Greenhouse Gas Emissions Reductions from Wind Energy: Location, Location, Location?

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Preliminary and incomplete. Comments welcome.

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Abstract

Increased deployment of intermittent renewable energy resources — wind energy in particular — has the potential to deliver cost effective GHG emissions in the near term. Accurate quantification of the environmental benefits from these resources has an important role to play in policy design, implementation, and evaluation. This paper develops an empirical approach to estimating marginal operating emissions impacts of new grid connected resources that captures both spatial and temporal variation in (and correlation between) marginal emissions rates and energy resource profiles. Using hourly data from mesoscale climate modeling of wind sites in New England and New York as an example, we demonstrate our methodological approach and explore the policy implications of our findings.

1 Introduction

The US electricity sector is increasingly being targeted by policies designed to accelerate investment in renewable energy and energy efficiency improvements. This sector accounts for

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approximately 40 percent of domestic greenhouse gas (GHG) emissions; increased investment in clean energy technologies is seen as an essential means of mitigating the climate change impacts of domestic electricity production and consumption. Accurate quantification of the emissions reductions achieved through these investments has an important role to play in policy design, implementation, and evaluation. In this paper, we develop methods to estimate the marginal environmental impacts of new grid-connected renewable and energy efficiency resources on electricity sector emissions. We apply these methods to a particularly promising class of investment opportunities: new wind energy projects. The policy implications of estimated emissions displacement patterns are explored.

The environmental impacts of a renewable energy project or demand side efficiency improvement accrue through the displacement of electricity generated using energy sources with adverse environmental impacts. When a wind turbine generates electricity, or end use equipment is replaced with a new, more efficient appliance, electricity output decreases among marginal incumbent electricity producers. The resulting emissions reduction per unit of electricity displaced (i.e. the marginal operating emissions rate) will depend on operating characteristics and environmental impacts of these marginal producer(s). It is this near-term effect on the so-called "operating margin" (in contrast to the "build margin" which relates to long run effects on future capacity additions) that we analyze in this paper.

We are particularly interested in estimating the near term environmental impacts of new wind investment. Several factors complicate the precise measurement of emissions displaced by new wind capacity. First, due to intertemporal and spatial variation in wind resource availability, the quantity of electricity generated by a single turbine can vary significantly across sites and over time. Second, because technology operating characteristics, electricity system infrastructure, and demand patterns vary significantly across regional markets, marginal operating emissions rates (MOERs) vary significantly across space. Third, within a region, there can be significant and systematic intertemporal variation in MOERs (both across hours of the day and seasons of the year). Correlations in spatial and temporal variation in wind resource availability and MOERs will affect, perhaps significantly, the quantity of emissions displaced by a new wind project.

However complicated, credible and accurate measurement of the emissions displaced by new grid connected resources is important. These measurements are increasingly used in state proceedings to site turbines, in regulatory processes to compensate project owners on the basis of avoided emissions benefits, and in the implementation of policies that seek to reward investments in new resources based on the level of environmental benefits they provide.[1] As the environmental and economic stakes get higher, there is heightened concern about measuring these environmental benefits precisely. Recently, government agencies and industry stakeholders have commissioned reports to investigate this issue (ISO NE, 2006; Jacobson 2006; Jacobson, 2007; NAS, 2007; US EPA, 2006). In general, all studies arrive at similar conclusions: Measurement of emissions displacement in the electricity sector is a complicated but essential input into policy design, implementation, and analysis. More

[1] For instance, states and municipalities can receive emission reduction credit in their State Implementation Plans (SIPs) for wind power purchases that reduce air emissions and help achieve attainment of the National Ambient Air Quality Standards; "certified emission reductions" can be used to achieve emissions reduction obligations under the framework of the Kyoto Protocol.

research is needed to develop credible and transparent methods to evaluate potential projects and guide investment decisions.

This work has three related objectives. The first is methodological. We develop an empirical approach to estimating net emissions impacts of new grid connected resources that captures both spatial and temporal variation in and correlation between marginal emissions rates and renewable resource profiles. We use detailed historical data to econometrically estimate the reduced form relationships between regional hourly emissions and the various factors that determine electricity system dispatch decisions (including electricity demand, forecast demand, weather conditions, fuel prices, etc). The estimated model parameters are used to construct regional MOER profiles.

Our second objective is to demonstrate how these methods can be used to quantify site specific environmental impacts of new wind development. Estimated MOER profiles and hourly meso-scale climate model data are used to evaluate how temporal and spatial variation in wind resources map into short run environmental impacts of wind resource development. In this working paper, we present results from a proof of concept exercise using a sub-sample of data from New York and New England. In future work, we will use more comprehensive wind data from over a hundred thousand sites to examine variation in emissions displacement across larger spatial scales.

Our third and final objective is to understand the policy implications of spatial variation in marginal emissions displacement. Many existing policy incentives for renewable energy and energy efficiency, such as renewable portfolio standards and production tax credits, offer production-based incentives. Under the auspices of these programs, the incentives for which a project is eligible are determined based on electricity generated, versus emissions displaced. If emissions displacement per unit of electricity produced varies significantly across sites, these production-based incentives may fail to coordinate optimal investment in renewables deployment. We explore the potential efficiency implications of observed spatial variation in emissions displacement under alternative policy regimes. Based on our preliminy data sample, our results suggest that policy implications are unlikely to be significant, conditional on current fuel prices, market conditions, industry structure, and fairly conservative estimates of emissions damages.

The paper proceeds as follows. Section 2 uses a simple example to lay the foundations for the more detailed analysis. Section 3 summarizes the state-of-the-art in measuring marginal emissions displacement rates. Section 4 describes the data we use. Section 5 introduces our econometric model. Section 6 summarizes our preliminary findings. Section 7 concludes.

2 Conceptual framework

The most complicated aspect of estimating the near term environmental impacts of a new grid connected resource is identifying how emissions from incumbent producers would respond to the addition of this resource. In this section, we use a stylized example to illustrate how variation in marginal operating emissions rates, both across regions and across hours, leads to variation in emissions displacement across different wind sites. This simple framework is then used to highlight the potential policy implications of spatial variation in emissions displacement.

2.1 A stylized example of emissions displacement

In this illustrative example, we consider only two wind sites. Figure 1 plots hourly average summer wind power production over the course of a day for two sites in New York. These sites have virtually the same daily wind power generating potential. However, this potential is distributed differently across hours: At site A, wind blows fairly steadily throughout the day; at site B, the wind blows much stronger at night versus during daylight hours.

Let $R_m(h)$ represent the emissions change in electricity market m in hour h given an incremental change in the aggregate production of incumbent generators. Figure 2 plots marginal emissions displacement profiles for two hypothetical regional markets $m = 1, 2$. The vertical axes measure R_m; the horizontal axes indicate the hour of day ($h = 1...24$). In this stylized example, we assume that all demand is met using natural gas fired generation in market 1. If we assume an emissions rate equal to the national average for natural gas fired electricity producers, then $R_1(h) = 1135 \text{ lbs CO}_2\text{/MWh}$ for all h. In market 2, we assume a generation portfolio comprised of both coal-fired and gas-fired generation. We further assume that there is sufficient installed coal capacity to meet demand in off-peak hours (*i.e.* hours when demand is relatively low), but not peak hours. Coal plants will be dispatched first because they have relatively low marginal operating costs. Off-peak, R_2 is assumed to be equal to the national average emissions rate among coal-fired generators (2249 lbs CO2/MWh). In peak hours, coal continues to run, but natural gas plants must also be dispatched to meet higher load levels. Thus, in peak hours, the R_2 decreases to 1135 lbs CO2/MWh.

Let E_{sm} denote the emissions displaced by a single turbine installed at site s in market m over the period of one day. Let $q_{sm}(h)$ denote the electricity produced by the turbine in hour h conditional on being located at site s in market m. The quantity of emissions displaced by a turbine located at site s in market m is given by:

$$E_{sm} = \sum_{h=1}^{24} R_m(h) q_{sm}(h) \tag{1}$$

$$= 24\overline{R}_m \overline{q}_{sm} + \sigma_{R_m(h),q_{sm}(h)}, \tag{2}$$

where the upper bar notation denotes daily averages and $\sigma_{R_m(h),q_{sm}(h)}$ denotes the covariance between hourly emissions displacement and hourly production potential.

Table 1 reports daily emissions displacement using the resource profiles depicted in figure 1 and the stylized MOER profiles depicted in Figure 2.[2] Note that if sites 1 and 2 are located in market A, turbines installed at either site displace the virtually the same quantities of emissions because daily output potential is virtually the same across sites and R_1 does not vary across hours. If the two sites are located in market B, emissions displacement at both sites increases relative to market 1 because $\overline{R}_1 < \overline{R}_2$. Moreover, emissions displacement varies across sites within market 2 due to intertemporal correlation between wind and MOER patterns . Daily emissions displacement is 310 tons/day at site 1. At site 2, emissions displacement is 354 tons/day because more electricity is generated in hours when coal is on the margin.

[2] These calculations assume a 50 MW turbine.

2.2 Policy implications of spatial variation in emissions displacement

When emissions displacement rates vary across sites, production-based policy incentives may fail to efficiently coordinate investment in wind energy resource deployment. We use this simple example to examine how spatial variation in emissions displacement can affect outcomes under emissions and production-based incentives.

