Overlapping Environmental Policies and the Impact on Pollution

Kevin Novan*

February 22, 2016

Abstract

In an effort to reduce pollution from the electricity sector, governments are heavily subsidizing production from clean, renewable energy sources. However, the subsidies for renewable electricity are not being used in isolation. Instead, it has become the norm for governments to support renewables in regions where some pollutants are already regulated. In this paper, I examine how increases in renewable generation interact with market-based environmental regulations to affect the the emissions of both regulated and unregulated pollutants. Using a simple analytical model, I first demonstrate that, when combined with a cap-and-trade program, expansions in renewable generation have the potential to cause an undesirable outcome – they can increase emissions of unregulated pollutants. To explore whether this unintended increase in unregulated pollution could occur in practice, I look back at a NO_X cap-and-trade program that was in place in the eastern U.S. from 2009 through 2014 – the EPA's Clean Air Interstate Rule. Using hourly generation and emissions data, I estimate how unregulated emissions of CO_2 and SO_2 would have been affected by adding new wind turbines and solar panels to the regulated region. I show that, once the interaction with the NO_X cap is taken into consideration, renewable capacity additions would have offset much less CO_2 than was previously thought. Moreover, I find that the renewable additions would have increased SO_2 emissions.

JEL Codes: Q58, Q48, H23

Keywords: Environmental Regulation; Market Based Instruments; Clean Air Interstate Rule

*Department of Agricultural and Resource Economics, UC Davis, One Shields Avenue, Davis, CA 95616. Email: *knovan@ucdavis.edu*. Funding support for this project from the UC Office of the President and the University of California Center for Energy and Environmental Economics is gratefully acknowledged.

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] For example, production from wind turbines in the U.S. 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 increases in renewable output necessarily reduce the amount of pollution emitted by the electricity sector.

To determine how renewable electricity affects pollution, it is important to note that policies supporting renewables are not being used in isolation. Instead, it has become the norm for governments to subsidize renewables in regions where certain pollutants are already regulated. For example, in the market studied in this analysis – the electricity sector in the eastern U.S. – the Environmental Protection Agency (EPA) has used a cap-and-trade program to limit the amount of NO_X emitted by power plants since 2003. Over the same time period, federal tax credits and state-level renewable portfolio standards have spurred steady increases in renewable capacity throughout the region.[2] Previous theoretical 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, it remains unknown how the emissions of the other pollutants, the majority of which are not regulated by emissions caps, may be affected by renewables. Contributing to the existing literature, this paper analytically and empirically examines how renewables interact with market-based environmental regulations to affect the emissions of both regulated and unregulated pollutants.

[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.

Looking back at a NO_X cap-and-trade program that was in place in the eastern U.S. during 2009, I present evidence that, in the presence of a binding cap on NO_X, additional investments in renewable capacity would have lead to increases in the emissions of unregulated pollutants.

To provide intuition for how renewables and pollution regulations can interact, I first present a simple analytical model of an electricity sector 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 uncapped pollutants. In particular, the composition effect can dominate, increasing the emissions of unregulated pollutants.

To explore whether this unintended increase in unregulated pollution could occur in practice, I estimate how hypothetical additions of wind turbines and solar panels in the eastern U.S. would have interacted with a NO_X cap-and-trade program run by the EPA. My analysis focuses specifically on 2009 – the first year the EPA imposed the Clean Air Interstate Rule which capped annual NO_X emissions in twenty seven eastern states. Using historical data on the hourly output and emissions from fossil fuel power plants in the region, I estimate how the unregulated emissions of CO_2 and SO_2 would have been affected by the scale and composition effects caused by increasing renewable capacity. Building on the empirical strategy employed in several recent studies (Callaway, Fowlie and McCormick (2015), Siler-Evans, Azevedo and Morgan (2012), Carson and Novan (2013), Graff Zivin, Kotchen and Mansur (2014), Jacobsen (2014)), I first predict the scale effect that would have been caused by increasing renewable output by estimating how pollution responded to equal reductions 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 – would have caused significant reductions in the emissions of each pollutant.

However, with a binding cap-and-trade program in place, the net change in NO_X would not have equaled the NO_X reduction caused by the scale effect. Instead, the permit price would have declined until the net change in NO_X emissions was ultimately zero. To determine how the resulting decline in the permit price would have affected the unregulated pollutants, I examine how generation from fossil fuel power plants responded to an abrupt, policy-induced change in the NO_X permit price during 2009. I find evidence that, during the period studied, a decrease in the NO_X permit price would have caused a harmful composition effect. Specifically, a permit price decline would have driven a shift away from relatively clean, natural gas generation towards dirtier, coal-fired output that would have negated much of the scale reduction in unregulated pollution. In particular, I show that, once the composition effect is taken into consideration, renewable electricity expansions would have offset substantially less CO_2 than was previously thought. Moreover, renewable expansions would have actually increased the emissions of SO_2.

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

[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).

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 can be very poor substitutes for the missing emissions prices.

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

[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.

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 produced using a non-polluting, renewable energy source. 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] It is important to note that, while I explicitly solve for the impact of renewable generation on pollution, the analytical 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 by 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.

It is also important to stress that the analytical model, as well as the subsequent empirical analysis presented in this paper, focus on the short-run impacts of renewable electricity. In particular, I do not directly examine how (a) the non-renewable generation capacity mix may change in response to greater levels of renewable output, and (b) the future level of the pollution caps or taxes may respond to current levels of renewable output. These long-run considerations are discussed following the empirical analysis.

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

[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.

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:

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

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:

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

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

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

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

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

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

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

[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.

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, 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).

[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.

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 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

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

[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, $d\lambda_\mu/dr = -(c_2''\cdot\mu_1+c_1''\cdot\mu_2)/(\mu_2-\mu_1)^2<0$.

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.

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, in theory, increase the emissions of unregulated pollutants. The remainder of this paper examines whether this perverse outcome could have occurred in practice. To do so, I focus on a specific regional cap-and-trade program – the EPA's CAIR program which established NO_X emission limits in the Eastern U.S. from 2009 through 2014. This section describes the CAIR 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

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

particularly a problem during the summer when NO_X combined with longer, sunnier 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 CAIR in 2009. The CAIR program consisted of two separate NO_X cap-and-trade programs. The first established a cap on the annual NO_X emissions from electricity generating units. The second placed 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 had to surrender one annual permit and one ozone season permit. For each ton of NO_X emitted during October through April, only an annual permit was required. The 27 states covered by the CAIR program are highlighted in Figure 2.[13]

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 – suggesting that both the annual and ozone season caps represented binding regulations during 2009.[14] Specifically, I use the term binding to mean that a marginal increase in the cap will cause an equal increase in the aggregate amount of NO_X emitted. 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 no longer binding. This is supported

[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 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.

by the fact that, during each year of the CAIR program, the annual and ozone season NO_X caps exceeded the actual emissions.[15]

It is important to note that, in addition to the the NO_X caps established by CAIR, other pollutants were subject to market based regulations as well. Beginning in 1995, the EPA's Acid Rain Program (ARP) established a nationwide cap on the aggregate emissions of SO_2. In addition, beginning in 2010, the CAIR program also established a tighter cap on the annual emissions of SO_2 from generators located specifically in the eastern CAIR states. However, during the period of time the CAIR NO_X caps were in place (2009 through 2014), neither the ARP or the CAIR SO_2 program created a binding cap on SO_2. From 2008 and onwards, the aggregate emissions of SO_2 from generators covered by the ARP remained well below the mandated emission cap.[16] This was due to a number of factors including reduced overall demand for electricity, a large decline in the price of natural gas, and an increase in the penetration of pollution control equipment reducing SO_2 emissions – largely in response to more stringent state requirements and federal new source review settlements.[17] As a result, generators covered by the ARP were able to bank a large number of allowances that, while they could be used to meet the CAIR SO_2 mandates, could not be carried over to be used in the future CAIR replacement program. Consequently, SO_2 permits which were being traded at a price of over $500 per ton during 2007 fell to almost zero dollars – trading at an average of $2.12 during 2011.

