

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

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April 2016 Draft; Comments Welcome; Do Not Cite

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. Using matching and fuzzy regression discontinuity designs, we find that wind farms choosing the capital subsidy produce 8 to 14 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 17 to 20 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 on 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 in lieu of the PTC.¹ Designed to address the unprecedented challenges of monetizing tax credits during the financial crisis, the 1603 grant was a truly unique and unexpected policy innovation.

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

¹ 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.

matching strategy exploits a panel of electricity generation for wind projects placed into service between 2002 and 2012. Using exact and propensity score 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. 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 temporal bandwidths.

In our baseline ordinary least squares model using the full sample, we find that 1603-recipient wind farms are approximately 9 to 12 percent less productive than PTC recipients. Our matching analysis on this same sample produces an estimated policy effect of approximately 8 to 14 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 an 8 to 14 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 17 to 20 percent more per unit of output from the wind farms claiming the 1603 grant than those claiming the PTC. Although a full welfare analysis requires estimating the value of emissions displaced by both subsidies, these findings suggest the form of subsidy available has important implications for the social benefits of investment.

The rest of this paper proceed as follows. The remainder of the this section reviews the 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. After conceding that input subsidies may be politically attractive or easier to implement, he concludes that they 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.

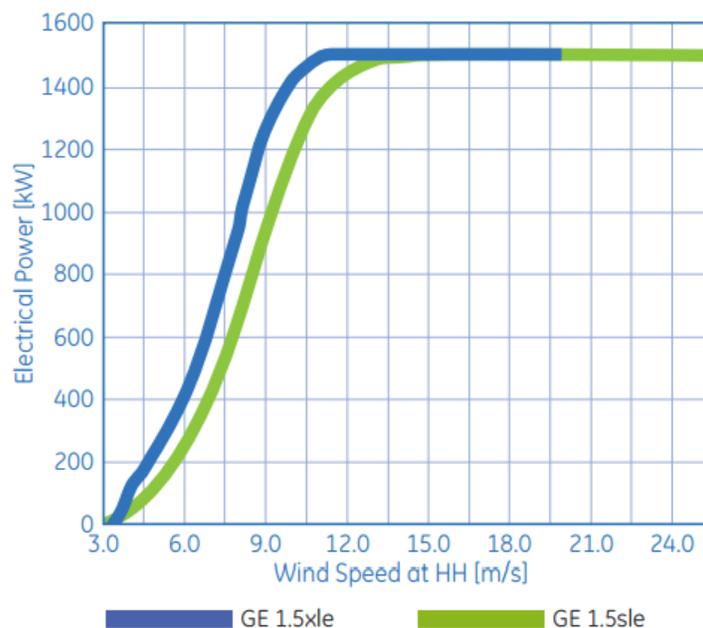
Although capital and output subsidies are used interchangeably in many settings, few have been studied empirically. In the context of affordable housing, where some policies support inputs (housing units) while others support outputs (housing services), “the empirical literature is unanimous in finding 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.

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.

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



Building a wind farm involves large up-front costs. During the time period we study, Wisner 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. 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. 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.² 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.³

Although wind operators 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 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 Q_{it} generated by a wind turbine at a given point in time t ,

$$Q_{it} = a_{it}e_i(w_{it}, m_{it})K_i$$

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. 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 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. 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. PEF, 2010).

In this financial context, wind farm developers sought new ways to realize the value of the PTC.

²Turbine 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.

³Authors' estimate based on MISO data.

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.⁴ 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: they could claim the production tax credit or 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 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 pro-

⁴One 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.

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

⁶While 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.

⁷The 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.

gram 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 renewable portfolio standards which mandate that a minimum share of the states consumption come from qualified renewable sources, resulting in a price premium for wind power. While Schmalensee (2012) notes that transparency into renewable energy credit markets is heterogeneous around the country and, in many states, quite poor, under some state RPS programs, wind power generation has generated renewable energy credits worth 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.

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. Let the universe of potential wind farms be defined by the tuple $\theta = \{K, \alpha, F\}$, where K is generation capacity that can be sited at a location, α is the latent productivity of the site (which captures wind quality, location on the grid, etc.), and F is the fixed cost of developing the site. Under a subsidy that pays τ for each unit of output, firm profits are,

$$\pi^O = [(p + \tau)q(\alpha, \omega) - c(\omega)]K - F$$

where ω represents the amount of effort the operator exerts to increase output per unit of capacity ($q = \frac{Q}{K}$) once the plant is online. This effort comes at cost c per unit of capacity, with $\frac{\partial c}{\partial \omega} > 0$ and $\frac{\partial c^2}{\partial^2 \omega} \geq 0$.⁸

Conditional on operating, the firm sets ω such that $(p + \tau)q' = c'$. Denote this optimal output level under the output based subsidy q^O .

Under a capital subsidy which pays s percent of fixed costs in lieu of τ , firm profits become,

$$\pi^C = [pq(\alpha, \omega) - c(\omega)]K - (1 - s)F$$

Conditional on operating, the firm now chooses operating effort such that $pq' = c'$. Denote this optimal output level under the capital subsidy q^C . If $\frac{\partial q}{\partial \omega} > 0$ and $\frac{\partial q^2}{\partial^2 \omega} < 0$, then $q^O > q^C$.

