Intermittency and CO_2 reductions from wind energy*

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Abstract

Using detailed 5-minute electricity generation data, we examine the impact of wind intermittency on carbon dioxide (CO_2) emissions savings from wind energy in the Southwest Power Pool from 2012-2014. Parametric and semi-parametric analysis confirms concerns that intra-hour wind intermittency reduces CO_2 emissions savings from wind - in the top decile of wind intermittency, emission savings are reduced by nearly 10 percent. However, the average wind intermittency effect on emission savings is modest, on the order of 4 percent, with reductions in savings on the order of 6.5 percent when accounting for dynamic effects. Evidence suggests the intermittency effect is likely to remain modest in the near-term.

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1 Introduction

In light of the dramatic worldwide growth in renewable electricity, particularly wind, there is substantial interest in understanding the costs and benefits of these technologies. U.S. electricity generation from wind has grown from less than 1% in 2007 to more than 6% in 2017 and growth is likely to continue as costs continue to fall. One longstanding area of concern is that renewable technologies such as wind and solar are intermittent, in contrast to conventional electricity sources that can be dispatched as needed. Intermittency can raise the costs of renewable technologies (Gowrisankaran et al. 2016), and the need to balance renewable intermittency with conventional backup (e.g. coal and gas) may also affect the emissions savings potential of renewable technologies. Matching the variability of renewables typically requires the emissions-intensive process of "ramping" of generation from fossil fuel generators, potentially undercutting the emission savings from wind or solar. Given emissions reductions, CO_2 in particular, are a primary economic justification for the substantial policy interventions supporting renewable energy (Ambec and Crampes 2015), it is crucial to understand the extent to which intermittency may undercut emissions savings from wind generation. As such, this paper asks: How does the grid respond to wind generation and intermittency? Does wind intermittency reduce the CO_2 savings associated with wind generation? What is the magnitude of this effect, and to what extent does it undercut the economic justification for renewable policies as the share of wind grows?

A unique feature of this study is the use of 5-minute generation data from the Southwest Power Pool (SPP).[1] This 5-minute data provides a high-frequency look at the intra-hour

[1] The Southwest Power Pool is a Regional Transmission Organization (RTO) and is mandated by FERC to operate the electrical grid to ensure reliability, adequate transmission, and a competitive wholesale market. SPP primarily covers Nebraska, Kansas, and Oklahoma, with some coverage in neighboring states. During

evolution of the generation mix. In particular, it allows statistical comparisons of emissions in two otherwise identical hours (including the same level of wind generation), but with different levels of intra-hour wind intermittency. Given the plausibly exogenous variation in intermittency, we can interpret our estimates as the causal impact of intra-hour intermittency on emission savings.[2]

To our knowledge, this is the first study to empirically identify the effects of intra-hour intermittency on emission savings. In perhaps the most closely related study, Dorsey-Palmateer (2014) provides empirical evidence from Texas that intermittency over longer time spans (5 hours) shifts the grid from coal to natural gas, generating a reduction in emissions through a compositional effect. Wheatley (2013) examines 30-minute data in Ireland and argues intermittency substantially reduces emissions savings, but does not causally identify its impact. Di Cosmo and Valeri (2017) also examine the Irish market, but find no evidence of a strong negative effect on thermal plant efficiency and thus emissions. Graf and Marcantonini (2017) examine the impact of increases in intermittent renewable generation on thermal plant annual emission rates and find evidence of modest increases in emission factors, though they are unable to separate the specific effects of intermittency from other channels by which increased renewables may affect emission rates (e.g. heat rate changes due to merit order effects). The remainder of the literature has typically relied on simulation dispatch models to examine emission savings (Lamont 2008; Lueken et al. 2012; Gutiérrez-Martín et al. 2013;

the sample period, 2012-2014, roughly 10% of SPP's generation came from wind power.

[2] By way of simple analogy, the fuel-efficiency of automobiles depends on how they are driven. Two drivers who each cover 30 miles at an average speed of 60 mph may have very different fuel consumption depending on stops, starts, acceleration, etc (Langer and McRae 2013). In the case of electricity, the emission savings from one hour of steady wind generation will likely be larger than from the same amount of wind generation with larger intra-hour volatility (Katzenstein and Apt 2009).

Gowrisankaran et al. 2016).[3] While such studies have clear value, our data and approach allows us to empirically estimate and identify the impact of intermittency on emissions savings without making assumptions about grid operator behavior or plant operations.

We first confirm several of the assumptions described above. We find coal and natural gas are the primary sources of generation offset by wind, whereby 1 megawatt hour (MWh) of wind on average offsets 0.52 MWh of coal and 0.37 MWh of gas.[4] Next, we show intra-hour intermittency in wind generation (measured as the intra-hour root-mean-square of changes in 5-minute generation levels) is also primarily balanced by intra-hour variation in coal and gas, and this intra-hour variation in coal and gas increases CO_2 emissions. Finally, our key parametric estimation finds 1 MWh of wind reduces CO_2 emissions in SPP by 0.726 tons holding intermittency constant, but an increase in the intra-hour intermittency of wind generation offsets emissions reductions to some extent. Similarly, our semi-parametric approach finds that in the lowest decile of intermittency, 1 MWh of wind generation reduces CO_2 emissions in SPP by 0.773 tons, while in the highest decile of intermittency, wind generation reduces CO_2 emissions by a substantially smaller 0.703 tons per MWh.

Evaluating the parametric point estimates at the mean values of wind generation and intermittency, marginal CO_2 emissions savings from a MWh of wind are reduced by a modest 3.8% due to intermittency in a static, contemporaneous model, and 6.5% in a dynamic model

[3] Gutiérrez-Martín et al. (2013) in particular focus on the effects of wind intermittency on emission savings in Spain, and find little evidence intermittency substantially reduces emission savings, which is similar to the conclusions for renewables in the Italian market examined in Graf and Marcantonini (2017) and Irish market examined in Di Cosmo and Valeri (2017). This stands in sharp contrast to the arguments in Wheatley (2013) that intermittency is responsible for large reductions in emissions savings in Ireland.

[4] The remainder is met by small reductions in fuel oil and hydro, as well as modest changes in imports. While gas accounts for only 24% of total generation, it is offset by wind more frequently than its average share. Natural gas generation often plays this role, as it is designed to adjust output levels more quickly than coal (Green and Staffell 2016). That said, there is substantial research into alternative approaches for accommodating intermittency, primarily involving storage (Carson and Novan 2013; Jacobson et al. 2015).

that considers lagged effects. In terms of a Pigovian subsidy for wind, this represents the difference between a $28.31/MWh subsidy and a $27.22/MWh subsidy for the static estimates. Furthermore, while we find intermittency concerns will grow as wind share increases, the effect is likely to remain modest in the near-term (wind shares of 10-20%). Thus, at current wind generation shares, the concern that intermittency reduces CO_2 emissions savings is borne out, but concerns of its overall importance for policy are not.

2 Emissions savings and intermittency

2.1 Measuring emission savings

This paper contributes to a growing empirical literature that measures the emissions savings from various renewable technologies, which are often supported through a variety of subsidies and other policy supports. Economic theory suggests correcting pollution externalities via a Pigouvian tax on emissions or a Pigouvian subsidy on emissions avoided can yield equal and efficient outcomes, at least to a first-order approximation. And while there has been substantial work exploring when that equivalence breaks down from a theoretical or behavioral perspective, a perhaps less obvious distinction between the two policy instruments is the issue of *measurement*.

Standard theory shows the efficient tax should be set equal to the marginal external damages of emissions, which is then applied to the measured level of emissions. Though determining the marginal external damages may be challenging, the measurement of the emission levels themselves is typically straightforward (from the perspective of economists)

- that is to say, the measurement of emissions generated is primarily a matter of physics, chemistry, and engineering, and not often something economists have much to contribute towards.[5]

By contrast, in the context of an efficient subsidy policy, one must be able to measure the emissions *avoided*, and this is no longer quite so straightforward from the perspective of measurement. While one can measure the carbon dioxide (CO_2) emissions from a coal-fired power plant's smokestack and apply a carbon tax, there is no smokestack to measure the "non-emissions" from a wind turbine or solar panel. One must determine the counterfactual level of emissions, which depends on market processes and behavioral responses, and this is a task economists are better-suited to consider. Similar challenges arise in measuring the energy consumption avoided through energy efficiency adoption.

A substantial literature has emerged to measure the emissions and energy consumption avoided from various technologies, driven in part by the fact that subsidies are viewed as more politically palatable and more frequently utilized than taxes. Recent studies have examined emission savings from wind (Cullen 2013; Kaffine et al. 2013; Novan 2015; Di Cosmo and Valeri 2017), solar (Baker et al. 2013; Callaway et al. 2015; Millstein et al. 2017), electric vehicles (Zivin et al. 2014; Holland et al. 2016), biofuels (Bento et al. 2015), and energy savings from energy efficiency investments and codes (Fowlie et al. 2015; Levinson 2016). Our paper contributes to this growing literature by measuring the emission savings from wind power, accounting for the intermittent nature of wind generation.

[5] In the case of ambient pollution problems (Segerson 1988), while it may difficult to attribute emissions to any particular emitter, the measured level of pollution in the water or the air is not in doubt.

2.2 Intermittency and Emissions

As discussed above, intermittency of renewables is oft-noted as one of the primary concerns regarding renewable expansion and integration into the grid (Jacobson et al. 2015). Indeed, the substantial body of literature on accommodating renewables into the grid, primarily using simulation methods, is a testament to its importance. Furthermore, much of this existing literature focuses on what might be described as "big picture" issues of intermittency; in other words, how should one optimally design and operate the electricity grid to account for renewable intermittency? By contrast, this study focuses on the very short-run implications of intermittency on CO_2 emissions.

To motivate the following regression analysis, consider the following simple model of hourly electricity sector emissions E_h as a function of wind generation W_h:

$$E_h(W_h) = \sum_i \delta_i Q_{ih}(W_h), \tag{1}$$

where δ_i is the emission rate per MWh from fossil plant i, and $Q_{ih}(W_h)$ is the output from plant i, which depends on the level of wind generation. The change in emissions from increasing wind power is:

$$\frac{dE_h}{dW_h} = \sum_i \delta_i \frac{dQ_{ih}}{dW_h}, \tag{2}$$

or simply the sum of changes in generation from each plant times their emissions rate.[6] Given the grid has to balance, $dW_h = -\sum_i \frac{dQ_{ih}}{dW_h}$ and thus $\frac{dE_h}{dW_h}$ can (typically) be signed as negative.[7]

[6] Early examinations of the emission savings from wind adopted an even simpler approach, whereby the average emissions rate of a state, region or country was simply multiplied by the amount of wind power generated.

