Valuing the Wind: Renewable Energy Policies and Air Pollution Avoided

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Abstract

Exploiting variation in the hourly production from wind turbines, this paper quantifies the heterogeneity in the marginal impact of renewable electricity on pollution. The results reveal that output from competing renewable capacity additions – e.g. wind turbines versus solar panels – provide different marginal external benefits. This finding suggests that, if governments continue to subsidize renewables, an emphasis should be placed on designing policies that internalize the heterogeneous benefits. More generally, my results highlight that, by incorrectly assuming renewable electricity is a homogenous good, we will understate the relative efficiency of the first-best pollution prices.

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The U.S. generates 70 percent of its electricity from fossil fuels. As a consequence, the electric sector is a major source of several pollutants, including 40

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percent of CO\textsubscript{2}, 23 percent of NO\textsubscript{X}, and 67 percent of SO\textsubscript{2} emitted in the U.S.\textsuperscript{1} These pollutants increase the risks posed by climate change, lead to the formation of smog and acid rain, and cause severe health problems. To efficiently reduce the flow of pollution, economists have consistently argued that prices should be placed on each pollutant (Pigou (1920), Dales (1968), Montgomery (1972), Baumol and Oates (1988)).\textsuperscript{2} In practice, however, emission prices have received limited use.\textsuperscript{3} Instead, policymakers are focusing on increasing generation from renewable energy sources. For example, 29 states have adopted renewable portfolio standards which mandate minimum levels of renewable generation. In addition, the federal government provides sizable production and investment tax credits for renewables. Combined, these policies have driven a recent surge in investment in renewable capacity (Hitaj (2013)).

In this paper, I examine whether the current policies encourage investments in the socially optimal renewable capacity additions. To do so, I quantify the heterogeneity in the pollution avoided by marginal increases in renewable generation. In contrast, previous studies have focused on estimating the average pollution avoided by marginal increases in renewable output (Cullen (2013), Kaffine, McBee and Lieskovsky (2013)).\textsuperscript{4} By uncovering the heterogeneity in the marginal impacts, I am able to explore two questions that have yet to be addressed. First, does output from different renewable investments – e.g. a wind turbine versus a solar panel – provide different marginal external benefits? Second, how do the marginal external benefits change as renewable capacity grows?

My empirical results highlight an important point – renewable electricity is far from a homogenous good. Not only does wind generation and solar generation provide different marginal external benefits, the difference increases as renewable

\textsuperscript{1}The U.S. Energy Information Administration provides generation and pollution statistics.
\textsuperscript{2}Palmer and Burtraw (2005) and Fischer and Newell (2008) focus solely on the electric sector.
\textsuperscript{3}In the U.S., cap-and-trade programs only cover a subset of pollutants, and often only apply to certain regions or during specific times of the year. Furthermore, when cap-and-trade programs are used, the caps are frequently set at inefficiently high levels.
\textsuperscript{4}Cullen’s estimation strategy allows the marginal emissions avoided to vary linearly with the level of wind generation while Kaffine, McBee and Lieskovsky allow the marginal impact of wind generation to vary across hours of the day. In contrast, my empirical approach allows renewable output to have heterogeneous impacts on emissions across multiple dimensions.
capacity expands. These findings suggest that, if governments continue to subsidize renewables, an emphasis should be placed on designing policies that internalize the heterogeneous external benefits. More importantly, however, my results highlight that, by incorrectly assuming renewable electricity is a homogenous good, we will underestimate the relative efficiency of the first-best pollution prices.

My analysis focuses on the Texas electricity market. Texas leads the nation in installed wind capacity. As a result, there is substantial variation in the hourly generation from wind turbines. Exploiting this variation, I identify how the short-run level of emissions is affected by supplying an additional megawatt hour (MWh) of wind during hours with different levels of demand and different levels of wind generation.\(^5\) The results reveal that during low-demand hours, each additional MWh of renewable electricity offsets successively more pollution than the previous MWh. During high-demand hours, the exact opposite pattern emerges – each additional MWh of renewable output offsets less pollution than the previous MWh.

Using my estimates of the marginal impacts of wind generation, I quantify the external benefits provided by marginal increases in wind capacity. By the end of 2011, almost 6,000 wind turbines were installed in the Texas market. I find that, on average, a MWh generated by the last wind turbine added to the region offsets 15 percent more CO\(_2\), 20 percent more NO\(_X\), and 56 percent more SO\(_2\) than a MWh produced by the first wind turbine installed in the region. This is due to the fact that the wind turbines produce most heavily during the low-demand hours, when the marginal emissions avoided are increasing. Using estimates of the social costs of the pollutants, I find the marginal wind turbine provides an average external benefit of $27.58/MWh – 20 percent more than the external benefit provided by the first wind turbine installed.

To examine how a competing renewable technology will affect pollution, I predict how adding solar panels will affect emissions. In contrast to the increasing external returns displayed by wind turbines, my simulation reveals that each additional solar panel will offset successively less pollution than the previous solar panel. This is due to the fact that the solar generation occurs exclusively during the

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\(^5\)Recent studies also examine the potential long-run impacts renewable investments may have on the composition of conventional generation technologies (Lamont (2008), Bushnell (2010)).
higher-demand, daytime hours – when the marginal emissions avoided are decreasing. While the initial investments in wind and solar capacity generate very similar external benefits, the external benefits provided by the marginal wind turbine and the marginal solar panel diverge as the installed capacity grows.

This paper builds on a growing literature exploring the environmental benefits of renewable electricity. Previous studies highlight that, due to differences in the emission rates of generation capacity across regions, output from renewable generators located in different markets will offset different amounts of pollution (Callaway and Fowlie (2009), Siler-Evans, Azevedo and Morgan (2012), Kaffine, McBee and Lieskovsky (2013), Graff Zivin, Kotchen and Mansur (2014)). Contributing to this literature, my findings reveal that, even within a single market, output from different renewable investments will provide different marginal external benefits. Current renewable policies, however, are not designed to internalize the heterogeneity in the external benefits. For example, Texas’ renewable portfolio standard provides solar producers with a per MWh subsidy that is twice as large as the per MWh wind subsidy. This is in direct contrast to my findings which demonstrate that, in Texas, a MWh of wind offsets more pollution than a MWh of solar output.

On one hand, my results suggest that incremental efficiency gains can be realized by designing subsidies that more accurately internalize the external benefits of competing renewable investments. More generally, however, my results reiterate that renewable subsidies present a poor option for reducing pollution. While previous work clearly demonstrates that emission prices will reduce pollution more efficiently than the current renewable policies – e.g. renewable portfolio standards, production tax credits, feed-in-tariffs – past studies often abstract from the heterogeneity in the external benefits of renewable electricity. In doing so, previous work has underestimated the relative efficiency of emission prices.

The remainder of the paper proceeds as follows. Section I provides background on the electricity dispatch process and current renewable energy policies. Section II describes the identification strategy and data used in this study. Section III presents

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6Previous studies have noted this possibility (Callaway and Fowlie (2009), Metcalf (2009), Borenstein (2012)), but no studies have quantified the differences.

7For example, see Fischer and Newell (2008).
estimates of the average impact of a marginal increase in renewable generation. Section IV examines the heterogeneity in the marginal impact of renewable generation on pollution. Section V estimates the external benefits of various renewable capacity investments. Section VI concludes.

I Background

A. Electricity Dispatch Process

To maintain the stability of an electric grid, the quantity of electricity supplied must always equal the quantity demanded. Balancing the real time supply and demand is a complex optimization problem which is subject to the transmission limits of the grid and the production constraints of each interconnected generating unit. Procedures to determine the level of generation from each unit vary across markets. In regulated regions, central planners schedule output while in deregulated regions, like the market examined in this study, supply and demand are balanced through the operation of both centralized and decentralized markets.

Conventional generating units with the lowest variable costs regularly produce close to their maximum capacities during all hours. To meet the remaining demand, generation is dispatched from additional units with the highest marginal cost generators supplying electricity at peak levels of demand. When not off-line for maintenance or repairs, these dispatchable sources are essentially capable of increasing or decreasing the quantity of electricity supplied at any time.\(^8\)

While dispatchable sources account for the majority of generation, a small share of electricity is produced using intermittent, renewable energy sources such as wind and solar energy. A key difference between intermittent renewable generators and dispatchable generators is that once the fixed costs of building and installing a wind turbine or solar panel have been sunk, only the regular maintenance and repair costs must be paid. Unlike combustion generators, there are no fuel costs and unlike hydroelectric plants, there are no opportunity costs to using the resource.

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\(^8\) Conventional generating units are often subject to minimum/maximum operating levels, ramping constraints, and minimum start-up or shut-down times.
A temporary increase in generation from intermittent renewables effectively shifts the electricity supply curve outwards. While this shift can be expected to reduce wholesale electricity prices, the quantity demanded will likely remain unchanged due to the fact that consumers generally face fixed, short-run retail prices. As a result, an increase in renewable generation must result in a decrease in conventional output.\(^9\) If any of the offset conventional generation comes from units burning fossil fuels, the aggregate level of pollution may be reduced.

**B. Policies Supporting Renewable Generation**

Motivated largely by the belief that renewable electricity can reduce pollution, policies designed to induce investment in renewable capacity are receiving substantial support. However, under the current set of policies, there is wide variation in how different renewable investments are supported. For example, at the federal level, the U.S. offers the Renewable Electricity Production Tax Credit (PTC) which provides a tax credit of $23 for each MWh generated by qualified renewable energy sources – which includes wind but not solar.\(^{10}\) In addition, the federal government provides an Investment Tax Credit (ITC) worth 30 percent of the fixed costs for qualified investments – which includes solar but not grid-level wind farms.

On top of the federal tax credits, 29 states have adopted renewable portfolio standards (RPS) which mandate a minimum share of electricity that must be purchased from renewables.\(^{11}\) For each MWh generated, renewable producers receive a renewable energy certificate (REC). REC’s can then be sold in compliance markets to the electricity providers who must fulfill their renewable electricity obligations.\(^{12}\) The additional revenue each MWh of renewable output receives from these

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\(^9\)During 2007, 6.42 percent of electricity generated in Texas was lost during transmission and distribution (see the eGRID State Import-Export Generation and Consumption Data Files). If the loss rates differ between renewables and the non-renewable units serving as substitutes, then the quantity of conventional output avoided could be slightly greater or less than the renewable generation.

\(^{10}\)For comparison, during the period studied in this paper, the average wholesale electricity price in the Texas electricity market is just over $50/MWh.

\(^{11}\)As of August, 2013, 29 states, plus D.C. and two territories, had adopted renewable mandates. Additionally, 8 states had renewable portfolio ‘goals’.

\(^{12}\)REC’s can also be sold in voluntary markets as well. For an analysis of compliance and voluntary REC prices, see Heeter and Nicholas (2013).
REC’s varies across states. In addition, the level of support varies across technologies. For example, under the RPS established in Texas, wind farms receive a single REC for each MWh of output while solar generators receive two REC’s for each MWh.\textsuperscript{13} In total, 16 of the 29 states with RPS policies have adopted similar provisions which increase the subsidies provided to solar generators relative to wind.\textsuperscript{14}

Combined, the federal and state policies have certainly been effective at inducing renewable investment (Hitaj (2013)).\textsuperscript{15} However, have they been effective at spurring investment in the renewable capacity additions that provide the largest social benefits? To answer this question, it is crucial to determine how pollution is affected by increases in renewable capacity. Moreover, it is important to understand whether different types of investments (e.g. wind turbines versus solar panels) provide different external benefits.

C. Existing Estimation Strategies

In order to evaluate the current renewable policies, there is widespread interest in producing transparent estimates of the pollution avoided by renewable generation. The most simplistic strategy estimates the emissions avoided as the product of the aggregate renewable output and the average emission rate of the dispatchable producers in a market. This method assumes that an equal percentage of output from each conventional technology is offset by renewable generation. In reality, certain technologies are on the margin more often than others. For example, low variable cost nuclear generators are unlikely to serve as the marginal source of electricity.

To accurately quantify the pollution avoided, one must identify the change in emissions from the marginal producers that adjust output in response to renewable

\textsuperscript{13}During the period examined, the Texas REC’s fluctuated between $5 and $10 per MWh.

\textsuperscript{14}For example, Delaware, Michigan, Nevada, and Oregon multiply the number of credits that solar receives per MWh by a factor ranging from 2 to 3. In addition, several states explicitly create two REC markets – one for solar and one for other renewable sources. In most cases, the solar REC prices far exceed the non-solar REC prices. For an overview of the current state of the compliance REC markets, see Heeter and Nicholas (2013).