In order to describe the net effects of moving from an output based subsidy to a system where firms can choose between capital and output subsidies, it is useful to allocate potential wind farms into one of four groups based on how they behave under either regime (Figure 2). We can then derive conditions for categorizing wind farms into these groups.

The first group is the “output preferred” group. These wind farms enter the market under either subsidy regime, and always opt for output subsidies. These plants can be characterized by a profitability condition: $\pi^O > 0$, and a preference condition, $\pi^O > \pi^C$. Let f denote the construction

⁸This simple two period model abstracts away from the fact that output is generated over many periods.

Figure 2: Taxonomy of wind farms by subsidy preference

		<u>Subsidy Choice</u>		
		Output	Capital	No Entry
<u>Output Only</u>	Output	Output preferred	Capital Preferred	
	No Entry		Capital Required	Never Enter

cost per unit capacity ($\frac{F}{K}$). Applying the envelope theorem $p(q^O - q^C) - (c^O - c^C) \approx 0$, the preference condition reduces to

$$\tau q^O > sf \quad (1)$$

So output subsidies are preferred if the output subsidy per unit of capital is higher than subsidized portion of fixed costs per unit capital. Intuitively, wind farms that are more productive conditional on f are more likely to prefer a subsidy that rewards production.⁹

The second group in the figure always enters, but prefers capital subsidies if they are available. The preference condition (1) for this group is reversed, so output subsidies must now be lower than the subsidized portion of capital. Since this group always enters, $\pi^C > \pi^O$ implies that the profitability constraint remains the same.

The next group to consider only enters if capital subsidies are available. As this group prefers capital subsidies when available, the preference condition is the same as the previous group (“capital preferred”). However, the profitability condition is now only satisfied under the capital subsidy, $\pi^C > 0 > \pi^O$. Applying the envelope theorem again, this implies $\pi^C + \tau q^O < sf$. Intuitively, for plants on the extensive margin, adding the total revenue from the output subsidy to their profits under a capital subsidy does not make up for the loss in subsidized fixed costs. The “never enter” group is included for completeness and is characterized by the profitability conditions $\pi^O < 0$ and $\pi^C < 0$.

We can now use these conditions to characterize the net effect of introducing capital subsidies. For a given distribution of θ , and subsidy parameters s and τ , let N^{CP} be the number of wind farms in the capital preferred cell, and N^{CR} be the number in the capital required cell. The net effect of allowing subsidy choice on total wind production is,

$$\Delta Q = N^{CR}Q^C - N^{CP}(Q^O - Q^C) \quad (2)$$

In order to compute this for the 1603 grant program, we need two pieces of information. First, we need to estimate how much more 1603 plants would have produced under an output subsidy ($Q^O - Q^C$). Second, we need to classify all 1603 firms as being marginal or inframarginal to the policy (N^{CR} and N^{CP}). This requires knowing the sign of $\pi^C + \tau q^O - sf$.

⁹Which constraint binds, the preference or the entry condition, depends on the sign of the term in brackets: $\tau q^O + [pQ^O - c^O - (1-s)f] > sf$

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, 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) and 3TIER. The AWEA database contains additional cross-sectional information on each wind farm, including the exact wind turbine used and whether projects contract output through long-term power purchase agreements (PPAs) or sell on spot markets (the latter is used to code the “offtake type” indicator variable in the estimated regression models). 3TIER uses global wind and weather monitor data to interpolate half-hourly wind speed and direction data 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.

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 (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 1: Summary Statistics by Entry Date

Entry Year	Wind Farms	1603	Nameplate	Turbines	Wind Speed	Regulated	Capacity Factor
2002	20	0	53.27	65.65	7.34	0.05	24.91
2003	23	0	68.38	57.48	7.29	0.00	30.82
2004	17	0	28.22	43.00	7.37	0.06	25.07
2005	29	0	67.78	47.90	7.60	0.03	36.94
2006	43	0	44.69	28.07	7.35	0.12	33.62
2007	40	0	123.73	76.65	7.44	0.10	33.24
2008	90	0	93.55	54.48	7.40	0.11	34.74
2009	88	51	86.01	52.51	7.22	0.15	31.53
2010	60	45	88.40	50.80	7.10	0.07	32.41
2011	76	50	74.69	39.85	6.76	0.05	30.88
2012	115	55	99.58	48.97	7.08	0.12	33.88

Table 2 compares projects placed into service after the introduction of the 1603 program by subsidy type along observable dimensions. Although the overall size of the projects 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 capacity factors by almost four 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.¹⁰ 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 decomposing this observed difference in productivity across subsidy types into a selection effect and a treatment effect.

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

	PTC	1603	Difference	(p-value)
Nameplate Capacity	95.26	83.80	11.46	0.18
Turbines	51.41	45.93	5.48	0.26
Mean Wind Speed	7.30	6.82	0.47	0.00
Regulated	0.21	0.03	0.18	0.00
Capacity Factor	33.86	30.12	3.74	0.00
New Wind Farms	138	202		

¹⁰Capacity factors are a commonly used metric of operational activity in the electric power sector.