An "emissions-based" policy incentive increases the returns generated daily by a wind turbine generating electricity at site s in market m by $\tau \sum_{h=1}^{24} e_{mh} q_{sh}$, where τ represents the monetary payment per unit of emissions displaced. Alternatively, "production-based" incentives can be used to encourage new wind resource development. This is the approach taken by some important current policy initiatives, such as the federal production tax credit. For ease of comparison across policy designs, we consider a production incentive that pays wind generators $\tau\bar{e}$ per unit of output, where $\bar{e}$ is defined to be the average marginal emissions displacement rate (averaged across all markets). Under this incentive structure, daily earnings at site s are increased by $\tau\bar{e} \sum_{h=1}^{24} q_{sh}$.

Table 2 reports daily subsidy payments for the two policy regimes and the four site/market combinations under consideration. These calculations assume $\tau = \$14$ (*i.e.* the median damage estimate reported by Tol, 2008). Whereas a production-based subsidy fails to discriminate between investment opportunities with different emissions displacement rates, an emissions-based policy offers stronger incentives to develop wind resources at sites with the largest emissions displacement potential. In this example, profile B in market 2 receives the largest incentive (because electricity production is relatively high in off-peak hours when marginal emissions rates in market 2 are relatively high).

Social benefits or value generated daily by a wind turbine generating electricity at site s in market m includes not only the benefits associated with displaced emissions, but also avoided fuel and variable operating costs. The value generated daily by a wind installation at site s in market m can be summarized by:

$$\begin{aligned} J_{1,s,m} &= \sum_{h=1}^{24} P_m(h) q_{sm}(h) + \tau \sum_{h=1}^{24} e_m(h) q_{sm}(h) && (3) \\ &= 24(\overline{q}_{sm}(h)(\overline{P}_m + \tau \bar{e}_m) + \sigma_{P_m(h),Q_{sm}(h)} + \tau \sigma_{e_m(h) q_{sm}(h)}), && (4) \end{aligned}$$

where $P_m(h)$ measures the marginal operating costs incurred at the marginal unit in market m at site s in hour h. Covariance between two variables x and y is represented using σ_{xy}. We assume that the τ captures the monetized damages associated with a unit of emissions. If we further assume that the price paid for electricity generated by wind turbines accurately reflects avoided marginal operating costs P_m, investing in the development of a wind resource at site s in market m will be cost effective provided that the following holds:

$$FC_{sm} \leq \sum_{h=1}^{T} P_m(h) q_{sm}(h) + \tau \sum_{h=1}^{T} e_m(h) q_{sm}(h),$$

where FC_{sm} measures fixed investment costs and T denotes the investment time horizon.[3]

Equation [4] measures the daily revenues earned by a wind development at site s in market m assuming an emissions-based subsidy τ.Daily returns to investment under a

[3]For expositional clarity, we assume all benefits accruing in future benefits are measured in present value terms.

production-based policy regime are:

$$J_{2,s,m} = \sum_{h=1}^{24} P_m(h) q_{sm}(h) + \tau \bar{e} \sum_{h=1}^{24} q_{sm}(h) \quad (5)$$

$$= 24(\bar{q}_{sm}(h)(\overline{P}_m + \tau \bar{e}_m) + \sigma_{P_m(h),Q_{sm}(h)} \quad (6)$$

Our simple example is extended to incorporate both internal and external (*i.e.* emissions displacement) benefits of wind generation. Table 3 reports daily revenues using national average fuel prices, fuel specific heat rates for a low ($\tau = \$14$) and high ($\tau = \$70$) marginal damage scenario. Daily revenues differ significantly across policy regimes. In the low damage scenario, note that the ranking of these four potential projects does not change. Put differently, for an assumed $\tau = \$14$, the order in which a profit maximizing manager would deploy these projects is independent of policy incentive structure, although the level of deployment may change depending on fixed investment costs. This is not true for the high damage case. Under the emissions-based regime, larger subsidies paid to projects with relatively higher emissions displacement are sufficient to reverse the daily revenue rankings; sites in market 2 (where MOERs are higher off peak) move ahead of sites in market 1. Moreover, the deployment order of site A and B are reversed in market 2 because power production at site B is positively correlated with the MOER profile in market 2. In sum, in the high damage scenario, both the order and the level of investment can vary across policy regimes.

This example helps to provide foundation for a more detailed analysis presented in subsequent section. This example also helps to clarify the two essential data inputs will be used in the analysis: site specific resource profiles $q_{sm}(h)$ and region specific MOER profiles $R_m(h)$. Resource profiles are relatively straightforward to obtain. Estimation of MOER profiles presents more of a challenge. In what follows, we summarize the state-of-art in measuring emissions displacement.

2.3 Estimating Marginal Emissions Displacement in the Electricity Sector

Over the past five years, there has been a surge of interest in measuring the net GHG emissions impacts of newly grid connected resources, renewable electricity generation and energy efficiency resources in particular (e.g. Biewald, 2005; Broekhoff, 2007; Jacobson, 2007; Price 2003; Schiller, 2007). Methodological approaches fall into three general categories which we summarize here.

(i) **System average emissions factors**

System average emissions factors, typically measured in pounds of pollutant emitted per MWh of electricity produced, are often used to estimate displaced emissions from specific resources. System average rates are calculated by dividing total system emissions by total system generation. This emissions factor is then applied to the output of specific resources to estimate emissions displacement. Because these factors are readily available, this is a very common approach (EPA, 2006; Jacobson, 2006**?**).

One limitation of this approach is that the overall average emissions rate will rarely equal the average MOER. For example, in regions with significant hydro and/or nuclear generation capacity, average emissions rates will over-estimate marginal rates because these zero-emitting resources have relatively low fuel and marginal operating costs (and are typically inframarginal). A second limitation is that the approach fails to capture intertemporal variation emissions rates. More precisely, the covariance between hourly output and hourly variation in emissions displacement rates is implicitly assumed to be zero.

(ii) **Grid-system dispatch analysis**

The production activities of generators in restructured electricity markets are typically coordinated through bid-based security-constrained dispatch. Producers submit bids to an independent system operator. The operator dispatches plants to minimize the cost of meeting demand subject to the constraints imposed by the transmission and distribution infrastructure, system operating requirements, etc. Intertemporal operating constraints, transmissions and distribution constraints, security protocols, and idiosyncrasies on the part of both plant and system operators all play an important role in coordinating production (and thus emissions).

In order to replicate actual system operations as closely as possible, analysts have developed proprietary unit dispatch models that try to explicitly represent complex relationships between integrated market mechanisms, network constraints, electricity generation infrastructure, and demand systems.[4] These models can be used to estimate the changes in emissions that would result from marginal changes in system infrastructure (i.e. improvements in energy efficiency or increased renewable energy generation capacity) (Keith, 2002; Keith, 2003). System-wide emissions are first simulated under a baseline scenario (in which existing infrastructure and operating conditions are represented) and then simulated under a scenario which incorporates the renewables generation and/or energy efficiency investments being evaluated. Marginal emissions rates are calculated based on comparisons between the

[4] The most commonly used dispatch models are: PROSYM, PROMOD, GE MAPPS.

baseline and counterfactual scenarios.

This approach has some drawbacks. First, it is time consuming and resource intensive. Second, because models typically proprietary, results can also non-transparent and thus hard to evaluate. Finally, the emissions patterns generated using system dispatch models can deviate significantly from observed emissions (ISO NE, 2006). In general, these models assume deterministic least cost dispatch based on detailed, stylized representation of generating units and system infrastructure. If actual market and plant operations deviate from assumed operating conditions, fuel costs, emissions rates, transmission constraints, and transfers between different regions, predicted patterns of production and emissions can be inaccurate.

(iii) **"Medium effort" approaches: identifying load following units**

Increasingly, independent system operators, international non-profit organizations, state and federal agencies are moving away from the aforementioned two approaches towards alternative "medium effort" approaches that provide reasonably accurate estimates of the operating marginal emissions reductions resulting from renewable projects and investments in energy efficiency in a way that is less resource intensive and/or more transparent than detailed grid dispatch simulations (Broekhoff, 2007; Hathaway, 2006; ISO NE, 2006; Jacobson, 2007; Schiller, 2007). One approach uses the average emissions rate among producers that are assumed to "follow load" (*i.e.* units that do not provide baseload, must-run, or intermittent power). Another approach arranges generating units in ascending order operating costs and matches this dispatch order with the corresponding load duration curve in order to identify the units on the margin at different load levels (Broekhoff, 2007; Price, 2003).

Table 4 presents alternative estimates of the average marginal operating emissions rates for the regional markets we will ultimately analyze. In New York and New England, system average emissions rates are substantially lower than the estimates of marginal operating emissions rates obtained using grid dispatch models. In both regions, a significant share of installed capacity is comprised of hydro and nuclear generation. These units have very low marginal operating costs; they are likely infra-marginal in most (or all) hours. In PJM, base load is likely served by coal-fired units with relatively high CO_2 emissions rates. Thus, infra-marginal units are more likely to be relatively more polluting in PJM; system average rates exceed estimates of marginal emissions rates.

