital investment but the incremental flow of output that delivers on the policy objectives. Stimulus that yields productive factories will do more to increase aggregate demand than building pyramids. R&D spending subsidies matter more when they accelerate the rate of innovation. Building wind farms effectively cuts pollution when their power generation reduces the residual demand for coal-fired power in electricity markets. Low-income housing construction reduces distributional disparities when more low-income households can live in affordable housing.

The government often employs output subsidies aimed at each of these objectives, such as government procurement, research prizes, production tax credits, and Section 8 housing vouchers. The availability to the policymaker of both investment subsidies and output subsidies begs the question: which approach is more effective in promoting socially-valuable output for a given amount of public expenditure? Addressing this question empirically is challenging because both investment and output subsidies are rarely available simultaneously for a given economic activity and, when they are both available, they are typically not mutually exclusive. To provide some insights into this research question, we focus on government subsidies for wind power and exploit a natural experiment in which wind farm developers could choose between investment and output subsidies. We estimate the impact of subsidy choice on wind farm productivity and 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 $20 for each megawatt hour (MWh) of output produced during the first ten years of operation. In 2009, an alternative Federal subsidy, the section 1603 grant, was introduced, providing developers with the option to take an up-front cash payment equal to 30 percent of investment costs instead of the PTC. The 1603 grant was a unique and unexpected policy innovation designed to address the unprecedented challenges of monetizing tax credits during the financial crisis.

We use this unexpected temporal discontinuity in 1603 grant eligibility to implement two complementary empirical strategies aimed at estimating the impact of marginal incentives on wind farm productivity: a matching estimator 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. Using exact matching, we infer counterfactual subsidy selection for projects that entered before the 1603 grant was available based on the observed choices of similar plants that entered during the period in which both subsidies were available. We then use this inferred subsidy preference 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. The long lead time of wind project development ensures that 1603 grant recipients in this window would have been well underway before the grant program was 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 specifications and multiple temporal bandwidths.

In our baseline ordinary least squares model using the full sample, we find that 1603-recipient wind farms are approximately 6 to 10 percent less productive than PTC recipients. Our matching analysis on this same sample produces an estimated policy effect of approximately 8 to 13 percent. In our fuzzy RD estimates using only the plants that entered within one year of the policy announcement, we also find that 1603 grant receipt results in a roughly 10 percent drop in output. 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.

Having estimated that allowing wind farms to take capital subsidies instead of output subsidies reduced production conditional on operating, we then consider the impacts of subsidy choice on the extensive margin. We combine our productivity estimates with data on output prices and assumptions about operating costs and the benefits of other subsidies available to wind farms (e.g., accelerated depreciation) to generate estimates of profits and production under both subsidy regimes for each wind farm in the 1603 grant program. This allows us to estimate the cost-effectiveness of the two subsidy instruments accounting for their impacts on market entry. We find that the Federal government pays 18 to 21 percent more per unit of output from the wind farms claiming the 1603 grant than those claiming the PTC.

The rest of this paper proceed as follows. The remainder of the this section summarizes related literature. Section 2 provides a brief introduction to the economics of wind energy and a detailed description of the policy environment, and then presents a theoretical model of subsidy choice based on these details. Section 3 describes the data and section 4 discusses our empirical strategy. Section 5 reports the results and sections 6 and 7 discuss policy implications and conclude.

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 (2016) 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 evaluate the efficacy of alternative subsidy types. In this sense, our results build upon the work of Fabrizio et al. (2007), Davis and Wolfram (2012), and Cicala (2015).

Despite extensive research on both optimal taxation and instrument choice, there is little research on the relative performance of input and output subsidies. Schmalensee (1980) considers the merits of government policy to increase energy production generally, and evaluates the economic case for alternative approaches. He concludes that input subsidies build in "potentially huge inefficiencies" relative to an output subsidy. Starting from a higher level of abstraction, 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.

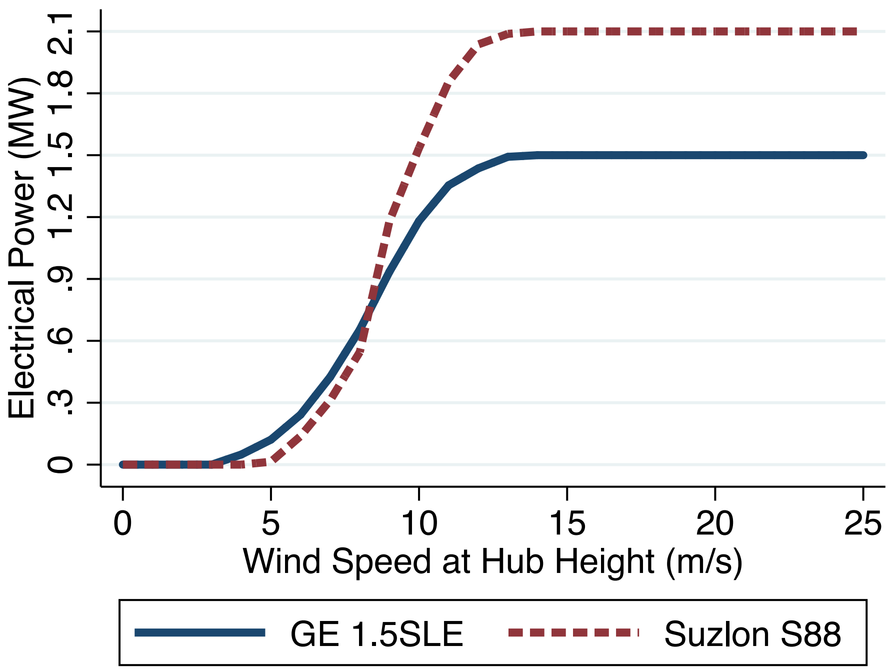
Although capital and output subsidies are used interchangeably in many settings, few have been studied empirically. Research on affordable housing finds subsidies to tenants for housing services are more cost-effective than subsidies to property investments (Olsen, 2000). In the case of education, randomized 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.

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 wind turbine models in our sample, demonstrating the nonlinear relationship between windspeed and output.

Figure 1: Reported Power Curves for Two Common Turbines



Building a wind farm involves large up-front costs. During the time period we study, Wiser and Bolinger (2014) report average initial costs of $2 million per MW at a sample of medium and large scale wind farms. Developers first have to 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. The construction phase of a wind project takes 9 to 12 months (Brown and Sherlock, 2011), with site permitting and turbine lead times often double that. 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] Wind farms coming online in 2009 and 2010 in the Midcontinent Independent System Operator (MISO) footprint spent an average of 2.7 and 3.5 years in the interconnection queue.[2]

Although wind operators do not incur fuel costs, there are a number of variable costs associated

[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.

with running a wind farm efficiently once it is installed. Turbines need to be monitored and serviced regularly 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. Software services that optimize wind farm operations can also boost output. In 2013, operations and maintenance costs at U.S. wind farms were 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).