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 sample restrictions:

$$q_{it} = \delta D_i + \beta X_{it} + \nu_{it} \quad (3)$$

Here i indexes wind farms and t indexes months. The dependent variable q is the plant’s “capacity factor”, which is net generation as a percent of rated capacity. D is an indicator for whether the wind farm took the 1603 grant and X is a vector of controls (e.g., wind farm capacity, wind quality, 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 (3) 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 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 first strategy combines matching and difference-in-differences. Through this approach, we aim to distinguish between the effects of the subsidy and other time invariant unobservables that may affect productivity. In this setting, the standard difference-in-differences approach is not available, as there is no variation in subsidy choice within a facility. We divide our sample into two groups corresponding to the two regimes in Figure 2: wind farms that entered between 2002 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 observables, and assign a subsidy preference to the pre plants based on the observed choice of their matched post counterparts.

Let \hat{D} be this new matched assignment. We regress output per unit capacity on the constructed assignment variable \hat{D} interacted with an indicator for whether the plant entered before or after the 1603 became available:

$$q_{it} = \eta \hat{D}_i + \zeta 1\{1603 \text{ eligible}\}_i + \delta \hat{D}_i \cdot 1\{1603 \text{ eligible}\}_i + \beta X_{it} + \mu_t + \epsilon_{it} \quad (4)$$

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

In addition to this “synthetic” difference-in-differences approach, we also estimate the model by simply taking the difference between each matched pair for each month and running OLS on those differences. Let j represent the pre-period match for post period plant i . We estimate

$$(q_{it} - q_{jt}) = \delta D_i + \beta(X_{it} - X_{jt}) + (\epsilon_{it} - \epsilon_{jt}) \quad (5)$$

By differencing, we effectively remove any time varying unobservables shared across matched pairs. We also include month-year dummies in all specifications. The model is estimated using OLS, such that each post-period observation gets a weight of 1 and it’s N_i pre-period matches get a weight of $1/N_i$.

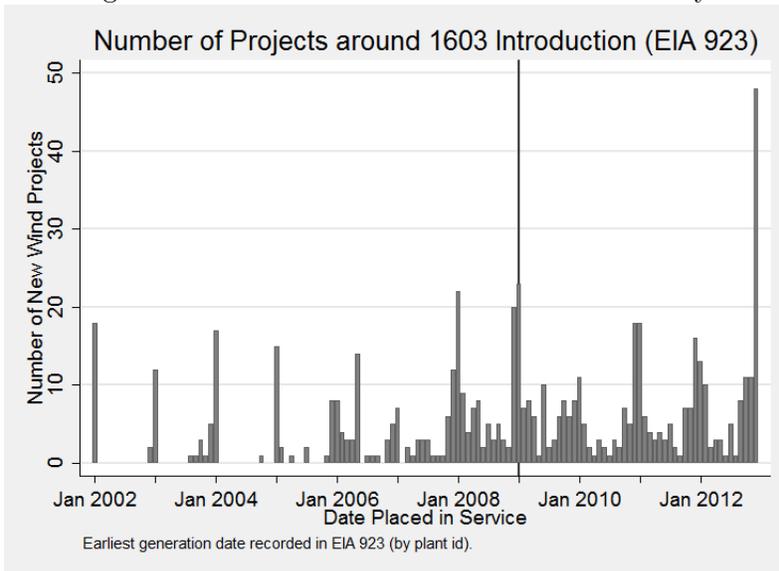
4.2.1 Identification

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

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 3). 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 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 3: Evidence of Seasonal Variation in Entry



Our RD design attempts to harness the natural experiment created by the 1603 cash grant program. 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,

$$D_i = \gamma \cdot 1\{1603 \text{ eligible}\}_i + \xi X_{it} + \nu_i \tag{6}$$

where $1\{1603 \text{ eligible}\}_i$ 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 (3) 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.¹¹ 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).

¹¹We 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.

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.

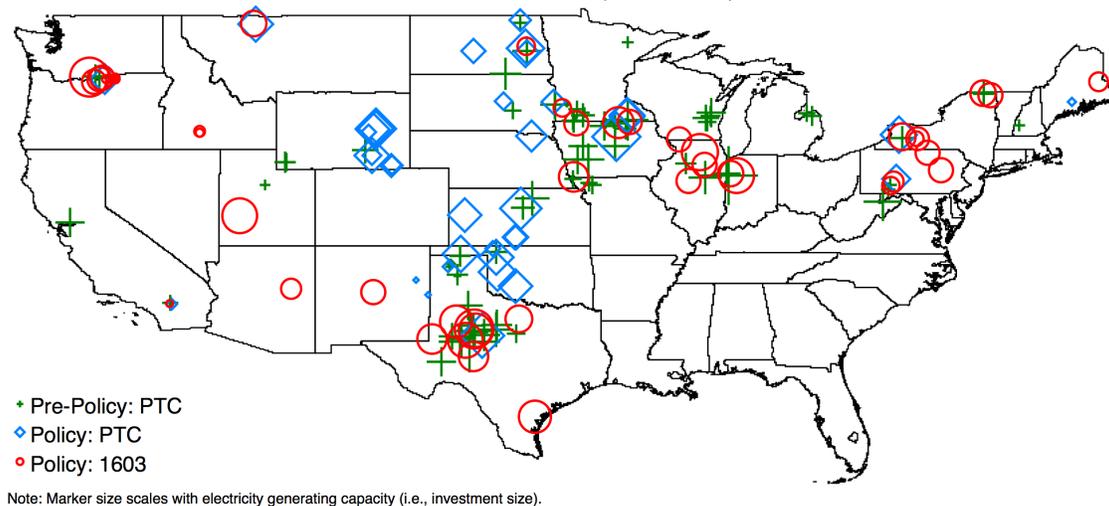
Table 3: Comparison of projects entering one year before and after the policy