\textsuperscript{15}From 2005 through 2011, total U.S. electricity generation capacity grew by 8 percent. During the same seven year span, U.S. wind capacity increased by 425 percent and solar capacity increased by 271 percent – accounting for over half of the growth in total generation capacity. Capacity statistics are available from the U.S. Energy Information Administration.
generation. Several reduced form strategies have been developed to estimate this ‘marginal emission rate’. One method utilizes a Load Duration Curve framework to predict which units are on margin at specific levels of demand (Broekhoff (2007), Gil and Joos (2007), Price et al. (2003)). Connors et al. (2005), instead, determine the set of ‘load following’ plants – the generators that increase and decrease output in response to demand shifts – and use a weighted average of these plants’ emission rates as the marginal emission rate. Alternatively, Callaway and Fowlie (2009) and Siler-Evans, Azevedo and Morgan (2012) directly estimate the marginal emission rate by regressing changes in hourly emissions on changes in the hourly conventional generation.\footnote{To explore the impact of demand-side interventions (e.g. electric vehicles and electricity storage), Graff Zivin, Kotchen and Mansur (2014) and Carson and Novan (2013) use similar strategies to estimate hour-specific marginal emission rates.}

Each of the preceding strategies assumes that an increase in renewable generation has the same impact on emissions as an equal decrease in the quantity of electricity demanded. In the case of intermittent renewable energy sources, which can produce fairly volatile streams of output, this assumption may not be valid.\footnote{For a comparison of the short-run (e.g. 4-second to 1-hour) variability of wind generation and aggregate demand, see Wan (2005). The author highlights that, over time frames of 1-minute and longer, the volatility of wind power exceeds the volatility of aggregate demand.} For example, in a given hour, a 1 MWh decrease in the total quantity demanded may be caused by demand shifting back by 1 megawatt (MW) for the entire hour.\footnote{MW’s are a measure of the power consumed or supplied at a specific instant in time. In contrast, MWh’s are a measure of the energy consumed or supplied over an hour – i.e. MW’s integrated over an hour.} In contrast, a 1 MWh increase in wind generation could be supplied by a wind turbine generating 2 MW’s of output for thirty minutes and zero MW’s of output for the remaining thirty minutes. If fossil fuel units operated with constant emission rates, this within-hour volatility would not pose a serious problem. However, fossil fuel-fired generators can produce large spikes in emissions when they are forced to rapidly alter production. In fact, a frequent argument against the use of volatile wind and solar energy is that fossil fuel units will be forced to constantly ramp up and down, resulting in more emission intensive generation (Katzenstein and Apt (2009)). As a result, the pollution offset by the additional MWh of wind could...}
differ from the pollution offset by the MWh decrease in the quantity demanded.

In contrast to the previous studies, which use shifts in demand to predict the impact of changes in renewable supply, Cullen (2013) presents the first econometric estimates of the actual substitution pattern between wind generation and conventional generators. Using short-run changes in the aggregate generation from wind turbines as a natural experiment, Cullen estimates the average impact marginal increases in wind generation have on the production from conventional generators in the Texas electricity market. To predict the resulting average reduction in emissions caused by marginal increases in wind, the historical, plant-level, average emission rates are multiplied by the output avoided from each fossil plant.

While Cullen relaxes many of the previous simplifications, one untenable assumption remains. By using average emission rates, each fossil fuel plant is assumed to have a constant emission rate. In reality, a plant’s marginal emission rate varies systematically over its range of production. Relaxing the assumption that fossil fuel generators have constant emission rates, Kaffine, McBee and Lieskovsky (2013) estimate the average impact a marginal increase in wind generation has on the actual emissions from the Texas market. Compared to Cullen, the authors find significantly smaller amounts of pollution are offset. However, by limiting their analysis to fossil fuel generators located in the footprint of the Texas electricity market’s service territory, Kaffine, McBee and Lieskovsky exclude a large number of fossil fuel units that can directly, and indirectly, supply electricity to the Texas market. If wind turbines reduce production from these excluded generators, then emission reductions will occur outside of the service territory as well.

In this paper, I reexamine the impact of Texas wind generation on pollution.

\[\text{\textsuperscript{19}}\text{In a robustness check, Cullen relaxes the constant emission rate assumption and estimates the average impact of a marginal increase in wind generation on the actual emissions from a subset of the fossil fuel units in his dataset. In the static model, the estimates of the marginal impact of wind on emissions do not change significantly. In a dynamic model, there is evidence that the constant emission rate assumption produces significantly different estimates of the impact of wind generation on emissions.}\]

\[\text{\textsuperscript{20}}\text{Compared to the static estimates presented by Cullen, Kaffine, McBee and Lieskovsky find that, on average, a MWh of wind offsets 16 percent less CO}_2\text{, 22 percent less NO}_X\text{, and 25 percent less SO}_2\text{. Cullen’s analysis also presents estimates of the emissions offset from a model that allows wind generation to dynamically affect fossil generation. In an appendix I present estimates from a similar dynamic model.}\]
Similar to Kaffine, McBee and Lieskovsky, I estimate the effect wind generation has on the actual level of emissions from fossil fuel generators. However, my analysis differs from Kaffine, McBee and Lieskovsky in two key ways. First, to ensure that I identify the full impact of wind on pollution, I examine how emissions from fossil fuel-fired generators located outside of Texas are affected. My subsequent results demonstrate that wind generation supplied to the Texas market does in fact cause pollution reductions from generators outside of the state. Second, while Kaffine, McBee and Lieskovsky estimate the average marginal impact of wind generation on pollution, I focus on estimating the heterogeneity in the marginal impacts. By uncovering the heterogeneity, I am able to explore how the external benefits provided by renewable capacity additions differ across technologies. Moreover, I am able to explore how the marginal external benefits change as the amount of installed capacity grows.

II Data and Identification Strategy

This paper utilizes data spanning January 1, 2007 through December 31, 2011. The Electric Reliability Council of Texas (ERCOT) – the system operator responsible for managing the scheduling, transmission, and settlement in the Texas market – provides data on the hourly net generation supplied to the market by fuel source. Included with the ERCOT data is the total hourly generation from wind turbines. The Environmental Protection Agency (EPA) provides hourly data on the gross electricity generated and CO\textsubscript{2}, NO\textsubscript{X}, and SO\textsubscript{2} emitted from fossil fuel generating units in ERCOT as well and the surrounding markets.\(^{21}\) The Federal Energy Regulatory Commission (FERC) provides data on the hourly electricity demanded. I collect demand data for the ERCOT market as well as the Southwest Power Pool (SPP) to the north.

To estimate the impact of wind generation on emissions, I identify how the hourly aggregate generation from ERCOT wind turbines affects the contemporane-

\(^{21}\)The EPA’s *Plain English Guide to the Part 75 Rule* (2009) describes the Continuous Emissions Monitoring Systems. Occasionally, hourly CO\textsubscript{2} is missing from specific gas units. To account for these missing observations, I calculate the pollution by multiplying the unit’s hourly heat input by the average emission intensity for natural gas fired units, .062 tons CO\textsubscript{2}/MMBtu.
ous level of emissions from fossil fuel units.\textsuperscript{22} The identification strategy I employ takes advantage of the fact that, in the short-run, variation in the hourly generation from wind turbines is determined almost entirely by exogenous changes in the available wind energy \textit{(e.g.} wind speed, wind direction, air density\textit{)}. Given that the marginal cost of wind generation is essentially zero, whenever electricity is available from wind turbines, it will be supplied to the market. The only exceptions occur when output from wind turbines must be intentionally reduced (curtailed).\textsuperscript{23}

Wind generation curtailments can arise for several reasons. First, during periods with high wind, the potential output from wind farms in a region can exceed the transmission limits of the electric grid. Therefore, potential generation from the wind turbines will not be supplied to the market. Given that these curtailments are determined exogenously by the fixed transmission limits and wind speeds, they do not introduce endogeneity in the observed variation in hourly wind generation.

Curtailments can also be caused by shifts in the short-run demand for electricity or shocks to the supply from conventional sources. For example, if the short-run demand in a region with wind turbines falls, electricity exports out of the region may need to increase. If the quantity of electricity to be exported exceeds the transmission limits of the grid, then generation from the region with wind farms may need to be reduced. While the reductions can be expected to come from generators with the highest marginal costs first, once these conventional generators reach their lower operating limits, output from near zero marginal cost wind turbines may be curtailed. In this case, the reduction in demand, which likely reduces short-run emissions, also causes a reduction in renewable generation.\textsuperscript{24}

To identify the impacts of wind generation, I must control not only for curtailments, but also a variety of other factors that can affect the level of emissions. The main determinant of hourly emissions is electricity demand. In ERCOT, demand peaks during the daytime hours and over the summer months while wind gener-

\textsuperscript{22}In an appendix, I present estimates from an alternative specification which allows wind generation to affect emissions in subsequent hours. The results demonstrate that the full impact of wind generation occurs largely within the same hour.

\textsuperscript{23}Data on when, and how much, wind generation is curtailed is not available. Fink et al. (2009) discuss case studies of wind curtailments across markets.

\textsuperscript{24}Similarly, a fossil unit unexpectedly shutting down may tighten or weaken the transmission constraints, altering both the level of wind curtailments and fossil emissions.
ation typically peaks overnight and during the winter months. In addition, daily weather fluctuations can cause a link between wind generation and demand. To account for correlation between the hourly wind generation and demand, I include the hourly electricity usage as a control variable. The hourly usage also controls for wind curtailments which may be endogenously caused by shifts in electricity demand.

The Texas region has two key characteristics that make it an excellent market for this study. First, there is a large amount of installed wind capacity. As a result, there is substantial variation in the hourly wind generation which makes it possible to precisely estimate the impact of renewable electricity on emissions. A summary of the average hourly net generation from ERCOT plants between January, 2007 and December, 2011 is provided in Table 1. Production from natural gas, coal, and nuclear generators account for 41.5 percent, 38 percent, and 13 percent, respectively, of the electricity supplied to ERCOT. The next largest source of generation comes from wind turbines. The second advantage of ERCOT is the market has very little hydroelectric capacity. If wind generation replaces hydroelectric output, the renewable generation would effectively be stored as potential energy. As a result, the avoided emissions would occur at a different point in time, making the identification more challenging.

(Table 1)

To estimate the pollution reductions caused by ERCOT wind generation, I must determine how emissions from the interconnected fossil fuel units are affected. While the ERCOT grid is one of the most isolated markets in the U.S., there are nonetheless several fossil fuel generators located outside of the region that are di-

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25 A potential drawback of including demand controls is that this strategy estimates the partial impact of wind generation on emissions, holding demand constant. While residential consumers face fixed retail prices, if industrial electricity consumption varies in response to short-run changes in wind generation, the estimates of the partial impact of wind generation on emissions will not capture the net impact on emissions. However, the price elasticity of demand for industrial consumers in ERCOT is essentially zero (Zarnikau and Hallett (2008)).

26 In an appendix, I present estimates from an alternative specification in which I use hourly wind speeds to instrument for the output from wind turbines.

27 ERCOT aggregates generation from the burning of biomass, landfill gases, petroleum, diesel, and solar units into ‘other’ generation.
rectly connected to the ERCOT grid.\textsuperscript{28} For example, the Kiamichi Energy Facility, one of the largest natural gas plants supplying the ERCOT market, is located in Oklahoma. Additionally, electricity can flow across direct current (DC) ties connecting ERCOT to Oklahoma – part of the Southwest Power Pool (SPP).\textsuperscript{29}

To accurately estimate the emissions offset by wind generation, the impact on generators outside of the ERCOT service region must be considered. In addition to the units located in the footprint of the ERCOT service territory, I obtain hourly emissions data from fossil fuel units located in the SPP service region in the northern panhandle of Texas as well as in Oklahoma.\textsuperscript{30} Table 2 summarizes the fossil fuel generating units in the EPA dataset. The emission rates vary based on the fuel source – coal-fired units have the highest emission rates. Even among units using the same fuel, there is significant variation in the average emission rates across technologies. Combined cycle natural gas generators – which achieve high generation efficiencies by using waste heat from the combustion of natural gas to produce additional electricity – have lower emission rates than single cycle natural gas turbines. These differences highlight why it is crucial to identify the set of units that actually reduce output in response to wind generation.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|}
\hline
\thead{Fuel Source} & \thead{Emission Rates} \\
\hline
Coal & High \\
Natural Gas & Low \\
\hline
\end{tabular}
\caption{Fossil fuel generating units in the EPA dataset.}
\end{table}

\textsuperscript{28}The United States is separated into three interconnections: the Eastern and Western Interconnections, and the Texas Regional Entity which is overseen by ERCOT. Within each interconnection, electricity is produced and transmitted at a synchronized frequency. Electricity traded between interconnections must first be converted from alternating current to direct current (DC) and flow through a limited number of DC lines or be transmitted through a variable frequency transformer.

