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INVESTMENT VERSUS OUTPUT SUBSIDIES: IMPLICATIONS OF ALTERNATIVE INCENTIVES FOR WIND ENERGY

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ABSTRACT

This paper examines the choice between subsidizing investment or output to promote socially-desirable production. We exploit a natural experiment in which wind farm developers could choose an investment or output subsidy to estimate the impact of these instruments on productivity. Using regression discontinuity and matching estimators, we find that wind farms claiming the investment subsidy produced 10 to 11 percent less power than wind farms claiming the output subsidy, and that this effect reflects subsidy incentives rather than selection. The introduction of investment subsidies caused the Federal government to spend 12 percent more per unit of output from wind farms.

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A Github code and data repository is available at
https://github.com/rlsweeney/public_ags_output_subsidies

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 (House and Shapiro, 2008; Auerbach et al., 2010). To address the public goods market failure characterizing innovation, the government subsidizes research and development spending (Wright, 1983). To increase the supply of affordable housing, the government subsidizes specific types of real estate development (Desai et al., 2010). To spur the replacement of pollution-intensive facilities, policymakers subsidize the construction of low-emission power plants (Aldy, 2013).

In each of these cases, it is noteworthy that, while the subsidy directly targets investment, the social benefits of the intervention are tied to the eventual output from these investments, not just the investment itself. Stimulus that yields productive factories will do more to increase aggregate demand than building pyramids. Innovation policy that increases the knowledge stock will increase social welfare more than policy that simply raises scientists' salaries. This paper is motivated by the observation that governments also often employ *output* subsidies aimed at each of these objectives, such as government procurement, research prizes, Section 8 housing vouchers, and tax credits for clean energy production. This begs the question: does subsidizing investment or subsidizing output more cost-effectively promote socially-desired outcomes?

Economic theory does not provide a clear answer to this question. If production effort is costly, then output-based subsidies may lead to more effort on the intensive margin. Investment subsidies reduce the price of capital relative to other inputs, which could raise the social cost of production by distorting the input mix (Goolsbee, 2004). However, in the long run, it is theoretically possible for investment subsidies to yield greater output per dollar of public funds spent if the production function is characterized by decreasing returns to scale (Parish and McLaren, 1982).

In this paper, we provide the first empirical evidence on the relative cost-effectiveness of investment subsidies and output subsidies. We focus on the U.S. wind power industry, where a unique policy innovation temporarily allowed project developers to choose between investment and output subsidies. Leveraging the abrupt timing of this policy change, we first estimate the impact of this subsidy choice on wind farm productivity, and then use these estimates to evaluate the public economics of Federal renewable energy subsidies. Consistent with a simple model of costly effort, we find that claiming an investment subsidy causes a 10 to 11 percent reduction in production per unit of operating capital (relative to claiming an output subsidy). This results in the Federal government paying 12 percent more per unit of output under the investment subsidy. While we do not directly estimate the impact of the change in subsidy policy on entry, we provide evidence that few plants are profitable under one regime but not the other, suggesting any extensive margin effects are likely small in this setting.

Wind power capacity in the United States increased fivefold from 2007 to 2016, representing the largest share of new power production capacity to come online over this decade, with annual investment as high as $25 billion (Administration, 2017; Wiser and Bolinger, 2013). While wind power technology has improved over time, these investments were encouraged by an array of Federal and state renewable energy subsidies. Historically, the primary Federal subsidy program has been the Production Tax Credit (PTC), which provides eligible owners with approximately $23 for each megawatt hour (MWh) of output produced during the first ten years of operation. In 2009, the Federal government introduced an alternative subsidy, the Section 1603 grant. This program provided developers with the choice between an upfront cash payment equal to 30 percent of investment costs and 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, as we describe in Section 2.

We use this unexpected temporal discontinuity in investment subsidy eligibility to implement two complementary empirical strategies aimed at estimating the impact of marginal incentives on wind farm productivity. Our first strategy is a fuzzy regression discontinuity (RD) design on a restricted sample of wind farms coming online within 12 months of the January 1, 2009 policy innovation. The long lead time of wind farm development ensures that 1603 grant recipients in this restricted time period would have been well underway, with major siting and capital decisions fixed, before the grant program was even created. By instrumenting for 1603 grant recipient status with a binary indicator of grant eligibility, we are able to exploit this timing to isolate the local average treatment effect of cash grant receipt on subsequent electricity generation outcomes for these plants. In our preferred specification, we find that 1603 grant receipt results in a roughly 10 percent drop in output per unit of installed capacity.

We also implement a matching estimator on the full population of wind farms placed into service between 2005 and 2012. We first split the sample into two groups, "pre" projects coming online over 2005-2008, when only the output subsidy was available, and "post" projects coming online over 2009-2012, when developers had a subsidy choice. We then use matching to create pairs of projects that are observably similar across these two groups. Finally, we use pair-time fixed effects to estimate the "pre" plant versus "post" plant difference in productivity within pairs, and compare this difference between "post" plants that opted for the investment subsidies and the "post" plants claiming output subsidies. Conceptually, this empirical approach is akin to difference-in-differences within matched pairs, where the pairing stage is necessary because there is no variation in subsidy assignment within wind farms. Our preferred matching specification finds that productivity declined by 11 percent due to the removal of output subsidies, which is very close to our preferred RD result, despite using a different sample and relying on different identifying assumptions. The similarity of these results mitigates potential concerns about the use of time as the running variable in our regression discontinuity design.

These results are consistent with a model of costly marginal effort, and we present such a model in Section 2.3. However, the unique features of electric power markets suggest another possible mechanism: negative prices. In electricity markets, prices can drop below zero due to inflexibilities in the power system and the absence of electricity storage. An output-based subsidy encourages wind farms to continue to supply power profitably when prices are negative, while a wind farm receiving an investment subsidy may shut down at such times. Using high-frequency price data, we assess the sensitivity of our RD and matching results by estimating models with subsamples that exclude specific periods of the year and/or regions characterized by prevalent negative prices. We conclude that the negative price mechanism explains some, but not all of the observed productivity decline at 1603 plants.

We then discuss that while understanding the mechanism behind the estimated decline in productivity is important for assessing the plausibility of this result, it does not necessarily alter the policy implications in this particular setting. The primary social objective of these subsidies is to reduce electricity sector emissions, which still occur when prices are negative. We use estimated marginal carbon dioxide emission rates from Callaway et al. (2017) to show that, in fact, for four of the largest electricity markets in the U.S., marginal emissions are likely to be *higher* during negative price periods, not lower. This suggests that wind subsidies are still achieving their intended objective by displacing production from polluting plants even when the market value for their output is negative. Nevertheless, we find that in two other important markets, California and Texas, this correlation is reversed. Thus, while output subsidies may encourage more production, they are still less effective at targeting the environmental externality from carbon emissions than a Pigouvian tax.

Although this particular program was short lived, we also look for evidence of capital bias in the composition of wind farm inputs over time in response to the shift in relative input prices induced by the investment subsidy. Due to long wind farm development lead times, the initial claimants of the Section 1603 grants in 2009 and 2010 had contracted for turbines before the establishment of the grant program (i.e., at a time when they expected to claim the production tax credit). Wind farms coming online in 2011 and 2012, however, would have had the opportunity to adjust their development plans to account for the option of claiming an investment subsidy. We find that the post-2010 wind farms claiming the 1603 grant installed wind turbines approximately 15 percent larger in capacity than pre-2011 wind farms claiming the grant.

We conclude by considering the impacts of this subsidy choice on the extensive margin. We combine our preferred productivity estimates with plant-level data on output prices to generate estimates of profits and production under both subsidy regimes for each wind farm that received a 1603 grant. We then use these measures to perform a back-of-the-envelope cost-effectiveness comparison of the two subsidy instruments, accounting for their predicted impacts on market entry. We find that the Federal government paid 12 percent more per unit of output from the wind farms claiming the 1603 grant than they would have under the PTC.

Despite extensive research on both optimal taxation and instrument choice, there is little research on the relative performance of input and output subsidies.[1] 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

[1] There is a large literature on the effects of investment tax incentives across industries (e.g., Goolsbee, 1998, 2004; House and Shapiro, 2008), but these papers do not compare investment incentives to alternative instruments that target output instead of investment.

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 depends on two key context-specific factors. First, the shape of the production function matters: with decreasing returns, an input subsidy can achieve a given increase in output at lower 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.

This paper also contributes to a growing literature on renewable energy policy. Most papers focus on estimating the environmental benefits of renewable electricity generation (e.g., Cullen, 2013; Novan, 2015; Callaway et al., 2017; Graff Zivin et al., 2014). More closely related to our research, several papers have studied the impact of subsidies on renewable energy penetration. Hitaj (2013) finds that Federal and state production incentives were significant drivers of U.S. wind capacity additions from 1998 to 2007. Metcalf (2010) relates the PTC to the user cost of capital and finds that wind investment is highly responsive to changes in tax policy. Schmalensee (2016) compares U.S. renewable subsidies to policy alternatives such as a feed-in tariff or a cap-and-trade program to limit emissions. Our paper represents the first attempt to directly estimate the efficacy of alternative types of renewable subsidies by explicitly considering their implications for firm productivity. In that sense, our results build upon other work focusing on the impacts of electricity restructuring and deregulation that shows how altering marginal incentives can have economically significant impacts on nuclear power and coal-fired power, as well as other electricity market outcomes (Fabrizio et al., 2007; Davis and Wolfram, 2012; Cicala, 2015).

The rest of this paper proceeds as follows. 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.

2 The Economics of Wind Power

2.1 Wind Farm Production

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 and the velocity of the wind. Nameplate capacity, denominated in megawatts (MW), is the maximum rated output of a turbine operating in ideal conditions. 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) to prevent damage. Figure A.1 presents the marketed power curves for two common wind turbine models in our sample, demonstrating the nonlinear relationship between wind speed and output.

Building a wind farm involves large upfront costs. The average implied investment cost for plants receiving a 1603 grant in our data is $165 million. Wind farm development also requires long lead times. 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 farm takes 9 to 12 months, with site permitting and turbine lead times often double that (Brown and Sherlock, 2011). 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] For wind farms coming online in 2009 and 2010 in the Midcontinent Independent System Operator (MISO), an average of 2.7 and 3.5 years passed between when the wind farms began the process of connecting to the grid and when they actually began supplying electricity.[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 (Wiser and Bolinger, 2014). 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. For example, General Electric offers a product called "PowerUp", which it describes as "a customized suite of software and hardware-enabled technologies created to increase a wind farm's output by up to 10%, taking into account environmental conditions."[4] 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 per MWh (Wiser and Bolinger, 2014).

2.2 Renewable Power Policies

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 PTC. The PTC is a tax credit for electricity generated by qualified energy

[2] Turbine lead times approached two years during the peak demand period in the first half of 2008 (Lantz et al., 2012, p. 12). Market fundamentals have since changed, and lead times have dropped significantly. Nevertheless, there is a natural lag between turbine contract signing and project commissioning such that turbines ordered in early 2008 were employed in projects that were completed in 2010.