	2008	2009	Difference	p-value
Nameplate Capacity	93.51	85.96	7.55	0.57
Turbines	54.45	52.51	1.93	0.82
Mean Wind Speed	7.29	7.16	0.13	0.33
Regulated	0.11	0.15	-0.04	0.47
Capacity Factor	32.52	30.46	2.06	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 4. 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. 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 post period (2009) to similar firms entering in the pre period (2008). Most projects completed in 2009, the policy period, are located near a facility built in 2008.

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.

Figure 4: Wind Farm Locations by Period
New Wind Farms (2008-2009)



5 Results

5.1 Matching

Table 4 reports the matching results. The dependent variable in each regression is the ratio of net electricity generation to installed generation capacity (in percentage points). The table contains six estimates of the operational impact of the 1603 grant program (δ) for each method of matching pre and post period observations. Models 1, 3, and 5 estimate equations (3), (4), and (5), and models 2, 4, and 6 add state fixed effect to each of these respectively. Covariates X_{it} include wind speed and wind speed squared, estimated potential capacity factor, age and age squared, and indicator variables for regulatory status, ISO/RTO status, and offtake type¹². All regressions are restricted to a balanced panel from 2013-2014 and include year-month dummies and cohort dummies.

The first column describes how the pre and post observations were matched for each row. For example, in row (A), matches were constructed by matching exactly on ISO/RTO, median wind class, and offtake type, and then restricting to all plants within one log capacity point of the post period plant. The second and third columns report the number of post-period 1603 and PTC plants with at least one pre-period match under this criteria. Row (B) is similar to (A), but requires plants to be in the same state, but not the same ISO/RTO.

Rows (C) - (F) collapse the many potential subsidy choice determinants into a single propensity score, and then match on this score within each ISO or state. This score is constructed by first estimating a probit model on subsidy choices using the post period entrants only. The results are presented in Appendix Table A.1. Subsidy choice is estimated to be a function of the average values of a cubic in wind, a cubic spline in nameplate capacity, and indicators for regulatory

¹²Potential capacity factor is calculated by combining the estimated hourly wind data from each site with the power curve for the wind turbine used according to AWEA data. As some wind turbines ramp up our cutout at different wind speeds, this adds site-specific information on this nonlinear relationship.

Table 4: Matching Results

Matching Description	# 1603	# PTC	(1)	(2)	(3)	(4)	(5)	(6)
(A) Plants in the same ISO/RTO, median wind class, and offtake type within one log point capacity.	87	60	-4.8 (1.2)***	-3.5 (1.2)***	-2.6 (1.9)	-3.4 (1.7)**	-4.1 (1)***	-3.5 (1)***
(B) Plants in the same state, median wind class, and offtake type within one log point capacity.	103	47	-3.7 (1.2)***	-2.6 (1.2)**	-1.3 (2.1)	-2.7 (1.6)*	-2.4 (1.1)**	-2.4 (1.1)**
(C) Five nearest propensity scores within same ISO/RTO.	101	73	-4.9 (1.1)***	-3.8 (1.1)***	-4.0 (2.2)*	-4.2 (2.2)*	-4.2 (1.1)***	-3.7 (1.1)***
(D) Five nearest propensity scores within same state.	123	68	-3.7 (1.1)***	-3.0 (1.1)***	-2.6 (1.7)	-3.2 (1.6)**	-3.5 (1.1)***	-3.5 (1.1)***
(E) Nearest propensity score within same ISO/RTO.	101	73	-5.0 (1.1)***	-3.8 (1.1)***	-5.0 (2.2)**	-4.2 (2.2)*	-4.4 (1.2)***	-5.0 (1.4)***
(F) Nearest propensity score within same state.	123	68	-3.7 (1.1)***	-3.0 (1.1)***	-2.6 (1.7)	-2.6 (1.5)*	-3.0 (1.2)**	-2.9 (1.2)**
Method			OLS	OLS	MDD	MDD	Diff	Diff
State Dummies			N	Y	N	Y	N	Y

This table reports the estimated marginal impact of the 1603 grant program (δ) from 30 different regressions. The dependent variable is the ratio of net generation to installed capacity in percentage points. Models 1, 3, and 5 estimate equations (3), (4), and (5), and models 2, 4, and 6 add state fixed effects to each of these respectively. The first column describes how the pre and post observations were matched for each row, and the second and third columns report the number of post-period 1603 and PTC plants with at least one pre-period match under these criteria, out of 202 1603 plants and 138 PTC plants. All regressions are restricted to a balanced panel from 2013-2014 and include year-month dummies and cohort dummies. Standard errors, clustered at the plant level, are reported in parentheses.

status, ISO/RTO status, and offtake type. The second and third columns add ISO/RTO and state indicator variables, respectively. These regressions are then used to generate a 1603 propensity score for the entire sample, including those plants that entered prior to the 1603 grant becoming available. Figure A.2 presents the propensity score densities for the pre and post period entrants. While the upper part of the distributions look similar, the post period actually has larger mass in the the range were plants are very likely to prefer the PTC.