\textsuperscript{29}The Eagle Pass, Laredo, and Railroad DC ties connect ERCOT to the \textit{Comision Federal de Electricidad} (CFE) grid serving Mexico. However, I do not have data on the emissions from plants outside of the United States.

\textsuperscript{30}Additional estimates were made using emissions from generators located in the entire SPP region (Kansas, western Missouri, western Arkansas, western Louisiana, and eastern New Mexico). There are no significant impacts on emissions from plants outside of Texas and Oklahoma.
III Average Emissions Offset by Wind Generation

A. Econometric Specification

To estimate the impact of wind generation on emissions, I use the general model:

\[ E_t = \beta \cdot W_t + \phi \cdot Z_t + \epsilon_t, \]

where \( t \) indexes each individual hourly observation during the five year sample and

- \( E_t \): Aggregate hourly emissions of \( \text{CO}_2 \) (tons), \( \text{NO}_X \) (lbs), or \( \text{SO}_2 \) (lbs),
- \( W_t \): Aggregate hourly ERCOT wind generation (MWh),
- \( Z_t \): Vector of controls.

The coefficient of interest, \( \beta \), represents the average change in emissions caused by a MWh of ERCOT wind generation.

To identify the impact of wind generation, I must control for a variety of factors that are correlated with \( W_t \). First, wind generation is correlated with electricity consumption. To control for this, the vector \( Z_t \) includes the electricity consumed in the ERCOT and SPP markets during hour \( t \). To allow consumption to affect emissions non-linearly, I also include the squares and cubes of the hourly consumption. Variation in factors other than the hourly demand for electricity also affect emissions. This is evidenced by the fact that, conditional on the hourly level of electricity demanded, emissions differ by season, by time of day, and by day of the week.\(^{31}\)

To control for hourly and seasonal patterns in emissions and wind generation, I include hourly fixed effects that are allowed to vary across each of the 60 months in the sample. Of course, if wind generation is entirely determined by the available wind energy, it would not be necessary to control for differences in the hourly fixed effects across individual days of the week. For example, the average wind speed during the 8 a.m. hour on Mondays should equal the average wind speed during the same hour on Fridays. However, given that wind generation is partly determined by

\(^{31}\)In a simple regression of the hourly emissions on the hourly levels of demand, fixed effects for the hour of day, day of week, and month are highly significant.
the amount of energy curtailed, patterns across days of the week can occur.\textsuperscript{32}

To control for differences in the hourly patterns in emissions and wind generation across days of the week, I also allow the hour-of-day fixed effects to vary by the day of the week. In total, this results in 10,080 fixed effects (24 hours×12 months×5 years×7 days of the week). In addition to the preceding fixed effects, a variety of unobserved factors can alter the level of emissions during each hour of a day. For example, if a coal plant is taken off-line for maintenance, cleaner gas-fired generation may replace the missing output. As a result, the emissions will fall across many hours. To control for the possibility that the unobserved fixed effects are correlated with the included regressors, I estimate the model using an additional fixed effect for each of the 1,826 days in the sample.

The full specification I estimate is:

\begin{equation}
E_t = \beta \cdot W_t + \sum_{n=1}^{3} (\theta_{1,n} \cdot D_{1,t}^n + \theta_{2,n} \cdot D_{2,t}^n) + \alpha_{h,m,y,w} + \delta_d + \epsilon_t,
\end{equation}

where

- $E_t$ = Aggregate hourly CO$_2$ (tons), NO$_X$ (lbs), or SO$_2$ (lbs),
- $W_t$ = Aggregate hourly ERCOT wind generation (MWh),
- $D_{1,t}^n$ = Hourly ERCOT demand (MWh) raised to $n = [1, 2, 3]$,
- $D_{2,t}^n$ = Hourly SPP demand (MWh) raised to $n = [1, 2, 3]$,

and $\alpha_{h,m,y,w}$ represents the hour-of-week fixed effect and $\delta_d$ represents the daily fixed effect. To account for serial correlation, Newey-West standard errors are calculated using a 24-hour lag.

\textsuperscript{32}For example, over my sample period, the highest average hourly wind generation occurs during the last hour of Sunday nights and the first hour of Monday mornings – average wind generation during these two hours is 2,753 MWh. In contrast, during the last hour of Thursday nights and the first hour of Friday mornings, the average wind generation was 2,560 MWh – which is significantly different, at the 5 percent level, from than the Sunday-night/Monday-morning average generation. This suggests that, on average, roughly 7 percent of the potential wind generation is curtailed during the last hour of Thursday and first hour of Friday.
B. Average Emissions Offset

Table 3 presents the estimates of $\beta$ from Eq. (2). The first three columns display the average impact of a MWh of wind generation on the aggregate emissions from fossil fuel units directly connected to the ERCOT market. On average, a MWh of wind offsets 0.63 tons of CO$_2$, 0.90 pounds of NO$_X$, and 1.77 pounds of SO$_2$ from this subset of generators. Each point estimate is significant at the 1 percent level.

The last three columns present the estimates of the changes in emissions from ERCOT and SPP fossil fuel units. On average, a MWh of wind generation offsets 0.67 tons of CO$_2$, 1.05 pounds of NO$_X$, and 1.82 pounds of SO$_2$. Compared to the estimates made using only the units directly connected to ERCOT, the average reduction in SO$_2$ is not significantly different. However, I find statistically larger reductions in CO$_2$ and NO$_X$. These results reveal that ERCOT wind reduces emissions from generators located in both markets.

C. Average Generation Avoided

Recall, the quantity of electricity supplied must always equal the quantity demanded. Therefore, controlling for shifts in demand, an increase in wind generation must result in an equal and opposite decrease in non-wind generation. In this section, I test whether this engineering identity holds by estimating the reduction in dispatchable output caused by ERCOT wind generation. If less than 1 MWh of non-wind generation is avoided by a MWh from ERCOT wind turbines, then units serving as substitutes to ERCOT wind turbines are not included in my dataset. In this case, the estimates of the pollution reductions will be biased towards zero.

Alternatively, if I find that greater than 1 MWh of non-wind generation is avoided by a MWh of wind, then my estimates will overstate the emissions offset. This could occur due to the fact that I am unable to directly control for non-ERCOT

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33This includes all of the generators in the ERCOT service territory as well as units located outside of the service territory but still listed as ERCOT suppliers in the EIA-860 Generator Database.

34There are two potential reasons fossil fuel units could be missing: 1) the EPA does not require units with capacities below 25 MW to report hourly emissions, and 2) generators outside of Texas and Oklahoma could adjust output in response to ERCOT wind generation.
wind generation. If output from ERCOT wind turbines is positively correlated with the unobserved output from wind farms in the SPP region, and the set of fixed effects do not control for this correlation, then I will incorrectly attribute pollution reductions provided by SPP wind generation to the ERCOT wind turbines.

It is important to note that I observe two different measures of electricity production. The ERCOT dataset provides the net generation, separated by fuel source, supplied directly to the ERCOT grid. In contrast, the EPA provides the gross generation from fossil fuel units. Gross generation equals the net generation plus any electricity consumed at the plants (e.g., electricity used to operate water pumps and pollution control equipment). If an increase in renewable output causes fossil fuel units to reduce on-site electricity usage, the gross fossil generation avoided by a MWh of wind generation will exceed the net fossil generation avoided.

To identify the average impact ERCOT wind has on the gross generation from fossil fuel units in the EPA dataset, I re-estimate Eq. (2) using the aggregate hourly gross generation from coal units, combined cycle natural gas units, and natural gas turbines as the dependent variables. The coefficient of interest, $\beta$, now represents the average change in gross generation caused by a MWh of ERCOT wind.\textsuperscript{35} The top panel of Table 4 provides the estimates of the average change in gross generation from units directly connected to the ERCOT market.\textsuperscript{36} On average, a MWh of wind offsets 0.32 MWh from coal units, 0.32 MWh from combined cycle units, and 0.30 MWh from gas turbines. Aggregating across all ERCOT fossil fuel units, each

\textsuperscript{35}One concern with the CEMS data is that some combined cycle units may underreport their gross generation. While this does not impact the estimates of the emissions avoided – emissions are directly measured or calculated as a function of the hourly heat input, which is correctly reported – it does suggest that the estimates of the gross output avoided may be biased. To shed light on how large of a concern this is, I compare the gross, plant-level generation – from the CEMS data – to the monthly, plant-level, net generation – from EIA Form 923. In the CEMS sample, 16 plants report monthly levels of gross generation that are consistently below the EIA reported net generation – suggesting that they underreport gross output. To predict how much gross output is “missing” from my data, I predict the actual gross output by multiplying the net generation at the 16 plants by 1.06 (on average, gross generation is 6 percent higher than the net among the plants in my dataset). Comparing the CEMS gross generation to the predicted gross generation, I estimate that only 3 percent of the gross ERCOT and SPP output is missing from my sample. While this could lead to a small underestimation of the impact of wind on gross fossil output, I cannot test for this using the presently available data.

\textsuperscript{36}This includes the impact on output from units that are located outside of the ERCOT market’s footprint but can directly supply energy to the ERCOT grid.
MWh of wind generation reduces an average of 0.94 MWh of gross generation.

(Table 4)

The bottom panel of Table 4 presents estimates of the average change in gross generation from all fossil fuel units in the EPA dataset – located in Texas and Oklahoma combined. Consistent with the results in Table 3, ERCOT wind generation reduces additional production from units in the SPP region. On average, each MWh of wind generation reduces 0.33 MWh from coal units, 0.35 MWh from combined cycle units, and 0.34 MWh from gas turbines. All together, each MWh of wind generation reduces an average of 1.02 MWh of gross fossil fuel generation.

To estimate the impact of wind generation on non-fossil generation, I estimate the average reduction in the net generation supplied to the ERCOT grid. Table 5 reveals that nearly all of the reduction in ERCOT supply comes from fossil fuel units. On average, a MWh of wind generation only offsets 0.004 MWh of ERCOT nuclear output and 0.008 MWh of ERCOT ‘other’ production. In contrast, a MWh of wind reduces net natural gas generation supplied directly to ERCOT by 0.66 MWh and net coal generation supplied directly to ERCOT by 0.31 MWh. Summing across all fuel sources, I find that a MWh of wind generation offsets an average of 0.97 MWh of supply from units directly connected to the ERCOT market. This implies that, on average, a MWh of wind generation reduces net imports from units not directly connected to ERCOT by 0.03 MWh.\(^\text{37}\)

(Table 5)

To provide evidence that my identification strategy is not over or understating the impact of ERCOT wind generation, I sum the net non-fossil generation avoided

\(^{37}\text{Recall that some fossil units connected to the ERCOT grid can also supply electricity directly to the SPP market. If an increase in wind generation causes these units to reduce supply to the ERCOT grid and increase supply to the SPP market, then the actual decrease in production will take place at units not directly connected to the ERCOT grid. There is evidence that this is possibly taking place. While a MWh of wind reduces the quantity of electricity supplied from fossil units directly connected to the ERCOT grid by an average of 0.96 MWh, there is only a 0.94 MWh reduction in gross generation from fossil units directly connected to the grid. Of course, this small difference could also be the result of missing gross generation in the EPA CEMS data – either due to missing units with capacities below 25 MW or missing generation from combined cycle units.}\)
and the gross coal and natural gas generation avoided:

\[
\beta_{\text{Coal}} + \beta_{\text{Gas}} + \beta_{\text{Nuclear}} + \beta_{\text{Hydro}} + \beta_{\text{Other}} = -1.029 \quad (0.011).
\]

The absolute value of the sum is slightly larger than one, which is expected given that gross fossil generation is used. The fact that the generation offset is not substantially greater than 1 MWh suggests the estimates of the emissions offset are not suffering from an upward bias. Additionally, the fact that the absolute value is not significantly less than one provides evidence that generating units that alter output in response to ERCOT wind generation are not excluded from the EPA dataset.

IV Heterogeneity in Marginal Emissions Offset

A. Econometric Specification

Intuitively, an increase in renewable output displaces production from the marginal generating units. As the demand for electricity shifts, or as the level of renewable output changes, the non-renewable units on the margin vary. Given that the emission rates differ across non-renewable generators, the quantity of pollution reduced by a marginal increase in renewable output can vary based on when the generation occurs.