[7] Hypothetically, increased wind could cause a compositional shift, such that total fossil generation decreases, but relatively dirtier plants are dispatched more frequently such that $\frac{dE_h}{dW_h} > 0$. However, when

However, assuming a constant emission rate of δ_i ignores the noted impact of intermittency on fossil plant operations and emissions, and ignores the fact that wind generation itself can affect emission rates (e.g. due to operation at less efficient heat-rates (Graf and Marcantonini 2017)). Thus, if we allow the emission rate to depend on wind W_h and intermittency σ_h, then given $E_h(W_h, \sigma_h) = \sum_i \delta_i(W_h, \sigma_h) Q_{ih}(W_h)$, the total differential of emissions is:

$$dE_h = (\sum_i \delta_i(\sigma_h) \frac{dQ_{ih}}{dW_h} + \sum_i \frac{\partial \delta_i}{\partial W_h} Q_{ih}(W_h)) dW_h + \sum_i \frac{\partial \delta_i}{\partial \sigma_h} Q_{ih}(W_h) d\sigma_h. \quad (3)$$

The first term in parenthesis is the change in emissions from decreased fossil fuel generation holding emission rates constant plus the change in emissions due to changes in the emissions rate, holding fossil generation constant. Our focus is on the second term, as this term will be positive (increased emissions) to the extent increased intermittency increases emission rates. It is this term that drives the concern emission savings from wind may be overstated, or may even be overturned entirely if the second term grows as the share of wind generation grows.

Looking towards the empirical analysis, we note several important points. First, existing estimates of emissions savings from wind generation such as Kaffine et al. (2013) and Novan (2015) are effectively estimating the total marginal effect of wind on emissions, $\frac{dE_h}{dW_h}$. In other words, the effect of intermittency is reflected in their estimates, but is not separately identified. Second, the following estimates of emissions savings from wind generation embed any changes in the composition of dispatched technologies due to the level of wind generation, e.g. gas being relatively more preferred for dispatch (Dorsey-Palmateer 2014). Finally, while the above expression reflects the total change in emissions from wind, the empirical estimates below will decompose the effect of wind on emissions into $\frac{\partial E_h}{\partial W_h}$, the change in emissions due

the generator-by-generator output estimates in Cullen (2013) are aggregated for Texas, both coal and gas fall, implying the more expected case of $\frac{dE_h}{dW_h} < 0$.

to wind while holding intermittency constant, and $\frac{\partial E_h}{\partial \sigma_h}$, the change in emissions due to intermittency holding wind generation constant.

To further motivate our approach, consider the following thought experiment: Imagine two hours, identical in every way except for the fact one hour has 2000 MWh of steady intra-hour wind generation, while the other hour has 2000 MWh of volatile and intermittent intra-hour generation. The difference in emissions between those two hours will reflect the causal impacts of intermittency on emission savings. The 5-minute SPP generation data (discussed in more detail to follow) allows us to empirically approximate this thought experiment and causally identify the effect of intermittency on emissions. Figure 1 provides a nice illustration of the research design, whereby 5-minute wind generation for six different hours is plotted. All six hours had 2000 MWh of generation over the course of the hour, and from the perspective of hourly data are effectively identical. However, two hours show a dramatic increase in intra-hour wind generation, two hours decline substantially, and two hours are relatively flat. It is this variation in the shape of the intra-hour generation profile that will allow us to identify the effect of intermittency on emissions.

3 Data

The key feature of the dataset used in this analysis is that we have 5-minute generation data from the SPP RTO, which operates primarily in Kansas, Nebraska, and Oklahoma. This data covers the period from January 1st, 2012, to April 9th, 2014 and reports 5-minute generation for wind, gas, coal, nuclear, hydro, fuel oil (DFO), as well as load (demand).[8] From this

[8] More recent data available from SPP does not include 5-minute load. Given that load intermittency is also likely important for emissions, we use the earlier time period for which 5-minute load data is available.

5-minute data, we construct intra-hour measures of intermittency σ_h for all generation types and load, with the intra-hour root-mean-square of changes in 5-minute generation as our preferred measure.[9]

$$\sigma_h = \sqrt{\frac{1}{12}\sum_{m=1}^{12}(W_{hm} - W_{hm-1})^2} \tag{4}$$

Thus, for each hour in the dataset, we have the hourly aggregates from each source of generation, as well as the intra-hour measure of intermittency.

To this generation data, we then add hourly emission data for SPP, available from Ventyx/ABB Velocity Suite (ultimately sourced from EPA's Continuous Emissions Monitoring System (CEMS)), as well as hourly, population-weighted temperatures.[10] While emissions data for sulphur dioxide SO_2 and nitrogen oxides NO_x are available, we initially focus on CO_2 emissions, returning to the other emissions later in the analysis.

Summary statistics for key variables are reported in Table 1. Coal is the largest share of generation, at 60% of total generation, followed by gas at 23% of total generation. Wind is the third largest source of generation at 10% and then nuclear at 6%. Hydro and fuel oil provide less than 1% of total generation. SPP is an exporter of electricity on average, though on any given hour may import substantial quantities of electricity.[11] Relative to ERCOT in Texas, where many of the previous wind studies have been conducted, this is a comparable level of wind share, though the existing fossil generation mix is tilted more heavily towards coal (but not as much as in neighboring MISO). Given the relatively large

[9] We also examine the intra-hour range (max-min), standard deviation, and "mileage" (total change in intra-hour generation) as measures of intermittency. All measures were very correlated with the root-mean-square (correlation matrix in Appendix Table A.1) and as such estimation results were extremely similar.

[10] CEMS reports hourly emissions from all plants greater than 25 MW. For SPP this implies 10 small coal plants are excluded from reporting requirements (0.4% of total coal capacity), as well as a number of small gas plants (around 5% of total gas capacity).

[11] Neighboring regions include the Electric Reliability Council of Texas (ERCOT), the Midcontinent Independent System Operator (MISO), and the Western Electricity Coordinating Council (WECC).

share of coal, average CO_2 emissions per MWh are fairly high at 0.83 tons/MWh, though there is considerable heterogeneity across hours of the sample from a low of 0.59 tons/MWh to a high of 1.04 tons/MWh.

4 Econometric Strategy

Our econometric strategy follows the existing literature in exploiting the exogenous and stochastic variation in hourly wind power generation and intra-hourly intermittency (e.g. Kaffine et al. (2013)).[12] We estimate a series of reduced-form regressions of the following general form:

$$y_{hdmy} = \boldsymbol{x_{hdmy}\beta} + f(\mathbf{z_{hdmy}}) + \zeta_{hm} + \theta_{my} + \eta_d + \epsilon_{hdmy}, \tag{5}$$

where y_{hdmy} is the outcome variable of interest (e.g. emissions, generation by type) for hour h, day d, month m, and year y. The variable $\boldsymbol{x_{hdmy}}$ represents the explanatory variable(s) of interest, such as hourly wind generation levels or intra-hour wind intermittency, with $\boldsymbol{\beta}$ representing the coefficient(s) of interest. The function $f(\mathbf{z_{hdmy}})$ captures flexible control variables, such as load and temperature.[13] Standard errors for all estimations reported below are clustered at the weekly level to account for serial correlation.[14]

While the outcome, explanatory variables of interest, and control variables will vary depending on the specific regression, the fixed effects strategy remains constant across all regressions below. These fixed effects control for other sources of variation in our outcome

[12] While wind is typically taken by the grid as a "must-run" generation source, there is the potential for curtailment of wind power at low load levels. However, regressing wind generation on load and conditioning on fixed effects (discussed below), there is no relationship between wind and load ($p = 0.98$), even for the subsample of the smallest 5% of load observations ($p = 0.46$).

[13] Temperature is included in addition to load to account for any thermal effects on plant efficiencies.

[14] Estimations using Newey-West standard errors with 24-hour lags (Novan 2015) or daily clustered errors yielded similar standard errors (slightly tighter) as those reported below.

variables that may be correlated with our explanatory variables of interest. Hour-by-month fixed effects ζ_{hm} control for changes in wind patterns over the course of the day (diurnal variation) that may be correlated with changes in the shape or composition of the load profile. For example, if wind generation was more volatile during daytime hours (due to more unstable atmospheric conditions) when lower-emission natural gas is a greater share of generation, then estimations of the effect of intermittency on emissions would be biased negatively. Similarly, month-by-year fixed effects θ_{my} will control for longer-run trends such as increasing wind capacity and changes in the generation mix due to changing natural gas prices or other factors affecting emissions (Fell and Kaffine 2018). Finally, day-of-week fixed effects η_d captures within-week variation in the load and generation profile, though wind generation and intermittency should be uncorrelated with the day of the week.

5 Results

In this section, we report the results from a variety of investigations of the effects of wind generation and intermittency. We begin with a series of parametric regressions to establish what sources of generation respond to wind generation and intermittency, and then examine the emissions implications. Further analysis examines a semi-parametric approach to estimate emissions savings by decile of intermittency as well as a dynamic model that considers lagged effects of wind and wind intermittency.

5.1 Generation and emission response to wind

Our initial regressions examine a) which sources of generation respond to increases in wind generation, and b) which sources of generation respond to intra-hour wind intermittency. Table 2 regresses each generation type (coal, gas, fuel oil, nuclear, hydro, and imports) against hourly wind generation, controlling for load (quadratic) and temperature (quadratic). As expected, natural gas and coal account for the bulk of the response to changes in wind generation levels, whereby a 1 MWh increase in wind generation reduces coal generation by 0.52 MWh and natural gas generation by 0.37 MWh.[15] Finally, note the sum of coefficients in Table 2 gives a 1.0004 MWh response per 1 MWh change in wind, suggesting our general control variable and fixed effects strategy is appropriate.

Next, Table 3 shows how intra-hour volatility (root-mean-square) of each generation type responds to intra-hour intermittency of wind. For each generation type, the intra-hour intermittency measure is regressed against wind levels, the intra-hour intermittency of wind, the intra-hour intermittency of load, and the control variables from above. The coefficient on *Wind inter* can be interpreted as the effect of wind intermittency, holding wind generation levels (and everything else) constant. From Table 3, coal, natural gas, and import intermittency responds the most to intra-hour wind intermittency, with a slight response from fuel oil (which is used for peak hours). As expected, hydro and nuclear do not exhibit any intra-hour variation due to wind intermittency.

