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Overlapping Environmental Policies and the Impact on Pollution

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Abstract

In an effort to reduce pollution from the electricity sector, governments are heavily subsidizing renewables. The subsidies, however, are not being used in isolation. Instead, they are often provided in regions where certain pollutants are regulated by cap-and-trade programs. I demonstrate that, when combined with a cap-and-trade program, renewable subsidies can cause an undesirable outcome – they can increase emissions of unregulated pollutants. Focusing on the region regulated by the Clean Air Interstate Rule, I show that, if the EPA sets a binding cap on NO_X, expanding renewable capacity not only offsets zero tons of NO_X, it will increase SO_2 emissions.

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The electricity sector is not only the largest source of carbon dioxide (CO_2), it is also a major contributor of a variety of regional pollutants including sulfur dioxide (SO_2) and nitrogen oxides (NO_X). Motivated largely by a desire to reduce the flow of these pollutants, governments have implemented an array of policies – *e.g.*, tax credits, feed-in-tariffs, and renewable portfolio standards – designed to increase the supply of electricity from clean, renewable energy sources. In terms of spurring growth in renewable generation, these policies are clearly succeeding.[1] In the U.S., for example, production from wind turbines has grown at an average annual rate of 30% since 2001 – increasing from less than 7,000 gigawatt-hours (GWh) during 2001 to over 180,000 GWh in 2014. In contrast, production from conventional fossil fuel sources grew by less than 0.3% per year over the same period. In this paper, I explore whether these increases in renewable generation will in fact reduce the amount of pollution emitted by the electricity sector.

To determine how renewable electricity affects pollution, it is important to note that our efforts to expand renewable generation are not being used in isolation. In particular, it is now the norm for governments to subsidize renewables in regions where certain pollutants are already regulated. For example, in the eastern U.S. – the region studied in this paper – the Environmental Protection Agency (EPA) uses a cap-and-trade program to regulate the amount of NO_X emitted by power plants. At the same time, federal tax credits and state-level renewable portfolio standards are increasing renewable capacity throughout the region.[2] Previous work shows that, once a pollutant is subject to a binding cap, adding renewable output will not affect the aggregate emissions of the capped pollutant (Sijm (2005), Pethig and Wittlich (2009), Böhringer and Rosendahl (2010), Fischer and Preonas (2010)). However, an open question remains – how are the emissions of the other pollutants, the majority of which are unregulated, affected by renewables? Contributing to the existing literature, this paper examines how renewables interact with market-based environmental regulations to affect the emissions of regulated and unregulated pollutants. Focusing on the electricity sector in the eastern U.S., I show that if the EPA sets a binding cap on NO_X, ex-

[1] For studies exploring the impacts of the various renewable policies on renewable investment, see Bird et al. (2005), Yin and Powers (2010), and Hitaj (2013).

[2] Similarly, in markets with CO_2 cap-and-trade programs (*i.e.*, the European Union, California, the northeastern RGGI states), renewables benefit from generous government support.

panding renewable capacity will cause an undesirable outcome – it will increase the emissions of unregulated pollutants.

To demonstrate how renewables can increase pollution, I first present a simple analytical model of an electricity market that emits multiple pollutants. Focusing on the case where the policymaker can only regulate a single pollutant, I show that, if a cap-and-trade program is being used, increasing renewable output will impact emissions through two distinct channels. First, holding the pollution permit price constant, an increase in renewable output reduces the required production from non-renewable sources. If any fossil fuel output is offset by this 'scale effect', the emissions of each pollutant will fall. However, by reducing emissions of the capped pollutant, demand for pollution permits will also fall. The result will be a decline in the permit price which causes an additional 'composition effect' – a redistribution of output from non-renewable sources. While previous work shows that the scale and composition effects exactly offset to leave the emissions of the regulated pollutant unchanged (Böhringer and Rosendahl (2010), Fischer and Preonas (2010)), I show this need not be the case for any unregulated pollutants. In particular, the composition effect can dominate, increasing the emissions of unregulated pollutants.

To explore whether this unintended increase in unregulated pollution will occur in practice, I predict how adding new wind turbines and solar panels in the eastern U.S. will interact with the EPA's NO_X cap-and-trade program. Using data on the hourly output and emissions from power plants in the region, I separately quantify how the resulting scale and composition effects will impact unregulated emissions of CO_2 and SO_2. Building on the empirical strategy employed in several recent studies (Callaway and Fowlie (2009), Siler-Evans, Azevedo and Morgan (2012), Carson and Novan (2013), Graff Zivin, Kotchen and Mansur (2014), Jacobsen (2014)), I first estimate the scale effect the increase in renewable output will cause by identifying how pollution responds to an equal reduction in non-renewable generation. My estimates reveal that the scale effect – *i.e.*, the reduction in non-renewable output, holding NO_X permit prices constant – will lead to significant reductions in the emissions of each pollutant.

However, with a binding cap-and-trade program in place, the NO_X reductions caused by the scale effect will not equal the net change in NO_X. Instead, the permit price will decline until the net change in NO_X is ultimately zero. To determine how the decrease in the permit price will affect the unregulated pollutants, I examine how generation from fossil fuel power plants responds to an abrupt, policy-induced change in the NO_X permit price. I find evidence that a permit price decrease will cause a harmful composition effect. Specifically, there will be a shift away from relatively clean, natural gas generation towards dirtier, coal-fired output that negates much of the scale reduction in unregulated pollution. In particular, I show that, once the composition effect is taken into consideration, renewable electricity offsets substantially less CO_2 than was previously thought. Moreover, the renewable expansions will increase the amount of SO_2 emitted.

These findings contribute to a large literature examining the relative efficiency of various combinations of environmental policies. In the presence of a single, unpriced pollutant, economists have consistently argued in favor of using a single policy that internalizes the external cost of the pollutant – *i.e.*, an emission tax or a cap-and-trade program (Pigou (1920), Dales (1968), Montgomery (1972), Baumol and Oates (1988)).[3] Once the cost of emitting the pollutant has been internalized, using additional policy instruments – such as renewable subsidies – has been shown to result in efficiency losses.[4] In practice, however, power plants emit more than one pollutant. Moreover, governments have only managed to impose prices on, at most, a small subset of the many pollutants being emitted. In contrast, policymakers have successfully implemented countless subsidies targeted at specific channels of abatement (*e.g.*, renewable electricity, energy efficiency). The general belief is that, by reducing emissions, these subsidies act as imperfect substitutes for the missing prices on pollutants. However, this paper demonstrates that, when combined with a binding cap-and-trade program, subsidies for specific channels of abatement are very poor substitutes for the missing emissions prices. In settings where we are unable to regulate each pollutant, my results suggest that large efficiency gains can be achieved by combining renewable subsidies

[3]In contrast, in situations where there are additional market failures (*e.g.* knowledge spillovers), combining renewable subsidies and pollution prices can achieve the lowest cost emissions reductions (Jaffe, Newell and Stavins (2005), Bennear and Stavins (2007), Fischer and Newell (2008)).

[4]For example, see Sorrell and Sijm (2003), Palmer and Burtraw (2005), Sijm (2005), Fischer and Newell (2008), Goulder and Parry (2008), Pethig and Wittlich (2009), Böhringer and Rosendahl (2010), Fischer and Preonas (2010), and Levinson (2012).

with emissions taxes – as opposed to combining subsidies with emission caps.

The remainder of this paper proceeds as follows. In Section I, I analytically examine the impact of renewable generation on regulated and unregulated pollutants. Section II describes the EPA's NO_X cap-and-trade program and the data I use to examine the market. Section III presents estimates of the scale effect of renewable generation on pollution. Section IV presents estimates of the composition effect and the resulting net changes in pollution. In addition, Section IV discusses the policy implications of my results. Section V concludes.

I Analytical Model of an Electricity Market

A. Model

This section introduces a simple model of a perfectly competitive, wholesale electricity market. Extending the work of Fischer and Preonas (2010), I consider how environmental policies interact to affect more than one pollutant. For simplicity, I assume that electricity demand (D) is perfectly inelastic with respect to the wholesale price and that the market clears in a single period.[5] In the model, firms can generate electricity using two conventional energy sources (*e.g.*, coal and natural gas). I define X_1 and X_2 as the total generation from the two conventional sources. The private generation costs incurred are expressed by the cost functions $c_1(X_1)$ and $c_2(X_2)$, where $0 < c_i'(\cdot) < \infty$ and $0 < c_i''(\cdot) < \infty$ for $i = 1,2$. In addition, I assume that producing electricity from the conventional energy sources results in the emissions of two pollutants – μ and ρ. I assume that both conventional technologies have constant emission rates. That is, each unit of X_i produced results in μ_i and ρ_i units of pollution. Therefore, the aggregate emissions are equal to $\mu = \mu_1 \cdot X_1 + \mu_2 \cdot X_2$ and $\rho = \rho_1 \cdot X_1 + \rho_2 \cdot X_2$.[6]

In the model, electricity is also be produced using a non-polluting, renewable energy source.

[5] The zero-elasticity assumption can be relaxed without qualitatively changing the following analytical results. Intuitively, as demand becomes more elastic, the resulting scale and composition effects will both decrease by the same proportion. As a result, the sign of the net change in pollution will be unchanged.

[6] In the subsequent empirical analysis, I do not assume that conventional generators have constant emission rates.

Total renewable output is equal to r. Rather than solving for the competitive level of renewable generation, I treat the level of r as exogenous. Using this simple framework, I examine how an increase in renewable generation affects the emissions of μ and ρ under two different regulatory settings. In the first case, a regulator levies a tax (τ_μ) on each unit of μ. In the second case, the regulator sets a binding cap ($\overline{\mu}$) on the aggregate emissions of μ. In both cases, I assume the regulator faces an exogenous constraint which prevents a tax or cap from being placed on the emissions of ρ.[7]

While I explicitly solve for the impact of renewable generation on pollution, the results are directly applicable to examining how demand reductions affect emissions. To see this, first note that for the market to clear, conventional production must equal the residual demand not met be renewables – that is, $X_1 + X_2 = D - r$. Given that an increase in r has the same effect on residual demand as an equal decrease in D, both will have the same impact on conventional output and emissions.

B. Impact of Renewables with a Tax

First, consider the case where the regulator taxes each unit of μ. Assuming the market is perfectly competitive, the problem can be expressed using a representative firm. The firm's objective is to maximize profits by choosing X_1 and X_2:

$$\underset{X_1,X_2}{\text{Max}} \quad \pi = P \cdot (X_1 + X_2) - c_1(X_1) - c_2(X_2) - \tau_\mu \cdot (\mu_1 \cdot X_1 + \mu_2 \cdot X_2), \tag{1}$$

[7] If the regulator can choose any value for τ_μ, then, as the theory of the second-best highlights, the socially optimal choice may not be the first-best Pigouvian tax (*e.g.*, Lipsey and Lancaster (1956), Bennear and Stavins (2007)). In particular, if one of the conventional sources has higher emission rates for both μ and ρ, the regulator will optimally set τ_μ above the Pigouvian rate – consistent with previous studies highlighting that a tax on a single pollutant can serve as a tax on unregulated co-pollutants (Burtraw et al. (2003), Holland (2011)). Instead, I assume the tax on μ cannot exceed the Pigouvian level, and therefore, cannot proxy for the missing tax on ρ. This ensures that a reduction in the unregulated emissions of ρ will provide an external benefit.

where P is the wholesale price of electricity. The first-order conditions of the representative firm's problem and the market clearing condition are:

$$c_1'(X_1) + \mu_1 \cdot \tau_\mu = P \tag{2}$$

$$c_2'(X_2) + \mu_2 \cdot \tau_\mu = P \tag{3}$$

$$X_1 + X_2 = D - r. \tag{4}$$

To determine the impact of an increase in renewable generation, I totally differentiate Eq. (2)-(4) assuming that $dr > 0$ and $dD = 0$. This results in the following equations:

$$c_1'' \cdot dX_1 = c_2'' \cdot dX_2 \tag{5}$$

$$dX_1 + dX_2 = -dr. \tag{6}$$

Solving for the change in conventional generation caused by a change in renewable output from Eq. (5) and Eq. (6) yields the following results:

$$dX_1 = \left(\frac{-c_2''}{c_1'' + c_2''}\right) \cdot dr \tag{7}$$

$$dX_2 = \left(\frac{-c_1''}{c_1'' + c_2''}\right) \cdot dr. \tag{8}$$

Eq. (7) and Eq. (8) reveal that an increase in renewable output reduces generation from both conventional energy sources. As a result, an increase in renewable output – or similarly, a decrease in demand – will strictly reduce the aggregate emissions of both pollutants.

C. Impact of Renewables with a Cap

Next, I explore how renewable generation affects pollution when the regulator sets a cap ($\overline{\mu}$) on the aggregate emissions of μ. I assume the cap is binding and firms can freely trade permits which allow the holder to emit a unit of μ. The equilibrium price of the permits is represented by λ_{μ}.