Aside from the SO_2 cap-and-trade program, there were also 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.[18] In addition, very localized cap-and-trade programs also exist.[19] With these few small exceptions,

[15] For a summary of the annual and ozone season emissions int he CAIR region, see EPA (2013).

[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. For information on the annual emissions, see EPA (2013).

[17] From 2008 through 2011, approximately 69 gigawatts (GW) of coal-fired generating capacity added flue gas desulfurization and 23 GW added selective catalytic reduction.

[18] 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.

[19] For example, in an effort to achieve attainment of the federal ozone standard, the Houston, TX metropolitan area

during 2009, when the CAIR NO_X cap was perceived to be a binding regulation, there was effectively one regulated pollutant (NO_X). The remaining pollutants – including CO_2 and SO_2 – were effectively unregulated.

The remainder of this paper focuses on the regional electricity markets that were covered by the CAIR NO_X cap-and-trade programs. My analysis focuses specifically on 2009, the first year of the CAIR program. This market, and this period of time, provides a unique setting to examine how emissions of unregulated pollutants (i.e. CO_2 and SO_2) were affected by renewable capacity expansions under the assumption that a binding cap exists on the annual emissions of NO_X.

Before discussing the empirical anlaysis, it is important to stress that the estimates of the emission impacts presented in this paper apply only to the CAIR region during 2009. Since 2009, the policy environment in the eastern U.S. has undergone important changes. In 2015, the CAIR program was replaced by the Cross-State Air Pollution Rule (CSAPR). While the CSAPR program is similar to CAIR, there are some key differences. First, the CSAPR program established more stringent emission limits on both NO_X and SO_2. As a result, unlike in 2009 when there was perceived to be only one binding pollution cap, there are likely now multiple binding caps. Second, the CSAPR program has introduced "assurance provisions" which restrict the level of interstate trading that is allowed – effectively ensuring that state's emissions stay close to the state-specific emissions budget allocations. As a result of these policy changes, the impact renewable electricity has on CO_2, SO_2, and NO_X may now be fundamentally different than it was in 2009. Nonetheless, it is still useful to look back at the early years of the CAIR program to gain insights into how renewables and market-based pollution regulations can interact.

B. Fossil Fuel Generation and Emissions Data

To explore how renewable capacity expansions may have interacted with a binding NO_X cap in 2009, I seek to answer the following question. Assuming power plants in the eastern U.S. were regulated by a binding, annual NO_X cap-and-trade program during 2009, how would the annual

operates an annual NO_X cap-and-trade program.

emissions of CO_2, SO_2, and NO_X have been affected by adding 1,000 megawatts (MW) of wind or solar generation capacity to the region?[20] To examine how emissions would have responded to the additional renewable capacity, 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 was binding, the annual level of NO_X emitted would not have changed. Instead, the increase in renewable output would have caused NO_X prices to decline, causing a potential change in the composition of fossil generation. Therefore, the second step is to estimate how much the resulting composition effect would have altered the annual emissions of each pollutant.

To estimate the scale effect that would have been caused by adding 1,000 MW of renewable capacity, I must first determine which conventional generators would have been 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 that was covered by the CAIR program.

While very little trading occurs across the Interconnections, electricity is traded between NERC regions located within the Eastern Interconnection.[21] 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 would have directly offset conventional generation only within the same NERC region. The second set of estimates is based on the assumption that an

[20]For comparison, wind capacity in the entire CAIR region grew from 18,767 MW during 2009 to 20,509 MW by the end of 2010 and grid scale solar capacity grew from 54 MW by the end of 2009 to 259 MW by the end of 2010. Electricity capacity statistics are available from the U.S. Energy Information Administration.

[21]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.

increase in renewable generation would have 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 would be an imperfect substitute for electricity generated at a different point in the Interconnection. However, the results presented in the subsequent sections demonstrate that the estimates are quite insensitive to the trading assumption imposed.

To examine how 2009 emissions would have been affected by increasing renewable capacity, I use data from the EPA's Continuous Emission Monitoring System (CEMS). The CEMS data records the gross, hourly generation from almost every fossil fuel generating unit in the U.S.[22] 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 would have been affected by the 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 would have been

[22] 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.

on the margin at any point in time in any region.[23] 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 have been the marginal source of electricity and would have been 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.[24]

C. Simulating Renewable Generation

To determine how increases in wind or solar capacity would have affected emissions during 2009, I of course need to predict how much additional renewable generation would have been supplied. In reality, both the quantity and timing of electricity supplied by additional wind or solar capacity would depend on where the wind turbines or solar panels were 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 would have impacted emissions – and to explore whether the impact would have differed 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.[25] Assuming that new wind turbines or solar panels installed in the Texas

[23]The results presented in Novan (2015) provide evidence that, in the Texas Interconnection, output from nuclear generators is unaffected by production from wind turbines.

[24]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 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.

[25]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.

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 have been identical in each region and equal to the simulated, hourly time series of renewable output in the Texas Interconnection.

III Estimating the Scale Effect

A. Empirical Strategy

I first estimate the scale effect that would have been caused by the increase in renewable generation. That is, holding NO_X permit prices constant, how much NO_X, CO_2, and SO_2 would have been reduced during 2009 by increasing renewable capacity? My empirical strategy relies on the fact that an increase in renewable generation would have caused an equal and opposite decrease in conventional output.[26] Recall, I assume that only fossil generation would have been offset by renewables. In addition, I assume that only fossil generation in the same NERC region – or alternatively, in the same Interconnection – would have been reduced. Therefore, rather than directly estimating how an increase in renewable generation would have affected pollution, I instead estimate how an equal reduction in fossil generation affected emissions.

Several recent studies employ a similar strategy to estimate how increases in renewable output – or shifts in electricity demand – will affect emissions (Callaway, Fowlie and McCormick (2015), 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

[26] 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.

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 – using hourly data spanning 2009:

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

where

$$
\begin{aligned}
E_t &= \text{Hourly NERC (or Interconnection) } CO_2 \text{ (tons), } SO_2 \text{ (lbs), or } NO_X \text{ (lbs),} \\
G_t &= \text{Hourly NERC (or Interconnection) fossil fuel generation (MWh).}
\end{aligned}
$$

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.[27] 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 were 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 have been taken off-line. As a result, for the same level of fossil output, different units may have been 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.