[15] Disaggregating natural gas generation by technology type using hourly CEMS data finds that the gas response is roughly split between combined cycle (CC) plants and non-CC plants. Note, the response of natural gas to wind generation is roughly twice its average share of generation. However the coal-response is much larger than that found in Cullen (2013) for ERCOT in the mid-2000s. This difference is likely driven by a) SPP simply having more coal-fired generation than ERCOT, and b) the growing share of wind and falling natural gas prices over this time-period and their joint effects on coal-fired generation (Fell and Kaffine 2018; Millstein et al. 2017).

The previous tables have established two important facts: First, variation in wind generation levels is primarily met by changes in the level of coal and gas generation, and second, holding wind generation constant, a more volatile intra-hour wind profile leads to more variability in intra-hour generation from coal and gas. Table 4 links these changes in coal and gas generation and intermittency to CO_2 emission outcomes. The first column simply regresses CO_2 emissions on coal, gas and fuel oil generation.[16] As expected, an additional MWh of coal produces around 1 ton of CO_2 while an additional MWh of gas produces around a half ton of CO_2. The next column disaggregates natural gas generation into CC and non-CC generation, where non-CC gas generation produces considerably more CO_2 than CC gas generation. The third column adds in the intra-hour intermittency of coal and gas generation and importantly shows that, holding generation levels constant, a more variable intra-hour generation profile increases CO_2 emissions.[17] This is precisely the concern motivated in Section 2 whereby more variable operation of fossil plants (ramping) leads to increased emission rates. The last three columns repeat the previous exercise, but add simple year fixed effects to control for any longer term trends (e.g. scrubber technologies). Estimates of the emission impacts from coal and gas generation and variability are similar.

Finally, we turn to the key estimation that motivated this paper. While the above regressions confirm the links between intra-hour wind intermittency and intra-hour fossil generation variability, and between intra-hour fossil generation variability and increased CO_2 emissions, we now examine the reduced-form relationship between wind generation and in-

[16] Note that the specifications for this set of regressions are relatively parsimonious, reflecting the "technical" nature of the relationship between fossil generation and emissions, as observed in the very high R^2. See Appendix Tables A.2 and A.3 for equivalent results for SO_2 and NO_x.

[17] Unfortunately, the five-minute SPP data does not allow us to separate CC from non-CC generation so we cannot create disaggregated measures of intra-hour intermittency by gas technology.

termittency and emissions savings in Table 5. The first column regresses CO_2 emissions on wind generation and intermittency, while controlling for load (and its variability), temperature, and fixed effects. The coefficient on $Wind$ of -0.726 can be interpreted as the tons of CO_2 avoided from a MWh of wind generation, holding intermittency constant.[18] However, the coefficient on *Wind inter* of 2.393 implies that, holding wind generation constant, wind intermittency increases CO_2 emissions. We will return to the magnitudes and their relative economic importance below, but the positive and strongly statistically significant coefficient on *Wind inter* confirms wind intermittency does increase CO_2 emissions.

The first column of Table 5 provides causal estimates of the effect of wind generation and intermittency on CO_2 emissions in the SPP region; however, recall from Tables 2 and 3 that part of the change in wind generation and intermittency is accommodated by changes in imports (importing less or exporting more). While we cannot explicitly account for the corresponding changes in emissions in SPP's trading neighbors, the second column of Table 5 controls for imports and import variability, and as expected, emission savings are a bit higher. This coefficient provides a rough approximation of the total emission savings from wind in SPP, where the closeness of the approximation depends on the similarity between marginal emission rates in SPP and its trading neighbors. That said, from the perspective of the key contribution of this paper, importantly the wind intermittency coefficient is roughly the same in terms of magnitude and significance when controlling for imports. The remaining columns of Table 5 repeat the above analysis for SO_2 and NO_x, both measured in pounds. Consistent with previous results, wind generation reduces both of these pollutants. For SO_2,

[18] This estimate is roughly in line with previous estimates in the literature that have looked specifically at emission savings or marginal emission rates in SPP or at emissions savings across varying coal-gas mixes (Kaffine et al. 2012; Zivin et al. 2014; Fell and Kaffine 2018).

increases in wind intermittency increase emissions (marginally significant), similar to the case of CO_2. However, increases in wind intermittency *decrease* NO_x emissions, and while point estimates are insignificant, we return to this point below.[19]

5.2 Further analysis of intermittency effects

While the above analysis demonstrated that intra-hour wind intermittency increased CO_2 emissions, we further examine these intermittency effects along several dimensions. First, the above analysis assumed the emissions response to intermittency was linear. Below we consider a more flexible semi-parametric examination of emissions savings by decile of intermittency that also allows for a more direct examination of the relative importance of the intermittency effect in terms of emissions savings. Second, while the above analysis considers contemporaneous emission effects of wind and wind intermittency, there may be dynamic implications if effects in one hour spill over to subsequent hours (Cullen 2013).

Previously, we assumed intermittency enters linearly into our estimation equation. To more flexibly examine the effect of intermittency on emission savings, we next create deciles of wind intermittency, where D^b_{hdmy} is equal to 1 if wind intermittency falls into decile bin b. We then estimate the following regression on hourly CO_2 emissions E_{hdmy}:

$$E_{hdmy} = \sum_{b=1}^{10} \beta^b * W_{hdmy} * D^b_{hdmy} + f(\mathbf{z_{hdmy}}) + \zeta_{hm} + \theta_{my} + \eta_d + \epsilon_{hdmy}, \tag{6}$$

where β^b is the CO_2 emissions savings from wind generation W given intermittency is in decile bin b, and control variables $\mathbf{z_{hdmy}}$ and fixed effects are the same as in Table 5. Figure 2 plots

[19] These analyses are replicated using an alternative fixed effects specification of more restrictive hour-by-month-by-year fixed effects in Appendix Table A.4, as well as using the alternative measures of intermittency (the range of intra-hour generation, the standard deviation of intra-hour generation, and the sum of changes in intra-hour generation or "mileage") in Appendix Tables A.5, A.6, and A.7, yielding consistent results.

these emission savings coefficients by decile along with corresponding confidence intervals, with the solid and dashed lines excluding and including import controls, respectively.[20] The decile estimates for both panels are consistent with the results in Table 5 whereby CO_2 emission savings decline as wind intermittency deciles increase. Figure 2 also provides a sense of the magnitude of the intermittency effects on emissions savings, with a 0.07 tons/MWh statistically significant decline from the lowest decile to highest decile of intermittency when import controls are excluded (a 9% decline) and a 0.05 tons/MWh statistically significant decline when import controls are included (a 6% decline).[21]

Next, we look for any dynamic effects of wind or wind intermittency on emissions. We first include a series of lagged variables for wind and wind intermittency. As shown in Figure 3 Panel A, there is little evidence that lagged wind levels affect CO_2 emissions. By contrast, wind intermittency in Panel B exhibits a decaying lag structure that becomes insignificant after four lags.[22] Summing across the coefficients on wind intermittency gives an aggregate dynamic effect on CO_2 emissions of 4.383, or roughly double the "static" effect reported in Table 5.

We estimate generation and intermittency effects for each pollutant for two different dynamic specifications that include lagged values. Following Cullen (2013) and Novan (2015), we subtract the contemporaneous wind generation and/or intermittency value from each of the lags, such that the contemporaneous coefficient can be interpreted as the aggregate

[20] We can interpret the solid line excluding import controls as the emission savings strictly within SPP due to SPP wind generation, and the dashed line with import controls as an approximation of the total emission savings due to SPP wind generation, per the previous discussion regarding interpretation of models with import controls.

[21] Repeating this analysis for SO_2 shows a similar percentage decline in emission savings across deciles, while NO_x emission savings are non-monotonic across deciles.

[22] This pattern is consistent across a variety of specifications and alternative considerations.

dynamic effect of generation and/or intermittency. Specifically, we estimate:

$$E_{hdmy} = \beta_0 W_{hdmy} + \sum_{l=1}^{4} \beta_l * \tilde{W}_{h-l,dmy} + \gamma_0 \sigma_{hdmy} + \sum_{l=1}^{4} \gamma_l * \tilde{\sigma}_{h-l,dmy} + f(\mathbf{z_{h-l,dmy}}) + \zeta_{hm} + \theta_{my} + \eta_d + \epsilon_{hdmy}, \tag{7}$$

where $\tilde{W}_{h-l,dmy}$ and $\tilde{\sigma}_{h-l,dmy}$ are the transformed lag values of wind generation and intermittency, and the vector of controls $f(\mathbf{z_{h-l,dmy}})$ may include lagged values. The coefficients β_0 and γ_0 represent the aggregated dynamic effect of generation and intermittency and are reported in Table 6.

In columns (1)-(3) of Table 6 we include just the four transformed lags for wind intermittency, with all other variables included contemporaneously. In columns (4)-(6), we also include four transformed lags for wind generation, as well as four lags for all other controls. Taken together, the dynamic analysis suggests: a) there is no evidence of a lagged effect of wind generation on emissions, b) there are lagged effects of wind volatility on emissions, with dynamic effects roughly twice as large for CO_2 and roughly 30% larger for SO_2 and NO_x, and c) lagged controls do not appear to materially affect coefficient estimates.[23]

5.3 Robustness checks and further extensions

Several variations on the specifications above were also considered. First, as an alternative approach to addressing import/export issues, we also obtained hourly load and wind generation data for the neighboring regions of ERCOT and MISO. Including these as controls had little impact on qualitative or quantitative results (Appendix Table A.8). Second, for the parametric model, we looked for evidence of nonlinear effects of wind intermittency

[23] The lack of a lagged effect for wind generation (in levels) is consistent with Novan (2015) who finds little evidence for dynamic wind effects. By contrast, Cullen (2013) finds substantial dynamic effects of wind.

and wind generation on emissions (quadratic results in Appendix Table A.9). Interestingly, wind generation has a significant concave relationship with CO_2 and SO_2 emissions (greater marginal emission savings with more wind), but a convex relationship with NO_x emissions. By contrast, there is only weak evidence of a non-linear effect of intermittency. Finally, there were a small number of hours with very large wind intermittency levels (20 standard deviations above the mean intermittency) that may represent data errors. Removal of these few points did not alter the above estimates.

Moving into more substantive extensions, we consider whether or not the effects of intermittency on emission savings varied with the fossil generation mix, defined as the amount of coal generation relative to natural gas generation in a given hour. Given coal generation is more emissions-intensive, we expect intermittency effects would be more pronounced when coal is relatively more prevalent in the generation mix. Results of this exercise are displayed in Table 7, which confirms our intuition that intermittency matters more for CO_2 emission savings when coal is a greater share of generation. Intermittency effects for SO_2 and NO_x do not appear to vary significantly with generation mix.

