Title: "Projecting the Impact of the Clean Power Plan on SO2 and NOx Emissions: An Empirical Approach"

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Abstract

We estimate the impact of the Clean Power Plan (CPP) on SO_2 and NO_x emissions. We focus on these co-pollutants because while the amount of CO_2 emitted from electricity generation is well established, the same is not true for local pollutants, SO_2 and NO_x. Unlike previous papers, and unlike the EPA's own approach, we do not rely on engineering-based linear programming models to assess the effects of the policy. Instead, we use historical data from US power plants to empirically estimate the effects of compliance with the CPP on emissions of SO_2 and NO_x. In doing so, we provide an alternative approach to assessing the effects of the CPP. Our results suggest that the EPA may be substantially underestimating the reductions in SO_2, while likely overestimating the reductions in NOx emissions. These differences are important from a public health perspective, because of the health effects of these co-pollutants. We provide estimates of those health effects using an integrated assessment model. Overall, our results suggest that there is value in using an empirical approach to project the environmental impacts of EPA interventions, rather than relying exclusively on engineering-based analyses.

Keywords: Carbon, Clean Power Plan, Climate change, Co-Pollutant emissions, Coal, Electricity generation, Natural gas

1. Introduction

In August 2015, the Environmental Protection Agency (EPA) finalized a new set of regulations on CO_2 emissions by US power plants. The Clean Power Plan (CPP) sets CO_2 emissions reductions targets for each state's power plant sector, while allowing each state to develop its own plan for achieving the reductions. Overall, EPA projects that the CPP will reduce CO_2 emissions from power plants in 2030 by 32% from 2005 levels, and by 19% relative to baseline levels in 2030.

The EPA has provided states with three main mechanisms that they can draw on to reduce CO_2 emissions: (1) reduce demand for electricity; (2) shift the fuel mix from more carbon-intensive energy sources (coal) to less carbon-intensive source (natural gas) and zero-carbon fuels (renewables); and (3) increase the efficiency of the generation process in coal-burning plants (i.e. reduce the plant's heat rate).[1,2] These three mechanisms, in addition to reducing CO_2 emissions, are also expected to reduce emissions of two important co-pollutants: SO_2 and NO_x. These two pollutants have been shown to have serious negative effects on a variety of health outcomes including asthma attacks, heart disease, and mortality (Bell et al. 2008; Thurston and Bell 2014). Indeed, the EPA estimates that the health benefits from reducing co-pollutant emissions will be roughly as large, and perhaps more than twice as large as the climate change benefits of reducing CO_2 emissions (EPA 2015a).

As is the case with many environmental regulations, the CPP has so far been challenged several times in the courts. However, the legal battles surrounding the rule present an interesting and unique case study. Even before the rule was finalized, industry and 12 states filed a suit asking the D.C. Circuit Court to block the CPP in August 2014 (i.e. before the rule was finalized). The Court rejected those challenges citing the, at the time, draft nature of the rule. Immediately after the final rule was published in the Federal Register (in October 2015), a suit was filed and a stay was requested, which was subsequently declined by the D.C. Circuit Court. In an unexpected turn of events the US Supreme Court granted the stay in February 2016 with the late Justice Antonin Scalia casting the tie breaking vote[3]. The D.C. Circuit Court heard oral arguments in September 2016 and is expected to issue a decision in early 2017 (E&E News 2017). Given the uncertainty with regards to the future of the CPP, in particular considering the 2016 presidential election results as well as the change in the politically appointed leadership of the EPA, it is important for scientists and policy makers to have a clear understanding of not just the compliance costs, but also the projected benefits of the CPP.

In this paper, we estimate the impact of the CPP on SO_2 and NO_x emissions as well as the health benefits from the resulting emissions reductions. We focus on these co-pollutant emissions because while the amount of CO_2 emitted from the production of a unit (e.g, kilowatt hour) of electricity is well established, the same is not true for local pollutants, SO_2 and NO_x. This is mainly due to the limited

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[1] The three mechanisms as defined here are different than the building blocks included in the final version of the CPP. Those building blocks include: 1) heat rate improvements in the coal steam fleet, 2) switching from coal to natural gas, and 3) switching from coal to zero emitting renewable energy (RE) capacity. We use the term "mechanism" to capture the main ways fossil fuel powered plants can reduce CO_2 emissions.