2.4 A reduced form approach

We aim to incorporate some of the strengths of the aforementioned approaches while addressing some of the more problematic limitations. We treat wind energy production as a "load modifier" in the sense that marginal changes in wind production in a given region are considered functionally equivalent, from the perspective of power system operation, to an equal and opposite change in electricity demand. This assumption justifies using observed variation in production (and emissions) from generators that respond to changes in electricity demand to predict how an electricity system would respond to the addition of a wind turbine at a given site. We specify a reduced form model that relates changes in hourly CO_2 emissions (at the electricity market level) to changes in the factors that determine how producers are dispatched. Section 4 describes our empirical model in detail.

One advantage of our approach *vis a vis* more structural, system dispatch modeling is that it is less labor intensive and more transparent. Our models can be estimated using standard statistical packages and publicly available data. Furthermore, because of the reduced form nature of our approach, we need not worry about explicitly representing all of the complex market relationships and characteristics. The combined effects of system protocols, technology operating constraints, idiosyncratic bidding behavior, and other institutional details that affect how electricity production is coordinated are captured by our model (albeit in reduced form). One disadvantage of our approach (relative to system-dispatch modeling) is that our estimates are conditional on the processes, regulations, and infrastructure that generate the data we use. Our approach cannot be used to evaluate long run impacts and/or non-marginal changes in system infrastructure.

The methods we develop are similar to the "medium effort" approaches discussed above in that we use historical data to estimate how an electricity market will respond to changes in renewable energy production. However, in addition to information about existing infrastructure and load profiles, we use additional data on when and how units in a market are actually operating. In all the markets that we study, for technical and institutional reasons, system dispatch routinely deviates from the least cost unconstrained dispatch ideal. An important advantage of our approach is that our estimates of marginal operating emissions rates are based on how system-wide emissions actually respond to changes in load, versus how emissions would respond under an assumed unconstrained least-cost dispatch protocol.

3 Data

The data set used to estimate the model consists of hourly emissions, load, electricity production, fuel prices, and weather data over the period 2004-2007. In this section we provide a description of the data.

3.1 Emissions and production data

Almost all combustion-based electricity generating units in 22 states in the Eastern United States are required to participate in a regional Nitrogen Oxide emissions trading program. During "ozone season" (May-September), these units must continuously monitor and report hourly CO_2 mass emissions, heat inputs, and steam and electricity outputs to the U.S. Environmental Protection Agency.[5] Hourly, boiler-level data are summed within regional markets to estimate market-level production from thermal units and market-level CO_2 emissions.

Not all generators in New York and New England are required to report emissions under the Nitrogen Oxide emissions trading program. Specifically, small capacity plants are exempt from reporting. Maine, New Hampshire and Vermont do not participate in the program, although a majority of combustion-based producers in these states are required to report under the federal Acid Rain Program. .Non-reporting plants contribute relatively little to total generation in these regions: in the most recent release of the EPA's eGRID database (year 2005 data), 0.4 and 1.7 percent of total ozone season generation in New York and New England, respectively, came from generators that might be dispatched to respond

[5] Under Part 75, Volume 40 of the Code of Federal Regulations.

to changes in load[6] and did not report to the NO_x program.

In this paper, we will restrict our analysis to observations during ozone season, because the subset of generating units required to report emissions outside of ozone season (under the Acid Rain Program) is substantially smaller.

3.2 Wind data

Wind speed is a function of a variety of variables, including current meteorological conditions and the physical landscape. As one might expect, wind speeds can vary significantly for a given location, time of day, and season - at practically any location it is possible to observe calm conditions (e.g. 0 meters per second) on one day and very wind conditions (e.g., over 20 meters per second) on another. However, as with weather patterns, wind speed varies systematically. With accurate weather models and data on land cover and terrain, relatively precise wind forecasts can be made; state of the art methods operate with mean absolute errors on the order of 5 percent for hour-ahead forecasts and roughly 15 percent for day-ahead forecasts (Landberg, 2003).

There are a number of additional characteristics of wind speed variation that are useful to understand in the context of this paper. First, quite simply, some sites are windier than others: average wind speed at a relatively calm site might be less than 5 meters per second, whereas exceptionally windy sites might have average speeds in excess of 10 meters per second. Second, over the period of a month or a season, average wind speeds at a given

[6]This set of responsive generators excludes combined heat and power units, so-called "self generating" units, and existing wind generators (which are not typically controllable in response to changes in load) and hydropower and nuclear generators (which have very low marginal costs and are unlikely to ever be called upon to follow load).

hour of day and location are significantly less variable than individual observations, and these averages themselves vary systematically across hours and seasons. For example, winter months are typically windier than summer months, and nighttime hours are typically windier than daytime hours. Of course, there are exceptions to these rules; indeed, it is our goal in this research to understand the potential effects of variation in wind production patterns on electricity sector emissions.

For this study we obtained proprietary hourly wind speed data under a license agreement with 3TIER Environmental Forecast Group, Inc (3TIER). These data were generated by 3TIER using a sophisticated numerical weather prediction (NWP) model capable of simulating large-scale wind patterns with a microscale wind flow model responsive to local terrain and surface conditions. The model uses coarsely spaced (in both time and space) observational data produced in a joint effort (known as the Reanalysis Project) by the National Centers for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR). The wind flow model treats the reanalysis data as boundary conditions and simulates high resolution (in time and space) data that are subsequently verified against

The NWP models approximate the physics and dynamics of the atmosphere by dividing it into many small elements, both horizontally and vertically. The model computes how the state of each element changes in time as well as how much mass, energy, and momentum is exchanged between elements. Boundary conditions are derived from terrain maps as well as from coarsely spaced (in time and space) observed meteorological data provided by the National Centers for Environmental Prediction (NCEP) and the National Center for

Atmospheric Research (NCAR) in a joint effort called the Reanalysis Project.

The resulting simulated dataset has a spatial resolution of about 2-arcminutes (approximately 5 km), a temporal resolution of 1 hour, and spans 10 years (all derived from corresponding observed Reanalysis data). The data are validated against publicly available wind speed observations from another NCEP surface observations dataset.

For the preliminary results in this paper, we obtained hourly wind data from 3TIER for 67 sites distributed throughout New York and New England, all of which had average annual wind speeds of 6.5 meters per second or better. A map showing average wind speed at all sites in the region as well as the location of the chosen hourly data is shown in Figure 3. We used a generic megawatt-class turbine power curve (Fingersh, 2002) to convert wind speed to power. In future work, we will use hourly data from all sites in the 3TIER dataset.

One can see from the map in Figure 3 that there is spatial variation in resource quality, and as we shall see, this leads to significant spatial variation in avoided CO_2 emissions. However, there is also spatial variation in hourly wind production patterns, as demonstrated in Fig. 4, which shows average hourly wind production patterns at four sites in New England and New York [7]. The total emissions displacement attributable to a given wind site will depend not only on total wind production, but also on the shape of these patterns and their relationship to MOER patterns.

[7] Because these data are proprietary, we do not disclose the location of the specific wind production patterns.

3.3 Other covariates

We also include additional covariates in our analysis that could potentially affect system dispatch, including temperature, fuel prices (obtained from the Energy Information Administration), and electricity load, load forecasts and real-time hourly price (obtained for both the New York ISO and ISO New England, from their websites).

4 Estimating marginal emissions displacement rates

This section explains how region-specific marginal operating emissions rates are estimated. Our general econometric specification is given by:

$$\Delta E_{mht} = (\alpha_{mh} + \beta'_{mh}\widetilde{X}_{mht})\Delta Z_{mht} + \varepsilon_{mht} \tag{7}$$

The data used to estimate this equation span four years (2004-2007) and comprise each set of 3,672 hours in May-September. The subscript h indexes hour of day ($h = 1..24$), and t indexes all hours in the data, such that t uniquely determines h. The dependent variable is the change in the quantity of CO_2 emitted from generators in electricity market m between time period $t-1$ to time period t. As mentioned above, the data contain almost all generators in the market m that vary production in response to changes in electricity demand, and therefore E is an excellent record of emissions produced in the market footprint.

The argument in parentheses can be interpreted as the marginal emissions rate in market m and hour of day h. This rate is allowed to vary systematically with the variables included in the vector X_{mht} . Different model specifications include different observable determinants of dispatch, including weekend dummy variables; demeaned daily maximum load and fuel prices; hour-demeaned hourly load, forecast load, dew point and dry bulb temperatures. Hour-demeaned variables are calculated by subtracting the mean value of the variables in like hours (e.g. $h = 1$ only, $h = 2$ only, etc); all demeaning is done within market.

We assume that marginal changes in wind production in market m in hour h are functionally equivalent, from the perspective of power system operation, to an equal and opposite change in the variable Z_{mh}. This variable serves as a proxy for the electricity that would be generated by a wind turbine at a given site.

A number of factors need to be considered when defining the variable Z_m. One option would be to set Z_{mht} equal to total load in market m in time period t. We choose not to use this measure two reasons. First, changes in load are correlated with changes in hydropower production. Although hydro production does follow diurnal and seasonal changes in electricity demand, these generators are rarely marginal because their variable operating costs are zero.[8] Although hydropower can reduce its output in response to reductions in load (or increases in wind), if such an event occurs the displaced energy will likely be produced at another hour, effectively shifting the emissions benefit to that time. Second, load includes generation from out-of-market electricity imports (for which we do not have emissions measurements) and does not include within-region generator exports (whose emissions cannot easily be separated from our measurements). Although imports are relatively small (8 and

[8] Instead, hydropower plants typically vary production in order to maximize revenue subject to constraints on available energy (i.e., water). They do so by producing as much as possible during the day when market prices are high.