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. The PTC is a per-kilowatt-hour tax credit for electricity generated by qualified energy resources and sold to an unrelated party during the taxable year. Congress initially set the PTC at \$15/MWh, but automatic inflation adjustments made it worth \$23/MWh for qualifying generation in 2014. A qualifying generation source can claim the PTC for the first ten years of generation after the plant 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. 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 creating long carry-back provisions to the Presidential Transition Team and Congressional staffers, but these ideas were not acceptable to the bill writers. In early January 2009, Congressional and Presidential Transition Team members discussed for the first time the idea of availing the investment tax credit (ITC) to all renewable power sources.[3] 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. Wind projects were already eligible for

[3] One of the authors served as one of two staff who negotiated the energy provisions of the Recovery Act representing the Obama Presidential Transition Team. He regularly met with representatives of the renewable industry, including staff to trade associations, staff of wind power firms, and staff to various firms that finance wind power projects. 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.

the PTC under current law at the time.

The Recovery Act thus provided wind power developers with a new, mutually exclusive subsidy choice: they could claim the production tax credit or they could claim the section 1603 cash grant in lieu of tax credits.[4] This policy approach was novel and unexpected along two dimensions. First, wind power had never been supported by a Federal 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 cash payment in lieu of a 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).[5] 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 two Federal 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 developers to secure a Federal guarantee on project debt that could significantly lower the cost of financing the project. Many states also have a renewable portfolio standard (RPS) that mandates a minimum share of the state's consumption comes from renewable sources, resulting in a price premium for wind power. Under some state RPS programs, renewable energy credits for wind power generation have been worth more than $50/MWh, or more than twice the value of the production tax credit (Schmalensee, 2012). 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.

2.3 A Model of Subsidy Choice

In order to understand the impact of the 1603 grant program, we develop a simple model of subsidy and operational choices.[6] Let K be the generation capacity that can be sited at a location, and let

[4]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. The annual Internal Revenue Service Estimated Data Line Counts reports show that not one corporation claimed the ITC for a wind power project over 2009-2011.

[5]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.

[6]Thanks to Martin Weitzman for helping refine our model.

F be the fixed cost of developing the site. These are assumed to be fixed in the short run, as was the case during the early years of the 1603 program. The project developer can choose between an output subsidy, which pays τ for each unit of output, and a capital subsidy, which pays s percent of the fixed cost F.

Under the output subsidy, the firm chooses production per unity of capacity, q, to maximize[7]

$$\pi_O = [(p+\tau)q - c(q)]K - F \tag{1}$$

Let the optimal value of π_O be denoted π_O^*. The corresponding first order condition is

$$p + \tau = c'(q). \tag{2}$$

Under the capital subsidy, the firm chooses quantity q to maximize

$$\pi_C = [pq - c(q)]K - (1-s)F. \tag{3}$$

Let the optimal value of π_C be denoted π_C^*. The corresponding first order condition is

$$p = c'(q). \tag{4}$$

Without much loss of generality, assume assume the cost function is quadratic, such that

$$c(q) = \alpha + \beta q + \frac{\gamma}{2}q^2. \tag{5}$$

Plugging the derivative of this function into (2) and (4) yields closed form expressions for the optimal output under each subsidy,

$$q_O^* = \frac{p+\tau-\beta}{\gamma} \tag{6}$$

$$q_C^* = \frac{p-\beta}{\gamma} \tag{7}$$

This stylized model demonstrates that for any given project, the output will be greater under the output subsidy. However, the extent of the difference in output will depend on the convexity of the cost function, denoted by γ. If it is very costly to increase output on the margin, moving to marginal incentives will not have a large effect on output.

In the empirical section that follows, we estimate the average value of $(q_C^* - q_O^*)$. Before doing this, it is useful to consider what determines whether a plant prefers one subsidy type to the other by plugging (5), (6), and (7) into (1) and (3). Canceling terms and rearranging gives

$$\pi_O^* > \pi_C^* \leftrightarrow \tau\left(p + \frac{\tau}{2} - \beta\right) > s\gamma\,(F/K) \tag{8}$$

[7] This two period model abstracts away from the fact that output is generated over many periods.

Or, equivalently

$$\pi_O^* > \pi_C^* \leftrightarrow \tau \left(q_C^* + \frac{(q_O^* - q_C^*)}{2} \right) > s\,(F/K) \tag{9}$$

With quadratic costs, the left hand side of (9) is equal to the additional operating profit per unit of capacity under the output subsidy relative to the capital subsidy. Intuitively, the inequality states that wind farms will prefer output subsidies when this additional operating profit is greater than the forgone subsidy per unit of capacity.

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. Survey form EIA-860, which is collected annually, contains the following variables: first date of commercial operation, nameplate capacity, number of turbines, predominant turbine model, operator name, location, regulatory status, and operation within a regional transmission organization (RTO) or independent system operator (ISO). We combine this annual plant level information with monthly electricity generation data from survey form EIA-923.

We supplement these EIA data with proprietary data from the American Wind Energy Association (AWEA), 3TIER, and turbine manufacturers. The AWEA database contains additional cross-sectional information on each wind farm, including the wind turbine model and whether projects contract output through long-term power purchase agreements (PPAs) or sell on spot markets. We use the former to corroborate turbine data in the EIA-860 and the latter to construct "offtake type" indicator variables in the estimated regression models.

3TIER uses global wind and weather monitor data to interpolate hourly wind speed, wind direction, air pressure, and temperature for the entire continental United States at a spatial resolution of approximately 5 kilometers. We combine these high frequency wind data with power curves for each wind farm's installed turbines to produce an "engineering" estimate of the potential output attainable for each plant each month. To do this, we obtain power curves from turbine manufacturers for each turbine make and model in the EIA data. Where we cannot find power curve data for a given wind turbine, we assign the most common turbine in our time period (GE 1.5SLE). We use air pressure and temperature data to adjust for variation in air density, which affects the amount of power that can be extracted from a given wind speed. The result is a measure of potential output that accounts for the site-specific, nonlinear relationship between wind speeds and electricity generation. We also construct summary statistics of the 3TIER data at monthly frequency to use as an alternative to this engineering-based potential output in robustness analysis.

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 assume 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 span 2002 to 2014. We remove plants which came online prior to 2002 due to changes in the EIA survey format. We exclude facilities that came online after 2012 to ensure that we observe at least 24 months of production data for each plant. Finally, we remove plants that are publicly owned (e.g., municipal power plants), as these plants are not eligible for the PTC. Table 1 presents an annual summary of these data for this restricted sample.

