Where does the wind blow?
Green preferences and spatial misallocation in the renewable energy sector

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Abstract

Are "greener" investments less efficient? This paper looks at the location choices of wind power investors. I measures the efficiency loss in this sector due to wrong project location and explore the factors contributing to it. Using extensive information on wind resources, transmission, electricity prices and other restrictions are relevant for the siting choices of wind farms, I calculate the predicted profitability of wind power projects for all the possible places across the contiguous US, use the distribution of this profitability as a counterfactual for profit-maximizing wind power investments and compare it to the actual placement of wind farms. The average predicted profit of wind projects would have risen by 47.1% had the 1770 current projects in the continental US been moved to the best 1770 sites. It is also shown that 80% and 42% respectively of this observed deviation can be accounted for by within-state and even within-county distortions. I show further evidence that a large proportion of the within-state spatial misallocation is attributable to green investors' conspicuous generation" behaviour: wind farms in more environmental-friendly counties are more likely to be financed by local and non-profit investors, are closer to cities, are much less responsive to local fundamentals and have worse performance ex-post. The implementation of state policies such as Renewable Portfolio Standard (RPS) and price-based subsidies are related to better within-state locational choices through attracting more for-profit investments

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to the brown" counties, while lump-sum subsidies have the opposite or no effects. My findings have salient implications for environmental and energy policy: policy makers should take account of the non-monetary incentives of renewable investors when determining the allocative efficiency of policies.

Keywords: Spatial misallocation, Renewable energy policies, Productivity, Green preferences

JEL classification: R12 R38 Q42 Q48

1 Introduction

Location is the most important determinant of some industries' productivity. Large economic loss can occur when plants are located in wrong places due to insufficient information on site suitability, unnecessary restrictions on siting or certain place-based policies. However, it has been hard to measure the exact loss in productivity caused by poor location since a lot of the locational fundamentals that matter for specific industries are not observed by researchers and various agglomeration and dispersion forces exist. In this paper, I attempt to circumvent these problems by looking at the locational efficiency within the renewable energy sector, a sector where locational fundamentals are very important and largely observable, where agglomeration and dispersion forces are relatively weak, and where regional energy policies play a great role. I am able to uncover factors that contribute to the mislocation-induced efficiency loss within wind power sector. Surprisingly, compared to unequal state renewable energy incentives or insufficient experiences, a quantitatively more important contributor to the observed deviation of wind farm placement away from the optimum is investors' green preferences: investors who are more eager to display their preferences in environmental protection are much less likely to place their wind turbines in places that make economic sense. More interestingly, extra financial incentives are shown to improve the overall efficiency wind farm placement, partially through screening out profit-maximizing, as opposed to environmental-concern driven investments.

Economic efficiency and environmental impacts of renewable energy sector, as suggested by Cullen (2013) (16), Zivin et al. (2014) (19) and Callaway et al. (2015) (15), critically rely on the proper siting of these projects. For instance, wind turbines should be located in places with strong and stable winds, reasonably good access to electricity transmission, high wholesale electricity prices and no restrictions on wind farm development. In this paper, I adopt a novel method by directly comparing the location of the actual projects to a profit-maximization counterfactual project allocation using rich information on local wind intensity, grid access, electricity price, as well as restrictions on wind power placement.

In practice, I divide the contiguous US into 75147 10km*10km grid-cells and evaluate the profitability of placing wind power projects in each of these cells, subject to necessary exclusions. The loss from spatial misallocation is then calculated as the different in predicted profits between existing cells and the best N cells, where N is the number of grid-cells with wind power projects. I find a loss of 47.1% in predicted profits: if we move all the 1770 current wind projects to the best possible sites, the predicted average revenue of these projects will increase by 47.1%. Interestingly, I find *within-state* mislocation alone accounts for an efficiency loss of 37.4%, over 80% of the total observed distortion. After a further

zooming in into within county distortion, the most conservative loss in efficiency is still measured as 19.8%. Large efficiency gain is expected had wind power investors been better at picking sites within their own states or even within their own counties. In fact, equalizing state-level incentives for green energy is only able to boost aggregate efficiency by 1% to 5% [1] since cross-state distortion is not large in magnitude compared to within-state distortion.

The natural next step is to examine potential explanations for this particular pattern of locational inefficiency. A closer look at the data reveals that wind farms located in "greener" counties, measured by local support for the democratic and green party in presidential elections, are located in places with significantly less wind and perform worse ex-post. They also tend to be invested by non-profit and local investors. Finally, it is much more likely that they are placed in urban areas, commonly thought to be not suitable for wind power projects[2] but obviously make these wind turbines more salient to the public. These facts are all consistent with the hypothesis that investors with stronger green preferences do a more local search and display stronger local bias in wind farm siting. I also show that differences in green preferences are quantitatively important in accounting for the observed within-state and within-county distortion. Moving from 25 to 75 percentile in the local "greenness" measure leads to the location of wind farms 20% less responsive to local fundamentals and more than doubles the within-county distortion measure.

One possible explanation for this behavior is that instead of doing a global search for the most productive sites, "greener" developers of renewable energy projects might prominently install wind turbines on their own properties or at least within their local counties as a demonstration of preferences for environmental protection. It could also be that green investors are smaller and unspecialized organizations with disproportionally higher search and monitoring costs. In either case, the existence of non-monetary motives for renewable is central to this particular locational misallocation, a phenomenon spawns novel and interesting policy implications. Policies that are ex-ante equivalent and are equally attractive to profit-maximizing investors might actually screen investors with different levels of green preferences differently, resulting in starkly different ex-post allocative efficiency.

[1] The aggregate efficiency gain from equalizing state-level incentives is calculated by estimating the policy treatment effects and generating the predicted wind capacity addition for each state by assuming the intensity of policies to the same across states, while keeping the aggregate treatment effects of wind capacity addition to be the same. Some assumptions are needed to evaluate the change in aggregate efficiency level in the counterfactual configuration. I assume the average efficiency level for each state under the counterfactual allocation is the same as the mean/median/max estimated profitability of occupied cells (before any renewable policies are applied). The estimated change ranges from 1% to 5% under these different assumptions.

[2] "Locations in narrow valleys and canyons, downwind of hills or obstructions, or in forested or urban areas are likely to have poor wind exposure.", by the National Renewable Energy Lab (NREL), (http://www.bbc.co.uk/blogs/ethicalman/2009/12/why_micro_wind_turbines_dont.html)

Therefore, I further investigate the role of state-level renewable policies in changing allocative efficiency within-state and how it interacts with investors' green preferences. I collect information on these policies from DSIREUSA (Database of State Incentive for Renewables and Efficiency), and loosely divide them into three categories: quantity-based policies such as Renewable Portfolio Standard (RPS), per-unit-price-based (performance-based) policies such as feed-in-tariff and certain corporate tax breaks, and direct subsidies (non-performance-based) such as tax breaks on equipment and property. I try to aggregate several different policies into a single index of policy intensity under these three categories based on their impacts on the predicted profits of a typical wind farm project. In a difference-in-differences specification, I find RPS and price-based policies lead to a significantly better location of wind projects within-state. An important reason is that these policies are more attractive to pure profit-maximizing investors, who are adding capacities mainly in "brown" counties. Direct subsidies neither change within-state allocative efficiency nor have differential impacts on wind power capacity addition across counties with different environmental attitudes. For better identification, I restrict my sample to gridcells around state borders and check the dynamic effects of renewable policy incentives before and after their actual implementation. The key results are robust to these specifications.

I then come up with a model of private provision of public good features in heterogeneous green preferences, similar to Jacobsen et al. (2014) (10). I introduce search costs for picking a suitable site for wind farms and assume that green investors derive an extra source of utility from having wind farms in their local area, rendering fewer benefits from searching. This model nicely accommodates all my key empirical findings. It predicts that in terms of the extra public benefits generated, direct subsidies are dominated by other performance-based or mandate-type policies with the existence of green preferences.

As a cross-validation of the mechanisms at work, I further look at the Solar PV panel installation in California under the $3.3 billion California Solar Initiative (CSI) program, which provides 10 years of subsidies for solar PV panels. A nice feature of this program is that it provides both performance-based and non-performance-based quasi-experimental incentives for PV installation across CSI administrative boundaries and over time. I show that my previous findings on the allocative efficiency in wind farms hold in this solar panel setting: installations in greener zipcodes are more costly, less efficient, and respond less to monetary incentives, especially the performance-based ones.

My empirical findings have several novel and important policy implications. The most important rationale of renewable support schemes is that they are the more politically-accepted way to internalize the public benefits generated by renewable electricity generation. Therefore, they should be designed in a way to realign public and private benefits/costs of

renewable investments. One of the most important lessons we learn here is that we have paid too little attention to the importance of green preferences in green investors' private benefits, which is shown to be negatively correlated to the public benefits generated by a wind farm project given the same amount of private costs[3]. In light of this, non-performance-based renewable support schemes are clearly dominated since they tend to screen in greener but less efficient investments. The tradeoff between price-based instruments and renewable energy standard largely depends on to what extent the standard is able to incorporate each location's unique mix of electricity generation resources and other restrictions associated with the public benefits of renewable energy. On a related note, to engage agents with strong environmental preferences, promoting markets for green electricity where people can purchase electricity generated from renewable sources at a premium and get visible awards for it would be a better idea than encouraging them to invest in their own renewable energy projects.

This paper contributes to a burgeoning literature on green preferences and consumer behavior. Kahn and Kok (2014) (11) looks at the capitalization of green labels in California housing market. Sexton and Sexton (2014) (13) attributes consumers' enthusiasm on Prius to "conspicuous conservation", a costly signaling of one's concerns for the environment. Bollinger and Gillingham (2012) (3) underscores peer effects as the motives for people to install solar panels. Instead, I am exploring the importance of green preferences in steering investors' behavior and it is somewhat surprising to notice that the importance of green preferences is also significant in this setting, where agents are perceived to be more "rational" and profit-oriented. A major distinction of this paper from the previous research is that I explicitly document and quantify the loss in efficiency due to this special "conspicuous generation" motive of green investors and examine the effects of financial incentives in partially offsetting it. It also relates to the intrinsic incentive crowding out topics in psychology and public economics literature, also from a very different angle. I show that extrinsic incentives such as renewable energy subsidies, albeit crowd out intrinsic motivation in green investments, encourage the investors to adopt a more "profit-maximizing" thinking, which could be desirable from the policy makers' perspective.

I also evaluate the impacts of renewable energy policies from an unusual angle. In my paper, I assess how the implementation of state-level renewable energy policies reshape the cross-state and within-state allocative efficiency of wind farms. Among the large quantity of papers that explicitly looked at the effectiveness of renewable energy policies (Bird et el. 2005

[3]In the United States, the correlation between environmental friendliness and local wind resources is negative. Moreover, the additional emission cut benefits for extra wind power generation units are smaller with a higher proportion of renewable or clean energy in local energy mix.

(2),Yin and Powers 2010 (20)), Delmas and Montes-Sancho (2011) (5) systematically analyses the causes and effectiveness of typical US state-level policies in adding capacities. At a more micro level, Cook and Lin (2015) (4) finds that Danish renewable incentives significantly impacted the timing of shutdown and upgrade decisions made by turbine owners.

This paper is also related to the broader practical question of second-best energy policy design in face of large multidimensional heterogeneity when the first-best is unattainable. I document an unintended source of distortion in this case: the tendency of some subsidies to attract environmentalism-inspired but less efficient investments. Other papers have looked at different policies at different scenarios. Ryan (2012) (12) shows how regulation might hurt social welfare through increasing market power. Fowlie (2010) (6) shows that heterogeneity in plant ownership structure largely affects the effectiveness of environmental regulation. Ito and Sallee (2015) (9) discusses the pros and cons of attribute-based regulation, which helps to equalize compliance costs but brings in extra distortion.

Finally, this paper makes a contribution to the spatial economics literature by directly estimating the loss in aggregate productivity due to spatial misallocation. The particular setting of my problem allows me to quantify this kind of loss by directly comparing the actual location distribution to a well-established counterfactual using rich information specific to the industry, without relying on a structural model as in Bryan and Morten (2015) (14) and Fajgelbaum et al. (2015) (17). My findings underline the importance of investors' preferences in determining industrial location, consistent with a "jobs follow people" story.

The paper is structured as follows: section 2 prepares the readers with the background knowledge of US wind power industry and relevant renewable energy policies; section 3 introduces the data and methods to measure wind farm locational distortions; section 4 presents the main findings on different sources of distortion; section 5 shows evidence on the distorting roles of green preferences and counteracting policy effects; section 6 presents a simple model of private provision of public goods with green preferences that brings together all my empirical findings; section 7 concludes.

2 Background

2.1 Wind power in the US

Wind power in the United States expands quickly during the past several years and is taking up an increasingly important role in the energy mix of the US. As of the end of 2014, the total wind capacity was 65,879 MW, which generates 4.45% of the total electricity produced in the US. Over the past ten years, the US wind industry has had an average annual growth

of 25.6% over the last 10 years.

Wind power is widely considered to be the most cost-effective type of renewable energy apart from hydropower and is therefore expected to grow even more in the future as the country relies more on renewable energy. A US Department of Energy report finds 35% wind penetration by 2050 is “plausible”, in terms of grid reliability and cost, as well as the industry’s ability to scale up.[4] And the EPA projects that renewables could rise to 28 percent of the electricity supply by 2030 with Clean Power Plan in place.[5] Therefore it is time for us to think about how efficiently have we been able to place existing wind projects and what can we do to improve the allocative efficiency of this sector. Removing the persistent distortion in this sector may prove to be as important as innovation in wind power generation and storage technology in bringing renewable energy to be cost-competitive with fossil fuels.

Figure 1 shows the distribution of wind farms across the US. Figure 2 looks deeper into the allocative efficiency of them. Figure 2.1 plots the density of wind farm distribution across different wind power classes. Wind power class is a measure of wind resources, where 7 stands for the strongest wind and 1 stands for the weakest. The NREL (National Renewable Energy Lab) suggests that only areas with WPC greater or equal to 3 are suitable for utility-scale wind turbine applications[6]. However, from figure 1.1 we can see that about 30% of the current US wind projects are located in areas with WPC smaller than 3. Figures 2.2 and 2.3 further show that the wind farms that are located in low wind areas (WPC=1 & 2) are not closer to electricity grid or are in areas with higher retail electricity prices than their counterparts in the middle range wind areas (WPC=3 & 4), suggestive of a significant amount of spatial misallocation of wind farms across the country. Finally, Figure 2.4 plots the average local environmental attitude measure[7] of wind farms across different wind classes. Quite interestingly, I find that the wind farms exposed to little wind are located in counties with higher preferences for environmental protection. Therefore strong green preferences of the investors could work against incentivizing them to look for sites that make the most economic sense. In section 5, I am going to explore these phenomena quantitatively.