3 percent of generation in NYISO and ISONE, respectively[9]), because imports are not fully accounted for in the Z_m and E_m data, systematic hourly changes in imports could bias our estimates.

Instead, we set Z_m equal to electricity production from all generators within the region of interest that report to the NO_x trading program. As we mentioned above, these data comprise nearly all production and emissions from generators that could be called upon to increase or decrease production in an economic dispatch environment. With this approach we can rest assured that all generation captured in Z_{mht} is also captured by our dependent variable E_{mht}.

As an alternative, Z_m can be defined to include in-region generation less production from combined heat and power (CHP) generators and so-called "self generating" units[10]. The primary product of CHP units is steam for use in industrial processes or building space conditioning. Electricity output increases only when demand for steam increases. Consequently, electricity production from these units may appear to follow load, but could be the result of correlation between hourly steam demand and system wide electricity demand, rather than evidence of CHP units responding directly to changes in electricity demand. Therefore we will also report results with Z_m and E_m defined as in-region generation and emissions less CHP generation and emissions.

We choose not modify Z_m to reflect imports for two reasons. First, changes in interre-

[9] These percentages are computed by comparing ISO import data to generation numbers reported by EPA's eGRID in 2005 (the latest year for which data are available).

[10] These generators are installed on the customer side of the electricity meter and do not participate in system dispatch activities.

gional imports are more difficult to coordinate than changes in output of within control area generation, so imports are less likely to respond to marginal changes in wind production. Second, as mentioned above, imports in NYISO and ISONE are relatively small.

Hourly emissions are modeled using a panel of 24 cross-sectional hours that vary from day to day. This is a fairly conventional approach in the empirical literature that analyzes hourly electricity spot and forward prices (e.g. Guthrie *et al.*,2007; Huisman, 2007; Ramanathan, 1997). We adopt this approach because we are particularly interested in capturing systematic intraday variation in marginal emissions rates. The disturbance term ε captures idiosyncratic factors that give rise to variation in the dependent variable. We allow ε to be both heteroskedastic and clustered by market days. Let the subscript d denote day. The covariance structure reflects the following assumptions:

$$E(\varepsilon_{mdh}\varepsilon_{mdh}|X,Q) = \sigma^2_{mdh} \tag{8}$$

$$E(\varepsilon_{mdj}\varepsilon_{mdk}|X,Q) = \rho_{mdh} \ \forall \ j \neq k \tag{9}$$

$$E(\varepsilon_{d}\varepsilon^T_{d'}|X,Q) = 0 \ \forall \ d \neq d' \tag{10}$$

This block-diagonal structure is largely motivated by institutional features of electricity markets. In particular, given the way that information sets evolve in these markets, there is likely to be significant intraday correlation in the stochastic component of (7). In the restructured electricity markets we consider, agents submit 24 hourly bids and offers for electricity delivery in a given day by a deadline the day before. The majority of the scheduling and unit dispatch decisions are finalized and announced day ahead. This periodic updating of information and dispatch decisions introduces correlation in the disturbance terms within a day. Standard time series approaches (which assume that correlation between disturbances in different time periods depends only on the length of time between periods) cannot easily accommodate this correlation structure.

5 Estimation results

We estimate several variants of equation (7). In the most restrictive specification, the dependent variable is regressed on ΔZ_{mht}; no additional covariates are included. Less restrictive specifications include hourly forecast load, higher order ΔZ_{mht} terms, fuel prices, temperature, the daily maximum forecast, and a weekend dummy. All continuous covariates in X_{mht} are demeaned so that the estimates of α_{mh} can be interpreted as estimates of the MOER, conditional on all other covariates in the model taking on their hourly mean values. Models are estimated separately for New York and New England.

In all specifications, the estimated α_{mh} coefficients are statistically significant and positive at the one percent level. Figures 5a and 5b presents these coefficient point estimates for New England and New York, respectively. Estimation results are reported for the most restrictive specification (solid lines) and a less restrictive specification (broken lines) that allows the MOERs to vary systematically with forecast load, the daily maximum forecast load, a quadratic term, and a weekend dummy.[11] In each figure, we present results where Z_m is defined to be all generation reported to the NO_x trading program, as well as results where the Z_m excludes generation from combined heat and power and self-generating units.

[11] We estimated several intermediate specifications in which only a subset of these covariates were included. MOER estimates are generally robust to these alternative specifications.

Estimated MOERs vary systematically over the course of a day. In both regions, emissions rates are highest in the hours of the day when demand is lowest. This pattern is less pronounced in New England, suggesting that the emissions characteristics of generators on the margin in that region are relatively constant. In New England (Fig 5a), the definition of Z_m has relatively little bearing on the result, although conditioning on additional covariates does influence the estimation results somewhat, especially during peak hours. In New York (Fig. 5b), including CHP and self generation in Z_m significantly influences estimation results, which suggests we are picking up systematic variation in the output of these units. This is not unexpected, especially because CHP unit steam supply (which dictates electrical output as well) is likely to be correlated with daily variation in ambient conditions and work schedules. However, because CHP and self-generating units will not be dispatched to follow variation in wind, we view the result where Z_m excludes these units to be more informative for our purposes.

Of the additional covariates included, none are statistically significant in all hours. The interaction between ΔZ_{mht} and the demeaned ΔZ_{mht} is statistically significant in some hours, suggesting that the relationship between changes in emissions and changes in combustion-based production is non-linear in some hours of the day. The weekend dummy variables are also statistically significant in most hours.

In Figs. 5a and 5b, the black horizontal lines represent system average emissions rates. For both regions, the system average emissions are well below α_{mh}. This is to be expected because generating portfolios in both regions include a significant amount of hydro and nuclear generation. The grey horizontal lines represent the emissions rates used in the U.S. EPA emissions and generation resource integrated database (eGRID) to estimate GHG emissions reductions from reductions in electricity use.

In the analysis that follows, we will use the estimates obtained using the specification that controls on additional covariates and uses the subset of the data that excludes CHP and self-generation. Fig. 6 plots these point estimates along with 95% confidence intervals.

6 Interpretation and analysis

In this section, the MOER estimates are used to generate site-specific estimates of CO_2 displacement from new wind investment. In this proof-of-concept exercise, we focus only on a small subset of the available wind data (67 sites in New York and New England). In future work, this analysis will be extended to the full data set.

We are interested in understanding how intertemporal variation in wind availability and marginal emissions rates (and their covariance) affect CO_2 displacement potential of individual sites, and in exploring the policy implications of any spatial variation in emissions displacement benefits. With some additional data and assumptions, we can construct site-specific estimates of the $J1$ and $J2$ parameters introduced in section 2.

Hourly wholesale electricity prices are available from the New York and New England independent system operators. We use these hourly prices as a proxy or measure of the variable operating costs per MWh of the marginal generator. We assume $\tau = \$14$. We compute $J1$ by setting e_{mh} in Equation [3] equal to α_{mh} estimated using Equation [7] (see Figure 6). To construct the production subsidy, we compute $\bar{e}$ by averaging MOERs across hours and markets.

Determining the efficient level and pattern of wind resource development is beyond the scope of this study; we lack data on fixed investment costs, among other things. However, we can use our estimation results to rank investment opportunities in terms of daily revenues and evaluate the extent to which these rankings vary across policy regimes. If we assume that fixed investment costs do not vary significantly across sites, ranking sites in ascending order of $J1$ yields the order in which these development projects should be efficiently deployed. An emissions-based incentive of τ per unit of displaced emissions will achieve this efficient ordering. As demonstrated in section 2, a production-based incentive of $\tau\bar{e}$ can, under some conditions, imply an alternative (and less efficient, conditional on our assumptions) ranking.

Using equations [4] and [6], we derive two conditions under which the production-based policy will yield daily site-specific revenues that are ordinally equivalent to those associated with the emissions-based subsidy.

(i) **Condition 1**: Perfect positive correlation between $P_m(h)$ and $e_m(h)$ for all m.

Equations [4] and [6] can be rewritten as:

$$J_{1,s,m} = \sum_{h=1}^{24}(P_m(h) + \tau e_m(h))q_{sm}(h) \tag{11}$$

$$J_{2,s,m} = \sum_{h=1}^{24}(P_m(h)q + \tau\bar{e})q_{sm}(h). \tag{12}$$

Note that the ranking of sites based on daily revenues earned in the wholesale electricity market (not including any policy incentives) are unchanged by the introduction of a production-based subsidy. If $P_m(h)$ and $e_m(h)$ are perfectly positively correlated, an emissions based subsidy will not change this ranking. However, the ranking may be altered under an emissions based subsidy if $P_m(h)$ and $e_m(h)$ are negatively correlated.

(ii) **Condition 2**: $e_m(h)$ and $q_{sm}(h)$ are uncorrelated at all sites.

Note that if $\tau\sigma_{e_m(h)q_{sm}(h)}) = 0 \; \forall \; s, m$, $J1$ reduces to $J2$ and the both policies will yield the same project ranking.

Figure 7 plots the MOER profiles and the average hourly electricity price for New York and New England, respectively. In both cases, MOERs are highest in the early morning when hourly wholesale electricity prices are at their daily minimums. Put differently, condition 1 is not met. Thus, it is possible that daily revenue ranking of wind resource development opportunities may be different under emissions-based and production-based incentives. Figure 8 summarizes the distribution of correlation coefficients $\sigma_{e(h),q(h)}$observed in the data. On average, these correlations tend to be close to zero, suggesting that condition 2 is satisfied in a majority of cases.