Table 1: Summary Statistics by Entry Date

Entry Year	Wind Farms	1603	Nameplate	Turbines	Wind Speed	Regulated	Potential CF	Capacity Factor
2002	8	0	62.29	57.88	7.59	0.00	34.34	30.35
2003	34	0	47.08	33.85	7.48	0.00	36.68	31.37
2004	11	0	34.59	29.09	7.03	0.09	33.18	34.33
2005	18	0	115.14	78.00	7.51	0.11	37.50	35.80
2006	39	0	42.96	27.90	7.50	0.10	35.78	34.19
2007	48	0	124.92	75.90	7.43	0.08	35.84	34.50
2008	74	0	85.59	49.50	7.42	0.14	35.60	34.05
2009	89	61	100.11	57.57	7.15	0.10	35.10	31.48
2010	58	43	74.57	42.76	6.98	0.07	33.80	32.42
2011	78	57	80.79	42.29	6.78	0.06	33.22	30.80
2012	141	68	88.47	44.49	7.07	0.11	37.18	33.58

Table 2 compares projects placed into service after the introduction of the 1603 program by subsidy type along observable dimensions. Although the overall project sizes are comparable, 1603 recipients are located in areas with lower average wind speeds and are less likely to operate in a regulated market. Projects selecting the 1603 grant also have lower potential and realized capacity factors. The capacity factor is the ratio of output to the maximum attainable output of a plant if it had constantly produced at its nameplate capacity.[8] Thus, 1603 recipients produce less electricity than PTC recipients on average, relative to their total potential output. In the next section, we describe our strategy for distinguishing between the portion of this observed difference in productivity attributable to the subsidy.

4 Empirical Strategy

4.1 Model

To investigate whether shifting subsidies from the intensive to the extensive margin reduced wind farm productivity, we estimate the following regression under several different assumptions and

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

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

	PTC	1603	Difference	p-value
Nameplate Capacity	92.8	84.0	8.8	0.32
Turbines	49.8	45.1	4.7	0.35
Mean Wind Speed	7.26	6.82	0.4	0.00
Regulated	0.20	0.03	0.2	0.00
Potential Capacity Factor	38.9	32.5	6.4	0.00
Capacity Factor	34.9	29.8	5.1	0.00
New Wind Farms	137	229		

sample restrictions:

$$q_{it} = \delta D_i + \beta X_{it} + \nu_{it} \tag{10}$$

Here i indexes wind farms and t indexes months. The dependent variable q is the plant's capacity factor. D is an indicator for whether the wind farm took the 1603 grant and X is a vector of controls (e.g., engineering-based potential capacity factor, regulatory regime, presence of a power purchase agreement, location, etc.). The coefficient of interest, δ, is the effect of the 1603 grant on production outcomes. If wind farms were less productive under the 1603 grant, we would expect δ to be negative.

Estimating equation (10) using OLS is potentially problematic due to the fact that D_i was chosen. As was shown in section 2.3, plants that expect to have high output relative to their investment costs will prefer the PTC, while plants with relatively high investment costs per unit of expected output will prefer the section 1603 grant. Thus, OLS estimates could 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 complementary empirical approaches to identify the causal effect of the section 1603 grant on wind farm output: matching estimators and a fuzzy regression discontinuity estimator.

4.2 Matching

Our matching estimator uses information from the period before the section 1603 grant was available to infer counterfactual outcomes for 1603 grant recipients. Assume the unobserved component of production takes the form $\nu_{it} = A_i + \epsilon_{it}$, where A_i denotes the unobserved quality of wind farm i. It is correlation between A_i and D_i that generates selection. Conditioning on A_i would eliminate this bias, as $E[q_{it}|X_{it}, A_i, D_i = 1]$=$E[q_{it}|X_{it}, A_i, D_i = 0] + \delta$. Under the assumption that A_i is time-invariant, the use of plant fixed effects with panel data will remove this bias.

We do not observe subsidy variation within a plant, so we cannot use plant fixed effects. Instead, we adopt the additional assumption that unobserved heterogeneity takes the following form, $A_i =$

$g(X_i) + \phi Post_i$, where $g()$ is an unknown function of observable wind farm characteristics and $\phi Post_i$ is wind farm vintage fixed effect. Although $g()$ is unknown, constructing a fixed effect for each unique set of characteristics (i.e., each unique vector X_i) would fit any $g()$. The difference in productivity of two wind farms with the same characteristics that entered in different policy periods is ϕ.

While we cannot fit $g()$ exactly given that X_i contains continuous covariates and our sample is finite, we approximate $g()$ by matching wind farms of different vintages with similar characteristics. We divide our sample into two groups corresponding to policy regimes: wind farms that entered between 2005 and 2008 ("pre" plants), when there was no subsidy choice, and wind farms that entered over 2009-2012 ("post" plants), which could chose either the PTC or the 1603 grant. We then match pre and post wind farms on observable characteristics using coarsened exact matching (King and Nielsen (2016)). Let g index a group of pre and post plants that are matched together. Equation (10) becomes,

$$q_{it} = \delta D_i + \beta X_{it} + \eta_g + \phi Post_i + \epsilon_{it} \tag{11}$$

Where $Post_i$ is an indicator for whether a plant came online after the 1603 program was introduced. Intuitively, the estimator takes the average difference between 1603 recipients and pre-plants within the same group, and subtracts the difference between post-PTC plants and pre-plants within group. To see this, let D_g indicate the *observed* subsidy choice of the post- period plants in group g. Then

$$E[q_{it}|D_g = 0, Post_i = 1] - E[q_{it}|D_g = 0, Post_i = 0] = \phi$$

$$E[q_{it}|D_g = 1, Post_i = 1] - E[q_{it}|D_g = 1, Post_i = 0] = \phi + \delta$$

In practice, we replace ϕ with year-vintage fixed effects, and allow group-level unobservables to vary by time.