To estimate how emissions would have been 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 had increased in a given NERC region (or Interconnection)

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

by r_t MWh's, the required fossil fuel generation in the same NERC region (or Interconnection) would have fallen from G_t to $G_t - r_t$. As a result, the hourly emissions in the same NERC region (or Interconnection) would 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) 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 is increased, the relationship between hourly fossil generation and hourly emissions, $f_m(\cdot)$, is held constant. Recall that $f_m(\cdot)$ is largely determined by the order in which the fossil fuel units were dispatched. By not allowing $f_m(\cdot)$ to change with the increase in renewable output, I am assuming that fossil fuel units would have still been dispatched in the same order. For that to be the case, the input prices – including the NO_X permit prices – must have remained the same.[28] Therefore, the expression in Eq. (22) represents the annual change in emissions that would have been 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 also uncover the scale effect (Callaway, Fowlie and McCormick (2015), Siler-Evans, Azevedo and Morgan (2012), Graff Zivin, Kotchen and Mansur (2014), Carson and Novan (2013), Jacobsen (2014), Holladay and LaRiviere (2014)). One departure from the earlier studies is that my empirical approach pools observations across hours to estimate $f_m(\cdot)$ while many of the previous studies use within hour-of-day variation in G_t to estimate hour-specific marginal emission rates. While pooling observations across hours does increase the risk of confounding the effect of a change in G_t with a change in other factors varying

[28]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.

systematically over the course of a day, it does provide one potential advantage. Specifically, I am able to estimate a more flexible functional form for $f_m(\cdot)$ which allows me to predict the impact of discrete changes in renewable generation as opposed to strictly marginal changes in renewable output.[29] However, like the earlier literature studying marginal emission rates, 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 no changes would occur to the stock of non-renewable generators.

B. Estimates of the Scale Effect

To produce estimates of the scale effect that would have occurred during 2009, 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).[30] 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 –

[29] Estimates of the scale effect were also made without pooling the data across hours. Following the marginal emission rate literature, hour-specific marginal emission rates were estimated for each month for the Texas and Eastern Interconnections. To estimate the scale effect, the month-by-hour-specific marginal emission rates were then multiplied by the simulated renewable output added during each hour of each month. Aggregating the products across all months and hours results in an estimate of the scale impact on pollution. The point estimates of the scale effect for each pollutant, and in each interconnection, were nearly identical to the estimates made using the pooled approach.

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

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.[31] 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 that would have been caused by 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 that would have been offset by each MWh of new renewable output. The results reveal that significant reductions in each of the pollutants would have been achieved during 2009. Moreover, the estimates highlight that scale effect varies by technology and location. First, within the same region, the two technologies would have offset different amounts of pollution. For example, in the TRE Interconnection, wind turbines would have 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 would have produced more heavily during the low demand hours when the marginal SO_2 rates were higher and the marginal NO_X rates were lower.[32] 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, would have resulted in larger decreases in emissions.

[31] 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.

[32] These results are consistent with the estimates of the impact of wind and solar generation on TRE emissions presented by Novan (2015).

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 would have reduced 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 would have offset 0.6% of the CO_2, 0.9% of the NO_X, and 0.2% of the SO_2.[33]

IV Estimating the Composition Effect

The preceding section quantifies the pollution reductions that would have occurred during 2009 solely due to the scale effect caused by adding renewable capacity. With a binding cap on NO_X, however, the annual reduction in NO_X would not have been achieved. Instead, the scale effect would have pushed the NO_X permit price downwards until the cap was again binding and the net change in NO_X reached zero.

As the analytical model in Section I demonstrates, the resulting decrease in the permit price could change the relative composition of generation from conventional sources, potentially causing 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.[34] If a reduction in the NO_X permit price would have caused fossil fuel units to alter their NO_X emission rates, and not change their level of production, then it is possible that there would have been no meaningful composition effect – and therefore, no additional change in

[33] 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).

[34] 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)).

the levels of the unregulated emissions.

In this section, I provide evidence that a decrease in NO_X permit prices would have caused a composition effect that would have increased 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 that would have occurred during 2009.

A. Identification Strategy

To determine if a change in the NO_X permit price would have caused a composition effect that would have altered 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, affected the level of emissions. Unfortunately, much of the historical variation in the price of NO_X permits was likely driven by factors that affected 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 cost of emitting NO_X that occured between the ozone season and the non-ozone season.[35] Recall, during the CAIR program's non-ozone season (October through April), only a permit from the annual market had to be surrendered for each ton of NO_X emitted. However, during the ozone season (May through September), an annual permit and an ozone season permit were required. Referring to Figure 3, on April 30, 2009, the last day before the start of the CAIR program's first 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

[35]Focusing on the period of time when the NBP was in place, Deschenes, Greenstone and Shapiro (2012) use a similar strategy to estimate the impact of air quality changes on health and defensive expenditure.

pounds/MWh, it would have 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.

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 affected 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 am forced to 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 was no discontinuity in the cost they faced for emitting NO_X. 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 lead 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 did in fact decrease pollution, I focus on how emissions changed 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.[36] It is important to note that I do not estimate the model separately for each individual NERC region in the Eastern Interconnection. If the discontinuity in the NO_X prices caused 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

[36] 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.

to differ across weekends and weekdays.[37] 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 caused a decrease in the average hourly emissions of CO_2 and SO_2. Under the assumption that fossil fuel generators would 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 have resulted in a composition effect that would increase the emissions of all three pollutants. Of particular interest will be the following two ratios:

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

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

The first ratio represents how much additional CO_2 (tons) would have been emitted for each additional pound of NO_X emitted. Similarly, the second ratio represents how much additional SO_2 (pounds) would have been 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 fell by 16,809 pounds, hourly CO_2 fell by 2,582 tons, and hourly SO_2 fell by 90,629 pounds. Relative to the

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

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 were 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 caused the observed change in emissions. To provide supporting evidence that this was not the case, I re-estimate the model specified by Eq. (23) using hourly data from the Texas Interconnection. Recall, Texas generators were 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 had 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 did not have a significant impact on any of the pollutants.

To provide evidence that the effect of $Ozone_t$ on emissions was driven by the change in NO_X prices, and not by other regulations that could have coincided 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 was no discontinuity in the expected cost of emitting NO_X. Therefore, if the effect of $Ozone_t$ on emissions was 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.[38] 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 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 caused decreases in Eastern Interconnection emissions of each pollutant.

[38] 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.

D. Net Pollution Changes

This section presents estimates of the net changes in 2009 emissions that would have been 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 would have resulted in significant reductions in each of the pollutants. Under the assumption that the cap on NO_X remained binding, the scale reduction in NO_X would not represent the net change in NO_X. Instead, the equilibrium NO_X permit prices would have decreased to the point where the NO_X cap was again binding and the net change in NO_X was zero.

To predict the net changes in annual emissions, I must estimate how much the CO_2 and SO_2 emissions would have changed as the NO_X prices fell and the net change in NO_X returned 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 that would have occurred for each additional pound of NO_X emitted – holding the level of fossil generation constant.[39] Similarly, $\alpha_{SO_2}/\alpha_{NO_X}$ represents the additional SO_2 that would have been 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 price fell, and the NO_X emissions re-increased to the capped level, the emissions of CO_2 and SO_2 would have increased as well. To predict the net change in CO_2 and SO_2 emissions, I solve for the following two values:

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

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

where the annual scale 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

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

using observations surrounding the beginning of the 2009 ozone season switch. During a different part of the year, the same change in the cost of emitting NO_X could have resulted in different changes in emissions.[40] 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 larger or smaller change in NO_X prices, the ratios of $\alpha_{CO_2}/\alpha_{NO_X}$ and $\alpha_{SO_2}/\alpha_{NO_X}$ may differ. 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.

Estimates of the net changes in CO_2 and SO_2 – Eq. (24) and Eq. (25) – are presented in Table 4.[41] 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 a MWh of renewable output would have had on the annual emissions of CO_2 and SO_2 during 2009. Focusing first on the net effects on CO_2, the estimates reveal that the composition effect would have eroded a sizable portion of the pollution reductions caused by the scale effect. In the TRE region, the net CO_2 reductions caused 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.