[4] `http://energy.gov/sites/prod/files/WindVision_Report_final.pdf`

[5] `http://www.vox.com/2015/8/4/9096903/clean-power-plan-explained`

[6] `http://www.nrel.gov/gis/wind_detail.html`

[7] Local environmental attitude at county level is measured as a linear combination of average county income, college graduate share, votes share for democratic and green party in 2012 presidential election, similar to Allcott (2015) (1)

3 Data

My analysis draws on three main sources of data: the database on the fundamentals of wind farm location, information on the distribution and performance of wind power projects, and a comprehensive dataset on state-level renewable energy incentives. I will describe them in turn.

3.1 Locational fundamentals

To establish a reliable counterfactual of profit-maximizing wind farm distribution, we need information on the local fundamentals that are critical to the profitability of wind farms. I collect information on wind resources, electricity transmission line distribution, electricity prices, and the restrictions on wind placement. I generate a database of 75147 10km*10km gridcells covering the continental US and match all the locational fundamental attributes to each gridcell and work out a single measure of potential wind power project profitability at the cell level.

Wind resources: The main wind resource data I use are drawn from the annual average wind resource data used in the Renewable Electricity Futures Study (`http://www.nrel.gov/analysis/re_futures`) from the National Renewable Energy Laboratory (NREL). The majority of the onshore wind data was modeled at a 50 m hub height and vertically adjusted to 80 m height to better represent current wind technology. Wind resources are divided into 7 categories with 1 representing the worst and 7 the best.

One particular drawback of using an annual average wind resource measure lies in the fact that there is a large variation in wind intensity from time to time, and the revenue generated from wind production largely depends on how the peak of wind power coincides with that of electricity demand. To deal with this issue, I obtain alternative simulated wind production data the National Renewable Energy Laboratory's (NREL) Eastern Wind dataset[8] and Western Wind dataset[9]. These datasets are created for energy integration study by NREL and its partners. Simulated power production from hypothetical wind plants every ten minutes from 2004 to 2006 is generated for 32,043 sites across the Western United States and 1326 across the Eastern United States. Mapping these sites to my gridcells generates time-series wind production information for 5866 gridcells.

Electricity transmission: I draw the information on electricity transmission infrastructure from a GIS file on 2001 US main electricity transmission lines above 60KV.

[8]`http://www.nrel.gov/electricity/transmission/eastern_wind_methodology.html`
[9]`http://www.nrel.gov/electricity/transmission/western_wind_methodology.html`

Agricultural land value: The county-level agricultural land value for 2014 is collected from the United States Department of Agriculture (USDA) statistics service dataset [10].

Electricity prices: Retail electricity prices on over 4000 pricing units are 2010 rates calculated for residential, commercial and industrial sectors from data reported by Energy Information Agency of the US (EIA). Rates were matched from EIA data and Ventyx (2010) territory shapes. Wholesale electricity prices are 2004-2010 yearly average from 24 pricing hubs gathered from Bloomberg.

Exclusions: I rely on the National Land Cover Database 2001 (NLCD2001) to eliminate places that are not suitable for wind power development. Incompatible land use includes urban, wetlands and perennial snow areas. Mountainous areas with a slope steeper than 20 degrees, calculated using the USGS national 90 m spatial resolution National Elevation Dataset, are also excluded. Finally, I exclude BLM and NSF protected areas, brownfield, national parks, federally owned land, national trails and tribal lands, according to the Bureau Of Land Management. GIS data on exclusion are matched to the gridcell database. A gridcell is defined as not suitable for wind power development if over 70% of its area is covered by excluded areas.

3.2 Wind power projects distribution and performance

Here I merge three different datasets to get an as complete as possible picture of the characteristics and performances of current wind power projects across the continental US. US Geological Survey (USGS) gather information on the exact location, mode, operation date and owner wind farm of over 48000 wind turbines in the US through March 2, 2014. Energy Information Agency (EIA) publishes annual reports on power plant generation (EIA-923) and generators (EIA-861) up to 2013, which includes information on capacity, generation, emission, interconnection and other characteristics of 821 wind power plants whose operation commenced before 2013. I also obtain detailed ownership, developer and operator information on over 1214 wind projects from Thewindpower (`www.thewindpower.net`). I merge the three datasets together by the names of the plant/project and year of operation. Over 70% plants in the EIA dataset are matched to both USGS turbine-level dataset and Thewindpower project-level dataset.

3.3 State level renewable policies

There are various support schemes for renewables across the US implemented at different levels. At the federal level, we have the Production Tax Credit (PTC) and the Investment

[10] `www.nass.usda.gov`

Tax Credit (ITC), which reduces federal income taxes for qualified tax-paying owners of renewable energy facilities based on either electrical output or capital investment in renewable energy projects.

At the state level, the most important policy is the Renewable Portfolio Standard (RPS), where utilities within the implementing states are required to source a given proportion of its electricity generation from renewable sources. Apart from it, there exists a number of different kinds of subsidies. I try to categorize them into performance-based and non-performance-based ones for my analysis. Support schemes can also be awarded by individual utilities or municipals, but many of them are direct responses to RPS. Therefore throughout this paper, I am going to focus my attention on state-level policies only.

Information on state-level renewable energy policies and incentives is gathered from Database of State Incentives for Renewables and Efficiency (DSIREUSA, `www.dsireusa.org`). Since there are so many different types of renewable policies and incentive schemes, I categorize them into three main groups and generate a single index of policy intensity within each group. I use a few criteria of exclusion to simplify my categorization. These three groups are:
(1) Direct fixed cost subsidies that compensate for part of the fixed cost of wind projects and are not dependent on performances, including equipment sales tax exemption, property tax exemption, grants, interconnection cost subsidy, support on feasibility studies etc.;
(2) Per unit price based subsides given to per unit electricity generated, hence depends on performances, including feed-in-tariff, performance-based rebates, and corporate tax credits;
(3) Quantity based policies that stipulate the minimum amount of renewable electricity generated, such as renewable portfolio standard (RPS).
I then apply the following rules to exclude policies that are not suitable for my analysis.
1. I focus only on state-level policies. Policies on the federal or municipal level are not considered. Policies implemented by individual utilities are not included as well.
2. I exclude policies that cannot be categorized loosely into the aforementioned three groups. Policies like green power purchase options or loan programs are not counted.
3. I exclude policies that are not awarded directly to wind farm developers, such as industrial support for wind turbine and parts manufacturers.
4. I exclude policies with too restrictive size or ownership requirements. (Policies with a maximum limit over 10MW and a minimum limit under 100MW, or are dedicated to particular ownership groups (i.e. residential only) are excluded)

With these requirements in mind, I define the index for per-unit-price-based (performance-based) policies as the total amount of extra money given to per unit electricity generation, the index for direct subsidies (non-performance-based) as the estimated percentage of total up-

front cost saved, and the index for quantity based policy (RPS) as the "real" measure of target stringency each year ($RPS_{st} = Norminal\, RPS_{st} - \frac{Renewable_{s,t-1}}{Total_{s,t-1}}$), where $Norminal\, RPS_{st}$ is the nominal RPS target on the minimum proportion of electricity sales from renewable sources, and $\frac{Renewable_{s,t-1}}{Total_{s,t-1}}$ is the actual proportion of electricity sales from renewable sources last year.

4 Measuring locational distortions

I follow three steps to obtain a systematic measure of locational misallocation at different levels in wind power industry. First, I evaluate the contribution of locational fundamentals to wind power plant performance. Second, I divide the continental US into 75,147 10km*10km gridcells and calculate the predicted profitability of each cells. Third, I define my distortion measure as the difference in the average profit of current wind projects and the average that can be attained should they be reallocated to the best gridcells.

To weigh the contribution of different locational factors such as local wind resources and transmission access to the general profitability of wind power projects, I define the location-varying predicted revenue per kW of wind capacity installed as:

$Predicted\, Capacity\, factor * (1 - \%Loss\, in\, Transmission) * average\, electricity\, price/kWh$

As there are different measures on wind resources and electricity prices, I come up with multiple measures of revenue for robustness, which I will discuss later.

On the cost side, two of the most important sources of location-varying fixed cost are grid interconnection cost and land rental cost[11]. I subtract the location-varying fixed cost from the revenue function to get a profitability measure of wind farms. The interconnection cost is calculated based on the distance of wind farms to the closest electricity grid. EIA-861 series report interconnection costs for most of the wind power generating units in the US. Therefore I regress the actual interconnection cost on the distance to electricity transmission lines and the size of the power plant to and get a prediction of interconnection costs for each wind turbine installed in any of the 75147 gridcells. I amortize these two sources of fixed cost over 15 years, the lifespan of a typical wind farm, with an annual interest rate of 3%.

To calculate predicted wind power production, capacity factor is a common measure in electrical engineering defined as the ratio between annual total electricity generation and the maximum amount of electricity generated at full capacity during one year. Since wind power is an intermittent energy source and wind turbines are not working when there is no wind,

[11] A report by the European Wind Energy Association `http://www.ewea.org/fileadmin/files/library/publications/reports/Economics_of_Wind_Energy.pdf` shows that grid connection and land rent takes up 8.9% and 3.9% of the total setting up cost of a typical 2 MW wind turbine

the capacity factor of a typical wind power plant usually ranges from 20% to 40%. I predict the capacity factor for a typical wind power plant in a given gridcell using information on the annual average wind speed of that gridcell. To obtain a reliable relationship between average wind speed and power plant capacity factor, I look into the National Renewable Energy Laboratory (NREL) Eastern and Western wind datasets, which reports wind speed per hour over two years and simulated capacity factor for over 30000 sites in the US. I regress the simulated capacity factor on yearly average wind speed to get a coefficient of the importance of wind resources to production efficiency.

A shortcoming of this method in predicting wind power generated revenue lies in the fact that there is a large variation in wind intensity from time to time, and the revenue generated from wind production largely depends on how the peak of wind power coincides with that of electricity demand. So as an alternative I also use the simulated capacity factor reported by the NREL Eastern and Western wind datasets directly. The advantage of the second source is that it provides us with detailed variation in simulated wind power production per hour for three years, and the disadvantage being this information is only available for only 5866 of my 75147 gridcells. Among them, only 317 of the 1770 occupied cells are covered. To avoid dropping too many occupied cells from my sample, for those occupied cells without detailed time-series wind production information, I use the information from the closest sites to them as a proxy if the distance between the cell and the observed simulation site is less than 30 km. This operation leaves me with 1128 occupied cells in the end.

I use both wholesale and retail electricity prices in my revenue calculation. Both have their respective pros and cons. Wholesale electricity prices are the prices faced by wind power plants and they are available at high frequency, allowing us to capture the fluctuation of electricity demand across different points of time. But they are only observed at 24 trading hubs. Retail electricity prices are available at over 4000 price units across the US annually. But they are the prices faced by consumers and markups between retail and wholesale prices could be different across places. I use the retail prices for my main specification as I believe it could better capture the demand side differences but I use wholesale prices for robustness. I then factor in the loss in transmission and get an estimate of the amount of money received per unit electricity generated by the wind farm ($(1-\%Loss\,in\,Transmission)*average\,electricity\,price$). The loss in transmission depends, of course, on the type of prices I use. With retail prices, the loss depends on the distance to the distribution lines, and with wholesale prices, the loss depends on both the distance to the closest 375 kV electricity transmission lines and the distance to the electricity trading hub.

For robustness, I define four alternative profitability measures. On the production side,

I use either the predicted wind power production based on annual average wind speed, or the simulated wind power production by NREL-based on hourly data that are available only for a subset of gridcells. As for the price, I use either retail or wholesale price data. For simplicity, in generating the profitability measure using hourly simulated data and wholesale prices, I define off-peak time to be 12:00 p.m. to 8:00 a.m. next morning, and peak time to be the rest. I then aggregate both wholesale electricity price data and simulated wind production data to a peak and an off-peak one and generate the total predicted revenueTheir combination produces four profitability measures. The baseline one is the one that uses annual average wind speed and retail electricity price. Table 1 reports the correlation across these four measures. As Eastern and Western Wind datasets use a different methodology in simulation. I split them into two separate samples and report the correlation separately. It is clear that the correlation between them are quite high.

With a reliable measure of potential profitability of wind power projects across the continental US, I define the total loss in wind farm spatial misallocation as:

$$\frac{Average\,profit\,of\;1770\,best\,cells\,nationwide - Average\,profit\,of\,1770\,built\,up\,cells\,nationwide}{Average\,profit\,of\;N\,built\,up\,cells\,nationwide} \tag{1}$$

Over concerns about grid stability, I impose a restriction on the upper bound of wind penetration: in the optimal allocation, the proportion electricity coming from the wind should not be more than 30% of the total generation for any states.

Similarly, I am able to produce a within-state(county) measure of mis-location loss:

$$\frac{Average\,profit\,of\,the\,N\,best\,cells\,in\,state(county) - Average\,profit\,of\;N\,built\,up\,cells}{Average\,profit\,of\;N\,built\,up\,cells} \tag{2}$$

As mentioned, for robustness I generate four different measures of wind power profitability. Accordingly, I come up four distortion measures. Table 2 report these spatial misallocation measures at national level. The baseline reveals a total efficiency loss measure of 47.1%. That being said, the average profit of 1770 continental US wind farms will increase by 47.1% should they be moved to the best 1770 gridcells in the US. The measured distortion (43.6%) is slightly smaller if we are using wholesale other than retail electricity prices. Because the simulation method is different across the Eastern and Western datasets, I generate the distortion measures for Eastern/Western US separately. So the distortion measure from Row 3 to Row 6 can be interpreted as the change in average profit by moving the current wind farms to the best cells in Eastern/Western US. Since the simulation data are only available for a subset of gridcells (4661 for the Western US, 2003 for tEastern US.),

distortion measures based on them are more likely to be underestimated, and the extent of underestimation is larger for the Eastern subsample with less alternative gridcell's. They report alternative distortion measures from 11% to 37%.

Within-state allocative efficiency loss for different states is reported in Table 3. The first column and the second column reports the distortion measure based on profitability measures using predicted production data based on annual average wind speed. The third and fourth columns report distortion measure based on the simulated production measures that take account of fluctuation in wind resources across time. It is clear that these four within-state distortion measures are highly correlated. I stick to the first column as my baseline.

We can see that there is a large variation in the current allocation efficiency across the US states: In Iowa, the observed efficiency loss is less than 10% due to mislocation of wind projects. While in Maine, the average profit of wind power plants can go up by 110% if they are placed optimally. Weighting state-specific within-state efficiency loss with the total wind capacity of each state gives us a 37.4% efficiency loss driven purely by wrong wind farm siting choices within state. Even more surprisingly, the measured efficiency loss remains at 19.8% even if we only consider within-county distortion for counties with two or more wind farms, which should be free of most concerns on scheduled electricity demand and supply at the state level. It means that instead of placing wind farms in the wrong states, we should worry more about wind power investors not choosing the right sites within their own states or even within their own counties. To take a closer look at what might drive within-county misallocation, Figure 2 plots the relationship between measured within-county misallocation and the support for the democratic party at the county level, revealing a significant and negative relationship. Moving from 25 to 75 percentile in the local "greenness" measure more than doubles the within-county distortion measure.