[3] Authors' estimate based on MISO interconnection queue data. New electricity generators enter the interconnection queue to request the ability to connect to the electricity grid and supply electricity once construction is complete.

[4] Source: General Electric website (accessed 1/29/2018).

resources and sold to an unrelated party during the tax 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 this market, such as Lehman Brothers and AIG. This 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 as part of what would become the American Recovery and Reinvestment Act of 2009 ("The Recovery Act").[5] 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 grant options available retroactively to projects placed into service on or after January 1, 2009. Wind farms were already eligible for the PTC under current law at the time. The Recovery Act extended the sunset date for the wind PTC until December 31, 2012 (which has been extended again in several subsequent tax laws). A wind project could claim a 1603 grant if it was placed into service before the end of 2012 and its construction began in 2009, 2010, or 2011.

The Recovery Act thus provided wind power developers with a new, mutually exclusive subsidy choice: they could claim the PTC or they could claim the Section 1603 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 a Federal investment subsidy and the policy proposals discussed by wind industry advocates focused on modifying the existing PTC. 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

[5] 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 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.

[6] While the Recovery Act 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.

in any tax policy context (John Horowitz, Office of Tax Policy, U.S. Treasury, 2015).[7] In total, the Treasury made about 400 Section 1603 grant awards to large 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 farm 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 power 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 PTC (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.[8]

2.3 A Model of Subsidy Choice

In order to motivate our empirical evaluation of the 1603 grant program, we begin with a simple model of firm behavior under the two subsidy regimes. Consider a wind farm with K megawatts of capacity that has already been constructed. In each time period, if the wind farm is available, it generates electricity and receives a price p per unit of electricity. Availability, a, follows a Bernoulli distribution with success probability α. Wind farms can influence this success rate through costly effort, e, exerted in advance at maintenance cost m (both denoted per unit capacity). Effort is assumed to have decreasing returns, with $\alpha(e)' > 0$, $\alpha(e)'' < 0$. Since effort is chosen in advance, availability realizations are independent of the realized price, $E[a|e,p] = E[a|e] = \alpha(e)$.[9] Per period

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

[8] In the few cases where states changed their policies, they typically only modified renewable portfolio standard targets ten or more years in the future. For example, in 2009, California and Nevada established new goals for their state renewable portfolio standards through 2020 and 2025, respectively, but did not change their near-term (e.g., 2010) targets. In 2020, Delaware extended its final target year from 2020 to 2025 without changing pre-2020 targets.

[9] This assumes that wind farm availability and output have no impact on equilibrium prices. Given that wind farms are small relative to demand and that electricity markets are relatively well integrated, this is a reasonable assumption in this setting.

operating profits are

$$\pi_0 = K[p\alpha(e) - me]. \tag{1}$$

At the start of each operating period, the firm selects e to maximize expected operating profits. Its optimization program selects maintenance by equating the marginal cost of effort with the marginal induced change in availability times the expected price

$$E[p]\alpha'(e) - m = 0. \tag{2}$$

Denote this optimal effort level e_0 and the corresponding availability rate α_0.

Now consider an output subsidy s per unit of quantity produced. Expected operating profits per period become

$$\pi_1 = K[(E[p] + s)\alpha(e) - me], \tag{3}$$

with corresponding first order condition

$$(E[p] + s)\alpha'(e) - m = 0. \tag{4}$$

Denote this optimal effort level e_1 and the corresponding availability rate α_1. Under the assumption that $\alpha'' < 0$, the effort level with the subsidy (e_1) will be higher than without (e_0). This implies that, all else equal, expected output ($K\alpha$) will be higher with output subsidies as well.

Now consider an alternative subsidy which reduces up front capital costs F by ϕ percent. Lifetime expected profits under this investment subsidy are

$$\Pi_0 = TK[E[p]\alpha_0 - me_0] - (1 - \phi)F, \tag{5}$$

where T is the lifetime of a wind farm.[10] At the start of operation, the firm must decide if it prefers those profits to the profits under the output subsidy,

$$\Pi_1 = TK[(E[p] + s)\alpha_1 - me_1] - F, \tag{6}$$

which is the case if

$$\phi(F/K) \quad > \quad T\{(E[p] + s)(\alpha_1 - \alpha_0) - m(e_1 - e_0)\} + sT\alpha_0. \tag{7}$$

For small changes in effort, the term in braces on the right will be zero under the envelope theorem, and equation 7 predicts that investment subsidies will be preferred by firms with high per unit capital costs (F/K) relative to their baseline (unsubsidized) expected operating level (α_0). 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. For larger changes in effort, the choice may depend on the concavity of α.

[10] We do not explicitly include a discount factor for clarity, and instead subsume discounting into T.

It is this correlation between subsidy preference and latent productivity which generates selection in subsidy choice and confounds our evaluation of the 1603 grant program. There are measures that wind farm operators can take that will increase output conditional on other attributes.[11] If these measures are costly, then increasing the marginal price received for output will make adoption more likely under the PTC. Thus, conditional on operating, we predict that removing the PTC will result in lower output, conditional on operating. Ideally we would estimate $\tau = E[K_i(\alpha_{i0} - \alpha_{i1})]$. However, the policy was implemented with a choice, so we are only able to observe $\hat{\tau} = E[K_i\alpha_{i0}|\Pi_{i0} > \Pi_{i1}] - E[K_i\alpha_{i1}|\Pi_{i0} < \Pi_{i1}]$.

3 Data

In this Section, we concisely summarize the data sources used and sample restrictions imposed. We provide additional detail on the sources and the sample in Appendix A. We compiled data on wind farm characteristics and output from two publicly available Energy Information Administration (EIA) surveys covering all utility-scale wind farms in the United States. The EIA-860 database, which reflects an annual survey of power plants, contains: first date of commercial operation, nameplate capacity, number of turbines, predominant turbine model, operator, 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 collected through the EIA-923 survey of power plants.

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 which control for potentially differential contracting arrangements across 1603 and PTC recipients 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.[12] We combine these high frequency wind data with power curves from turbine manufacturers for each turbine make and model in the EIA data.[13] Using this information, we compute an "engineering" estimate of the potential output for each plant-month that accounts for the site-specific, nonlinear relationship between wind speeds and electricity generation. Further detail on this variable and its construction is provided in Appendix A.2.

[11] For example, manufacturers like GE and consulting companies like McKinsey offer turbine maintenance and optimization services which claim to boosts output.

[12] For more information on how this dataset is constructed, see: http://www.3tier.com/en/support/wind-prospecting-tools/how-was-data-behind-your-prospecting-map-created/ (Accessed 2/14/2017).

[13] Power curves were primarily obtained from http://www.wind-power-program.com/ (last accessed 2/14/2017), and supplemented with information obtained directly from turbine manufacturer marketing materials (generously provided to us by Joern Huntelaar).

The final dataset comes from the U.S. Department of Treasury. The dataset provides information on every large wind project recipient of a 1603 grant, including the amount awarded (equal to 30 percent of eligible investment costs), the date of the award, and the date placed in service.[14] We assume that all developers of non-1603 recipient wind farms claimed the PTC based on both guidance provided by staff at the American Wind Energy Association and Internal Revenue Service data. Specifically, we 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.

Table 1 presents an annual summary of these data for plants entering service between 2002 and 2014.[15] In our empirical analysis, we restrict attention to plants characterized as either being independent power producers or part of an investor owned utility by EIA. Commercial and industrial facilities are excluded, as are plants that are publicly owned (e.g., municipal power plants), as these plants are not eligible for the PTC, and a small number of plants that appear to have claimed the PTC for some turbines that came online pre-2009 and a Section 1603 grant for some turbines that came online in 2009 or later (see the Appendix for further details).

Table 1: Summary Statistics by Entry Date

Entry Year	Wind Farms	Sample	1603 Plants	Regulated	IOU or IPP	Capacity	Turbine Size	Wind Speed	Capacity Factor
2002	12	9	0	0.33	0.75	48.46	1.21	17.97	29.83
2003	36	30	0	0.08	0.86	44.93	1.33	18.64	31.34
2004	14	11	0	0.21	0.86	26.89	1.49	17.69	32.33
2005	23	17	0	0.17	0.74	92.38	1.50	18.59	35.38
2006	44	38	0	0.14	0.93	43.08	1.44	17.86	34.91
2007	52	46	0	0.12	0.94	105.65	1.77	18.48	35.74
2008	95	71	0	0.15	0.95	84.74	1.80	17.89	34.48
2009	103	84	65	0.17	0.84	91.70	1.81	17.65	31.85
2010	62	51	44	0.08	0.89	67.50	1.76	17.02	32.12
2011	91	68	62	0.13	0.80	74.47	1.92	17.22	31.15
2012	149	113	74	0.11	0.93	87.77	1.99	17.22	34.33
2013	11	0	0	0.09	0.73	71.64	1.75	18.14	34.86
2014	38	0	0	0.16	0.84	92.59	1.82	18.59	31.30

[14] The Department of the Treasury distinguished between "large" wind projects, which are eligible for the production tax credit, and "small" wind projects, which must have nameplate capacity no greater than 100 kilowatts and are eligible for investment tax credits. All utility-scale wind projects and all wind farms in the data compiled from the EIA fall into the "large" wind project category.

[15] There are two potential ways to define online date based on the EIA data. One is the date that the survey respondent reports to EIA that the plant began commercial operation on form EIA-860; the other is the first date that its generation appears in the EIA-923 production data. Although these by and large coincide, discrepancies can appear due to "pre-commercial" plant testing (923 date < 860 date) or due to the delay with which EIA begins tracking new plants (860 date < 923 date). This is important because the online date determines 1603 grant eligibility (our instrument). In conversations with EIA, we were told that EIA 860 would be more accurate for our purposes. Nevertheless, IV results are robust to using the 923 date instead. In all specifications, plants with conflicting 923 and 860 dates around the 2009 eligibility cutoff are excluded from the sample.

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.[16] 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 identifying the portion of this observed difference in productivity attributable to the subsidy.

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

	PTC	1603	Difference	p-value
Nameplate Capacity	98.72	88.77	9.95	0.31
Turbine Size (MW)	1.83	1.95	-0.12	0.06
Design Wind Speed (MPH)	17.83	17.25	0.57	0.17
Regulated	0.23	0.03	0.20	0.00
IPP	0.69	0.87	-0.17	0.00
PPA	0.68	0.84	-0.17	0.00
Potential Capacity Factor	39.21	33.98	5.23	0.00
Capacity Factor	36.46	30.78	5.67	0.00
New Wind Farms	111	205		

4 Empirical Strategy

4.1 Model

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

$$q_{it} = \delta D_i + \beta X_{it} + \nu_{it} \tag{8}$$

Here i indexes wind farms and t indexes month-year time periods. The dependent variable q is the plant's capacity factor (in percentage points). D is an indicator for whether the wind farm took the 1603 grant and X is a vector of controls, such as engineering-based potential capacity factor, regulatory regime, presence of a power purchase agreement, and location dummies. The

[16] Capacity factors are a commonly used metric of operational activity in the electric power sector (see, for example, Davis and Wolfram, 2012). Potential capacity factor is a constructed "engineering" based capacity factor estimate using only a plant's wind turbine and wind speed information. Additional detail provided in Appendix A.2.