Focusing next on the net impacts on SO_2, the results are striking. In each region, and for each technology, the estimates reveal that the increases in renewable capacity would have resulted 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 would have increased SO_2 by 2.175 pounds while each MWh from new solar capacity would have increased SO_2 by 4.068 pounds. These differences are driven by the fact that, compared to solar panels, the wind turbines in Texas would have reduced more SO_2 and less NO_X through the scale effects.

[40]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.

[41]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.

E. Discussion

The preceding estimates provide evidence that, in the presence of a binding CAIR NO_X cap, adding renewable capacity would have increased the aggregate emissions of some pollutants during 2009 and decreased the emissions of others. Given this result, an obvious question is the following – would the renewable expansions have provided an external benefit, or cost, during 2009? Before this question can be addressed, it is important to note that the estimates presented in Table 4 represent the net changes in emissions that would have occurred 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 have occurred. 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) depends on the time and location. Therefore, I cannot directly estimate the external benefits that would have been provided by the various renewable investments examined.[42]

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 that would have been provided by the renewable capacity additions. To place a dollar value on the social benefit of reducing a ton of CO_2, I rely on an 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.[43]

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

[43] 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

Using the estimates of the social costs of CO_2, SO_2, and NO_X, I first predict the social benefits that would have been 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 would have provided average external benefits of $21.84/MWh and $23.53/MWh, respectively. In the Eastern Interconnection, the average external benefits would have been even larger – $28.25 per MWh of solar and $28.81 per MWh of wind. Therefore, over the course of 2009, the scale effects caused by adding 1,000 MW of solar capacity would have provided 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 would have been $55 million in the Texas Interconnection and $67 million in the East.

However, with a binding cap on NO_X, the net changes in emissions would have been substantially smaller than the scale reduction in emissions. Therefore, the external benefits would have been dramatically smaller. The last two columns of Table 5 provide the estimates of the external benefits that would have been provided by the net changes in pollution (i.e. the net decrease in CO_2 and the net increase in SO_2). In the Texas Interconnection, the additional solar output would have provided an external benefit of only $7.74/MWh and the additional wind would have provided an external benefit of $13.37/MWh. In the Eastern Interconnection, the additional solar generation would have provided an average external benefit of $6.98/MWh and the wind would have provided 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.

In the case of the CAIR NO_X program, several potential policy changes could have prevented, or at least mitigated, the detrimental composition effect uncovered in this analysis. For one, my

based on the share of total fossil generation in CAIR region), however, the average social cost predictions were very similar.

analytical and empirical results suggest that renewable electricity expansions would have provided much larger pollution reductions had the investments been combined with a tax on NO_X emissions – as opposed to combining renewable expansions with the NO_X cap-and-trade program established by CAIR. 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, had NO_X been regulated by a tax instead of a binding NO_X cap-and-trade program, the external benefits that would have been provided by renewable capacity expansions during 2009 would have been quite large.

In practice, however, pollution taxes have consistently received less political support than cap-and-trade programs. If a NO_X tax was not on the table, then an alternative strategy to mitigate the composition affect could have been to establish NO_X 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 a potential additional benefit – the permit price floor would ensure that expansions in renewable production, or reductions in electricity demand, do not push permit prices below a specified level. If a permit price floor was binding, then increases in renewable output, or reductions in demand, would not cause a composition effect.

Similarly, the expected decline in pollution permit prices caused by the addition of renewable capacity could have, in theory, been mitigated by dynamically updating the pollution cap. Typically, policymakers set emission caps many years into the future. For example, the CAIR NO_X cap-and-trade program was in place from 2009 through 2014. Assume for a second that the NO_X cap was binding over that entire time period. If renewable subsidies induced renewable expansions during 2009, then the renewable output would have pushed NO_X permit prices down and caused a composition effect that negated 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 have been 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.

Finally, an alternative approach to mitigate the composition effect could have been to include wider use of permit 'set-asides' within the CAIR NO_X program. 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.[44] 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.

It is important to again stress that the empirical results presented in this analysis apply directly to the first year of the CAIR program. With the transition to CSAPR, the regulatory environment in the eastern U.S. has undergone significant changes. As a result, the preceding empirical results should not be used to predict how renewable expansions will impact emissions in the eastern U.S. going forward. Nonetheless, the analytical and empirical results presented in this study emphasize that combining subsidies for specific channels of abatement (e.g., renewable electricity or

[44] For information on these programs, see EPA (2007).

energy efficiency) with existing pollution cap-and-trade programs can have unintended, negative consequences. Moreover, to fully understand the consequences of combining environmental policies, the preceding analysis clearly illustrates that it is crucial to consider how the various policy instruments interact to affect the entire range of pollutants emitted by burning fossil fuels.

V Conclusion

Policies designed to expand renewable generation are being used extensively. However, they are not being used in isolation. Instead, financial support for renewable electricity is regularly combined with pollution cap-and-trade programs. Previous theoretical work highlights 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 can interact with existing, market-based environmental regulations to affect the emissions of 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 it is possible for expansions in renewable capacity to increase in pollution in practice, I look back at a NO_X cap-and-trade program that was in place in the eastern U.S. from 2009 through 2014 – the EPA's Clean Air Interstate Rule (CAIR). Using hourly generation and emissions data, I estimate how the quantity of CO_2 and SO_2 emitted during the first year of the CAIR program would have been affected by adding new wind turbines or solar panels. My estimates suggest that the new renewable output would have caused a scale effect – i.e. a reduction in total non-renewable generation – that would have provided sizable reductions in the emissions of each pollutant. However, I also provide evidence that, assuming the CAIR NO_X cap was set at a binding level, the increase in renewable output would have also caused a composition effect – in the form of a shift away from relatively clean, natural gas generation towards dirtier, coal-fired output – that would have negated much of the pollution savings achieved by the scale effect. In particular, I find that renewable capacity additions would have increased SO_2 emissions.

The CAIR program has since been replaced by a new NO_X cap-and-trade program – the Cross-State Air Pollution Rule. As a result, the empirical estimates presented in this paper should not be used to predict the impact renewable electricity will have on emissions in the eastern U.S. going forward. Nonetheless, the analytical and empirical results presented in this analysis clearly illustrate that subsidies for renewable electricity – or similarly, subsidies for energy conservation – can combine with existing pollution regulations to produce unintended, harmful outcomes. Moreover, to fully understand the consequences of combining energy and environmental policies, it is important to consider how the full range of pollutants – both regulated and unregulated – are ultimately affected.

References

Banzhaf, Spencer H., and Andrew B. Chupp. 2012. "Fiscal federalism and interjurisdictional externalities: New results and an application to US Air pollution." *Journal of Public Economics*, 96(5): 449–464.

Baumol, William J., and Wallce E. Oates. 1988. *The Theory of Environmental Policy.* Cambridge University Press.

Bell, Michelle L., Aidan McDermott, Scott L. Zeger, Jonathan M. Samet, and Francesca Dominici. 2004. "Ozone and Short-term Mortality in 95 US Urban Communities, 1987-2000." *The Journal of the American Medical Association*, 292(19): 2372–2378.

Bennear, Lori S., and Robert N. Stavins. 2007. "Second-best theory and the use of multiple policy instruments." *Environmental and Resource Economics*, 37(1): 111–129.

Bird, Lori, Mark Bolinger, Troy Gagliano, Ryan Wiser, Matthew Brown, and Brian Parsons. 2005. "Policies and market factors driving wind power development in the United States." *Energy Policy*, 33(11): 1397–1407.

Böhringer, Christoph, and Knut E. Rosendahl. 2010. "Green promotes the dirtiest: on the interaction between black and green quotas in energy markets." *Journal of Regulatory Economics*, 37(3): 316–325.