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38I assume that non-fossil fuel generation from the SPP market is unaffected.
39As an additional test, I estimate the impact of ERCOT wind generation on Colorado and New Mexico emissions. Just as ERCOT wind generation is likely correlated with SPP wind generation, ERCOT wind generation would be expected to be correlated with wind generation in New Mexico and Colorado. With the exception of a small portion of eastern New Mexico, both states are located in the Western Interconnection, which has no direct links to the ERCOT market. Therefore, ERCOT wind generation is unlikely to affect emissions from New Mexico and Colorado. Re-estimating Eq. (2) using the aggregate emissions from fossil fuel units in New Mexico and Colorado as the new dependent variable, I find no significant impact of ERCOT wind generation on emissions.
40Previous studies predict the marginal emission rates for specific hours (Connors et al. (2005), Callaway and Fowlie (2009), Graff Zivin, Kotchen and Mansur (2014), Carson and Novan (2013)) or for different levels of demand (Price et al. (2003), Broekhoff (2007), Gil and Joos (2007), Siler-Evans, Azevedo and Morgan (2012)). However, these studies do not identify the causal impact of renewable generation. Kaffine, McBee and Lieskovsky (2013) present estimates of the average marginal emissions offset for specific hours of the day, but the authors do not explore the factors driving the heterogeneity.
To identify how a marginal increase in wind affects emissions during hours with different levels of demand and total wind generation, I estimate the model:

$$E_t = \sum_{i=1}^{3} \sum_{j=0}^{3} \beta_{i,j} W_i^j D_{1,t}^j + \sum_{n=1}^{3} \left( \theta_{1,n} D_{1,t}^1 + \theta_{2,n} D_{2,t}^2 \right) + \alpha_{h,m,y,w} + \delta_d + \epsilon_t,$$

where \((W_i^j \cdot D_{1,t}^j)\) represents the interaction between the hourly wind generation, raised to the \(i^{th}\) power, and ERCOT demand, raised to the \(j^{th}\) power.\(^{41}\) The levels, squares, and cubes of ERCOT and SPP demand are included as controls. In addition, daily fixed effects and hour-of-week fixed effects are again included. To account for serial correlation, Newey-West standard errors are estimated using a 24-hour lag.

From Eq. (3), the marginal emissions avoided (MEA) by an additional MWh of wind generation, supplied during an hour in which the ERCOT demand equals \(D\) and total ERCOT wind generation equals \(W\), is given by the expression:

$$MEA(W,D) = -\frac{\partial E(W,D)}{\partial W} = -\sum_{i=1}^{3} \sum_{j=0}^{3} i \cdot \beta_{i,j} \cdot W^{i-1} \cdot D^j.$$

**B. Marginal Emissions Offset**

Figure 1 presents estimates of Eq. (4), the emissions offset by a marginal increase in wind, for hourly ERCOT demands ranging from 23,500 MWh to 55,000 MWh – approximately the 5\(^{th}\) and 95\(^{th}\) percentiles of the ERCOT demand distribution. \(MEA(W,D)\) is plotted for four different levels of hourly ERCOT wind generation: the 5\(^{th}\), 25\(^{th}\), 50\(^{th}\), and 75\(^{th}\) percentiles of hourly wind generation.\(^{42}\)

(Figure 1)

The left panel displays the estimates of the CO\(_2\) offset by an additional MWh of wind. For each level of wind generation, a marginal increase in \(W\) causes the largest reductions in CO\(_2\) during hours with the lowest demand. As the demand initially

\(^{41}\)In an appendix, I present estimates of a semiparametric model. Rather than specifying the marginal emissions avoided as a polynomial function of the hourly ERCOT demand, I allow the impact of wind generation to vary nonparametrically across different levels of demand.

\(^{42}\)Estimates of coefficients from Eq. (3) are provided in Appendix Table 4.
increases, the quantity of CO\textsubscript{2} reduced by an additional MWh of wind falls. As demand increases beyond 40,000 MWh, the marginal reduction in CO\textsubscript{2} increases.

The left panel also reveals another crucial pattern. At levels of demand below 35,000 MWh, the quantity of CO\textsubscript{2} reduced by an additional MWh of wind generation increases as the level of wind generation grows. Conversely, for levels of demand above 40,000 MWh, the quantity of CO\textsubscript{2} reduced by an additional MWh of wind generation falls as the total wind generation increases.

The middle panel displays a similar pattern in the NO\textsubscript{X} offset by marginal increases in wind. For levels of demand below 35,000 MWh, the quantity of NO\textsubscript{X} reduced by an additional MWh of wind increases as the hourly level of wind grows. For levels of demand above 40,000 MWh, the quantity of NO\textsubscript{X} reduced by each additional MWh of wind falls as \( W \) increases. The right panel reveals that almost all of the SO\textsubscript{2} reduced by wind generation occurs during hours with levels of demand below 40,000 MWh. Additionally, during these lower demand hours, the quantity of SO\textsubscript{2} reduced by a marginal increase in wind generation grows as \( W \) increases.

C. Marginal Generation Avoided

To determine what is driving the variation in the marginal emissions avoided, I examine how the composition of generation offset changes. I re-estimate Eq. (3) using the aggregate hourly gross generation from coal units, combined cycle (CC) units, and gas turbines (GT) as the dependent variables. The expression defined by Eq. (4) now represents the reduction in coal, combined cycle, or gas turbine generation caused by supplying an additional MWh of wind during an hour with ERCOT demand equal to \( D \) and total wind generation equal to \( W \).

Figure 2 presents estimates of Eq. (4) for the three types of fossil units. I focus first on how the substitution pattern differs across levels of demand. During low-demand hours, low private cost coal and combined cycle units account for the vast majority of generation avoided by marginal increases in wind. As the level of demand initially increases, the quantity of emission-intensive coal generation avoided falls while combined cycle output avoided increases. This explains why the marginal emissions avoided initially fall as demand increases. As demand grows be-
yond 35,000 MWh, marginal increases in wind offset less and less generation from fuel-efficient combined cycle units and more generation from emission-intensive gas turbines. This explains why the marginal reductions in CO$_2$ and NO$_X$ increase as the level of demand grows to the highest levels.

(Figure 2)

Focusing next on how the substitution pattern differs across levels of wind, two clear trends emerge. During hours in which ERCOT demand is below 35,000 MWh, each additional MWh of wind offsets successively more coal-fired output and successively less generation from cleaner, combined cycle units. This result explains why the marginal emissions avoided are increasing with total wind during low-demand hours. During hours in which ERCOT demand exceeds 40,000 MWh, each additional MWh of wind offsets a larger amount of combined cycle generation and a smaller amount of gas turbine production. Given that the combined cycle units have the lowest average emission rates, this result explains why the marginal emissions offset by wind generation are decreasing during high-demand hours.

V External Benefits of Renewable Capacity Additions

A. Specifying Impact of Marginal Capacity Additions

This section uses the preceding estimates of the marginal emissions avoided to predict the external benefits provided by marginal increases in renewable capacity. From January, 2007 through December, 2011, the installed wind capacity in ERCOT steadily increased from 2,703 MW to 9,682 MW. The vast majority of wind turbines are located in the northwest portion of the market – consistently the windiest region in Texas.

A common measure of a wind turbine’s productivity is the ‘capacity factor’. For a given hour, a wind turbine’s capacity factor is equal to the total hourly generation – measured in MWh’s – divided by the turbines capacity – measured in MW’s. Unfortunately, I do not observe the hourly production from individual wind turbines. Therefore, in order to estimate the emissions offset by each additional ERCOT wind turbine, I need to impose a key assumption. Specifically, I assume the hourly ca-
Capacity factors are identical for each wind turbine. This implies, first, that each wind turbine is exposed to the same potential wind energy. Given that the wind turbines are located in a small region which experiences very similar hourly wind patterns, this is a reasonable approximation. In addition, the assumption that each wind turbine has the same hourly capacity factor implies that any curtailments that take place affect each unit of wind capacity equally.

Assuming the wind turbines have identical hourly capacity factors, the total hourly ERCOT wind generation ($W$) in any given hour can be expressed as the product of a single, ERCOT-wide wind capacity factor ($x$) and the installed wind capacity ($K$). Moreover, the joint distribution of the hourly ERCOT wind capacity factor and the hourly ERCOT demand, $f(x,D)$, will be invariant to the level of wind capacity. For any given level of $K$, the probability of observing an hour with wind generation $W$ and demand $D$ is equal to $f(W/K, D)$. As $K$ grows, the probability of observing any given combination of $(x, D)$ does not change. However, the probability of observing an hour with aggregate wind generation and demand $(W, D)$ does change. Given that the quantity of pollution avoided by a marginal increase in $W$ varies substantially across different levels of wind and demand, this suggests that each additional wind turbine may not have the same affect on pollution.

Let $MEA(W, D)$ represent the quantity of pollution offset by an additional MWh of wind generation supplied during an hour with $W$ total MWh’s of wind generation and $D$ MWh’s of demand. Consider the impact of increasing the installed wind capacity by 1 MW. During an hour with a capacity factor of $x$, the additional unit of capacity will reduce $x \cdot MEA(x \cdot K, D)$ units of pollution. Taking the expectation of $x \cdot MEA(x \cdot K, D)$ over all possible combinations of $(x, D)$ results in the expression:

$$\text{(5) Average Avoided Emissions}(K) = \int_{x=0}^{x=1} \int_{D} x \cdot MEA(x \cdot K, D) \cdot f(x, D) \, dD \, dx$$

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43 This assumption is required to interpret my subsequent estimates of $AEA(K)$ as the emission reductions caused by the observed ERCOT capacity additions. Relaxing the assumption, my estimates of $AEA(K)$ can be interpreted as the average emissions offset by an equal percentage increase in capacity at each ERCOT wind farm.

44 Therefore, as the installed wind capacity increases, I assume the transmission capacity increases proportionally.
where \( \bar{D} \) and \( D \) equal the maximum and minimum levels of hourly ERCOT demand.

Eq. (5) represents the average hourly pollution reduced by the \( K^{th} \) MW of wind capacity. Dividing the expression in Eq. (5) by \( \bar{x} \), the average hourly generation from each MW of wind capacity, yields the average emissions avoided by a MWh of electricity produced by the \( K^{th} \) unit of wind capacity – which I define as \( AEA(K) \).\(^{45}\) It is important to note that \( AEA(K) \) is a short-run value. While I allow the renewable capacity and the transmission capacity to increase, the stock of conventional generators in the market is assumed to be constant. In the long-run, if increases in renewable capacity lead to retirements of existing conventional generators, or installations of new generators, then the function \( MEA(W,D) \) would likely change over time.

B. Emissions Offset by Marginal Capacity

To estimate \( AEA(K) \), I use the estimates of \( MEA(W,D) \) from Eq. (4). In addition, I use the 43,795 hourly pairs of \( (x_t, D_t) \) over my five year sample to approximate the joint distribution \( f(x,D) \). To solve for the hourly capacity factors \( x_t \) I divide the hourly aggregate wind generation \( W_t \) by the total wind capacity \( K \) in the ERCOT market on the specific date: \( x_t = W_t / K \).\(^ {46}\) Separating the hourly capacity factors, as well as the hourly demands, into 40 equally sized bins, I calculate the frequency distribution \( \hat{f}(x_i, D_j) \) over the 1,600 individual bins.\(^ {47}\) I use the bin midpoints \( (x_i, D_j) \), for \( i = 1, \ldots, 40 \) and \( j = 1, \ldots, 40 \), as the possible combinations of \( x \) and \( D \).

To highlight how the distribution of hourly capacity factors varies across levels of demand, Figure 3 displays the conditional distribution \( \hat{f}(x|D) \) for four different levels of demand. The figure highlights that the installed ERCOT wind capacity generates most heavily during low demand hours.\(^ {48}\) For example, when hourly ERCOT demand is equal to 25,000 MWh, the conditional distribution of the hourly

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\(^{45}\)During the five years examined, the average hourly ERCOT wind capacity factor was \( \bar{x} = 0.308 \).

\(^{46}\)The Public Utility Council of Texas records the month of capacity additions. To attribute the additions to a specific date within a month, I gathered information from local newspaper articles.

\(^{47}\)The bins range from \( 0 \leq x \leq 0.92 \) and \( 18,872 \leq D \leq 69,196 \).