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 (8) 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: a fuzzy regression discontinuity estimator and a matching estimator.

4.2 Regression Discontinuity Design

Our primary empirical strategy harnesses the natural experiment created by the 1603 grant program by comparing wind farms that came online just before and just after the program went into effect. While the Section 1603 grant was not randomly assigned, its creation came as a plausibly exogenous shock to the industry. We exploit this shock by implementing a fuzzy regression discontinuity research design. Specifically, we use a binary indicator for whether the project came online after January 1, 2009 as an instrument for cash grant recipient status,

$$D_i = \gamma \cdot 1\left\{1603 \text{ eligible}\right\}_i + \xi X_{it} + \nu_i \tag{9}$$

We then use the predicted values from this first stage, $\hat{D}$, to estimate δ using equation (8) in a two-stage least squares (2SLS) framework with wind farms' monthly output data over 2010-2014.

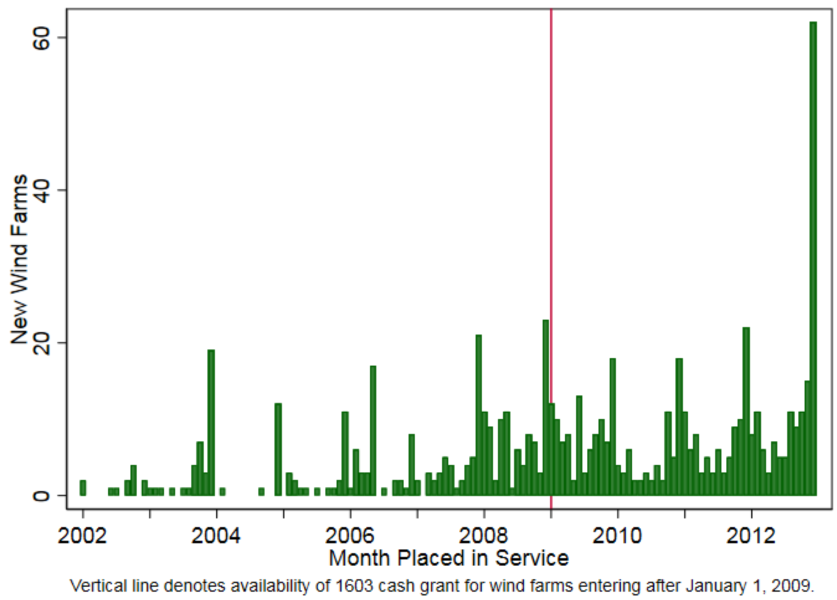
Identification and interpretation of δ relies on two key assumptions: (1) that the running variable cannot be manipulated, and (2) that the instrument (subsidy eligibility) only affects outcomes through its effect on the endogenous variable (subsidy choice).[17] To provide evidence on assumption 1, we plot the number of new projects coming online each month and highlight the January 1, 2009 date when wind power developers gained access to the the policy choice described above (Figure 1). This plot highlights the seasonal variation in projects coming online. In general, projects are more likely to come online in the first and last months of the year than in other months.[18] 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

[17]Identification and interpretation as a local average treatment effect also relies 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.

[18]In some years, this variation is driven by uncertainty around the expiration of the PTC. Note that developers knew by October 4, 2008 (the date that President Bush signed the Emergency Economic Stabilization Act of 2008, which included energy tax provisions such as the PTC extension as well as the Troubled Asset Relief Program) that the wind PTC would not expire before December 31, 2009. These developers knew by February 17, 2009 (the date that President Obama signed the American Recovery and Reinvestment Act) that the PTC would expire no earlier than December 31, 2012.

developers did not appear to adjust the timing in entry to the policy innovation.

Figure 1: Wind Farm Entry over Time



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 (or earlier), 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.

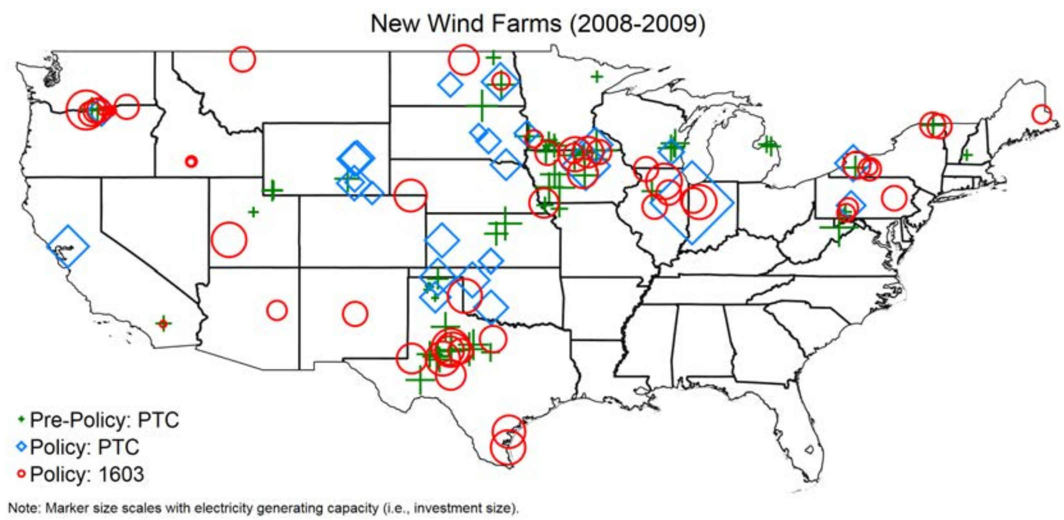
Table 3 compares projects coming online in 2008 with those coming online in 2009 using two-sample t-tests. These two groups are statistically indistinguishable for an array of characteristics including capacity, turbine size, wind speed, regulatory status, whether a wind farm has entered into a PPA, and the engineering-based potential capacity factor. The capacity factor, our outcome variable, is lower (and statistically distinguishable) for projects coming online in 2009 than for projects coming online in 2008.

As a final piece of descriptive evidence, we map the location of new wind farms in 2008 and 2009 in Figure 2. 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.

Table 3: Projects Entering One Year Before and After the Policy

	2008	2009	Difference	p-value
Nameplate Capacity	84.23	102.16	-17.93	0.15
Turbine Size (MW)	1.85	1.82	0.03	0.68
Design Wind Speed (MPH)	18.04	17.32	0.72	0.12
Regulated	0.14	0.11	0.03	0.53
IPP	0.58	0.74	-0.16	0.03
PPA	0.75	0.69	0.06	0.44
Potential Capacity Factor	37.03	35.84	1.19	0.38
Capacity Factor	34.35	31.75	2.60	0.01
New Wind Farms	71	84		
1603 Recipients	0	58		

Figure 2: Wind Farm Locations by Period and Subsidy



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.

4.3 Matching

Our second empirical strategy uses a combination of matching and differencing 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. Selection in our context would manifest itself in a correlation between A_i and D_i. 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 would remove this bias.

Since subsidies are irreversibly chosen at the commencement of operations, we do not observe subsidy variation within a plant, and thus cannot include 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 ϕ is a wind farm vintage fixed effect for plants entering post-ARRA. Although $g()$ is unknown, including a dummy variable for each unique combination of characteristics X_i would fit any $g()$. The difference in productivity between two wind farms with the same characteristics that entered in different policy periods would then simply be 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 with similar characteristics across different vintages. We divide our sample into two groups corresponding to two policy regimes: wind farms that entered between 2005 and 2008 ("pre" plants), when there was no subsidy choice, and wind farms that entered between 2009 and 2012 ("post" plants), which could choose either the PTC or the 1603 grant. We then match pre and post wind farms on observable characteristics using coarsened exact matching (CEM).[19] Let g index a group of pre and post plants that are matched together. Equation (8) becomes,

$$q_{it} = \delta D_i + \beta X_{it} + A_g + \phi Post_i + \epsilon_{it} \tag{10}$$

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 their pre-period matched counterparts, and subtracts the difference between post-period PTC plants and matched pre-plants within their 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.

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 changes across pre and post plants 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 large responses

[19] Iacus et al. (2012) outline the CEM algorithm and derive its statistical properties. More information and implementation packages can be found at http://gking.harvard.edu/cem.

on this dimension. Moreover, the RD analysis addresses precisely this concern.

The primary concern with the RD estimator is that the instrument, time, may be picking up other trending factors that affect productivity. Our matching estimator relaxes this by allowing unobservable dimensions of wind farm entry cohorts to evolve over time. The key assumption is parallel trends in these unobservable factors across the types of plants that choose each subsidy in the post period.

5 Results

5.1 Regression Discontinuity Design

Table 4 reports the instrumental variable 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. The dependent variable in each regression is the capacity factor in percentage points.

Table 4: Regression Discontinuity Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
1603 Grant	-5.002***	-3.308***	-2.620***	-3.613***	-2.540**	-2.958***
	(0.849)	(0.868)	(0.800)	(1.235)	(1.164)	(1.132)
Regulated		-1.367	-5.796***		-1.015	-5.809***
		(1.579)	(1.695)		(1.561)	(1.698)
PPA		-1.166	-2.875***		-1.013	-2.899***
		(0.954)	(0.826)		(0.961)	(0.836)
IPP		-0.873	-2.620**		-0.882	-2.566**
		(1.307)	(1.249)		(1.274)	(1.215)
Potential Capacity Factor		0.497***	0.565***		0.500***	0.567***
		(0.0345)	(0.0368)		(0.0351)	(0.0364)
Var(Wind Speed)		-0.0912	-0.517***		-0.0695	-0.524***
		(0.143)	(0.101)		(0.149)	(0.105)
log(Capacity)		-0.990**	0.409		-1.024**	0.409
		(0.438)	(0.460)		(0.433)	(0.456)
Regression Type	OLS	OLS	OLS	2SLS	2SLS	2SLS
Controls	N	Y	Y	N	Y	Y
State FE	N	N	Y	N	N	Y
R-sq.	0.342	0.520	0.625	0.338	0.519	0.625
N	9292	9292	9292	9292	9292	9292
F-stat					199	119

The dependent variable is the capacity factor in percentage points. Data include a balanced panel of monthly observations from 2010 to 2014 for all wind farms. All models contain year-month dummies. Standard errors clustered by wind farm reported in parentheses.

