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 intrahour wind intermittency reduces CO_2 emissions savings from wind - in the top decile of wind intermittency, emission savings are reduced by 15% when intrahour wind generation is falling. However, the average wind intermittency effect on emission savings is modest, on the order of 2 percent, and the 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 has been 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 5% in 2016 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 to meet net load. 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)

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may also affect the emissions savings potential of these 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 (estimated in prior studies such as Novan (2015)). 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 intrahour evolution of the generation mix. In particular, it allows us to statistically compare emissions in two otherwise identical hours (including the same level of wind generation), but with different levels of intrahour wind intermittency. Given the plausibly exogenous variation in intermittency, we can interpret our estimates as the causal impact of intrahour intermittency on emission savings.[2]

[1] The Southwest Power Pool is a Regional Transmission Organization 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, Oklahoma, with some coverage in neighboring states. During 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 60mph 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 intrahour volatility (Katzenstein and Apt 2009).

To our knowledge, this is the first study to empirically identify the effects of intrahour 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 renawables may affect emission rates (e.g. heat rate changes due to merit order effects). Aside from these studies, 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; 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 megawatthour (MWh) of

[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.

wind on average offsets 0.52 MWh of coal and 0.37 MWh of gas.[4] Next, we show intrahour intermittency in wind generation (measured as the intrahour standard deviation in generation levels) is also primarily balanced by intrahour variation in coal and gas, and this intrahour variation in coal and gas increases CO_2 emissions. With the above facts established, our key parametric estimation finds 1 MWh of wind reduces CO_2 emissions in SPP by -0.717 tons holding intermittency constant, but an increase in the intrahour intermittency of wind generation offsets emissions reductions to some extent.[5] Similarly, our semi-parametric approach finds that in the lowest decile of intermittency when intrahour wind generation levels are declining, 1 MWh of wind generation reduces CO_2 emissions in SPP by -0.765 tons, while in the highest decile of intermittency, wind generation reduces CO_2 emissions by a substantially smaller -0.652 tons per MWh. However, this represents only 5% of our observations and reductions in emissions savings due to intermittency are much more modest otherwise.

The above results confirm intermittency does diminish the CO_2 emission saving potential of wind power, but further analysis is required to understand the magnitude and implications of this intermittency effect. 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 -0.702 tons, a modest 2% reduction in CO_2 emission savings. In terms of a Pigovian subsidy

[4] The remainder is met by small reductions in fuel oil, hydro and nuclear, as well as modest changes in imports. Note 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, due to the fact 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).

[5] Note we distinguish between intermittency during hours where wind generation is increasing versus decreasing. One would expect intrahour variability in wind to be more problematic when wind levels are falling and fossil fuel is ramping up in response, and indeed we find this to be the case.

for wind, this represents the difference between a \$28.00/MWh subsidy and a \$27.30/MWh subsidy. 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, it appears at current wind penetration levels, 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.[6]

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.

As such, 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 examples include studies examining 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). This paper contributes to this growing literature by measuring the emission savings from wind power, accounting for the intermittent nature of wind generation.

[6] 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 then:

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

or simply the sum of changes in generation from each plant times their emissions rate.[7] 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.[8]

[7] 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.

[8] 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 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 then:

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

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 (increase 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 focus on $\frac{\partial E_h}{\partial W_h}$, the change in emissions due to wind while holding intermittency

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

constant, and $\frac{\partial E_h}{\partial \sigma_h}$, the change in emissions due to intermittency holding wind generation constant. This will allow us to decompose these two effects, and we will return to the implications for the total emissions effect in subsequent analysis.

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 intrahour wind generation, while the other hour has 2000 MWh of volatile and intermittent intrahour 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 intrahour wind generation, two hours decline substantially, and two hours are relatively flat. It is this variation in the shape of the intrahour 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 ISO, 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).[9] From this 5-minute data, we construct intrahour measures of intermittency for all generation types and load, with the intrahour standard deviation as our preferred measure.[10] Furthermore, an indicator variable (*winddrop*) is created for each hour and is set equal to 1 if generation levels fell from the beginning to the end of each hour, and set equal to 0 otherwise.[11] Thus, for each hour in the dataset, we have the hourly aggregates from each source of generation, as well as the intrahour 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 database), as well as hourly, population-weighted temperatures.[12] While emissions data for sulphur dioxide SO_2 and nitrogen oxides NO_x are available, for the initial analysis below we focus on CO_2 emissions, returning to the other emissions later in the analysis.

Summary statistics for key variables are reported in Table 1 ("sd*" variables are the intrahour standard deviations). 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

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

[10] We also considered the intrahour range (max-min) as a measure of intermittency; however the range measures were highly correlated with the standard deviation (R^2 around 0.98 across generation types), and as such estimation results were extremely similar.

[11] One might imagine the intermittency associated with the falling wind generation curves in Figure 1 may have relatively worse implications for emissions, and this indicator will allow us to examine whether or not that is true.

[12] 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).

import substantial quantities of electricity.[13] Relative to ERCOT in Texas, where many of the existing 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 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 intrahourly intermittency (e.g. Kaffine et al. (2013)).[14] We estimate a series of reduced-form regressions of the following general form:

$$y_{hdmy} = \boldsymbol{x_{hdmy}\beta} + f(\mathbf{z_{hdmy}}) + \gamma_{hm} + \theta_{my} + \eta_d + \epsilon_{hdmy}, \tag{4}$$

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 intrahour wind intermittency, with $\boldsymbol{\beta}$ representing the coefficient(s) of interest. The function $f(\mathbf{z_{hdmy}})$ captures flexbile control variables, such as load and temperature.[15] Standard errors for all estimations reported below are clustered at the weekly level to account for serial correlation.

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

[14] 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 ($p = 0.46$).

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

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 variables that may be correlated with our explanatory variables of interest. Hour-by-month fixed effects γ_{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 2017). 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 whether the direction of intermittency (ramping up or ramping down) matters for emissions, as well as a semi-parametric approach to examine emissions savings by decile of 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 intrahour 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.[16] Finally, note the sum of coefficients in Table 2 gives a 1.0005 MWh response per 1 MWh change in wind, suggesting our general control variable and fixed effects strategy is appropriate.

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

[16] Note the response of natural gas is roughly twice its average share of generation, consistent with the idea that gas is well-suited for responding to changes in the level of wind 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 the fact a) SPP simply has 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 2017; Millstein et al. 2017).

The previous two 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 intrahour wind profile leads to more variability in intrahour generation from coal and gas. Next, Table 4 links these changes in coal and gas generation and intrahour variability in generation to CO_2 emission outcomes.[17] The first column simply regresses CO_2 emissions on coal and gas generation, controlling for load, temperature, and fixed effects. 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 adds in the intrahour standard deviation of coal and gas generation and importantly shows that, holding generation levels constant, a more variable intrahour generation profile increases emissions. This is precisely the concern motivated in Section 2 whereby more variable operation of fossil plants (ramping) leads to increased emission rates. The last two columns repeat the previous exercise, but drop the load control in favor of explicitly including the other forms of generation. Estimates of the emission impacts from coal and gas generation and variability are similar.[18]

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

[17] See Appendix Tables A.1 and A.2 for equivalent results for SO_2 and NO_x.

[18] Including imports and its square as controls yields similar coefficients for coal and gas generation and coal and gas intrahour variability.

effects. The coefficient on *wind* of -0.717 can be interpreted as the tons of CO_2 avoided from a MWh of wind generation, holding intermittency constant.[19] However, the coefficient on *sdwind* of 0.521 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 *sdwind* 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, increases in wind intermittency increase emissions, similar to the case of CO_2. However, and somewhat surprisingly, increases in wind intermittency *decrease* NO_x emissions (while

[19] 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 2017).

increases in load intermittency increase NO_x emissions), a point we return to below.