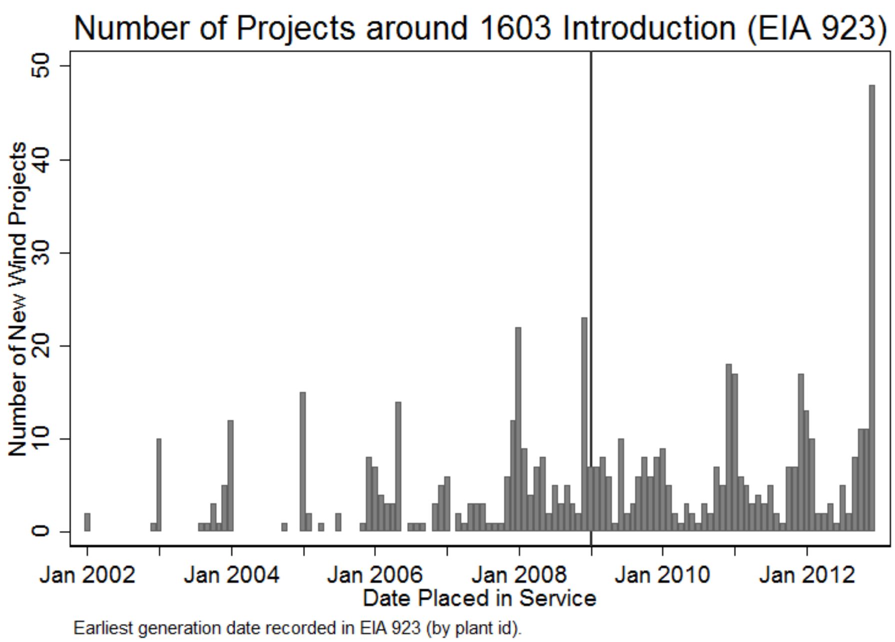
4.2.1 Identification

Matching requires us to drop plants that do not lie within the common support of pre and post period entrants on key observable dimensions. Within the set of plants that remain, identification requires assuming there are no unobservables that affect both production decisions and subsidy choice (i.e., unconfoundedness). We also assume the covariates used for matching are unaffected by the availability of the 1603 grant. While we cannot directly assess this assumption, the long development timeline of wind farms reduces concern over any response of project covariates to treatment. In our RD analysis, we use a narrow time period around the policy change to address this concern.

4.3 Regression Discontinuity Design

Our second empirical approach harnesses the natural experiment created by the 1603 cash grant program by comparing wind farms that came online just before and just after the program went into effect. While the section 1603 cash grant was not randomly assigned, its creation came as a plausibly exogenous shock to the industry. To provide evidence of this, 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, this variation is driven by uncertainty around the expiration of the PTC. The frequency of project entry 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 implement a fuzzy regression discontinuity research design, using a binary indicator for initial date of electricity generation to instrument for cash grant recipient status,

$$D_i = \gamma \cdot 1\left\{1603 \text{ eligible}\right\}_i + \xi X_{it} + \nu_i \tag{12}$$

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 δ using equation (10) in a two-stage least squares (2SLS) framework.

4.3.1 Identification

The key assumption that identifies δ and allows interpretation as a local average treatment effect is the exclusion restriction.[9] The exclusion restriction requires that subsidy eligibility (the instrument) only affects outcomes through its effect on subsidy choice (the endogenous variable). 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.1). 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 support of the exclusion restriction. Therefore, we also address possible violations of the exclusion restriction through a sensitivity analysis using alternative bandwidths (see Section 5.2).

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, regulatory status, and the engineering-based potential capacity factor – 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.

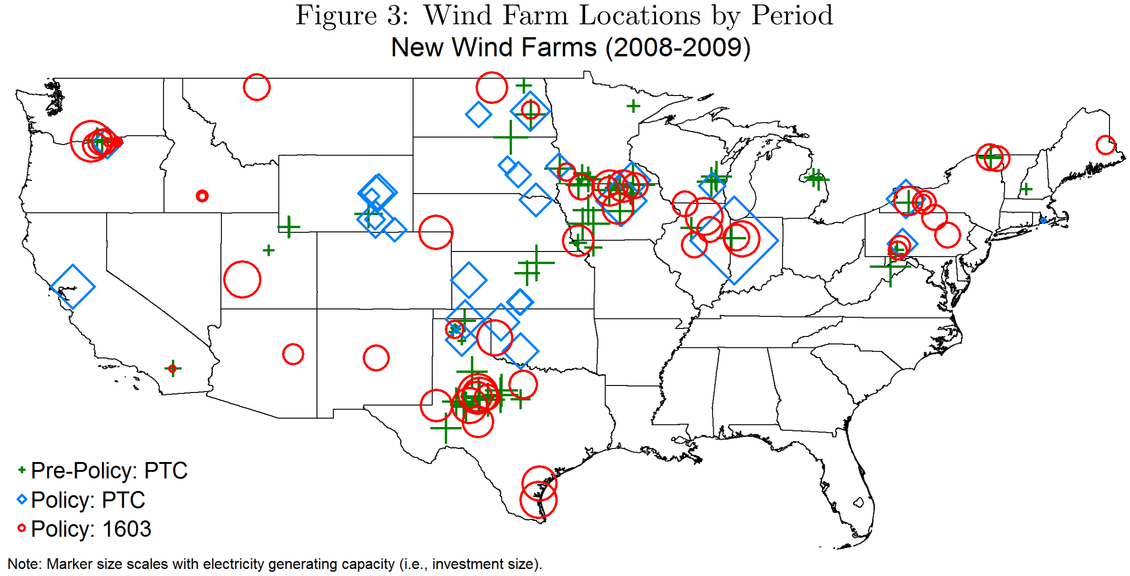
[9]We also rely on three other restrictions/assumptions. First, we know from data that the first stage is non-zero. Second, the monotonicity assumption holds by virtue of the policy environment: firms cannot "defy" treatment assignment because the 1603 grant is only available from the Federal government. 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	85.5	100.0	-14.4	0.23
Turbines	49.4	57.5	-8.1	0.28
Mean Wind Speed	7.31	7.09	0.2	0.14
Regulated	0.14	0.10	0.03	0.50
Potential Capacity Factor	34.2	34.3	-0.1	0.95
Capacity Factor	32.0	30.4	1.6	0.09
New Wind Farms	74	89		
1603 Recipients	0	61		

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, and, for the latter group, we further distinguish between PTC and 1603 recipients. This map suggests there are regional factors that affect subsidy choice. This selection is not surprising and does not undermine our empirical strategy, as our approach compares firms entering in 2009 to similar firms entering in 2008. Most projects completed in 2009, the policy period, are located near a plant 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 grant on electricity generation.

5 Results

5.1 Matching

To illustrate how this method works, Table 4 reports the results from several specifications where groups are defined using coarsened exact matching on NERC region, ISO dummy, EIA wind class, regulated dummy and log capacity. The dependent variable in each regression is the capacity factor – the ratio of net electricity generation to installed generation capacity – in percentage points. Model (1) simply runs OLS on the full sample. Model (2) restricts the sample to plants matched across periods. Model (3) includes matched group fixed effects. Model (4) interacts those group fixed effects with year of sample, allowing for unobserved factors that affect specific groups across time. Model (5) includes group-month of sample fixed effects.

Restricting the sample to be balanced across periods increases the estimated effect. Allowing for time invariant unobservables across groups reduces this slightly. But further relaxing that to allow for time-varying group level unobservable impacts does not appear to affect the results.