The primary coefficient of interest (δ) appears in the first row of the table, labeled 1603 Grant. The first three columns present OLS estimates of equation (8). Column 1 simply includes time (month-year) dummies. The interpretation is that plants receiving output subsidies operated at 5 percentage points lower capacity factor compared to PTC recipients coming online between 2008 and 2009. Column 2 adds controls for plant size and monthly wind quality, as well as dummies for whether the plant is regulated, whether it is an independent power producer, and presence of a power purchase agreement.[20] Consistent with the descriptive evidence above, 1603 and PTC plants differ on observable dimensions, and controlling for these differences reduces the estimated productivity difference. Column 3 adds state fixed effects to account for other unobserved differences in markets and renewable policies across states, which attenuates the relationship further.

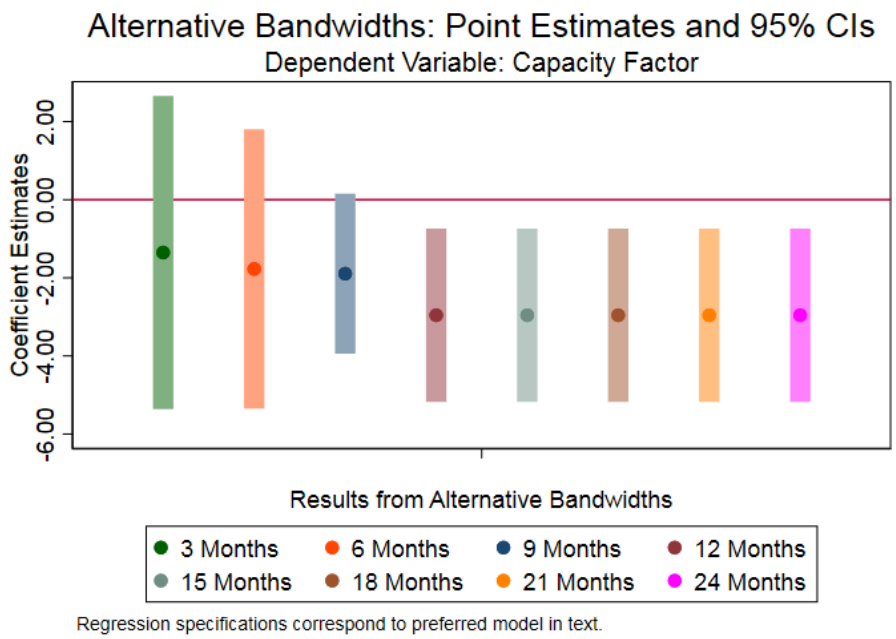
Columns 4-6 present RD estimates using the same covariates, instrumenting for 1603 receipt with an indicator for whether the wind farm was eligible for the 1603 program. Conditioning only on time dummies, 1603 plants are 3.6 percentage points less productive than their PTC counterparts. Adding controls results in a modestly lower estimated 1603 effect of 2.5 percentage points. Adding state fixed effects splits the difference between these two estimates, leaving a 3 percentage point gap in productivity across plants choosing the two subsidy types. This last estimate, our preferred specification, implies that 1603 grant recipients would have produced roughly 10 percent more power had they claimed the PTC. To provide context for the magnitude of this estimate, consider that it is in line with industry claims for how post-construction wind farm optimization services could increase output (see discussion in Section 2. Moreover, the marginal incentive of the PTC is quite substantial during this time period: the PTC represents more than a 40 percent premium over the average price of power sold by wind farms to the grid.

Robustness Analysis

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 increasingly insulated from concerns about identification. However, smaller bandwidths generate smaller samples, lessening statistical precision and generating possible concern over weak instruments. Figure 3 presents coefficients from the preferred specification in column 6 in graphical form using alternative bandwidths ranging from three months to twenty-four 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 PTC (output subsidy). Moreover, the fact that the estimated effect remains stable between twelve and twenty-four months suggests that trends alone are not driving the results.

[20] Unless otherwise noted, the same controls appear in every model throughout the paper. Additional discussion of the potential capacity factor and wind speed variables is provided in Appendix A.2

Figure 3: RD Estimates using Alternative Bandwidths



We also consider the possibility of trends within the 2008-2009 time period in technology, site quality, and other factors that could have persistent effects on output. Table A.3 presents results from a more conventional RD model that includes piecewise linear trends. Unfortunately, given the small sample size, these results are quite noisy. In models 4 and 5, the point estimates are larger in magnitude than the IV estimates, while in model 6 the results are smaller and not statistically distinguishable from either the IV estimates or zero. The variability in these estimates may be the result of weak instruments, as can be seen by the F-statistics in these models.

5.2 Matching

We now present results from the matching estimator described in Section 4.3. To illustrate how this method works, Table 5 compares pre- and post-period entrants after using coarsened exact matching on state, regulatory status, entity type (independent power producer or investor-owned utility), capacity, and two measures of wind quality collected by EIA.[21] Of the 488 wind farms in our sample entering between 2005 and 2012, 213 lie within the common support of these variables across the two policy periods.[22] The number of post-period 1603 matches is about double the number of PTC matches, which is in line with their underlying population probabilities. T-tests confirm that this restricted sample is in fact balanced across the two time periods on the matched dimensions.

[21]EIA form 860 asks operators to report each facilities design wind speed (MPH) and the site's overall wind class, which ranges from 1 to 4.

[22] The number of post-period matches is slightly higher than pre-period matches, due to the fact that some post-period plants are similar enough on these characteristics that they fall within the same coarsened cell.

Table 5: Matching Balance

	Pre	Post	Difference	p-value
Capacity(MW)	103.90	104.51	0.62	0.95
Design Wind Speed (MPH)	17.91	17.47	-0.44	0.14
Regulated	0.10	0.10	0.00	1.00
PPA	0.81	0.78	-0.03	0.57
Potential Capacity Factor	36.15	37.05	0.90	0.38
Capacity Factor	33.79	32.98	-0.80	0.32
Wind Farms	89	124		
1603 Recipients		88		

Comparison of characteristics of pre- and post-period entrants after using coarsened exact matching (CEM) on state, regulatory status, entity type, log capacity, and EIA wind quality.

Table 6 reports the results from regressions estimated through variations of this matching strategy with a balance sample of monthly wind farm production data. As before, the dependent variable in each regression is the capacity factor measured in percentage points. All models include the same controls as our preferred RD regressions as well as cohort dummies. Column 1 presents estimates from estimating OLS on the full sample including all 488 wind farms entering during the pre- or post-period. Column 2 restricts the sample to plants matched across periods. Column 3 includes matched group fixed effects. Column 4 interacts those group fixed effects with year of sample, allowing for unobserved factors that affect specific groups and vary over time. Column 5 includes group-month-year fixed effects, which is equivalent to running OLS after manually differencing the grouped pre-period observations from the post-period observations each month.

Simply restricting the sample to observably similar plants across periods increases the estimated impact of the 1603 grant from 2.2 to 3.5 percentage points. This suggests that there are low productivity PTC plants and/or high productivity 1603 plants that do not lie in the common support across periods. Allowing for increasingly time-varying group level unobservables has remarkably little effect on the estimates. This estimated productivity reduction of 3.5 percentage points (11 percent) is similar to our preferred RD estimate, despite relying on different identifying assumptions.

Robustness Analysis

The most restrictive matching criteria in the previous exercise is the requirement that pre and post plants be in the same state. In order to explore the impact of this assumption, and to incorporate more plants into the analysis, we re-estimate the model from column 4 under different geographic restrictions (Table 7). As above, all models use coarsened exact matching on regulatory status, capacity, entity type and wind quality. In addition, column 1 matches on NERC region as well as an indicator for whether the plant is in an ISO. Column 2 matches on the specific ISO a plant

Table 6: Matching Estimates

	(1)	(2)	(3)	(4)	(5)
1603 Grant	-2.189***	-3.476***	-3.622***	-3.527***	-3.488***
	(0.782)	(1.105)	(1.033)	(1.045)	(1.178)
Sample	All	Matched	Matched	Matched	Matched
FEs	State	State	Group	Group*Y	Group*Y*M
R-sq.	0.432	0.462	0.613	0.624	0.746
N	22344	10538	10538	10538	10538

Groups matched using coarsened exact matching (CEM) on state, regulatory status, entity type (IPP or IOU), capacity, and EIA wind quality measures. All models include controls for annual plant size and monthly wind quality, as well as dummies for whether the plant is regulated, whether it is an independent power producer, the presence of a power purchase agreement, and month-year dummies. Standard errors, clustered at the plant level, are reported in parentheses.

participates in, and column 3 matches on both NERC region and ISO. Finally, column 4 matches on state, repeating column 6 from the previous table. In addition to controls and month-year and group-year dummies, each of the first three models also include state fixed effects to account for differences in state-level renewable policies. As in the previous table, the results increase slightly as increasing restrictions are placed on the match. However, we cannot statistically discern among the coefficient estimates.

Table 7: Sensitivity of Matching Estimates to Geographic Restrictions

	(1)	(2)	(3)	(4)
1603 Grant	-2.790***	-3.178***	-3.258***	-3.527***
	(0.921)	(0.960)	(1.019)	(1.045)
# Pre-PTC	112	103	93	89
# Post-PTC	54	51	44	36
# Post-1603	121	90	81	88
Region	Nerc-1(ISO)	ISO	Nerc*ISO	State
R-sq.	0.622	0.671	0.654	0.624
N	13854	11984	10837	10538

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

6 Discussion

The previous Section found that wind farms receiving investment subsidies were less productive conditional on operating. Translating these short run, intensive margin results into broader conclusions about the 1603 policy specifically, or investment subsidies generally, requires us to consider the mechanism, the extensive margin, and any longer-run impacts caused by distorting relative prices. In this Section, we discuss each of these in turn.

6.1 Negative Electricity Prices

Our empirical results are consistent with a model of convex effort costs on the intensive margin. However, even in the absence of operating costs, output subsidies could mechanically encourage more output by incentivizing production when marginal willingness to pay for electricity is below zero. In electricity markets, prices sometimes fall below zero during periods of low demand due to a combination of inflexible supply, prohibitively expensive storage, and transmission constraints. Some critics of the PTC claim that it has exacerbated this problem by encouraging wind farms to produce power even when the wholesale electricity price is negative (Brown, 2012). Intuitively, wind farm operators should be willing to pay up to the value of the subsidy to be dispatched each time period.[23]

To formalize this intuition, we revisit the model of operating effort from Section 2.3. However, we now allow wind farms the option to choose to take their wind farms offline when the price is too low. Under the investment subsidy, a wind operator will shut its plant off if the price is less than zero, while under the output subsidy the plant will shut off only if the price goes below the output subsidy $-s$. With negative prices, expected operating profits per period become

$$\begin{aligned}
\tilde{\pi_0} &= K[E[p|p > 0]Pr(p > 0)\alpha(e) - me] \\
\tilde{\pi_1} &= K[(E[p|p > -s] + s)Pr(p > -s)\alpha(e) - me]
\end{aligned}$$

Denote the new optimal effort levels $\tilde{e_0}$ and $\tilde{e_1}$, with $(e_0 - \tilde{e_0}) > (e_1 - \tilde{e_1})$, if $Pr(0 > p > -s) > 0$.