[2] Heat rate is the amount of energy used to generate one kilowatt-hour (kWh) of electricity (EIA 2016b).

[3] Justice Scalia passed away on February 13th 2016, 4 days after the US Supreme Court issued the stay.

abatement mechanisms that exist for CO_2 versus the variety of pollution control devices that are available for SO_2 and NO_x.

The amount of CO_2 emissions depends largely on the carbon content of the fuel used for electricity generation (i.e. coal, natural gas, oil, etc.), along with the plants' heat rate. Information on the carbon content of the fuel can be used to calculate an accurate estimate of the amount of CO_2 emitted (assuming no sequestration takes place). However, emissions of co-pollutants depend not only on the carbon content of the fuel used but also on the type of abatement technology that a power plant uses. This adds to the complexity of estimating emissions coefficients for co-pollutants that are solely based on the amount of electricity generated.

Unlike previous papers, and unlike the EPA's own approach, we do not rely on engineering-based linear programming models to assess the effects of these mechanisms (i.e. demand reduction, change in fuel mix, and heat rate improvements) on emissions. Instead, we use historical data from US power plants to empirically estimate how much each of the three mechanisms described above affects emissions of SO_2 and NO_x. In doing so, we provide an alternative approach to assessing the effects of the CPP. More broadly, we offer an alternative to the standard approach used to estimate the emissions impact of policy interventions in the electricity sector that are aimed at reducing CO_2 emissions.

To conduct our empirical analysis, we construct a panel of US power plants, using information from the Emissions and Generation Resource Integrated Database (eGRID) (EPA 2015c). eGRID is a database of US electricity producers, reporting annual output and emissions of various pollutants (CO_2, NO_x, SO_2, etc.). Using these data, we first assess the validity of our model by estimating the impact of these three mechanisms - heat rate improvements, changes in fuel mix, and changes in output of electricity - on CO_2 emissions. We then use the EPA's projections of how much coal and gas plants will reduce output of electricity, and how much coal plants will reduce heat rate, along with our estimates of the effects of these mechanisms to estimate how much CO_2 emissions will fall, assuming that firms behave as projected by EPA. The reductions in CO_2 emissions that we estimate are within about 3% of the EPA's projections.

Having demonstrated the validity of our approach, we examine the impact of the three mechanisms on two criteria co-pollutants, SO_2 and NO_x. Again, we use the EPA's projected reductions in output and heat rate to compare our estimates with the EPA's estimated changes in SO_2 and NO_x emissions resulting from the CPP.

Our results suggest that the EPA may be substantially underestimating the reductions in SO_2, while it is likely overestimating the reductions in NO_x emissions. EPA projects that SO_2 emissions will fall by about 280,000 tons (21%) and NO_x emissions will fall by about 278,000 tons (21%) by 2030, relative to baseline levels[4]. Results using our full sample indicate a reduction of 389,449 tons (30%) for SO_2 emissions and a reduction of 197,405 tons (15%) for NO_x emissions. Using a variety of robustness checks with subsamples of the data, we find that SO_2 emissions will fall by as much as 646,527 tons (51%), while we project that NO_x emissions will decline by as much as 275,294 tons (21%). In other words, assuming that

[4] These estimates are based on EPA's mass based approach.

states achieve the mandated reductions in CO_2 emissions, and do so by inducing plants to reduce output and increase efficiency according to EPA projections, we predict reductions in SO_2 emissions that are 39%-131% larger than EPA projections, while we project reductions in NO_x emissions that are 1%-29% lower than EPA projections.

These differences are important from a public health perspective, because of the health effects of these co-pollutants. We provide estimates of the monetized values of those health effects using an intergrated assessment model. The EPA and the Obama administration have emphasized the public health benefits of reducing co-pollutants in their efforts to promote the CPP. Our results indicate that these benefits may be different, particularly in the case of SO_2 emissions. More generally, our results suggest that in the absence of strong evidence that the effects of these mechanisms will change markedly in the future, there is value in using an empirical approach to project the environmental impacts of EPA interventions, rather than relying exclusively on engineering-based analyses.