A straightforward, scalar measure of the extent to which site ranking changes for production- versus emissions-based subsidies is Spearman's rank correlation coefficient:

$$\rho = 1 - 6 \sum \frac{d^2}{N(N^2 - 1)},$$

where d is the difference in the statistical rank of a site's revenue using $J1$ versus $J2$. The closer this coefficient is to 1, the less site ranking changes across the two different measures.

Figure 9 shows the relationship between $J1$ and $J2$ for 67 wind sites in New York and New England. The two measures differ slightly (due to inter-market variation in MOERs), but correlation between them is strong and there is relatively little difference in ranking (Spearman's coefficient is 0.9966). Therefore, although positive and negative correlation between MOERs and wind speed and negative correlation between MOERs and electricity price suggests that re-ordering is possible, we see little evidence here. Several factors contribute to this result: First, the MOER-wind and MOER-energy price correlations are relatively weak. Second, there is substantial variation in production across sites. Third, τ sufficiently small that $J1$ and $J2$ are largely determined by the production quantity rather than the emissions subsidy.

6.1 Future work

In this proof-of-concept exercise, results from preliminary analysis using data from 67 sites in the Northeast are presented. In future work, we will estimate MOERs for the Pennsylvania-Jersey-Maryland (PJM)electricity market and extend our analysis to over a hundred thousand wind sites across the Eastern United States. Preliminary results using data from PJM suggests that we will find greater spatial variation in carbon emissions displacement potential in this region.

We have yet to address the statistical significance of the variation in emissions displacement potential. Relative to other marginal emissions estimation efforts, the approach we have outlined here has the distinct advantage that it can facilitate calculation of confidence intervals on our carbon displacement point estimates. Future work will exploit this advantage.

Finally, in future work, we also hope to address the possible influence of wind forecast accuracy (or lack thereof) on marginal operating emissions; a possible approach is to include some measure of load forecast error among the variables in X_{mht} in Eq. 3.

7 Discussion and Conclusions

With this paper, we seek to improve upon methods used to estimate the emissions displaced by new renewable energy generation projects. We apply standard econometric methods to the estimation of marginal operating emissions rates (MOERs) in the electricity sector. Our reduced form approach allows us to capture, albeit in reduced form, the effects of system operation constraints and protocols and complex electricity market interactions in the estimation of MOERs using public data.

We use our estimated MOER profiles to assess the extent to which intertemporal correlation in wind resource profiles and MOER profiles influences carbon emissions displacement across sites selected from New York and New England. Statistically significant hour-to-hour variation in estimated MOERs begets variation in carbon emissions displacement potential across the subset of wind sites. This raises the possibility that a production-based subsidy may fail to coordinate optimal deployment of wind resources.

Among the 67 sites we consider, we find that the cross-sectional variation in emissions displacement is small relative to the daily revenue generating potential of wind electricity. Intertemporal correlations between electricity production and MOERs are also low in most cases. Consequently, based on data from the one hundred sites we consider, we would not expect that a transition from production-based subsidy (such as the production tax credit) to an emissions displacement based incentive structure would significantly impact the order in which new wind resources are developed/deployed. Future analyses that capture greater intra- and inter-regional MOER variation may reach different conclusions.

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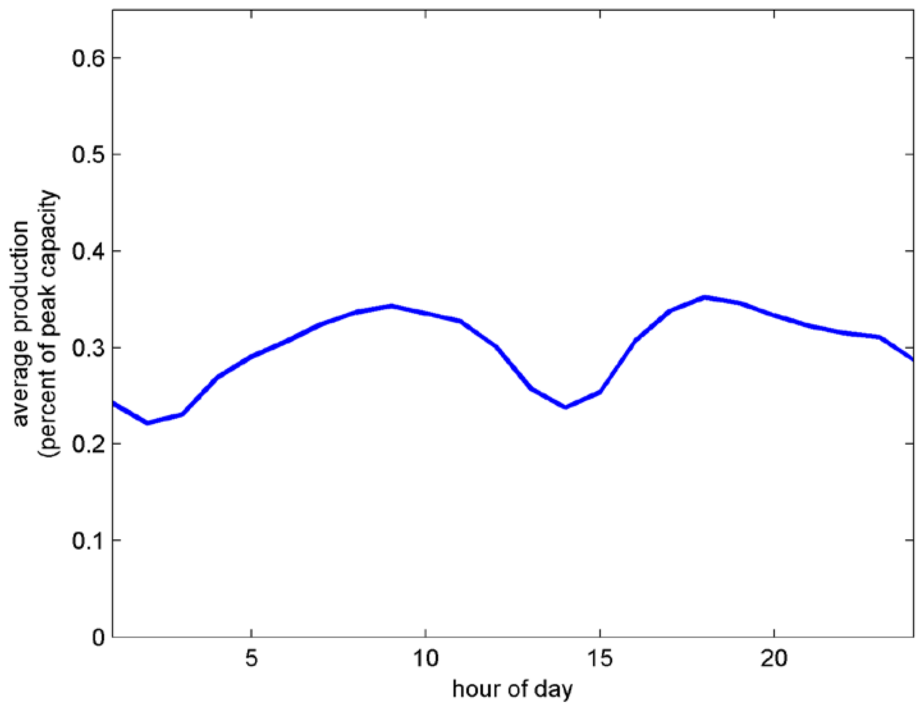

Figure 1a: Summer wind power profile in Upstate New York.

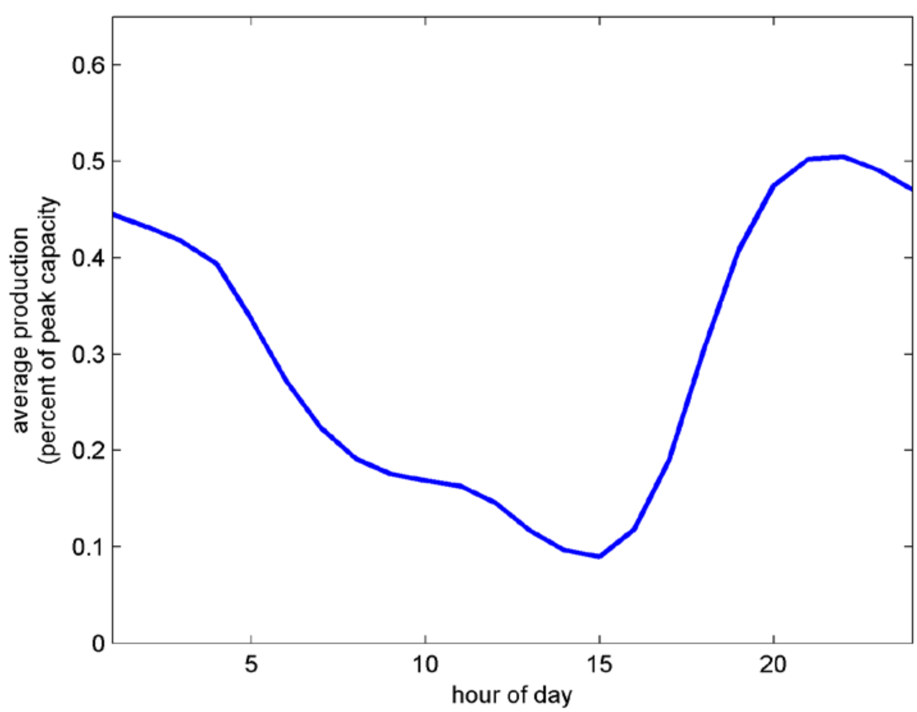

Figure 1b: Summer wind power profile near New York City.