The first order conditions of the representative firm's problem and the two market clearing conditions are shown below:

$$
\begin{aligned}
c_1'(X_1) + \mu_1 \cdot \lambda_\mu &= P && (9)\\
c_2'(X_2) + \mu_2 \cdot \lambda_\mu &= P && (10)\\
X_1 + X_2 &= D - r && (11)\\
\mu_1 \cdot X_1 + \mu_2 \cdot X_2 &= \overline{\mu}. && (12)
\end{aligned}
$$

Totally differentiating Eq. (9)-(12), again assuming $dr > 0$ and $dD = 0$, results in the following three equations:

$$
\begin{aligned}
c_1'' \cdot dX_1 + \mu_1 \cdot d\lambda_\mu &= c_2'' \cdot dX_2 + \mu_2 \cdot d\lambda_\mu && (13)\\
dX_1 + dX_2 &= -dr && (14)\\
\mu_1 \cdot dX_1 + \mu_2 \cdot dX_2 &= 0. && (15)
\end{aligned}
$$

Combining Eq. (14) and Eq. (15), the impact of a change in renewable generation on X_1 and X_2 is given by:

$$
dX_1 = \left(\frac{\mu_2}{\mu_1 - \mu_2}\right) \cdot dr \qquad (16)
$$

$$
dX_2 = \left(\frac{\mu_1}{\mu_2 - \mu_1}\right) \cdot dr. \qquad (17)
$$

Without loss of generality, assume $\mu_1 > \mu_2$. Eq. (16) and Eq. (17) reveal that $dX_1/dr > 0$ and $dX_2/dr < 0$. While an increase in renewable output reduces total conventional output, generation from the technology with the higher emission rate for μ must increase in order for the emission cap to be reached. This result replicates the findings presented by Böhringer and Rosendahl (2010) and Fischer and Preonas (2010).

Figure 1 graphically demonstrates the preceding result. Panel A plots the initial equilibrium levels of conventional generation, point A, prior to the increase in renewable generation. To satisfy the the market clearing condition, point A must fall on the residual demand level curve. In addition, to ensure the cap on μ is not exceeded, point A cannot fall to the right of the $\overline{\mu}$ level curve.[8] In the graph displayed, I continue to assume $\mu_1 > \mu_2$.

Panel B of Figure 1 demonstrates how a decrease in the residual demand, due to an increase in r or a decrease in D, affects conventional production. The total conventional output falls ($X_1'' + X_2'' < X_1' + X_2'$). However, under the assumption that the cap on μ is still binding, the generation from the technology with the higher emission rate of the capped pollutant will increase to continue to emit $\overline{\mu}$ units of the capped pollutant. As a result, the equilibrium levels of conventional output shift from point A to point C.

While the aggregate emissions of μ remain unchanged, the total quantity of ρ emitted can change as r increases, or as D falls. The total change in the unregulated pollution is given by $d\rho = \rho_1 \cdot dX_1 + \rho_2 \cdot dX_2$. Substituting Eq. (16) and Eq. (17) into the preceding expression, the total change in ρ caused by an increase in renewable electricity is:

$$d\rho = \left(\frac{\rho_1 \cdot \mu_2 - \rho_2 \cdot \mu_1}{\mu_1 - \mu_2}\right) \cdot dr. \tag{18}$$

Eq. (18) reveals that an increase in r can increase or decrease the aggregate emissions of ρ. Continuing to assume $\mu_1 > \mu_2$, if $\rho_1 < \rho_2$, then an increase in renewable generation will necessarily reduce emissions of ρ. That is, if one technology has the higher emission rate for one pollutant but not the other, then emissions of the unregulated pollutant will fall as renewable generation expands. Panel C of Figure 1 demonstrates the case where emissions of ρ decrease as r increases. The ρ level curves are less steep than the residual demand curve while the μ level curves are steeper – implying that $\rho_1 < \rho_2$ and $\mu_1 > \mu_2$. As the equilibrium shifts from point A to point C,

[8]To highlight that the emission cap is binding, Panel A includes one possible iso-private cost curve running through the bundle (X_1', X_2'). In the absence of a binding cap on μ, the representative firm could produce $D - r$ total units of conventional output at a lower private cost by increasing X_1 and decreasing X_2.

the equilibrium level of ρ falls from ρ' to ρ''.

Returning to Eq. (18), if the emission rates of the conventional technologies are positively correlated ($\mu_1 > \mu_2$ and $\rho_1 > \rho_2$), then $d\rho/dr$ is no longer necessarily negative. Panel D of Figure 1 demonstrates the case where an increase in r increases ρ. The ρ' and ρ'' level curves are now not only steeper than the residual demand level curve, they are also steeper than the level curve for the capped pollutant ($\rho_1/\rho_2 > \mu_1/\mu_2$). Moving from point A to point C, the aggregate emissions of ρ now increases.[9]

D. Separating Scale and Composition Effects

To further explore how increases in renewable generation interact with cap-and-trade programs, as well as to provide the intuition that underpins the empirical approach I take in this paper, it is helpful to expand the expressions for dX_1/dr and dX_2/dr presented in Eq. (16) and Eq. (17). Combining Eq. (13) and Eq. (14), the impacts of a change in renewable generation on production from energy sources 1 and 2 are given by:

$$dX_1 = \left(\frac{-c_2''}{c_1''+c_2''}\right)\cdot dr + \left(\frac{\mu_2-\mu_1}{c_1''+c_2''}\right)\cdot d\lambda_\mu \tag{19}$$

$$dX_2 = \underbrace{\left(\frac{-c_1''}{c_1''+c_2''}\right)\cdot dr}_{\text{Scale Effect}} + \underbrace{\left(\frac{\mu_1-\mu_2}{c_1''+c_2''}\right)\cdot d\lambda_\mu}_{\text{Composition Effect}}. \tag{20}$$

The first terms in Eq. (19) and Eq. (20) represent the change in X_1 and X_2 caused by an increase in renewable generation, *holding the pollution permit price constant*. I define this effect as the "scale effect". As r increases, the scale effect unambiguously reduces generation from both

[9]There are two more cases not displayed in Figure 1. First, I have not displayed the case where the ρ level curves are steeper than the residual demand level curve ($\mu_1 > \mu_2$ and $\rho_1 > \rho_2$) but not as steep as the μ level curve ($\rho_1/\rho_2 < \mu_1/\mu_2$). In this case, the shift from point A to point C will reduce the level of ρ. This result demonstrates that a positive correlation among the emission rates of the conventional technologies is a necessary condition, but not a sufficient condition, for an increase in r to increase ρ. Second, there is a final, trivial case that is possible as well. If the μ and ρ level curves have the same slope ($\rho_1/\rho_2 = \mu_1/\mu_2$), then the movement from point A to point C will not affect the aggregate emissions of either pollutant.

conventional sources. Intuitively, these reductions are identical to those presented in Eq. (7) and Eq. (8) – the impacts renewable generation has on conventional generation when μ is being taxed.

Returning to Figure 1, the scale effect is displayed as the movement from point A to point B. It is important to note that, regardless of the relative slopes of the pollution level curves, the scale effect will necessarily reduce the aggregate emissions of ρ.[10] However, just as the scale effect will reduce the emissions of ρ, it will also unambiguously decrease the aggregate emissions of μ. In a setting where μ is subject to a binding cap, the equilibrium price of the emissions permits, λ_μ, must decrease.[11] I define the change in conventional generation caused by the decrease in the permit price, *holding the residual demand constant*, as the "composition effect". The composition effects on X_1 and X_2 are displayed on the right side of Eq. (19) and Eq. (20). As the permit price falls, holding the residual demand constant, generation from the conventional technology with the higher emission intensity for μ increases while the technology with the lower μ emission rate will decrease.[12]

Returning again to Figure 1, the composition effect is shown as the movement, along the residual demand curve, from point B to point C. Unlike the scale effect, which necessarily reduces the emissions of ρ, the composition effect has an ambiguous effect on ρ. If $\mu_i > \mu_j$ and $\rho_i < \rho_j$, then the composition effect will reduce the emissions of ρ. This case is displayed in Panel C. Alternatively, if $\mu_i > \mu_j$ and $\rho_i > \rho_j$ – that is, if the technology with the higher emission rate of the regulated pollutant also has the higher emission rate of the unregulated pollutant – then the composition effect will increase the emissions of the unregulated pollutant. If the composition effect dominates the scale effect, as is the case in Panel D, then the aggregate emissions of the unregulated pollutant will increase.

[10] Combining the terms from Eq. (19) and Eq. (20), the aggregate change in ρ caused by the scale effects is given by $\frac{d\rho}{dr}\Big|_{d\lambda_\mu=0} = \rho_1 \cdot \left(\frac{-c_2''}{c_1''+c_2''}\right) + \rho_2 \cdot \left(\frac{-c_1''}{c_1''+c_2''}\right) < 0$.

[11] To see that the permit price falls, substitute the expressions from Eq. (16) and Eq. (17) into Eq. (13). Solving for $d\lambda_\mu/dr$ results in following expression, $d\lambda_\mu/dr = -(c_2''\cdot\mu_1 + c_1''\cdot\mu_2)/(\mu_2-\mu_1)^2 < 0$.

[12] Combining the expressions for the composition effects, the resulting change in unregulated emissions, holding the residual demand constant, is $\frac{d\rho}{d\lambda_\mu}\Big|_{d(D-r)=0} = \rho_1 \cdot \left(\frac{\mu_2-\mu_1}{c_1''+c_2''}\right) + \rho_2 \cdot \left(\frac{\mu_1-\mu_2}{c_1''+c_2''}\right) \gtreqless 0$.

II Empirical Setting and Data

The preceding section highlights that, in settings where a pollutant is subject to a cap, increasing renewable generation, or decreasing electricity demand, can actually increase the emissions of unregulated pollutants. The remainder of this paper examines whether this perverse outcome will occur in a specific regional cap-and-trade program – the EPA's NO_X cap-and-trade program in the Eastern U.S. This section describes the EPA program and the data I use to study the market.

A. EPA Clean Air Interstate Rule

One of the many pollutants emitted by fossil fuel power plants is NO_X. When NO_X interacts with other atmospheric chemicals and sunlight, the resulting byproduct is ground level ozone – a gas which has many negative health effects (Bell et al. (2004)). Throughout the 1990's, several regions in the eastern U.S. were failing to achieve federally mandated ozone standards. This was particularly a problem during the summer when NO_X combined with longer days, resulting in high ozone levels. To address this problem, the EPA implemented the NO_X Budget Trading Program (NBP) in 2003. The NBP capped NO_X emissions from power generators and industrial sources during the summer "ozone season" (May-September).

While the NBP led to substantial reductions in ozone season emissions, unregulated NO_X emitted during the non-ozone season still imposed external costs. Largely to address this fact, the NBP was replaced by the Clean Air Interstate Rule (CAIR) in 2009. The CAIR program consists of two separate NO_X cap-and-trade programs. The first places a cap on the annual NO_X emissions from electricity generating units. The second places a cap on ozone season NO_X emissions from electricity generators and large industrial sources. For each ton of NO_X emitted during May through September, a generator must surrender one annual permit and one ozone-season permit. For each ton of NO_X emitted during October through April, only an annual permit must be used. The 27 states covered by the CAIR program are highlighted in Figure 2.[13]

[13] Arkansas, Massachusetts, and Connecticut are not subject to the annual NO_X cap. Texas and Georgia are not subject to the ozone season cap. The annual NO_X cap does not cover any non-electric generating units. However, the

Figure 3 displays daily prices for the annual and ozone-season NO_X permits from the early stages of the CAIR market in 2009 to the end of 2011. When the CAIR program began, the annual NO_X permits were trading at prices above \$1,000 per ton and the ozone-season permits were trading for several hundred dollars per ton.[14] However, by 2011, the annual and ozone-season NO_X permit prices had plummeted – suggesting that, at the levels the NO_X limits were set, the caps were non-binding. Specifically, I use the term non-binding to mean that a marginal increase in the cap will have no impact on the aggregate amount of NO_X emitted. This is supported by the fact that, during each year of the CAIR program, the annual and ozone-season NO_X caps exceeded the actual emissions (EPA (2013)).

While the NO_X caps established by CAIR are currently in place, the future of the program is in flux. In 2015, the CAIR program is scheduled to be replaced by the Cross-State Air Pollution Rule (CSAPR). The CSAPR is similar to CAIR, but with two notable exceptions – CSAPR is more stringent and it differentiates between sources based on location.[15] As we continue to move forward with the EPA's NO_X cap-and-trade programs – as well as with similar policies elsewhere – it is important to uncover how emission caps, set at binding levels, will interact with the array of environmental policies also being implemented.