The rest of the paper proceeds as follows. Section 2 provides some background on linear programming models, the standard approach for projecting the impacts of environmental regulations such as the CPP, and discusses research using these models to assess the impact of CPP and other electricity-sector regulations. Section 3 presents the eGrid data that are used in the paper, while Section 4 describes the empirical strategy we follow. In section 5 we present our results on the co-pollutant estimates and the various robustness checks. In Section 6 we estimate the monetized health benefits from reducing co-pollutant emissions. The final section offers some concluding thoughts about our approach and the implications of our findings.

2. Related Research

Linear programming (LP) models have been widely used in forecasting the effects of environmental policies on pollutant emissions and subsequent health effects (EPA 2015a; EPA 2011; EPA 2015b; EIA 2015; Burtraw et al. 1998; Chestnut and Mills 2005; Smith et al. 2012; Beasley et al. 2013). A non-exhaustive list of such models includes the National Energy Modeling System (NEMS), maintained by the Energy Information Agency (EIA), the Market Allocation (MARKAL) model developed by the International Energy Agency's (IEA) Energy Technology System Analysis Program (ETSAP), the Integrated Planning Model (IPM) developed by the EPA with support from ICF Consulting Inc. and the Haiku model developed by Resources for the Future (RFF). While there are significant differences among those models, there is a common underlying structure in the way they operate. They all model a wide range of energy related sectors (i.e. energy generation, fuel production, transportation, etc.) with varying levels of detail and aim to minimize an objective function subject to a series of constraints. The objective function minimizes the net present value cost of investing and operating the energy sectors. Constraints include operational limitations (e.g., capacity at which power plants operate, fuel efficiency of light-duty vehicles, etc.), demand-related constraints (e.g., consumer demand for energy use) as well as policy-related constraints such as those imposed by the CPP.

Given that this paper focuses on the projected effects of the CPP, we examine the IPM in more detail, because it is the model on which EPA built its predictions regarding the CPP. The IPM is a multi-region, dynamic, deterministic LP model of the entire US energy sector. Under the assumption of perfect foresight, the model yields a least-cost solution that meets energy demands given a series of constraints. Power plants with similar characteristics are aggregated to construct what IPM calls the "model plant". For example, the 15,023 generating units in the US are aggregated into 4,738 model plants within the IPM. For each plant, the IPM considers a series of variables such as fuel used, heat rate, local pollutant control devices and capacity factors. Based on that information, the model provides emission estimates for a variety of pollutants including CO_2, SO_2, NO_x, PM and ozone, among others. However, the approach used by the IPM to generate these estimates relies on engineering parameters rather than econometric estimation of these emissions using historical data from power plants.

These kinds of models have long been used in environmental economics research to assess the effects of a variety of policy interventions. Examples of environmental policies affecting power plants that have been evaluated using LP models include the US Acid Rain Program (Burtraw et al. 1998; Chestnut and Mills 2005) and the Mercury and Air Toxics Standards Rule (Smith et al. 2012; Beasley et al. 2013).

Most relevant to our research, is a series of papers using the LP models discussed above to forecast the effects of climate-related policies (that resemble the CPP) on the emissions of CO_2 and co-pollutants (Burtraw, Woerman, and Krupnick 2015; Driscoll et al. 2015; Levy et al. 2016; Rudokas et al. 2015). Driscoll et al. (2015) use EPA's IPM to derive emissions estimates from 2,417 fossil fueled power plants in the US. Those projected emissions are then used to estimate public health co-benefits. Driscoll et al. (2015) is one of the few papers that develop alternative scenarios of CO_2 emissions reductions that closely follow the targets set by the CPP and estimate the co-benefits from reductions in ozone and particular matter. Their results suggest that carbon regulations can provide immediate health benefits whose magnitude and spatial distribution depends largely on the way the standards are designed. Burtraw et al. (2015) consider an expanded set of policy designs for carbon reductions by allowing for a tradable performance standard that affects different groups of power generators. They report results that allow trading between: 1) coal-fired power plants, 2) fossil fuel plants, and 3) all electric generators. The authors use the Haiku electricity market model to estimate emissions and compliance costs under the different policy scenarios. They find that under different rates of flexibility of the policy design (e.g., allowing for trading among a greater set of generating units) emissions rates and marginal abatement costs do not move in the same direction. However, all of the policy scenarios they examine provide positive net benefits. Rudokas et al. (2015) use the MARKAL model to estimate changes in SO_2, NO_x and CO_2 based on six climate change mitigation scenarios. The authors consider a series of policies that affect sectors other than electricity (e.g., the transportation and biofuel sectors). The majority of their scenarios include CO_2 targets that are less stringent than those of the CPP. Their low carbon tax scenario shows decreases in both SO_2 and NO_x while their more stringent high carbon tax scenario predicts NO_x increases by the electricity sector.