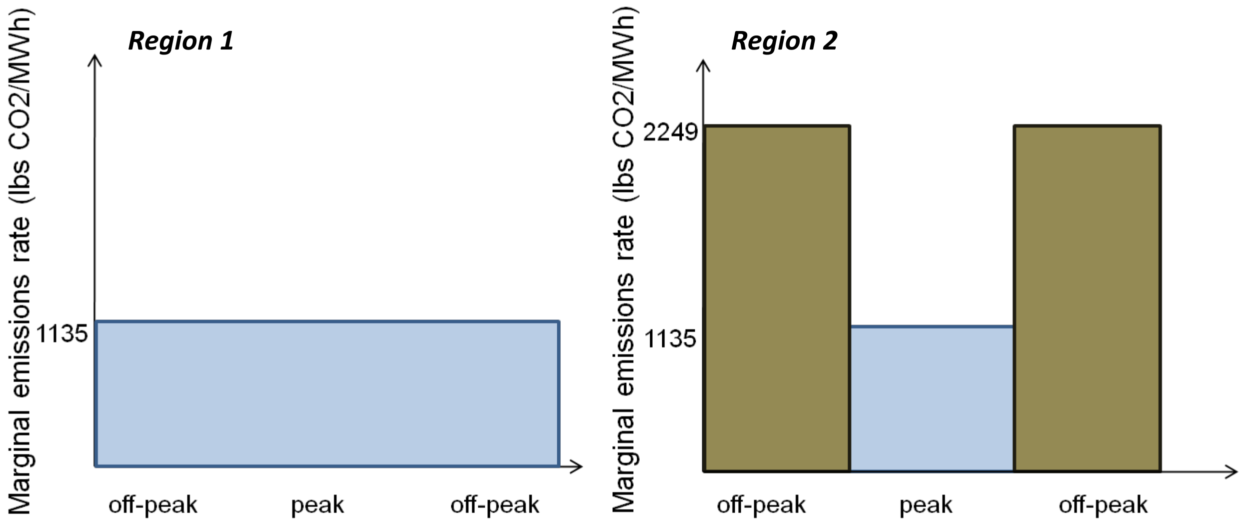

Figure 2: Marginal operating emissions rates for two hypothetical regions

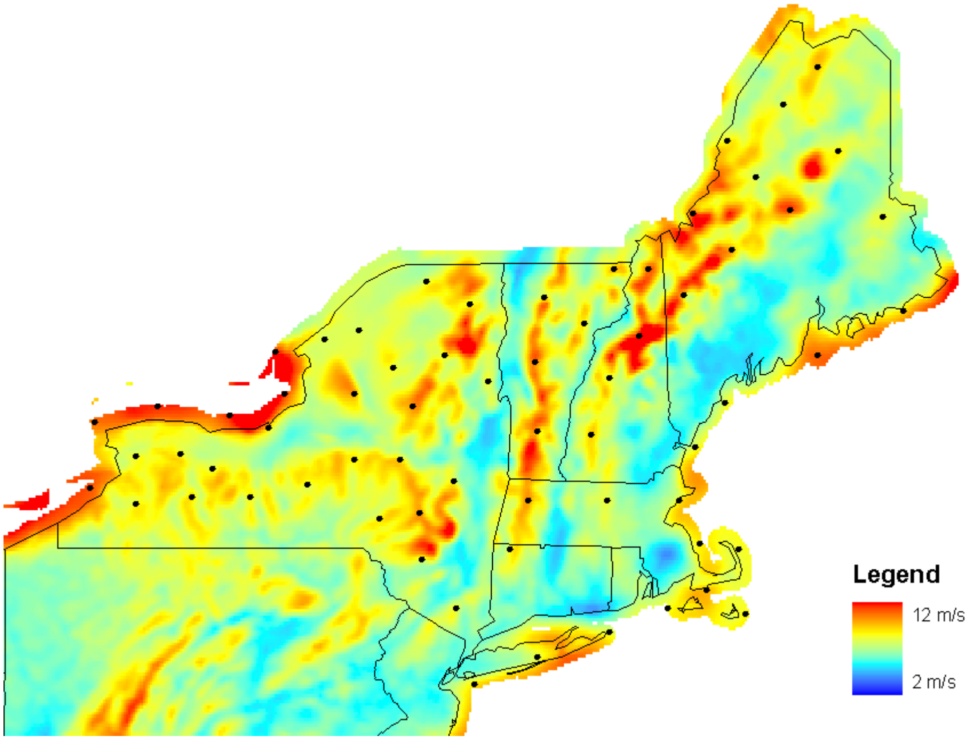

Figure 3: Average wind speed at 80 meters in the Northeast, with chosen locations for hourly data in New York and New England, to b e used in the emissions displacement analysis.

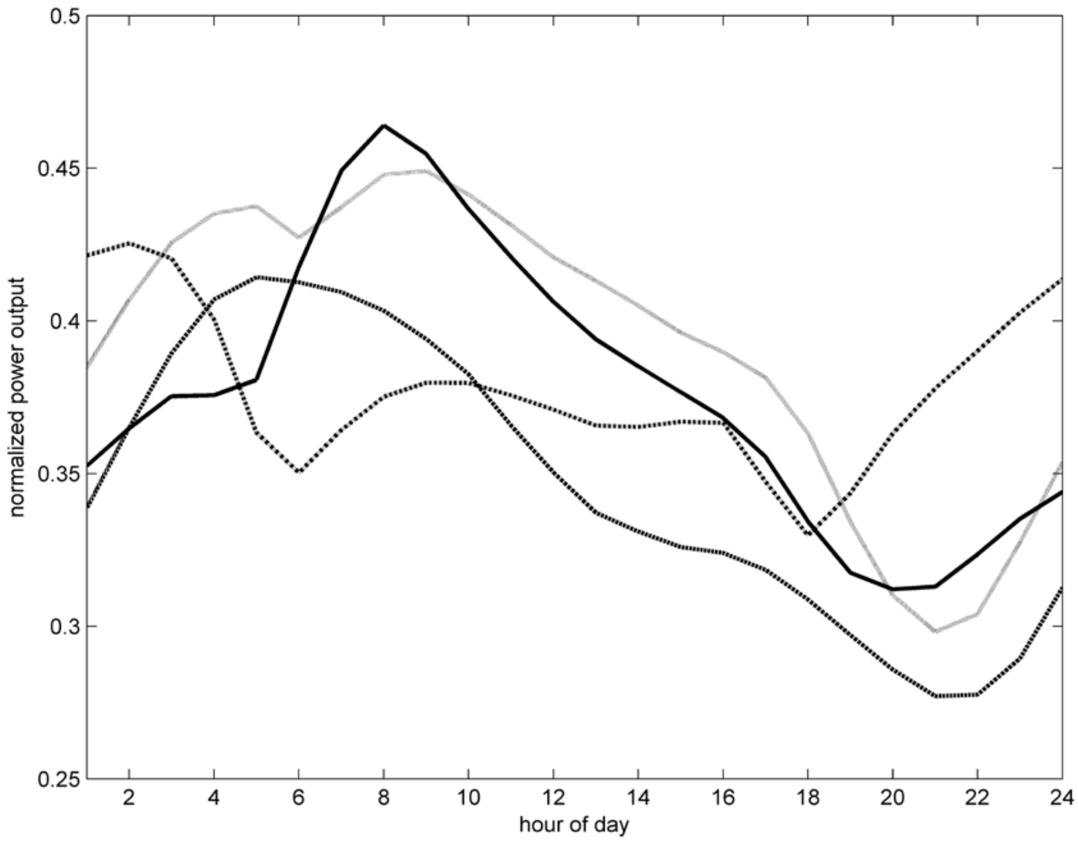

Figure 4: Hourly average wind power for four sites in New York and New England.