The remainder of this paper focuses on the regional electricity markets covered by the CAIR NO_X cap-and-trade programs. I examine how expansions in renewable capacity would affect emissions under the assumption that a binding cap exists on the annual emissions of NO_X from power plants. It is important to note that, in the CAIR region, other pollutants are subject to market

ozone season cap does cover a small number of non-electric generating, industrial units. For example, during 2011, 203 of the 3,307 ozone season sources covered were non-electric generating units. Estimating how production from these industrial sources is indirectly affected by increases in renewable electricity is beyond the scope of this analysis.

[14]Prior to the implementation of the CAIR program, the CAIR ozone-season NO_X permits – which were being traded in a forward market – were fairly stable around \$700 per ton of NO_X. In contrast, the forward price for the annual NO_X permits fluctuated substantially. During the beginning of 2008, the annual permits ranged between \$3,000 and \$6,000 per ton. In July, 2008, the D.C. Circuit Court ruled that the CAIR program had "fatal flaws" and vacated the program. As a result, forward prices for the annual permits plummeted and trading all but ceased. However, the Court reversed its ruling in December, 2008 and the annual NO_X permits rebounded to roughly \$4,000 per ton by the time CAIR program began in January, 2009.

[15]Recent work by Muller and Mendelsohn (2009) and Fowlie and Muller (2012) examine the potential efficiency gains that can be realized by using trading-ratios to account for spatial differences in the marginal external damage of pollutants by source.

based regulations as well. Beginning in 1995, the Acid Rain Program (ARP) placed a cap on the aggregate emissions of SO_2 from electricity generating units. However, from 2009 an onwards, the ARP cap has not been binding (EPA (2013)).[16] Aside from the SO_2 cap-and-trade program, there are smaller scale market-based pollution regulations within the region covered by CAIR. For example, ten Northeastern states are part of the Regional Greenhouse Gas Initiative (RGGI) which places a cap on CO_2 emissions.[17] In addition, very localized cap-and-trade programs also exist.[18] With these few small exceptions, during a period when the CAIR NO_X cap is binding, there is effectively one regulated pollutant (NO_X). The remaining pollutants – including CO_2 and SO_2 – are effectively unregulated.

B. Fossil Fuel Generation and Emissions Data

To explore how renewable capacity expansions would interact with a binding NO_X cap, I pose the following thought experiment. Assuming power plants in the eastern U.S. are regulated by a binding, annual NO_X cap-and-trade program, how would the annual emissions of CO_2, SO_2, and NO_X be affected by adding 1,000 megawatts (MW) of wind or solar generation capacity to the region?[19]

To answer this question, I build on the intuition provided by the analytical model. First, I estimate the scale effect – the reduction in the emissions of each pollutant, holding NO_X permit prices constant. Of course, assuming the annual NO_X cap is binding, the annual level of NO_X emitted will not change. Instead, the increase in renewable output will cause NO_X prices to decline,

[16] In 2010, the SO_2 cap reached its final level of 8.95 million tons – roughly half of the 1980 level of emissions from the electricity sector. During 2011, the annual emissions of SO_2 from generators covered by the ARP was only 4.54 million tons. In addition, beginning in 2010, the CAIR program also sets an annual cap on SO_2 emissions. However, given that the ARP cap is no longer binding, generators that are covered by both CAIR and the ARP have been able to used banked permits to meet the CAIR SO_2 cap. As a result, the CAIR SO_2 cap is also non-binding.

[17] The states included in RGGI are Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont. However, only four of the RGGI states are also participating in the CAIR annual NO_X cap-and-trade program.

[18] For example, in an effort to achieve attainment of the federal ozone standard, the Houston, TX metropolitan area operates an annual NO_X cap-and-trade program.

[19] For comparison, there was 59,629 MW of grid-connected wind capacity and 3,215 MW of solar capacity installed in the U.S. in 2012. Electricity capacity statistics are available from the U.S. Energy Information Administration.

causing a potential change in the composition of fossil generation. Therefore, the second step is to estimate how much the resulting composition effect alters the annual emissions of each pollutant.

To estimate the scale effect caused by adding 1,000 MW of renewable capacity, I must first determine which conventional generators would be affected by the new renewable output. Figure 3 displays the ten North American Electric Reliability Council (NERC) regions that make up the U.S. electricity grid. The continental U.S. transmission network can be thought of as three separate interconnections: the Western Interconnection (the WECC region), the Texas Regional Entity (the TRE region), and the Eastern Interconnection (the FRCC, MRO, NPCC, RFC, SERC, and SPP regions combined). My empirical analysis focuses exclusively on the NERC regions in the Texas and Eastern Interconnections – which combined, fully encompass the region covered by the CAIR program.

While very little trading occurs across the Interconnections, electricity is traded between NERC regions located within the Eastern Interconnection.[20] To address this fact, I present two sets of estimates of the scale effect. The first set of estimates are based on the assumption that an increase in renewable generation in a given NERC region will directly offset conventional generation only within the same NERC region. The second set of estimates is based on the assumption that an increase in renewable generation can directly offset output from conventional generators located anywhere in the same Interconnection. In reality, the truth is in between the two extremes. Due to transmission constraints, congestion, and losses, electricity generated at one point in the Eastern Interconnection is an imperfect substitute for electricity generated at a different point in the Interconnection. The results presented in the subsequent sections, however, demonstrate that the estimates are quite insensitive to trading assumption imposed.

To examine how emissions would be affected by increasing renewable capacity, I use data from the EPA's Continuous Emission Monitoring System (CEMS). The CEMS data records the

[20]Within each Interconnection, electricity is produced and traded at a synchronized frequency. To trade electricity between Interconnections, electricity can either be converted from alternating current to direct current (DC) and transmitted across a limited number of DC transmission lines, or be transmitted through a limited number of variable frequency transformers.

gross, hourly generation from almost every fossil fuel generating unit in the U.S.[21] In addition, the CEMS data records the hourly CO_2, SO_2, and NO_X emitted by each generating unit. Table 1 summarizes the emissions rates from three broad groups of generators: combined cycle natural gas units, coal units, and 'other' units. The generators are all located in the states participating in the CAIR program. The median emission rates represent the 50th-percentile of the unit-level, average emission rates from January 1, 2009 through December 31, 2012. It is worth noting that there is a clear positive correlation in the emission rates across technologies. Combined cycle generators typically have the lowest emission rates for all three pollutants while coal units have the highest emission rates for all three. Recall from the analytical model, a necessary condition for renewable output to increase unregulated pollution is for the emission rates of the various pollutants to be positively correlated across conventional generators.

Within the CEMS data, I do not observe the hourly generation from non-fossil fuel sources. As a result, I must assume that only fossil fuel units will be affected by an increase in renewable output. While I cannot directly test this assumption, there is evidence that suggests it is reasonable. Figure 4 provides the generation shares by different technologies in each of the NERC regions. The main non-fossil fuel sources are nuclear and hydroelectric. Nuclear generators have very low marginal generation costs. As a result, it is unlikely that nuclear units will be on the margin at any point in time in any region.[22] On the other hand, hydroelectric generation is not a zero marginal cost source of electricity – there is an opportunity cost incurred by using water to produce electricity. As a result, it is possible that hydroelectric generation may be the marginal source of electricity and will be offset by renewable output. However, given that the CAIR states are primarily located in the SERC, RFC, TRE, and FRCC regions – which do not have substantial amounts of non run-of-river hydroelectric potential – this is not a major concern.[23]

[21] While the CEMS data is the best available data, there are two potential shortcomings. First, fossil units with capacities below 25 MW are not required to report their hourly generation and emissions. Second, some combined cycle units may under report their gross generation – the output from the second cycle could be missing. Nonetheless, the CEMS data captures the vast majority of generation that takes place in the Texas and Eastern Interconnections.

[22] The results presented in Novan (Forthcoming) provide evidence that, in the Texas Interconnection, output from nuclear generators is unaffected by production from wind turbines.

[23] If an increase in renewable output does offset hydroelectric output, the stored water will simply be used at a different point in time. Therefore, the renewable output will still have a direct effect on emissions – however it will

C. Simulating Renewable Generation

To determine how increases in wind or solar capacity will affect emissions, I of course need to predict how much additional renewable generation would be supplied. In reality, both the quantity and timing of electricity supplied by additional wind or solar capacity will depend on where the wind turbines or solar panels are located. However, the goal of this analysis is not to examine how the renewable potential differs across locations. Rather, the goal is to explore how a given increase in renewable electricity will impact emissions – and to explore whether the impact differs across regions. Therefore, I abstract from the fact that wind patterns and solar potential differ across locations.

To simulate a realistic time series of hourly wind or solar generation, I collect data on the hourly aggregate capacity factors – the total hourly megawatt-hours (MWh) produced dividied by total installed capacity (MW) – from wind turbines and solar photovoltaic panels installed in the Texas Interconnection.[24] Assuming that new wind turbines or solar panels installed in the Texas market would have similar hourly capacity factors as the existing capacity, a time series of the hourly output provided by 1,000 MW of new capacity can be predicted by simply multiplying the hourly capacity factors by the added capacity (1,000 MW). To estimate the impact of adding renewable generation in different NERC regions, I simply assume that the output from the 1,000 MW of new wind or solar capacity would be identical in each region and equal to the simulated, hourly time series of renewable output in the Texas Interconnection.

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not occur immediately when the renewable generation occurs. Identifying how the hydroelectric generation is re-optimized is beyond the scope of the present study. As a result, I abstract from the impact renewable generation may have on hydroelectric units.

[24]Beginning in 2012, the Texas system operator, ERCOT, provides information on the hourly generation from both wind farms and solar plants connected to the market. In addition, the Texas Public Utility Commission provides information on the installed wind and solar capacity. Dividing the hourly generation by the installed capacity provides the hourly capacity factors during 2012.

III Estimating the Scale Effect

A. Empirical Strategy

I first estimate the scale effect that would be caused by the increase in renewable generation. That is, holding NO_X permit prices constant, how much NO_X, CO_2, and SO_2 is reduced annually by increasing renewable capacity? My empirical strategy relies on the fact that an increase in renewable generation will cause an equal and opposite decrease in conventional output.[25] Recall, I assume that only fossil generation will be offset by renewables. In addition, I assume that only fossil generation in the same NERC region – or alternatively, in the same Interconnection – will be reduced. Therefore, rather than directly estimating how an increase in renewable generation affects pollution, I instead estimate how an equal reduction in fossil generation affects emissions.

Several recent studies employ a similar strategy to estimate how increases in renewable output – or shifts in electricity demand – will affect emissions (Callaway and Fowlie (2009), Siler-Evans, Azevedo and Morgan (2012), Graff Zivin, Kotchen and Mansur (2014), Carson and Novan (2013), Jacobsen (2014), Holladay and LaRiviere (2014)). The results reveal that, in different markets, and at different points in time, a change in fossil output will have very different impacts on pollution. The variation across markets stems from the fact that the mix of generation technologies differs regionally. The variation over time stems from the fact that different generators are on the margin at different levels of demand.

Therefore, to accurately estimate the scale effect, I must allow renewable generation to have heterogeneous impacts on emissions. To accomplish this, I first estimate the following model for each individual NERC region – or alternatively, for each Interconnection:

$$E_t = f_m(G_t) + \alpha_m + \varepsilon_t, \tag{21}$$

[25] Again, this assumes that demand is perfectly inelastic to wholesale, electricity prices. Relaxing this assumption will reduce the magnitude of the scale and composition effects. However, it will not change the sign of the net pollution changes.

where

$$E_t = \text{Hourly NERC (or Interconnection) CO}_2 \text{ (tons), SO}_2 \text{ (lbs), or NO}_X \text{ (lbs),}$$

$$G_t = \text{Hourly NERC (or Interconnection) fossil fuel generation (MWh).}$$

The function $f_m(\cdot)$, which I specify as a 5^{th} degree Chebyshev polynomial, captures the relationship between the hourly level of fossil generation and the hourly emissions.[26] While $f_m(\cdot)$ can be expected to be strictly increasing, the shape will vary across regions based on the emission rates of the generators in the region and the order in which they are dispatched. In addition, I allow $f_m(\cdot)$ to vary by month (m) to account for seasonal differences in the availability of conventional generators. For example, during months with low demand, certain fossil units may be taken off-line. As a result, for the same level of fossil output, different units may be on the margin during different months. Monthly fixed effects control for trends that can create a spurious correlation between fossil generation and emissions. To account for serial correlation, I calculate Newey-West standard errors using a 24-hour lag. It is important to note that the subsequent estimates of the composition effect – presented in a later section – are made specifically for the first year of the CAIR program, 2009. To produce estimates of the scale effects during the same time period, the estimates of Eq. (21) are made using hourly data spanning 2009.