Borenstein, Severin, James Bushnell, Frank A Wolak, and Matthew Zaragoza-Watkins. 2014. "Report of the Market Simulation Group on Competitive Supply/Demand Balance in the California Allowance Market and the Potential for Market Manipulation." Energy Institute at Haas Working Paper.

Burtraw, Dallas, Allan Krupnick, Karen Palmer, Anthony Paul, Michael Toman, and Cary Bloyd. 2003. "Ancillary benefits of reduced air pollution in the US from moderate greenhouse gas mitigation policies in the electricity sector." *Journal of Environmental Economics and Management*, 45(3): 650–673.

Burtraw, Dallas, Karen Palmer, and Danny Kahn. 2010. "A symmetric safety valve." *Energy Policy*, 38(9): 4921–4932.

Callaway, Duncan, Meredith Fowlie, and Gavin McCormick. 2015. "Location, location, location: The variable value of renewable energy and demand-side efficiency resources." Energy Institute at Haas – Working paper 264.

Carson, Richard T., and Kevin Novan. 2013. "The Private and Social Economics of Bulk Electricity Storage." *Journal of Environmental Economics and Management*.

Dales, John H. 1968. *Pollution, Property, and Prices: An Essay in Policy-Making and Economics.* Vol. 83, University of Toronto Press.

Deschenes, Olivier, Michael Greenstone, and Joseph S Shapiro. 2012. "Defensive Investments and the Demand for Air Quality: Evidence from the NO_X Budget Program and Ozone Reductions." National Bureau of Economic Research.

EPA. 2007. "Creating an Energy Efficiency and Renewable Energy Set-Aside in the NO_X Budget Trading Program." United States Environmental Protection Agency.

EPA. 2013. "Clearn Air Interstate Rule, Acide Rain Program, and Former NO_X Budget Trading Program: 2012 Progress Report." United States Environmental Protection Agency.

Fell, Harrison, and Richard D. Morgenstern. 2010. "Alternative Approaches to Cost Containment in a Cap-and-Trade System." *Environmental and Resource Economics*, 47(2): 275–297.

Fischer, Carolyn, and Louis Preonas. 2010. "Combining Policies for Renewable Energy: Is the Whole Less Than the Sum of Its Parts?" *International Review of Environmental and Resource Economics*, 4: 51–92.

Fischer, Carolyn, and Richard G. Newell. 2008. "Environmental and Technology Policies for Climate Change." *Journal of Environmental Economics and Management*, 55(2): 142–162.

Fowlie, Meredith. 2010. "Emissions Trading, Electricity Restructuring, and Investment in Pollution Abatement." *The American Economic Review*, 100(3): 837–869.

Goulder, Lawrence H., and Ian WH Parry. 2008. "Instrument Choice in Environmental Policy." *Review of Environmental Economics and Policy*, 2(2): 152–174.

Graff Zivin, Joshua, Matthew Kotchen, and Erin Mansur. 2014. "Temporal and Spatial Heterogeneity of Marginal Emissions: Implications for Electric Cars and Other Electricity-Shifting Policies." *Journal of Economic Behavior and Organization*, 107: 248–268.

Hitaj, Claudia. 2013. "Wind power development in the United States." *Journal of Environmental Eco-*

nomics and Management, 65(3): 394–410.

Holladay, J. Scott, and Jacob LaRiviere. 2014. "How Does Welfare from Non-Pecuniary Policies Vary with Market Prices? Evidence from Fracking, Natural Gas and Emissionsfrom Electricity Generation." Working Paper.

Holland, Steven P. 2011. "Spillovers from Climate Policy to Other Pollutants." In *The Design and Implementation of US Climate Policy*. 79–90. University of Chicago Press.

IAWG. 2013. "Interagency Working Group – Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis - Under Executive Order 12866."

Jacobsen, Grant D. 2014. "Estimating End-Use Emissions Factors For Policy Analysis: The Case of Space Cooling and Heating." *Environmental Science & Technology*.

Jaffe, Adam B., Richard G. Newell, and Robert N. Stavins. 2005. "A tale of two market failures: Technology and environmental policy." *Ecological Economics*, 54(2): 164–174.

Levinson, Arik. 2012. "Belts and suspenders: Interactions among climate policy regulations." In *The Design and Implementation of US Climate Policy*. 127–140. University of Chicago Press.

Lipsey, Richard G., and Kelvin Lancaster. 1956. "The general theory of second best." *The Review of Economic Studies*, 24(1): 11–32.

Montgomery, David W. 1972. "Markets in Licenses and Efficient Pollution Control Programs." *Journal of Economic Theory*, 5(3): 395–418.

Novan, Kevin. 2015. "Valuing the Wind: Renewable Energy Policies and Air Pollution Avoided." *American Economic Journal: Economic Policy*, 7(3): 291–326.

Palmer, Karen, and Dallas Burtraw. 2005. "Cost-effectiveness of Renewable Electricity Policies." *Energy Economics*, 27(6): 873–894.

Pethig, Rudiger, and Christian Wittlich. 2009. *Interaction of Carbon Reduction and Green Energy Promotion in a Small Fossil Fuel Importing Economy.* CESifo, Center for Economic Studies & Ifo Institute for economic research Working Paper 2749.

Pigou, Arthur C. 1920. "The Economics of Welfare." *London: Macnillam*.

Pizer, William A. 2002. "Combining price and quantity controls to mitigate global climate change." *Journal of Public Economics*, 85(3): 409–434.

Roberts, Marc J., and Michael Spence. 1976. "Effluent charges and licenses under uncertainty." *Journal of Public Economics*, 5(3): 193–208.

Sijm, Jos. 2005. "The interaction between the EU emissions trading scheme and national energy policies." *Climate Policy*, 5(1): 79–96.

Siler-Evans, Kyle, Ines Azevedo, and M. G. Morgan. 2012. "Marginal Emissions Factors for the US Electricity System." *Environmental Science & Technology*, 46(9): 4742–4748.

Sorrell, Steven, and Jos Sijm. 2003. "Carbon trading in the policy mix." *Oxford Review of Economic Policy*, 19(3): 420–437.

Weitzman, Martin L. 1978. "Optimal rewards for economic regulation." *The American Economic Review*, 683–691.

Yin, Haitao, and Nicholas Powers. 2010. "Do state renewable portfolio standards promote in-state renewable generation?" *Energy Policy*, 38(2): 1140–1149.