The contribution of our work lies in proposing a different approach for predicting the impact of a policy intervention on pollution emissions. Instead of relying on the engineering-based calibrated parameters of LP models like the IPM, we take a more empirical approach by utilizing historic data on CO_2, SO_2 and NO_x from observed power plant emissions in order to estimate the impact of policy-induced changes in plant behavior. While previous studies have examine the empirical relationships between CO_2 and various co-pollutants (Boyce and Pastor 2013), our work is the first to econometrically examine the relationships that underlie the EPA's projections of the effects of the CPP. We do not view this approach as a substitute to existing LP models. Rather we believe that our work contributes a complementary approach to projecting the impacts of regulations that induce changes in plant behavior.

While our work is very closely connected to the literature projecting regulatory impacts using LP models (discussed above), we also see a linkage with the literature of retrospective studies that estimate the ex post effects of regulations and compare them with ex ante projections (for an overview of retrospective studies see Kopits et al. 2014). Work in that literature includes several case studies estimating regulatory compliance costs, which the authors then compare with ex ante projections of these costs. These case studies examine a variety of EPA regulations including the Cluster Rule and the MACT 2 Rule (Morgan, Pasurka, and Shadbegian 2014), regulations on the use of methyl bromide (Wolverton 2014), limits on arsenic in drinking water (Morgan and Simon 2014), and the 1998 Locomotion Emissions Standards (Kopits 2014).

Similarly, the Resources for the Future (RFF) Regulatory Performance Initiative focuses on estimating the effects of different EPA regulations and comparing these estimates with ex ante projections. Research under this Initiative has looked at a wide variety of regulations including the Air Toxics Program, the Endangered Species Act, and the Clean Water Act (Taylor, Spurlock, and Yang 2015; Fraas and Egorenkov 2015). In general, these papers tend to find that ex ante costs and benefits are overestimated (Morgenstern 2015; Simpson 2014). Although these papers exploit ex post data, which are not currently available for the CPP, they is similar in spirit to ours, as they focus on assessing ex ante projections of regulatory impact. We take a similar approach, but rather than using ex post data, we use historical data to empirically derive projections of the impact of the CPP, and compare our projections with those derived using LP models.

3. Data

We obtain our data from eGRID, for the following nine years: 1998-2000, 2004-2005, 2007, 2009-2010, and 2012[5] (EPA 2015c). eGRID reports annual electricity output as well as emissions of various pollutants (CO_2, NO_x, SO_2, etc.) at the plant level for utility and non-utility steam units with a capacity of at least 25 megawatts (EPA 2008). Two separate approaches are used to gather the emissions data reported in eGRID. For the majority of facilities, the emissions data are not observed, but instead are imputed based on electricity output. However, for the remaining facilities, the emissions data come from direct observations that are reported to EPA's Emissions Tracking System/Continuous Emissions Monitoring (ETS/CEM). Because our approach is based on estimating the relationship between electricity output and emissions, the observations with imputed (as opposed to observed) emissions data are not useful. Therefore, we only use data from plants whose emissions are observed directly (not imputed) in our analysis.

[5] We did not use eGRID data from 1996 and 1997 because for those years, the heat rate information was not available. Data for intervening years (i.e. 2001-2003, 2006, 2008 and 2011 are not available in eGrid. We are currently working to incorporate the 2014 recently released data into our model.