As a more rigorous attempt to examine the factors that contribute to this observed within county spatial misallocation, I turn to regression analysis. Table 4 reports the correlation between this normalized distortion measure and county-level greenness measures, the mean and standard deviation of profitability within-county, the percentage of cells that are not suitable for wind power placement, as well as a variety of demographic and social economic measures. It is shown that the support for the democratic and green party is positively correlated with the county-level distortion measures. Apart from that, the distortion measure is also increasing in the college graduates share in some specifications. Other observables do not seem to correlate with this within-county distortion measure in a systematic way.

5 Green Preferences and Spatial Misallocation

In this section, I attempt to evaluate the efficiency loss from the suboptimal siting choices made by those who invest in wind power out of environmental concerns. My main hypothesis is that for either inner satisfaction or a demonstration of the pro-social behavior with respect to environmental protection, wind farm developers who invest out of environmental concerns display stronger local bias: instead of surveying more sites to place their wind turbines they are prone to have them in their backyards or in local communities. This behavior can be interpreted as a particular way to signal one's "greenness" through producing their own electricity, a phenomenon we term "conspicuous generation". Previous papers have documented this kind of behavior looking at solar panel placement patterns across "green" and "brown" communities. (Bollinger and Gillingham (2012) (3)) I will focus more on the potential efficiency loss stemming from this "produce my own clean energy" behavior and explore further how the implementation of renewable energy policies might interact with these intrinsic motives and shifts the overall allocative efficiency level in particular ways.

In the following sections I document the following empirical findings:

(1) Wind farms in "greener" counties locate in less profitable places, are less responsive to local fundamentals and perform worse ex-post. The relationship between inferior wind farm performance and county level environmental attitude only exists for wind farms that are invested by local investors, but not those invested by national or international developers.

(2) Wind farms in "greener" counties are more likely to be invested by non-profit organizations, located in cities, and invested by local investors.

(3) Performance-based renewable energy policies improve the within-state allocation of wind farms, partly through attracting more wind investments to "brown counties".

5.1 "green" wind farm performance

Here I use the combined plant-level data to look for any significant disparities in ex-ante location choices and ex-post performances between wind farms located in "green" and "brown" counties. The baseline specification is:

$$y_{it} = \alpha * demrate_c + \beta_{state} + \gamma_t + \epsilon_{it} \tag{3}$$

The sample is the plant-level dataset with 774 plants (out of 821 in total) fully matched to the project level dataset. y_{it} are characteristics of wind power plant i that starts operating in year t, including capacity factor (productive efficiency), predicted profitability based on locational fundamentals, actual profit calculated using capacity factor and retail price, ownership type,

whether or not the investor is local and whether or not the plant is located in cities. I control for state and operation year fixed effects for the first three variables in linear regressions and only year fixed effects for the latter three in logit regressions. Standard errors are clustered at state level. $demrate_c$ is the votes share for the democratic party in 2012 presidential election.

The results are shown in the upper panel of Table 5. Column 1-3 indicate that wind farms located in greener counties are placed in worse location ex-ante and perform worse in terms of productivity and revenue ex-post. Column 4 shows that their investors are more likely to be non-profit, such as governments, public organizations (NGOs and universities), municipal and cooperative utilities, revealing significant differences in the nature of renewable investments across counties with different green preferences. Column 5 shows that wind power projects in greener counties are also more likely to be set up by local investors whose investments are limited within the state, contrary to international or national developers such as EDF Renewables or GE energy, who spread their projects in various states. Column 6 indicates that the wind farms from "greener" counties are more likely to be located in urban areas, defined by the US Census Bureau. Having wind farms in urban areas is usually thought as suboptimal because it means more obstruction to incoming winds, higher land price and more restrictions on production due to noises and other potential disturbance of wind turbine operation to human activities. Therefore it is likely that locating their wind farms closer to cities serves other purposes for green investors: they could be signaling their concerns for environmental protection to people who can easily see their wind turbines working; or as non-profit organizations they are less efficient in monitoring and maintaining wind farms due to the lack of specialized personnel, which forces them to have their properties closer to where they are.

Another plausible interpretation of the worse site choice and ex-post performances for wind farms located in greener counties is that these counties are more welcoming to renewables and set lower entry barriers for wind farm investors. I address this issue in the lower panel of table 5 by splitting the sample of wind farms into a local subsample that contains only wind farms whose investors only invest within-state and a non-local one. It is quite clearly that the worse ex-ante site choice and ex-post profitability of wind farms in greener counties are almost purely driven by those owned by local investors, which is contradictory to what we would expect if the lower entry barriers of wind farms to greener counties are the main story behind my findings.

To check this hypothesis from another perspective, I further look at the gridcell level data and see if the placement of wind farms are less responsive to local fundamentals in greener counties.

$$Capacity_{it} = \alpha * profitability_i + \beta * demrate_c + \gamma * profitability_i * demrate_c + \theta_s + \delta_t + controls_i + \epsilon_{it} \tag{4}$$

In the above specification, $Capacity_{it}$ is the wind capacity added to cell i in year t, $profitability_{it}$ is a measure of predicted profit of cell i; $demrate_c$ represents the green preferences of county c, measured as the votes share for democratic party in the 2012 presidential election of that county. γ shows how the responsiveness of wind power placement to profitability varies across "green" and "brown" counties. State and year fixed effects, as well as the interactions between profitability and polynomials of year trends are controlled.

Since my dependent variable is lower-bounded by zero, for robustness I try different estimation methods that pay extra attention to the zeros in the left-hand side variables. Due to the censorship nature of this problem, I employ panel data Tobit estimation for all the regressions involving gridcell-level data. I follow Honore (1992)'s(8) practice to consistently estimate the coefficients in a panel Tobit setting with fixed effects. Since the distribution of the wind capacity added to each gridcell per year is highly dispersed with a large proportion (99.99%) of it clustered at zero, for the sake of computational convenience, I assemble a new sample with information on all the cell with wind farm placement, as well as a 10% sample randomly drawn from the remaining cells, keeping the panel structure.

Table 5 shows that profitability indeed matters less for the decision choices of wind farms in greener counties, mostly because they are less prone to be placed in windier places. One standard deviation in the greenness measure makes the placement of wind farms 12% less responsive to the profitability of potential sites. The results hold with an alternative measure of environmental friendliness, such as votes share of the green party.

The above results not only show that wind farms located in greener counties perform worse, they also indicate that the deviation of wind farm placement from the optimum *within county* is larger for more environmentally friendly counties. So it is not just that greener counties set lower entry barriers for green energy investments, but their investors are actually worse in placing given the amount of wind capacities within counties. The fact that green investors in renewable energy make worse location decisions grant us with novel and interesting policy implications: to maximize the impact of subsidies on renewable in generating public benefits, policy makers should focus on bringing more "brown" but profit-maximizing investors into the market instead of encouraging green and utility-maximizing agents to produce more. In the next part, I evaluate the role of three different types of renewable energy policies in correcting or exacerbating this green-preferences-related suboptimal misallocation within-state.

5.2 Renewable policies and allocative efficiency

As has been shown in section 4, most of the observed efficiency loss due to suboptimal siting of wind farms can be accounted for by spatial misallocation within-state, or even within-county. In this part, I manage to check if renewable policies affect the within-state allocation of wind farms. It is worth noting that in theory, if all the existing wind power investments are outcomes of profit-maximization and the search cost for better sites is a fixed cost, then only price-based subsidies should be effective in improving within-state allocation since it increases the benefit of conducting a more thorough search. Even if that is the case, we should not expect any differences in the policy impacts between "green" and "brown" counties, under the assumption that the only differences between investors from "green" and "brown" counties lie in their entry standards. The other two types of policies should only change participation constraints and attract less profitable projects. The baseline specification is:

$$Capacity_{it} = \Sigma_p^3 \beta_p * policies_{pst} + \Sigma_p^3 \gamma_p * profitability_i * policies_{pst} + \theta_i + \delta_t + \epsilon_{it} \tag{5}$$

$Capacity_{it}$ stands for wind capacity added to gridcell i in year t, $profitability_i$ is the measure of the predicted distant-varying profit for a typical wind farm operating in gridcell i, $policies_{pst}$ is the intensity of policy p implemented in state s in year t, where p indicates which group (per-unit-price-based, direct subsidies, RPS) does the policy index belong to. Cell and year fixed effects are controlled and the standard errors are clustered at the state level. I am also controlling for the interactions between profitability and polynomials of year trend in case there is a year trend governing the response of wind power placement to profitability.

Coefficients on $policies_{pst}$ are the estimates of the treatment effects of renewable energy policies on wind capacity addition in a basic difference in differences setting. The identification assumption is that conditional on the gridcell-level predicted profitability, as well as cell and year, fixed effects, the growth in wind capacity addition should follow a parallel trend across different states in absence of any policies. These assumptions are challenged if there are active business groups pushing for certain policies and they are also investing more heavily in local renewable energy programs, which could well be true in reality. I try some other measures to sharpen my identification in my robustness checks. First, I restrict my sample to only cells around state borders only, where they are much more similar to each other apart from the timing and intensity of state-level renewable policies. However, there is still the concern that apart from the policies I am examining there might be other unobservable policies or change of rules implemented at the same time. So furthermore, I

restrict my sample to gridcells in states that have implemented at least one of the policies so their effects are identified through the variation of *when* the policies are implemented and how significant these policies are, instead of which states manage to implement policies. Finally, since the lobbying usually takes time and for most of the policies and there is usually a time gap between the enacting and implementation of policies, if the concern for avid green investors pushing policies is valid, we should be able to see the capacity addition diverges across treated and control states even before the implementation of policies. So as another robustness check, I look at the leads and lags of incentive changes to trace the dynamic impacts of policies before and after their actual implementation. There seem to be no discernible differences in pretrends across treated and control cells. The results on these extra specifications are reported in the appendix and the main results are largely robust.

The coefficients of the interaction terms, $profitability_i * policies_{st}$, measure how the implementation of policies changes the responsiveness of wind farm placement to profitability. Positive coefficients indicate that with renewable energy policies in place, the placement of wind farms follows local fundamentals better. Even if we believe that the identification of the treatment effects of policies on wind capacity addition is plagued with concerns about policy endogeneity and anticipation effects, it is hard to think about an alternative explanation on why should the *responsiveness* of wind farm placement to profitability would change hand in hand with renewable policies.

As shown in table 7, both RPS and price-based subsidies improve the within state allocative efficiency of wind power projects. The magnitude is quite large: one standard deviation increase in the intensity of RPS increases the responsiveness of wind placement decision to profitability by 42% and one SD increase in the intensity of price-based policies improves that by 57%. Direct subsidies that are not performance-based do not seem to change the within-state allocation of wind farms quite significantly after we control for the cross terms of profitability and year fixed effects. Results from Tobit estimation are shown in the last two columns and the signs and significance of coefficients largely hold.

Needless to say, the interpretation of our results on the estimated coefficient of responsiveness γ_p largely depends on the distribution of cells by their measured potential profitability in different states. Suppose the states that implement renewable energy policies have larger dispersion in the higher end of the wind resources distribution, then even if both treated and control states experience the same trend that moves the placement of wind farms up to more profitable gridcells by the same percentiles, our estimates will pick up some improvement in allocative efficiency attributable to policies. Therefore it is crucial to adopt an alternative specification that looks at the role of renewable policies in shifting the placement of wind farms within the distribution of gridcells by potential profitability in each state. This specifi-

cation will also help us to know if subsidies lift efficiency level through reducing the number of worst located projects or attracting the best ones.To implement the idea, I adopt the expected profitability distribution of the occupied cells for each state before any renewable subsidies are placed as a benchmark, divide all the cells into different groups according to their places in the benchmark and check the differential impacts of policies across different groups. Specifically, I divide the cells within each state into three groups: the ones above the 75th percentile of pre-subsidy occupied cells, the ones below the 25th percentile and the ones in between. A particular type of renewable policy that significantly improves the efficiency level of wind projects may work through either increasing the number of projects in the first group, decreasing the number of projects in the second group, or both. I interact the indicators for these three groups with the intensity measures of renewable energy policies $policies_{pst}$ to examine the impacts effects of different kinds of renewable policies on shifting the profitability distribution of occupied cells.

The results are shown in table 7. As can be seen, price-based performance subsidies are most effective in reducing the probability of bad project placement in cells with expected profitability lower than the 25th percentile of pre-subsidy occupied cells, while quantity-based renewable portfolio standard (RPS) appears to be both reducing the occurrence of bad project placement and adding capacities to the good cells at the same time, Consistent with our intuition, non-performance-based fixed subsidies have similar effects in adding wind capacities in cells across different profitability groups.

5.3 Renewable policies and green preferences

The significance and magnitude of the previous results on the impacts of renewable policies on within-state allocative efficiency present a stark contrast to what we should expect if the investors had been following constrained profit maximization in making location decisions before the policies are put in place. Combined with the evidence on the characteristics of wind power plants in environmentally friendly counties, it is reasonable to conjecture that the improvement of within-state allocation of wind farms could come from the fact that these policies manage to counteract some pre-existing distortions: the local bias of green investors in choosing project sites seems to be a salient and prominent one.

We have reasons to believe that extra financial benefits related to wind power investments might incentivize "green" and "brown" investors differentially. A quick look at the incentive scheme of our three groups of policies reveals that direct subsidies should be equally attractive to all kinds of investors while profit-maximizing investors prefer price-based subsidies since they are getting more with higher productive efficiency. Under RPS, all the utilities within

the implementing states are required to source a given proportion of its electricity sold from renewable sources. To comply with this requirement, utilities are either investing in their own wind farms or trying to encourage efficient and stable sources of supply from private investors. Given its mandate nature, a utility serving mainly "brown" counties with less pre-existing green investments is required to expand its renewable energy supply much more aggressively than their "green" counterparts. Also, extra capacities invested by utilities as a purpose to meet the mandate are more likely to follow where the wind is in order to maximize the amount of "dirty" electricity replaced.

Therefore, we expect RPS and price-based subsidies to be more effective in adding capacities in "brown" counties with better wind resources as they have been under-targeted by previous wind power investments driven by environmental concerns. To sum up, assuming the existence of green preferences, there are two sources of potential gains in within-state allocative efficiency thanks to renewable policies. First, performance-based financial incentives and possibly RPS increase the returns to better site choice and encourage project developers to invest more in searching for better sites. Second and more interestingly, there exists a relocation effect: these policies are shifting new wind capacities from green counties to brown counties, where renewable investments are more profit-oriented and follow fundamentals more strongly.

I check it with the following simple regression:

$$Capacity_{it} = \Sigma_p^3 \beta_p * policies_{pst} + \Sigma_p^3 \gamma_p * demrate_c * policies_{pst} + \theta_i + \delta_t + \epsilon_{it} \tag{6}$$

This regression is aimed at checking if certain renewable energy policies that are proven to be effectively improving the within-state allocation of wind farms also manage to shift new capacities from "greener" but less efficiently located places to "browner" and more profit-oriented ones. From table 9, we see that both RPS and price-based subsidies are adding more wind capacities to "browner" counties disproportionally. On the contrary, direct subsidies are adding disproportionally more wind capacities to more environmentally-friendly counties, most likely due to the fact that their non-performance-based nature ensures the same amount of payments to different kinds of projects, and green but less efficient investors are not punished by their worse performances. This could be one of the reasons why RPS and price-based subsidies work better in improving the within-state responsiveness of wind farm placement to profitability while fixed subsidies do not.