\(^{48}\)For each year (2007-2011), the correlation coefficients between the hourly capacity factors and demand are -0.23, -0.19, -0.26, -0.24, and -0.18, respectively. The stability of the coefficients across years also supports the assumption that the joint distribution of \( (x,D) \) is independent of \( K \).
capacity factors has a large mass exceeding \( x = 0.4 \). In contrast, when demand equals 55,000 MWh, the conditional distribution shifts substantially to the left.

(Figure 3)

My estimate of the average emissions offset by a MWh of generation from the \( K^{th} \) unit of wind capacity is given by the expression:

\[
\hat{A}{\text{EA}}(K) = \frac{\sum_{i=1}^{40} \sum_{j=1}^{40} x_i \cdot \hat{M}{\text{EA}}(x_i \cdot K, D_j) \cdot \hat{f}(x_i, D_j)}{\sum_{i=1}^{40} \sum_{j=1}^{40} x_i \cdot \hat{f}(x_i, D_j)}.
\]

To predict the standard errors of \( \hat{A}{\text{EA}}(K) \), I assume that \( \hat{f}(x, D) \) is the true distribution. Therefore, the variance of \( \hat{A}{\text{EA}}(K) \) is calculated as the weighted sum of the elements of the \( 40 \times 40 \) covariance matrix of \( \text{Cov}(\hat{M}{\text{EA}}(x_i \cdot K, D_j), \hat{M}{\text{EA}}(x_l \cdot K, D_m)) \).

The first three columns of Table 6 provide estimates of \( \hat{A}{\text{EA}}(K) \) for values of \( K \) ranging from 0 to 10,000 MW. For each of the pollutants, a clear pattern emerges. As ERCOT wind capacity grows, the pollution offset by the marginal unit of wind capacity increases. The first MW of wind capacity installed in the region offsets an average of 0.65 tons of CO\(_2\)/MWh, 0.95 pounds of NO\(_X\)/MWh, and 1.40 pounds of SO\(_2\)/MWh. In contrast, the 10,000\(^{th}\) MW of wind capacity installed in the region offsets 15 percent more CO\(_2\), 20 percent more NO\(_X\), and 56 percent more SO\(_2\). Compared to the \( A{\text{EA}}(0) \), the values of \( A{\text{EA}}(10,000) \) are significantly larger at the 1 percent level for CO\(_2\) and SO\(_2\) and at the 10 percent level for NO\(_X\).\(^{49}\)

It is important to note that the estimates of \( \hat{A}{\text{EA}}(10,000) \) are made by extrapolating to a level of wind capacity that slightly exceeds the installed capacity – ERCOT wind capacity increased from 2,703 MW to 9,682 MW. Comparing the estimates of the average emissions offset by the 9,000\(^{th}\) MW of wind capacity and the 3,000\(^{th}\) MW, which are two within-sample wind capacity levels, I find that \( \hat{A}{\text{EA}}(9,000) \) is significantly larger than \( \hat{A}{\text{EA}}(3,000) \) for CO\(_2\) and SO\(_2\) at the 1 percent level and

\(^{49}\)Comparing the first and 10,000\(^{th}\) MW of wind capacity installed, I find that for CO\(_2\), \( \hat{A}{\text{EA}}(10,000) - \hat{A}{\text{EA}}(0) = 0.094 \) tons of CO\(_2\)/MWh with a standard deviation of 0.039 tons per MWh. For NO\(_X\), I find \( \hat{A}{\text{EA}}(10,000) - \hat{A}{\text{EA}}(0) = 0.192 \) pounds of NO\(_X\) per MWh with a standard deviation of 0.119 pounds/MWh. For SO\(_2\), I find \( \hat{A}{\text{EA}}(10,000) - \hat{A}{\text{EA}}(0) = 0.787 \) pounds of SO\(_2\) per MWh with a standard deviation of 0.314 pounds/MWh.
NO\textsubscript{X} at the 10 percent level.\textsuperscript{50} (Table 6)

The finding that $\hat{AEA}(K)$ is increasing in $K$ is driven by the fact that wind turbines in northwest Texas produce most heavily during the low-demand hours. As Figure 2 highlights, these low-demand hours are precisely when the marginal emissions offset by renewable generation are increasing.

C. External Benefits of Renewable Investments

To translate the offset emissions into external benefits, estimates of the social costs of the pollutants are needed.\textsuperscript{51} To place a dollar value on the benefit of reducing a ton of CO\textsubscript{2}, I rely on an estimate of the social cost of carbon reported by the Interagency Working Group (IAWG). Assuming an annual discount rate of 3 percent, the central estimate provided by IAWG (2013) suggests that each ton of CO\textsubscript{2} offset provides a benefit of $32 (in 2010 dollars).

In contrast to the unregulated CO\textsubscript{2} emissions, emissions of NO\textsubscript{X} and SO\textsubscript{2} are regulated by the EPA’s Clean Air Interstate Rule (CAIR) and the Acid Rain Program (ARP).\textsuperscript{52} If the pollution caps are binding, short-run reductions in NO\textsubscript{X} and SO\textsubscript{2} will not represent long-run reductions in the aggregate level of pollution. Instead, reductions in the short-run levels of NO\textsubscript{X} and SO\textsubscript{2} emitted will result in an increase in the number of permits that can be used to pollute at a different time or in a different location. While shifting when and where the NO\textsubscript{X} and SO\textsubscript{2} emissions occur can alter the social costs of the pollution, placing a value on the cost savings provided is beyond the scope of this study.\textsuperscript{53}

\textsuperscript{50}For CO\textsubscript{2}, NO\textsubscript{X}, and SO\textsubscript{2}, the point estimates of $\hat{AEA}(9,000) - \hat{AEA}(3,000)$, and the corresponding standard deviations, are as follows: 0.07 (0.02) tons of CO\textsubscript{2}/MWh, 0.09 (0.07) pounds of NO\textsubscript{X}/MWh, and 0.47 (0.18) pounds of SO\textsubscript{2}/MWh.

\textsuperscript{51}Aside from CO\textsubscript{2}, NO\textsubscript{X}, and SO\textsubscript{2}, a variety of other pollutants are emitted from electricity generators. Given that these other pollutants are not reported in the CEMS data, the external benefit estimates I report are effectively lower bounds on the external benefits provided by the renewable investments.

\textsuperscript{52}Annual NO\textsubscript{X} emissions from the Houston-Galveston-Brazoria ozone non-attainment area is also capped by the Mass Emissions Cap and Trade Program (MECTP).

\textsuperscript{53}Recent studies by Muller and Mendelsohn (2009) and Fowlie and Muller (2013) discuss the impacts of redistributing non-perfectly mixing pollutants.
Currently, however, NO$_X$ and SO$_2$ permit prices in the CAIR and ARP markets are extremely low – suggesting that the caps are non-binding.$^{54}$ Under the assumption that the NO$_X$ and SO$_2$ caps remain non-binding, short-run reductions in NO$_X$ and SO$_2$ will represent real, long-run reductions in aggregate emissions. To estimate the external benefits provided by reductions in these pollutants, I use social cost estimates from Banzhaf and Chupp (2012). The authors use a Tracking and Analysis Framework (TAF) to predict the social costs that accrue from a marginal increase in NO$_X$ or SO$_2$ from each state. The TAF model predicts that reducing Texas NO$_X$ emissions by one ton provides an external benefit of $548. In addition, the TAF model predicts that reducing Texas SO$_2$ emissions by one ton provides an external benefit of $3,194.

The last two columns of Table 6 provide two estimates of the average external benefit provided by a MWh of output from the marginal unit of wind capacity. The first estimate assumes that only CO$_2$ is being offset by renewable output. The second estimate assumes that the EPA caps are non-binding, and therefore CO$_2$, NO$_X$, and SO$_2$ are all being offset by renewable generation. To calculate the average external benefit, I first estimate Eq. (4) using the hourly external cost of pollution from Texas and Oklahoma as the dependent variable. Using the estimates of the marginal external benefits of wind generation, I again estimate Eq. (6). Under the assumption that the EPA pollution caps are non-binding, I estimate that, on average, a MWh of electricity generated by the first unit of wind capacity in the region provides an external benefit of $23.26. As the installed wind capacity increases, so do the external returns. Once 10,000 MW’s of wind capacity are installed in the region, the marginal wind turbine provides an external benefit of $27.58/MWh – 20 percent more than the first unit of wind capacity.$^{55}$

$^{54}$Evidence supporting that the caps are non-binding can also be seen by examining the annual aggregate emissions. For example, In 2010, the ARP cap reached its final level of 8.95 million tons. During 2011, the annual emissions of SO$_2$ from generators covered by the ARP was only 4.54 million tons. Starting in 2010, the CAIR program also started regulating annual SO$_2$ emissions. However, given that the ARP cap is not binding, generators covered by both CAIR and the ARP – which includes Texas generation – have been able to used banked permits to meet the CAIR SO$_2$ cap. For example, in 2011, SO$_2$ emissions from CAIR units equalled 3.9 million tons – exceeding the 3.6 million ton cap. For information on CAIR and the ARP, see the EPA’s Clean Air Interstate Rule, Acid Rain Program, and Former NO$_X$ Budget Trading Program 2011 Progress Report.

$^{55}$The 10,000th MW of wind capacity provides and estimated average external benefit that is
D. Comparing Different Renewable Technologies

The preceding section presents estimates of the marginal external benefits provided by investments in Texas wind capacity. In this section, I predict the external benefits that would be provided by investing in an alternative renewable technology – solar photovoltaic (PV) panels. Recall that, currently, there is wide variation in how governments subsidize wind and solar investments. For example, 16 of the 29 state-level RPS policies – including Texas’ RPS – provide a larger per MWh subsidy to solar generators compared to wind turbines. In contrast, the RPS policies adopted in the remaining 13 states subsidize a MWh from a wind turbine and a solar panel equally. To shed light on the efficacy of these alternative policy designs, it is important to determine if the external benefits differ across competing renewable investments – and if so, by how much.

To quantify how large the differences are in the external benefits provided by different investments, I compare my estimates of the emissions offset by wind turbines to predictions of the pollution reductions solar PV panels would provide. Currently, there is insufficient solar capacity in the Texas market to identify the short-run impact of hourly solar generation on emissions. However, by imposing the assumption that an additional MWh of wind generation has the same impact as an additional MWh of solar generation, I can utilize my estimates of \( MEA(W,D) \) to predict how solar capacity additions will affect pollution. While this assumption cannot be directly tested using the present data, there are two factors that suggest this is a reasonable approximation. First, the northwest portion of Texas has the most abundant solar energy potential. Therefore, grid-level solar installations are likely to be located in the northwestern region – the same region which contains the vast majority of the wind farms. Second, exploring data on the sub-hourly

$4.33/MWh more than the first unit of wind capacity installed. This difference is significant at the 1 percent confidence level. Comparing the average external benefits with \( K = 3,000 \) MW versus \( K = 9,000 \) MW, I again find the external benefits significantly increase as capacity grows.

56 The National Renewable Energy Laboratory’s Open PV Project, reports that as of 2013, less than 200 MW of solar capacity have been installed in Texas.

57 For a summary of the spatial distribution of solar potential, see the National Renewable Energy Laboratory’s solar maps: http://www.nrel.gov/gis/solar.html.

58 If the solar and wind installations are located in different regions, then the impact of a marginal increase in wind generation may differ from the impact of a marginal increase in solar generation.
ERCOT solar and wind generation—available for 2012—reveals that the two technologies produce similarly volatile streams of output.\footnote{Using data on the interval (15-minute) ERCOT output available for 2012, I find an average wind generation of 848 MWh. To summarize the volatility, I calculate the standard deviation across the 4 observations within each of the 8,784 hours and solve for the simple average of these standard deviations (31 MWh). Next, focusing between noon and 6p.m. when solar output is not trivially small, the average interval output is 9.6 MWh and the average within-hour standard deviation is 0.6 MWh. Solving for the ratio of the mean within-hour standard deviation and the mean interval output results in a statistic for wind of 0.04 and a statistic for solar of 0.06. The similarity of these two values suggests that the within-hour volatility does not differ substantially across the technologies. However, if the volatilities at the sub-15 minute level are substantially different, then the impact of an additional MWh of solar may differ from the impact of an additional MWh of wind.}

To estimate the average emissions avoided by a MWh from the marginal unit of solar capacity, Eq. (6), I again use the estimates of the marginal emissions avoided by renewable generation from Eq. (4), $\hat{\text{MEA}}$. Instead of representing the marginal emissions avoided during an hour with total wind and demand $(W, D)$, $\hat{\text{MEA}}$ now represents the marginal emissions avoided by an additional MWh of solar generation during an hour with given levels of solar generation and demand. To approximate the joint distribution $f(x_{\text{solar}}, D)$, I use the 8,760 observations of hourly solar generation and demand in ERCOT during 2012.\footnote{Starting in 2012, ERCOT provides information on the aggregate hourly generation from grid-connected solar PV generating units in the region. To calculate the hourly solar capacity factor, I divide the total hourly generation by the installed solar capacity.} Separating the hourly capacity factors and the hourly demands into 40 equally sized bins, and using the midpoints $(x_{i,\text{solar}}, D_j)$, for $i = 1, \ldots, 40$ and $j = 1, \ldots, 40$, as the possible combinations of $x_{\text{solar}}$ and $D$, I calculate the frequency distribution $\hat{f}(x_{i,\text{solar}}, D_j)$ over the 1,600 bins.