Rows (C) and (D) match post period observations to the five pre period plants within the same ISO that have the closest predicted propensity scores. Rows (E) and (F) match post period observations only to the closest plant.

Column (1) reports the results of estimating equation (3) on the matched sample using OLS. 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 3.7 to 5 percent of installed capacity across the various matching strategies. By adding state fixed effects to the OLS specification (Column 2), we estimate modestly smaller impacts in the range of -2.6 to -3.8 percent.

Columns (3) and (4) implement the matched difference-in-differences (MDD) estimator from equation (4). As was discussed above, this approach attempts to distinguish the effect of the 1603 program from other time-invariant unobservables that differentially affect productivity at firms inclined to prefer capital to output subsidies. The estimated coefficients in column (3) are of similar magnitude as those in columns (1) and (2), albeit less precisely estimated. Accounting for state fixed effects in column (4) shows similar magnitude, negative impacts at the 10 to 5 percent significance level.

Column (5) allows for a more flexible structure of unobservables by first differencing the post period observations and their pre period matches, and then running OLS on those differences (equation 5). This removes any time varying unobservables shared at the match level. This approach allows for unobserved trends at the regional or regulatory level that may differentially affect firms that prefer capital verses output subsidies (for example, if one state’s RPS policy changed during the sample, and the wind farms in this state favored the 1603 program). Comparing the estimates in columns (5) and (6) to (1) and (2) suggests that most of the difference in productivity between 1603 and PTC plants is due to the 1603 program, rather than selection. While the point estimates are smaller than the OLS estimates, the results are not statistically distinguishable. Under our preferred specification in column (5), the 1603 program reduced net generation by 2.4 to 4.4 percent of operating capacity. This implies an 8 to 14 percent reduction in production.

5.2 Regression Discontinuity Design

Table 5 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 month-year fixed effects.

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 (3). Conditioning on only output predictions and wind speed, net generation per unit of capacity at 1603 plants is 3.2 percent lower than their PTC counterparts. Adding the covariates from the matching regressions reduces the effect size slightly. With state fixed effects, in column (3), δ is not statistically distinguishable from zero.

Columns (4)-(6) present the 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 output predictions and wind speed, 1603 plants are 4.8 percent less productive than their PTC counterparts. Adding other covariates reduces this estimate slightly, to 4.5 percent. The effect size shrinks to 2.4 percent with the addition of state fixed effects but remains significant at

Table 5: RDD Results

	(1)	(2)	(3)	(4)	(5)	(6)
1603 Recipient	-3.170*** (0.834)	-2.809*** (0.851)	-1.149 (0.756)	-4.766*** (1.236)	-4.546*** (1.238)	-2.419** (1.087)
Wind Speed (m/s)	1.783 (1.432)	2.974** (1.361)	4.094*** (1.339)	1.549 (1.442)	2.728** (1.376)	4.216*** (1.306)
Wind Speed Squared	0.0328 (0.0782)	-0.0367 (0.0741)	-0.0724 (0.0655)	0.0369 (0.0790)	-0.0328 (0.0744)	-0.0784 (0.0645)
Potential Capacity Factor	17.30*** (4.683)	18.39*** (4.169)	19.63*** (3.927)	17.20*** (4.469)	18.48*** (4.067)	19.41*** (3.635)
Regulated		-4.735*** (0.815)	-1.965* (1.112)		-4.701*** (0.866)	-1.797 (1.129)
ISO/RTO		0.115 (0.797)	-0.674 (0.713)		-0.0917 (0.815)	-0.545 (0.734)
Deliver to grid		2.227 (1.853)	0.970 (1.314)		1.985 (2.012)	0.873 (1.306)
Regression Type	OLS	OLS	OLS	2SLS	2SLS	2SLS
State FE	N	N	Y	N	N	Y
Adjusted R-sq.	0.527	0.544	0.645	0.523	0.540	0.644
Observations	10560	10560	10560	10560	10560	10560
F-stat				136	136	96

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.

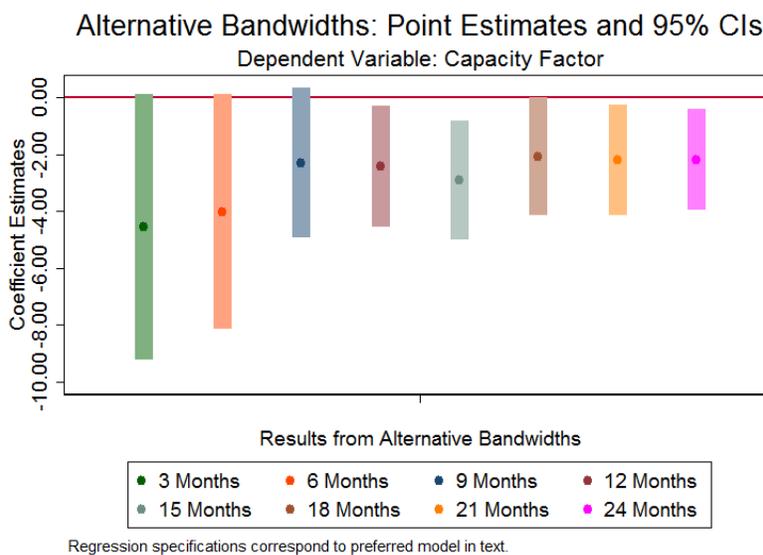
the 5 percent level.