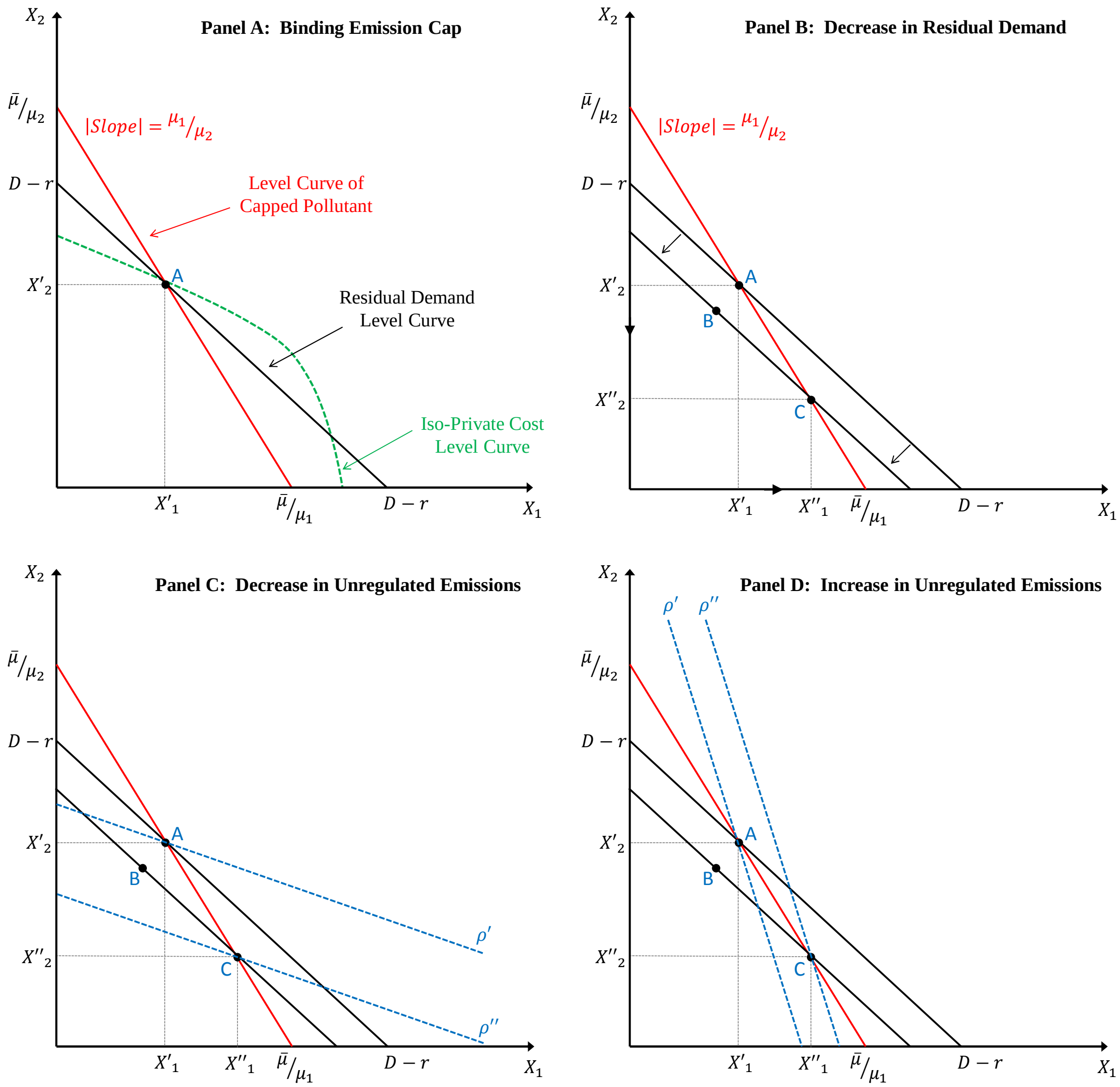

Figure 1: Panel A plots the initial equilibrium level of generation (X_1', X_2') in the presence of a cap on the emissions of μ. The iso-private cost level curve demonstrates that the residual demand could be met at a lower private cost – highlighting that the cap $(\bar{\mu})$ is a binding regulation. Panel B separates the effect of an increase in renewable output (r) into a "scale effect" – from A to B – and a "composition effect" – from B to the new equilibrium C. Panel C depicts a case where the net change in unregulated emissions of ρ are negative and Panel D displays a case where the net change in ρ is positive.

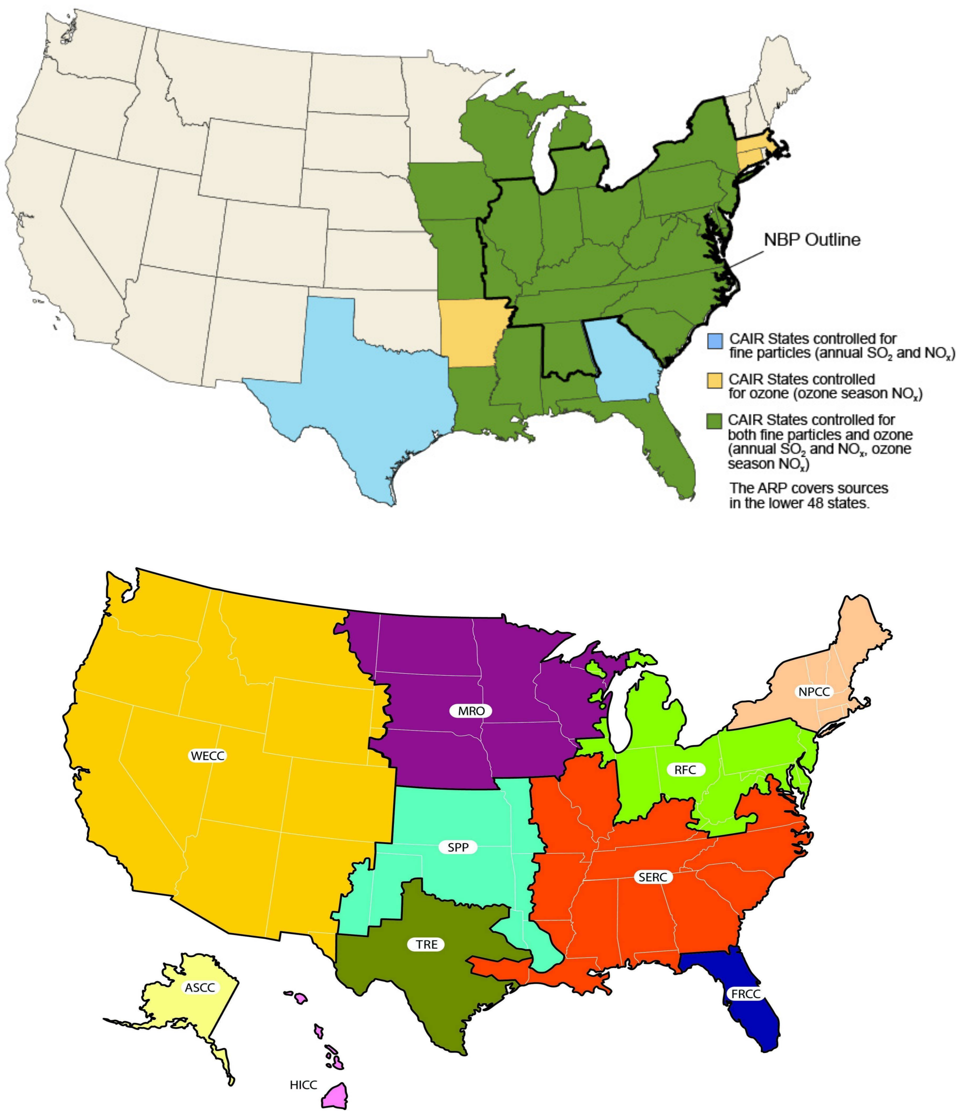

Figure 2: EPA CAIR states and NERC regions. Source: EPA.