Next, we examine a semiparametric model where both wind generation and wind intermittency are assigned to quartiles and CO_2 emission savings are estimated by joint quartile. Results are visualized in Figure 4, and are consistent with the above findings - in particular, emissions savings decline as wind intermittency increases. CO_2 emission savings are greatest in the top quartile of wind generation and bottom quartile of wind intermittency, and roughly 20% smaller in the bottom quartile of wind generation and top quartile of wind intermittency. Note, mean values of wind generation and wind intermittency have been increasing over time, moving "southeast" in the figure. For example, mean generation and intermittency levels in

January-March of 2012 fall in the second quartile for each variable, and then move to the third quartile of each in January-March of 2014. However, marginal emission savings remain roughly constant as the falling emissions savings due to increased intermittency are offset by the greater emission savings from increased hourly wind generation.[24]

Finally, we consider how the emissions savings coefficients on wind generation and intermittency vary by hour, whereby wind generation and intermittency are interacted with hourly dummy variables. Figure 5 plots the hourly coefficients for CO_2 emissions savings, comparing CO_2 emission savings absent intermittency (solid) with CO_2 emission savings including intermittency effects (dashed). From the figure, both CO_2 emission savings per MWh of wind and the effects of intermittency are generally greatest in off-peak hours when coal is a greater share of generation, and fall during the day as gas share increases to meet peak load. Appendix Figure A.2 repeats this exercise for SO_2 and NO_x. Similar to the findings above, SO_2 mirrors CO_2, with greater emission savings during off-peak hours when coal is a larger share of generation. By contrast, NO_x exhibits a drastically different pattern, with the greatest emission savings occurring during peak hours when gas is a larger share of generation. Consistent with Novan (2015), this reflects the fact that gas turbines in particular are used more intensely during peak periods - gas turbines have similar emission rates to combined-cycle gas generation for CO_2 and SO_2, but an order of magnitude higher emission rates of NO_x.[25]

[24] Appendix Figure A.1 displays equivalent figures for SO_2 and NO_x. Emissions savings for SO_2 are similar to those of CO_2, whereby emission savings are typically greatest in the top quartile of wind generation, likely reflecting the greater offsetting of coal generation. Interestingly, emissions savings for NO_x are generally greatest in the second quartile, and taper off considerably in the top quartile of wind generation.

[25] The fact that NO_x emissions consistently respond very differently to wind generation than the other two emission types is not unique to SPP, as Kaffine et al. (2013) and Novan (2015) find similar patterns in ERCOT. See Appendix Table A.10 for peak versus off-peak results.

5.4 Discussion

The above estimation results confirm intra-hour intermittency erodes CO_2 emissions savings from wind power. But to what extent does accounting for intermittency change policy prescriptions? Suppose avoided CO_2 emissions were the only external benefit associated with replacing fossil fuel generation with wind power. Then standard externality theory suggests a subsidy per MWh of wind equal to the marginal external benefit per MWh would be efficient.[26]

Recall from Table 5 that, holding intermittency constant, the average marginal CO_2 emissions savings in SPP from 1 MWh of wind is 0.726 tons/MWh. Similarly, holding generation constant, the average marginal increase in emissions due to intra-hour intermittency (also measured in MWh via the intra-hour rme) is 2.393 tons/MWh. Assuming an external damage value of \$39 dollars per ton of CO_2, this would imply an efficient subsidy of \$28.31 dollars per MWh of wind ignoring intermittency effects (reasonably close to the current federal Production Tax Credit of \$23/MWh).

To examine how intermittency would affect this subsidy, we evaluate the marginal emission savings per MWh at the mean levels of wind generation (2558 MWh) and intermittency (30 MWh). At the mean intermittency level, the marginal emissions savings rate is reduced to 0.698 tons/MWh, and the efficient subsidy declines by 3.8% to \$27.22/MWh.[27] Suffice to say, while intermittency does matter, the difference in efficient subsidies is very

[26] In practice of course, there are potentially other external benefits and costs associated with wind power. However, given the importance of reduced CO_2 emissions as a major economic justification for policy interventions to support renewable energy, we focus on them in order to understand the importance of intermittency.

[27] Average marginal emission savings per MWh of wind are calculated as $(0.726*2558-2.393*30)/2558) =$ 0.698 tons/MWh.

small. Even at the 95^{th} percentile of intermittency (64 MWh), the efficient subsidy would be \$25.98/MWh. Finally, using the larger dynamic estimates from Table 6, intermittency effects reduce the efficient subsidy by 6.5% to \$26.50/MWh.

Thus, it does not appear intermittency is a large factor in determining efficient subsidies or other policy interventions for wind power at currently observed wind generation levels. However, many of the concerns regarding intermittency are motivated about *future* levels of intermittency, under wind shares greater than the 10% in SPP during our sample years. If we examine the in-sample relationship between hourly generation and intermittency, intermittency exhibits an inverted U-shape (concave) with respect to wind generation (peaked around 3000 MWh). This would suggest doubling wind generation would actually *decrease* intermittency, though we have reason to believe this interpretation would be inappropriate due to the relationship between wind speed and power output at the turbine level.[28] Alternatively, a better way to think about how intermittency may change in the future is to note both average generation and average intermittency depend on wind *capacity*.

During the sample period, wind capacity grew by a substantial 60%, from 5326 MW to 8912 MW, with the bulk of the capacity additions in 2012. Figure 6 plots weekly wind generation, capacity and intermittency, normalized to the first week of 2012. Both wind generation and intermittency track capacity roughly proportionately, suggesting the 60% increase in wind capacity leads to a roughly 60% increase in generation and intermittency.[29]

[28] This observed decline in intermittency at higher levels of hourly generation is likely driven by the fact that at high wind speeds, wind turbines are hitting their rated capacity. At "normal" wind speeds, the power curve is cubic, such that small changes in wind speeds can lead to very different power levels; however, at wind speeds in excess of roughly 11 meters per second, the wind turbine is producing at 100% of rated capacity, such that even large changes in wind speeds do not alter power output (Kaffine and Worley 2010). Examination of the 5 minute generation data supports this - during hours with high wind generation (in excess of 6000 MWh for example), the 5 minute generation level is very constant as wind speeds have "buried the needle" in terms of generation.

[29] A simple regression of generation on capacity and intermittency on capacity, with Newey-West corrected

As such, a doubling of capacity would roughly increase wind's share of total generation to 20%, and would double mean generation from 2565 MWh to 5130 MWh and mean hourly intermittency from 30 MWh to 60 MWh, assuming this proportionality locally holds. This suggests the intermittency effect on emissions savings calculated above at 3.8% would also roughly double to 7.6% at a 20% wind share.[30] Thus, while it is true intermittency will have larger impacts on emissions savings at higher wind shares, given the linear relationships between capacity and intermittency and between intermittency and emissions, the effect remains rather modest in the near-term of 10-20% wind shares.

6 Conclusions

In this paper, we contribute to the growing literature on measuring the environmental benefits of low-emission technologies such as wind power. In particular, we provide causal estimates of the effect of wind intermittency on CO_2 emissions savings from wind power using a unique dataset of 5-minute generation observations from SPP. We show intra-hour wind intermittency does affect operations of coal and gas generators and correspondingly emissions, and thus it appears there is some merit to the concern that wind intermittency reduces emissions savings. For example, at the highest levels of intermittency, CO_2 emission savings may be reduced by just under 10%.

standard errors cannot reject a coefficient of 1. However, one should not extrapolate this proportional relationship too far, as the relationship between intermittency and new wind capacity in particular will depend on the spatial distribution of wind turbines. That said, based on Figure 6 there is little to suggest a convex relationship between capacity and intermittency over the span of our data.

[30] Note the above hypothetical doubling of wind capacity leads to average hourly generation and intermittency levels that are well within those observed during the sample period. For example, this aligns with marginal emission savings rates in Figure 2, whereby a doubling of intermittency moves us from the mid-deciles to the 9th decile. Evaluating increases in capacity beyond a doubling or so would require significant extrapolation beyond the generation/intermittency levels observed in the data.

However, at current levels of wind penetration (around 10% in SPP), concerns of the overall importance of wind intermittency for wind policy are not borne out, as intermittency reduces marginal CO_2 emissions savings by a modest 3.8% on average. Dynamic estimates suggest slightly larger reductions in emissions savings of 6.5%. Further examination of the relationships between wind capacity, generation and intermittency suggest that while the importance of intermittency will increase as the share of wind generation grows, the effect on emissions savings will likely remain modest in the near-term (wind shares in the 10-20% range).[31] Of course, as wind generation continues to grow as a share of generation, future research should examine whether intermittency does begin to considerably erode emissions savings at 40%, 60% or 80% wind shares.

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[31] Given that SPP has a similar generation mix as neighboring states, this is likely true in neighboring wholesale markets such as ERCOT and MISO. That said, the effect of renewable intermittency in vertically-integrated markets or in regions with dramatically different generation mixes is worthy of further inquiry.

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Table 1: Summary Statistics

	Mean	Standard Deviation	Min	Max
Generation (MWh)				
Wind	2,558	1,526	2	6,561
Coal	15,955	2,691	8,084	22,628
Hydro	123	127	-215	507
DFO	70.21	56.73	-0.01	409.3
Nat Gas	6,191	3,119	1,987	20,777
Nuclear	1,665	570	232	2539
Load	26,563	4,906	16,836	44,249
Imports	-311	744	-2,693	3,376
Intermittency (MWh)				
Wind inter	29.93	18.69	0	624.5
Coal inter	49.11	33.71	0	1,144
Hydro inter	6.64	6.55	0	85.4
DFO inter	1.71	2.85	0	40.67
Nat Gas inter	58.04	41.5	0	1,083
Nuclear inter	0.93	3.76	0	272.2
Load inter	90.12	56.19	0	2,130
imports inter	64.64	35.46	0	1,620
Other				
SO_2 (lbs)	63,335	11,666	31,229	99,637
NO_x (lbs)	38,627	9,843	18,504	80,060
CO_2 (tons)	21,940	4,272	11,820	36,200
Temp (°F)	57.35	20.62	1	106

Values are reported in MWh for generation sources, degrees Fahrenheit for temp, tons for CO_2 and lbs for SO_2, NO_x. Intermittency values report intra-hour calculations for intermittency based on the rme of intra-hour changes in generation.