5.2 Further analysis of intermittency effects

While the above analysis demonstrated that intrahour wind intermittency increased CO_2 emissions, we further examine these intermittency effects along several dimensions. First, it seems likely the emissions response to intermittency when intrahour wind generation is falling would be different than when wind generation is rising, as falling wind levels would require an emissions-intensive ramping of fossil generation in response. We examine this supposition below. Second, 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.

Recall the constructed variable *winddrop* is an indicator variable that captures whether wind generation rose or fell over the course of an hour. Table 6 reports the results from specifications similar to those in Table 5, but where we interact *winddrop* with wind intermittency.[20] Thus, *sdwind x up* gives the effect of intermittency on emissions when wind rises intrahour, and *sdwind x down* gives the effect of intermittency on emissions when wind falls intrahour. For CO_2 and SO_2 emissions, intermittency when intrahour wind is rising leads to small and often insignificant negative impacts on emissions. However, when intrahour wind generation is falling, wind intermittency leads to large and significant increases in emissions, consistent with the idea that fossil plants have to aggressively ramp to compen-

[20] These tables are replicated using an alternative fixed effects specification of more restrictive hour-by-month-by-year fixed effects in Appendix Tables A.3 and A.4, as well as using the range of intrahour variation in generation instead of the standard deviation in Appendix Tables A.5 and A.6, yielding consistent results.

sate. Interestingly, while NO_x emissions show a similar pattern when wind generation falls (emissions increase with intermittency as fossil ramps in response), intermittency leads to a substantial *decline* in emissions when intrahour wind generation increases.[21]

In the preceding analysis, we have assumed intermittency enters linearly into our estimation equation. To more flexible 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:

$$E_{hdmy} = \sum_{b=1}^{10} \beta^b * wind_{hdmy} * D^b_{hdmy} + f(\mathbf{z_{hdmy}}) + \gamma_{hm} + \theta_{my} + \eta_d + \epsilon_{hdmy}, \tag{5}$$

where β^b is the CO_2 emissions savings from wind generation 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 these emission savings coefficients by decile along with corresponding confidence intervals, with the top and bottom panels excluding and including import controls, respectively.[22] 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, though decile estimates are not statistically distinguishable. Figure 2 also provides a sense of the magnitude of the intermittency effects on emissions savings, with a roughly 0.05 tons/MWh decline from the lowest decile to highest decile of intermittency (a 7% decline in the top panel and a 5% decline in the bottom panel).[23]

[21] Given increases and decreases in intrahour wind are roughly equally likely, this explains the negative effect of intermittency for NO_x in Table 5. As documented below, while CO_2 and SO_2 emissions respond in similar ways to wind generation and intermittency (for example, typically larger responses when coal is a greater share of generation), NO_x emissions consistently respond very differently than the other two emission types. Note this phenomenon is not unique to SPP, as Kaffine et al. (2013) and Novan (2015) find similar patterns for emissions savings from wind in ERCOT.

[22] We can interpret the top panel as the emission savings in SPP due to SPP wind generation and the bottom panel as an approximation of the total emission savings due to SPP wind generation, per the previous discussion regarding import controls.

[23] Repeating this analysis for SO_2 shows a similar percentage decline in emission savings across deciles,

However, as noted in Table 6, the effects of intermittency depend on whether or not intrahour wind is rising or falling, with the primary emission consequences occurring when intrahour wind is falling (and fossil must ramp up generation in response). Interacting *winddrop* with intermittency per Table 6, Figure 3 displays CO_2 emission savings across deciles when intrahour wind is declining, excluding and including import controls. As expected, the effect of intermittency on emission savings is much more pronounced, particularly at the higher deciles, which are now statistically distinguishable from the lowest deciles.[24] Emissions savings decline by roughly 0.11 tons/MWh from the lowest to highest deciles, or just under 15% for both panels. Thus, taking all of the above into account, we conclude that intrahour intermittency can reduce CO_2 emission savings from wind by a sizeable amount, but that such reductions in emission saving occur relatively infrequently (the 5% of observations where intrahour wind declines and when intermittency is in the top decile). Outside of these infrequent occurrences, reductions in emission savings are modest at best.

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.7). Second, for the parametric model, we looked for evidence of nonlinear effects of wind intermittency and wind generation on emissions (quadratic results in Appendix Table A.8). We find little evidence

while NO_x emission savings are non-monotonic across deciles.

[24] The analogous plot for the case when intrahour wind is increasing is effectively flat.

to suggest a non-linear effect of intermittency. This is somewhat surprising as we might expect increased intermittency to have increasing effects on emissions, and it is also somewhat at odds with the decile estimations, which suggested an increasing effect on marginal emission savings for the highest deciles of intermittency. 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. 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 beyond robustness checks into more substantive extensions, we next considered 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, particularly when intrahour wind generation is falling.[25]

Next, we examined 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 5, and are consistent with the above findings. In particular, it shows that when intrahour wind generation is falling, emission savings are greatest in the

[25] Results for SO_2 were inconclusive, while results for NO_x exhibited the opposite pattern, such that intermittency matters less when coal generation has a relatively greater share. This is likely related to the odd results for NO_x in Tables 5 and 6 whereby intermittency increased emission savings.

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. The pattern is less clear for the case of rising intrahour wind generation, though on average CO_2 emission savings are larger than when intrahour wind generation declines.[26]

Finally, we considered 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 6 plots the hourly coefficients for CO_2 emissions savings. The top panel compares CO_2 emission savings absent intermittency (solid) with CO_2 emission savings including intermittency effects (dashed). The bottom panel compares CO_2 emission savings when intrahour wind generation is falling (solid) versus rising (dashed). From the figure, it is clear both CO_2 emission savings per MWh of wind and the effects of intermittency are 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

[26] 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.

exhibits a drastically different pattern, with the greatest emission savings occurring during peak hours when gas is a larger share of generation. Per Novan (2015), this likely 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.

5.4 Discussion

The above estimation results confirm intrahour intermittency erodes CO_2 emissions savings from wind power. But to what extent does accounting for this intermittency effect 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.[27]

Recall from Table 5 that, holding intermittency constant, the average marginal CO_2 emissions savings in SPP from 1 MWh of wind is -0.717 tons/MWh. Similarly, holding generation constant, the average marginal increase in emissions due to intrahour intermittency (also measured in MWh via the intrahour standard deviation) is 0.521 tons/MWh. Assuming an external damage value of \$39 dollars per ton of CO_2, this would imply an efficient subsidy of \$28.00 dollars per MWh of wind absent intermittency effects (quite close to the current federal Production Tax Credit of \$23/MWh).

To examine how intermittency would affect this subsidy, we evaluate the marginal emis-

[27] 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.

sion savings per MWh at the mean levels of wind generation (2565 MWh) and intermittency (75 MWh). At the mean intermittency level, the marginal emissions savings rate is reduced to 0.702 tons/MWh, and the efficient subsidy declines by roughly 2% to \$27.30/MWh.[28] Suffice to say, while intermittency does matter, the difference in efficient subsidies is very small. Even at the 95^{th} percentile of intermittency (194 MWh), the efficient subsidy would be \$26.40/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 of generation greater than the 10% currently seen in SPP. If we examine the in-sample relationship between hourly generation and intermittency, somewhat surprisingly 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.[29] 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*.

[28] Emission savings per MWh of wind are calculated as $(0.717 * 2565 - .521 * 75)/2565) = 0.702$ tons/MWh.

[29] 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.

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 4 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.[30] 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 75 MWh to 150 MWh, assuming this proportionality locally holds. This suggests the intermittency effect on emissions savings calculated above at 2% would also roughly double to 4% at a 20% wind share.[31] 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

[30] A simple regression of generation on capacity and intermittency on capacity, with Newey-West corrected 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 4 there is little to suggest a convex relationship between capacity and intermittency over the span of our data.