Out of the 7,491 power plants in the e-Grid dataset, 1,378 report observed emissions to ETS/CEM in at least one year. These plants comprise 7,708 plant-year observations. Importantly, these plants also tend to be the largest, and produce the majority of electricity. Table 1 presents annual net generation for the two sets of plants and shows that even though we are only using 18% of the total number of power plants in our sample, we are still capturing the majority of electricity produced, particularly in more recent years.

For each of these plants, eGRID provides data on our variables of interest: emissions of CO_2, SO_2, and NO_x, electricity, generation and the heat rate for coal plants. In addition, eGRID also provides boiler-level data on pollution-control devices for all plants (the list of devices is found in Appendix 1). Using the information on pollution control, we construct two variables that roughly capture the plant's use of pollution control devices, for SO_2 and for NO_x emissions. Specifically, for each plant we measure the proportion of boilers that are equipped with at least one pollution control device for SO_2 and for NO_x, respectively.

For our analysis, we restrict attention to coal and natural gas power plants. We only include coal plants that produce at least 99% of their electricity from coal, and the same for natural gas plants (at least 99% of output is from natural gas). We exclude the relatively small number of plants that use a mix of fuels, because in those cases we cannot attribute the emissions by fuel type; eGRID does not report emissions by fuel type. We also exclude the handful of plants that produce electricity using renewable energy sources (26 plant-year observations), because they emit trivial amounts of SO_2 and NO_x, and we exclude the small number of oil-burning plants (219 plant-year observations) because these plants are very small, too small to noticeably affect our results.[6] After excluding a small number of observations with missing data, we end up with a sample of 1,026 plants comprising 5,717 plant-year observations: 2,077 observations from 319 coal plants, and 3,640 observations from 709 natural gas plants.

Table 2 provides summary statistics for the coal and natural gas plants in our sample. The average coal plant in our sample is almost five times larger than the average gas plant in terms of electricity generation (and the median coal plant is about twelve times larger), and it emits more than ten times as much CO_2. While the difference in CO_2 emissions is large, when we compare emissions of local pollutants we observe truly enormous differences between coal and natural gas plants. Coal plants emit almost 35 times more NO_x than natural gas plants, and more than 4000 times more SO_2. These differences underlie the CPP's effort to shift from coal to natural gas.

Figure 1 shows how total net generation from coal and gas plants in our sample has changed over time.[7] Because coal plants are so much larger than natural gas plants, coal is responsible for the majority of net generation, even though there are more natural gas plants. However, over the past several years

[6] There are thousands of plants producing electricity from renewables or from oil. However, the overwhelming majority of these plants do not observe emissions directly (in the case of renewables plants because there are essentially no emissions to report).

[7] We show the comparable figure (Figure 1a) using all the plants in eGRID in Appendix 2.

generation from natural gas has increased markedly following the innovations in hydraulic fracturing and horizontal drilling technology as well as discoveries of new natural gas fields. At the same time, coal-fired generation remained fairly stable, until a recent decline.

Figure 2 shows the trends in emissions over time for the plants in our sample[8]. Emissions of SO_2 and NO_x have been declining over time, due primarily to the increasing adoption of pollution control devices (especially in coal plants). CO_2 emissions have remained fairly stable, increasing slightly over the time period of our sample.

One of the limitations of our work is that eGRID does not include data on emissions of particulate matter (PM). However, according to the EPA, directly emitted PM 2.5 produces less than 10% of the monetized health benefits derived from co-pollutants across the different emissions reductions scenarios. Therefore, we do not believe that this omission poses a serious challenge to the implications of our analysis.

4. Empirical Analysis

Our primary goal is to assess how much each of the three mechanisms for reducing CO_2 emissions highlighted by the EPA – increasing the efficiency of coal-fired plants by reducing the heat rate, shifting from coal to natural gas and renewables, and reducing demand for electricity – affect emissions of SO_2, and NO_x. To do so, we estimate a series of panel-data regressions. We estimate separate models for coal and gas-fired plants, as the effect of each mechanism will vary with the type of plant. Our baseline models have the following structure:

$$\text{Ln}(\text{Emissions}_{pit}) = B_1*\ln(\text{Output}_{it}) + B_2*\ln(\text{Heat rate}_{it}) + B_3*\text{Pollution controls}_{it} + c_{it} + w_{st} + e_{it}, \text{ (Coal plants)}$$