Table 2: Marginal generation response to wind generation

Variables	(1) Nat gas	(2) Coal	(3) DFO	(4) Nuclear	(5) Hydro	(6) Imports
Wind	-0.368***	-0.519***	-0.00352***	-0.0139	-0.00529***	-0.0907***
	(0.0178)	(0.0174)	(0.000711)	(0.00886)	(0.00123)	(0.00963)
Load/Temp	Y	Y	Y	Y	Y	Y
Hour-Month	Y	Y	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y	Y	Y
DOW	Y	Y	Y	Y	Y	Y
Observations	19,704	19,704	19,704	19,704	19,704	19,704
R-squared	0.952	0.926	0.624	0.705	0.795	0.699

Coefficients represent change in MWh of generation per MWh of wind. All regressions include hour-by-month, month-by-year, and day-of-week fixed effects, as well as quadratic controls for load and temperature. Robust standard errors clustered by week in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Marginal intermittency response to wind intermittency

Variables	(1) Coal inter	(2) Nat gas inter	(3) DFO inter	(4) Nuclear inter	(5) Hydro inter	(6) Imports inter
Wind	0.00394***	-0.00384***	-3.03e-05	-4.02e-05	-7.48e-05*	-0.000107
	(0.000205)	(0.000187)	(2.63e-05)	(3.32e-05)	(3.95e-05)	(0.000200)
Wind inter	0.252***	0.216***	0.00405***	0.00651*	0.00263	0.434***
	(0.0575)	(0.0265)	(0.00148)	(0.00374)	(0.00276)	(0.0842)
Load inter	0.282***	0.337***	0.00533***	0.0102	0.00872***	0.462***
	(0.0640)	(0.0723)	(0.00124)	(0.00671)	(0.00212)	(0.103)
Load/Temp	Y	Y	Y	Y	Y	Y
Hour-Month	Y	Y	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y	Y	Y
DOW	Y	Y	Y	Y	Y	Y
Observations	19,704	19,704	19,704	19,704	19,704	19,704
R-squared	0.486	0.671	0.222	0.032	0.386	0.328

Coefficients on "Wind inter" represent changes in intra-hour rme of generation source due to a 1 unit change in the intra-hour rme of wind generation. All regressions include hour-by-month, month-by-year, and day-of-week fixed effects, as well as quadratic controls for load and temperature. Robust standard errors clustered by week in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Marginal emissions response to fossil - CO_2

Variables	(1) CO_2	(2) CO_2	(3) CO_2	(4) CO_2	(5) CO_2	(6) CO_2
Coal	1.114***	1.140***	1.138***	1.130***	1.162***	1.160***
	(0.0153)	(0.0165)	(0.0166)	(0.0163)	(0.0181)	(0.0181)
Nat gas	0.557***			0.543***		
	(0.0171)			(0.0162)		
DFO	1.626***	1.740***	1.753***	1.666***	1.720***	1.730***
	(0.559)	(0.606)	(0.604)	(0.550)	(0.580)	(0.577)
CC gas		0.308***	0.307***		0.277***	0.275***
		(0.0251)	(0.0264)		(0.0256)	(0.0266)
Non-CC gas		0.806***	0.809***		0.805***	0.808***
		(0.0285)	(0.0288)		(0.0261)	(0.0265)
Coal inter			0.934***			0.880***
			(0.347)			(0.308)
Nat gas inter			0.360			0.490
			(0.355)			(0.308)
Observations	19,704	19,704	19,704	19,704	19,704	19,704
R-squared	0.987	0.986	0.986	0.987	0.987	0.987

Coefficients represent changes in tons of CO_2. Final three columns include year fixed effects. Robust standard errors clustered by week in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Marginal emissions response to wind generation and intermittency

Variables	(1) CO_2	(2) CO_2	(3) SO_2	(4) SO_2	(5) NO_x	(6) NO_x
Wind	-0.726***	-0.786***	-1.832***	-1.978***	-1.656***	-1.749***
	(0.0142)	(0.0145)	(0.0931)	(0.0985)	(0.0459)	(0.0483)
Wind inter	2.393***	2.379***	5.706*	6.028*	-1.873	-2.168
	(0.628)	(0.551)	(3.362)	(3.498)	(1.812)	(1.777)
Load/Temp	Y	Y	Y	Y	Y	Y
Hour-Month	Y	Y	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y	Y	Y
DOW	Y	Y	Y	Y	Y	Y
Imports	N	Y	N	Y	N	Y
Observations	19,704	19,704	19,704	19,704	19,704	19,704
R-squared	0.979	0.982	0.885	0.889	0.951	0.953

Coefficients represent changes in tons of CO_2, lbs of SO_2, lbs of NO_x. All regressions include hour-by-month, month-by-year, and day-of-week fixed effects, as well as quadratic controls for load and temperature (and imports if included), and linear controls for load and import intermittency. Robust standard errors clustered by week in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Marginal emissions response to wind generation and intermittency - dynamic

Variables	(1) CO_2	(2) SO_2	(3) NO_x	(4) CO_2	(5) SO_2	(6) NO_x
Wind	-0.789***	-1.981***	-1.748***	-0.784***	-1.950***	-1.732***
	(0.0147)	(0.0988)	(0.0484)	(0.0167)	(0.112)	(0.0545)
Wind inter	4.383***	8.155	-2.734	4.702***	8.477	-2.391
	(1.199)	(7.448)	(4.000)	(1.217)	(7.594)	(4.095)
Controls lagged	N	N	N	Y	Y	Y
Load/Temp	Y	Y	Y	Y	Y	Y
Hour-Month	Y	Y	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y	Y	Y
DOW	Y	Y	Y	Y	Y	Y
Imports	Y	Y	Y	Y	Y	Y
Observations	19,700	19,700	19,700	19,700	19,700	19,700
R-squared	0.982	0.889	0.954	0.983	0.891	0.954

Coefficients represent changes in tons of CO_2 , lbs of SO_2, lbs of NO_x. First three columns include 4 lags of wind intermittency, while final three columns also include 4 lags for all control variables. All regressions include hour-by-month, month-by-year, and day-of-week fixed effects, as well as quadratic controls for load, temperature, and imports, and linear controls for load and import intermittency. Robust standard errors clustered by week in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Marginal emissions response - generation mix

Variables	(1) CO_2	(2) CO_2	(3) SO_2	(4) SO_2	(5) NO_x	(6) NO_x
Wind	-0.762***	-0.821***	-2.048***	-2.191***	-1.716***	-1.805***
	(0.0125)	(0.0121)	(0.0812)	(0.0824)	(0.0468)	(0.0488)
Wind inter x Genmix	0.297**	0.271**	-0.954	-1.051	-0.307	-0.454
	(0.145)	(0.118)	(0.734)	(0.769)	(0.458)	(0.444)
Genmix	564.5***	569.3***	3,451***	3,515***	889.9***	857.4***
	(44.07)	(45.08)	(254.0)	(260.8)	(170.0)	(175.4)
Load/Temp	Y	Y	Y	Y	Y	Y
Hour-Month	Y	Y	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y	Y	Y
DOW	Y	Y	Y	Y	Y	Y
Imports	N	Y	N	Y	N	Y
Observations	19,704	19,704	19,704	19,704	19,704	19,704
R-squared	0.983	0.987	0.908	0.913	0.954	0.955

Coefficients represent changes in tons of CO_2, lbs of SO_2, lbs of NO_x. The variable “Genmix” is defined as total hourly coal generation divided by total hourly natural gas generation. All regressions include hour-by-month, month-by-year, and day-of-week fixed effects, as well as quadratic controls for load and temperature (and imports if included), and linear controls for load and import intermittency. Robust standard errors clustered by week in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

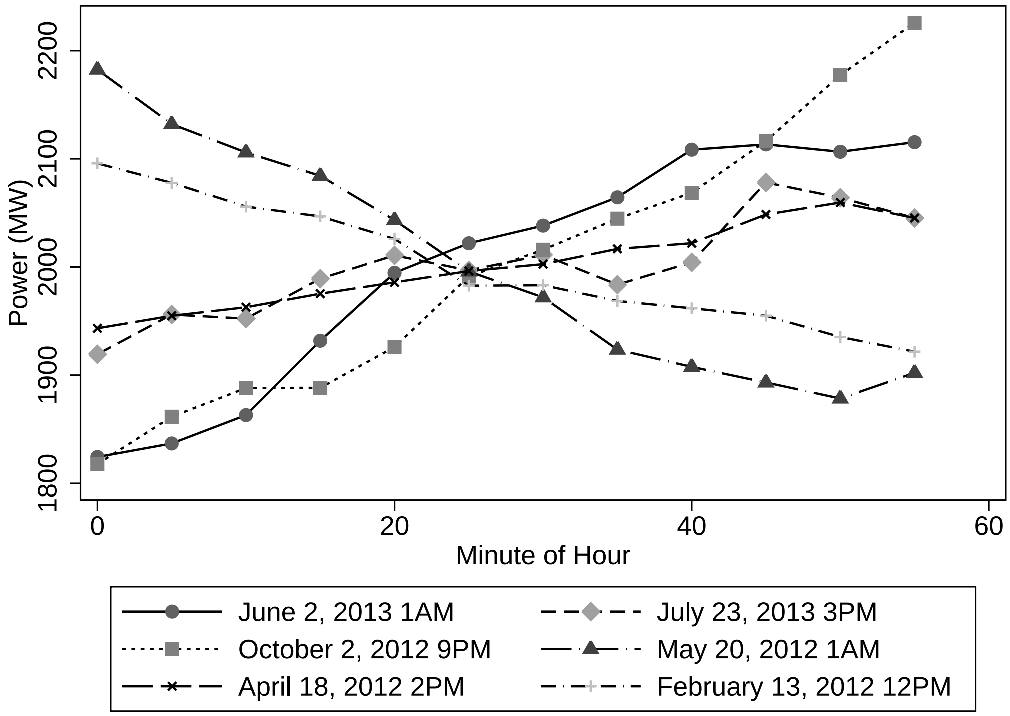

Figure 1: 5-minute wind power levels in SPP for 6 hours with 2000 MWh of hourly wind generation.