Table 4: Matching Results

	(1)	(2)	(3)	(4)	(5)
1603 Recipient	-2.006***	-3.218***	-2.748**	-2.702**	-2.769**
	(0.743)	(0.985)	(1.069)	(1.100)	(1.196)
Sample	All	Matched	Matched	Matched	Matched
FEs			Group	Group*Y	Group*Y*M
Adjusted R-sq.	0.536	0.546	0.565	0.592	0.641
Observations	30357	19137	19137	19137	19137

All models include controls for potential capacity factor, age and age squared, and state and month of sample dummies. Standard errors, clustered at the plant level, are reported in parentheses.

In Table 5, we estimate the model from column (3) under different regional definitions, in addition to matching on EIA windclass, regulation dummies, and log capacity. Model (1) matches on NERC region as well as an indicator for whether the plant is in an ISO. Model (2) matches on ISO, and Model (3) matches on both NERC region and ISO. Finally, model (4) matches on state. All models except the last include state fixed effects as well as matched group dummies.

As all models contain month-year dummies and entry-year cohort dummies, δ is identified under the assumption that, after restricting the sample to "similar" plants in the pre and post period, 1603 and non-1603 plants differ only on observable dimensions X. Under this assumption, the 1603 program reduces wind farm production, as measured by capacity factor, by 2.7 to 4.1 percentage points across the various matching models. While each of the models in Table 5 yield estimates of δ that are statistically different from zero, we cannot statistically discern among the coefficient estimates. These results indicate an approximate 8.5 to 13 percent reduction in total production, as opposed to capacity factor, for 1603 grant recipients.

Table 5: Matching Results

	(1)	(2)	(3)	(4)
1603 Recipient	-2.748**	-3.359***	-4.096***	-2.741**
	(1.069)	(1.240)	(1.331)	(1.180)
# Pre-PTC	135	99	96	99
# Post-PTC	50	43	38	40
# Post-1603	108	61	53	60
Region	Nerc-1(ISO)	ISO	Nerc*ISO	State
Adjusted R-sq.	0.565	0.644	0.641	0.613
Observations	19137	13295	12539	13386

All models include controls for potential capacity factor, age and age squared, and state and month of sample dummies. Standard errors, clustered at the plant level, are reported in parentheses.

5.2 Regression Discontinuity Design

Table 6 reports the fuzzy regression discontinuity results. The sample is restricted to a balanced panel of monthly generation from 2010 to 2014 at wind farms that came online in 2008 or 2009. All models contain year-month dummies.

Table 6: RDD Results

	(1)	(2)	(3)	(4)	(5)	(6)
1603 Recipient	-3.234***	-3.489***	-2.411***	-3.629***	-4.362***	-3.042***
	(0.856)	(0.851)	(0.853)	(1.170)	(1.159)	(1.090)
Potential Capacity Factor	0.438***	0.474***	0.486***	0.436***	0.472***	0.489***
	(0.0333)	(0.0296)	(0.0303)	(0.0329)	(0.0294)	(0.0295)
Regulated		6.200	-2.897*		6.334	-2.765*
		(7.298)	(1.540)		(7.320)	(1.503)
ISO/RTO		-0.817	-1.194		-0.960	-0.904
		(0.801)	(1.158)		(0.807)	(1.158)
Regression Type	OLS	OLS	OLS	2SLS	2SLS	2SLS
Offtake Type FE	N	Y	Y	N	Y	Y
State FE	N	N	Y	N	N	Y
Adjusted R-sq.	0.486	0.514	0.608	0.486	0.513	0.607
Observations	9733	9710	9710	9733	9710	9710
F-stat				196	189	125

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.

The primary coefficient of interest (δ) appears in the first row of the table, on the variable 1603 Recipient. The first three columns present OLS estimates of equation (10). Conditioning on only potential output, net generation per unit of capacity at 1603 plants is 3.2 percentage points lower than their PTC counterparts. The coefficient estimate is similar after incorporating information about the competitive environment firms face. In contrast, adding state fixed effects attenuates the effect size, as shown in column (3).

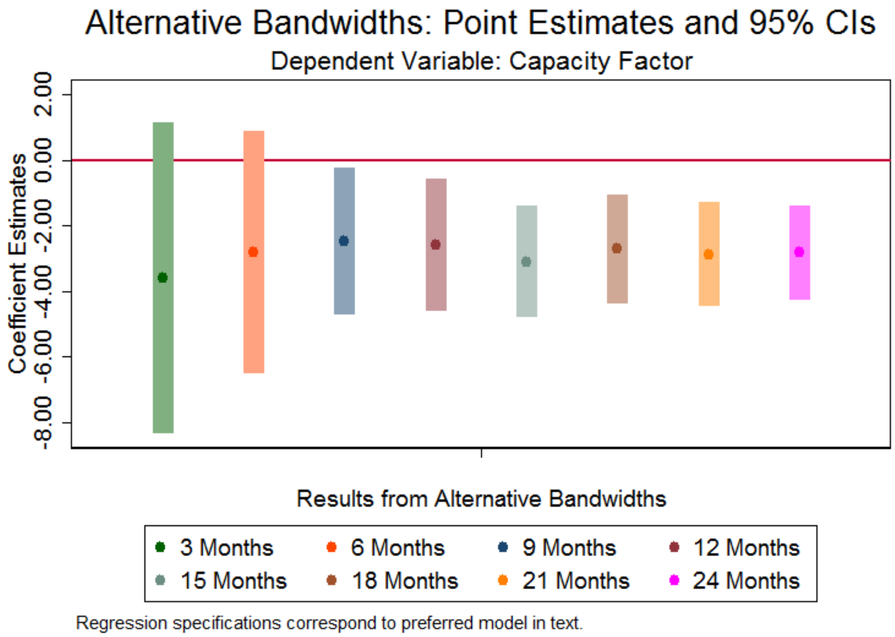
Columns (4)-(6) present IV estimates using the same covariates, instrumenting for 1603 status with an indicator for whether the wind farm was eligible for the 1603 program. Conditioning only on potential output, 1603 plants are 3.6 percentage points less productive than their PTC counterparts, while adding information on regulation, participation in an ISO/RTO, and offtake type increases this estimate slightly, to 4.4 percentage points. The effect size shrinks to 3.0 percentage points with the addition of state fixed effects. This last estimate implies a roughly 10 percent reduction in production, in line with our matching estimates.

Under our preferred specification that includes state fixed effects, the IV estimate is within the range of the preferred matching estimates. Comparing the IV estimates to the OLS estimates suggests that, in this narrow window, 1603 plants have a *higher* latent productivity than their PTC counterparts (although we cannot statistically distinguish the OLS and IV coefficient estimates). While this appears counterintuitive at first, the model presented in section 2.3 only makes predictions on latent capacity conditional on *investment costs*, not on capacity. Thus, plants opting for capital subsidies may have been more productive per unit of capacity, as long as this productivity came at a higher capital cost per unit capacity as well.