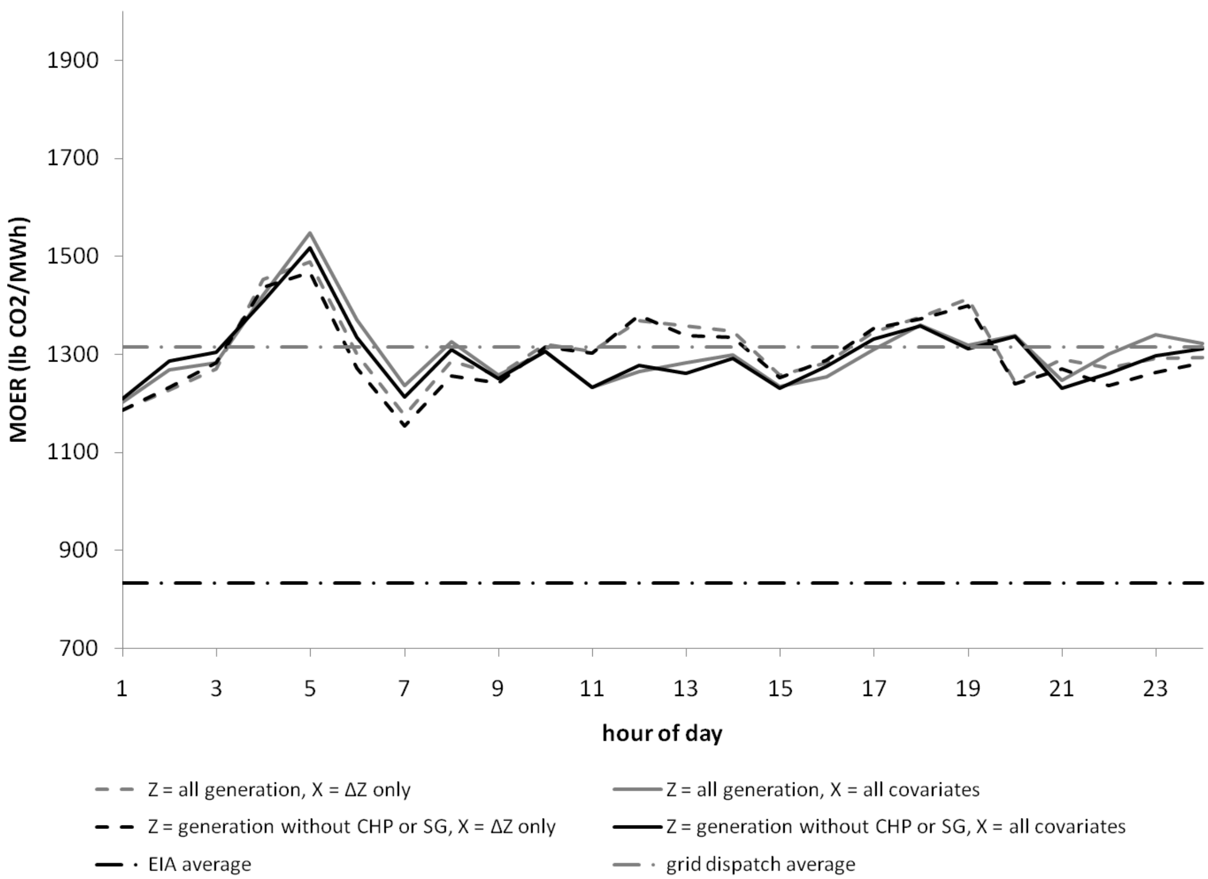

Figure 5a: Marginal operating emissions rates for ISONE

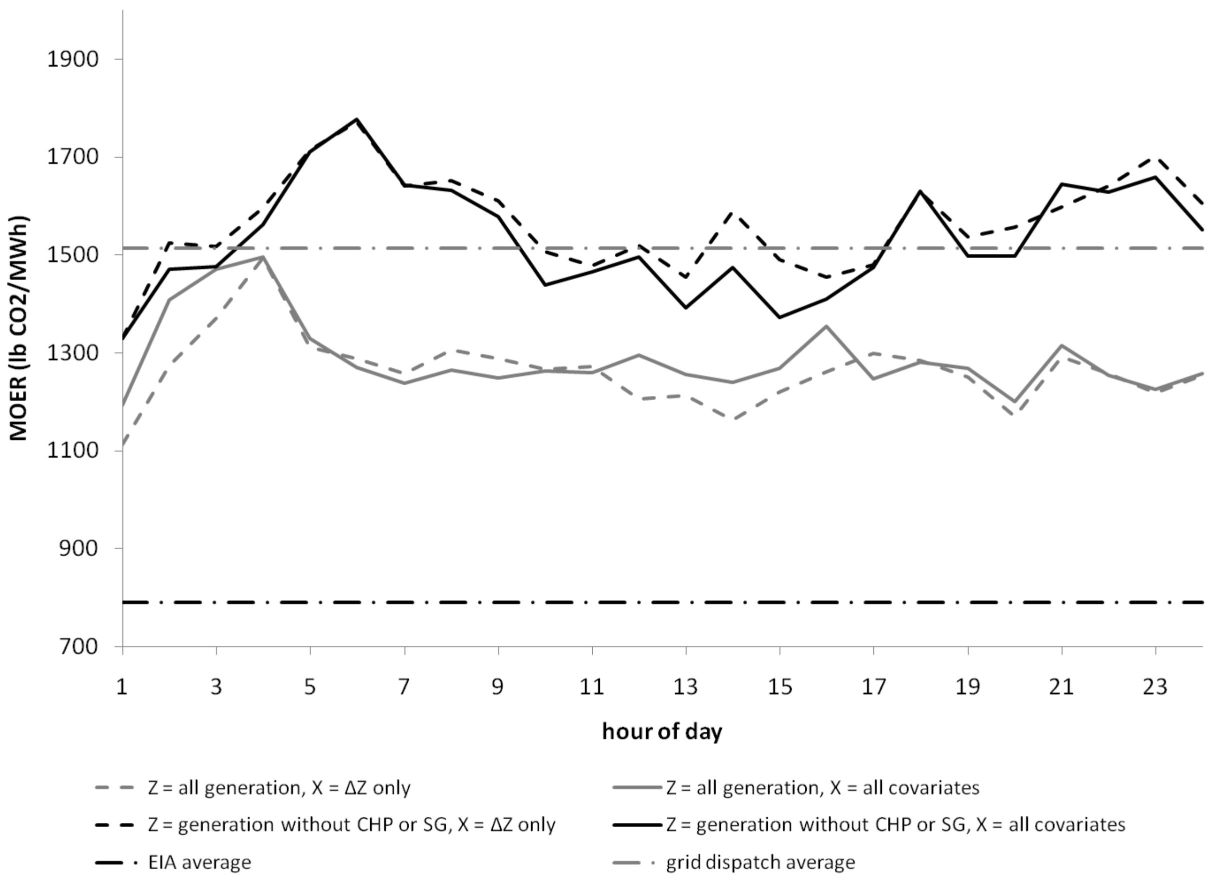

Figure 5b: Marginal operating emissions rates for NYISO

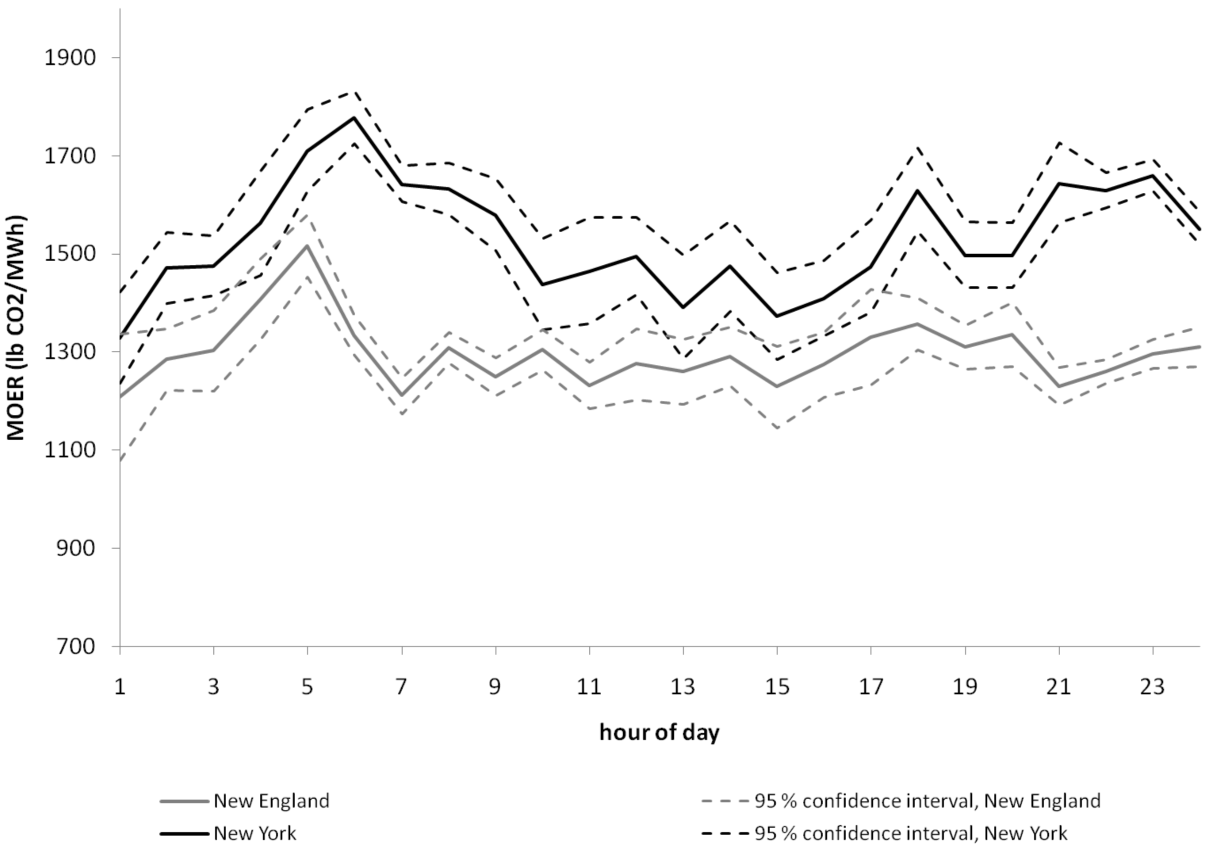

Figure 6: MOERs with confidence intervals for New England and New York. MOERs were computed using with covariates and without CHP or self generation.