To account for the importance of this relocation effect in explaining the policy-induced improved within-state allocation, I adopt a slight variation of specification (6) by replacing the greenness index with a dummy that switches to 1 for counties above the 75th percentile

of the continuous greenness index. We find green counties under this metric to be 40% less responsive to profitability and RPS/price-based policies seem to be adding capacities to brown counties only. These results indicate that the pure relocation of new capacities to brown counties by RPS and price-based subsidies is going to increase the responsiveness of wind farm placement to profitability by 10% and is hence able to explain about 25%-30% of the improved responsiveness due to RPS and price-based policies.

Another way to check the differential effects of different policies in screening investors is to check how these three types of renewable incentives manage to add wind capacities by types of owners differently. Obviously, RPS should be more effective in attracting utility-invested wind capacities as it directly applies to utilities. Meanwhile, private, and potentially for-profit investment should respond more to price subsidies than fixed subsidies. I test these hypotheses in Table 10. It is clear that the results are largely consistent with the mechanism examined in this paper previously, with RPS adding more utility-invested wind capacity and price subsidies more effective in adding private capacity.

6 Model

In this section, I will present a very simple model on the private provision of public goods. A distinctive feature of this model is that providers in public goods differ in their environmental attitudes.Those with green preferences display local biases when choosing sites, which decreases their incentives to search. Performance-based subsidies not only increase the return to site searching but also relax the participation constraint of for-profit investors more. Therefore the efficiency gains act through both intensive and extensive margins.

6.1 Wind power production

In the model, I assume that the production of renewable energy is solely determined by the locational fundamentals $x_i \in (0, 1)$ of location i. To model the location choices of wind farm investors, I assume that an investor based at i can search for better sites by paying a search cost s. By searching, she moves closer to the best spot for wind power production. The profit function for her is thus defined as:

$$\pi_i = x_i + s(1 - x_i)^{1/2} - s^2 - F \tag{7}$$

where x_i represents the local fundamentals at the investor's original place, s is the search cost and F is other fixed costs in setting up a wind power plant.

For a pure profit-maximizing agent, $s^* = \frac{(1-x_i)^{1/2}}{2}$, indicating that conditional on participation, the wind power investors coming from places with worse fundamentals search more.

6.2 Green preferences

We then start with a simple model of utility over a numeraire private good, c and the pleasure derived from supplying public goods. We assume there are two dimensions of heterogeneity for investor i: her local fundamentals for wind power development $x_i \in (0, 1)$ and her environmental preference $b_i \in (0, \bar{b})$. The pleasure from supplying public goods is proportional to her environmental preference b_i. In the meantime, investors display local biases to varying extent. My previous empirical evidence reveals that wind projects are more likely to be locally invested in "greener" counties, suggesting that more environmentally friendly investors might display stronger local biases, due to either demonstration effects or the fact that green investors are worse at searching for an ideal site. In the model, I assume that the dis-utility from locating a project further away from the investor's original place is an increasing function of her green preference b_i and the difference between the local fundamentals of her original and final location.

The final utility function is defined as:

$$U_i = c_i - sb_i(1 - x_i)^{1/2} + b_i$$
$$s.t.\ c_i = \pi_i = x_i + s(1 - x_i)^{1/2} - s^2 - F$$

The electricity price is normalized as 1.

The public benefit generated from a wind project is the amount of greenhouse gas emission reduction, thus should be proportional to the total amount of electricity it produces, $x_i + s(1 - x_i)^{1/2}$.

The utility-maximizing search effort can be solved as $s^* = \frac{(1-b_i)(1-x_i)^{1/2}}{2}$, the utility derived from wind investment is therefore $U^* = x_i + \frac{(1-b_i)^2(1-x_i)}{4} + b_i - F$, and the public benefit generated is $e^* = x_i + \frac{(1-b_i)(1-x_i)}{2}$. It is easy to see that the optimal search effort is decreasing in b_i, a direct consequence from green investors reluctance to locate their wind farms away.

Without subsidies, only investors with $U^* > 0$ invest in wind projects. Given b_i, the cutoff in local fundamental x_i is $\bar{x} = \frac{4F-(b_i+1)^2}{2b_i-b_i^2+3}$, where only investors located in places with local fundamentals $x_i > \bar{x}$ choose to invest.

Lemma 1. When $b_i < 1$, $\bar{x}$ is decreasing in b, greener investors are more likely to invest

Proof: $\frac{\partial \bar{x}}{\partial b_i} < 0$ when $b_i < 1$.

6.3 Policy choices

In this section, I discuss how the introduction of different types of renewable subsidies affect investors' search efforts and the participation constraints for wind power development.

Here I focus on two types of renewable energy policies. Performance-based subsidy changes the electricity price received by investors to be $p > 1$. With performance-based subsidy, the expected profit for Direct subsidy takes f from the fixed cost F. Therefore, the profit function becomes $\pi_i = p * (x_i + s(1-x_i)^{1/2}) - s^2 - F$ under performance-based subsidy and $\pi_i = x_i + s(1-x_i)^{1/2} - s^2 - F + f$ under fixed subsidy.

Corollary 1. Performance-based policies increase search efforts for all the investors. The effects do not differ across investors with different environmental attitudes.

Proof $s^* = \frac{(p-b_i)(1-x_i)^{1/2}}{2}$, $\frac{\partial s^*}{\partial p} > 0$, $\frac{\partial s^*}{\partial b_i \partial p} = 0$

Proposition 1. For sufficiently small b_i and reasonable restrictions on value of parameters F and p, in response to performance-based subsidies, the cutoff in x_i drops more for smaller b_i, in other words, performance-based policy is going to add more wind capacity to areas with less environmental oriented investors.

Proof: $\bar{x} = \frac{4F-(b_i+p)^2}{4-(b_i-p)^2}$, $\frac{\partial \bar{x}}{\partial b_i \partial p} > 0$ if $F > 0, 1 < p < 2$ and $0 < b_i < 2.71$

Proposition 2. In response to direct subsidies, the cutoff in x_i drops by the same proportion for investors with different b_i, in other words, direct subsidies add same amount of capacity to areas with different environmental orientation, conditional on local fundamentals,

Proof: $\frac{\partial \bar{x}}{\partial b_i \partial f} = 0$

This simple stylized model could accommodate the following empirical findings I have documented in the previous sections. First, "greener" investors are less responsive to fundamentals because they search less. Second, "greener" investors are more likely to invest in renewables. Third, performance-based policies are going to improve the allocative efficiency through inducing more wind capacity added by less environmental-friendly but more profit-oriented investors.

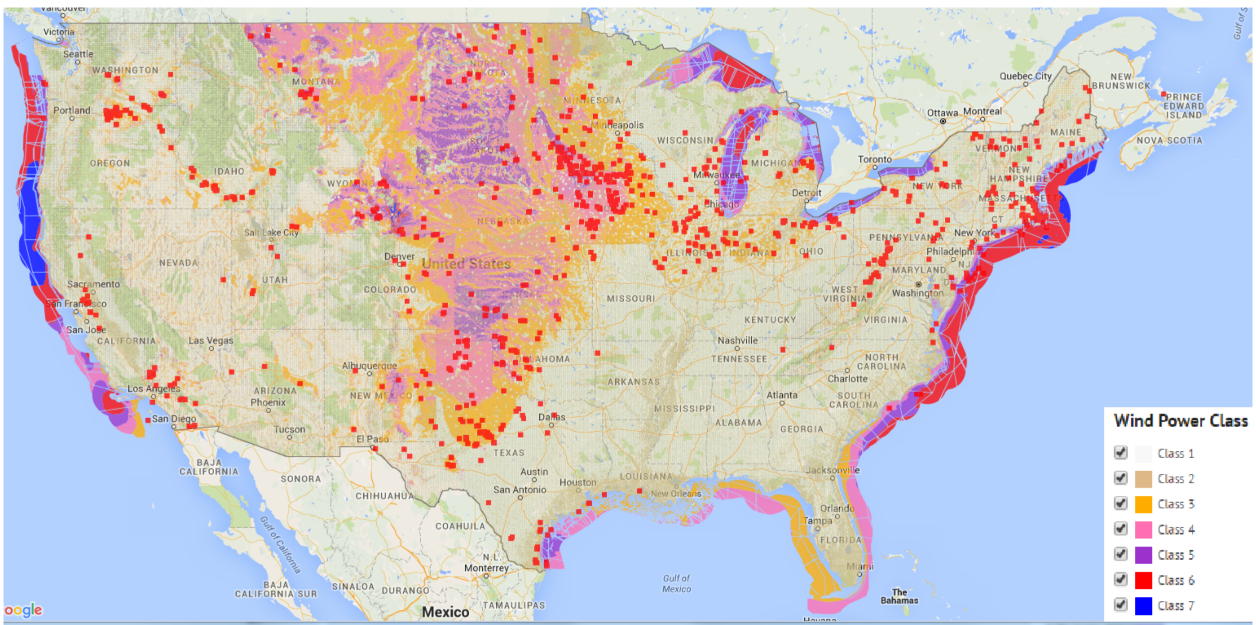
7 Concluding Remarks

This paper aims to make two primary contributions. First, I quantify the efficiency loss in the renewable energy sector due to spatial misallocation of wind farms and decompose it into a within-state and cross-state components. These measures are important for us to understand some special characteristics of this industry and to think about the potential

impacts of alternative policies on the overall efficiency of it. Second, I manage to link a significant proportion of the observed within-state distortion to green investors' "conspicuous generation" behavior, namely placing their wind turbines close to where they are instead of locating them in places that make more economic sense. I then come forward to evaluate the role of certain renewable energy policies in partially offsetting the efficiency loss in this way. In short, apart from the heterogeneity in the physical cost of producing GHG free energy, heterogeneity in people's green preferences is also quite important in determining the public benefits of renewable energy investments. Therefore policy makers should bear in mind the screening effects of policies on investors' non-pecuniary incentives in making a comparison across different types of incentive schemes that are equivalent in other dimensions. In light of this, to encourage people's involvement in supporting renewable energy, extra efforts should be made to create and promote a market for green electricity where people concerned with environmental protection can buy renewable electricity at a premium and possible awarded in a visible way, instead of encouraging individual households to generate their own clean electricity. Advocates of gird-free distributed energy generation and "home-energy independence" should not only look at the positive side of distributed generation on grid stability but also pay more attention to the potential gains from trade and economics of scale abandoned in this movement towards energy self-efficiency.

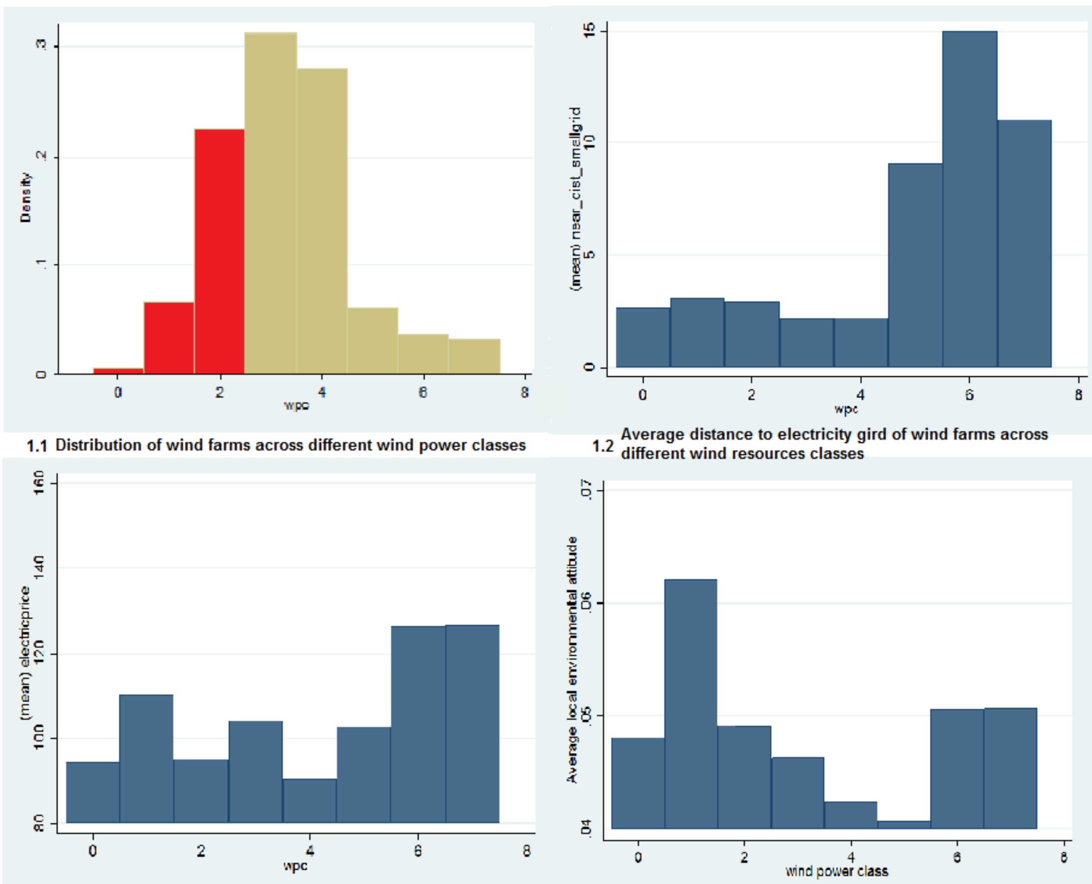
My next step is to quantify the effectiveness of different types of policies in (1) Adding renewable capacity; (2) Improving the efficiency of renewable investment; with the existence of large heterogeneity in green preferences across investors in a more structural way. Given the importance and observability of fundamentals in renewable energy sector, it would be interesting to know how much information on the profitability of typical projects in different locations would policy makers be able to incorporate into the amount of subsidies awarded.

Figure 1: Wind resources and wind farm distribution



Notes: Each red dot represents a wind farm. WPC (wind power class) is a categorical measure of wind resources on a 1-7 scale, 7 being the strongest. Each wind power class is represented by a color, as shown in the legend. Data visualization courtesy of The Wind Prospector - NREL.

Figure 2: Distribution of wind farms across different wind power classes



1.1 Distribution of wind farms across different wind power classes

1.2 Average distance to electricity gird of wind farms across different wind resources classes

1.3 Average electricity prices of wind farms across different wind resources classes

1.4 Average local environmental attitude of the county where the wind farms locate across different wind resources classes

Notes: WPC (wind power class) is a categorical measure of wind resources on a 1-7 scale, 7 being the strongest. Figure 1.1 plots the density of wind farms across WPC. Figure 1.2 and 1.3 shows the average distance to the electricity grid and the average local retail electricity prices of wind farms across different WPC, respectively. Figure 1.4 plots the average local environmental attitude of the county where the wind farms locate across different WPC classes.