Alternative Bandwidths We vary the temporal bandwidth in our analysis to address the concern that firm responses to a change in the policy environment could violate the exclusion restriction. 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.), and given the retroactive nature of the initial eligibility date, 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. Figure 4 presents coefficients from the model specification in column (6) of figure 6 in graphical form for using alternative bandwidths ranging from three months to 24 months. Although the confidence intervals are large for the very small bandwidths, 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 they would have if they had received the production subsidy.

Additional Robustness Analysis We address two other potential confounding factors in the appendix. One concern is that the engineering-based output measures we use could be biased by measurement error in the turbine models and associated power curves. As an alternative approach, we replicate our baseline estimates using several functions derived from the 3TIER wind data to allow output to vary flexibly with atmospheric conditions at each site in Table A.1. While this change attenuates our estimates somewhat, they remain in line with our matching estimates. Second, our baseline estimates do not account for trends within the 2008-2009 time period in technology, site quality, and other factors that could have persistent effects on output. Table A.2 presents results from a model that includes piecewise linear trends to capture this possibility. The point estimates are similar in magnitude to our baseline estimates.

Figure 4: Alternative Bandwidths



6 Discussion

6.1 Policy Implications

If the policy goal is to reduce externalities from conventional power sources, a Pigovian approach that set taxes on fossil fuel plants equal to their marginal damages would be optimal. 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 uniform subsidies to renewable energy, resulting in a cleaner average generation 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.

The previous section provided evidence that 1603 recipients would have generated more output during their first ten years of operation had they received the production tax credit. However, as was discussed in Section 2.3, in order to calculate the effect of the policy on net wind generation, we need to consider the fact that some 1603 recipients may not have found it profitable to enter under the PTC. We classify 1603 recipients as being marginal or inframarginal by estimating discounted profits under the 1603 and under the PTC.

$$\pi^{1603} = \sum_t \left(\frac{1}{1+r}\right)^t (p_t - c_t)Q_t^{1603} - (0.7) * F$$

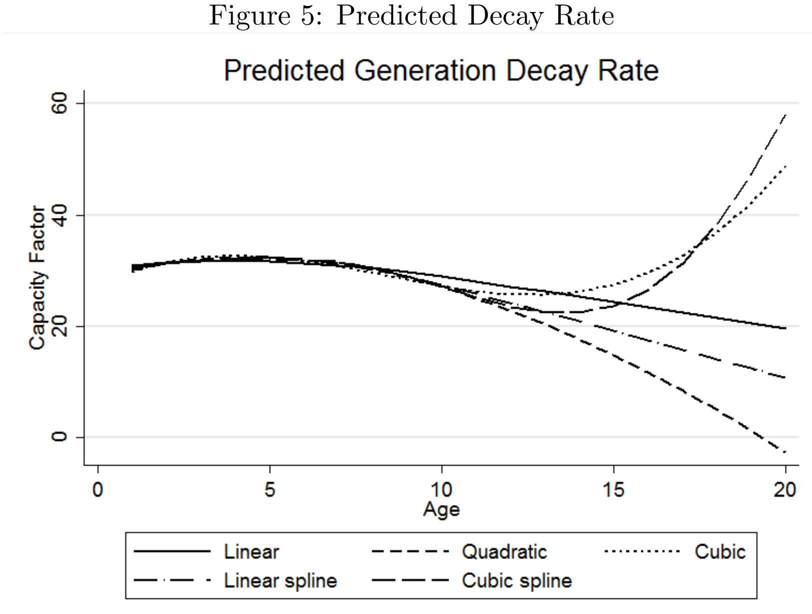
$$\pi^{PTC} = \sum_t \left(\frac{1}{1+r}\right)^t (p_t + PTC_t - c_t)Q_t^{PTC} - F$$

Wind farms are assumed to remain in service for twenty years. In order to predict output in future periods, we model capacity factor as a function of plant and month-year dummies and age,

$$q_{it} = g(age_{it}) + \alpha_i + \mu_t + \epsilon_{it}$$

The model is estimated under several specifications of $g()$: linear, quadratic and cubic functions of age, as well as linear and cubic splines. Figure 5 presents the average production path from each specification. Our preferred specification is the median path, using the linear spline, and we use this model to predict Q_t^{1603} for all future years. We then combine this prediction with the lower of our estimates of productivity gain from the PTC, 2.4 percent of capacity during the first ten years of generation, to obtain Q_t^{PTC}.

Figure 5: Predicted Decay Rate



In 2011, the EIA began collecting annual data on sales quantities at each plant. We use this to obtain an estimate of p_{it} for each 1603 plant.[10] Operating costs c_{it} are assumed to be quadratic

[10] Real prices assumed to remain at their current levels in future periods, and 2011 prices are used for years 2008-2011. The EIA refers to these data as "resale" prices, since the purchasing utility plans to resell the power to end-use consumers. Resale price information is missing for 11 of the 202 1603 facilities in the sample. This is likely because those wind farms dispose of their output directly through a nonstandard relationship. Where available, the EIA resale price matches the AWEA reported PPA price well (90% of observations in AWEA are within 10% of the EIA average resale price).

as in Equation (5) and estimated using the RDD sample and estimated treatment effect.[11] F is obtained by dividing the observed 1603 grant award amount by the fraction of investment costs covered by the program, 0.3. Wind farms are also eligible for accelerated depreciation, which are assumed equal to 10 percent of investment costs.[12] Finally, the real interest rate r is set equal to 5 percent.

Table 7 presents the results. 1603 recipients are broken up into three groups: an always profitable group ($\pi^{1603} > 0$ & $\pi^{PTC} > 0$), a marginal group ($\pi^{1603} > 0$ & $\pi^{PTC} < 0$), and a never profitable group ($\pi^{1603} < 0$ & $\pi^{PTC} < 0$). Surprisingly, 35 percent of 1603 recipients fall into this final category. There are many potential reasons for this. Most importantly, in this calculation, p_t only includes revenue from electricity sales, and does not include state level renewable subsidies.[13] O&M costs and discount rates could also be lower for these facilities. Even perfectly accounting for all of these factors, it is likely that some plants that appeared profitable ex ante will look unprofitable ex post due to poor price and generation realizations.