[31] 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.

using a unique dataset of 5-minute generation observations from SPP. We show intrahour 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 as much as 15%.

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 emissions savings by a modest 2% on average. 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). That said, 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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Table 1: Summary Statistics

variable	mean	sd	max	min
co2	21940.32	4271.954	36199.89	11820.41
wind	2564.881	1527.165	6560.834	2.002592
ngas	6176.589	3109.328	20776.93	1986.826
coal	15935.87	2688.084	22627.92	8083.989
hydro	123.091	127.7309	516.7228	-214.564
dfo	69.54915	56.85964	409.2625	-0.0066821
nuclear	1661.431	568.2263	2538.594	231.615
load	26225.24	5284.679	47182.47	16776.73
imports	-306.1637	742.7041	3376.15	-2693.277
temp	58.42732	19.62114	103.58	2.95
winddrop	0.5070607	0.4999627	1	0
sdwind	74.72731	61.19939	1252.946	0
sdngas	146.0925	141.4516	2220.168	0
sdcoal	132.7031	114.7857	905.0863	0
sdhydro	6.665561	8.470805	170.1632	0
sddfo	2.87301	5.734723	77.1159	0
sdnuclear	1.341475	6.100416	254.7246	0
sdload	240.5472	194.5966	2567.179	0
sdimports	79.10783	47.51325	1268.868	0

Values are reported in MWh for generation sources, degrees Fahrenheit for temp, and tons for co2. Variables with the "sd" prefix indicate intrahour calculations of the standard deviation of generation.

Table 2: Marginal response to wind generation

Variables	(1) ngas	(2) coal	(3) dfo	(4) nuclear	(5) hydro	(6) imports
wind	-0.368***	-0.519***	-0.00354***	-0.0140	-0.00530***	-0.0907***
	(0.0185)	(0.0198)	(0.000766)	(0.00862)	(0.00124)	(0.00959)
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	19,701	19,701	19,701	19,701	19,701	19,701
R-squared	0.952	0.926	0.624	0.705	0.796	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 response to wind intermittency

Variables	(1) sdcoal	(2) sdngas	(3) sddfo	(4) sdnuclear	(5) sdhydro	(6) sdimports
wind	0.0138***	-0.0131***	-4.01e-05	-4.21e-05	-0.000121**	0.000837***
	(0.000533)	(0.000571)	(4.92e-05)	(7.55e-05)	(4.95e-05)	(0.000316)
sdwind	0.195***	0.205***	0.00383***	0.00109	0.00153	0.120***
	(0.0179)	(0.0213)	(0.000933)	(0.000933)	(0.00158)	(0.0323)
sdload	0.322***	0.444***	0.00467***	0.000961	0.00460***	0.0776***
	(0.0183)	(0.0163)	(0.000694)	(0.000592)	(0.000956)	(0.0133)
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	19,701	19,701	19,701	19,701	19,701	19,701
R-squared	0.597	0.729	0.180	0.030	0.226	0.180

Coefficients represent change in intrahour standard deviation of generation source due to a 1 unit change in the intrahour standard deviation 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

Variables	(1) co2	(2) co2	(3) co2	(4) co2
coal	1.019***	1.024***	1.029***	1.027***
	(0.0115)	(0.0117)	(0.0156)	(0.0157)
ngas	0.481***	0.490***	0.514***	0.516***
	(0.0193)	(0.0194)	(0.0164)	(0.0164)
dfo			1.104***	1.122***
			(0.249)	(0.249)
hydro			-0.561**	-0.547**
			(0.259)	(0.258)
nuclear			-0.0392	-0.0462
			(0.0564)	(0.0567)
wind			0.00593	-0.00100
			(0.0121)	(0.0122)
sdcoal		0.603***		0.624***
		(0.0833)		(0.0867)
sdngas		0.148**		0.149**
		(0.0635)		(0.0600)
Load/Temp	Y	Y	N	N
Hour-Month	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y
DOW	Y	Y	Y	Y
Observations	19,701	19,701	19,701	19,701
R-squared	0.989	0.989	0.989	0.989

Coefficients represent changes in tons of CO2. All regressions include hour-by-month, month-by-year, and day-of-week fixed effects, as well as quadratic controls for load and temperature (except where indicated). 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) co2	(2) co2	(3) so2	(4) so2	(5) nox	(6) nox
wind	-0.717***	-0.772***	-1.804***	-1.935***	-1.649***	-1.735***
	(0.0168)	(0.0174)	(0.107)	(0.111)	(0.0506)	(0.0543)
sdwind	0.521***	0.506***	1.497	1.600*	-1.173**	-1.332***
	(0.165)	(0.139)	(0.958)	(0.927)	(0.510)	(0.498)
sdload	0.396***	0.480***	1.073*	1.373**	0.808**	0.839**
	(0.110)	(0.104)	(0.566)	(0.577)	(0.331)	(0.335)
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	19,701	19,701	19,701	19,701	19,701	19,701
R-squared	0.975	0.978	0.882	0.885	0.948	0.950

Coefficients represent changes in tons of CO_2, lbs of SO_2, lbs of NOX. 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 6: Marginal emissions response and direction of ramping

Variables	(1) co2	(2) co2	(3) so2	(4) so2	(5) nox	(6) nox
wind	-0.717***	-0.772***	-1.802***	-1.935***	-1.648***	-1.735***
	(0.0168)	(0.0175)	(0.108)	(0.111)	(0.0507)	(0.0544)
sdwind x up	-0.320	-0.464**	-0.605	-0.870	-3.293***	-3.593***
	(0.234)	(0.215)	(1.077)	(1.062)	(0.644)	(0.614)
sdwind x down	1.496***	1.615***	3.915***	4.407***	1.265**	1.235**
	(0.194)	(0.178)	(1.194)	(1.163)	(0.635)	(0.613)
sdload	0.404***	0.486***	1.091*	1.387**	0.826**	0.850**
	(0.109)	(0.104)	(0.564)	(0.576)	(0.329)	(0.332)
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	19,701	19,701	19,701	19,701	19,701	19,701
R-squared	0.975	0.979	0.882	0.886	0.948	0.950

Coefficients represent changes in tons of CO2, lbs of SO2, lbs of NOX. The variable "sdwind x up" is the effect of intrahour wind intermittency when intrahour wind generation is increasing, and "sdwind x down" is the effect of intrahour wind intermittency when intrahour wind generation is decreasing. 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 7: Marginal emissions response and direction of ramping - generation mix

Variables	(1) co2	(2) co2	(3) co2	(4) co2
wind	-0.755***	-0.754***	-0.809***	-0.809***
	(0.0137)	(0.0137)	(0.0133)	(0.0133)
sdwind x genmix	0.0710*		0.0637*	
	(0.0384)		(0.0323)	
sdwind x up x genmix		-0.105*		-0.146***
		(0.0574)		(0.0545)
sdwind x down x genmix		0.293***		0.324***
		(0.0537)		(0.0483)
genmix	562.3***	564.5***	565.5***	568.5***
	(47.00)	(46.92)	(49.03)	(49.08)
sdload	0.577***	0.588***	0.640***	0.651***
	(0.103)	(0.102)	(0.0974)	(0.0965)
Load/Temp	Y	Y	Y	Y
Hour-Month	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y
DOW	Y	Y	Y	Y
Imports	N	N	Y	Y
Observations	19,701	19,701	19,701	19,701
R-squared	0.980	0.980	0.983	0.983

Coefficients represent changes in tons of CO_2, lbs of SO_2, lbs of NOX. 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. Robust standard errors clustered by week in parentheses.