Table 1: Correlation across different measure of wind farm profitability

NREL Western Wind Dataset Sample

	Measure 1	Measure 2	Measure 3	Measure 4
# of gridcells	4661	4661	75147	75147
Correlation	Measure 1	Measure 2	Measure 3	Measure 4
Measure 1	1.0000			
Measure 2	0.8519	1.0000		
Measure 3	0.6558	0.3671	1.0000	
Measure 4	0.3814	0.4856	0.6662	1.0000

NREL Eastern Wind Dataset Sample

	Measure 1	Measure 2	Measure 3	Measure 4
# of gridcells	2003	2003	75147	75147
Correlation	Measure 1	Measure 2	Measure 3	Measure 4
Measure 1	1			
Measure 2	0.601	1		
Measure 3	0.6091	0.1176	1	
Measure 4	0.2598	0.1594	0.7979	1

Notes: I report the correlation of four different wind power profitability measures. Measure 1 is the baseline measure that combines predicted production based on wind speed data with retail electricity price. Measure 2 is generated with predicted production based on wind speed data with Bloomberg wholesale price data. Measure 3 and 4 takes account of the variation in wind power production. Measure 3 is generated using Eastern/Western Wind datasets wind power simulated production data and Bloomberg wholesale price data. Measure 4 uses Eastern/Western Wind datasets wind power simulated production data and average retail electricity data, under the assumption that offpeak electricity price is 0.63 of peak electricity price. As the methodology in simulating wind power production is different for the Eastern and Western wind datasets, I split the sample into two (Eastern and Western US) and report the correlation separately for them.

Table 2: Alternative measures of aggregate spatial misallocation

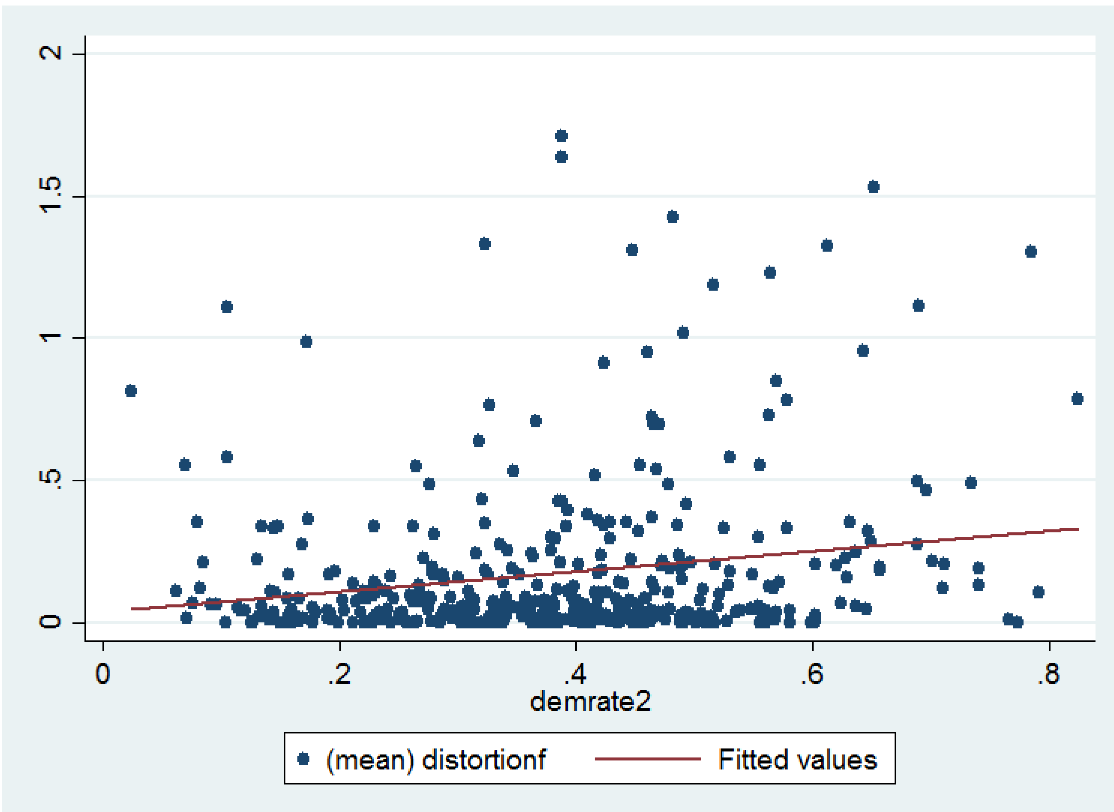
Specification	Sample	Measure
NREL wind power class data & retail electricity price (baseline)	Full sample	0.4719
NREL wind power class data & wholesale electricity price	Full sample	0.4366
NREL Eastern/Western datasets & retail electricity price	Eastern sample	0.1846
NREL Eastern/Western datasets & retail electricity price	Western sample	0.3761
NREL Eastern/Western datasets & wholesale electricity price	Eastern sample	0.1177
NREL Eastern/Western datasets & wholesale electricity price	Western sample	0.2376

Table 3: Within-state locational misallocation

State	Measure 1	Measure 2	Measure 3	Measure 4
IA	0.140439	0.199903	0.049872	0.072414
IN	0.143414	0.14436	0.236253	0.2098
IL	0.148962	0.291946	0.074424	0.168646
WV	0.209326	0.173536	0.059405	0.003158
ND	0.221021	0.189135	0.073325	0.071608
WA	0.23381	0.135259	0.121944	0.129677
CO	0.256589	0.19782	0.252514	0.256425
NH	0.281912	0.308476	0.098451	0.128257
ID	0.305632	0.31702	0.158998	0.150273
VT	0.316129	0.332688	0.089663	0.113455
OR	0.321848	0.289195	0.316987	0.337921
KS	0.363492	0.145481	0.164593	0.17919
OH	0.385767	0.41451	0.410419	0.72385
NE	0.404587	0.177351	0.143211	0.237728
OK	0.416231	0.155157	0.167612	0.056249
NC	0.433151	0.799545	0.175103	0.15487
CA	0.460538	0.701351	0.289593	0.280029
MN	0.485057	0.23437	0.339635	0.206461
MD	0.565588	0.520721	0.213071	0.259811
MO	0.577686	0.405438	0.192134	0.183553
MT	0.633305	0.259725	0.377029	0.375105
SD	0.407496	0.219858	0.297603	0.414985
TX	0.373097	0.345533	0.149471	0.152742
WY	0.392716	0.367695	0.339811	0.338902
NM	0.822967	0.281664	0.425106	0.274453
PA	0.892974	0.959326	0.281608	0.182485
MI	0.908642	0.639816	0.210498	0.145349
WI	0.95731	1.229424	0.210885	0.505282
ME	1.194982	1.283586	0.30433	0.652842
NY	1.218893	1.353304	0.307033	0.18198
US	.37402001	.3447733	.1855745	.1846892

Notes: Distortion is the measure of within-state distortion in wind farm placement calculated from (2). Four different measures of distortion are reported. The first is the baseline measure that combines predicted production based on wind speed data with retail electricity price. The second one is generated with predicted production based on wind speed data with Bloomberg wholesale price data. The third one and fourth take account of the variation in wind power production. The third one is generated using Eastern/Western Wind datasets wind power simulated production data and Bloomberg wholesale price data. The fourth one uses Eastern/Western Wind datasets wind power simulated production data and average retail electricity data, under the assumption that offpeak electricity price is 0.63 of peak electricity price. For the whole US, the distortion measure is a weighted average of within-state distortion by total capacity.

Figure 3: Within-county distortion and county level green preferences



Notes: The construction of within-county measure of locational distortion in wind farm placement is described in section 4. Demrate is the votes share for democratic party in the 2012 presidential election of that county. The slope of fitted line is 0.35 (standard error 0.088).

Table 4: Within county distortion and county characteristics

VARIABLES	distortion	distortion	distortion	distortion
demrate	1.185*	1.024**		
	(0.694)	(0.518)		
greenrate			59.70	90.29**
			(57.29)	(45.46)
SD(profitability)	0.00590	-0.00501	0.0144	0.000617
	(0.0262)	(0.0348)	(0.0284)	(0.0371)
Mean(profitability)	0.0115	0.0241**	0.0117	0.0264**
	(0.0118)	(0.0106)	(0.0123)	(0.0115)
No. of wind farms in county	-0.0239	-0.0118	-0.0262	-0.0150
	(0.0245)	(0.0257)	(0.0245)	(0.0257)
% of non-suitable cells	-0.779***	-0.756***	-0.798***	-0.697***
	(0.279)	(0.222)	(0.298)	(0.249)
Median household income	9.11e-05	0.000104**	7.35e-05	8.97e-05
	(6.97e-05)	(5.24e-05)	(7.34e-05)	(5.85e-05)
Building permits	-0.000162	-0.000451*	-0.000158	-0.000490*
	(0.000122)	(0.000271)	(0.000124)	(0.000269)
Retail sales pc	-1.01e-05	1.31e-05	-6.78e-06	1.60e-05
	(1.08e-05)	(1.70e-05)	(1.09e-05)	(1.75e-05)
% of college graduates	0.0393**	0.0120	0.0364*	0.0110
	(0.0196)	(0.0192)	(0.0196)	(0.0191)
% of high school graduates	-0.0234	-0.00878	-0.0101	-0.00358
	(0.0265)	(0.0211)	(0.0236)	(0.0201)
% female	0.00829	-0.0298	0.00872	-0.0309
	(0.0295)	(0.0346)	(0.0295)	(0.0349)
% while alone	0.0259	0.0112	0.0277	0.0106
	(0.0295)	(0.0312)	(0.0291)	(0.0307)
% African alone	-0.0117	-0.0368	-0.00742	-0.0406
	(0.0406)	(0.0464)	(0.0404)	(0.0469)
% Asian alone	0.0168	0.00311	0.0235	0.00584
	(0.0309)	(0.0331)	(0.0302)	(0.0328)
Mean travel time to work	0.00838	0.0109	0.00774	0.0103
	(0.0185)	(0.0205)	(0.0187)	(0.0206)
Housing units	1.02e-06	4.45e-06	1.27e-06	4.31e-06
	(2.12e-06)	(4.64e-06)	(2.17e-06)	(4.70e-06)
Homeownership rate	0.0167	0.00144	0.0142	-0.00203
	(0.0163)	(0.0110)	(0.0162)	(0.0114)
Median housing value	5.63e-07	-9.52e-07	6.99e-07	-9.24e-07
	(1.26e-06)	(2.93e-06)	(1.26e-06)	(2.97e-06)
No. of firms	-2.04e-06	-7.70e-06	-2.92e-06	-5.99e-06
	(7.75e-06)	(1.75e-05)	(7.93e-06)	(1.75e-05)
Observations	398	262	398	262
R-squared	0.075	0.082	0.068	0.080

Notes: Distortion is the normalized measure of deviation from the optimal level at the county level, defined as the ratio between the percentage gain in average profitability should current projects be placed at the best positions and the percentage gain from a random allocation to the optimal allocation. Robust clustered standard error at the state level. I exclude the counties that have only one gridcell occupied from the sample and report the regression results in column 2 and 4.

Table 5: Characteristics and performances of wind farms in Counties with different level of greenness

Method	Linear regression			Logit		
VARIABLES	CF	wpc	Revenue	1(nonprofit)	1(local)	1(urban)
Demrate	-0.049**	-1.516**	-1.290*	1.483*	1.385*	1.974**
	(0.023)	(0.667)	(0.732)	(0.806)	(0.720)	(0.957)
Observations	756	760	756	774	774	774
R-squared	0.433	0.509	0.368	0.0123	0.00981	0.0159
STATE FE	YES	YES	YES	NO	NO	NO
YEAR FE	YES	YES	YES	YES	YES	YES

Sample	Non-local			Local		
Method	Linear regression					
VARIABLES	CF	wpc	nonprofit	CF	wpc	nonprofit
Demrate	-0.0071	-0.918	-0.008	-0.144*	-2.771**	0.246*
	(0.034)	(0.744)	(0.005)	(0.071)	(1.0681)	(0.122)
Observations	414	417	418	354	355	355
R-squared	0.473	0.561	0.027	0.445	0.61	0.207
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: In the upper panel, the sample is a matched wind power plants data. Column 1-3 show results for linear regressions with state and operating year fixed effects. CF is the capacity factor of the power plant (total electricity produced/maximum electricity production at full capacity). WPC stands for the wind resource category measure of where the plant is. Revenue is the product of the capacity factor and wholesale electricity price (deducting transmission loss). Column 4-6 are logit regressions where the dependent variable is a dummy on whether or not the power plant is invested by non-profit investors, by local investors and located in urban areas. In the lower panel, I split the full sample into a local and a non-local subsamples. The local subsample includes only wind farms whose investors only invest within the state. The non-local one contains the wind farms whose investors have wind power projects in more than one state. Robust clustered standard error at the state level. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 6: Responsiveness to fundamentals of wind farms with different level of greenness: linear regressions

Variables	capacity	capacity	capacity	capacity	capacity	capacity
wind speed	0.000240***	0.000245***	4.62E-05	7.66E-05		
	(8.60E-05)	(8.60E-05)	(7.30E-05)	(6.92E-05)		
distgrid	-2.27e-06*	-2.46e-06*	-2.02e-06**	-2.19e-06**		
	(1.22E-06)	(1.30E-06)	(8.75E-07)	(9.69E-07)		
urban			0.00015	-3.37E-05		
			(0.00012)	(0.00013)		
profitability					0.000043***	0.000041***
					(8.14e-06)	(6.80e-06)
wind speed*greenrate	-0.0135***		-0.0109***			
	(0.00386)		(0.00343)			
distgrid*greenrate	0.000737***		0.000327			
	(0.00025)		(0.00024)			
urban*greenrate			0.0209*			
			(0.0128)			
profitability*greenrate					-0.00183**	
					(0.000798)	
wind speed*demrate		-0.000143*		-0.000103**		
		(8.20E-05)		(4.44E-05)		
distgrid*demrate		1.58E-05		1.24E-06		
		(1.80E-05)		(9.84E-06)		
urban*demrate				0.000314*		
				(0.00022)		
profitability*demrate						-0.000016*
						(9.30e-06)
Observations	1,421,225	1,421,225	2,464,110	2,464,110	1,421,225	1,421,225
R-squared	0.002	0.002	0.001	0.001	0.002	0.002
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Sample is gridcell level panel data. The dependent variable is the amount of wind capacity installed per km^2 to a gridcell in a year. Wind speed is the average wind speed of the gridcell calculated according to NREL wind resrouces categorization. distgrid is the distance from the gridcell to the closest main electricity grid (in km). Profitability is the distance-varying profit measure of the gridcell. Urban is a dummy on whether or not the gridcell is inside urban areas. The first two and last two columns report results on a sample leaving out the cells that are considered to be not suitable for wind power development, while results on the middle two columns are estimated on the full sample. State and year fixed effects, as well as state-specific year trends are controlled. Robust clustered standard error at the state level. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 7: Renewable policies and within-state allocation: profitability measure