The bottom panel of Table 6 presents the estimates of $\hat{\text{AEA}}(K)$ from Eq. (6) for levels of solar capacity $K$ ranging from 0 to 3,000 MW.\footnote{To avoid producing estimates of the average emissions avoided that rely on extrapolating the predicted $\text{MEA}(W, D)$ to unobserved combinations of $(W, D)$, I do not present estimates of $\text{AEA}(K)$ for $K > 3,000$ MW. This is due to the fact that the average wind capacity factor during hours with high levels of demand $(D > 55,000$ MWh) is only 20 percent. In contrast, the average solar capacity factor during these high demand hours is 70 percent. Therefore, with greater than 3,000 MW of solar capacity installed, the level of solar generation that would be realized in the high demand periods would begin to regularly exceed the levels of wind generation observed from the roughly 10,000 MW’s of installed wind capacity.} The results suggest that the emissions offset by the marginal solar panel are decreasing in solar capac-
ity. While the differences are not statistically significant, compared to the first solar panel installed in the region, the 3,000\textsuperscript{th} MW of solar capacity will offset, on average, 10 percent less CO\textsubscript{2} per MWh, 20 percent less NO\textsubscript{X} per MWh, and 35 percent less SO\textsubscript{2} per MWh.\textsuperscript{62} The pattern displayed is driven by the fact that solar panels generate exclusively during the higher-demand, daytime hours when the marginal emissions offset by renewable generation are decreasing. Of course, once the installed solar capacity in the region reaches well beyond 3,000 MW, the marginal solar generation will likely begin to offset successively more coal fired generation. Therefore, beyond some level of installed solar capacity, each additional solar panel will begin to offset greater amounts of pollution. However, my results demonstrate that, over a large range of solar capacity additions, the average emissions avoided by each additional solar panel will continue to decrease.

While the initial investments in wind and solar capacity generate very similar external benefits, the external benefits provided by the marginal wind turbine and the marginal solar panel diverge as the installed capacity grows. Assuming that each ton of CO\textsubscript{2}, NO\textsubscript{X}, and SO\textsubscript{2} offset provides a social benefit of $32, $548, and $3,194, respectively, I find that the first units of solar capacity installed provide an average external benefit of $23.50/MWh. This is not statistically different from the average external benefit provided by the first wind turbine installed in the region. However, once 3,000 MW’s of solar capacity have been installed, the external benefit provided by the marginal solar panel will fall to an average of $20.72/MWh – which is 25 percent less than the average external benefit provided by generation from the 10,000\textsuperscript{th} MW of wind capacity. The difference between $\textit{AEA}_\text{wind}(10,000)$ and $\textit{AEA}_\text{solar}(3,000)$ is significant at the 1 percent level.\textsuperscript{63}

\section*{E. Policy Discussion}

The preceding results reiterate an important point – renewable electricity is far from a homogenous good. Previous studies demonstrate that marginal emission rates

\textsuperscript{62}The point estimates of $\textit{AEA}(3,000) - \textit{AEA}(0)$, and the corresponding standard errors in parentheses, for CO\textsubscript{2}, NO\textsubscript{X}, and SO\textsubscript{2} are -0.067 (0.052) tons/MWh, -0.312 (0.250) pounds/MWh, and -0.411 (0.386) pounds/MWh, respectively.

\textsuperscript{63}The point estimate of $\textit{AEA}_\text{solar}(3,000) - \textit{AEA}_\text{wind}(10,000)$ equals -$6.862$/MWh and the standard error is $1.309$/MWh.
vary widely from one regional market to the next (Callaway and Fowlie (2009), Siler-Evans, Azevedo and Morgan (2012), Kaffine, McBee and Lieskovsky (2013), Graff Zivin, Kotchen and Mansur (2014)). Moreover, the marginal external costs of many pollutants (e.g. NO\textsubscript{X} and SO\textsubscript{2}) vary spatially. Combined, these facts suggest that the marginal external benefit provided by renewable output varies across markets.\footnote{Previous studies also stress that the marginal private benefits of renewable generation differs based on when and where the generation occurs (Borenstein (2008), Metcalf (2009), Joskow (2011), Borenstein (2012)). However, these differences are internalized by the temporal and spatial variation in wholesale electricity prices.}

Going one step further, my results reveal that, even within a market, output from different renewable technologies provides different marginal external benefits. The fact that renewables provide heterogeneous external benefits has a clear policy implication. Specifically, to ensure that the socially optimal renewable investments are made, a policy must differentiate between competing investments. This is exactly what the first-best policy (i.e. emission taxes or cap-and-trade programs) would accomplish. By pricing emissions, a renewable producer that generates when the marginal emission rate is the highest will benefit the most from the increased wholesale electricity prices. In contrast, a renewable generator that produces when the marginal emission rate is low will receive less support from emission prices.

In practice, however, emission prices have received limited use. Instead, policymakers have focused on a less efficient option – subsidizing renewables. Unlike emission prices, renewable subsidies will not induce pollution abatement through demand reductions, switching between conventional fuels, or adoption of end-of-pipe pollution treatments. Nonetheless, if governments are going to continue to subsidize renewables, it is important to consider whether the current policies incentivize investments in the socially optimal renewable capacity additions.

Just as the first-best pollution prices would differentiate between renewable investments, a subsidy would optimally provide more financial support to investments that provide larger external benefits. Given that the marginal external benefits vary from one market to the next, the optimal subsidy for renewable electricity should first vary across markets. For example, Siler-Evans, Azevedo and Morgan (2012) estimate that, on average, reducing a MWh of fossil fuel generation in the Texas market – which has relatively low marginal emission rates – results in a reduction of
0.58 tons of CO$_2$. In contrast, offsetting a MWh of fossil output in the Mid-Atlantic (RFC) region – which has relatively high marginal emission rates – results in an average reduction of 0.81 tons of CO$_2$. This suggests that, if a renewable subsidy was designed to internalize the external benefits provided by the short-run reductions in CO$_2$, it should provide renewable generators located in the Mid-Atlantic region 40 percent more per MWh compared to renewable generators in Texas.

However, my findings demonstrate that market-specific subsidies will only internalize a portion of the heterogeneity in the marginal external benefits of renewable investments. In the Texas market, for example, output from a new wind turbine will offset more pollution than output from a new solar panel. At low levels of installed capacity, these differences turn out not to be large. However, as the installed capacity grows, the difference in the marginal impacts of the competing technologies also increases. For example, the 3,000$^{th}$ MW of Texas solar capacity would offset 0.60 tons of CO$_2$ per MWh. In contrast, the 10,000$^{th}$ MW of wind capacity offsets an average of 0.74 tons of CO$_2$ per MWh – 24 percent more than the solar panel. Therefore, once the installed renewable capacity reaches these higher levels, my results indicate that the within-market heterogeneity in the marginal external benefits will be similar in magnitude to the previously explored heterogeneity across markets.

This within-market variation that I uncover is driven by two factors. First, there is substantial temporal variation in the market’s marginal emission rates. Second, different renewable investments will generate electricity more heavily at different points in time. Given that neither factor is unique to Texas, it is reasonable to conclude that the within-market heterogeneity will persist across markets.\textsuperscript{65}

Despite the wide variation in the external benefits of renewable investments, the current renewable policies are simply not designed to internalize the heterogeneity – either across markets or within markets. For example the federal PTC provides the same per MWh tax credit to every wind farm, regardless of where they are located. Of course, given that states have adopted their own RPS’s, financial support for

\textsuperscript{65}Callaway and Fowlie (2009), Siler-Evans, Azevedo and Morgan (2012), and Graff Zivin, Kotchen and Mansur (2014) all document temporal variation in the average marginal emission rates within different regions of the United States.
renewable generation does vary spatially. However, the variation in support is not driven by differences in the external benefits of renewable output. Even if the levels of the federal and state policies were coordinated to internalize the variation in the external benefits of renewable output across markets, they would still fail to internalize the within-market heterogeneity. For example, simply adjusting the stringency of Texas’ RPS – which would alter the REC prices – would not reflect the fact that output from the marginal wind turbine offsets more pollution than output from the marginal solar panel.

It is important to again note that the empirical analysis in this paper focuses on the short-run impacts of renewable generation on emissions. If investments in renewable capacity affect the decision to retire existing conventional generators, or the decision to add new conventional generators, then there could be long-run impacts on the level of pollution. This introduces yet another potential source of heterogeneity in the external benefits of competing renewable capacity investments.

Overall, this analysis highlights how difficult it is to design renewable subsidies that accurately internalize the external benefits of renewable investments. An important topic for future work is to explore how large the resulting efficiency costs are from deviating from the optimal renewable subsidies. Specifically, what is the deadweight loss incurred by assuming each MWh of renewable output provides a constant external benefit – either across markets or within markets? To shed light on this question, the decision to invest in a specific technology and in a particular market must be modeled. While this is beyond the scope of the present paper, such an analysis can provide important insights into how the current portfolio of renewable policies can be improved.

For example, renewable energy certificates (REC’s) in Maine’s compliance market were trading for $20 per MWh in early 2013 (Heeter and Nicholas (2013)). During the same time period, REC prices in New Hampshire exceeded $50 per MWh. Despite the large gap in the REC prices, the neighboring states are connected to the same regional grid. Therefore, renewable electricity supplied to either state will provide roughly the same external benefit.
VI Conclusion

Taking advantage of hourly variation in wind generation supplied to the Texas electricity market, I quantify the pollution avoided by marginal increases in renewable electricity. My results reveal that, in the Texas market, output from different renewable capacity investments – i.e. wind turbines versus solar panels – provides different reductions in pollution. Moreover, as the quantity of renewable capacity continues to grow, the differences in the pollution avoided will increase.

The results presented in this paper reiterate an important point – renewable electricity is not a homogeneous good. Previous studies highlight that the marginal external benefit of renewable electricity varies across markets. On top of this spatial heterogeneity, my findings reveal that, even within a market, output from competing renewable investments provides different marginal external benefits. Despite the heterogeneity, both across and within markets, the current renewable policies are not designed to internalize the variation in the marginal external benefits of renewable electricity. This suggests that, if efforts to reduce pollution continue to focus on expanding renewable generation, incremental efficiency gains can be achieved by designing policies that more accurately internalize the heterogeneous benefits.

More generally, this paper highlights that the current set of renewable energy policies, including the federal PTC, the state-level RPS’s, and the often proposed national renewable energy standard, do not provide the incentives necessary to achieve the lowest cost emission reductions available from renewable electricity. While previous work clearly demonstrates that emission prices will reduce pollution more efficiently than renewable subsidies, these studies often abstract from the heterogeneity in the external benefits of renewable electricity. By doing so, previous work has underestimated the relative efficiency of emissions prices versus the current renewable energy policies.

References


Fowlie, Meredith, and Nicholas Muller. 2013. “Designing Markets for Pollution
When Damages Vary Across Sources: What are the Gains from Differentiation?”