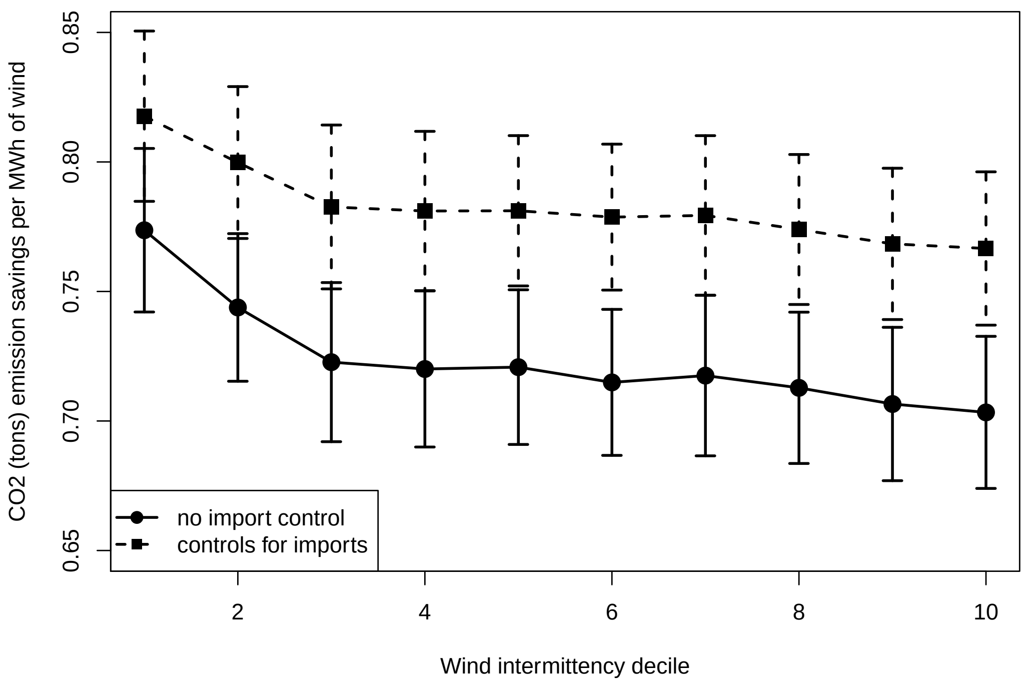

Figure 2: CO_2 emissions savings from wind (tons/MWh) by decile of wind intermittency. Solid line excludes import controls, dashed line includes controls for imports.

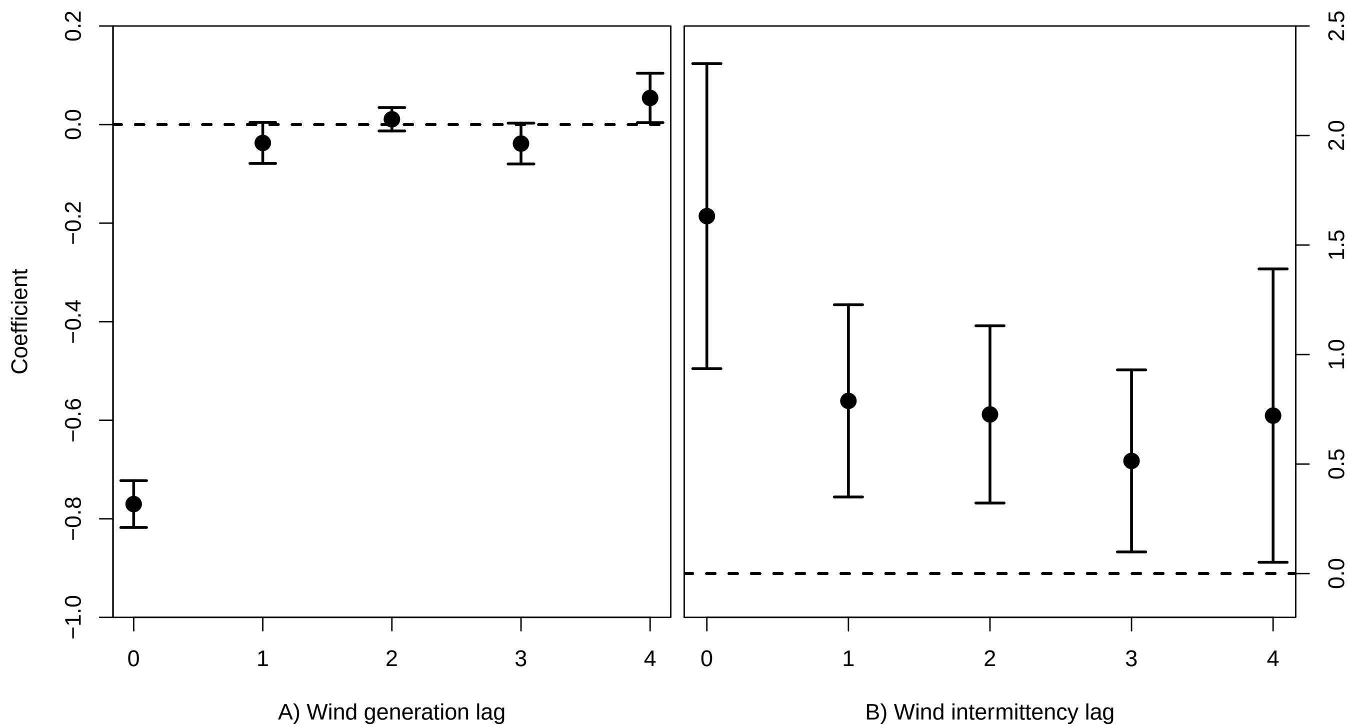

Figure 3: Panel A) Wind coefficient for CO_2 emissions savings (tons/MWh) with four lags. Panel B) Wind intermittency coefficient for CO_2 savings with four lags.

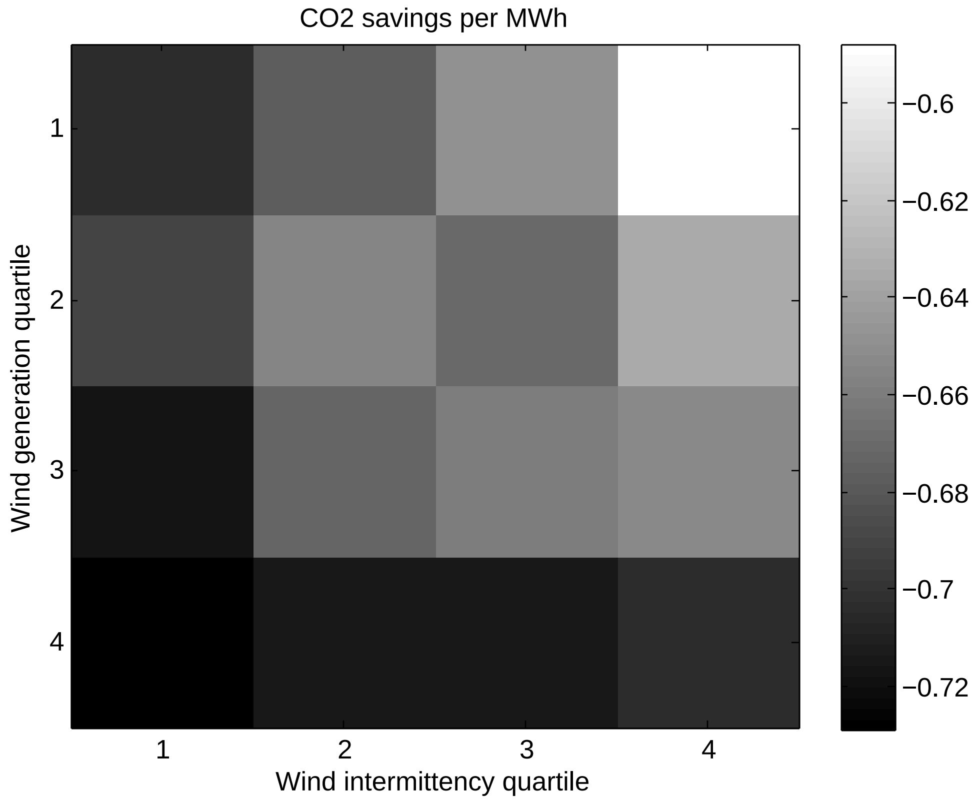

Figure 4: CO_2 emissions savings from wind (tons/MWh) by quartiles of wind intermittency and wind generation.

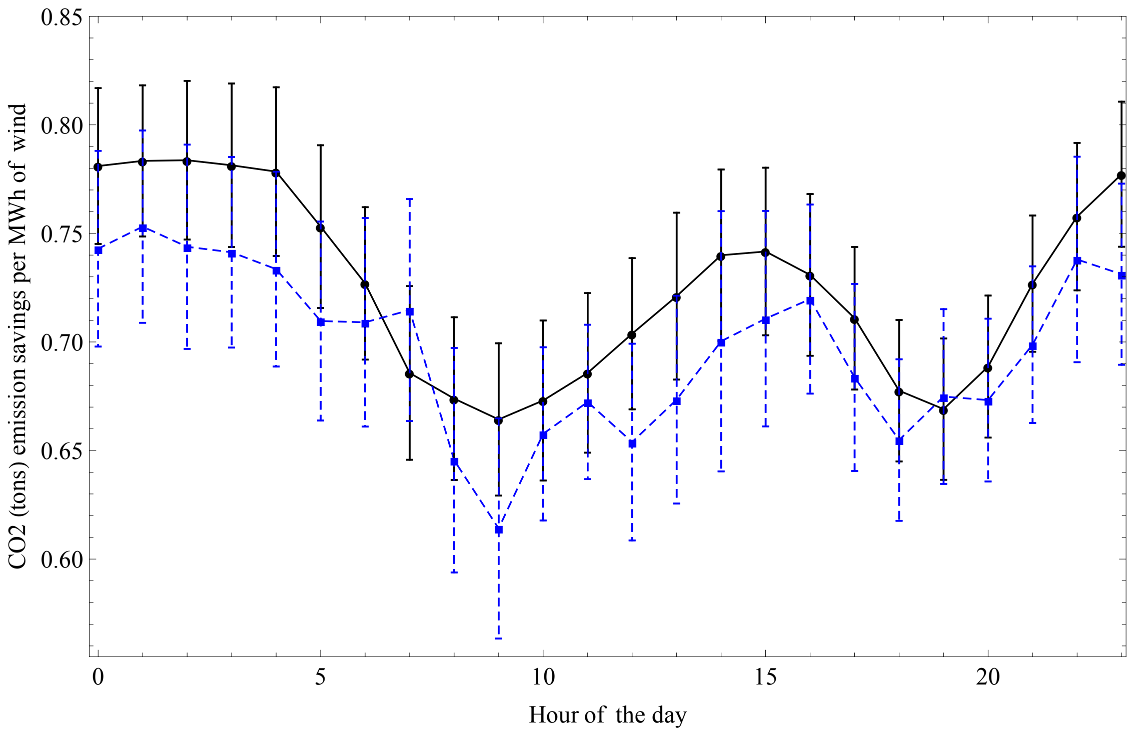

Figure 5: CO_2 emissions savings from wind (tons/MWh) by hour of day. Top panel - solid line is emissions savings without intermittency, dashed line is emissions savings with intermittency. Bottom panel - solid line is emissions savings inclusive of intermittency when intra-hour generation is falling, dashed line is emissions savings inclusive of intermittency when intra-hour generation is rising.