$$\text{Ln}(\text{Emissions}_{pit}) = A_1*\ln(\text{Output}_{it}) + A_2*\text{Pollution controls}_{it} + g_{it} + v_{st} + u_{it}, \text{ (Natural gas plants)}$$

where Emissions_{pit} indicates the annual emissions of pollutant p, by facility i, in year t. We only include heat rate in the coal plant regressions, because in the EPA projections, increasing efficiency is only a mechanism for coal plants to reduce emissions. The coefficient on output will identify two mechanisms: reducing demand for electricity, and shifting output from higher-carbon coal, to lower-carbon gas and zero-carbon renewables. In the case of switching from coal to gas, the net effect will depend on the difference in the output coefficient in the coal and gas models. In contrast, in the case of switching from coal to renewables, the coefficient on output in the coal model captures the full reduction of emissions, because renewables do not emit substantial amounts of SO_2 and NO_x.

In some models we include a dummy variable indicating whether or not the facility has adopted any of the pollution controls devices listed in Appendix 1. In all models, we include plant and state-year fixed effects to control for unobserved differences in abatement technology and efficiency across facilities and unobserved variation in economic conditions, regulatory stringency, and other state-level factors. We cluster our standard errors at the state level to account for any correlation over time and across

[8] We show the comparable figure (Figure 2a) using all the plants in eGRID in Appendix 2.

plants within a state. Finally, because we are interested in aggregate emissions, we weight observations by the plant's output level.

While these fixed effects eliminate a substantial amount of the potential endogeneity bias, we recognize that output, heat rate, and emissions are all chosen simultaneously, and it is not possible to perfectly identify a causal relationship in our model. In particular, it seems plausible that as plants discover cleaner processes and technologies, they would increase output, reduce heat rate, and reduce emissions. As a result, the coefficients on output and heat rate would be inflated by the underlying effect of these innovations. However, we do not believe that this is a big problem empirically, because our results change very little when we omit plant fixed effects from our model. The plant fixed effects should purge the large majority of these kinds of effects (more efficient plants produce more, at lower heat rate, and with lower emissions). Moreover, we control for some of these technologies with our control device dummy variables. We believe that any remaining time-varying sources of endogeneity should have very little impact.

5. Results

5.1 CO_2 emissions

We first estimate our baseline model on CO_2 emissions. Although we focus on the impact of the CPP on emissions of SO_2 and NO_x, we can validate our approach by comparing our projected CO_2 emissions reductions with those reported by EPA. We can do this in two ways: 1) by comparing our estimated marginal effect of an additional MWh on CO_2 emissions with the established emissions factors, such as those reported by the EIA (EIA 2016a), and 2) by comparing our overall estimated reductions in CO_2 emissions with the EPA's estimates. If our model produces marginal effects similar to these reported by the EIA and estimated effects similar to those reported by the EPA, then this would suggest that our approach is valid.

The results, in Table 3, indicate that for coal-fired facilities, the elasticity of CO_2 emissions with respect to output is about one (0.998); when a coal plant increases output by one percent, CO_2 emissions rise by roughly one percent. Similarly, the heat rate elasticity is a bit less than one (0.979). The second column reports the results for natural gas facilities. The results for the baseline model indicate that the elasticity of CO_2 emissions is smaller for natural gas-fired plants; when a natural gas facility increases output by one percent, CO_2 emissions increase by about 0.92 percent. Note, that we do not estimate the effect of heat rate in the natural gas facilities because reducing heat rate is not one of the EPA mechanisms for reducing emissions in natural gas plants.

As a first check on the validity of our approach, we compare our estimated marginal effects of output with those of the EIA. According to the EIA, one MWh of electricity produced by burning coal emits a little more than one ton of CO_2 (EIA 2016a).[9] By comparison, one MWh of electricity produced by

[9] The exact amount depends on the type of coal burned (i.e. bituminous coal, subbituminous coal, lignite). The EIA estimates range from 1.035-1.085 tons of CO_2/MWh from coal and 0.61 tons of CO_2/MWh from natural gas

burning natural gas emits about 0.6 tons of CO_2. Thus, if our model produces marginal effects similar to these reported by EIA, then this would suggest that our approach is valid.