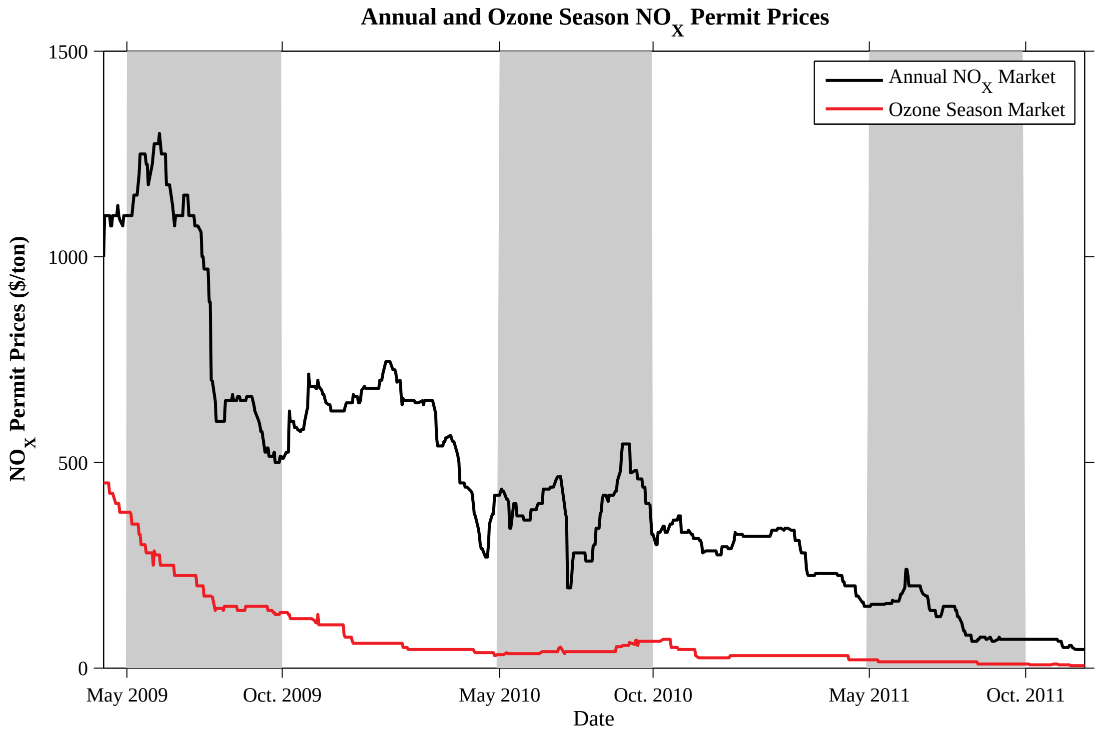

Figure 3: Daily permit prices for the CAIR NO_X cap-and-trade programs. Ozone season months (May-September) are shaded.

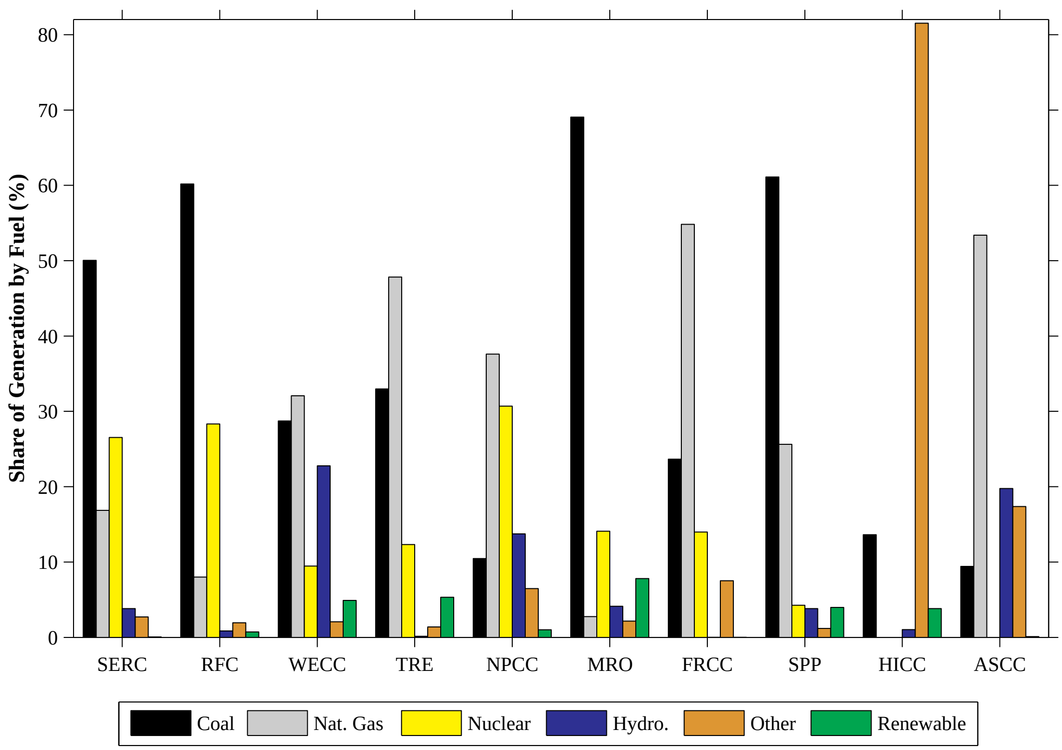

Figure 4: Share of Generation by Fuel Source (2009). Source: EIA.