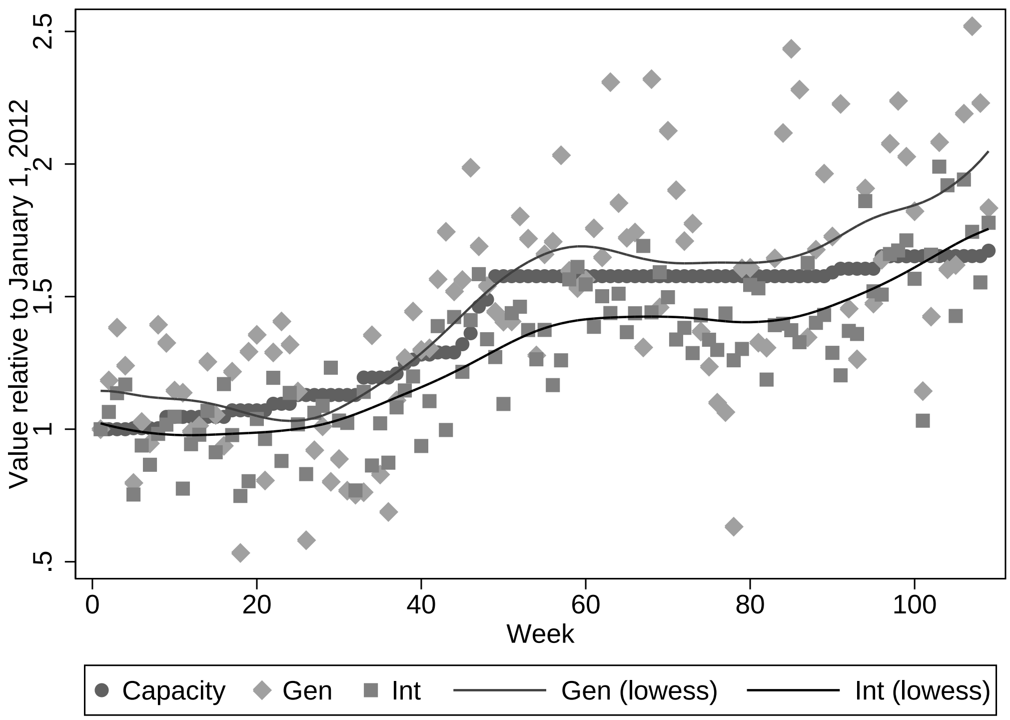

Figure 6: Wind capacity, average generation, and average intermittency by week during sample period, normalized to January 1, 2012.

A Appendix Tables and Figures

Table A.1: Correlation between alternative intermittency measures - wind generation

	Standard Deviation	Range	RMS	Mileage
Standard Deviation	1.0000			
Range	0.9912	1.0000		
RMS	0.8775	0.8822	1.0000	
Mileage	0.9173	0.9318	0.9659	1.0000

Correlation between alternative wind intermittency measures. "Standard Deviation" is the intra-hour standard deviation of 5-minute wind generation. "Range" is the difference between intra-hour min and max wind generation. "RMS" is the intra-hour root-mean-square of changes in 5-minute wind generation. "Mileage" is the intrahour sum of changes in 5-minute generation.

Table A.2: Marginal emissions response - SO_2

Variables	(1) SO_2	(2) SO_2	(3) SO_2	(4) SO_2	(5) SO_2	(6) SO_2
Coal	3.804***	3.842***	3.845***	4.144***	4.249***	4.245***
	(0.103)	(0.107)	(0.107)	(0.116)	(0.122)	(0.122)
Nat gas	0.341***			0.0418		
	(0.106)			(0.0997)		
DFO	-3.494	-4.026	-3.810	-2.851	-5.231	-5.106
	(5.542)	(5.817)	(5.777)	(5.153)	(5.251)	(5.242)
CC gas		0.0229	0.0697		-0.558***	-0.544***
		(0.183)	(0.205)		(0.192)	(0.208)
Non-CC gas		0.679***	0.699***		0.678***	0.694***
		(0.237)	(0.239)		(0.211)	(0.212)
Coal inter			7.492**			5.479*
			(3.534)			(3.136)
Nat gas inter			-2.934			0.149
			(3.408)			(2.557)
Observations	19,704	19,704	19,704	19,704	19,704	19,704
R-squared	0.849	0.849	0.849	0.872	0.875	0.876

Coefficients represent changes in lbs of SO_2. Final three columns include year fixed effects. Robust standard errors clustered by week in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.3: Marginal emissions response - NO_x

Variables	(1) NO_x	(2) NO_x	(3) NO_x	(4) NO_x	(5) NO_x	(6) NO_x
Coal	1.595***	1.637***	1.665***	1.985***	2.079***	2.099***
	(0.0789)	(0.0786)	(0.0798)	(0.100)	(0.0955)	(0.0980)
Nat gas	1.834***			1.491***		
	(0.0814)			(0.100)		
DFO	7.239*	7.320*	7.476*	7.918***	6.112**	6.168**
	(3.703)	(3.844)	(3.794)	(2.781)	(2.986)	(2.957)
CC gas		1.267***	1.364***		0.636***	0.701***
		(0.167)	(0.192)		(0.154)	(0.163)
Non-CC gas		2.454***	2.439***		2.451***	2.432***
		(0.263)	(0.257)		(0.219)	(0.215)
Coal inter			-3.066			-5.135**
			(2.343)			(2.029)
Nat gas inter			-11.26***			-7.991***
			(3.843)			(2.567)
Observations	19,704	19,704	19,704	19,704	19,704	19,704
R-squared	0.847	0.854	0.856	0.891	0.899	0.900

Coefficients represent changes in lbs of NO_x. Final three columns include year fixed effects. Robust standard errors clustered by week in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A.4: Marginal emissions response to wind generation and intermittency - alternative fixed effects

Variables	(1) CO_2	(2) CO_2	(3) SO_2	(4) SO_2	(5) NO_x	(6) NO_x
Wind	-0.727***	-0.786***	-1.831***	-1.987***	-1.669***	-1.742***
	(0.0144)	(0.0146)	(0.0943)	(0.0998)	(0.0466)	(0.0483)
Wind inter	2.450***	2.407***	5.250	5.556	-1.333	-1.718
	(0.636)	(0.560)	(3.411)	(3.550)	(1.752)	(1.766)
Load/Temp	Y	Y	Y	Y	Y	Y
HMY	Y	Y	Y	Y	Y	Y
DOW	Y	Y	Y	Y	Y	Y
Imports	N	Y	N	Y	N	Y
Observations	19,704	19,704	19,704	19,704	19,704	19,704
R-squared	0.979	0.983	0.887	0.891	0.957	0.958

Coefficients represent changes in tons of CO_2, lbs of SO_2, lbs of NO_x. All regressions include hour-by-month-by-year and day-of-week fixed effects, as well as quadratic controls for load and temperature (and imports if included), and linear controls for load and import intermittency. Robust standard errors clustered by week in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A.5: Marginal emissions response - intermittency as intra-hour wind range

Variables	(1) CO_2	(2) CO_2	(3) SO_2	(4) SO_2	(5) NO_x	(6) NO_x
Wind	-0.723***	-0.783***	-1.826***	-1.971***	-1.658***	-1.752***
	(0.0141)	(0.0144)	(0.0930)	(0.0985)	(0.0460)	(0.0484)
Wind inter	0.226***	0.209***	0.544	0.534	-0.281*	-0.353**
	(0.0534)	(0.0449)	(0.335)	(0.332)	(0.164)	(0.158)
Load/Temp	Y	Y	Y	Y	Y	Y
Hour-Month	Y	Y	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y	Y	Y
DOW	Y	Y	Y	Y	Y	Y
Imports	N	Y	N	Y	N	Y
Observations	19,704	19,704	19,704	19,704	19,704	19,704
R-squared	0.979	0.982	0.885	0.889	0.951	0.954

Coefficients represent changes in tons of CO_2, lbs of SO_2, lbs of NO_x. The variable "Wind inter" measures intermittency as the maximum range in intra-hour wind generation for a given hour. All regressions include hour-by-month, month-by-year, and day-of-week fixed effects, as well as quadratic controls for load and temperature (and imports if included), and linear controls for load and import intermittency. Robust standard errors clustered by week in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A.6: Marginal emissions response - intermittency as intra-hour standard deviation

Variables	(1) CO_2	(2) CO_2	(3) SO_2	(4) SO_2	(5) NO_x	(6) NO_x
Wind	-0.723***	-0.783***	-1.826***	-1.970***	-1.658***	-1.753***
	(0.0141)	(0.0144)	(0.0930)	(0.0985)	(0.0460)	(0.0484)
Wind inter	0.644***	0.598***	1.585*	1.612*	-0.768*	-1.003**
	(0.152)	(0.127)	(0.947)	(0.934)	(0.462)	(0.449)
Load/Temp	Y	Y	Y	Y	Y	Y
Hour-Month	Y	Y	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y	Y	Y
DOW	Y	Y	Y	Y	Y	Y
Imports	N	Y	N	Y	N	Y
Observations	19,704	19,704	19,704	19,704	19,704	19,704
R-squared	0.979	0.982	0.885	0.889	0.951	0.954

Coefficients represent changes in tons of CO_2, lbs of SO_2, lbs of NO_x. The variable "Wind inter" measures intermittency as the intra-hour standard deviation of wind generation for a given hour. All regressions include hour-by-month, month-by-year, and day-of-week fixed effects, as well as quadratic controls for load and temperature (and imports if included), and linear controls for load and import intermittency. Robust standard errors clustered by week in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A.7: Marginal emissions response - intermittency as intra-hour “mileage”

Variables	(1) CO_2	(2) CO_2	(3) SO_2	(4) SO_2	(5) NO_x	(6) NO_x
Wind	-0.725***	-0.785***	-1.831***	-1.976***	-1.657***	-1.750***
	(0.0142)	(0.0144)	(0.0931)	(0.0984)	(0.0459)	(0.0483)
Wind inter	0.246***	0.235***	0.591*	0.604*	-0.192	-0.233
	(0.0562)	(0.0513)	(0.335)	(0.346)	(0.184)	(0.179)
Load/Temp	Y	Y	Y	Y	Y	Y
Hour-Month	Y	Y	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y	Y	Y
DOW	Y	Y	Y	Y	Y	Y
Imports	N	Y	N	Y	N	Y
Observations	19,704	19,704	19,704	19,704	19,704	19,704
R-squared	0.979	0.982	0.885	0.889	0.951	0.953

Coefficients represent changes in tons of CO_2, lbs of SO_2, lbs of NO_x. The variable “Wind inter” measures intermittency as the sum of intra-hour changes in wind generation - “mileage” - for a given hour. All regressions include hour-by-month, month-by-year, and day-of-week fixed effects, as well as quadratic controls for load and temperature (and imports if included), and linear controls for load and import intermittency. Robust standard errors clustered by week in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A.8: Marginal emissions response - MISO/ERCOT controls