To calculate the marginal effect of a MWh of electricity produced in a coal-fired plant at the average value of CO_2 emissions/output for coal plants, we multiply our estimated elasticity of output (0.998) by the average value of CO_2 emissions/output (1.102 tons of CO_2/MWh) for coal-fired plants in 2012 (the most recent year for which eGRID data are available). This yields a marginal effect of 1.1 tons of CO_2 for an additional MWh of electricity produced by burning coal. Using the same approach for gas plants, we again calculate the marginal effect by multiplying our estimated elasticity of output (0.92) by the average value of CO_2/output (0.462 tons of CO_2/MWh) in 2012, which yields a marginal effect of 0.43 tons of CO_2 for an additional MWh of electricity produced with natural gas. Our marginal effect is consistent with the EIA's carbon emission factor for coal, a bit less so for natural gas. Regardless, these results provide evidence for the validity of our approach, particularly for the coal-fired plants. Importantly, as will become apparent below, the CPP's effect on emissions of CO_2 and local pollutants is driven almost completely by reductions in coal generation.

As a second validity check, we use our estimated marginal effects, along with EPA projections of changes in generation and heat rate, to assess how much emissions will change if states achieve the CPP-mandated CO_2 emissions reductions targets (i.e., by reducing output and heat rate as projected by EPA). To do so, we examine the impact of the three mechanisms and then add up the effects. We begin by assessing the impact of the first mechanism: increasing the efficiency of coal-fired plants by reducing the heat rate.

To project the heat rate reduction, the EPA assumed the following heat-rate improvements for the three major interconnections (EPA 2015a):

- Western Interconnection: 2.1 %.
- Eastern Interconnection: 4.3 %.
- Electric Reliability Council of Texas (ERCOT): 2.3 %.

In our sample, the vast majority (81%) of coal plants are in the Eastern Interconnection, and account for about 77% of output each year. Therefore, we simply take an output-weighted average of the three heat rate reduction estimates, which yields a 3.8 percent average reduction in heat rate. However, the EPA projects that only about 51% of coal capacity in 2030 will actually reduce its heat rate. Therefore, to estimate the impact of this projected 3.8% heat rate reduction, we first multiply our estimated elasticity of CO_2 emissions with respect to heat rate (0.979) by 3.8%, which yields a 3.7% reduction in emissions in a plant that reduces heat rate by 3.8%. We then calculate the aggregate emissions reduction resulting from coal plants reducing heat rate. To do so, we multiply the 3.7% reduction in emissions by total baseline CO_2 emissions in 2030 (2,227 million tons), and then take 51% of that reduction to reflect the 51% of coal capacity that EPA projects will reduce heat rate. This yields a reduction of 42.3 million tons of CO_2 emissions in 2030 relative to the baseline level of projected emissions.

Next, we jointly consider the effect of shifting output from coal-fired plants to natural gas plants and to renewables, and any demand-side efficiencies. We can combine these mechanisms together because, as we noted above, we assume that renewables have zero CO_2 emissions. Therefore, any changes in emissions from shifting from coal to gas or renewables, and any reduction in emissions from coal and gas plants due to demand-side efficiencies are all captured by the changes in output in coal and gas facilities; increased output from renewables has no effect on CO_2 emissions, while demand-side efficiencies are already reflected in the reductions in output of coal and gas plants.

To assess the magnitudes of the effects of these mechanisms, we need to use EPA estimates for changes in output in coal and gas plants, along with our estimated marginal effects for output in coal and gas plants. The EPA projects that electricity output in coal plants will fall by 322 million MWh in 2030, relative to the base case (EPA 2015a)[10]. At the same time, it projects that electricity output in gas plants will fall by 69 million MWh[11]. Note, that despite shifting output from coal to gas plants, output in gas plants (existing and new) is projected to fall due to increased demand-side efficiencies.