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

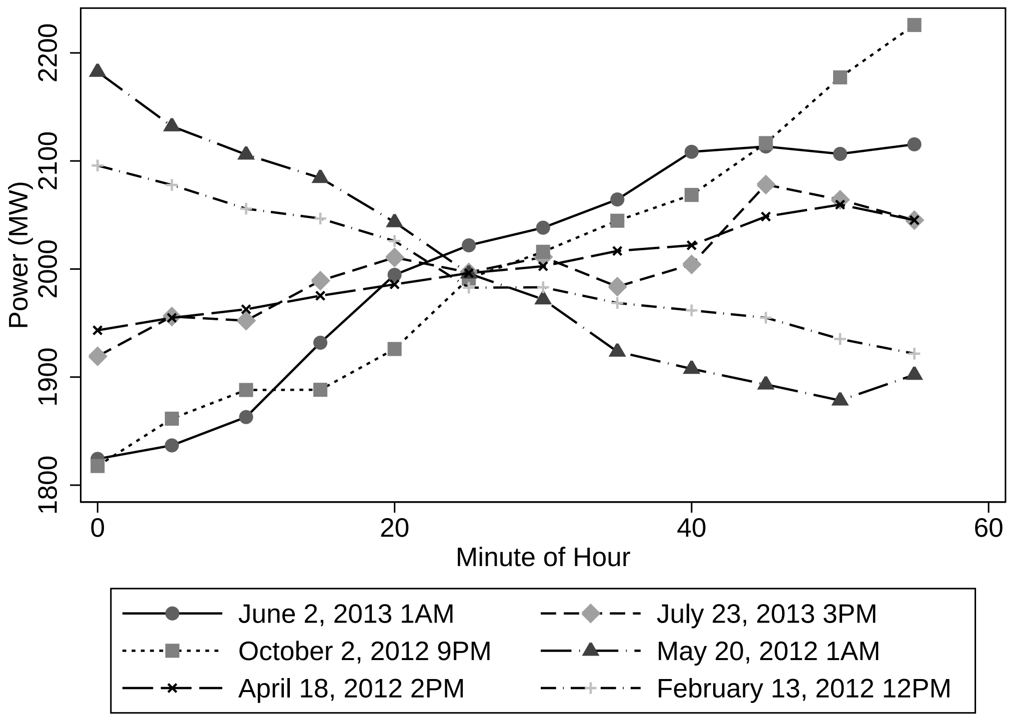

Figure 1: 5-minute wind power levels in SPP for 6 hours with 2000 MWh of hourly wind generation.

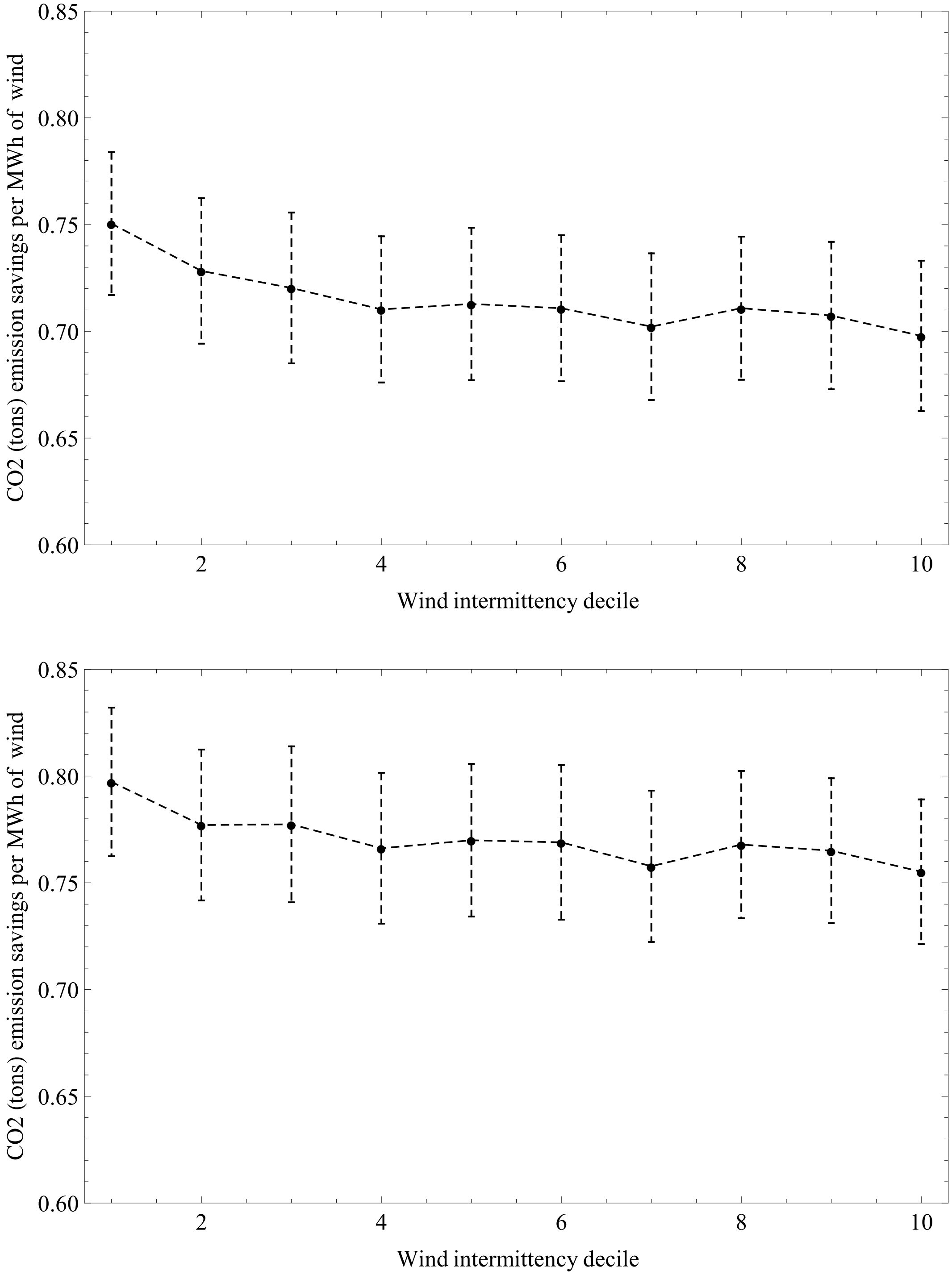

Figure 2: CO_2 emissions savings from wind (tons/MWh) by decile of wind intermittency. Top panel excludes import controls while bottom panel includes controls for imports.