The average difference in expected production across the two subsidy regimes for an individual wind farm in the presence of negative prices is,

$$\begin{aligned}
\tilde{\tau} &= E[\tilde{q}_0] - E[\tilde{q}_1] \\
&= K[Pr(p > 0)(\tilde{\alpha}_0)] - K[Pr(p > -s)(\tilde{\alpha}_1)] \\
&= K[Pr(p > 0)(\tilde{\alpha}_0 - \tilde{\alpha}_1)] - K[Pr(0 > p > -s)\tilde{\alpha}_1]
\end{aligned}$$

The first term is the difference in output during periods when the price is positive due to differences in availability, which are driven by differences in optimal effort levels. The second is the difference in output when prices are between $-s$ and zero, which is driven by the endogenous decision of wind farms that do not receive the PTC to cease production until the price is no longer below zero.

How much of the difference in output across PTC and 1603 plants estimated in Section 5 can be attributed to negative prices? If we observed hourly price and dispatch for all the plants in our

[23] This intuition is readily confirmed in data from the Texas electricity market. We compile data on bid curves for wind generators in ERCOT, match these to 23 wind farms in our dataset that entered during the policy period (2009-2012), and construct aggregate supply curves by subsidy type. We find that 88 percent of capacity linked to PTC recipients is bid in at or below -$22 per MWh, while 85 percent of 1603 recipient capacity is bid in close to $0 per MWh (plus or minus $5 per MWh). In theory, the value of renewable energy credits under state renewable portfolio standards could likewise encourage generation when market prices are negative—for PTC and 1603 claimants alike. These incentives are weak, however, in Texas where the prices of such credits did not exceed $3 per MWh over 2010-2014.

sample, we could compute this directly. Unfortunately, these data are not available.

In lieu of this plant-specific negative price data, we construct estimates of the likely difference in dispatch probabilities due to negative prices using publicly available price data. We obtain high frequency price data for six large U.S. electricity markets: California (CAISO), Texas (ERCOT), the Eastern U.S. (PJM), the Midcontinent Independent System Operator (MISO), New England (ISONE), and New York (NYISO). For these markets, hourly market clearing prices are available at each node (location) from 2011 to 2014.[24] We first create an indicator if the price in a given hour is negative, and then average that indicator for the entire month to get the fraction of hours that are negative at a given location each month.

Table 8 summarizes the results of this exercise. The first row presents the mean share of negative hours across all nodes and months in each region over the four-year sample, which ranged from 0.1 percent in New England to 3.9 percent in California. The next two rows report the median and the 95th percentile of this variable. Negative price events are highly skewed, with some nodes experiencing much higher shares of negative prices in a given month. At the same time, even the median node, which is unlikely to be near a wind farm receiving the PTC, experiences negative prices fairly frequently. This is likely the result of the combination of variable demand and adjustment costs for coal and nuclear plants, as well as unobserved long-term contracting arrangements.

Next we restrict the nodal price data to nodes near wind farms. We obtained node location information from SNL Energy.[25] For each wind farm in our sample, we find the closest node within the same ISO. The second Section of table 8 presents the negative price frequencies for these nodes. Negative prices are more common at nodes near wind turbines than across all nodes in each ISO, although the difference varies considerably. Comparing across the ISOs, negative prices are now most common in MISO. Negative prices are much less common during the summer months in every ISO. Negative prices declined significantly in Texas and California after 2012, and remained essentially flat in the other markets.

Comparing these averages to our policy treatment effects requires making an assumption about the correlation between these negative price events and the availability of each wind farm to be dispatched. As was discussed above, on average wind farms only have sufficient wind conditions to operate about one-third of the time. If we assume that availability perfectly coincides with negative prices, then these marginal frequencies can be compared directly to the estimated policy effects. If they are uncorrelated, then these marginal frequencies should be divided by three (on average).

An alternative way to assess the extent to which negative prices are driving the difference in productivity for 1603 recipients is to see how this effect varies as regions and time periods with relatively more frequent negative prices are excluded from the sample. Table 9 presents results from

[24]In these markets, the system operator employs location-specific pricing by calculating high-frequency wholesale prices at each node within its system. With thousands of pricing nodes in these markets, the clearing prices reflect the value of power delivered to the grid accounting for location-specific supply, demand, and transmission congestion.

[25]Nodes were matched across the two sources using the name of the node listed in the ISO data. Approximately 8 percent of price nodes had no match in the SNL data.

Table 8: Frequency of Negative Prices in Six ISOs (2011-2014)

	CAISO	ERCOT	ISONE	MISO	NYISO	PJM
All nodes						
Mean	3.87	1.19	0.09	2.88	0.56	0.54
Median	2.53	0.00	0.00	0.97	0.28	0.13
95th pctile	16.26	6.11	0.00	13.04	1.88	2.36
Summer(mean)	4.56	0.62	0.01	2.54	0.63	0.68
Post 2012 (mean)	2.25	0.51	0.16	2.65	0.59	0.39
Near wind						
Mean	3.94	4.21	0.09	5.44	1.05	1.21
Summer(mean)	2.26	0.26	0.01	3.18	0.77	1.01
Post 2012 (mean)	2.51	1.10	0.17	5.48	1.40	1.06
CO2 MOER						
Mean	896	1,378	1,262	1,870	1,312	1,776
Mean(weighted)	873	1,457	1,169	1,916	1,408	1,778
Correlation	-0.46	0.60	-0.72	0.69	0.41	0.02

Frequencies (in percentage points) based on hourly nodal price data from the six listed ISOs, collapsed to the node-month level. Summer months are defined by the NOx regulation season, when begins in May and ends in October. In the second Section, the sample is restricted to nodes that are the closest node to a wind farm in the sample. The third Section of the table presents the average marginal operating emission rates (MOER) in pounds of carbon dioxide per MWh estimated for each ISO by Callaway et al. (2017). The second row re-weights the average by the share of negative prices in each ISO-season-hour. The final row presents the correlation between negative prices and MOER across 48 season-hour averages for each ISO.

estimating our preferred RD and matching specifications on restricted samples motivated by Table 8. Column 1 repeats our preferred specifications from above. Column 2 excludes CAISO, as it has the highest average and median frequency of negative nodes in the sample. Column 3 excludes both CAISO and MISO, the latter of which has the highest average and median frequency of nodes in the subset of nodes near wind farms. Column 4 includes all plants but restricts the sample to summer months (May to October), as negative prices are less common in the summer. Column 5 restricts the sample to power production in years 2013 and 2014, during which the frequency of negative prices declined sharply in some markets. Finally, column 6 excludes plants which are matched to a node in the ISO data and have negative prices more frequently than the median node in that matched sample.

Across these specifications, the results vary but are consistent with a model of additional effort on the intensive margin. The RD results are less precise, particularly when MISO wind farms are excluded. This is due to the fact that all models include state fixed effects, and, during this narrow window from 2008 to 2009, we have relatively little within-state variation outside the California and Mid-Continent markets. The matching sample includes more within-state variation by construction. Under this empirical strategy, the results remain fairly consistent, even when excluding wind farms near nodes experiencing negative prices most frequently.

These results suggest that negative prices explain some, but not all, of the electricity generation

Table 9: Productivity Estimates and Negative Electricity Prices

	(1)	(2)	(3)	(4)	(5)	(6)
1603 Grant	-2.958***	-3.254***	-0.988	-1.727	-2.759**	0.183
	(1.132)	(1.228)	(1.402)	(1.122)	(1.143)	(1.671)
R-sq.	0.625	0.654	0.633	0.703	0.699	0.634
N	9292	8932	5876	4650	3720	5815

(a) RD Results

	(1)	(2)	(3)	(4)	(5)	(6)
1603 Grant	-3.488***	-3.480***	-3.213**	-4.416***	-2.902***	-2.724**
	(1.178)	(1.131)	(1.606)	(1.086)	(1.049)	(1.103)
R-sq.	0.746	0.654	0.636	0.676	0.650	0.630
N	10538	10111	7698	5298	4809	7171

(b) Matching Results

Panel (a) includes results from RD regressions with controls, state and month-year fixed effects. Panel (b) reports results from exact matching at the state level and includes controls and matched group-year fixed effects. In both panels, column 1 includes the full sample, column 2 excludes CAISO, and column 3 excludes MISO plants as well. Column 4 includes all plants, but restricts the sample to summer months May through October. Column 5 includes all plants and months, but restricts the sample to observations post 2012. Column 6 excludes the bottom 50 percent of plants matched to nodes in the ISO data based on average frequency of negative prices. Standard errors, clustered at the plant level, are reported in parentheses.

difference between investment subsidies and output subsidies. If one compares the point estimates of the precisely estimated 1603 Grant coefficients in the matching framework, then negative prices could explain as much as 20 percent of our productivity result in Column 1.While it is useful to understand the mechanism behind our productivity estimates, the extent to which they are driven by negative prices does not necessarily alter their policy implication. The motivation for subsidizing wind energy is to displace conventional, polluting generation with zero-emissions electricity. This logic does not necessarily change simply because the equilibrium wholesale price is below zero, as the full social value depends on the emissions intensity of marginal generation during these hours. 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.

Determining whether the marginal emissions displaced from wind energy are higher or lower during periods of negative prices is beyond the scope of this paper. However, Callaway et al. (2017) provide estimates of the average marginal operating emission rates (MOER) of generating resources by hour of day and season for each ISO. Plots of the MOER by ISO-season-hour are reproduced in appendix Figure A.3. Electricity prices typically fall below zero when demand is lowest, during the middle of the night. However, for four of the six ISOs, marginal emissions are actually *higher* at night than during peak hours. This is not surprising due to the fact that natural gas is likely to be on the margin during the day, whereas coal is more likely to be on the margin at night. Comparing across the seasons, average emission rates are fairly constant, compared to the variation in negative price frequency.

The bottom Section of Table 8 summarizes these results. Marginal emissions vary across regions, but are still positive and large everywhere, even when weighted by the negative prices in each ISO-season-hour. In four of the six markets, negative prices are actually positively correlated with marginal operating emissions, suggesting that the external social value of the PTC during these hours is at least as high as during any other time period. Thus, in these markets, the fact that some of the estimated treatment effect comes from willingness to operate at negative prices could be considered a feature of incentivizing this output, not a bug. The purpose is to reduce emissions, and emissions are still positive, even when prices are not.