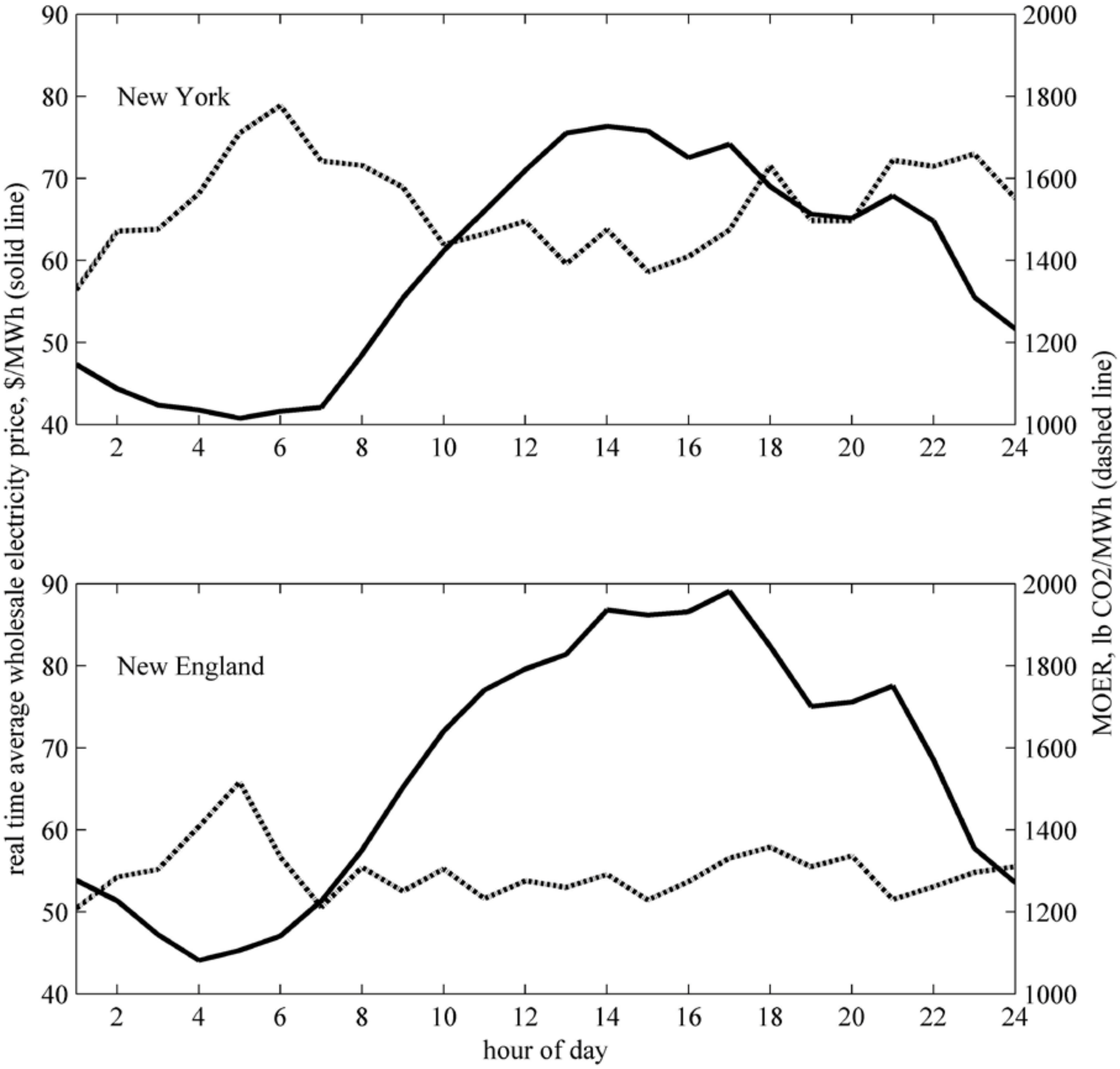

Figure 7: Direct comparison of MOERs (computed using generation without CHP and self-gen and with covariates included in the regression) to average real-time in ozone season.

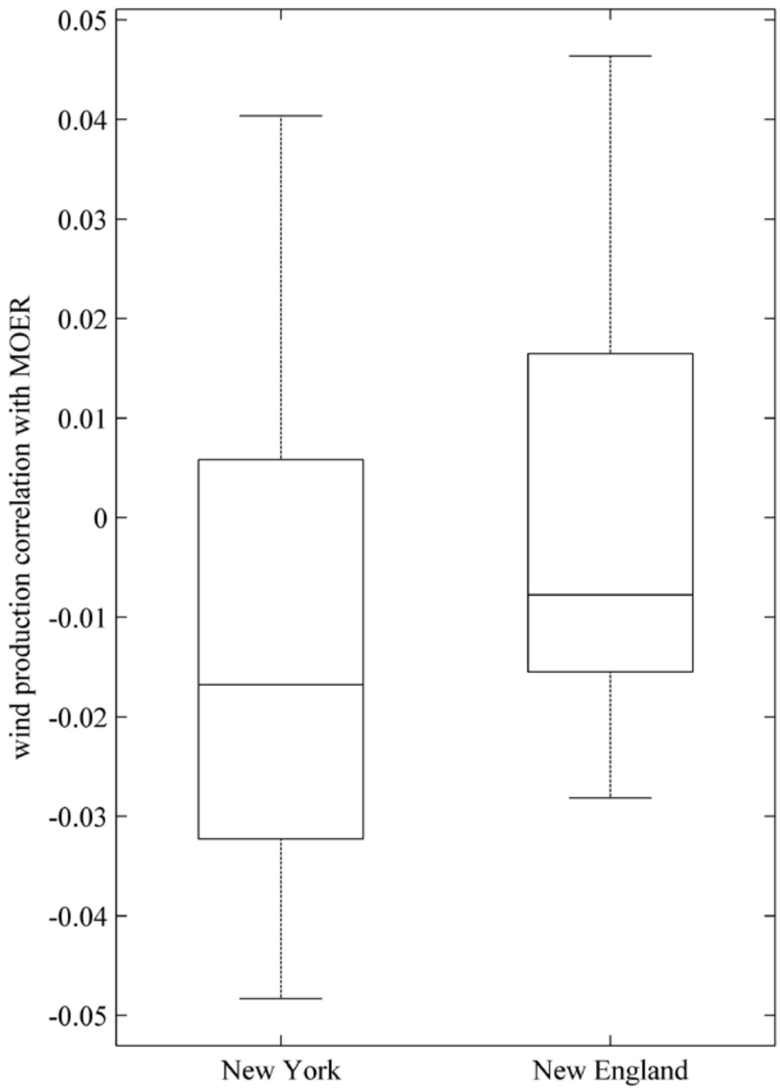

Figure 8: Distribution of correlation coefficients between hourly wind production and MOER for sites in New York and New England.

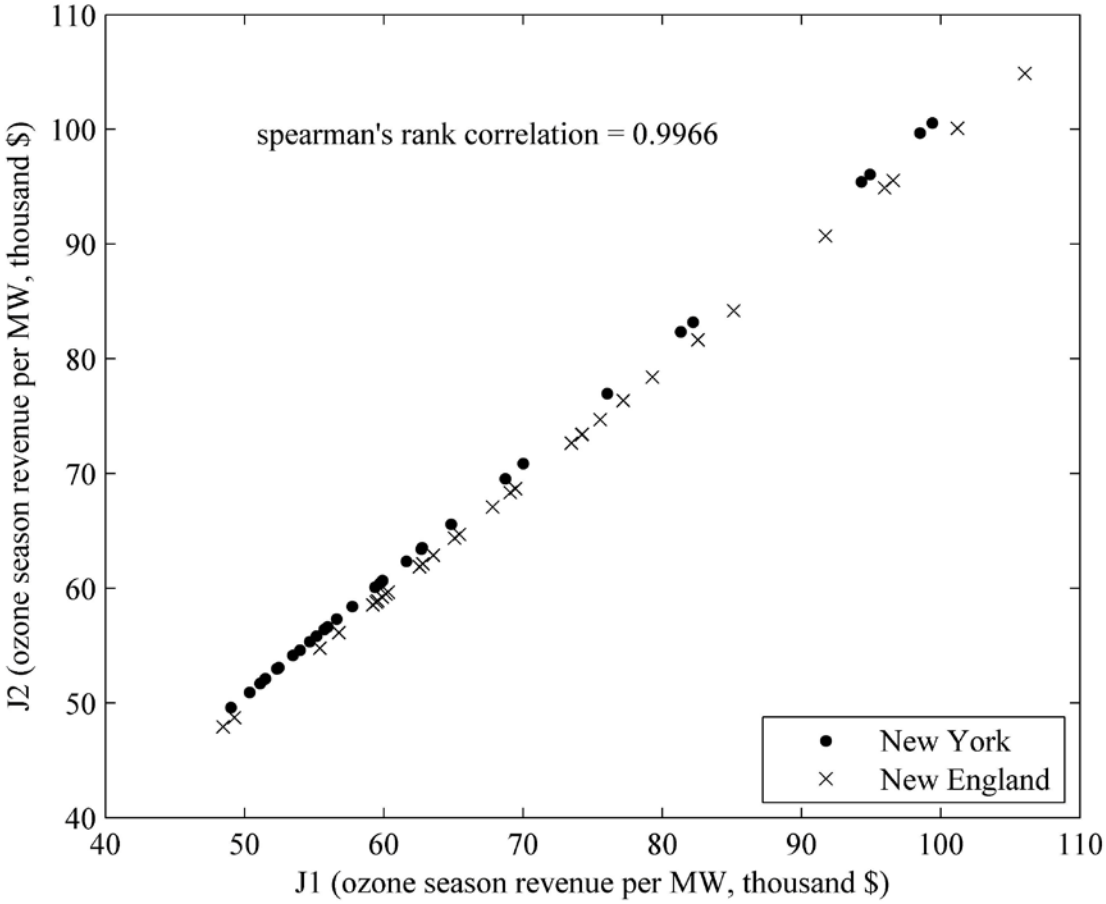

Figure 9: *J2* versus *J1*, where *J1* is computed using the inter-regional average marginal emissions rate.

Table 1: Emissions displacement in two hypothetical regions and two New York wind profiles.

	Profile *a*[1]	**Profile *b*[1]**
Region 1[2]	204 tons/day (1135 lbs/MWh)	202 tons/day (1135 lbs/MWh)
Region 2[2]	301 tons/day (1681 lbs/MWh)	347 tons/day (1945 lbs/MWh)

[1] Profiles a and b are shown in Figure 1.
[2] Regions 1 and 2 correspond to the marginal emissions rate profiles in Figure 2.

Table 2: 2006 Displaced CO2 Emissions Rate Estimates (lbs CO2/MWh)

	New England	**New York**	**PJM**
System average[1]	833	790	1,196
Grid dispatch analysis[2]	1,080	1,110	1,140
Generation-weighted average of load following units[3]	1,072	n/a	n/a

[1] Source: EIA State Electricity Profiles (2006)
[2] Source: Keith *et al* (2002) "The OTC Emission Reduction Workbook 2.1"
[3] Source: NEISO (2006) "2004 New England Marginal Emission Rate Analysis"