To estimate how emissions are impacted by the scale effect caused by the new wind or solar output, I use my NERC-specific (or Interconnection-specific) estimates of $f_m(\cdot)$. During hour t, if renewable output increases in a given NERC region (or Interconnection) by r_t MWh's, the required fossil fuel generation in the same NERC region (or Interconnection) will fall from G_t to $G_t - r_t$. As a result, the hourly emissions in the same NERC region (or Interconnection) will change by $[f_m(G_t - r_t) - f_m(G_t)]$. Using my NERC-specific (or Interconnection-specific) estimates of $f_m(\cdot)$ and the simulated series $\{r_t\}_{t=1}^{t=8,760}$, the hourly renewable output added by installing 1,000 MW of new wind or solar capacity, the annual scale effect for the given NERC region (or Interconnection)

[26] Estimates were also made using 3rd through 7th degree polynomials. The resulting estimates of the scale effects were statistically indistinguishable.

can be estimated as follows:

$$\text{Annual Scale Effect} = \sum_{t=1}^{t=8,760} \left[\hat{f}_m(G_t - r_t) - \hat{f}_m(G_t) \right]. \tag{22}$$

In the specification of the scale effect above, a key assumption is being imposed. Specifically, as the level of renewable output increases, the relationship between hourly fossil generation and hourly emissions, $f_m(\cdot)$, remains constant. Recall that $f_m(\cdot)$ is largely determined by the order in which the fossil fuel units are dispatched. By not allowing $f_m(\cdot)$ to change with the increase in renewable output, I am assuming that fossil fuel units are still dispatched in the same order. For that to be the case, the input prices – including the NO_X permit prices – must be the same.[27] Therefore, the expression in Eq. (22) represents the annual change in emissions caused by an increase in renewable output, holding NO_X prices the same – which is the definition of the scale effect.

It is important to note that the previous studies focused on estimating how pollution would respond to marginal changes in renewable output or demand are also only uncovering the scale effect (Callaway and Fowlie (2009), Siler-Evans, Azevedo and Morgan (2012), Graff Zivin, Kotchen and Mansur (2014), Carson and Novan (2013), Jacobsen (2014), Holladay and LaRiviere (2014)). The only notable difference between the previous studies and my empirical approach is that my strategy enables me to predict the impact of discrete changes in renewable generation, as opposed to strictly marginal changes in renewable output. However, it is important to highlight that my estimates do not allow increases in renewable output to have a dynamic impact on fossil generation. That is, an increase in renewable output during hour t only affects emissions during the same hour. While this is a reasonable approximation for small to moderate increases in renewable output, large increases in renewable production may affect fossil generation decisions across multiple hours. Therefore, my estimation strategy should not be used to predict the impact of large shifts in renewable supply. In addition, it is important to note that the scale effects I am estimating are short-run values. I am assuming that there are no changes to the stock of non-renewable generators.

[27] Throughout the analysis, I continue to assume that the supply curves of the fossil fuels used to generate electricity are perfectly elastic over the relevant ranges. Specifically, I am assuming that renewable generation changes of the magnitude I am studying will not affect the market price for coal or natural gas.

B. Estimates of the Scale Effect

To produce estimates of the scale effect, I first estimate the relationship between hourly fossil generation and hourly emissions, $f_m(G_t)$ from Eq. (21), for each of the NERC regions and for both of the Interconnections. To highlight two key patterns that are important for understanding the subsequent estimates of the scale effects, Figure 5 presents the estimates of $f_m(\cdot)$ for two NERC regions (TRE and RFC) during a single month (July, 2009).[28] In addition, the 744 hourly observations of (E_t, G_t) during July, 2009 are plotted to highlight the goodness of fit.

The estimates of $f_m(\cdot)$ first reveal that, in each region, there is variation in the slope of the fitted polynomial across levels of fossil generation. This is most pronounced for SO_2 and NO_X – especially in the TRE region. For example, the relationship between hourly SO_2 and hourly fossil generation becomes flatter at higher levels of generation. This is driven by the fact that less coal generation is on the margin at higher levels of fossil output. In the case of NO_X, the relationship between the hourly emissions and the hourly fossil output becomes steeper at the higher levels of G_t. This is driven by the fact that less fuel-efficient natural gas generators are primarily on the margin at the highest levels of fossil output.

Second, Figure 5 reveals that there is substantial variation in the marginal emission rates across regions. To highlight this fact, I calculate the average marginal emission rate in each region.[29] For each of the three pollutants, the average marginal emission rates are substantially higher in the RFC region compared to the TRE region. This is driven by the fact that, in the RFC region, a substantially larger share of output comes from coal units – which is shown in Figure 4.

Using the NERC-specific (or Interconnection-specific) values of $\hat{f}_m(\cdot)$, I estimate Eq. (22) – the annual scale effect of adding 1,000 MW of wind or solar capacity to a specific NERC region (or Interconnection). To summarize the results, Table 2 presents the estimates of the average emissions offset by a MWh of renewable output supplied by the new wind or solar capacity. The

[28] Of the NERC regions in the Eastern Interconnection, I highlight the RFC region because it is the largest in terms of total generation.

[29] To estimate the average marginal emission rate, I re-estimate Eq. (21) and restrict $f_m(G_t) = \beta_m \cdot G_t$ – where $\hat{\beta}_m$ is the estimate of the average marginal emission rate during month m.

results reveal that significant reductions in each of the pollutants would be achieved. Moreover, the estimates highlight that the scale effects are heterogeneous. First, within the same region, the two technologies can offset different amounts of pollution. For example, in the TRE Interconnection, wind turbines offset more SO_2 per MWh than solar panels but less NO_X per MWh. This is due to the fact that the wind turbines will produce more heavily during the low demand hours when the marginal SO_2 rates are higher and the marginal NO_X rates are lower.[30] There is even greater variation in the scale effects across Interconnections. Consistent with the results presented in Figure 5, offsetting fossil generation from the Eastern Interconnection, as opposed to the TRE Interconnection, will result in larger decreases in emissions.

To get a sense of the magnitude of the predicted emissions reductions, I compare the estimates of the annual emissions offset to the total pollution emitted in the region during 2009. For example, in the Texas Interconnection, the scale effect caused by adding 1,000 MW of new wind capacity will reduce 0.8% of the annual CO_2 emitted in the Texas Interconnection, 0.8% of the NO_X, and 0.5% of the SO_2 while the new solar capacity will offset 0.6% of the CO_2, 0.9% of the NO_X, and 0.2% of the SO_2.[31]

IV Estimating the Composition Effect

The preceding section quantifies the annual pollution reductions caused solely by the scale effect. With a binding cap on NO_X, however, the annual reductions in NO_X will not be achieved. Instead, the scale effect will push the NO_X permit price downwards until the cap is again binding and the net change in NO_X is zero.

As the analytical model in Section I demonstrates, the resulting decrease in the permit price can change the relative composition of generation from conventional sources, potentially causing

[30]These results are consistent with the estimates of the impact of wind and solar generation on TRE emissions presented by Novan (Forthcoming).

[31]To calculate the changes in the level of emissions, the estimates of the per MWh scale effects can simply be multiplied by the predicted annual increases in wind or solar output. The predicted annual increase in wind generation is 2,338,858 MWh (an average capacity factor of 0.27) and the predicted increase in solar output is 2,022,861 MWh (an average capacity factor of 0.20).

a change in the amount of unregulated pollution emitted. Of course, in the analytical model, the emission rates of the conventional technologies are fixed. As a result, the only way for conventional producers in the model to change their level of emissions is to alter their level of generation. In reality, it is possible for a generator to alter the level of NO_X emitted without changing the level of electricity produced.[32] If a reduction in the NO_X permit price causes fossil fuel units to alter their NO_X emission rates, and not change their level of production, then it is possible that there will be no meaningful composition effect – and therefore, no additional change in the levels of the unregulated emissions.

In this section, I provide evidence that a decrease in NO_X permit prices will cause a composition effect that increases the level of CO_2 and SO_2 emitted. Combining the estimates of the scale and composition effects caused by adding renewable capacity, I also present estimates of the net changes in CO_2 and SO_2.

A. Identification Strategy

To determine if a change in the NO_X permit price will cause a composition effect that alters the level of unregulated emissions, ideally I would be able to directly identify how changes in the NO_X permit price, holding the total level of fossil generation constant, affect the level of emissions. Unfortunately, much of the observed variation in the price of NO_X permits is likely driven by factors that affect emissions through other channels as well (*e.g.*, fuel price changes or demand shifts).

To identify the impact of permit price changes on emissions, I instead take advantage of the abrupt change in the price of emitting NO_X that occurs between the ozone season and the non-ozone season. Recall, during the non-ozone season (October through April), only a permit from the annual market must be surrendered for each ton of NO_X emitted. During the ozone season

[32] For example, generators can achieve small reductions in their NO_X emission rates by modifying their combustion process. In addition, the vast majority of generators have end-of-pipe pollution control technologies which can be turned on or off. For example, selective catalytic reduction (SCR) add-ons reduce NO_X rates by up to 90% and selective non-catalytic reduction (SNCR) add-ons reduce NO_X rates by roughly 35% (Fowlie (2010)).

(May through September), an annual permit and an ozone season permit must be used. Referring to Figure 3, on April 30, 2009, the last day before the start of the ozone season, emitting a ton of NO_X effectively had an expected cost of \$1,100. On the following day, the first day of the 2009 ozone season, emitting a ton of NO_X had an expected cost of \$1,479 – the ozone permits were trading for \$379/ton.

To get a sense of the magnitude of this change, consider the impact on the generation costs of a coal fired unit. Depending on the type of coal burned, the fuel costs typically range between \$20 and \$30 MWh. For the median coal fired unit in my sample with a NO_X emission rate of 2.85 pounds/MWh, it cost \$1.57/MWh to pay for the NO_X emissions on April 30, 2009. On the very next day, it cost \$2.11/MWh. Therefore, the switch from non-ozone to ozone season causes roughly a 3% increase in the marginal generation cost of a typical coal unit. While this is not a substantial change in the marginal generation cost, it certainly may be large enough to affect generation decisions. Moreover, it is reasonable to expect that moderate increases in renewable output – as I am considering in this study – will have similarly small impacts on NO_X permit prices.

The discrete change in the cost of emitting NO_X at the beginning of the 2009 ozone season serves as a natural experiment. Comparing the average hourly emissions during the periods immediately before and after the switch, I can estimate how a change in the cost of emitting NO_X affects the emissions from fossil fuel generating units. Unfortunately, by the end of the 2009 ozone season, the ozone season permit prices had fallen dramatically. Therefore, with the exception of Spring 2009, the price discontinuity between the ozone and non-ozone seasons is trivially small. Therefore, I must identify the impact of NO_X prices using a single event.

My objective is to determine whether, after controlling for the level of fossil generation, the average hourly emissions of CO_2, SO_2, and NO_X decrease in the Eastern Interconnection after the 2009 ozone season begins. Recall from Figure 2, generating units in the TRE interconnection are not part of the ozone season NO_X market. Therefore, there will be no discontinuity in their NO_X prices. Instead, I use the set of fossil fuel generators in the Texas market to conduct a falsification test of my main results.

Figure 6 plots the hourly emissions and fossil generation in the Eastern Interconnection during a 20 day window surrounding the beginning of the 2009 ozone season. If the relationship between emissions and generation shifts down after the ozone season begins, this would suggest that a higher NO_X price leads to lower levels of each pollutant. From the figures, there is some visual evidence that the ozone season emissions were in fact lower. In particular, for a given level of fossil output, the aggregate emissions of CO_2 and SO_2 appear to be lower during the period with higher NO_X prices.

B. Econometric Specification

To test whether the switch to the higher NO_X prices does in fact decrease pollution, I focus on how emissions change in the narrow 20 day window surrounding the beginning of the 2009 ozone season. Using hourly CEMS data spanning April 21, 2009 through May 10, 2009, I estimate the following model:

$$E_t = \alpha \cdot Ozone_t + f(G_t) + \theta \cdot Date_t + \delta_{h,w} + \varepsilon_t, \tag{23}$$

where

$$\begin{aligned} E_t &= \text{Hourly Eastern Interconnection } CO_2 \text{ (tons), } SO_2 \text{ (lbs), or } NO_X \text{ (lbs),} \\ Ozone_t &= \text{Indicator for Ozone Season (1 if during Ozone Season),} \\ G_t &= \text{Hourly Eastern Interconnection gross fossil fuel generation (MWh).} \end{aligned}$$

In the specification above, α represents the average change in hourly Eastern Interconnection emissions, holding fossil generation constant, caused by the start of the ozone season.[33] It is important to note that I do not estimate the model separately for each individual NERC region in the Eastern

[33] The Eastern Interconnection emissions and generation includes output and pollution from fossil fuel unit located in the MRO, SPP, and NPCC NERC regions – even though these regions are not fully covered by the CAIR program. These regions are included due to the fact that an increase in the NO_X permit prices could induce pollution leakage into the non-CAIR Eastern Interconnection states. This leakage would nonetheless be part of the resulting composition effect that I would like to capture.