VARIABLES	Linear capacity	Linear 1(plant)	Tobit capacity	Logit 1(plant)
profitability	2.09e-05***	4.95e-05***	0.0702***	0.0343***
	(5.32E-06)	(7.54E-06)	(0.0160)	(0.0133)
RPS	-0.0306**	-0.0778***	-10.07	-3.238
	(0.012)	(0.0267)	(8.909)	(3.065)
fixsubsidy	-0.00235	-0.00678	2.215	0.797
	(0.00664)	(0.0237)	(2.473)	(1.075)
pricesub	-0.0251	-0.0553	-38.85***	-14.44***
	(0.0153)	(0.0354)	(13.88)	(4.839)
profitability*rps	0.00294***	0.00732***	0.649***	0.202***
	(0.0008)	(0.00186)	(0.221)	(0.0749)
profitability*fixsub	0.000735*	0.00304*	-0.0954	-0.0198
	(0.00038)	(0.00129)	(0.132)	(0.0564)
profitability*pricesub	0.00463**	0.00908*	2.419***	1.045***
	(0.00183)	(0.00472)	(0.695)	(0.283)
Observations	2,464,143	2,464,143	254,331	254,331
State FE	NO	NO	YES	YES
Gridcell FE	YES	YES	NO	NO
Year FE	YES	YES	YES	YES
R-squared	0.002	0.004	0.012	0.015

Notes:Sample is gridcell level panel data. Dependent variables in column (1) and (3) are the amount of wind capacity installed per km^2 to a gridcell in a year. Dependent variables in column (2) and (4) are dummies on whether or not a wind power plant is built at a gridcell in a year. RPS is the real stringency of Renewable Portfolio Standard for implementing states, defined in section 3.3. Pricesub is the amount of subsidy given to per unit electricity generation. Fixsub is the proportion of total upfront cost reduced by subsidies. Robust clustered standard error at the state level. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 8: Renewable policies and within-state allocation: Change in wind farm profitability distribution

VARIABLES	Linear capacity	Linear 1(plant)	Tobit capacity	Logit 1(plant)
1(above 75th pct)*pricesub	0.0147	0.0078	6.891	11.9
	(0.00201)	(0.00428)	(4.84)	(7.98)
1(75th-25th pct)*pricesub	0.0249**	0.0493***	1.419	-2.092
	(0.0117)	(0.0123)	(3.193)	(7.993)
1(below 25th pct)*pricesub	-0.00303***	-0.00740**	-3.916	-14.62
	(0.00087)	(0.00323)	(4.476)	(13.7)
1(above 75th pct)*fixsub	0.00936	0.0368	1.257	2.665
	(0.0178)	(0.0511)	(0.917)	(1.962)
1(75th-25th pct)*fixsub	0.0151	0.0127	0.293	0.897
	(0.0126)	(0.0527)	(0.304)	(0.752)
1(below 25th pct)*fixsub	0.00152	0.0186	1.426	3.279
	(0.00327)	(0.0137)	(0.962)	(2.011)
1(above 75th pct)*RPS	0.0347***	0.110***	3.555*	9.559*
	(0.0121)	(0.031)	(1.902)	(5.196)
1(75th-25th pct)*RPS	0.0153	0.032	0.562	1.453
	(0.0126)	(0.0271)	(2.387)	(6.05)
1(below 25th pct)*RPS	-0.00739***	-0.0131***	-3.19	-5.714
	(0.00174)	(0.00429)	(2.939)	(7.976)
Observations	1,937,364	1,937,364	224,532	210,924
State FE	NO	NO	YES	YES
Gridcell FE	YES	YES	NO	NO
Year FE	YES	YES	YES	YES
R-squared	0.002	0.004	0.012	0.015

Notes:Sample is gridcell level panel data. Dependent variables in column (1) and (3) are the amount of wind capacity installed per km^2 to a gridcell in a year. Dependent variables in column (2) and (4) are dummies on whether or not a wind power plant is built at a gridcell in a year. 1(above 75th pct) is a dummy that switches to one if expected profitability of the cell is higher than the 75th percentile of existing wind projects within the state before any renewable subsidies are applied. 1((75th-25th pct) is the indicator of whether or not the profitability of the cell falls into the 75th and 25th percentile of existing wind projects within the state before any renewable subsidies are applied, while 1(below 25th pct) indicates whether or not the profitability of cell is lower than the 25th percentile of existing pre-subsidy wind projects. RPS is the real stringency of Renewable Portfolio Standard for implementing states, defined in section 3.3. Pricesub is the amount of subsidy given to per unit electricity generation. Fixsub is the proportion of total upfront cost reduced by subsidies. Robust clustered standard error at the state level. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 9: Differential Impacts of Policies on wind capacity across “green” and “brown” counties

VARIABLES	Linear capacity	Linear capacity	Tobit capacity	Logit capacity
RPS	0.014	0.00202*	2.281	1.573
	(0.0168)	(0.0167)	(3.828)	(3.981)
pricesub	0.0241*	0.0153**	0.103	-3.721
	(0.0131)	(0.0073)	(7.409)	(6.054)
fixsubsidy	-0.0175**	-0.0009	-1.604**	-1.543
	(0.00628)	(0.00406)	(0.784)	(0.839)
greenrate*RPS	-0.388		-45.994	
	(0.284)		(66.886)	
greenrate*pricesub	-1.885**		-10.516	
	(0.329)		(153.610)	
greenrate*fixsub	1.732		47.015***	
	(1.118)		(14.999)	
demrate*RPS		-0.0248		-2.861
		(0.0294)		(7.304)
demrate*pricesub		-0.0397**		-7.302
		(0.0198)		(11.025)
demrate*fixsub		0.0542***		4.556***
		(0.0165)		(1.266)
Observations	2,464,110	2,464,110	284658	284658
R-squared	0.002	0.002	0.14	0.14
State FE	NO	NO	YES	YES
Gridcell FE	YES	YES	NO	NO
Year FE	YES	YES	YES	YES

Notes:Sample is gridcell level panel data. The dependent variable is the amount of wind capacity installed per km^2 to a gridcell in a year. The first two columns report results from linear regression in the full grid-cell sample and the last two columns report results from Tobit estimation in a sample with all the built-up cells and 10% of the other cells. Demrate and greenrate are the democratic and green party votes share in 2012 presidential election of the county. RPS is the increment in RPS requirement for implementing states. Pricesub is the amount of subsidy given to per unit electricity generation. Fixsub is the proportion of total upfront cost reduced by subsidies. Robust clustered standard error at the state level. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 10: Differential impacts of policies on wind different types of investments

VARIABLES	Utility capacity(MW)	Nonprofit capacity(MW)	Private capacity(MW)	1(Utility)	1(Nonprofit)	1(Private)
RPS	0.00295*	-0.000059	0.010546	0.00184	0.000134	0.018026
	(0.00178)	(0.000078)	(0.007972)	(0.00126)	(0.00034)	(0.01532)
pricesub	0.00254	0.000081	0.008287	0.0016	0.000303	0.023791***
	(0.0029)	(0.000145)	(0.006103)	(0.00179)	(0.000434)	(0.011433)
fixsub	0.00026	0.000089	0.004007***	0.0004	0.000123	0.012869***
	(0.00065)	(0.000021)	(0.001464)	(0.00067)	(0.000159)	(0.004166)
Obs	142,3073	142,3073	142,3073	142,3073	142,3073	142,3073
Gridcell FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
R-squared	0.0002	0.0001	0.0013	0.0002	0.0001	0.0026

Notes: Sample is gridcell level panel data. Gridcells that are considered not suitable for wind power development are dropped The dependent variables of the first three columns are the amount of wind capacity installed per km^2 by utilities, nonprofit investors and private profit-oriented investors to a gridcell in a year. The dependent variables of the last three columns are whether or not a gridcell has wind power capacity installed by utilities, nonprofit investors, and private profit-oriented investors. RPS is the increment in RPS requirement for implementing states. Pricesub is the amount of subsidy given to per unit electricity generation. Fixsub is the proportion of total upfront cost reduced by subsidies. Robust clustered standard error at the state level. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

A Robustness

A.1 Dynamic impacts of renewable subsidies

As mentioned in section 5.2, as an extra robustness check, I manage to trace the dynamic impacts of renewable policies before and after their actual implementation, based on the idea that if these policies are seriously endogenous, their "treatment effects" might show up even before the actual implementation of them. In practice, I adopt the following specification:

$$Capacity_{it} = \alpha_i + \beta_t + \sum_{m=1}^{3} \gamma_{mp} * \Delta policies_{p,s,t-m} + \sum_{n=0}^{2} \gamma_{np} \Delta policies_{p,s,t-m} + Controls_{it} + \epsilon_{it} \quad (8)$$

where $\Delta policies_{p,s,t}$ is the increment in the intensity of policy p implemented in state s in year t, while $\Delta policies_{p,s,t-m}$ and $\Delta policies_{p,s,t+n}$ are the m-th lead and n-th lag of the variable. The estimated coefficients are reported in Figure A1. I interact $\Delta policies_{p,s,t-m}$ and $\Delta policies_{p,s,t+n}$ with cell-level profitability to check if the changes in responsiveness to profitability also go hand in hand with the actual implementation of policies.The exact specification is:

$$Capacity_{it} = \alpha_i + \beta_t + \sum_{m=1}^{3} \gamma_{mp} * \Delta policies_{p,s,t-m} + \sum_{n=0}^{2} \gamma_{np} \Delta policies_{p,s,t-m} + \sum_{m=1}^{3} \zeta_{mp} * \Delta policies_{p,s,t-m} * profitability_i + \sum_{n=0}^{2} \zeta_{np} \Delta policies_{p,s,t-m} * profitability_i + Controls_{it} + \epsilon_{it} \quad (9)$$

Similarly, I interact them with support for the democratic party at county level following specification (6) to see if different kinds of policies add capacities to counties with different environmental attitude. The coefficients on the interaction terms, as well as their 95% confidence intervals, are shown in Figure A2 and A3.

A.2 Responses of other projects attributes to renewable policies

Another related question is whether of not the observed response of location choices of wind farms to changes in renewable policies is just a proxy of other responses. The investment of a wind farm involves a series of joint decisions, including the choices of project size, turbine type, and location. These choices depend on each other in different ways. For instance, a fixed non-performance-based subsidy might help the project with upfront costs, inducing

the investor to pursue larger projects and more advanced turbine types. In the meantime, large projects have a higher land requirement, resulting in different location choices that might be more or less efficient depending on the context. Although these explanations will not invalidate my main story directly, as they are also examples of the selection effects of financial incentives. It would be interesting to check if other attributes of the wind projects other than location also respond to renewable energy subsidies, and if so, to which direction.

In this section, I look at two other project attributes: the size of the project, measured in total capacity installed, and the characteristics of the turbines, measured by turbine height and blade length. It is generally believed that higher turbine and longer blade makes use of wind resources more efficiently. [12] I check how they correlate with the local fundamentals and respond to renewable subsidies.

Table A2 shows the results. The upper panel reports the regression results on the relationship between various project characteristics and local wind resources, and the lower panel reports results on how these characteristics respond to state renewable energy policies and differ across counties with different environmental attitudes. The analysis on project size is carried out with plant level data and that on turbine height and blade size uses turbine level data. It is clear from the upper panel that there's no strong correlation between all these three project attributes to local wind conditions, suggesting that location decision is probably made relatively independent from project size and turbine type choices, or at least the latter decisions does not seem to push the relevant project to a place with definite better or worse wind conditions. It is also not the case that less than desirable location choices are compensated by more powerful wind turbines.

Results reported from the lower panel of Table A2 suggest that the introduction of price-based subsidies and RPS do not lead to significant changes in project size and the quality of wind turbines. However, larger non-performance-based fixed subsidies do seem to encourage larger projects. A possible explanation is that larger fixed subsidies paid out upfront help the wind power investors overcome financial constraints that prevent them from building larger wind farms. The right three columns show the relationship between wind farm characteristics and local environmental attitudes and there is no significant correlation between green preferences and the wind arm attributes that we are interested in.

Therefore one conclusion we can draw from the previous analysis is that the robust relationship between renewable energy policies and improved efficiency of wind farms documented in the paper is most likely capturing the direct responses of wind farm site choices

[12] `http://www.siemens.com/innovation/en/home/pictures-of-the-future/energy-and-efficiency/sustainable-power-generation-windpower-hexcrete-tower.html`; `http://cleantechnica.com/2015/03/23/us-energy-dept-prowl-bigger-longer-wind-turbine-blades/`

to financial incentives instead of proxies of other responses regarding other aspects of the wind farm projects.

B Other evidence

B.1 Time-series evidence from federal level tax credit expiration and extension

This paper tells a story of financial incentives improving renewable energy projects allocation efficiency through crowding out non-pecuniary preferences. In the previous sessions, I exploit the variation in renewable subsidies at the state-year level to examine how financial incentives might correct inefficiency in wind power placement across the continental US. Albeit being a nice variation, some may argue that state-level incentives are not the most important subsidies to be considered in wind power investors' decisions, with the existence of federal level renewable electricity production tax credit (PTC) and investment tax credit (ITC). Therefore for the sake of external validity, it makes sense to look at how the efficiency of wind projects correlates with other important financial incentives in renewable energy development, most notably federal level subsidies. Although there is no variation in these subsidies across states and the subsidy size is stable across years, in some particular years these subsidies expired until the congress passed a new tax extenders bill to reinstate them, creating substantial policy uncertainty and usually large slumps in the wind capacity installed in those years. The upper left graph of Figure A4 plots the amount of new wind power capacity installed per year from 1999 to 2013 and it is clear that there are large drops in new wind capacity in the years with PTC and ITC expiration and extension.

It is, therefore, interesting to look deeper at how the changes in wind power allocative efficiency might react to the expiration/extension of federal tax credits. If the main mechanisms in my paper still work here, we should observe drops in the efficiency of wind farms around the tax credits expiration and extension years, accompanying the drops in the total amount of capacity installed, as one would expect the investors who still go ahead with their wind projects under these circumstances are more driven by strong green preferences and might even sacrifice profits for them, in a way consistent with the evidence in the main text exploiting state-level policy variation.

Figure A4 plots the changes in different measures of wind farm efficiency, including local wind power class, predicted profitability and actual measured profitability based on production efficiency and electricity prices of wind farms across years when they start operating. Years with PTC/ITC expiration and extension are specially marked by arrows. It is shown

that for most of the years with PTC/ITC expiration and extension there are dips in both average wind conditions, predicted profitability and actual profitability for the wind farms installed in those years.

B.2 Evidence from California Solar Initiative

In the previous sections, I explore how environmental attitude affects the efficiency of wind farm distribution and the role of subsidies in changing allocative efficiency. In short, wind farms invested by environmentally-inspired investors tend to be worse located and under perform as a result, while monetary incentives, especially the performance-based ones, improves the efficiency of wind farms by attracting more for-profit investors.

In this section, I explore the mechanism in a different context: solar panel installation in California under California Solar Initiative(CSI). A nice feature of this project is the plausibly exogenous variation in the amount and type of subsidies across utility administrative borders and time, allowing me to causally evaluate the responses of project quality to the amount and type of subsidies, as well as the differential responses across zipcodes with different environmental attitude.