Table 7: Estimated Subsidy by Group

		1603			PTC		
Group	N	Output (MMWh)	Subsidy ($M)	Subsidy ($/MWh)	Output (MMWh)	Subsidy ($M)	Subsidy ($/MWh)
Always Profitable	121	465	5,848	12.57	492	5,743	11.68
Marginal	18	33	563	17.05	35	449	12.68
Never Profitable	74	299	4,542	15.17	320	3,950	12.35

The first two columns of the table report (predicted) lifetime output for each group along with the total 1603 award amount. The third column is simply the ratio of these two, which can be interpreted as a public funds levelized cost of energy. The final three columns present predicted output and subsidy levels for each project had they received the PTC instead. The government subsidy per (lifetime) kilowatt hour is estimated to be larger under the 1603 program in each group, although this average masks the fact that 61 plants are estimated to earn a higher total subsidy under the PTC.

Estimating the net effect of the 1603 program requires taking a stand on the counterfactual entry status of the never profitable group. One assumption would be to combine these plants with

[11] As written in (5), q is just the capacity factor, making $\gamma = \frac{dPrice}{dq}$. β can then be found based on the average observed q and P for 1603 recipients in the data. Finally, fixed operating costs α are assumed to be zero. Under the assumptions, average estimated operating in the data are $6.38/MWh For comparison, Wiser and Bolinger (2014) report average O&M costs of $9/MWh post-2010.

[12] In a 2010 White House Memorandum to the President, leaked to multiple news outlets, the Shepherds Flats Wind Farm in Oregon was revealed to have approximately $200 million in accelerated depreciation benefits on a $2.1 billion investment. Borenstein (2015) also finds accelerated depreciation benefits on the order of 10-12% of investment costs for solar PV.

[13] During this time period, REC prices were around $4/MWh on average, but varied considerably across states and within states over time. It is also important to note that some wind farms sold power through PPAs in which the sale price is for a bundled good comprised of power and renewable energy credits.

the marginal group and assume that they would not have entered without the 1603 program. This would imply that the 1603 program increased lifetime wind production by 292 MMWh. It would also imply that the 1603 grant increased the average public cost per wind MWh from $11.68 to $14. An alternative approach is to assume that the lack of profitability of the third group implies a policy invariant unobservable (possibly in expectation) that would have encouraged these wind farms to enter with or without the 1603 grant. Therefore, only the production of the marginal plants was screened in by the 1603 grant program, while the production at inframarginal plants actually declined by over 7 percent. Under this assumption, total wind output from would have actually been over 28 million MWh higher without the 1603 program, while total government expenditure would have declined by $1.3 billion.

6.2 Negative Electricity Prices

Prices in electricity markets sometimes may fall below zero during periods of low demand due to a combination of inflexible supply and storage constraints. Some critics of the PTC claim that it encourages wind farms to produce power when the wholesale electricity price is negative. To investigate whether negative price events contribute to the differences in power generation we estimate, we compiled hourly nodal prices for three markets: ERCOT, the Midcontinent ISO (MISO), and ISO New England. MISO has the largest fraction of negative price hours among these markets, with 2.8% of hourly nodal prices falling below zero over the course of 2011-2014. Negative prices are next most common in ERCOT, where 1.3% of hourly nodal prices fell below zero in 2011-2014. ISO New England does not experience negative hourly nodal prices in excess of 1/3 of 1 percent in any given year in our sample. We focus our attention on ERCOT and MISO due to the prevalence of negative prices and the significant number of wind farms operating in these markets.

We make two comparisons to evaluate the potential importance of negative prices. First, we compare trends over 2011-2014. In both ERCOT and MISO, the frequency of negative prices declined during this period (Table A.3). We present estimates of our baseline regression discontinuity specification by year in the first row of Table A.4. These effects do not show a clear temporal trend. The second row of Table A.4 presents estimates from a separate model that only includes data from MISO. In MISO, the magnitudes of the point estimates actually increase over time (although they are not precisely estimated).

Second, we compare seasonal variation in negative prices and our estimates (Table A.5). The difference in electricity production between PTC and 1603 recipients is larger and more likely to be statistically significant in months when negative prices are more frequent in ERCOT and MISO. However, our estimates are negative and economically significant in all months, even where they are statistically indistinguishable from zero.

These comparisons suggest that negative prices may explain some, but not all, of the difference between electricity generation under capital and output subsidies. While it is useful to understand the mechanism behind our productivity results, the extent to which they are driven by negative prices does not necessarily affect their policy interpretation. The rationale behind wind subsidies is to displace conventional, polluting generation with zero-emissions electricity. This logic does not necessarily fail simply because the equilibrium wholesale price is below zero. In other words, the wholesale electricity price is not a sufficient statistic for the welfare impact of a given unit of electricity generated from wind.[14] Estimating the full welfare impact of the policy would require estimating the emission intensity of displaced generation with and without the 1603 grant program, and is beyond the scope of this paper.

7 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 generated 8 to 13 percent less power per unit of capacity than those projects choosing the output subsidy. Preliminary analysis suggest the Federal government paid 18 to 21 percent more per unit of output from these wind farms through the 1603 grants than they would have under the PTC.

This research provides evidence on the trade-offs between investment subsidies and output subsidies that is relevant to many areas of public finance. In contexts where output determines (or proxies for) the social benefits of a policy, 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. This empirical evidence also highlights opportunities for structuring input subsidies such that they reflect the expected output from the investment (Schmalensee, 1980).

[14] Thanks to Erin Mansur for making this comment on an earlier draft.

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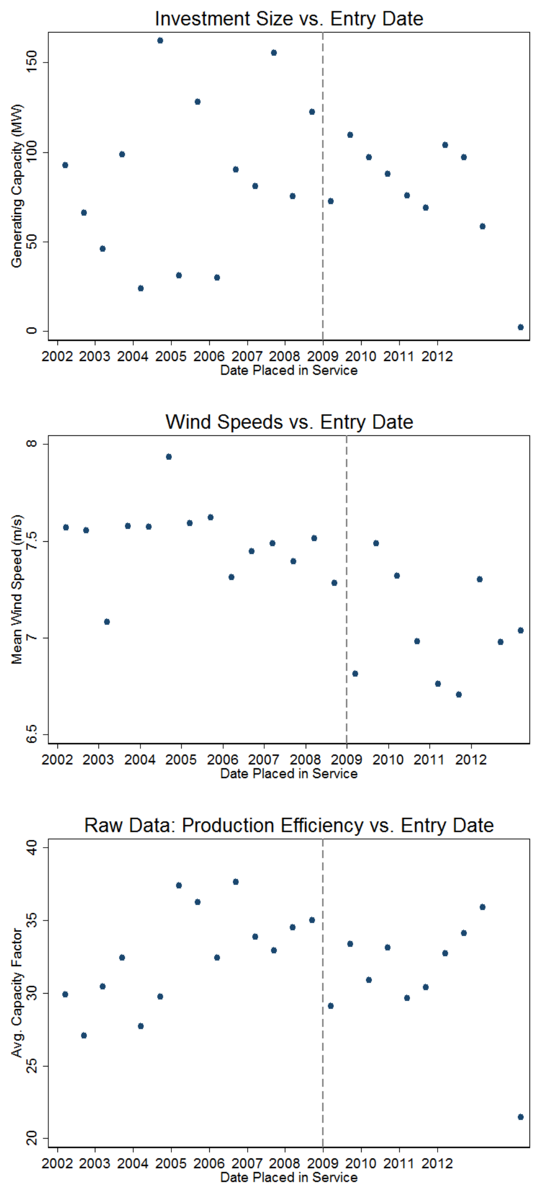
A Appendix

A.1 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.1. 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 5).