Interconnection. If the discontinuity in the NO_X prices causes a redistribution of the generation across NERC regions, then this is part of the composition effect that I want to capture in α. Estimates are also made using 14 and 28 day windows. The results from these robustness checks – which are presented in Appendix Table 1 – are very similar.

In Eq. (23), $f(\cdot)$ is a 3^{rd} degree Chebyshev polynomial that flexibly controls for the fact that the hourly level of pollution emitted from the Eastern Interconnection varies with the level of generation in the region. To control for potential differences between the composition of units generating on weekdays versus weekends, $\delta_{h,w}$ is a set of hourly fixed effects that are allowed to differ across weekends and weekdays.[34] To control for potential correlation between the *Ozone* indicator and continuous trends in emissions over the 20 day window, I also include a simple linear time trend. Additional estimates are also made with higher order time trends. These results are presented in Appendix Table 1. To account for serial correlation, I calculate Newey-West standard errors based on 24-hour lags.

Intuitively, the increase in the cost of emitting NO_X is expected to reduce the average hourly NO_X emitted. Therefore, I expect $\hat{\alpha}_{NO_X} < 0$. If $\hat{\alpha}_{CO_2} < 0$ and $\hat{\alpha}_{SO_2} < 0$, this would provide evidence that, holding the level of fossil generation constant, the increase in the cost of emitting NO_X also causes a decrease in the average hourly emissions of CO_2 and SO_2. Under the assumption that fossil fuel generators respond symmetrically to NO_X price changes, observing $\hat{\alpha}_{NO_X}$, $\hat{\alpha}_{CO_2}$, and $\hat{\alpha}_{SO_2}$ all less than zero would provide evidence that a decrease in the NO_X price would result in a composition effect that increases the emissions of all three pollutants. Of particular interest will be the following two ratios:

$$\text{CO}_2 \text{ Composition Effect} = \frac{\partial \text{CO}_2/\partial \text{Ozone}}{\partial \text{NO}_X/\partial \text{Ozone}} = \frac{\alpha_{CO_2}}{\alpha_{NO_X}},$$

$$\text{SO}_2 \text{ Composition Effect} = \frac{\partial \text{SO}_2/\partial \text{Ozone}}{\partial \text{NO}_X/\partial \text{Ozone}} = \frac{\alpha_{SO_2}}{\alpha_{NO_X}}.$$

[34] Estimates of the model were also made by simply dropping weekends from the sample. The results are again very similar.

The first ratio represents how much additional CO_2 (tons) would be emitted for each additional pound of NO_X emitted. Similarly, the second ratio represents how much additional SO_2 (pounds) would be emitted for each one pound increase in NO_X.

C. Event Study Results

The first row of Table 3 presents the estimates of α for each pollutant. On average, after the beginning of the 2009 ozone season, hourly Eastern Interconnection NO_X emissions fall by 16,809 pounds, hourly CO_2 falls by 2,582 tons, and hourly SO_2 falls by 90,629 pounds. Relative to the average hourly emissions during the same 20 day period, these reductions represent 5.7% of the Eastern Interconnection NO_X, 1.4% of the CO_2, and 8.4% of the SO_2.

To highlight how these changes are being driven by shifts in the composition of generation, I estimate Eq. (23) using the aggregate hourly Eastern Interconnection generation (MWh) from different technologies as the new dependent variables. I separate the fossil generation reported in the CEMS data into three different types of output: generation from coal units, generation from combined cycle natural gas units, and all 'other' generation, which is almost entirely from natural gas turbines. The estimates of α, which are presented in the third row of Table 3, represent the average change in hourly generation from the various sources following the start of the ozone season. The results reveal that the higher NO_X prices lead to a decrease in coal fired production – which is typically the most emission intensive – and a corresponding increase in combined cycle natural gas output – which, on average, has the lowest emission rates.

An obvious concern with the preceding estimates is that they are identified off of a single event. It is certainly possible that some other event, which coincides with the beginning of the 2009 ozone season, actually causes the observed change in emissions. To provide supporting evidence that this is not the case, I re-estimate the model specified by Eq. (23) using hourly data from the Texas Interconnection. Recall, Texas generators are not required to participate in the ozone season NO_X market. Moreover, there is very little trading between the Texas and Eastern Interconnection. Therefore, the $Ozone_t$ indicator – which switches from 0 to 1 on May 1, 2009 – should have no impact on the average hourly emissions from the Texas generators. If the previous estimates of the composition effects had been driven by something other than the discontinuity in NO_X prices (*e.g.*, fuel prices changes), then the significant impacts would likely not be confined to the region covered by the ozone season market. Estimates of $\hat{\alpha}$ for the Texas Interconnection (TRE) are presented in the second row of Table 3. The ozone switch does not have a significant impact on any of the pollutants.

To provide evidence that the effect of $Ozone_t$ on emissions is driven by the change in NO_X prices, and not by other regulations that could coincide with the ozone season switch, I also re-estimate the model using each 20 day window around the Spring and Fall ozone switches occurring after the Spring 2009 switch – Fall 2009 through Fall 2012. Given that the ozone season NO_X prices were very close to zero during these later periods, there effectively is no discontinuity in the expected cost of emitting NO_X. Therefore, if the effect of $Ozone_t$ on emissions is caused by something other than the NO_X prices, there may still be significant impacts of the ozone season switch on emissions. However, I find no significant impacts from the later ozone switches.

Finally, it is possible that the estimates of the standard errors of $\hat{\alpha}_{NO_X}$, $\hat{\alpha}_{CO_2}$, and $\hat{\alpha}_{SO_2}$ are biased towards zero.[35] Therefore, I may be concluding that α_{NO_X}, α_{CO_2}, and α_{SO_2} are significantly less than zero when the true values are in fact zero. To provide evidence that this is not the case, I estimate a number of "placebo ozone effects". Specifically, I split the period from January 1, 2009 through December 31, 2012 into 72 mutually exclusive 20 day periods. For each of these 72 windows, I treat the mid-point as the beginning of a placebo ozone season and I re-estimate the model specified in Eq. (23). Given that there is no ozone switch occurring on these placebo dates, I expect the estimates of $\hat{\alpha}$ to be centered around zero. If the true values of α_{NO_X}, α_{CO_2}, and α_{SO_2} – from the actual 2009 ozone season beginning – all equal zero, then the previous estimates of $\hat{\alpha}_{NO_X}$, $\hat{\alpha}_{CO_2}$, and $\hat{\alpha}_{SO_2}$ would simply be drawn from a distribution similar to the distribution of placebo estimates.

Figure 7 presents the cumulative distribution of the 72 placebo estimates for each pollutant. As

[35] For example, using Newey-West standard errors based on a 24-hour lag may not fully account for a complicated autocorrelation structure in the errors.

expected, the placebo effects are centered around zero. The plots also include the actual estimates of the Spring 2009 ozone treatment effect. For each of the pollutants, the estimates of the true ozone effect are in the extreme left tail of the distribution. Only three placebo estimates are more negative than $\hat{\alpha}_{CO_2} = -2,582$ tons. No placebo estimates are less than $\hat{\alpha}_{SO_2} = -90,629$ pounds. Finally, only one placebo estimate is less than $\hat{\alpha}_{NO_X} = -16,809$ pounds. Combined, these results provide strong evidence that the discontinuous increase in the cost of emitting NO_X at the beginning of the 2009 ozone season causes decreases in Eastern Interconnection emissions of each pollutant.

D. Net Pollution Changes

This section presents estimates of the net changes in annual emissions that would be caused by adding 1,000 MW of solar or wind capacity to the various NERC regions. Recall, the estimates from Table 2 reveal that, holding NO_X prices constant, the increase in renewable generation will result in significant reductions in each of the pollutants. Under the assumption that the cap on NO_X is binding, the scale reduction in NO_X will not represent the net change in NO_X. Instead, the equilibrium NO_X permit prices will decrease to the point where the NO_X cap is again binding and the net change in NO_X is zero.

To predict the net changes in annual emissions, I must estimate how much the CO_2 and SO_2 emissions change as the NO_X prices fall and the net change in NO_X returns to zero. To estimate this resulting composition effect, I use the estimates of α from Eq. (23). The ratio $\alpha_{CO_2}/\alpha_{NO_X}$ represents the increase in CO_2 for each additional pound of NO_X emitted – holding the level of fossil generation constant.[36] Similarly, $\alpha_{SO_2}/\alpha_{NO_X}$ represents the additional SO_2 emitted for each extra pound of NO_X.

Using the estimates from Eq. (23), I find $\hat{\alpha}_{CO_2}/\hat{\alpha}_{NO_X} = 0.15$ tons of CO_2 per pound of NO_X and $\hat{\alpha}_{SO_2}/\hat{\alpha}_{NO_X} = 5.39$ pounds of SO_2 per pound of NO_X. These positive point estimates suggest that, as the NO_X permit prices fall, and the NO_X emissions re-increase to the capped level, the emissions of CO_2 and SO_2 will increase as well. To predict the net change (Δ) in CO_2 and SO_2

[36] Again, this assumes that the response of generators is symmetric to equal increases and decreases in NO_X prices.

emissions, I solve for the following two values:

$$\text{Net } \Delta\text{CO}_2 = (\text{Scale } \Delta\text{CO}_2) - \left(\frac{\hat{\alpha}_{CO_2}}{\hat{\alpha}_{NO_X}}\right) \cdot (\text{Scale } \Delta\text{NO}_X), \tag{24}$$

$$\text{Net } \Delta\text{SO}_2 = (\text{Scale } \Delta\text{SO}_2) - \left(\frac{\hat{\alpha}_{SO_2}}{\hat{\alpha}_{NO_X}}\right) \cdot (\text{Scale } \Delta\text{NO}_X), \tag{25}$$

where the annual effects – Scale ΔCO_2, Scale ΔSO_2, and Scale ΔNO_X – are specified by Eq. (22).

There are two important caveats to note. First, the estimates of α_{NO_X}, α_{CO_2}, and α_{SO_2} are made using observations surrounding the beginning of the 2009 ozone season switch. During a different year or season, the same change in the cost of emitting NO_X may result in different changes in emissions.[37] Nonetheless, it is reasonable to expect that the values of α_{NO_X}, α_{CO_2}, and α_{SO_2} would remain negative given the expected substitution away from coal towards cleaner gas units. Second, the estimates of α_{NO_X}, α_{CO_2}, and α_{SO_2} correspond specifically to the change in the cost of emitting NO_X that was observed at the beginning of the 2009 ozone season. With a different change in NO_X prices, the ratios of $\alpha_{CO_2}/\alpha_{NO_X}$ and $\alpha_{SO_2}/\alpha_{NO_X}$ may differ. However, recall that the start of the 2009 ozone season caused a fairly small change in the cost of emitting NO_X – which resulted in roughly a 3% change in the marginal generation cost for a typical coal unit. This small price change serves as a reasonable proxy for the magnitude of permit price changes that would likely be driven by moderate expansions in renewable electricity – or similar decreases in electricity demand.

Estimates of the net changes in CO_2 and SO_2 – Eq. (24) and Eq. (25) – are presented in Table 4.[38] Estimates are made using the NERC-specific scale effect estimates as well as the Interconnection-specific scale effects. The results presented in Table 4 represent the net impact of a MWh of renewable output on the annual emissions of CO_2 and SO_2. Focusing first on the net effects on CO_2, the estimates reveal that the composition effect erodes a sizable portion of the pollution reductions caused by the scale effect. In the TRE region, the net CO_2 reductions caused

[37] Differences over time in the values of α could stem from variation in the level of demand or in the relative fuel prices – both of which would alter the set of fossil fuel units operating and the magnitude of their responses.

[38] To calculate the standard errors of the point estimates, I treat the point estimates of $\hat{\alpha}_{CO_2}/\hat{\alpha}_{NO_X}$ and $\hat{\alpha}_{SO_2}/\hat{\alpha}_{NO_X}$ as known constants. For example, the variance of the estimate of the net CO_2 avoided is solely a function of the variance of the scale impacts on CO_2 and NO_X and the covariance of the CO_2 and NO_X scale effect estimates.

by solar and wind are 21% and 15% smaller than the predicted scale effects, respectively. In the Eastern Interconnection, the net CO_2 avoided by solar and wind are 28% and 26% smaller than the predicted reductions provided by the scale effects.

Turning our attention to the net impacts on SO_2, the results are striking. In each region, and for each technology, the estimates reveal that increases in renewable capacity will result in sizable increases in SO_2 emissions. There is some variation in the net impacts of different investments on SO_2. For example, in the TRE region, each MWh from new wind turbines increases SO_2 by 2.175 pounds while each MWh from the new solar capacity will increase SO_2 by 4.068 pounds. These differences are driven by the fact that, compared to solar panels, wind turbines in Texas reduce more SO_2 and less NO_X through the scale effects.