A Alternative Specifications

A. Controlling for Dynamic Impact of Wind Generation

The empirical strategy used in this analysis identifies the impact of hourly wind generation on the contemporaneous, hourly emissions. Given that fossil fuel units face dynamic costs and constraints (e.g. start-up costs, ramping constraints), output from wind turbines may affect emissions not only within the concurrent hour, but also in future hours. Using 15-minute level data, Cullen (2013) presents results which suggest that abstracting from the dynamic impacts of wind will result in overestimation of the emissions offset by wind generation. To test whether this is the case using the hourly CEMS data, I estimate the average impact of ERCOT wind generation on aggregate Texas and Oklahoma emissions using two alternative specifications. The first alternative model is given by:

\[
E_t = \beta W_t + \sum_{l=1}^{6} \beta_l \tilde{W}_{t-l} + \sum_{l=0}^{6} \sum_{n=1}^{3} (\theta_{1,n,l} D_{1,t-l}^n + \theta_{2,n,l} D_{2,t-l}^n) + \alpha_{h,m,y,w} + \delta_d + \epsilon_t,
\]

where

- \( E_t \) = Aggregate TX and OK CO\(_2\) (tons), NO\(_X\) (lbs), or SO\(_2\) (lbs),
- \( W_t \) = Aggregate ERCOT wind generation (MWh),
- \( \tilde{W}_{t-l} \) = \( W_{t-l} - W_t \),
- \( D_{1,t-l} \) = ERCOT demand (MWh) during \( t - l \),
- \( D_{2,t-l} \) = SPP demand (MWh) during \( t - l \),

and \( \alpha_{h,m,y,w} \) represents the hour-of-week fixed effect and \( \delta_d \) represents the daily fixed effect. The model specified by Eq. (7) follows the strategy employed by Cullen (2013). By subtracting the level of wind generation in hour \( t \) from the lagged levels of wind generation, the contemporaneous and lagged impacts of wind generation on emissions will be captured by the estimate of \( \beta \). To account for serial correlation, Newey-West standard errors are calculated using a 24-hour lag.

The second alternative specification identifies the average impact of the daily
level of wind generation on the daily level of pollution. By estimating the impact of wind generation on the daily emissions, the renewable output is allowed to impact pollution across any hour of the day. The daily specification is:

\[
E_d = \beta \cdot W_d + \sum_{n=1}^{3} \left( \theta_{1,n} \cdot D_{1,d}^n + \theta_{2,n} \cdot D_{2,d}^n \right) + \alpha_{m,y,w} + \epsilon_d,
\]

where

\[
\begin{align*}
E_d &= \text{Aggregate daily CO}_2 \text{ (tons), NO}_X \text{ (lbs), or SO}_2 \text{ (lbs)}, \\
W_d &= \text{Aggregate daily ERCOT wind generation (MWh)}, \\
D_{1,d}^n &= \text{Daily ERCOT demand (MWh) raised to } n = [1, 2, 3], \\
D_{2,d}^n &= \text{Daily SPP demand (MWh) raised to } n = [1, 2, 3],
\end{align*}
\]

and \( \alpha_{m,y,w} \) represents a month\times\text{year}\times\text{day-of-week} fixed effect. To account for serial correlation, Newey-West standard errors are calculated using a 7-day lag.

The first three columns of Appendix Table 1 present the estimates of \( \beta \) from Eq. (7) for each of the three pollutants. The second three columns present the estimates of \( \beta \) from Eq. (8). The estimates from both alternative specifications yield similar results to the estimates of the contemporaneous emissions offset presented in Table (3). This provides strong evidence that the impact of wind generation on emissions largely occurs within the same hour. As the quantity of intermittent capacity continues to grow, dynamic impacts of wind generation on conventional generation will likely play an important role. However, at the current levels, there is little evidence of a dynamic impact of wind generation on emissions.

(Appendix Table 1)

**B. Instrumental Variable Specification**

Wind generation curtailments can be endogenously determined by shifts in the short-run demand or through shocks to the supply from conventional sources. To test whether this potential endogeneity biases the estimates of the emissions offset, I instrument for the hourly level of ERCOT wind generation using wind speeds.
In contrast to the actual output from wind turbines, wind speeds are certainly not affected by changes in electricity demand. Therefore, fluctuations in hourly wind speeds serve as a natural experiment which enable me to identify exogenous variation in hourly wind generation.

Ideally, I could instrument for the aggregate hourly wind generation using the wind speeds at the face of each wind turbine. While data is available from weather stations scattered throughout the region, these wind speeds are not representative of the potential wind generation for two reasons. First, the weather stations are located near population centers while the wind farms are sited outside of the populations centers. Second, the weather stations record the ground level wind speed while the wind turbines are installed on towers that are typically 80 meters tall.\(^67\) If the relationship between the ground level speeds and speeds at 80 meters is constant, the height would not present a problem. However, the pattern between upper and lower level wind speeds varies substantially (Schwartz and Elliott (2006)).

To instrument for the hourly wind generation, I use wind speed data from the Alternative Energy Institute (AEI) of West-Texas A&M University. The AEI operates wind monitoring towers at a variety of locations in Texas. One of the towers, located in Sweetwater, Texas, provides hourly average wind speeds from January, 2007 through September, 2008. At the beginning of 2007, there is 2,631 MW of wind generation capacity in ERCOT. Of this, 1,877 MW is in the ten counties surrounding the Sweetwater test site.\(^68\) At the end of September, 2008, the surrounding region has 78 percent of the 6,068 MW of ERCOT wind capacity. Therefore, wind speeds at the test tower serve as a good measure of the wind energy in the region containing the majority of the installed wind capacity.

To account for potential endogeneity in the observed hourly wind generation, I re-estimate Eq. (2) using the following first stage to instrument for \(W_t\):

\[
W_t = \tau \cdot S_t + \sum_{n=1}^{3} (\rho_{1,n} \cdot D_{1,f}^{n} + \rho_{2,n} \cdot D_{2,f}^{n}) + \tilde{\alpha}_{h,m,y,w} + \tilde{\delta}_{d} + \varepsilon_t,
\]

\(^67\) At the end of September, 2008, 76 percent of the wind capacity in the northwest is installed on 80 meter tall towers. I use the wind speeds at a height of 75 meters recorded at the Sweetwater tower.

\(^68\) The ten counties include Borden, Howard, Martin, Mitchell, Nolan, Scurry, Shackelford, Sterling, Taylor, and Tom Green.
where

\[ W_t = \text{Aggregate hourly ERCOT wind generation (MWh)}, \]
\[ S_t = \text{Average hourly AEI wind speed (meters/sec)}, \]
\[ D_{1,t}^n = \text{Hourly ERCOT demand (MWh) raised to } n = [1, 2, 3], \]
\[ D_{2,t}^n = \text{Hourly SPP demand (MWh) raised to } n = [1, 2, 3], \]

and \( \alpha_{h,m,y,w} \) represents the hour-of-week fixed effect and \( \delta_d \) represents the daily fixed effect. The errors are clustered at the daily level. For comparison, I also re-estimate Eq. (2) without using the above first stage and using only the hourly observations from 2007 and 2008 for which I observe the AEI wind speed.

From the first stage, Eq. (9), the estimate of the coefficient on the AEI wind speed is positive and significant at the 1 percent significance level. In addition, the partial-\( R^2 \) for the single excluded instrument is 0.52 and the Kleibergen-Paap Wald F-statistic of 2002.43 is well beyond the critical value. Therefore, I can conclude that the AEI wind speed is not a weak instrument.

For each of the three pollutants, Appendix Table 2 presents two estimates of \( \beta \) from Eq. (2). The first estimates continue to assume hourly wind generation is exogenous. The second set of estimates use the first stage specified by Eq. (9) to instrument for \( W_t \). For each model, the dependent variable is the aggregate hourly emissions from fossil fuel units located in Texas and Oklahoma. The estimates of the average reductions in emissions are all significant at the 1 percent level. For each of the pollutants, the estimates of the impact of a MWh of wind generation are very similar between the exogenous and the IV specifications. These results provide evidence that the identification strategy employed in this paper does not result in biased estimates of the emissions offset by wind generation.

(Appendix Table 2)

C. Semiparametric Estimates of MEA

In addition to the parametric estimates of \( MEA(W,D) \), I also estimate a semiparametric model of the marginal impact of wind generation on emissions. Rather than
specifying the marginal emissions avoided as a polynomial function of the ERCOT hourly demand, I allow the impact to vary flexibly across different levels of demand. I separate the hourly ERCOT demand into 13 mutually exclusive, 2,500 MWh wide bins ranging from 25,000 MWh to 52,500 MWh. The first bin contains all hours with loads less than 25,000 MWh – roughly 6 percent of the sample. The last bin contains all hours with loads greater than 52,500 MWh – again, roughly 6 percent of the sample.

To identify how a marginal increase in wind affects emissions during hours with different levels of both demand and total wind generation, I estimate the model:

\[ E_t = \sum_{i=1}^{13} Bin_i(D_t) \cdot (\beta_{i,1}W_t + \beta_{i,2}W_t^2 + \beta_{i,3}W_t^3) + \sum_{i=1}^{13} \gamma_i \cdot Bin_i(D_t) + \theta \cdot X_t + \epsilon_t, \]

where \( Bin_i \) is an indicator variable which equals 1 if the hourly ERCOT demand, \( D_t \), falls in bin \( i \). The vector of control variables, \( X_t \), includes the full set of controls previously included – the levels, squares, and cubes of the hourly ERCOT and SPP demands, hour-of-week fixed effects which are allowed to vary with each month of the sample, and daily fixed effects. To account for serial correlation, the Newey-West standard errors are calculated using a 24-hour lag.

From Eq. (10), the marginal emissions avoided (MEA) by an additional MWh of wind generation, supplied during an hour in which the ERCOT demand equals \( D \) and total ERCOT wind generation equals \( W \), is given by the expression:

\[ MEA(W,D) = \frac{-\partial E(W,D)}{\partial W} = -\sum_{i=1}^{13} Bin_i(D) \cdot (\beta_{i,1} + 2\beta_{i,2} \cdot W + 3\beta_{i,3} \cdot W^2). \]

Appendix Figure 1 presents estimates of Eq. (11) over the hourly ERCOT demand bins and for different levels of wind generation. The results are very similar to the parametric estimates of \( MEA(W,D) \) presented in Figure 1.

In addition, I re-estimate the AEA(\( K \)) using the semiparametric estimates of \( MEA(W,D) \). Now, \( \hat{f}(x_i, D_j) \) represents the frequency distribution over 40 capacity factor bins and the 13 ERCOT demand bins. Appendix Table 3 presents the estimates of \( AEA(K) \) for various levels of wind and solar capacity. Again, the point
estimates are very similar to the parametric estimates presented in Table 6.  
(Appendix Table 3)  
(Appendix Table 4)
Table 1: Hourly Net ERCOT Generation by Fuel Source

<table>
<thead>
<tr>
<th></th>
<th>Natural Gas</th>
<th>Coal</th>
<th>Nuclear</th>
<th>Wind</th>
<th>Hydro.</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (MWh)</td>
<td>14,841</td>
<td>13,589</td>
<td>4,656</td>
<td>2,188</td>
<td>96</td>
<td>390</td>
</tr>
<tr>
<td>Std. Dev. (MWh)</td>
<td>7,488</td>
<td>2,030</td>
<td>768</td>
<td>1,599</td>
<td>86</td>
<td>267</td>
</tr>
<tr>
<td>Min. (MWh)</td>
<td>1,963</td>
<td>2,342</td>
<td>909</td>
<td>0</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>Max. (MWh)</td>
<td>42,052</td>
<td>18,606</td>
<td>5,189</td>
<td>7,279</td>
<td>446</td>
<td>1,210</td>
</tr>
<tr>
<td>Share (%)</td>
<td>41.5</td>
<td>38.0</td>
<td>13.0</td>
<td>6.1</td>
<td>0.3</td>
<td>1.1</td>
</tr>
</tbody>
</table>

Hourly net generation is from ERCOT. ‘Other’ generation includes production from biomass, landfill gas, other fossil fuels, and solar. Share of total generation is calculated by dividing the aggregate generation by fuel source over the total ERCOT generation between January 1, 2007-December 31, 2011.