With that being said, the fact that there is substantial variation in average marginal operating emission rates but no variation in the subsidy awarded for each unit of electricity under the PTC indicates that the PTC fails to approximate a Pigouvian emissions tax. In two markets, California and New England, nuclear power and hydropower often provide zero-emissions baseload generation. This suggests that in these regions, output subsidies to renewable generators could actually *undermine* long-run, system-wide emissions objectives. By reducing revenue for these high capacity factor, high fixed cost, low-emissions electricity sources, the PTC could expedite their retirement. It is unlikely that this effect dominates the environmental benefits of the PTC, but this highlights another shortcoming of subsidizing renewable electricity relative to pricing the emissions externality directly.

6.2 Capital Bias

Our empirical analysis focused on estimating changes in marginal effort conditional on operating. To isolate this effect, our RD sample is restricted to wind farms whose capital and siting decisions were fixed before the policy was announced. Furthermore, our preferred specifications for both estimation strategies include plant-turbine-specific estimates of potential output each month, recovering the decline in output *conditional on* these previously made investment decisions. In this Section, we look for evidence of impacts on these previously conditioned-on dimensions. While this particular program was short-lived, it is worth considering what might have happened had subsidy choice persisted or, as in other settings, had the government switched to investment subsidies entirely. Faced with a certain shift in the relative price of capital inputs, wind developers may alter their input mix, either employing more capital relative to other inputs or selecting higher quality capital (as found for other industries in Goolsbee, 2004).

As was discussed in Section 2.1, capital and siting decisions for large wind farms are made two or more years in advance. Given that the 1603 program was only in effect for four years, this suggests a natural partition: plants coming online in the first two years are unlikely to have time to respond, while those coming online during the last two years may have had time to adjust their planning and investment to the availability of subsidy choice. We take advantage of this break in available response margins midway through the policy to look for evidence of a shift in capital investment decisions.

Faced with lower investment costs, wind developers could choose to invest in more turbines, invest in better turbines, or select sites with different wind speeds on which to develop a project. Table 2 showed that PTC and 1603 grant recipients were statistically indistinguishable along these dimensions on average over the course of the 1603 program. We test whether that relationship changed over time using the following regression,

$$y_i = \alpha + \beta\{1603\} + \gamma\{1603 \text{ \& Post } 2010\} + \eta_{year} + \epsilon_i, \tag{11}$$

where 1603 indicates that a wind farm claimed the 1603 grant, "Post 2010" is an indicator for whether the plant came online in 2011 or 2012, and η_{year} represents year of entry fixed effects to account for general trends among these variables over time.

Table 10 reports the results. The first row reports economically small and statistically insignificant differences in plant size, turbine size and wind speed across subsidy types in the first two years of the program. The second row provides estimates of the change of these characteristics for 1603 grant plants over time relative to PTC plants. In the last two years of the program there is a large, but statistically noisy, decline in the average total capacity of 1603 grant plants relative to PTC plants. However, this decline in total size is concurrent with an increase in the capacity of each turbine at these plants, and that difference is large and significant. The 0.29 coefficient estimate for the post-2010 1603 grant indicator variable corresponds to a sixteen percent increase in the capacity of wind turbines. From an engineering perspective, larger turbines are generally thought to be more efficient, all else equal.[26]

Table 10: Change in Wind Farm Characteristics over Time

	Capacity (MW)	Turbine Size (MW)	Design Wind (MPH)
1603 Grant	-2.19	-0.057	-1.01
	(19.7)	(0.12)	(0.84)
1603 Grant - Post 2010	-9.05	0.29^{**}	0.64
	(22.9)	(0.14)	(0.98)
Mean(Y)	85.41	1.79	17.76
R-sq.	-0.0044	0.044	-0.0074
N	316	316	316

Three specifications of equation 11, varying the dependent variable (listed at the top of each column). Sample restricted to plants coming online during the 1603 grant eligibility period, 2009-2012. All models contain cohort dummies. Standard errors reported in parentheses.

The timing of the program limits our ability to draw conclusions about how the capital stock might change under a more permanent policy change. Nevertheless, there does appear to be some evidence that firms respond over time and adjust their input mix in response to a change from output to investment subsidies. This illustrates the importance for policymakers of considering the impacts of subsidy design on firms' long-run responses when choosing between investment subsidies

[26]We also inspected the 1603 grant subsidy amount per MW over time for evidence of an impact of the investment subsidy on the price of inputs as observed in other industries (e.g., Goolsbee, 1998; House and Shapiro, 2008). However, we observe neither investment costs for PTC recipients nor the counterfactual investment costs for 1603 recipients had the investment subsidy not been introduced, which limits our ability to draw conclusions from the time series.

and output subsidies.

6.3 Extensive Margin and 1603 Program Evaluation

Section 5 provided evidence that 1603 recipients would have generated significantly more output had they claimed the PTC. Moreover, investment subsidy induced some developers to alter the capital mix of their wind farms. In order to calculate the full effect of the policy, however, we need to consider that some 1603 grant recipients may not have found it profitable to enter without investment subsidies. A full model of wind farm entry is beyond the scope of this paper and, given the small number of wind farms entering each year, it is difficult to discern any break in entry rates in the time series. In lieu of these approaches, we perform a simple back-of-the-envelope calculation to identify "marginal" plants, i.e., power plants claiming the 1603 grant that appear profitable under the investment subsidy but not the PTC.

We specify the following discounted profit functions under each subsidy regime:[27]

$$\pi^{1603} = \sum_{t=1}^{t=25} \left(\frac{1}{1+r}\right)^t (p_t - c_t) q_t^{1603} - (0.7) * F$$

$$\pi^{PTC} = \sum_{t=1}^{t=25} \left(\frac{1}{1+r}\right)^t (p_t - c_t) q_t^{PTC} + \sum_{t=1}^{t=10} \left(\frac{1}{1+r^{PTC}}\right)^t (PTC) q_t^{PTC} - F$$

Wind farms are assumed to remain in service for 25 years, while we observe at most seven years of data for 1603 recipients. Censored time periods are predicted to decay at a linear rate estimated using the full panel of wind farms.[28] Plant-specific output prices p_{it} are computed based on revenue and sales quantities reported on EIA Form 923.[29] We also construct estimated marginal revenue from the sale of renewable energy credits under state-level renewable portfolio standards using data from Marex Spectron and Lawrence Berkeley National Laboratory (see Appendix A.3 for more details).[30] Operating costs (c_{it}) of $9/MWh, taken from Wiser and Bolinger (2016), are subtracted to obtain per period net revenue, which is discounted at an assumed 5 percent real interest rate. Fixed investment costs F are obtained by dividing the observed 1603 grant award amount from Treasury by the fraction of investment costs covered by the program (0.3).[31]

Counterfactual output under the PTC (q^{PTC}) is obtained by increasing predicted output (q_t^{1603}) by 10 percent (reflecting the range of our preferred RD and matching estimators results) during

[27] The full details of this back-of-the-envelope calculation are presented in Appendix A.3.

[28] The details of this regression are presented in Appendix Section A.3

[29] Of the 209 1603 plants in the sample, 10 do not report any resale quantities in the EIA data and are thus excluded from this analysis. Future prices are assumed to remain constant in real terms.

[30] As of 2017, 29 states and Washington D.C. had enacted renewable portfolio standards (RPS). Wind farms generated credits for each unit of production, which they then sell to covered non-renewable generators.

[31] Wind farms are also eligible for accelerated depreciation, which we assume is equal to 10 percent of investment costs. In a 2010 White House Memorandum to the President, leaked to multiple news outlets, the Shepherds Flat 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 power.

the first ten years of operation. During this period, each MWh produced also generates \$23 in tax credits, in addition to the marginal revenue collected under the 1603. However, we need to account for the fact that these tax credits need to monetized, and are thus less valuable than cash. As discussed in Section 2, the creation of the 1603 grant program reflected concerns that wind developers could not find tax equity partners—large financial companies with sufficient tax liabilities to monetize the production tax credits—due to the financial crisis. Bolinger (2014) reports that the tax equity yield remained fairly stable at six percent over 2005-2007. Over 2008-2009, this yield increased by as much as 450 basis points, reflecting the contraction in tax equity supply. In order to account for this additional cost of monetizing tax equity, we discount the PTC revenue streams by an assumed 8 percent tax equity yield, which is the modal value of the tax equity yield over 2009-2012 presented in Bolinger (2014).[32]

Table 11 summarizes these two constructed profit measures. 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 ($\pi^{1603} < 0$ & $\pi^{PTC} < 0$). Somewhat surprisingly, 22 percent of 1603 recipients fall into this final category. There are many potential reasons for this. We may have underestimated state and local subsidies or overestimated O&M costs and discount rates for these facilities. Even perfectly accounting for all of these factors, it is likely that some plants that appeared profitable *ex ante* will appear unprofitable *ex post* due to low price and wind realizations.

Table 11: Estimated Subsidy by Group

Group	N	1603			PTC		
		Output (MMWh)	Subsidy (\$M)	Subsidy (\$/MWh)	Output (MMWh)	Subsidy (\$M)	Subsidy (\$/MWh)
Always Profitable	151	697	7,807	11.20	732	7,593	10.38
Marginal	4	9	181	19.25	10	109	10.89
Never Profitable	44	188	2,423	12.90	198	2,103	10.60

The first two columns of the table report (predicted) lifetime output for each group along with the total 1603 award amount. The third column presents the ratio of total output to total subsidy, which can be interpreted as a public funds levelized cost of energy. The final three columns present predicted output, subsidy, and subsidy per unit of output for these projects had they claimed the PTC instead of the 1603 grant. While we estimate a larger average government subsidy per (lifetime) megawatt-hour under the 1603 program than the PTC for each group, we also find that more than one-third of these 1603 grant-claiming plants would earn a higher total subsidy under the PTC.

Estimating the full effect of the 1603 program requires taking a stand on the counterfactual entry status of the never-profitable group. We consider two cases. In the first case, we combine

[32] Using the maximum observed yield of 10.5 percent does not meaningfully change the results.

the never-profitable plants with the marginal group and assume that they would not have entered without the 1603 grant program. Under this assumption, the 1603 program increased lifetime wind production by 162 MMWh (reflecting the difference between the total output under the 1603 column of 894 MMWh and the 732 MMWH for the always-profitable group under the PTC column). It would also imply that the 1603 grant increased the average public cost per wind MWh from $10.38 to $11.64 , a 12 percent reduction in cost-effectiveness.

In the second case, we 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. In this case, the 1603 grant program screened in 9 MMWh of production at the four marginal plants. At the same time, the production at inframarginal plants declined by over 4 percent (from 198 to 188 MMWh in the never-profitable row of table 11). Under this assumption, total wind output would have been modestly *higher* without the 1603 program (by less than 1 MMWh), while total government expenditure would have declined by $714 million.