E. Discussion

The preceding estimates provide evidence that, in the presence of a binding NO_X cap, renewable expansions will increase the emissions of some pollutants and decrease the emissions of others. Given this result, an obvious question is the following – will the renewable expansions provide a net external benefit? Before this question can be addressed, it is important to note that the estimates presented in Table 4 represent the net changes in emissions throughout the entire eastern U.S. I am not able to explore where, or during what times of the year, the pollution increases or decreases would occur. While the spatial and temporal distributions of the emissions changes are irrelevant for estimating the social benefit provided by the avoided CO_2, the social benefits, or costs, provided by changes in the emissions of non-perfectly mixing pollutants (*e.g.*, SO_2, NO_X) do depend on the time and location. Therefore, I cannot directly estimate the external benefits provided by the various renewable capacity investments examined.[39]

Nonetheless, I can use estimates of the average social costs – across both time and space – of the various pollutants to provide rough estimates of the external benefits of the renewable capacity additions. To place a dollar value on the social benefit of reducing a ton of CO_2, I rely on an

[39] I also do not observe the emissions of the other pollutants emitted by fossil fuel generators.

estimate of the social cost of carbon reported by the Interagency Working Group. The central estimate provided by IAWG (2013) suggests that each ton of CO_2 offset provides a benefit of \$32. To estimate the external benefits provided by reductions – or similarly, the external costs imposed by increases – in SO_2 and NO_X, I use social cost estimates from Banzhaf and Chupp (2012). The authors use a Tracking and Analysis Framework to predict the social costs that accrue from a marginal increase in SO_2 and NO_X in each individual state. Among the 27 states participating in the CAIR program, an additional pound of SO_2 imposes an estimated average cost on society of \$1.99. An additional pound of NO_X imposes an estimated average social cost of \$0.33.[40]

Using the estimates of the social costs of CO_2, SO_2, and NO_X, I first predict the social benefits provided by the pollution reductions stemming solely from the scale effects. To do so, I multiply the estimates of the average reduction in each pollutant (Table 3) by the corresponding pollutant's social cost. Aggregating across pollutants results in an estimate of average external benefit per MWh of renewable generation. The results are presented in the first two columns of Table 5. In the Texas Interconnection, the scale effects caused by additional solar and wind generation provide average external benefits of \$21.84/MWh and \$23.53/MWh, respectively. In the Eastern Interconnection, the average external benefits are even larger – \$28.25 per MWh of solar and \$28.81 per MWh of wind. Therefore, over the course of a year, the scale effects caused by adding 1,000 MW of solar capacity provide an estimated external benefit of \$44 million in the Texas Interconnection and \$57 million in the Eastern Interconnection. The annual external benefit of the scale effect caused by adding 1,000 MW of wind capacity is \$55 million in the Texas Interconnection and \$67 million in the East.

As my results demonstrate, however, if the expansions in renewable capacity are combined with a binding cap on NO_X, the net changes in emissions will be substantially smaller than the scale reduction in emissions. Therefore, the external benefits will be dramatically smaller. The last two columns of Table 5 provide the estimates of the external benefits provided by the net changes in

[40]To determine the average social cost of SO_2 and NO_X, I calculate the simple average of the state specific estimates of the average annual cost per ton of pollution. Alternative weighting options were considered (*e.g.*, weighted averages based on the share of total fossil generation in CAIR region), however, the average social cost predictions were very similar.

pollution (*i.e.*, the net decrease in CO_2 and the net increase in SO_2). In the Texas Interconnection, the additional solar output provides an external benefit of only \$7.74/MWh and the additional wind provides an external benefit of \$13.37/MWh. In the Eastern Interconnection, the additional solar generation provides an average external benefit of \$6.98/MWh and the wind provides an average external benefit of \$8.89/MWh. Compared to the external benefits from the scale effects alone, the external benefits from the net changes in pollution are 47% to 75% smaller.

The analytical and empirical results presented in this paper have clear policy implications. If governments continue to subsidize specific channels of abatement – for example, supporting renewable electricity or energy conservation – then my findings suggest that efficiency gains could be achieved by minimizing the resulting composition effects. The most straightforward way to accomplish this goal would be to combine the subsidies with a tax on NO_X – as opposed to combining the subsidies with a cap-and-trade program. As the analytical model highlights, if a tax is levied on a subset of pollutants, there will be no composition effect, only a scale effect. The estimates in the first two columns of Table 5 reveal that the external benefits provided by renewable capacity expansions will be quite large in this case.

In practice, however, pollution taxes have consistently received less political support than cap-and-trade programs. If taxes are not an option, then the results presented in this analysis suggest that cap-and-trade programs should be designed to minimize, or even prevent, the composition effect. One clear option to accomplish this goal is to establish permit price collars – *i.e.*, a permit price floor and ceiling. In the economic literature, permit price collars in cap-and-trade programs have received support for a variety of reasons. For example, in the presence of uncertainty, hybrid price-quantity instruments can achieve efficiency gains (Roberts and Spence (1976), Weitzman (1978), Pizer (2002)). In addition, previous work highlights that price collars will dampen potentially costly permit price volatility (Burtraw, Palmer and Kahn (2010), Fell and Morgenstern (2010)) and can also mitigate the incentive for market participants to exercise market power (Borenstein et al. (2014)). The analysis presented in this paper highlights an additional benefit – the permit price floor will ensure that expansions in renewable production, or reductions in electricity demand, do not push permit prices below a specified level. If the permit price floor is binding, then increases in renewable output, or reductions in demand, will not cause a composition effect.

Similarly, the expected decline in pollution permit prices caused by the addition of renewables or energy efficiency could in theory be mitigated by dynamically updating the pollution cap. Typically, policymakers set emission caps many years into the future. For example, the CSAPR NO_X cap-and-trade program scheduled to replace the CAIR program sets NO_X limits from 2015 through 2020. If subsidies induce renewable expansions during 2015, for example, then the renewable output will push NO_X permit prices down and lead to a composition effect that negates a large portion of the external benefits the renewable output could have provided over the subsequent five year period. However, had policymakers reduced the NO_X cap following the introduction of the new renewable capacity, the decline in NO_X permit prices, and the resulting composition effect, would be avoided. Of course, such a policy would be quite difficult to implement. Ideally, only the renewable expansions – or energy efficiency investments – that are additional (*i.e.*, caused by the renewable or energy efficiency subsidies) should be considered when adjusting the pollution cap. Any renewable additions caused by the cap-and-trade program itself would simply be part of the cost minimizing strategy to meet the cap, and therefore, should not result in reductions in the cap.

An alternative approach would be to include permit 'set-aside' programs with cap-and-trade programs (EPA (2007)). With a set-aside program, governments initially hold a portion of the pollution permits out of the market. As improvements in energy efficiency and increases in renewable electricity cause scale effects that reduce the emissions of the capped pollutant, the set-aside permits can be retired in proportion to the avoided emissions. By retiring the permits, there will be no corresponding decline in the market price of permits, and therefore, no composition effect. In practice, permit set-aside programs have received some limited use in the EPA's cap-and-trade programs. However, instead of retiring the set-aside permits, they are often allocated to the renewable suppliers that provided the initial scale reduction in emissions. Unless the permits are voluntarily retired, these set-aside permits will be sold on the open market and the composition effect will still occur.

V Conclusion

Policies designed to expand renewable generation are being used extensively. However, they are not being used in isolation. Frequently, renewables are subsidized in regions with overlapping environmental policies. For example, 17 of the 25 eastern states participating in the EPA's NO_X cap-and-trade programs have also adopted Renewable Portfolio Standards. Previous studies highlight that, in the presence of a binding emissions cap, increasing renewable generation will have no impact on the aggregate emissions of the capped pollutant (Sijm (2005), Pethig and Wittlich (2009), Böhringer and Rosendahl (2010), Fischer and Preonas (2010)). However, the literature exploring the interactions between multiple policy instruments largely abstracts from the fact that the electricity sector produces a wide variety of pollutants, many of which are not directly regulated.

In this paper, I examine how renewable subsidies interact with existing, market-based environmental regulations to affect the emissions of both regulated and unregulated pollutants. I first consider a simple analytical model of an electricity market that emits multiple pollutants. I show that, if the regulated pollutants are taxed, increasing renewable output necessarily reduces emissions of each and every pollutant. In contrast, if the regulated pollutants are subject to caps, expanding renewable generation can inadvertently increase emissions of the unregulated pollutants.

To explore whether this unintended increase in unregulated pollution would occur in practice, I predict how investments in new wind turbines and solar panels would interact with the EPA's NO_X cap-and-trade program in the eastern U.S. Using hourly generation and emissions data, I quantify how unregulated CO_2 and SO_2 emissions would be affected by the scale and composition effects caused by the renewable capacity additions. My estimates reveal that the scale effect – the reduction in non-renewable generation caused by the new renewable output – will lead to sizable reductions in the emissions of each pollutant. However, I also provide evidence that, in the presence of a binding cap on NO_X, the increase in renewable output will cause a composition effect – in the form of a shift away from relatively clean, natural gas generation towards dirtier, coal-fired output – that negates much of the unregulated pollution savings achieved by the scale effect. In particular, I find that adding renewable capacity would increase the annual emissions of SO_2.

In settings where policymakers are only able to regulate a subset of the pollutants emitted by power plants, the results presented in this paper provide a clear argument in favor of combining subsidies for renewable electricity – or similarly, subsidies for energy conservation – with emission taxes, as opposed to combining subsidies with emission caps.

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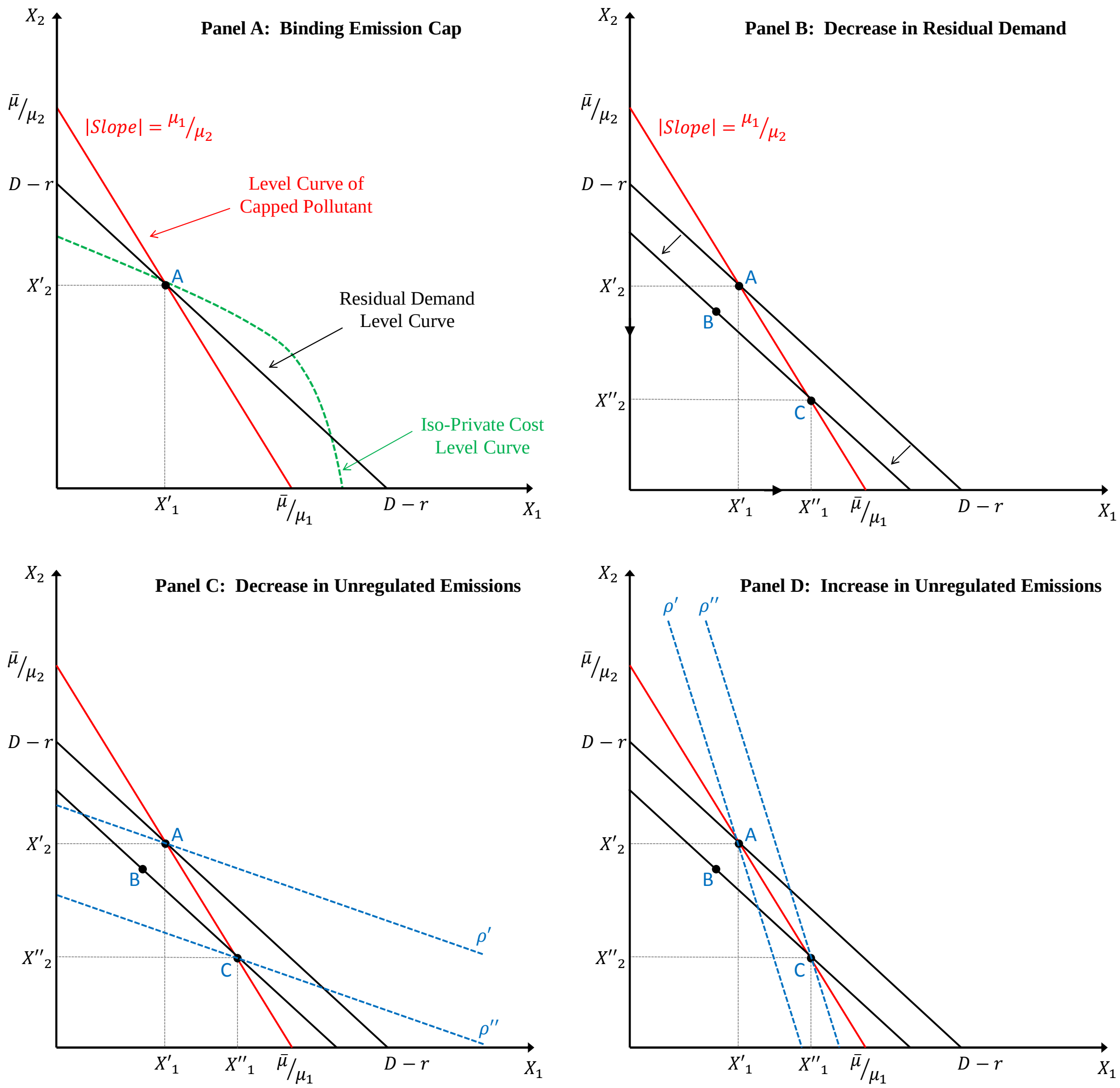

Figure 1: Change in conventional generation and emissions with an overlapping emission cap.