Variables	(1) CO_2	(2) CO_2	(3) SO_2	(4) SO_2	(5) NO_x	(6) NO_x
Wind	-0.715***	-0.792***	-1.869***	-2.064***	-1.607***	-1.725***
	(0.0139)	(0.0152)	(0.0946)	(0.103)	(0.0444)	(0.0481)
Wind inter	2.443***	2.508***	6.551*	6.932*	-1.866	-2.120
	(0.623)	(0.549)	(3.406)	(3.562)	(1.822)	(1.801)
Load/Temp	Y	Y	Y	Y	Y	Y
Hour-Month	Y	Y	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y	Y	Y
DOW	Y	Y	Y	Y	Y	Y
MISO/ERCOT Load	Y	Y	Y	Y	Y	Y
MISO/ERCOT Wind	Y	Y	Y	Y	Y	Y
Imports	N	Y	N	Y	N	Y
Observations	19,698	19,698	19,698	19,698	19,698	19,698
R-squared	0.979	0.983	0.886	0.891	0.952	0.954

Coefficients represent changes in tons of CO_2, lbs of SO_2, lbs of NO_x. All regressions include hour-by-month, month-by-year, and day-of-week fixed effects, as well as quadratic controls for load and temperature (and imports if included), and linear controls for load and import intermittency and ERCOT and MISO load and wind levels. Robust standard errors clustered by week in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.9: Marginal emissions response to wind generation and intermittency - nonlinear

Variables	(1) CO_2	(2) CO_2	(3) SO_2	(4) SO_2	(5) NO_x	(6) NO_x
Wind	-0.590***	-0.607***	-0.519*	-0.607*	-2.184***	-2.154***
	(0.0456)	(0.0439)	(0.304)	(0.307)	(0.164)	(0.169)
Wind^2	-2.36e-05***	-3.11e-05***	-0.000227***	-0.000238***	9.09e-05***	7.01e-05***
	(7.19e-06)	(6.84e-06)	(4.69e-05)	(4.76e-05)	(2.60e-05)	(2.62e-05)
Wind inter	2.091***	1.276*	-4.053	-5.657	4.541*	2.814
	(0.796)	(0.699)	(4.592)	(4.685)	(2.479)	(2.414)
Wind inter^2	-0.00440**	-0.00126	0.00165	0.0106	-0.0167***	-0.0127**
	(0.00199)	(0.00153)	(0.00818)	(0.00858)	(0.00549)	(0.00529)
Load inter	-0.920**	-0.594*	-1.673	-0.620	-3.050***	-2.766**
	(0.353)	(0.316)	(2.040)	(2.100)	(1.165)	(1.201)
Load inter^2	0.000623**	0.000769***	0.000498	0.00153	0.00216**	0.00164*
	(0.000281)	(0.000277)	(0.00168)	(0.00167)	(0.000977)	(0.000982)
Load/Temp	Y	Y	Y	Y	Y	Y
Hour-Month	Y	Y	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y	Y	Y
DOW	Y	Y	Y	Y	Y	Y
Imports	N	Y	N	Y	N	Y
Observations	19,704	19,704	19,704	19,704	19,704	19,704
R-squared	0.979	0.983	0.887	0.891	0.952	0.954

Coefficients represent changes in tons of CO_2, lbs of SO_2, lbs of NO_x. All regressions include hour-by-month, month-by-year, and day-of-week fixed effects, as well as quadratic controls for load and temperature (and imports as noted). Robust standard errors clustered by week in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A.10: Marginal emissions response to wind generation and intermittency - offpeak vs peak

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	CO_2	SO_2	NO_x	CO_2	SO_2	NO_x
Wind	-0.779***	-2.253***	-1.541***	-0.689***	-1.538***	-1.746***
	(0.0175)	(0.105)	(0.0473)	(0.0163)	(0.106)	(0.0547)
Wind inter	3.128***	2.564	0.0365	1.744***	3.639	-0.292
	(0.911)	(4.745)	(2.536)	(0.621)	(3.460)	(1.836)
Time	Offpeak	Offpeak	Offpeak	Peak	Peak	Peak
Load/Temp	Y	Y	Y	Y	Y	Y
Hour-Month	Y	Y	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y	Y	Y
DOW	Y	Y	Y	Y	Y	Y
Imports	N	N	N	N	N	N
Observations	8,210	8,210	8,210	11,494	11,494	11,494
R-squared	0.971	0.896	0.938	0.977	0.859	0.949

Coefficients represent changes in tons of CO_2, lbs of SO_2, lbs of NO_x. All regressions include hour-by-month, month-by-year, and day-of-week fixed effects, as well as quadratic controls for load and temperature and linear controls for load intermittency. Robust standard errors clustered by week in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

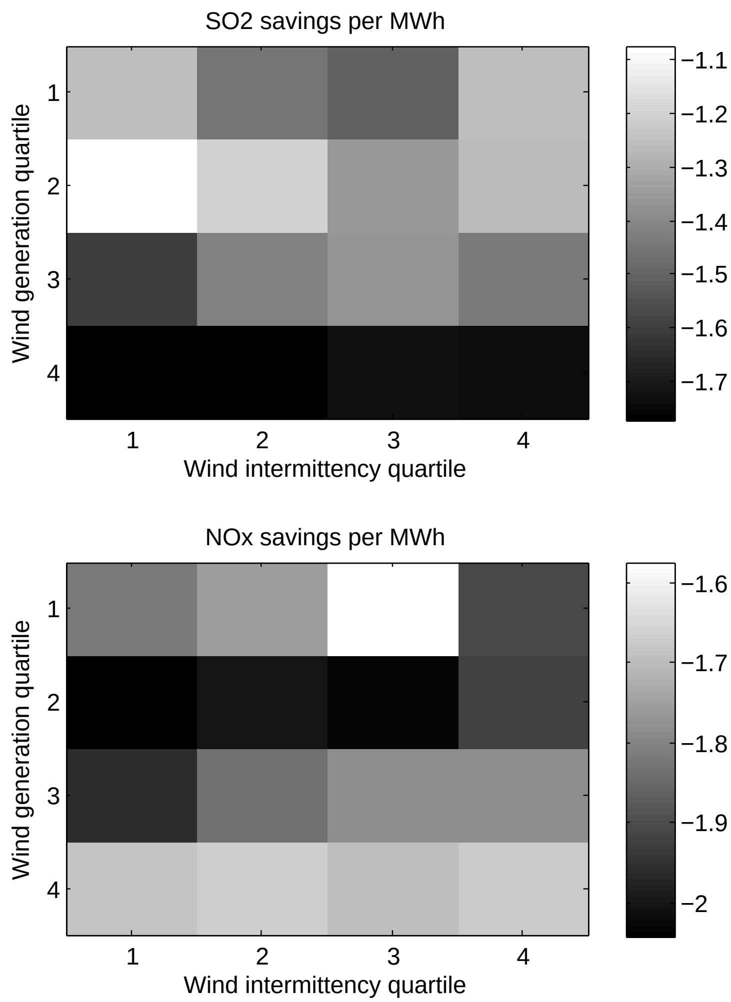

Figure A.1: SO_2 emissions savings (top) and NO_X emissions savings (bottom) from wind (lbs/MWh) by quartile of wind intermittency and wind generation.

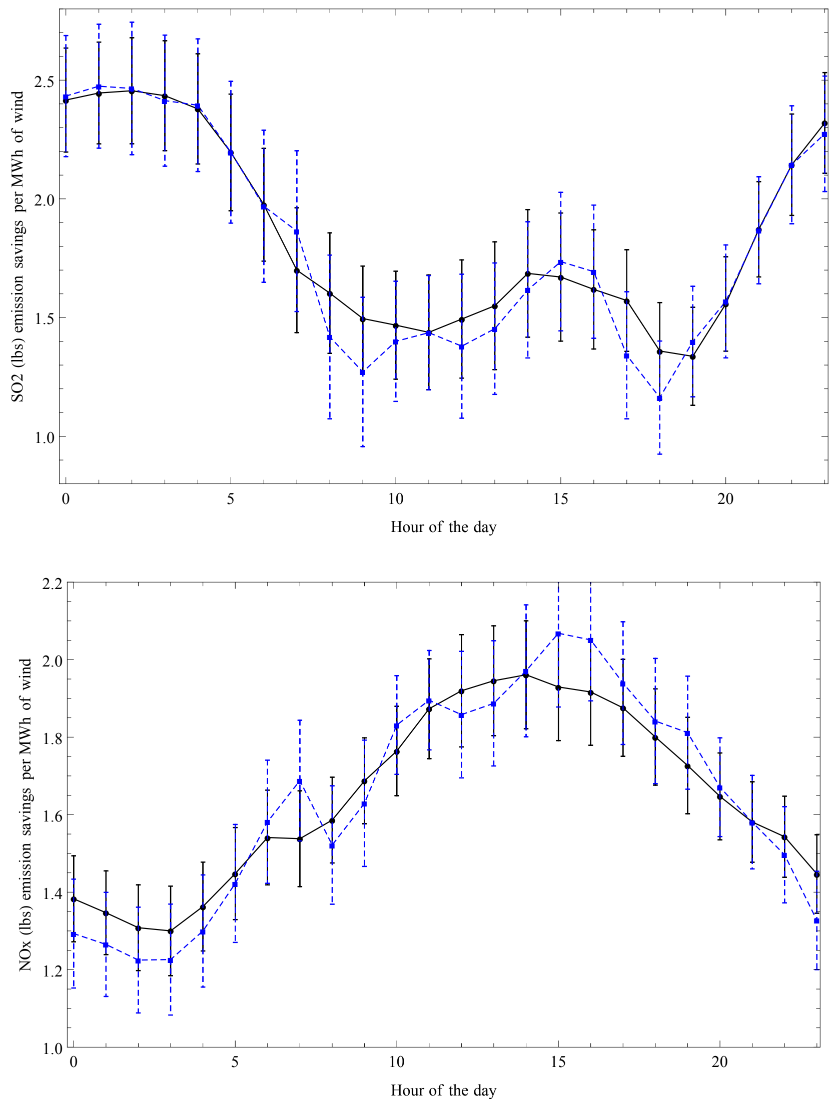

Figure A.2: Emissions savings from wind (tons/MWh) by hour of day. Top panel - solid line is SO_2 emissions savings without intermittency, dashed line is SO_2 emissions savings with intermittency. Bottom panel - solid line is NO_x emissions savings without intermittency, dashed line is NO_x emissions savings with intermittency.