Let us acknowledge a few caveats to this analysis. First, our estimate of always-profitable wind farms may be too high based on our assumption of the discount rate associated with the PTC. The tax equity supply shock associated with the financial crisis motivated the creation of the Section 1603 grant program. This decline in supply is evident in the spike in tax equity yields in 2009. We employed a higher rate for discounting the PTC streams in evaluating the counterfactual for our 1603 grant-claiming wind farms to reflect the increase in tax equity yields during this time period. This higher discount rate may be valid for evaluating the marginal project, but it could be too low when considering the counterfactual of all of the 151 always-profitable 1603 grant claimants going to the tax equity market to monetize their production tax credits. Second, note that our conclusions about the Section 1603 grant program reflect the specific policy design of a grant equal to 30 percent of eligible investment costs relative to the specific PTC design of awarding 2.3 cents per kilowatt-hour of output. Modifying either policy parameter could influence the cost-effectiveness of the investment and output subsidy approaches. Third, our analysis reflects realized outcomes to date and forecast outcomes estimated from past realized outcomes. To the extent that realizations deviate from ex ante expectations, this analysis may be an imperfect representation of the wind farm developer's decisions (a) to move forward with a wind power project and (b) to claim the 1603 grant.

7 Conclusion

Policymakers have long relied on tax expenditures and government outlays to promote socially-beneficial activity. Similar to the experience with the 1603 grant program, governments have frequently "turned on" investment subsidies for relatively short periods of time House and Shapiro (2008). The unique situation of providing a taxpayer the *choice* of investment or output subsidy, however, provided the real-world policy experiment to enable this evaluation of the causal impacts of subsidy design on productivity.

In exploiting the 2009 Recovery Act's natural experiment in tax policy, we find that wind farms choosing the investment subsidy generated 10 to 11 percent less power per unit of capacity than those projects choosing the output subsidy. We examine one distinctive characteristic of power markets—the prospect of negative prices–and our analysis suggests that sub-zero prices explain some but not all of the estimated output impacts of investment subsidies. This loss in productivity implies that the Federal government paid 12 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 of the productivity impacts of subsidy design that fills a gap in the empirical public finance scholarship and sheds light on a theoretical ambiguity in the literature. This work also illuminates energy and climate policy design. While a Pigouvian approach that taxes fossil fuel plants at their marginal damages delivers the optimal incentive for them to reduce externalities, such a policy has been politically difficult to implement. Instead, governments offer various types of subsidies to renewable energy to promote a cleaner 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 cost-effectively. While the particular policy under study in this paper has ended, its experience has important implications for the seemingly ad hoc mix of both investment subsidies—such as federal and state investment tax credits, accelerated depreciation, loan guarantees, and property tax waivers—and output subsidies—such as the production tax credit, renewable portfolio standards, and net metering for distributed power—still in operation today targeting wind, solar, geothermal, nuclear, and other low- and zero-emitting power technologies.

In contexts where output determines (or proxies for) the social benefits of a policy, output subsidies can outperform investment subsidies. If an investment subsidy is preferred, say on administrative simplicity or political economy grounds, then it could be modified in a way to mitigate the adverse productivity effect. For example, policymakers could structure input subsidies such that they reflect the expected output from investment (Schmalensee, 1980), as was done by the California Solar Initiative. Based on this analysis, doing so considerably improve the cost-effectiveness of the subsidy and improve the environmental efficacy of the tax-preferred investment.

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A Appendix

A.1 Additional information on data sources and cleaning

Information on how to obtain each data source, along with code for replication is available on GitHub.

Additional information on the primary data sources.

- Survey Form EIA-860 collects generator-specific information on an annual basis about existing and planned generators and associated environmental equipment at electric power plants with 1 megawatt or greater of combined nameplate capacity.

- Survey Form EIA-923 collects detailed electric power data – with both monthly and annual frequency – on electricity generation, fuel consumption, fossil fuel stocks, and receipts at the power plant and prime mover level.

- The American Wind Energy Association (AWEA) collects detailed information about all of its members and makes these data available as part of its membership subscription. The database includes more than 60 fields. We primarily use the data to determine the presence and size of any power purchase agreements.

- 3Tier windspeed data provided hourly estimated wind speed data from 2000 to 2014 for every wind farm in the EIA database.[33] These hourly data are collapsed to the monthly level and combined with monthly electricity generation data from the EIA.

- The Department of the Treasury reports data on Section 1603 grant claims. We matched Treasury Section 1603 grant projects to EIA data based on business name, plant name, county and state identifiers, and placement in service date. For 152 Section 1603 grants, we could not identify a match in the EIA data. One of these is a Puerto Rico project, which is excluded due to geography from the EIA databases. The other 151 projects received very small grants, indicating that these projects were too small to be covered by EIA's EIA-860 and EIA-923 surveys. In aggregate, they represent one-half of one percent of 1603 grant outlays for large wind projects.

  A grant could be submitted for a single wind turbine, a set of turbines, or an entire wind farm. This created two data issues. First, a wind farm could receive multiple Section 1603 grants. In these cases, we aggregated 1603 grants to the wind farm level (the level of observation in the EIA databases). For example, the large Alta wind farm in California came online in phases starting in late 2010 and its developers submitted more than twenty 1603 grants.

[33] These data were provided by Joern Huenteler, Gabe Chan, Tian Tang, and Laura Diaz Anadon, collected as part of their (unpublished) research on "Why Hasn't China's Wind Power Generation Lived up to its Potential?". A handful of EIA plant locations were either entered erroneously or downloaded improperly, and are excluded from the sample.

Second, a wind farm could be built with N turbines that come online before 2009, for which it claims the PTC. It may then expand with M turbines in 2009 and claim a 1603 grant for these new turbines. The EIA-observed output for that wind farm after 2009 would reflect the aggregate production of the N+M turbines. Since we cannot distinguish the output between the N PTC-claiming turbines and the M 1603 grant-claiming turbines at such a wind farm, we drop the wind farm from our sample. We identified such cases as wind farms that claimed a 1603 grant over 2009-2012, but had either substantial pre-2009 generation or a significant change in installed capacity post-2012. Using these decision rules, we dropped thirteen wind farms that represent less than four percent of total 1603 grant outlays for large wind farms.

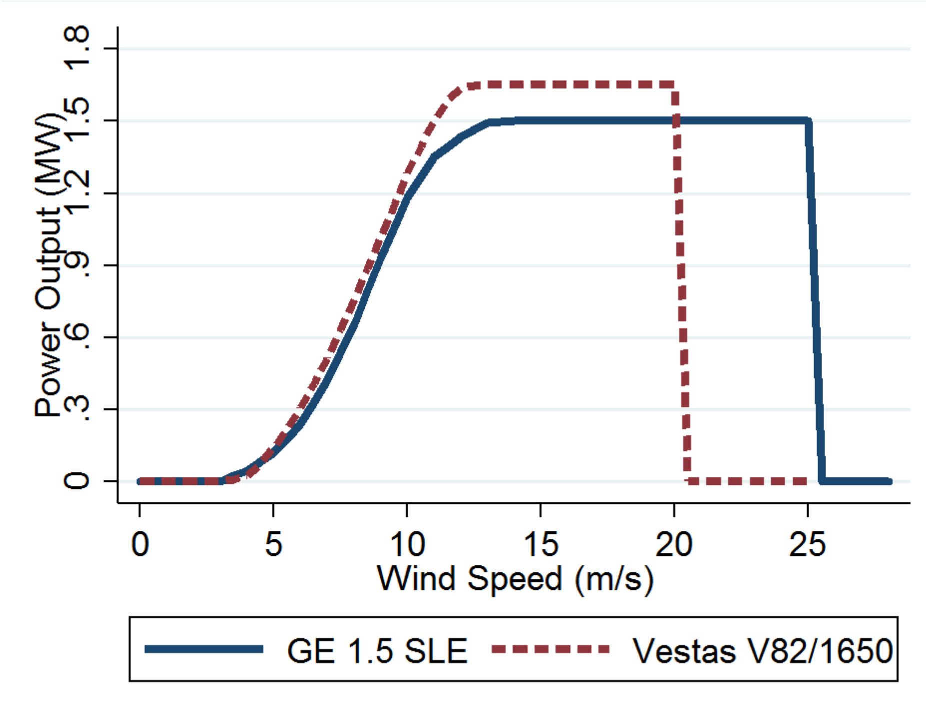
Additional sample Restrictions There are 941 wind farms in the continental U.S. in the EIA data. We restrict attention to plants that are private and operate as either independent power producers or part of an investor-owned utility based on subsidy eligibility, which reduces the sample to 817 wind farms. We also restrict the sample to plants entering before the end of the 1603 grant period (end of 2012). There are two ways of determining when a plant is placed into service using on the EIA data: we could use either the date plants submit to the EIA as their first date of commercial operation or the month that a plant's production first appears in the production date. Conversations with EIA staff confirm that the former should be used for determining 1603 grant eligibility. However, to avoid concerns about potential misclassification, we exclude plants whose two entry dates suggest conflicting 1603 elgibility status. Finally, we exclude plants that we were unable to locate in the AWEA database or for which we did not have site-specific wind and turbine powercurve informaiton. This final sample of 538 plants represents our population.

A.2 Potential Capacity Factor Construction

As described in Section 2.1, wind farm production is a nonlinear function of wind speed. This nonlinear function is turbine-specific, as some turbines are engineered to perform particularly well at low wind speeds, while others are optimized for high wind speeds. Wind turbine manufacturers provide power curves for each turbine that summarize how much electricity it should generate at a given wind speed. Figure A.1 presents example power curves for two of the most common wind turbines in the U.S. The Vestas turbine has a higher maximum capacity, but the GE turbine is rated to produce power at higher wind speeds. Other turbines are designed to generate more electricity at lower wind speeds at the expense of generating less electricity at higher speeds.

Rather than try to approximate this function with turbine-specific higher order polynomials of wind speed, we compute an "engineering" estimate of expected output for each turbine in each month. We begin with estimates of the wind speed every hour at every wind farm in our sample that come from 3TIER. We combine this with a site-specific power function based on the wind turbine used at each wind farm to predict hourly electricity generation. We use the ideal gas law to adjust for variation in air density, which affects the kinetic energy available to each turbine, using time- and site-specific data on temperature and pressure from 3TIER. Aggregating hourly

Figure A.1: Reported Power Curves for Two Common Turbines



predicted output over the month and dividing by the turbine's rated output provides us with a measure of "potential capacity factor," which we include as a control in our primary specifications.

Table A.1 demonstrates that this one-dimensional, time-varying control explains significantly more of the observed variation in capacity factor than time-invariant, site-specific wind quality information. It also fits slightly better than a third order polynomial in wind speed.