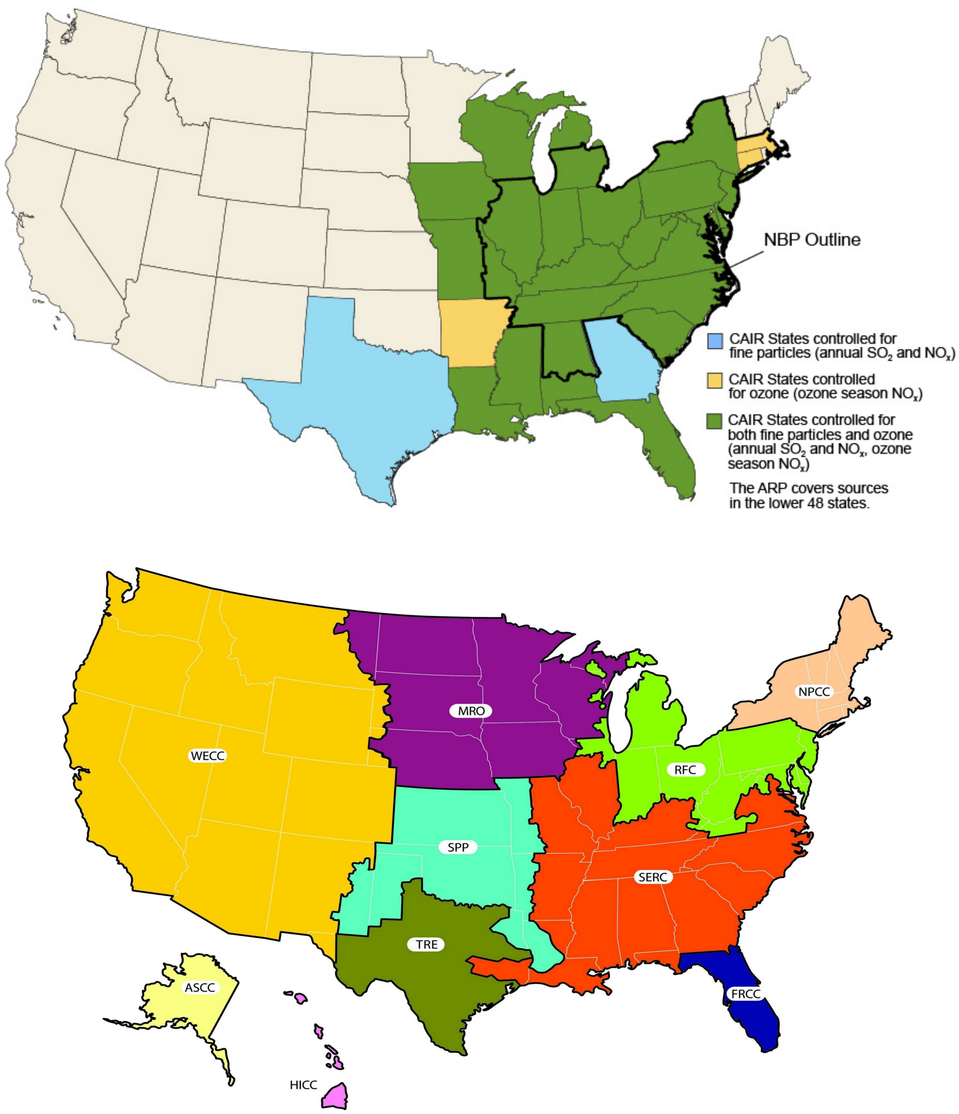

Figure 2: EPA CAIR states and NERC regions. Source: EPA.

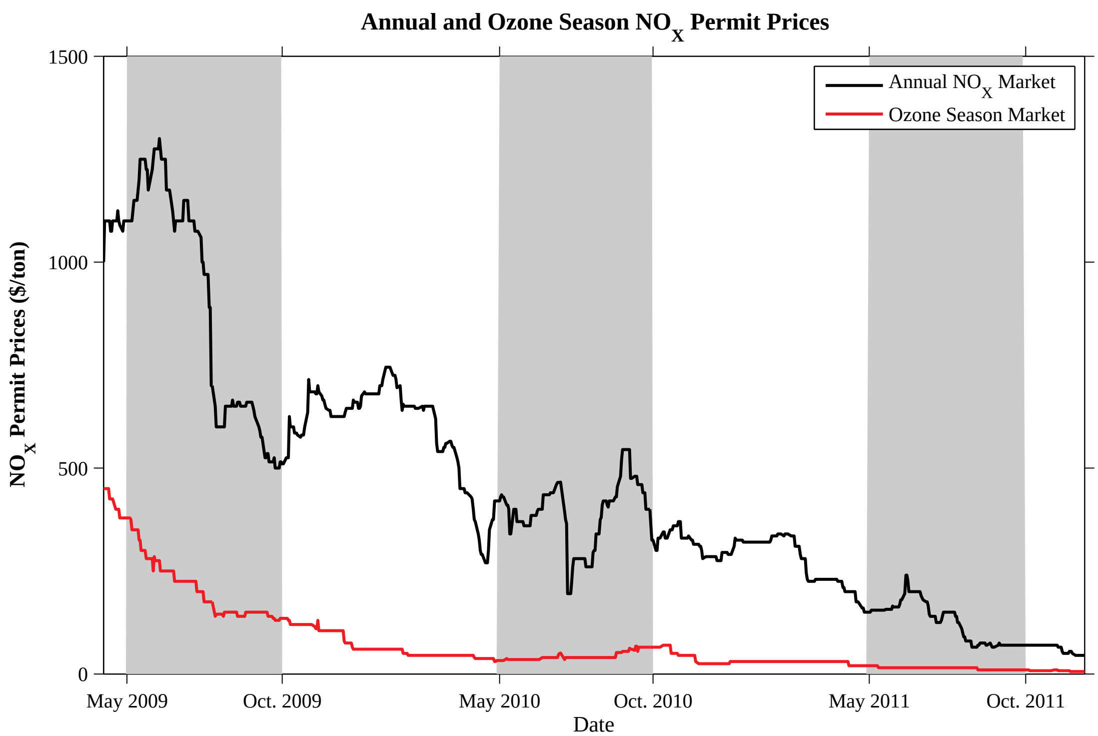

Figure 3: Daily permit prices for the CAIR NO_X cap-and-trade programs. Ozone season months (May-September) are shaded.

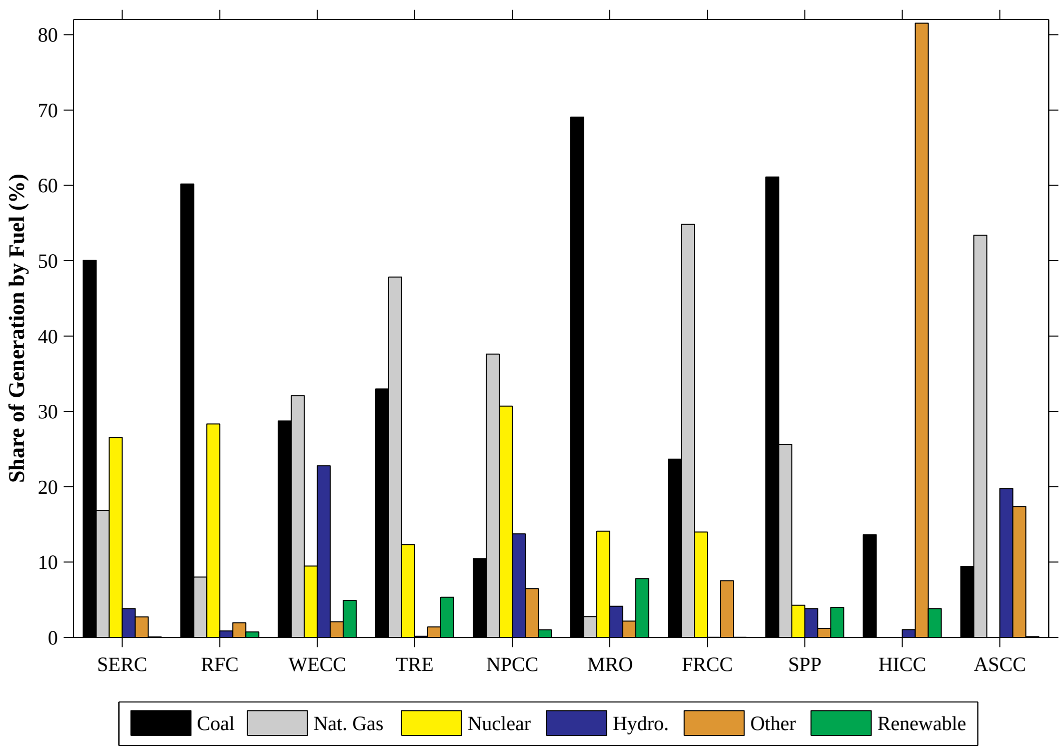

Figure 4: Share of Generation by Fuel Source (2009). Source: EIA.

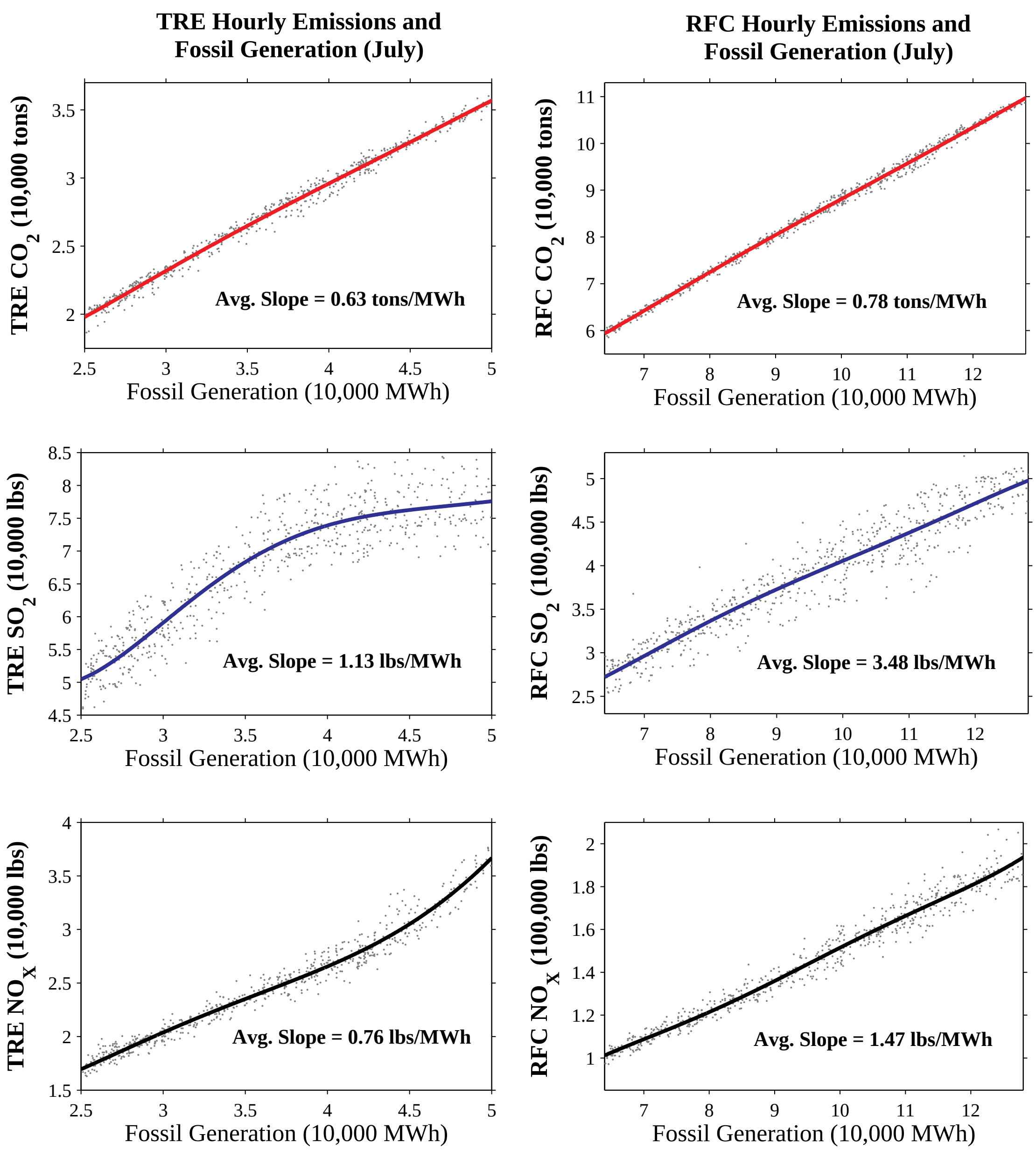

Figure 5: Polynomial estimates of the relationship between hourly emissions and hourly fossil generation. The estimates are displayed for two NERC regions (TRE and RFC) during July, 2009.