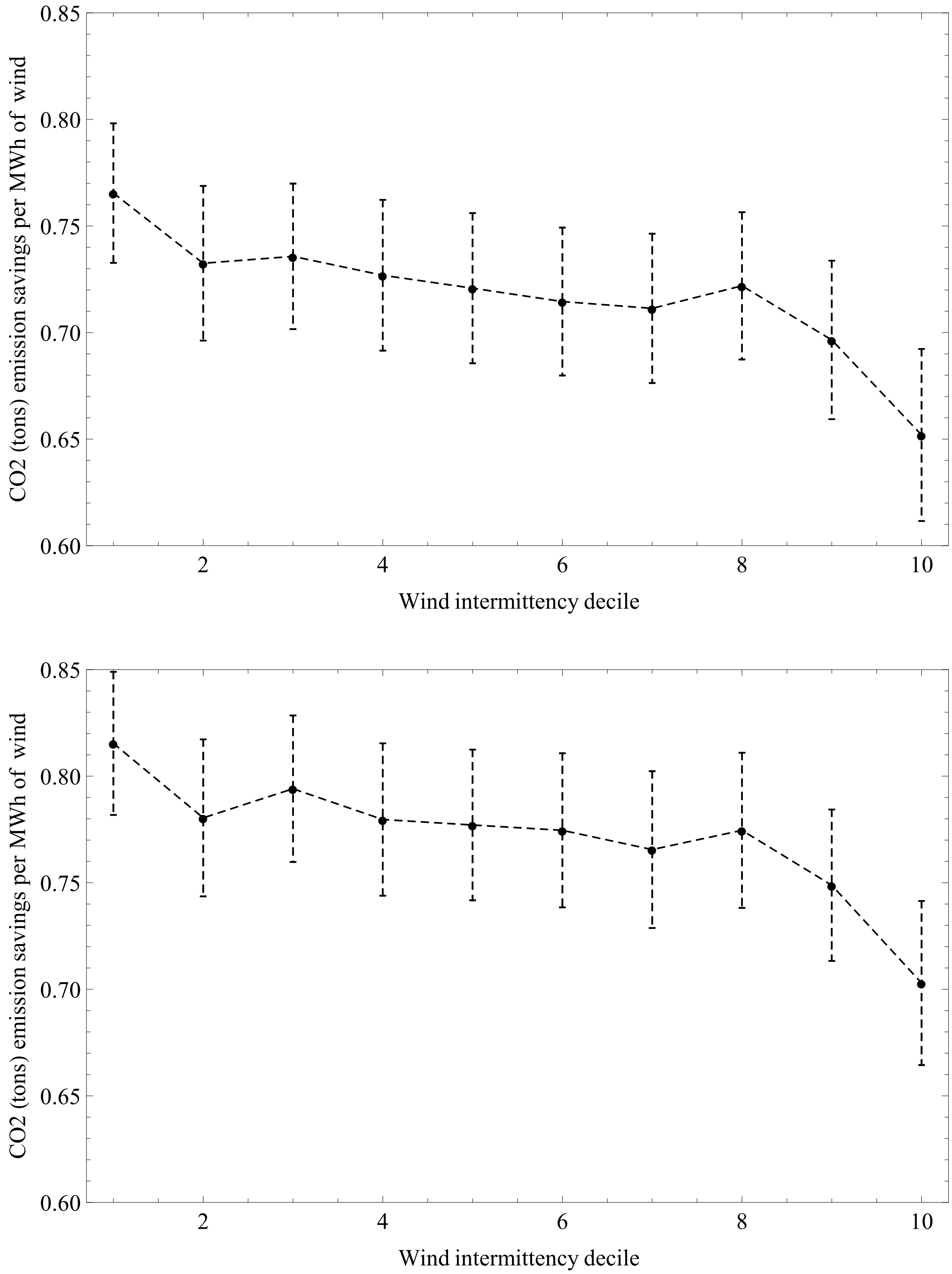

Figure 3: CO_2 emissions savings from wind (tons/MWh) by decile of wind intermittency when intrahour wind generation declines. Top panel excludes import controls while bottom panel includes controls for imports.

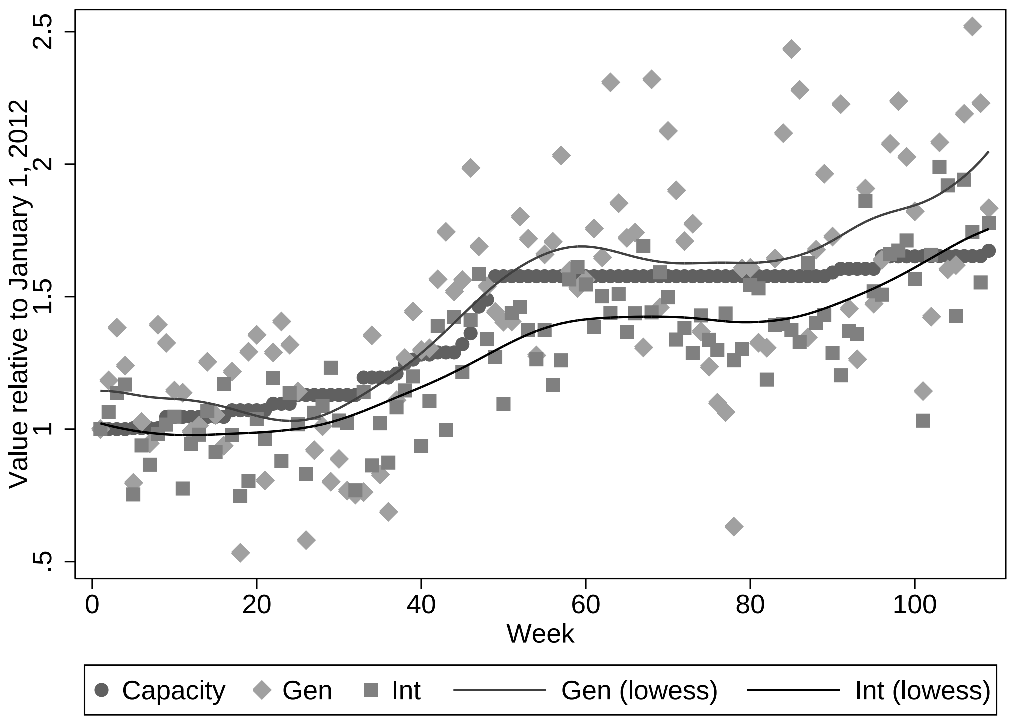

Figure 4: Wind capacity, average generation, and average intermittency by week during sample period, normalized to January 1, 2012.

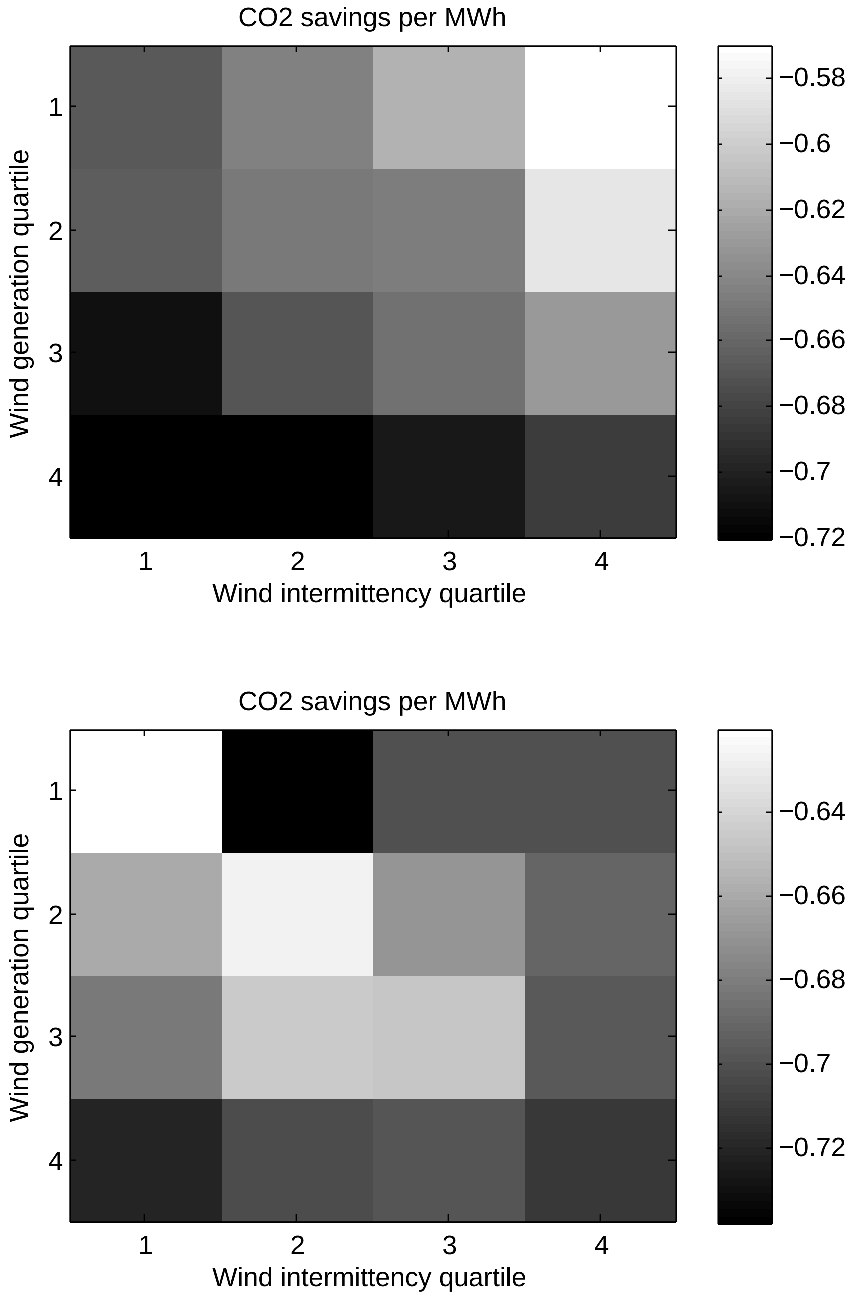

Figure 5: CO_2 emissions savings from wind (tons/MWh) by quartile of wind intermittency and wind generation when intrahour wind generation declines (top) and rises (bottom).