Table A.1: Explanatory Power of Alternative Measures of Potential Generation

	(1)	(2)	(3)	(4)	(5)
Design Wind Speed	0.297***	-0.0585	-0.00345	-0.0570	0.00596
	(0.104)	(0.107)	(0.0929)	(0.107)	(0.0930)
Wind Speed (m/s)		-0.926		-1.480	
		(3.289)		(3.393)	
Wind Speed Squared		1.027***		1.077***	
		(0.397)		(0.400)	
Wind Speed Cubed		-0.0476***		-0.0482***	
		(0.0144)		(0.0143)	
Potential Capacity Factor			0.575***		0.603***
			(0.0236)		(0.0274)
Var(Wind Speed)				-0.0750	-0.230**
				(0.140)	(0.0930)
Adjusted R-sq.	0.269	0.465	0.521	0.465	0.523
N	11680	11680	11680	11680	11680

A.3 Profitability Calculation Details

Calculating discounted profits under both subsidy regimes for 1603 grant recipients requires assumptions about lifetime production, prices, operating costs, and discount rates. This Section discusses each of these assumptions in turn.

Predicting lifetime capacity factor Wind farms are assumed to remain in service for 25 years. In order to predict output in future periods, we model realized capacity factor as a function of plant and month-year dummies, potential capacity factor, and age:

$$q_{it} = \alpha(age_{it}) + \beta \text{PtnlCF}_{it} + \alpha_i + \mu_t + \epsilon_{it}$$

The model is estimated using the full sample of plants that enter between 2002 and 2012. Table A.2 presents the results using both capacity factor and log(generation) as dependent variables.[34]

Table A.2: Generation Decline

	(1)	(2)
Age (years)	-0.84***	-0.079***
	(0.16)	(0.0073)
Observations	36112	36077

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

We use this model to predict q_{it}^{1603} for all future periods. We then scale this output up by our preferred RD estimate during the first ten years of generation to obtain q_t^{PTC}.

Converting generation into revenue In 2011, EIA Form 923 began collecting annual resale revenue and quantity for each plant.[35] We use these data to estimate the price received by each plant.[36] Figure A.2 shows that, where PPA information is available from AWEA, the rate closely matches the EIA implied price (90% of observations in AWEA are within 10% of the EIA average resale price). We assume real prices remain at their current levels in future periods and use 2011 prices for 2009-2011.

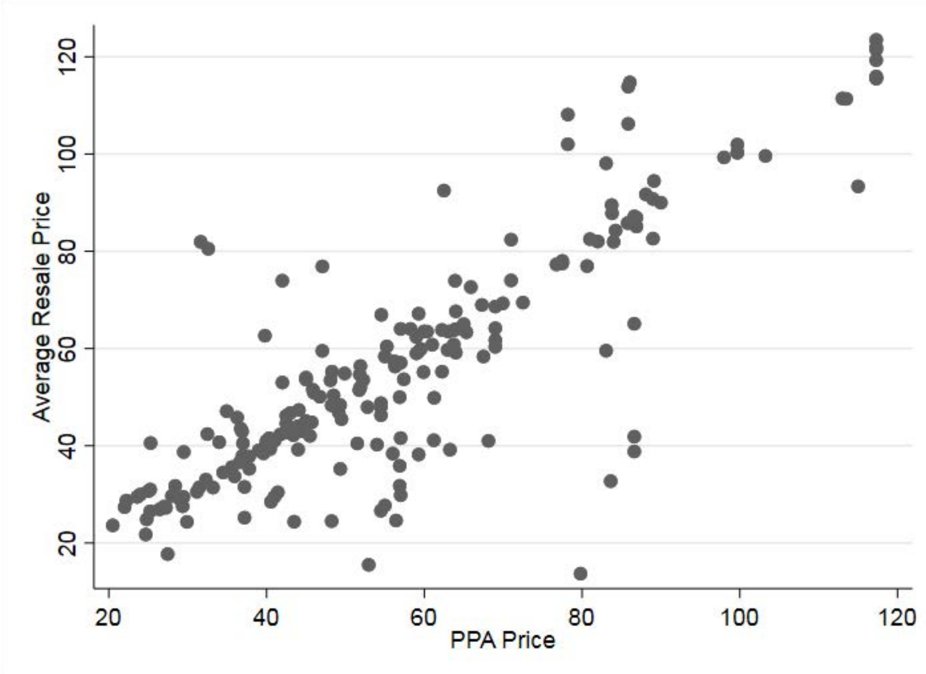
Renewable Energy Certificates Data As of 2017, 29 states and Washington D.C. had enacted renewable portfolio standards (RPS). Wind farms generated credits for each unit of production, which they then sell to covered non-renewable generators. Unfortunately, these payments are not observed in the EIA data.

[34] Using higher order polynomials led to implausible predictions.

[35] 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 10 of the 202 1603 facilities in the sample. This is likely because those wind farms dispose of their output directly through a nonstandard relationship. These plants are excluded from the policy evaluation analysis.

[36] Some plants report retail sales. For these sales, we use average annual resale price information at the state level from Survey EIA 861M.

Figure A.2: Average Resale Price (EIA) vs PPA Rate (AWEA)



We construct estimates of the RPS payments available to wind farms in a given state month using bid-ask data on Renewable Energy Certificates (RECs) trades from all active state RECs markets dating to 2007 from Marex Spectron in May 2015. To account for the fact that some states allow covered non-renewable entities to obtain credits from qualifying renewable facilities outside the state, we combine these state level prices with annual estimates of cross-state REC compliance flows from Lawrence Berkeley National Lab.[37] This expected REC payment is added to the average resale price to get marginal revenue each period.

[37]More information on this project tracking cross-state RECs at https://emp.lbl.gov/projects/renewables-portfolio.

B Additional Tables and Figures

B.1 Linear RD Results

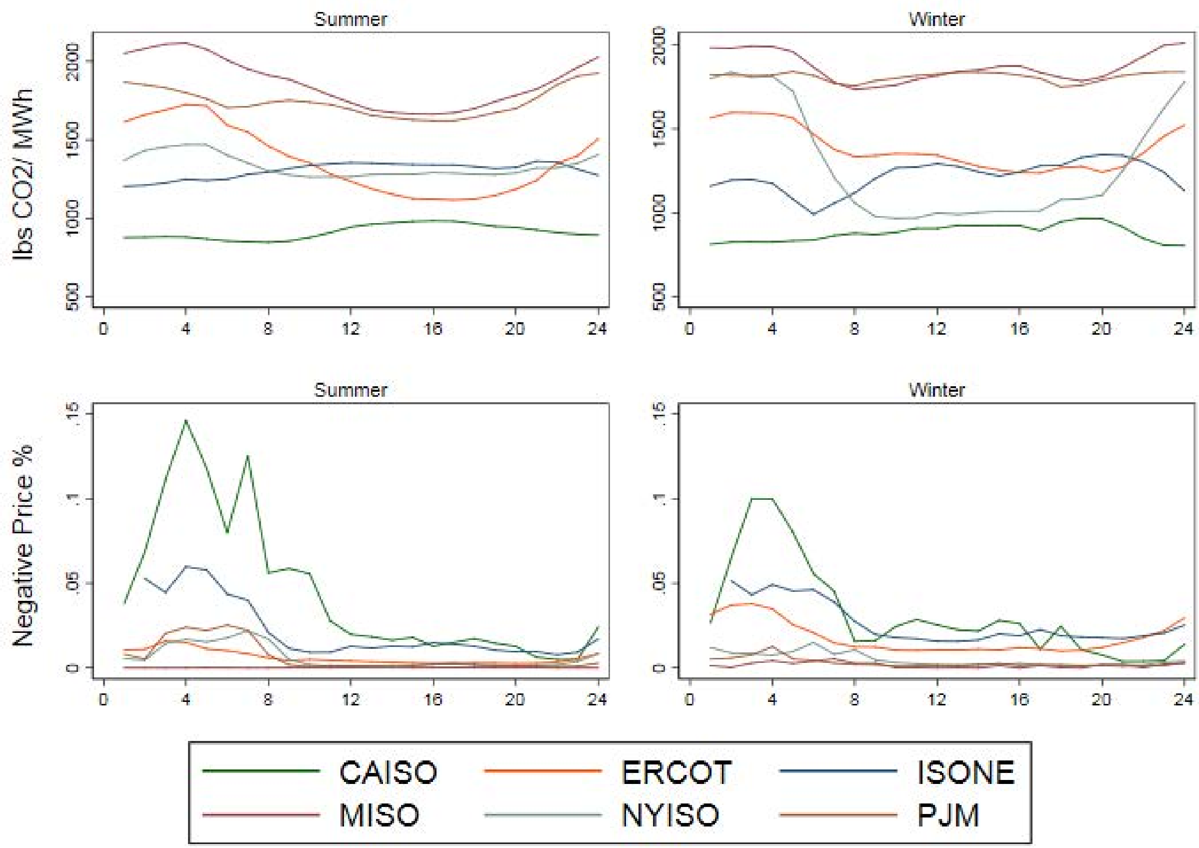
Table A.3: IV Results Sensitivity: Linear RD

	(1)	(2)	(3)	(4)	(5)	(6)
1603 Grant	-3.613***	-2.540**	-2.958***	-6.136***	-5.027**	-1.361
	(1.235)	(1.164)	(1.132)	(2.308)	(2.206)	(2.253)
Regulated		-1.015	-5.809***		-2.242	-6.275***
		(1.561)	(1.698)		(1.782)	(1.648)
PPA		-1.013	-2.899***		-0.875	-2.936***
		(0.961)	(0.836)		(0.969)	(0.854)
IPP		-0.882	-2.566**		-1.513	-3.142**
		(1.274)	(1.215)		(1.313)	(1.279)
Potential Capacity Factor		0.500***	0.567***		0.499***	0.573***
		(0.0351)	(0.0364)		(0.0364)	(0.0338)
Var(Wind Speed)		-0.0695	-0.524***		-0.137	-0.527***
		(0.149)	(0.105)		(0.154)	(0.106)
log(Capacity)		-1.024**	0.409		-1.074**	0.428
		(0.433)	(0.456)		(0.434)	(0.462)
Constant	32.54***	19.55***	20.75***	32.38***	22.33***	22.10***
	(0.824)	(1.982)	(1.920)	(1.140)	(2.707)	(2.182)
Regression Type	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Controls	N	Y	Y	N	Y	Y
State FE	N	N	Y	N	N	Y
Trend	N	N	N	Y	Y	Y
R-sq.	0.338	0.519	0.625	0.353	0.523	0.627
N	9292	9292	9292	9292	9292	9292
F-stat	.	199	119	.	34	21

Data include a balanced panel of monthly observations from 2010 to 2014 for all wind farms. For models 4 - 6, distance to the policy cutoff, and that distance interacted with the a post-policy indicator are included as controls. All models contain year-month dummies. Standard errors clustered by wind farm reported in parentheses.

B.2 Marginal Operating Emissions Rates from Callaway et al. (2017)

Figure A.3: Marginal emissions and negative price frequency by hour of day and season



Estimates of marginal operating emission rates (MOER) by hour of day and season were extracted from the appendix of Callaway et al. (2017). Figures in the second row plot the mean share of negative price hours by ISO for the same hours and seasons.