These IV estimates are very similar to 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 fuzzy regression discontinuity design 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 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 5 presents coefficients from the model specification in column (6) of figure 5 in graphical form for using alternative bandwidths ranging from three months to 24 months. Although the confidence intervals are large in 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 if they received the production subsidy.

Figure 5: Alternative Bandwidths - Capacity Factor



6 Discussion

6.1 Policy Implications

If the policy goal is to reduce 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 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 8 to 14 percent 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.

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

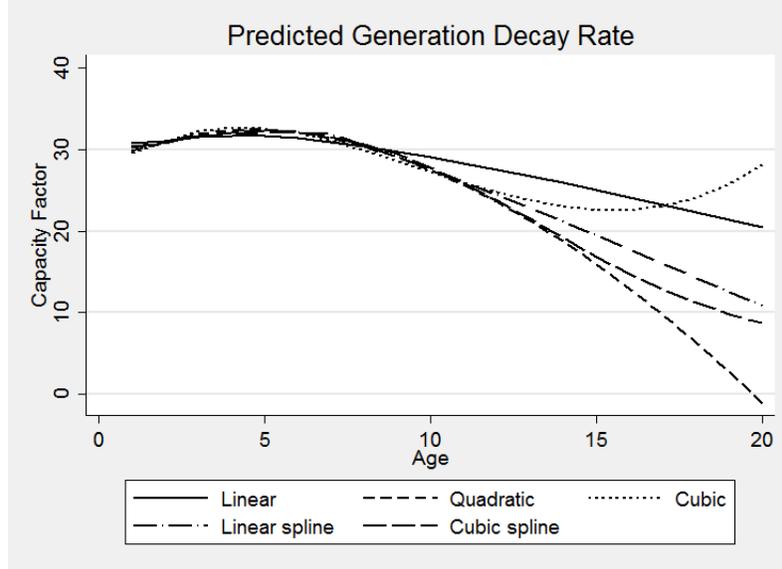
$$\pi^{PTC} = \sum_t \left(\frac{1}{1+r} \right)^t (p_t + PTC_t - c_t) Q_t^{PTC} - F$$

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,

$$q_{it} = g(\text{age}_{it}) + \alpha_i + \mu_t + \epsilon_{it}$$

The model is estimated under several specifications of $g()$: linear, quadratic and cubic functions of age, as well as linear and cubic splines. Figure 6 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 6: Predicted Decay Rate



In 2011, the EIA began collecting annual data on sales quantities at each facility. We use this to obtain an estimate of p_{it} for each 1603 facility.¹³ We assume operating costs c_{it} of \$9/MWh, which is the average of post-2010 O&M costs reported in Wisner and Bolinger (2014). F is obtained by

¹³Real 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 resale the power to end-use consumers. Resale price information is missing for 11 of the 202 1603 facilities in the sample. This is most 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).

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.¹⁴ Finally, the real interest rate r is set equal to 5 percent.

Table 6 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, 40 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.¹⁵ 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 6: Estimated Subsidy by Group

Group	N	1603			PTC		
		Output (MMWh)	Subsidy (\$M)	Subsidy (\$/MWh)	Output (MMWh)	Subsidy (\$M)	Subsidy (\$/MWh)
Always Profitable	105	377	5,230	13.86	396	5,079	12.83
Marginal	12	13	265	20.96	13	184	13.73
Never Profitable	74	235	4,146	17.66	249	3,406	13.65

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 47 plants are estimated to earn a higher total subsidy under the PTC.

Estimating the net effect of the 1603 program (equation 2) requires taking a stand on the counterfactual entry status of the never profitable group. One assumption would be to combine these plants with 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 228 MMWh. It would also imply that the 1603 grant increased the average public cost per wind MWh from \$12.83 to \$15.43. An alternative approach is to assume that the lack of profitability

¹⁴In 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.

¹⁵We plan to incorporate state level RPS information in future drafts. 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.

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 5 percent. Under this assumption, total wind output from would have actually been over 20 million MWh higher without the 1603 program, while total government expenditure would have declined by \$1.2 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.2). We present estimates of our baseline regression discontinuity specification by year in the first row of Table A.3. These effects do not show a clear temporal trend, with the rank-ordering of point estimates by magnitude as follows: 2011, 2014, 2012, and 2013. The second and third rows of Table A.3 present estimates from separate models that only include data from ERCOT and MISO. In ERCOT, the estimated difference in generation between PTC and 1603 recipients decreases over time. In MISO, in contrast, the magnitudes of the point estimates are fairly consistent over time (although not precisely estimated).