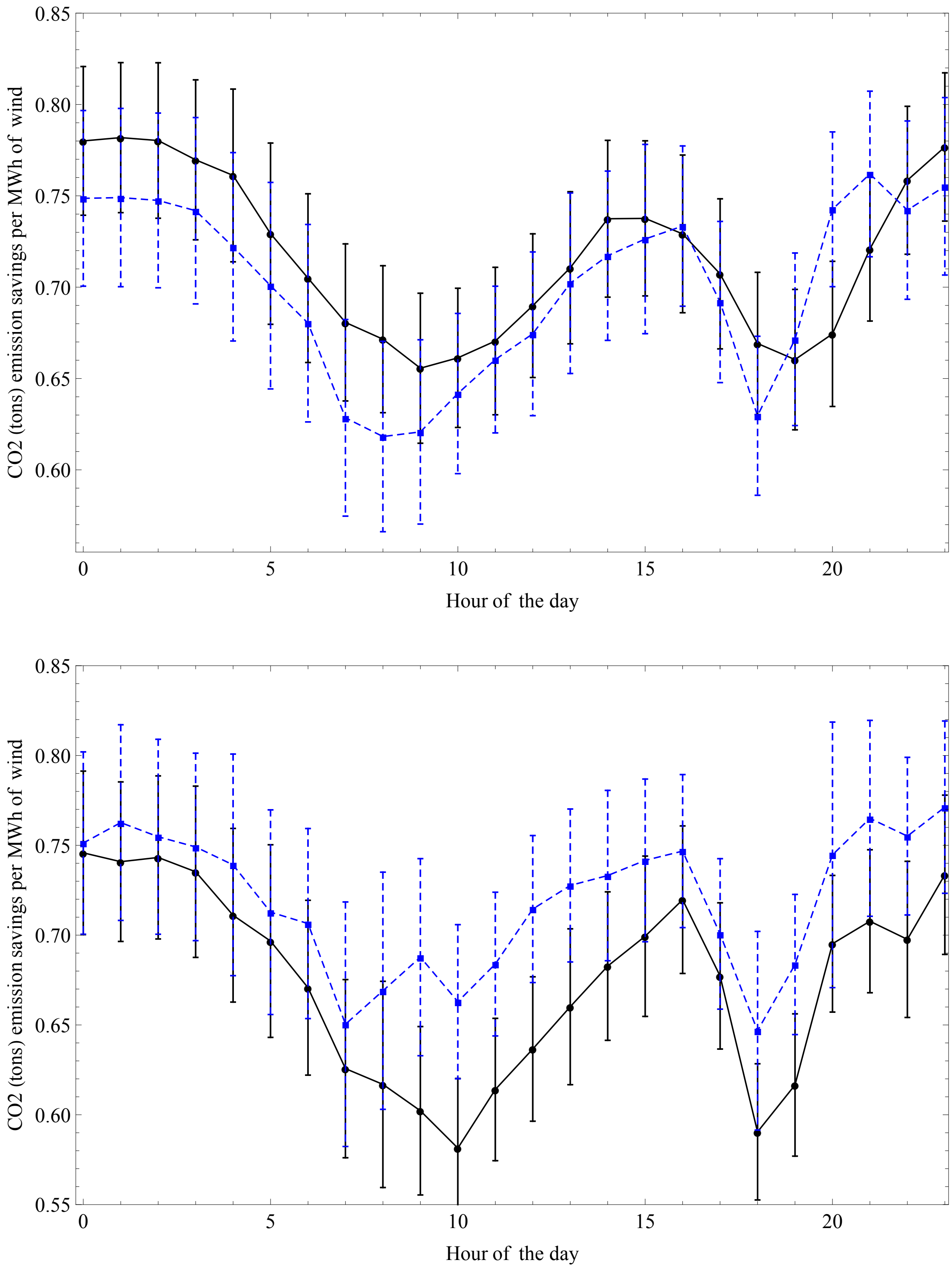

Figure 6: CO_2 emissions savings from wind (tons/MWh) by hour of day. Top panel - solid line is emissions savings without intermittency, dashed line is emissions savings with intermittency. Bottom panel - solid line is emissions savings inclusive of intermittency when intrahour generation is falling, dashed line is emissions savings inclusive of intermittency when intrahour generation is rising.

A Appendix Tables and Figures

Table A.1: Marginal emissions response - SO_2

Variables	(1) so2	(2) so2	(3) so2	(4) so2
coal	3.468***	3.468***	3.634***	3.616***
	(0.104)	(0.105)	(0.108)	(0.108)
ngas	-0.0176	-0.0295	0.244**	0.220**
	(0.136)	(0.135)	(0.107)	(0.104)
dfo			2.325	2.337
			(2.529)	(2.527)
hydro			-2.790	-2.797
			(1.826)	(1.824)
nuclear			-0.253	-0.266
			(0.414)	(0.416)
wind			0.161*	0.148*
			(0.0858)	(0.0839)
sdcoal		0.959**		0.973**
		(0.452)		(0.470)
sdngas		1.452***		1.507***
		(0.456)		(0.452)
Load/Temp	Y	Y	N	N
Hour-Month	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y
DOW	Y	Y	Y	Y
Observations	19,701	19,701	19,701	19,701
R-squared	0.929	0.929	0.929	0.929

Coefficients represent changes in lbs of SO_2. All regressions include hour-by-month, month-by-year, and day-of-week fixed effects, as well as quadratic controls for load and temperature (except where indicated). Robust standard errors clustered by week in parentheses.

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

Table A.2: Marginal emissions response - NO_x

Variables	(1) nox	(2) nox	(3) nox	(4) nox
coal	1.916***	1.919***	1.745***	1.749***
	(0.0692)	(0.0701)	(0.0856)	(0.0860)
ngas	1.648***	1.654***	1.606***	1.615***
	(0.105)	(0.107)	(0.0811)	(0.0829)
dfo			4.575**	4.585**
			(2.093)	(2.091)
hydro			-3.690**	-3.678**
			(1.531)	(1.534)
nuclear			-0.305	-0.306
			(0.288)	(0.288)
wind			-0.187***	-0.189***
			(0.0654)	(0.0647)
sdcoal		0.0970		0.232
		(0.367)		(0.368)
sdngas		-0.223		-0.292
		(0.301)		(0.306)
Load/Temp	Y	Y	N	N
Hour-Month	Y	Y	Y	Y
Month-Year	Y	Y	Y	Y
DOW	Y	Y	Y	Y
Observations	19,701	19,701	19,701	19,701
R-squared	0.951	0.951	0.952	0.952

Coefficients represent changes in 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 (except where indicated). Robust standard errors clustered by week in parentheses.