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.1. 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, although 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.1: Trends



A.2 Sensitivity Analysis of IV Results

Table A.1: IV Results Sensitivity: Wind Data

	(1)	(2)	(3)	(4)	(5)	(6)
1603 Recipient	-1.954**	-2.075**	-1.343	-2.095*	-2.242*	-0.832
	(0.886)	(0.903)	(0.865)	(1.189)	(1.219)	(1.157)
Wind Speed (m/s)	-10.54**	-8.924**	-4.401	-10.59**	-8.946**	-4.501
	(4.351)	(4.239)	(3.192)	(4.415)	(4.223)	(3.188)
Wind Speed Cubed	-0.0710***	-0.0633***	-0.0304**	-0.0711***	-0.0633***	-0.0307***
	(0.0189)	(0.0172)	(0.0118)	(0.0189)	(0.0170)	(0.0118)
Wind Speed Squared	1.914***	1.727***	1.055***	1.918***	1.729***	1.064***
	(0.513)	(0.483)	(0.351)	(0.517)	(0.480)	(0.350)
Var(Wind Speed)	0.183	-0.0293	-0.772***	0.179	-0.0341	-0.772***
	(0.216)	(0.200)	(0.140)	(0.216)	(0.199)	(0.140)
Temperature (K)	-0.239***	-0.213**	-0.617***	-0.237***	-0.211**	-0.620***
	(0.0780)	(0.0838)	(0.0996)	(0.0779)	(0.0836)	(0.0996)
Air Pressure (atm)	15.28**	15.80*	36.43*	15.31**	15.99*	34.58*
	(7.601)	(9.466)	(19.42)	(7.516)	(9.399)	(20.04)
Cov(Wind Speed, Pressure)	403.6***	334.9***	86.29*	402.8***	334.1***	85.06*
	(71.52)	(57.77)	(44.80)	(71.75)	(57.48)	(44.47)
Cov(Wind Speed, Temperature)	-0.129	-0.125	-0.0976	-0.130	-0.126	-0.0958
	(0.0875)	(0.0859)	(0.0670)	(0.0875)	(0.0858)	(0.0669)
Regulated		5.344	-0.963		5.390	-1.084
		(6.756)	(2.004)		(6.748)	(1.984)
ISO/RTO		0.589	-1.004		0.552	-1.234
		(1.136)	(1.595)		(1.136)	(1.574)
Regression Type	OLS	OLS	OLS	2SLS	2SLS	2SLS
Offtake Type FE	N	Y	Y	N	Y	Y
State FE	N	N	Y	N	N	Y
Adjusted R-sq.	0.504	0.523	0.635	0.504	0.523	0.635
Observations	9733	9710	9710	9733	9710	9710
F-stat				198	178	113

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.

Table A.2: IV Results Sensitivity: Linear RD

	(1)	(2)	(3)	(4)	(5)	(6)
1603 Recipient	-3.629***	-4.362***	-3.042***	-3.306*	-4.131**	-3.014
	(1.170)	(1.159)	(1.090)	(1.746)	(1.957)	(2.225)
Potential Capacity Factor	0.436***	0.472***	0.489***	0.437***	0.478***	0.490***
	(0.0329)	(0.0294)	(0.0295)	(0.0363)	(0.0339)	(0.0287)
Regulated		6.334	-2.765*		6.078	-2.495
		(7.320)	(1.503)		(7.037)	(1.770)
ISO/RTO		-0.960	-0.904		-1.002	-0.888
		(0.807)	(1.158)		(0.857)	(1.284)
1603 Eligible=0 × Distance				-0.0419	0.0393	0.0431
				(0.118)	(0.129)	(0.108)
1603 Eligible=1 × Distance				0.0114	-0.0799	-0.0585
				(0.118)	(0.148)	(0.173)
Regression Type	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Offtake Type FE	N	Y	Y	N	Y	Y
State FE	N	N	Y	N	N	Y
Adjusted R-sq.	0.486	0.513	0.607	0.486	0.514	0.608
Observations	9733	9710	9710	9733	9710	9710
F-stat	196	189	125	70	41	26

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.

A.3 Negative Electricity Prices and Wind Power Generation

Table A.3: Variation in Frequency of Prices below $0/MWh, 2011-2014

	MISO	NEISO	ERCOT
2011	3.24	0.01	2.51
2012	2.87	0.01	1.67
2013	2.56	0.01	0.60
2014	2.47	0.34	0.61

Table A.4: Variation in RD Estimates over Time and ISO - Capacity Factor

	2010-2014	2011 only	2012 only	2013 only	2014 only
1603 Recipient	-3.08***	-3.79***	-2.57**	-2.74**	-2.89**
	(1.02)	(1.20)	(1.04)	(1.16)	(1.26)
1603, MISO Only	-4.58**	-3.43	-4.31*	-4.84*	-5.20*
	(2.33)	(2.13)	(2.62)	(2.58)	(2.80)

Models correspond to baseline RD specification with state fixed effects.
Standard errors clustered by wind farm reported in parentheses.
Each row presents results from separate regressions on separate samples.

Table A.5: Seasonal Variation in Negative Prices and RD Estimates

	$p <$ \$0/MWh		$p <$ -\$20/MWh		RD Estimate
	ERCOT	MISO	ERCOT	MISO	
January	1.42	2.81	0.14	0.97	-3.564***
February	2.15	2.40	0.33	1.04	-4.565***
March	2.65	3.64	0.66	1.20	-4.103***
April	2.47	3.81	0.73	1.12	-3.596***
May	1.52	3.83	0.20	1.37	-2.891***
June	1.31	3.18	0.21	0.99	-2.081***
July	0.09	0.86	0.04	0.24	-0.234
August	0.19	0.84	0.05	0.31	-0.510
September	0.40	3.32	0.08	0.92	-1.350
October	0.94	2.94	0.12	0.86	-2.540**
November	2.08	3.78	0.17	1.03	-3.906***
December	0.93	2.12	0.06	0.66	-2.615**
Average	1.35	2.79	0.23	0.89	-3.083***

Note: Columns 2-5 display frequencies taken over all electricity market nodes in all time periods within a given month using data from 2011-2014.