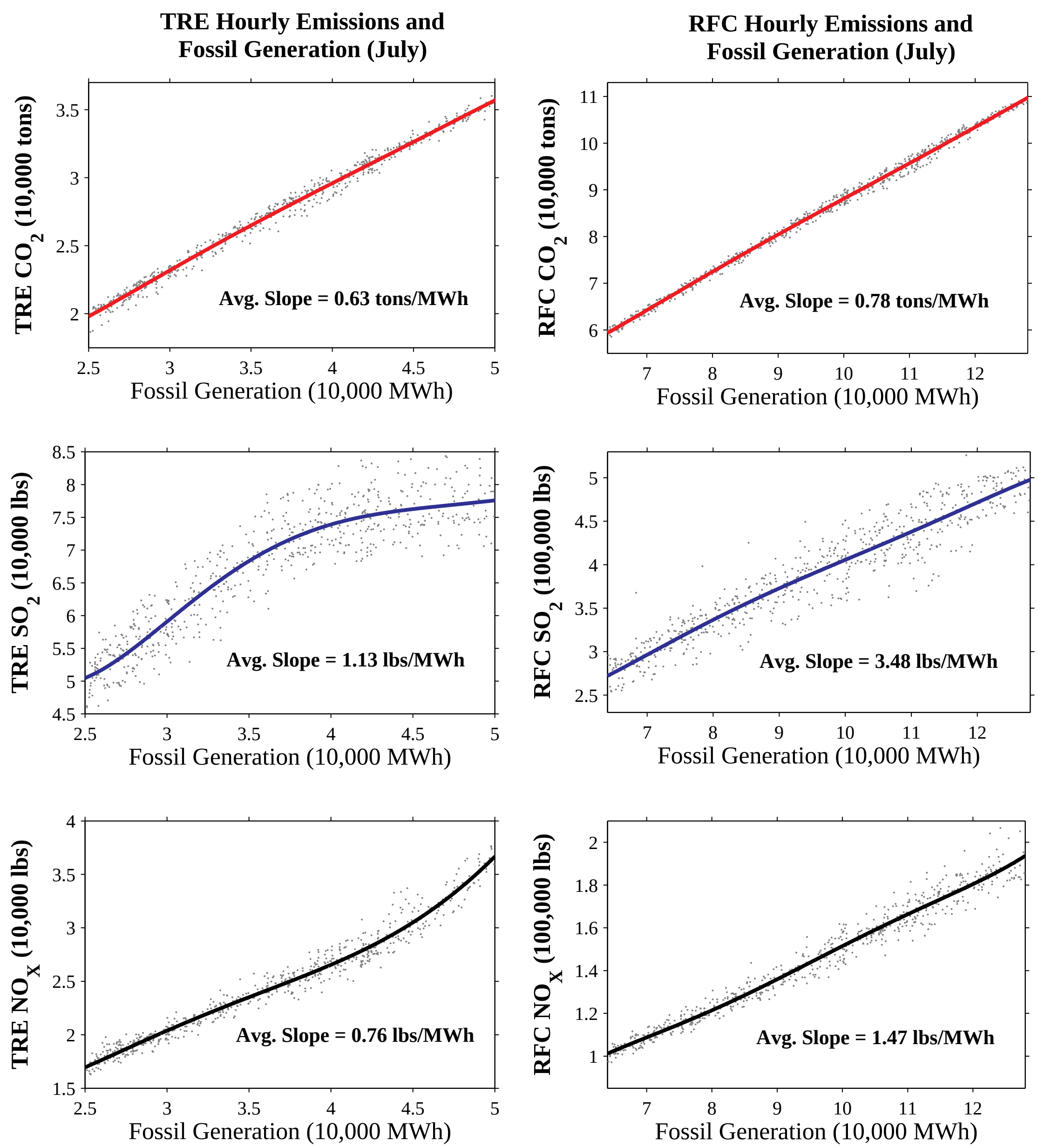

Figure 5: Polynomial estimates of the relationship between hourly emissions and hourly fossil generation. The estimates are displayed for two NERC regions (TRE and RFC) during July, 2009.

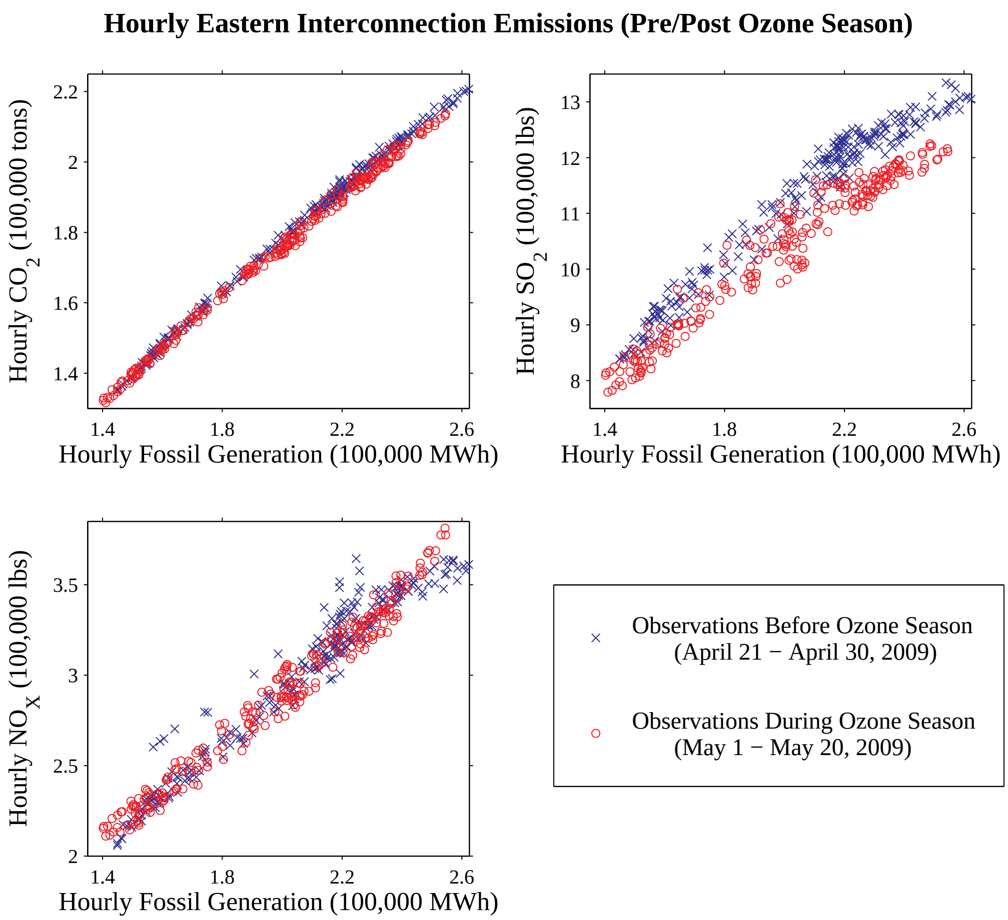

Figure 6: Hourly Eastern Interconnection emissions during the 10 days before and after the beginning of the Spring, 2009 ozone season.

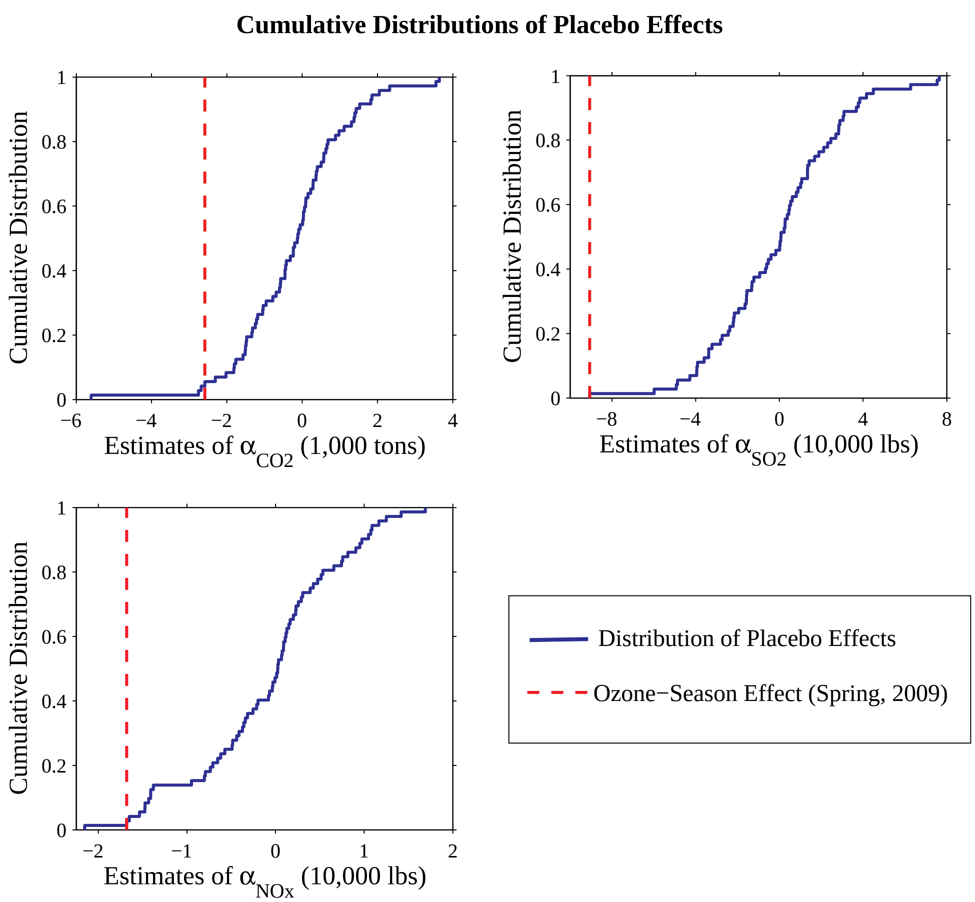

Figure 7: Cumulative distributions of the point estimates of the average change in hourly emissions caused by placebo ozone season treatments.

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

Market	Average Change in Hourly Emissions		
	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

Market	Net Effect of Solar		Net Effect of Wind	
	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.