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

Table A.3: Marginal emissions response to wind generation and intermittency - alternative fixed effects

Variables	(1) co2	(2) co2	(3) so2	(4) so2	(5) nox	(6) nox
wind	-0.719***	-0.773***	-1.804***	-1.945***	-1.664***	-1.729***
	(0.0170)	(0.0175)	(0.109)	(0.113)	(0.0514)	(0.0540)
sdwind	0.517***	0.487***	1.243	1.305	-0.997**	-1.165**
	(0.173)	(0.146)	(0.968)	(0.935)	(0.499)	(0.494)
sdload	0.421***	0.498***	1.076*	1.384**	1.086***	1.083***
	(0.110)	(0.106)	(0.593)	(0.599)	(0.309)	(0.312)
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	19,701	19,701	19,701	19,701	19,701	19,701
R-squared	0.976	0.979	0.884	0.887	0.954	0.955

Coefficients represent changes in tons of CO_2, lbs of SO_2, lbs of NOX. All regressions include hour-by-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 A.4: Marginal emissions response and direction of ramping - alternative fixed effects

Variables	(1) co2	(2) co2	(3) so2	(4) so2	(5) nox	(6) nox
wind	-0.718***	-0.772***	-1.802***	-1.945***	-1.662***	-1.729***
	(0.0171)	(0.0176)	(0.109)	(0.113)	(0.0515)	(0.0541)
sdwind x up	-0.344	-0.499**	-0.999	-1.280	-3.027***	-3.350***
	(0.247)	(0.227)	(1.070)	(1.046)	(0.614)	(0.593)
sdwind x down	1.516***	1.617***	3.825***	4.249***	1.338**	1.317**
	(0.197)	(0.180)	(1.227)	(1.199)	(0.635)	(0.627)
sdload	0.433***	0.509***	1.103*	1.408**	1.110***	1.102***
	(0.110)	(0.106)	(0.591)	(0.598)	(0.306)	(0.309)
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	19,701	19,701	19,701	19,701	19,701	19,701
R-squared	0.976	0.979	0.884	0.888	0.954	0.955

Coefficients represent changes in tons of CO2, lbs of SO2, lbs of NOX. The variable "sdwind x up" is the effect of intrahour wind intermittency when intrahour wind generation is increasing, and ''sdwind x down" is the effect of intrahour wind intermittency when intrahour wind generation is decreasing. All regressions include hour-by-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 A.5: Marginal emissions response to wind generation and intermittency - intrahour wind range

Variables	(1) co2	(2) co2	(3) so2	(4) so2	(5) nox	(6) nox
wind	-0.717***	-0.772***	-1.804***	-1.935***	-1.649***	-1.735***
	(0.0168)	(0.0174)	(0.107)	(0.111)	(0.0506)	(0.0543)
rangewind	0.179***	0.173***	0.508	0.534	-0.431**	-0.480***
	(0.0587)	(0.0495)	(0.338)	(0.328)	(0.182)	(0.177)
sdload	0.397***	0.480***	1.075*	1.374**	0.809**	0.840**
	(0.110)	(0.104)	(0.565)	(0.576)	(0.331)	(0.335)
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	19,701	19,701	19,701	19,701	19,701	19,701
R-squared	0.975	0.978	0.882	0.885	0.948	0.950

Coefficients represent changes in tons of CO_2, lbs of SO_2, lbs of NOX. The variable "rangewind" represents the maximum range in intrahour 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. Robust standard errors clustered by week in parentheses.

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

Table A.6: Marginal emissions response and direction of ramping - intrahour wind range

Variables	(1) co2	(2) co2	(3) so2	(4) so2	(5) nox	(6) nox
wind	-0.717***	-0.772***	-1.802***	-1.934***	-1.647***	-1.735***
	(0.0168)	(0.0174)	(0.108)	(0.111)	(0.0507)	(0.0544)
rangewind x up	-0.119	-0.170**	-0.220	-0.326	-1.157***	-1.250***
	(0.0831)	(0.0746)	(0.388)	(0.382)	(0.231)	(0.219)
rangewind x down	0.526***	0.569***	1.349***	1.521***	0.407*	0.401*
	(0.0681)	(0.0622)	(0.418)	(0.406)	(0.227)	(0.220)
sdload	0.404***	0.487***	1.092*	1.388**	0.826**	0.853**
	(0.109)	(0.104)	(0.563)	(0.575)	(0.329)	(0.332)
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	19,701	19,701	19,701	19,701	19,701	19,701
R-squared	0.975	0.979	0.882	0.886	0.948	0.950

Coefficients represent changes in tons of CO2, lbs of SO2, lbs of NOX. The variable "rangewind" represents the maximum range in intrahour wind generation for a given hour. The variable "rangewind x up" is the effect of intrahour wind range when intrahour wind generation is increasing, and ''rangewind x down" is the effect of intrahour wind range when intrahour wind generation is decreasing. All regressions include hour-by-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 A.7: Marginal emissions response and direction of ramping - MISO/ERCOT controls

Variables	(1) co2	(2) co2	(3) so2	(4) so2	(5) nox	(6) nox
wind	-0.708***	-0.781***	-1.857***	-2.038***	-1.598***	-1.713***
	(0.0163)	(0.0172)	(0.108)	(0.114)	(0.0522)	(0.0547)
sdwind x up	-0.334	-0.430**	-0.256	-0.437	-3.490***	-3.733***
	(0.226)	(0.210)	(1.014)	(0.998)	(0.668)	(0.640)
sdwind x down	1.501***	1.600***	3.780***	4.224***	1.355**	1.284**
	(0.189)	(0.170)	(1.193)	(1.156)	(0.624)	(0.604)
sdload	0.393***	0.421***	0.909*	1.064**	0.751**	0.689**
	(0.107)	(0.0990)	(0.528)	(0.534)	(0.318)	(0.322)
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	19,701	19,701	19,701	19,701	19,701	19,701
R-squared	0.976	0.979	0.884	0.888	0.949	0.950

Coefficients represent changes in tons of CO2, lbs of SO2, lbs of NOX. The variable "sdwind x up" is the effect of intrahour wind intermittency when intrahour wind generation is increasing, and "sdwind x down" is the effect of intrahour wind intermittency when intrahour wind generation is decreasing. 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 controls for 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.8: Marginal emissions response to wind generation and intermittency - nonlinear

Variables	(1) co2	(2) co2	(3) so2	(4) so2	(5) nox	(6) nox
wind	-0.578***	-0.593***	-0.477*	-0.559**	-2.192***	-2.166***
	(0.0459)	(0.0441)	(0.273)	(0.267)	(0.165)	(0.173)
$wind^2$	-2.43e-05***	-3.14e-05***	-0.000231***	-0.000241***	9.44e-05***	7.55e-05***
	(6.95e-06)	(6.82e-06)	(4.36e-05)	(4.34e-05)	(2.66e-05)	(2.75e-05)
sdwind	0.475*	0.156	-0.781	-1.596	0.541	0.0768
	(0.262)	(0.233)	(1.407)	(1.404)	(0.756)	(0.729)
$sdwind^2$	-0.000782	-4.76e-05	-0.00134	0.00133	-0.00203*	-0.00179
	(0.000503)	(0.000528)	(0.00201)	(0.00233)	(0.00114)	(0.00118)
sdload	0.403***	0.489***	1.128**	1.444**	0.792**	0.814**
	(0.111)	(0.105)	(0.569)	(0.577)	(0.323)	(0.330)
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	19,701	19,701	19,701	19,701	19,701	19,701
R-squared	0.975	0.979	0.884	0.887	0.948	0.950

Coefficients represent changes in tons of CO2, lbs of SO2, lbs of NOX. 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