Second, we compare seasonal variation in negative prices and our estimates (Table A.4). 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.¹⁶ 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 14 percent less power per unit of capacity than those projects choosing the output subsidy. Preliminary analysis suggest the Federal government paid 17 to 20 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 may also highlight opportunities for structuring input subsidies such that they reflect the expected output from the investment (Schmalensee, 1980).

¹⁶Thanks to Erin Mansur for making this comment on an earlier draft.

References

- Aldy, J. E. (2013, January). A Preliminary Assessment of the American Recovery and Reinvestment Act's Clean Energy Package. *Review of Environmental Economics and Policy* 7(1), 136–155.
- Bolinger, M., R. Wiser, and N. Darghouth (2010, November). Preliminary evaluation of the Section 1603 treasury grant program for renewable power projects in the United States. *Energy Policy* 38(11), 6804–6819.
- Borenstein, S. (2015, May). The Private Net Benefits of Residential Solar PV: And Who Gets Them. Working Paper 259, UC Berkeley.
- Brown, P. and M. F. Sherlock (2011). ARRA Section 1603 Grants in Lieu of Tax Credits for Renewable Energy: Overview, Analysis, and Policy Options. CRS Report for Congress R41635, Congressional Research Service, Washington, D.C.
- Cicala, S. (2015). When Does Regulation Distort Costs? Lessons from Fuel Procurement in US Electricity Generation. *American Economic Review* 105(1), 411–44.
- Davis, L. W. and C. Wolfram (2012). Deregulation, Consolidation, and Efficiency: Evidence from US Nuclear Power. *American Economic Journal: Applied Economics* 4(4), 194–225.
- Fabrizio, K. R., N. L. Rose, and C. D. Wolfram (2007). Do Markets Reduce Costs? Assessing the Impact of Regulatory Restructuring on US Electric Generation Efficiency. *The American Economic Review* 97(4), 1250–1277.
- Fryer, R. G. (2011, November). Financial Incentives and Student Achievement: Evidence from Randomized Trials. *The Quarterly Journal of Economics* 126(4), 1755–1798.
- Fullerton, D. (1997). Environmental Levies and Distortionary Taxation: Comment. *The American Economic Review* 87(1), 245–251.
- Hitaj, C. (2013, May). Wind power development in the United States. *Journal of Environmental Economics and Management* 65(3), 394–410.
- John Horowitz, Office of Tax Policy, U.S. Treasury (2015). Personal Communication.
- Lantz, E., R. Wiser, and M. Hand (2012). IEA Wind Task 26: The Past and Future Cost of Wind Energy. Technical Report NREL/TP-6A20-53510, National Renewable Energy Laboratory, Golden, CO.
- Metcalf, G. E. (2010, August). Investment in Energy Infrastructure and the Tax Code. In J. R. Brown (Ed.), *Tax Policy and the Economy*, Volume 24, pp. 1–33. Chicago: University of Chicago Press.

- Olsen, E. O. (2000, December). The Cost-Effectiveness of Alternative Methods of Delivering Housing Subsidies. SSRN Scholarly Paper ID 296785, Social Science Research Network, Rochester, NY.
- Parish, R. M. and K. R. McLaren (1982, April). Relative Cost-Effectiveness of Input and Output Subsidies. *Australian Journal of Agricultural Economics* 26(1), 1–13.
- Parry, I. W. H. (1998, May). A Second-Best Analysis of Environmental Subsidies. *International Tax and Public Finance* 5(2), 153–170.
- Schmalensee, R. (1980). Appropriate Government Policy Toward Commercialization of New Energy Supply Technologies. *The Energy Journal* 1(2), 1–40.
- Schmalensee, R. (2012, January). Evaluating Policies to Increase Electricity Generation from Renewable Energy. *Review of Environmental Economics and Policy* 6(1), 45–64.
- Schmalensee, R. (2016, January). The Performance of U.S. Wind and Solar Generators. *The Energy Journal* 37(1).
- U.S. PEF (2010, July). Prospective 2010-2012 Tax Equity Market Observations.
- Wibulpolprasert, W. (2013, December). Optimal Environmental Policies and Renewable Energy Investment in Electricity Markets. Job Market Paper, Stanford University.
- Wiser, R. and M. Bolinger (2014). 2013 Wind Technologies Market Report. Technical Report LBNL-6809E, Lawrence Berkeley National Laboratory.