B.2.1 Institutional Background

In January 2006, the California Public Utilities Commission (CPUC) established the California Solar Initiative (CSI), a program with a total budget of $2.167 billion between 2007 and 2016 and a goal to install approximately 1,940 MW of new solar generation capacity[13].

As shown in Figure A1, the CSI has a separate step schedule for each of the three major investor-owned utilities in California: Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E). The rebates automatically decline in "steps" based on the volume of solar megawatts (MWs) with confirmed project reservations within each utility service territory. This program design creates a certain degree of randomness in the amount of incentives available for individual investors within a short period of time. The design of this step rebate plan is illustrated in Figure 1A.

CSI offers two tracks of incentive schemes that the applicants can choose from: an Expected Performance Based Buydown (EPBB) track where the applicant receives the entire incentive payment at the time the system is installed according to a formula that determines the expected performance of the system, and a Performance Based Incentive (PBI) track, where the applicant receives a payment based on the actual metered output of the system every month over a period of five years. Systems over 30 KV are required to join PBI so I

[13] `http://www.gosolarcalifornia.org/about/csi.php`

focus on smaller systems only. Although the amounts of EPBB and PBI incentives change together when a utility moves into a new step, the ratio between EPBB and PBI differs across steps. For instance, as shown in Figure 1A, the ratio of PBI subsidy (cents/kWh) and EPBB subsidy (dollars/Watt) jumps from 0.12 to 0.15 moving from step 9 to step 10. Therefore, moving across steps, we not only obtain exogenous variation in the size of subsidies, but also the extent to which the incentive bundle encourages investors to go on the performance track.

B.2.2 Data and Specification

The project level data include the zipcode of the customer, utility, size of the installation and incentive step, PV installer and manufacturer, the design factor of the program that used to evaluate its performance ex-ante, the date when the customer reserved solar incentives for an installation, the date payment was submitted for the installation, and the date of completion.

I attempt to test two main hypotheses using CSI data. First, I check if solar panels installed in more environmentally friendly communities make less economic sense, just like wind farms in "greener" counties. Second, I evaluate how the efficiency and installation cost of projects respond to changes in the incentives and how the responses differ across "green" and "brown" zipcodes. The empirical specification for the first test is:

$$y_i = \alpha * demrate_{zip} + \beta_{county} + \eta_{month} + \epsilon_i \tag{10}$$

where y_i represents several efficiency measures of solar project i, including design factor, a measure used to determine the amount of EPBB rebate, log average installation cost per KV, and the capacity factor for PBI projects that measures actual productive efficiency. $demrate_{zip}$ is the zip level votes share for the democratic party at 2012 presidential election. County and monthly fixed effects, as well as a variety of other zip code level demographic and socioeconomic characteristics, are controlled. Throughout my analysis, I also use the support for the green party as an alternative measure of environmental friendliness.

The empirical specification for the second test is:

$$\begin{aligned} y_i =& \alpha * PBI/EPBBratio + \beta * PBI/EPBBaverage + \gamma * PBI/EPBBratio * demrate_{zip} \\ &+ \delta * *PBI/EPBBaverage * demrate_{zip} + \theta_{zipquarter} + \eta_{month}\epsilon_i \end{aligned} \tag{11}$$

where y_i $PBI/EPBBratio$ is the ratio between PBI and EPBB incentives that measures the relative attractiveness of performance-based incentive; $PBI/EPBBaverage$ is a normal-

ized average of PBI and EPBB incentive that measures the relative size of the incentives. I do not use the amount of PBI and EPBB incentive directly as they are highly correlated with each other. I interact them with the zip level democratic party support to check if agents with different environmental attitudes react differently to monetary incentives. Controlling for zip*quarter fixed effects and monthly fixed effects, I believe the variation in the incentives is solely driven by rebate step changes exogenous to individual installers.

There are several differences in the settings compared to the wind farm study. First, since most of the solar panels installed under CSI are residential projects. So the location choice for potential investors is as simple as whether or not to have a new system installed on their roofs, and does not involve looking for sites elsewhere as in the wind farm case. Therefore, in this case, the impacts of financial incentives work almost purely through selection instead of inducing search efforts. Second, I only observe the existence and characteristics of solar panels installed under CSI, which means that I am only able to identify the impacts of subsidies on the efficiency of projects at intensive but not extensive margins. Third, the fixed subsidy (EPBB) in the solar panel example is to some extent performance-based as it is calculated using a formula that takes into consideration of several parameters of the relevant project. So if we assume these two incentives are financially equivalent for a typical project and an investor chooses PBI over EPBB as a result of profit maximization, then either she has hidden information about the project not known to the utility that sets EPBB standards, or she makes extra efforts to make her project perform better ex-post.

B.2.3 Results

Table A3 reports results of specification (7). It is clear that the solar panels located in more environmentally friendly zip codes are less efficient both ex-ante and ex-post (if they opt in for PBI track), and more costly. Of the various socioeconomic characteristics that I am controlling, only the ratio of commuters driving cars work in the same direction for all three sets of variables.

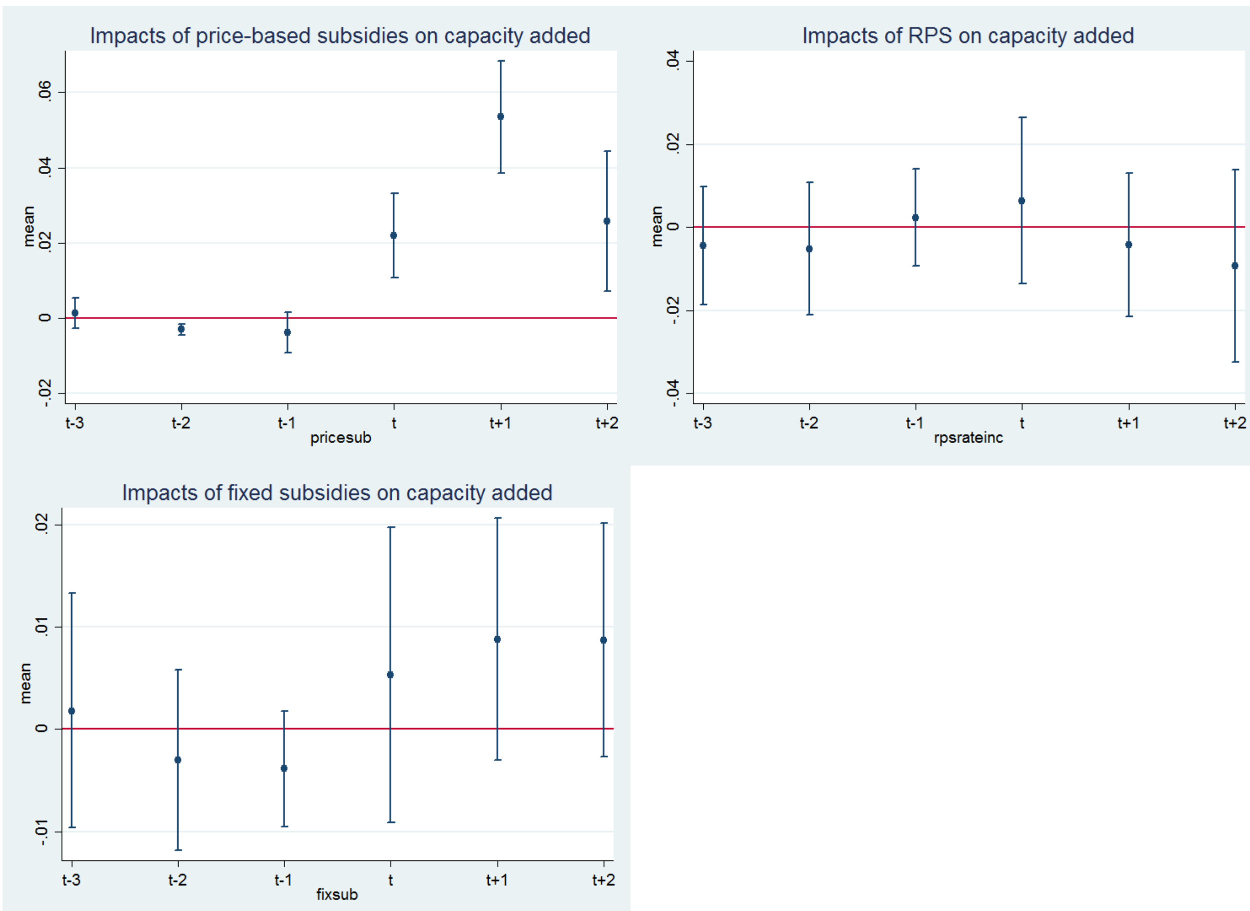
Results on the plausibly causal impacts of monetary incentives on project efficiency are reported in table A4. Column 1 shows that consistent with our intuition, larger subsidies decrease the overall efficiency of projects while higher PBI/EPBB ratio is related to projects with better quality. The interaction terms show that projects in "greener" zips respond less to monetary incentives, especially the performance-based ones.

Table A1: Robustness: Cells on state borders

VARIABLES	capacity	capacity	capacity
RPS	-0.00675	0.00836	0.00861
	(0.00638)	(0.0146)	(0.013)
pricesub	-0.0132	0.107***	0.126***
	(0.0149)	(0.0297)	(0.0282)
fixsubsidy	-0.0244***	-0.0184**	-0.0076
	(0.00891)	(0.00769)	(0.00932)
profitability*RPS	0.000803		
	(0.0005)		
profitability*pricesub	0.00450***		
	(0.00136)		
profitability*fixsubsidy	0.00074		
	(0.00067)		
demrate*RPS		-0.00755	
		(0.0195)	
demrate*pricesub		-0.162***	
		(0.0508)	
demrate*fixsubsidy		0.0452**	
		(0.0182)	
greenrate*RPS			-0.0806
			(0.152)
greenrate*pricesub			-2.130***
			(0.491)
greenfix			0.209
			(0.141)
Observations	748,869	748,869	748,869
R-squared	0.002	0.002	0.002
Number of cells	22,693	22,693	22,693

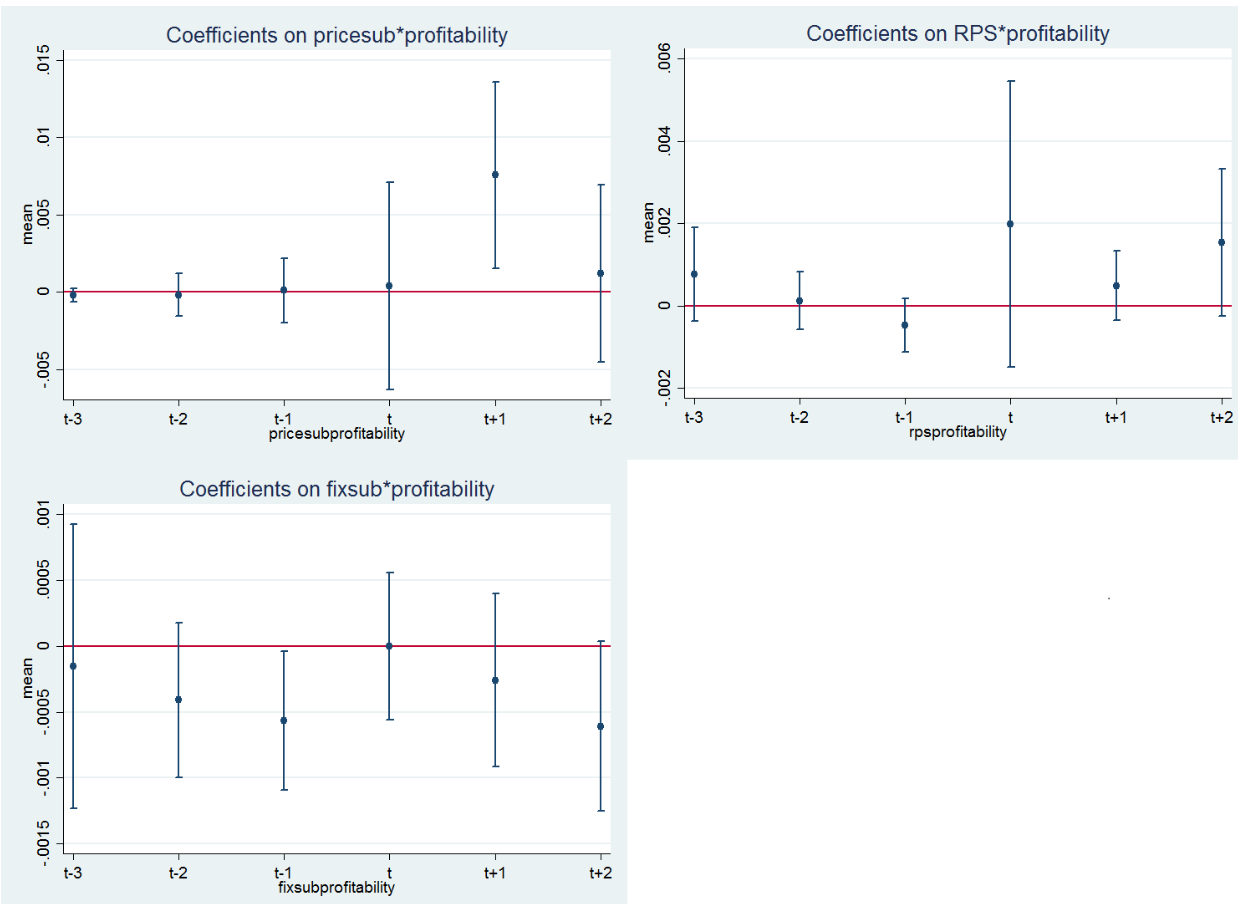
Notes:Sample is gridcell level panel data, limited to gridcells within 25 kilometers distance from state borders. The dependent variable is the amount of wind capacity installed per km^2 to a gridcell in a year. Robust clustered standard error at the state level. RPS is the real stringency of Renewable Portfolio Standard for implementing states, defined in section 3.3. Pricesub is the amount of subsidy given to per unit electricity generation. Fixsub is the proportion of total upfront cost reduced by subsidies. Profitability is the predicted profitability of a typical wind farm at the gridcell. Demrate and greenrate are county level votes shares for the democratic and green party at 2012 presidential election. Cell FE and year FE are all controlled. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Figure A1: Coefficients on the leads and lags of renewable policy intensity