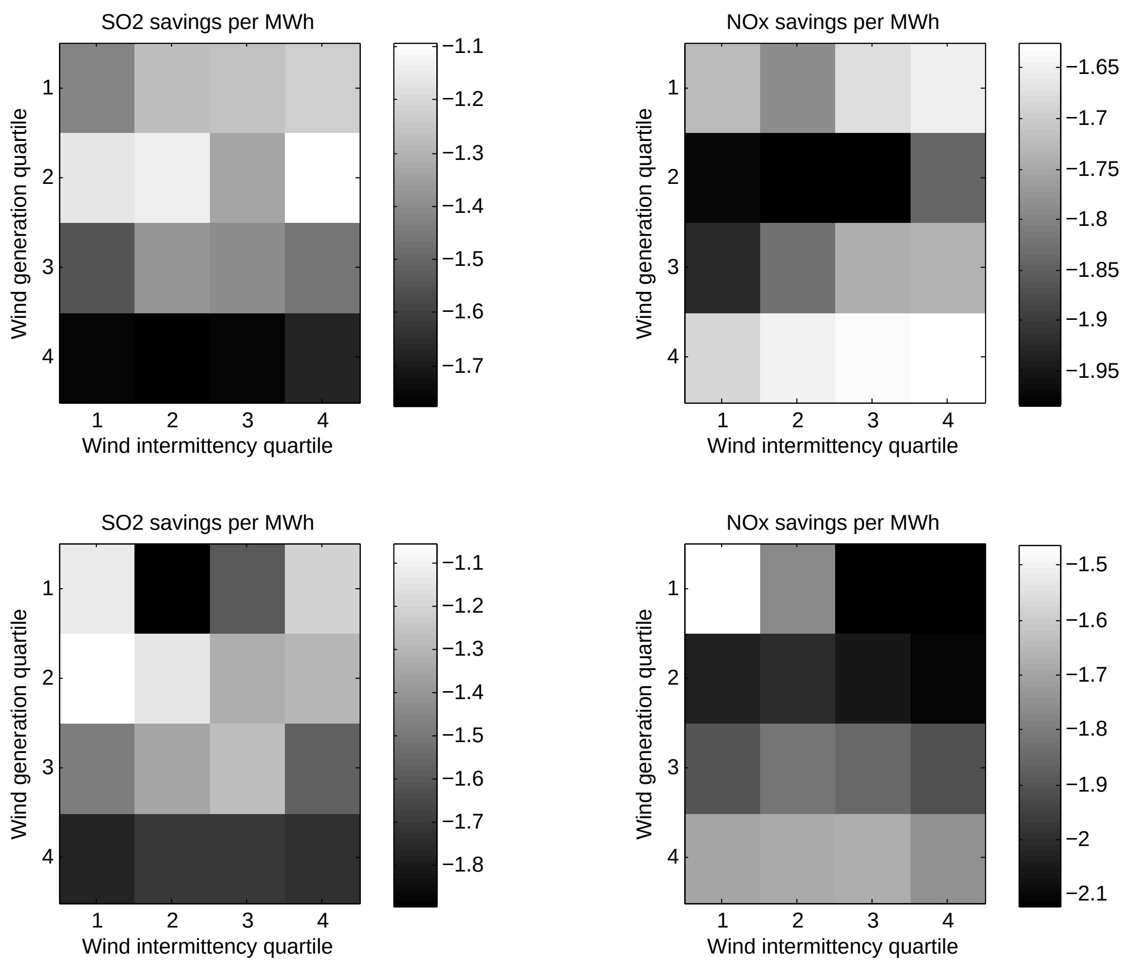

Figure A.1: SO_2 emissions savings (left) and NO_X emissions savings (right) from wind (tons/MWh) by quartile of wind intermittency and wind generation when intrahour wind generation declines (top) and rises (bottom).

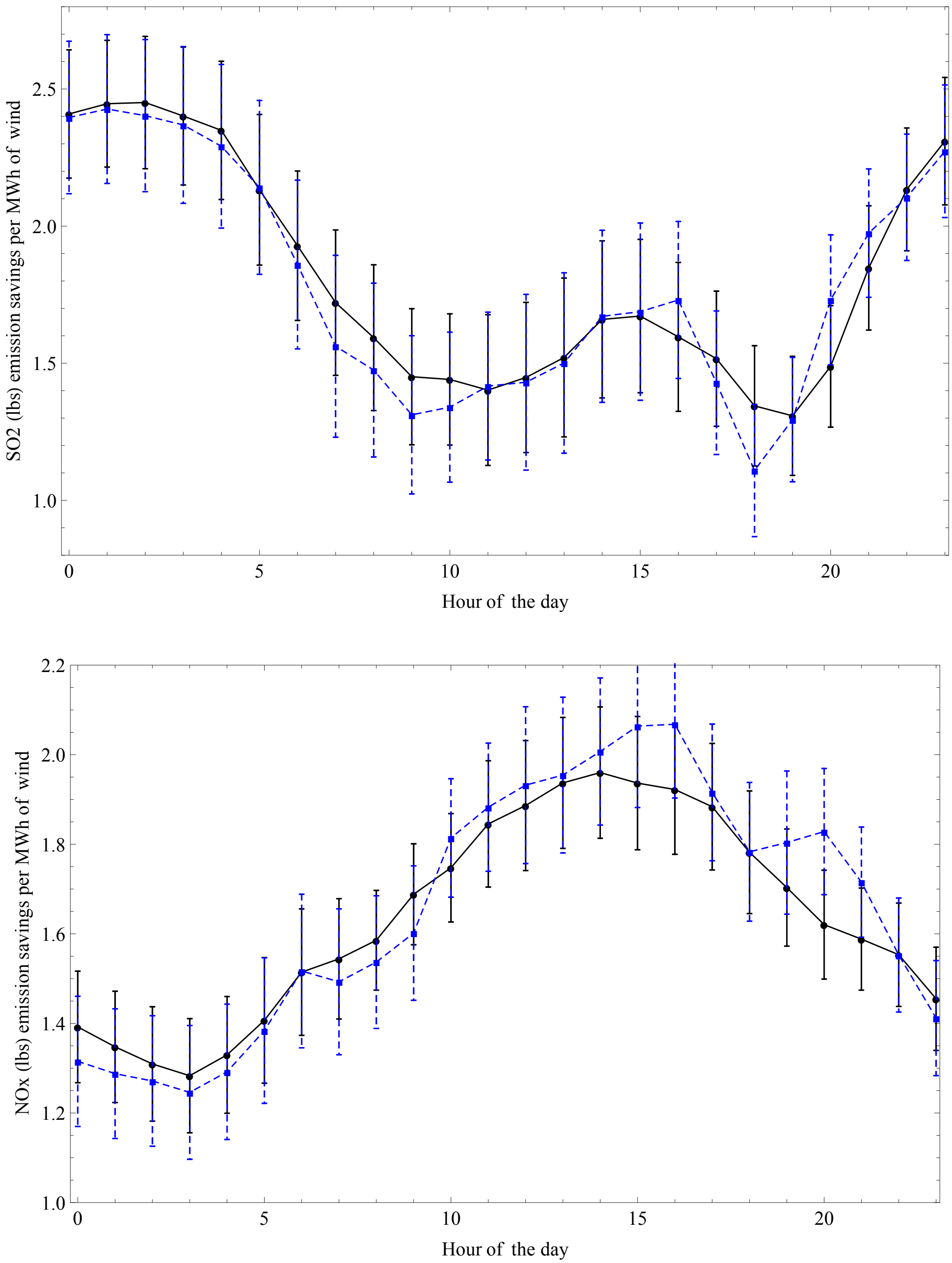

Figure A.2: Emissions savings from wind (tons/MWh) by hour of day. Top panel - solid line is SO_2 emissions savings without intermittency, dashed line is SO_2 emissions savings with intermittency. Bottom panel - solid line is NO_x emissions savings without intermittency, dashed line is NO_x emissions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