Hourly Eastern Interconnection Emissions (Pre/Post Ozone Season)

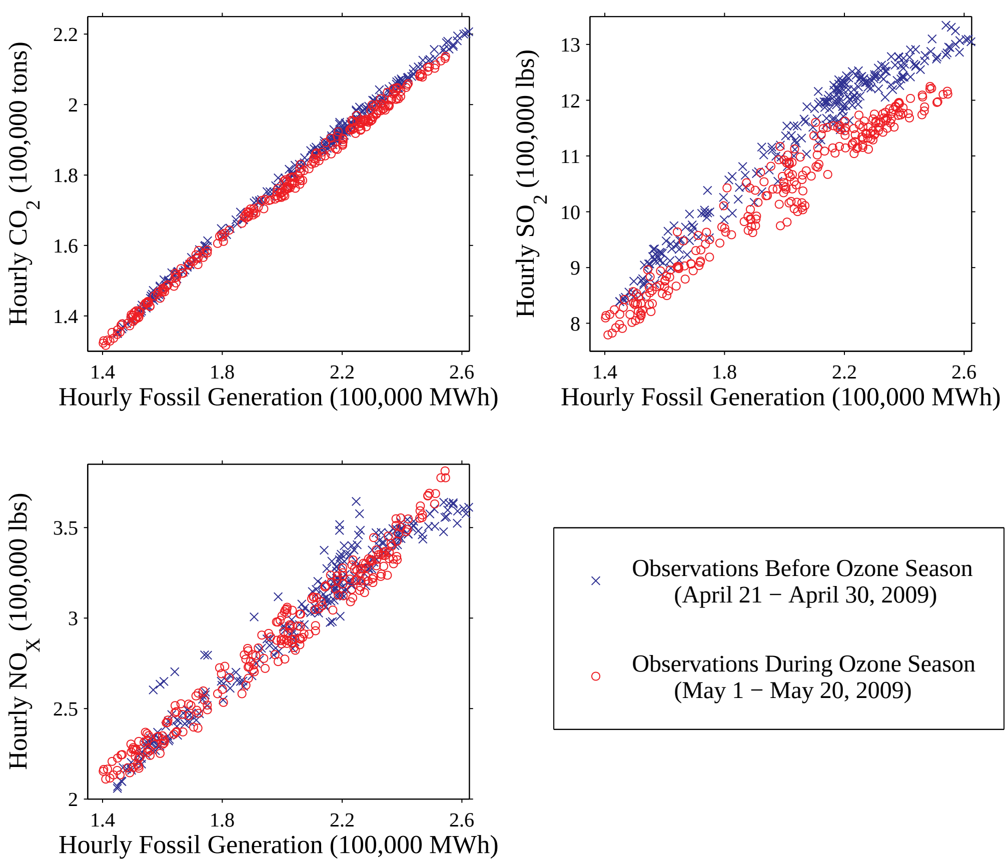

Figure 6: Hourly Eastern Interconnection emissions during the 10 days before and after the beginning of the Spring, 2009 ozone season.

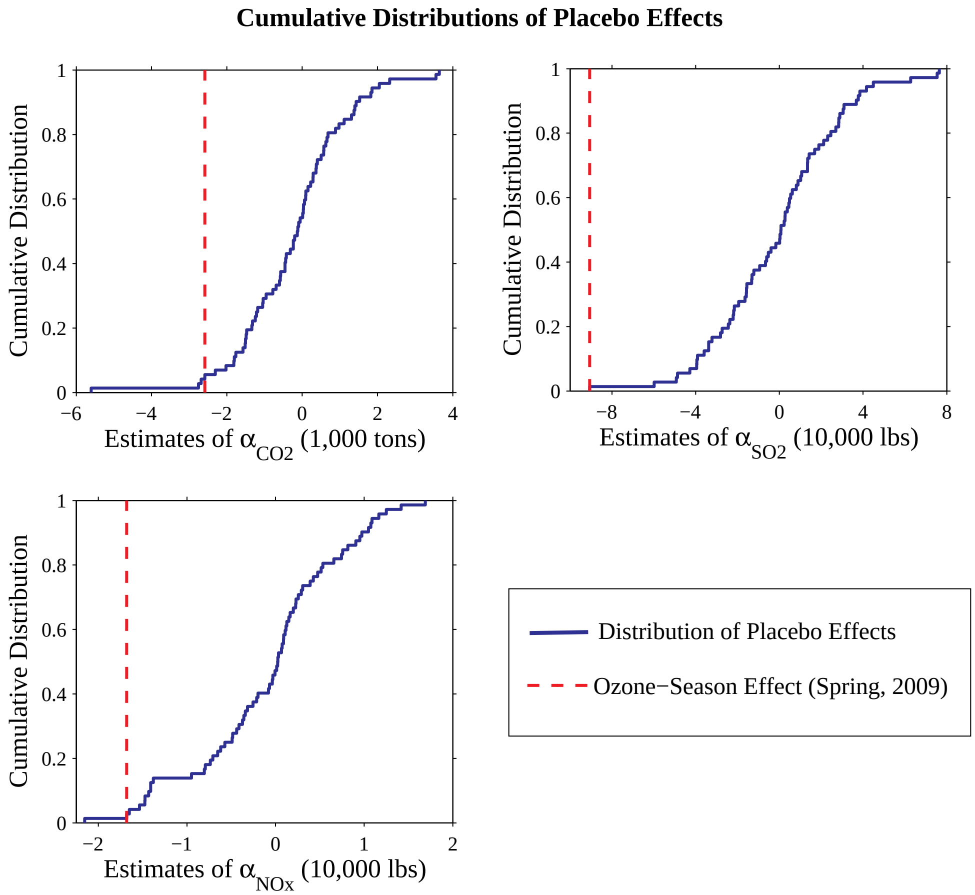

Figure 7: Cumulative distributions of the point estimates of the average change in hourly emissions caused by placebo ozone season treatments.

Table 1: Emission Rates by Technology

	Combined Cycle Gas	Coal Units	Other
N	535	1,911	1,029
Median CO_2 Rate *(tons/MWh)*	0.44	1.06	0.71
Median SO_2 Rate *(lbs/MWh)*	0.01	6.79	0.01
Median NO_X Rate *(lbs/MWh)*	0.12	2.85	0.95

'Other' generators are comprised of open-cycle natural gas turbines and diesel units. Median emission rates are equal to the 50th percentile of the unit-level, average emission rates between January 1, 2009 and December 31, 2012.

Table 2: Annual Scale Effect of Solar and Wind Generation

	Scale Effect of Solar			Scale Effect of Wind		
Market	CO_2 (tons/MWh)	SO_2 (lbs/MWh)	NO_X (lbs/MWh)	CO_2 (tons/MWh)	SO_2 (lbs/MWh)	NO_X (lbs/MWh)
TRE Interconnect	-0.630**	-0.698**	-0.884**	-0.651**	-1.251**	-0.635**
	(0.003)	(0.034)	(0.008)	(0.003)	(0.037)	(0.007)
Eastern Interconnect	-0.722**	-2.367**	-1.333**	-0.729**	-2.552**	-1.246**
	(0.002)	(0.039)	(0.011)	(0.002)	(0.023)	(0.007)
RFC	-0.796**	-3.536**	-1.559**	-0.797**	-3.717**	-1.512**
	(0.002)	(0.052)	(0.014)	(0.002)	(0.036)	(0.009)
SERC	-0.736**	-2.332**	-1.177**	-0.736**	-2.443**	-1.112**
	(0.003)	(0.059)	(0.015)	(0.002)	(0.034)	(0.012)
FRCC	-0.560**	-1.344**	-1.111**	-0.557**	-0.912**	-0.706**
	(0.003)	(0.037)	(0.017)	(0.003)	(0.020)	(0.009)

Point estimates represent the average annual scale effect of a MWh of renewable electricity supplied by additional solar or wind capacity. Newey-west standard errors, based on 24-hour lags, are reported. * = significant at the 5% confidence level; ** = significant at the 1% confidence level.

Table 3: Composition Effect: Spring 2009 Ozone Season

	Average Change in Hourly Emissions		
Market	NO_X (lbs)	CO_2 (tons)	SO_2 (lbs)
Eastern Interconnect	-16,809**	-2,582**	-90,629**
	(3,803)	(735)	(18,754)
TRE Interconnect	11	-93	-3,004
	(543)	(312)	(5,467)
	Average Change in Hourly Generation		
Market	Coal Units (MWh)	Combined Cycle Gas (MWh)	Other (Gas/Diesel) (MWh)
Eastern Interconnect	-2,361**	2,164**	197
	(870)	(696)	(1,035)

Point estimates represent the average hourly change in emissions, or generation, caused by the beginning of the 2009 ozone season. Newey-west standard errors, based on 24-hour lags, are reported. * = significant at the 5% confidence level; ** = significant at the 1% confidence level.

Table 4: Net Effect of Solar and Wind Generation

	Net Effect of Solar		Net Effect of Wind	
Market	CO_2 (tons/MWh)	SO_2 (lbs/MWh)	CO_2 (tons/MWh)	SO_2 (lbs/MWh)
TRE Interconnect	-0.495**	4.068**	-0.553**	2.175**
	(0.003)	(0.054)	(0.003)	(0.052)
Eastern Interconnect	-0.518**	4.820**	-0.537**	4.165**
	(0.003)	(0.074)	(0.002)	(0.043)
RFC	-0.556**	4.868**	-0.564**	4.436**
	(0.003)	(0.093)	(0.002)	(0.062)
SERC	-0.555**	4.017**	-0.566**	3.552**
	(0.004)	(0.101)	(0.003)	(0.075)
FRCC	-0.390**	4.646**	-0.449**	2.892**
	(0.004)	(0.102)	(0.003)	(0.055)

Point estimates represent the average annual net change in emissions caused by a MWh of renewable electricity supplied by the additional solar or wind capacity. * = significant at the 5% confidence level; ** = significant at the 1% confidence level.

Table 5: External Benefits of Solar and Wind Generation

	Scale Effect Only		Net Effect	
Market	Solar ($/MWh)	Wind ($/MWh)	Solar ($/MWh)	Wind ($/MWh)
TRE Interconnect	21.84**	23.53**	7.74**	13.37**
	(0.17)	(0.17)	(0.20)	(0.20)
Eastern Interconnect	28.25**	28.81**	6.98**	8.89**
	(0.15)	(0.11)	(0.24)	(0.15)
RFC	32.51**	33.40**	8.10**	9.22**
	(0.17)	(0.14)	(0.28)	(0.19)
SERC	28.20**	28.78**	9.76**	11.04**
	(0.22)	(0.14)	(0.33)	(0.25)
FRCC	20.60**	19.87**	3.23**	8.61**
	(0.18)	(0.14)	(0.33)	(0.21)

The point estimates represent the average external benefit provided by a MWh of renewable electricity supplied by the additional solar or wind capacity. Each ton of CO_2 offset is assumed to provide an external benefit of $32. Each ton of SO_2 offset is assumed to provide an external benefit of $3,982. Each ton of NO_X offset by the scale effect is assumed to provide an external benefit of $650. * = significant at the 5% confidence level; ** = significant at the 1% confidence level.

Appendix Table 1: Ozone Season Impact – Alternative Specifications

	Average Change in Hourly in Emissions		
Window Size	NO_X (lbs)	CO_2 (tons)	SO_2 (lbs)
+/- 7 Days	-19,249**	-3,119**	-69,045**
	(5,429)	(1,098)	(14,666)
+/- 10 Days	-16,809**	-2,582**	-90,629**
	(3,803)	(735)	(18,7548)
+/- 14 Days	-12,895**	-3,743**	-83,089**
	(4,552)	(811)	(15,556)

	Average Change in Hourly in Emissions		
Time Trend	NO_X (lbs)	CO_2 (tons)	SO_2 (lbs)
Linear	-16,809**	-2,582**	-90,629**
	(3,803)	(735)	(18,7548)
Second Order Polynomial	-11,716*	-3,178**	-78,545**
	(5,248)	(759)	(13,172)
Third Order Polynomial	-19,814**	-2,731*	-66,515**
	(6,781)	(1,131)	(17,496)

Point estimates represent the average hourly change in emissions, or generation, caused by the beginning of the 2009 ozone season. Newey-west standard errors, based on 24-hour lags, are reported. In the top three models, a linear time trend is used and the number of observations included varies with the size of the window around the ozone season switch. Each of the bottom three models is estimated using a +/-10 day window and Chebyshev polynomial time trends of varying degrees. * = significant at the 5% confidence level; ** = significant at the 1% confidence level.