Table 2: Summary of Fossil Fuel Generating Units

<table>
<thead>
<tr>
<th></th>
<th>Coal</th>
<th>Combined Cycle</th>
<th>Gas Turbine</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Units</td>
<td>89</td>
<td>147</td>
<td>387</td>
</tr>
<tr>
<td>Average Heat Rate (MMBtu/MWh)</td>
<td>10.36</td>
<td>7.64</td>
<td>12.38</td>
</tr>
<tr>
<td>(1.49) (0.80)</td>
<td></td>
<td>(4.35)</td>
<td></td>
</tr>
<tr>
<td>Average CO₂ Intensity (tons/MWh)</td>
<td>1.06</td>
<td>0.46</td>
<td>0.74</td>
</tr>
<tr>
<td>(0.10) (0.07)</td>
<td></td>
<td>(0.25)</td>
<td></td>
</tr>
<tr>
<td>Average NOₓ Intensity (lbs./MWh)</td>
<td>2.57</td>
<td>0.26</td>
<td>2.23</td>
</tr>
<tr>
<td>(2.05) (0.38)</td>
<td></td>
<td>(3.53)</td>
<td></td>
</tr>
<tr>
<td>Average SO₂ Intensity (lbs./MWh)</td>
<td>6.24</td>
<td>0.01</td>
<td>0.06</td>
</tr>
<tr>
<td>(5.75) (0.06)</td>
<td></td>
<td>(0.41)</td>
<td></td>
</tr>
</tbody>
</table>

Hourly gross generation, heat input, and emissions are available from the Environmental Protection Agency’s CEMS dataset. Average Heat Rates and Average Emission Intensities are calculated by taking the average across the unit level means. Standard deviations of the unit level means are presented in the parentheses.
Table 3: Average Emissions Offset per MWh of Wind Generation

<table>
<thead>
<tr>
<th></th>
<th>ERCOT</th>
<th>ERCOT + SPP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CO₂ (tons)</td>
<td>NOₓ (lbs)</td>
</tr>
<tr>
<td>Wind Generation</td>
<td>-0.628** (0.008)</td>
<td>-0.900** (0.020)</td>
</tr>
<tr>
<td>ERCOT Demandº</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>SPP Demandº</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Hourly FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>43,794</td>
<td>43,794</td>
</tr>
<tr>
<td>R²</td>
<td>0.83</td>
<td>0.63</td>
</tr>
</tbody>
</table>

Each model is estimated using daily fixed effects. Newey-West standard errors using a 24-hour lag are reported in parentheses. Explained within variation is given by $R^2$. * significant at 5 percent level, ** significant at 1 percent level.

Table 4: Gross Generation Offset per MWh of Wind Generation

<table>
<thead>
<tr>
<th></th>
<th>ERCOT Gross Fossil Fuel Generation (MWh)</th>
<th>ERCOT + SPP Gross Fossil Fuel Generation (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coal</td>
<td>Combined Cycle</td>
</tr>
<tr>
<td>Wind Generation</td>
<td>-0.315** (0.010)</td>
<td>-0.321** (0.008)</td>
</tr>
<tr>
<td>ERCOT Demandº</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>SPP Demandº</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Hourly FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>43,794</td>
<td>43,794</td>
</tr>
<tr>
<td>R²</td>
<td>0.43</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Each model is estimated using daily fixed effects. Newey-West standard errors using a 24-hour lag are reported in parentheses. Explained within variation is given by $R^2$*. * significant at 5 percent level, ** significant at 1 percent level.
Table 5: ERCOT Net Generation Offset per MWh of Wind Generation

<table>
<thead>
<tr>
<th></th>
<th>Coal</th>
<th>Gas</th>
<th>Nuclear</th>
<th>Hydro</th>
<th>‘Other’</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind Generation</td>
<td>-0.305**</td>
<td>-0.655**</td>
<td>-0.004**</td>
<td>0.000</td>
<td>-0.008**</td>
<td>-0.972**</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.002)</td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>ERCOT Demand(^{a})</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>SPP Demand(^{a})</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Hourly FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>43,794</td>
<td>43,794</td>
<td>43,794</td>
<td>43,794</td>
<td>43,794</td>
<td>43,794</td>
</tr>
<tr>
<td>R²</td>
<td>0.47</td>
<td>0.92</td>
<td>0.00</td>
<td>0.02</td>
<td>0.16</td>
<td>0.99</td>
</tr>
</tbody>
</table>

Each model is estimated using daily fixed effects. Newey-West standard errors using a 24-hour lag are reported in parentheses. Explained within variation is given by R². * significant at 5 percent level, ** significant at 1 percent level.
Table 6: Average Emissions Avoided (per MWh) by Marginal Renewable Capacity

<table>
<thead>
<tr>
<th>Wind Capacity (MW)</th>
<th>AEA(K)</th>
<th>Average External Benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CO₂ (tons)</td>
<td>NOₓ (lbs)</td>
</tr>
<tr>
<td>0</td>
<td>0.65** (0.05)</td>
<td>0.95** (0.14)</td>
</tr>
<tr>
<td>1,000</td>
<td>0.65** (0.03)</td>
<td>0.98** (0.10)</td>
</tr>
<tr>
<td>2,000</td>
<td>0.65** (0.02)</td>
<td>1.01** (0.07)</td>
</tr>
<tr>
<td>3,000</td>
<td>0.66** (0.02)</td>
<td>1.04** (0.05)</td>
</tr>
<tr>
<td>4,000</td>
<td>0.66** (0.01)</td>
<td>1.07** (0.03)</td>
</tr>
<tr>
<td>5,000</td>
<td>0.67** (0.01)</td>
<td>1.09** (0.03)</td>
</tr>
<tr>
<td>6,000</td>
<td>0.68** (0.01)</td>
<td>1.10** (0.02)</td>
</tr>
<tr>
<td>7,000</td>
<td>0.69** (0.01)</td>
<td>1.12** (0.01)</td>
</tr>
<tr>
<td>8,000</td>
<td>0.71** (0.01)</td>
<td>1.13** (0.01)</td>
</tr>
<tr>
<td>9,000</td>
<td>0.72** (0.02)</td>
<td>1.14** (0.05)</td>
</tr>
<tr>
<td>10,000</td>
<td>0.74** (0.03)</td>
<td>1.14** (0.08)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Solar Capacity (MW)</th>
<th>AEA(K)</th>
<th>Average External Benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CO₂ (tons)</td>
<td>NOₓ (lbs)</td>
</tr>
<tr>
<td>0</td>
<td>0.66** (0.05)</td>
<td>1.57** (0.24)</td>
</tr>
<tr>
<td>1,000</td>
<td>0.63** (0.03)</td>
<td>1.43** (0.14)</td>
</tr>
<tr>
<td>2,000</td>
<td>0.61** (0.02)</td>
<td>1.32** (0.07)</td>
</tr>
<tr>
<td>3,000</td>
<td>0.60** (0.01)</td>
<td>1.26** (0.05)</td>
</tr>
</tbody>
</table>

* significant at 5 percent level, ** significant at 1 percent level.
### Appendix Table 1: Controlling for Dynamic Impact of Wind

<table>
<thead>
<tr>
<th></th>
<th>Lagged Hourly Impacts</th>
<th>Aggregate Daily Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CO₂ (tons)</td>
<td>NOₓ (lbs)</td>
</tr>
<tr>
<td>Wind Generation (β)</td>
<td>-0.620**</td>
<td>-0.980**</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>ERCOT Demand*</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>SPP Demand*</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>ERCOT Demand* lagged</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>SPP Demand* lagged</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>h × m × y × d FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>m × y × d FE</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>43,788</td>
<td>43,788</td>
</tr>
<tr>
<td>N</td>
<td>0.83</td>
<td>0.63</td>
</tr>
</tbody>
</table>

The models in the first three columns are estimated using daily fixed effects. Newey-West standard errors based on a 24-hour lag are reported in parentheses. The models presented in the last three columns are estimated using daily levels of emissions, wind, and demand. Newey-West standard errors using a 7-day lag are reported in parentheses. * significant at 5 percent level, ** significant at 1 percent level.

### Appendix Table 2: Instrumental Variable Estimates

<table>
<thead>
<tr>
<th></th>
<th>CO₂ (tons)</th>
<th>NOₓ (lbs)</th>
<th>SO₂ (lbs)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Exogenous</td>
<td>IV</td>
<td>Exogenous</td>
</tr>
<tr>
<td>Wind Generation</td>
<td>-0.577**</td>
<td>-0.630**</td>
<td>-0.916**</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.054)</td>
<td>(0.138)</td>
</tr>
<tr>
<td>ERCOT Demand*</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>SPP Demand*</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Hourly FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>15,038</td>
<td>15,038</td>
<td>15,038</td>
</tr>
<tr>
<td>R²</td>
<td>0.76</td>
<td>0.76</td>
<td>0.65</td>
</tr>
</tbody>
</table>

Each model is estimated using daily fixed effects. Heteroskedasticity and autocorrelation robust standard errors are reported for IV models. Newey-West standard errors using a 24-hour lag are reported for the exogenous models. Explained within variation is given by R². * significant at 5 percent level, ** significant at 1 percent level.
Appendix Table 3: Semiparametric Estimates of Average Emissions Avoided (per MWh)

<table>
<thead>
<tr>
<th>Wind Capacity (MW)</th>
<th>AEA(K)</th>
<th>Average External Benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CO₂ (tons)</td>
<td>NOₓ (lbs)</td>
</tr>
<tr>
<td>0</td>
<td>0.66**</td>
<td>0.98**</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.14)</td>
</tr>
<tr>
<td>1,000</td>
<td>0.66**</td>
<td>1.00**</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>2,000</td>
<td>0.66**</td>
<td>1.03**</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>3,000</td>
<td>0.66**</td>
<td>1.05**</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>4,000</td>
<td>0.66**</td>
<td>1.07**</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>5,000</td>
<td>0.67**</td>
<td>1.08**</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>6,000</td>
<td>0.68**</td>
<td>1.10**</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>7,000</td>
<td>0.69**</td>
<td>1.11**</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>8,000</td>
<td>0.71**</td>
<td>1.12**</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>9,000</td>
<td>0.73**</td>
<td>1.13**</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>10,000</td>
<td>0.75**</td>
<td>1.13**</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.09)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Solar Capacity (MW)</th>
<th>AEA(K)</th>
<th>Average External Benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CO₂ (tons)</td>
<td>NOₓ (lbs)</td>
</tr>
<tr>
<td>0</td>
<td>0.68**</td>
<td>1.57**</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>1,000</td>
<td>0.64**</td>
<td>1.42**</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>2,000</td>
<td>0.61**</td>
<td>1.31**</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>3,000</td>
<td>0.59**</td>
<td>1.23**</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.06)</td>
</tr>
</tbody>
</table>

* significant at 5 percent level, ** significant at 1 percent level.
Appendix Table 4: Heterogeneity in Marginal Emissions Offset

<table>
<thead>
<tr>
<th></th>
<th>ERCOT + SPP</th>
<th>ERCOT + SPP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CO₂ (tons)</td>
<td>NOₓ (lbs)</td>
</tr>
<tr>
<td>Wind</td>
<td>-2.498</td>
<td>3.673</td>
</tr>
<tr>
<td>(Wind)^2</td>
<td>-0.001</td>
<td>-0.003</td>
</tr>
<tr>
<td>(Wind)^3</td>
<td>1.03e-07</td>
<td>3.92e-07</td>
</tr>
<tr>
<td>Wind × Demand</td>
<td>0.0001</td>
<td>-0.0003</td>
</tr>
<tr>
<td>(Wind)^2 × (Demand)^2</td>
<td>-3.34e-09</td>
<td>9.48e-09</td>
</tr>
<tr>
<td>(Wind)^3 × (Demand)^3</td>
<td>2.49e-14</td>
<td>-9.90e-14</td>
</tr>
<tr>
<td>(Wind)^2 × Demand</td>
<td>3.93e-08</td>
<td>1.99e-07</td>
</tr>
<tr>
<td>(Wind)^2 × (Demand)^2</td>
<td>-6.54e-13</td>
<td>-4.33e-12</td>
</tr>
<tr>
<td>(Wind)^3 × (Demand)^3</td>
<td>3.33e-18</td>
<td>3.30e-17</td>
</tr>
<tr>
<td>(Wind)^3 × Demand</td>
<td>-6.62e-12</td>
<td>-2.60e-11</td>
</tr>
<tr>
<td>(Wind)^3 × (Demand)^2</td>
<td>1.31e-16</td>
<td>5.66e-16</td>
</tr>
<tr>
<td>(Wind)^3 × (Demand)^3</td>
<td>-8.42e-22</td>
<td>-4.18e-21</td>
</tr>
<tr>
<td>ERCOT Demand</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>SPP Demand</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Hourly FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>43,794</td>
<td>43,794</td>
</tr>
<tr>
<td>R²</td>
<td>0.82</td>
<td>0.60</td>
</tr>
</tbody>
</table>

Interactions are between ERCOT hourly wind generation and ERCOT hourly demand. Each model is estimated using daily fixed effects. Newey-West standard errors using a 24-hour lag are reported in parentheses. Explained within variation is given by R². * significant at 5 percent level, ** significant at 1 percent level.
Figure 1: Marginal Emissions Avoided by Wind Generation
Figure 2: Marginal Generation Avoided by Wind Generation

Figure 3: Conditional Distributions of Wind Capacity Factors
Appendix Figure 1: Semiparametric Estimates of MEA