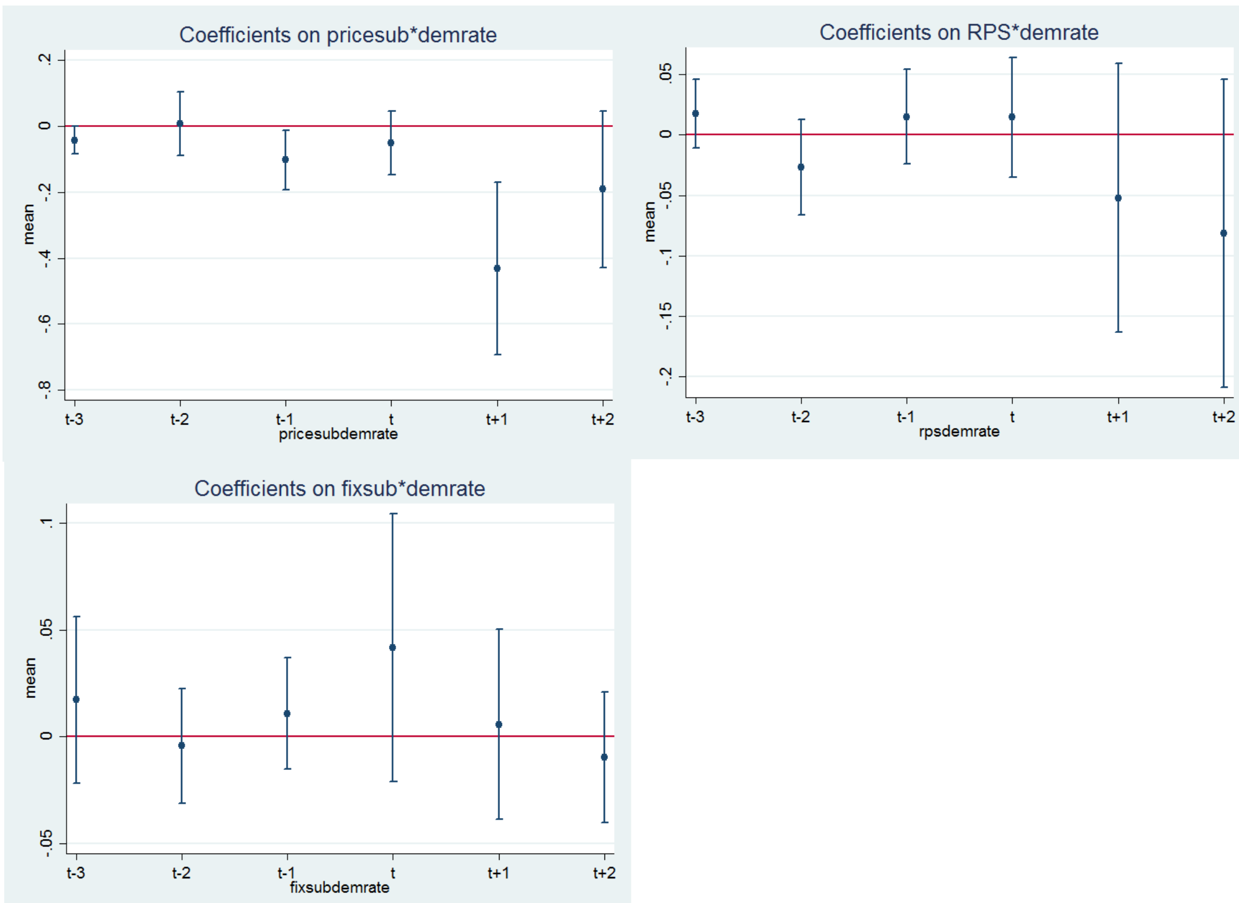
Notes: This graph plots the coefficients and 95% CI on the leads and lags of renewable energy policy intensity, as specified in equation (10).

Figure A2: Coefficients on the interactiosn of cell profitability and policy intensity leads/lags



Notes: This graph shows the coefficients and 95% CI on the interactions of the leads and lags of renewable energy policy intensity and cell level profitability measure, in a specification includes both leads/lags, profitability and their interaction terms.

Figure A3: Coefficients on the interactions of democratic party support and policy intensity leads/lags



Notes: This graph shows the coefficients and 95% CI on the interactions of the leads and lags of renewable energy policy intensity and county level support for democratic party, in a specification includes both leads/lags, democratic support and their interaction terms.

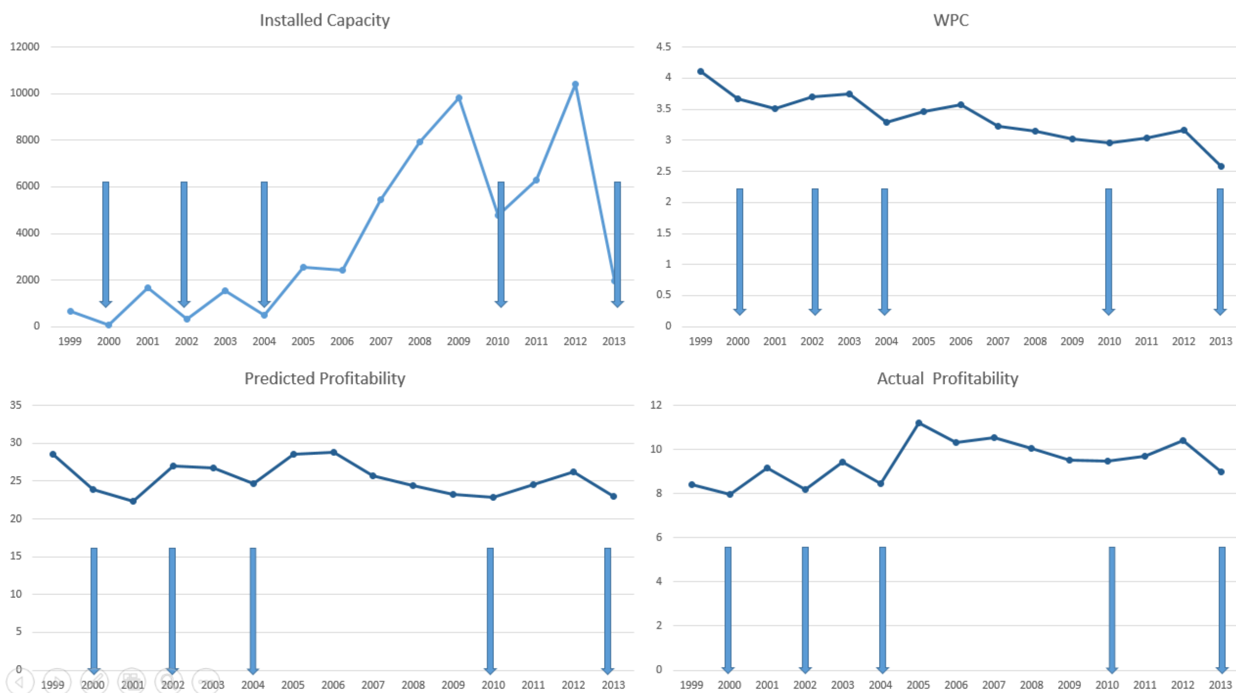
Table A2: Responses of other project attributes

VARIABLES	projectsize	bladelength	towerheight	projectsize	bladelength	towerheight
WPC	-1.738	-0.774	-1.648	0.646	0.391	0.743
	(7.177)	(0.521)	(0.99)	(6.23)	(0.301)	(0.595)
Observations	817	39,718	39,574	817	39,718	39,574
R-squared	0.291	0.949	0.913	0.311	0.941	0.907
State FE	NO	NO	NO	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

VARIABLES	projectsize	bladelength	towerheight	projectsize	bladelength	towerheight
Pricesub	-18.4	1.07	-3.644			
	(100.1)	(10.46)	(39.05)			
Fixsub	885.7**	54.85	-41.36			
	(388.5)	(43.04)	(59.92)			
RPS	-232.5	3.161	7.58			
	(273.8)	(9.211)	(35.99)			
Demrate				35.23	0.886	-2.18
				(37.99)	(1.957)	(2.398)
Observations	817	39,718	39,574	767	39,500	39,356
R-squared	0.319	0.919	0.95	0.311	0.92	0.952
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

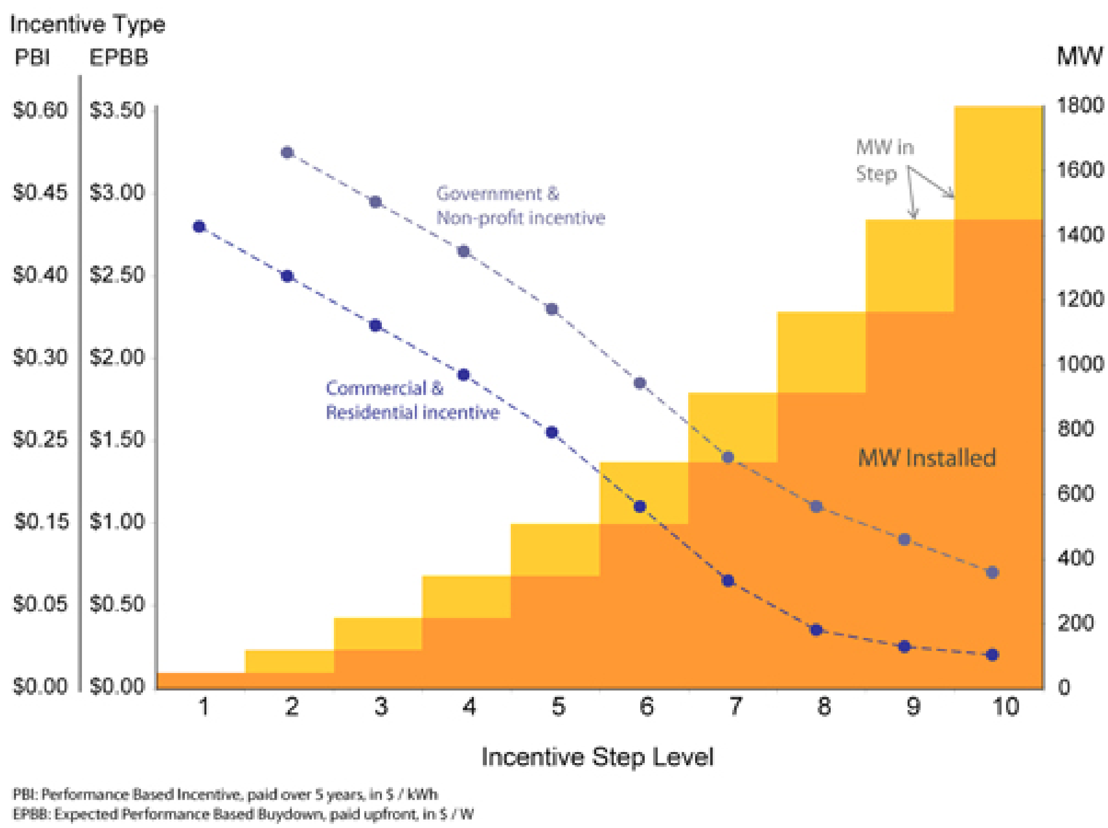
*Notes:*The dependent variables as listed are the size of wind project measured by total MW installed, turbine blade length and turbine tower height. The sample with wind project size as the dependent variable is matched plant-project level data and the sample with turbine blade length and tower height as dependent variables is turbine level data. WPC (wind power class) is a categorical measure of wind resources on a 1-7 scale, 7 being the strongest. RPS is the real stringency of Renewable Portfolio Standard for implementing states, defined in section 3.3. Pricesub is the amount of subsidy given to per unit electricity generation. Fixsub is the proportion of total upfront cost reduced by subsidies. Demrate is the county level votes shares for a democratic party at 2012 presidential election. Robust clustered standard error at the state level. * significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Figure A4: PTC/ITC Expiration and Extension



Notes: From up-left to downright in clockwise order: the yearly total wind power capacity installed, average wind power class level, average ex-ante predicted profitability level and actual profitability based on capacity factor and electricity prices of wind power projects installed in each year from 1999 to 2013. Years where federal renewable energy PTC and ITC expired and were extended are marked with blue arrows.

Figure A5: CSI: Incentive Step Level



Notes: This graph shows the design of CSI incentive steps. The horizontal axis shows the incentive step. The left vertical axis (and the dotted line) shows PBI and EPBB incentives for each incentive step. The right vertical axis (and the colored steps) shows the target MW level for each utility when the program switches from one step to the next.

Table A3: Evidence from California Solar Initiative

	designfactor	designfactor	averagecost	averagecost	capacityfactor	capacityfactor
demrate	-0.0327***		0.0465**		-0.0073	
	(0.0108)		(0.0214)		(0.0067)	
greenrate		-0.2615*		0.2729		-0.2958***
		(0.1401)		(0.1954)		(0.0945)
whiteratio	-0.0199***	-0.0153**	-0.0341*	-0.0404**	0.009*	0.0111**
	(0.0063)	(0.0067)	(0.0177)	(0.0186)	(0.005)	(0.0047)
highschoolratio	-0.0065	0.0067	0.1461***	0.1279***	0.0068	0.0134
	(0.0126)	(0.0116)	(0.026)	(0.0265)	(0.0202)	(0.0232)
bachelorratio	-0.0174	-0.0258*	-0.1922***	-0.1791***	-0.0693*	-0.071*
	(0.0125)	(0.0128)	(0.0386)	(0.0434)	(0.0363)	(0.0376)
logpop	-0.0023**	-0.0023**	0.0119***	0.0118***	-0.0021	-0.0022
	(0.0011)	(0.0011)	(0.0032)	(0.0031)	(0.0015)	(0.0015)
logincome	-0.0116**	-0.0098**	0.0114	0.0084	0.0065**	0.006**
	(0.0046)	(0.0048)	(0.0114)	(0.0114)	(0.0028)	(0.0027)
carratio	0.2322***	0.2534**	-0.6583***	-0.7087***	0.1961**	0.1578*
	(0.0856)	(0.0991)	(0.1578)	(0.173)	(0.0864)	(0.0837)
Observations	96536	96536	96528	96528	2382	2382
R2	0.1674	0.1674	0.4443	0.4441	0.1389	0.1403

Notes:Sample is all the residential and small commercial solar systems installed under the California Solar Initiative (CSI). Demrate and greenrate are the votes shares for the democratic and green party in the 2012 Presidential election at zip code level. Designfactor is an ex-ante measure of a system's efficiency. logaveragecost is the log average cost per KV. Capacity factor is an ex-post measure of a system's efficiency. County fixed effects and month fixed effects are controlled.

Table A4: Evidence from California Solar Initiative: Responses to financial incentives

	designfactor	averagecost	designfactor	averagecost	designfactor	averagecost
pbiratio	0.2077***	-0.1142	0.4246***	-1.7831	-0.3488	-0.0183
	(0.0445)	(0.2243)	(0.141)	(0.8491)	(1.737)	(0.3262
averageinc	-0.00401***	0.0068	0.0004	0.0171***	0.0122	0.0071
	(0.00111)	(0.0072)	(0.0034)	(0.0239)	(0.0351)	(0.0098)
pbiratio*demrate			-0.6222*	6.3472***		
			(0.3272)	(2.1596)		
averageinc*demrate			-0.007	-0.0441		
			(0.009)	(0.0531)		
pbiratio*greenrate					-14.6116	122.5238***
					(9.3044)	(47.4127)
averageinc*greenrate					-0.2278	-1.1712
					(0.1838)	(0.7591)
Observations	102759	102751	75186	75186	75186	75186
No. of zips	1129	1129	853	853	853	853
R2	0.3312	0.5886	0.3316	0.6089	0.3272	0.593

Notes:Sample is all the residential and small commercial solar systems installed under the California Solar Initiative (CSI). averageinc is the normalized average of performance based and non-performance-based incentives. pbiratio is the ratio of the performance-based and non-performance-based incentives. Demrate and greenrate are the democratic and green party votes share in 2012 presidential election at zipcode level. Zipcode*quarter fixed effects and month fixed effects are controlled.

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