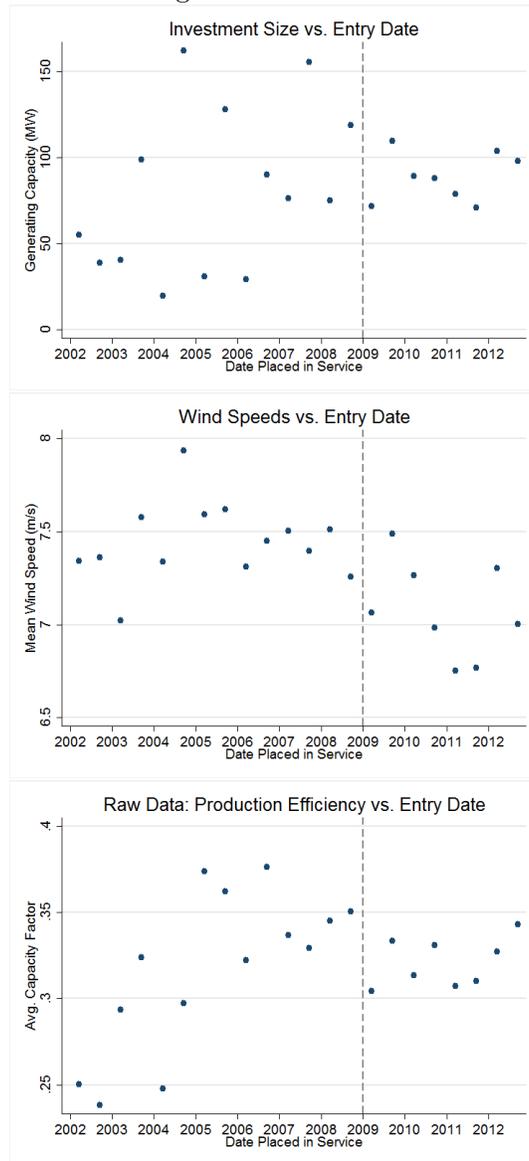
A Appendix

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, 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.1: Trends



A.2 Propensity score results used in matching

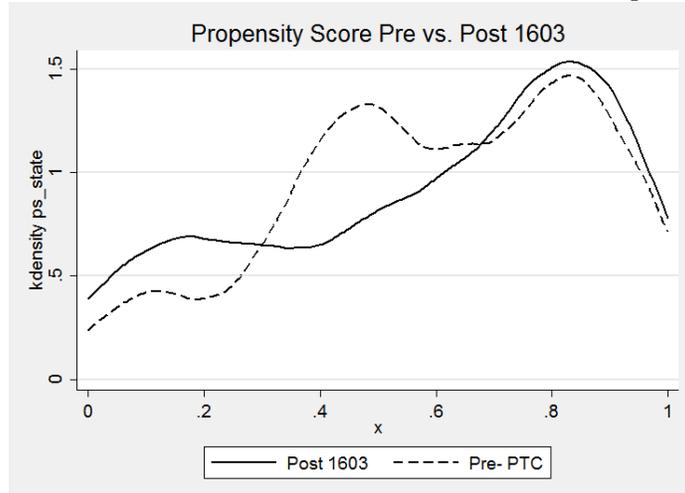
Table A.1: Propensity score estimation

	(1)	(2)	(3)
1603 Recipient			
spline.1	0.0177* (0.00957)	0.0183* (0.0109)	0.0309** (0.0126)
spline.2	-0.115* (0.0696)	-0.127 (0.0800)	-0.199** (0.0925)
spline.3	0.181 (0.114)	0.201 (0.131)	0.316** (0.151)
Regulated	0.126 (0.644)	0.313 (0.696)	5.419 (259.4)
Wind Speed (m/s)	-9.473** (4.390)	-15.17*** (5.340)	-18.89*** (6.753)
Wind Speed Cubed	-0.0530** (0.0209)	-0.0766*** (0.0246)	-0.0898*** (0.0317)
Wind Speed Squared	1.301** (0.558)	1.986*** (0.668)	2.421*** (0.852)
ISO/RTO	-0.537*** (0.207)	-0.877 (1.078)	-1.342* (0.736)
Constant	20.23** (9.702)	28.39 (150.7)	38.22** (14.93)
Region FEs		Nerc-ISO	State
Pseudo R-sq.	.173	.243	.302
Observations	283	281	246

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.2: Distributions of Estimated and Predicted Propensity Scores



A.3 Negative Electricity Prices and Wind Power Generation

Table A.2: 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.3: Variation in RD Estimates over Time and ISO - Capacity Factor (Separate)

	2010-2014	2011 only	2012 only	2013 only	2014 only
1603 Recipient	-2.419** (1.087)	-3.147** (1.241)	-2.334** (1.099)	-1.968 (1.291)	-2.379* (1.371)
1603 Recipient, ERCOT Only	-3.058** (1.460)	-6.320*** (2.143)	-4.831*** (1.696)	-0.596 (1.531)	-0.618 (1.864)
1603 Recipient, MISO Only	-4.024 (2.545)	-3.056 (2.353)	-3.187 (2.656)	-4.292 (2.963)	-4.755 (3.055)

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.4: Seasonal Variation in Negative Prices and RD Estimates

	$p < \$0/\text{MWh}$		$p < -\$20/\text{MWh}$		RD Estimate
	ERCOT	MISO	ERCOT	MISO	
January	1.42	2.81	0.14	0.97	-3.72***
February	2.15	2.40	0.33	1.04	-4.04***
March	2.65	3.64	0.66	1.20	-3.48***
April	2.47	3.81	0.73	1.12	-3.19**
May	1.52	3.83	0.20	1.37	-2.18*
June	1.31	3.18	0.21	0.99	-1.63
July	0.09	0.86	0.04	0.24	-0.16
August	0.19	0.84	0.05	0.31	-0.58
September	0.40	3.32	0.08	0.92	-1.11
October	0.94	2.94	0.12	0.86	-2.28**
November	2.08	3.78	0.17	1.03	-3.58***
December	0.93	2.12	0.06	0.66	-2.08*
Average	1.35	2.79	0.23	0.89	-2.42**

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.