Using the baseline model, and again calculating the marginal effect at the 2012 average value of CO_2 emissions/output, the reduction in output in coal plants will reduce CO_2 emissions by roughly 354 million tons (0.998*(1.102)*322,000,000). Using the same approach for gas plants, the reduction in output in gas plants will reduce CO_2 emissions in 2030 by roughly 29.5 million tons. Taken together, this mechanism will result in overall CO_2 emissions reductions of roughly 383.6 million tons. When we add the effect of efficiency improvements through heat rate reduction in coal plants (42.3 million tons), we estimate a total reduction in CO_2 emissions of about 426 million tons. By comparison, the EPA projects total reductions of 413 million tons of CO_2 emissions. Thus, our approach yields an estimated reduction in CO_2 emissions about 3% higher than EPA's. This provides strong evidence that our approach can be used to estimate the emissions impacts of the CPP. Taken together, the results in Table 3 provide strong support for the external validity of our model.

5.2 SO_2 Emissions

Having established the validity of our model, we now turn to the main focus of our paper: the effects on SO_2 and NO_x emissions. We begin with SO_2 emissions in Table 4. In the first column, we estimate our baseline model for coal-fired plants. The results indicate that the elasticity of SO_2 emissions with respect to output is about 0.61. At the same time, reducing the heat rate increases SO_2 emissions. We also find that having SO_2-pollution control technology in all boilers of a given plant reduces SO_2 emissions by about 74 percent[12]. In the second column we look at SO_2 emissions in gas plants. The elasticity for output there is 0.954. SO_2-pollution control devices were not used in any of the natural gas plants in our sample. Again, we do not include heat rate in our estimation for gas plants, because heat rate is not a mechanism for reducing emissions in these plants.

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[10] Using the projections based on the mass-based approach.

[11] Including generation from existing and new plants.

[12] Given a coefficient, B, the effect of a change from 0-1 in a variable when the left-hand side variable is logged is computed as exp(B)-1.

As we did above, we need to convert these output elasticities into marginal effects. We follow the same approach that we used for CO_2 emissions, evaluating the effects at the sample 2012 average value of SO_2 emissions/output. Doing so, yields a marginal effect of about 2.5 pounds (0.0013 tons) of SO_2 emissions from an additional MWh of electricity produced in a coal-fired plant. When we multiply these marginal effects by EPA's projected reductions in output, we see that reduced output reduces SO_2 emissions by about 402,799 tons. At the same time, the reduction in heat rate should increase SO_2 emissions by 13,547 tons. For natural gas plants, the marginal effect of one MWh of electricity is only about 0.006 pounds of SO_2 emissions. As a result, when we scale this marginal effect by the EPA's estimated reduction in output from natural gas plants, we find that SO_2 emissions from gas plants will fall by only about 197 tons.

Adding these effects together, we find that the CPP should result in a 389,449 ton (30%) reduction in SO_2 emissions in 2030 relative to base case emissions (1.314 million tons). By comparison, the EPA estimates that SO_2 emissions will be reduced by 280,000 tons (21%), relative to the 2030 baseline. Thus, we find a 39% larger reduction in SO_2 emissions than that projected by the EPA.

5.3 NO_x Emissions

In Table 5, we conduct the same analyses for NO_x emissions. The elasticity of NO_x emissions with respect to output is about 0.6 for coal plants, and about 0.72 for gas plants. The elasticity of NO_x emissions with respect to heat rate is about 0.44 in coal plants, but it is not statistically significant, so we do not account for the impact of heat rate change in our NOx reduction calculations. Similarly, the effect of NO_x pollution control devices is not statistically significant in either type of plant. When we convert the output elasticities into marginal effects, we find that an additional MWh of output in coal plants yields about 1.2 pounds of NO_x emissions, while the marginal effect of an additional MWh of output in gas plants is only about 0.16 pounds.

When we multiply these marginal effects by EPA's projected reductions in output, we find that NO_x emissions from coal plants should fall by 191,765 tons, while NO_x emissions from gas plants will fall by 5,640 tons, for a total projected reduction of 197,405 tons (15%) of NO_x emissions relative to the 2030 baseline emissions levels (1.293 million tons). The EPA estimates that NO_x emissions will fall by 278,000 tons (22%), relative to the 2030 baseline. Thus, we find a roughly 29% smaller reduction in NO_x emissions than that projected by the EPA.

5.4 Robustness Checks

We consider two robustness checks to assess the validity of our estimates. First, we limit our sample to more recent data. Second, we limit our sample to the plants that emit more CO_2 per unit of output.

5.4.1 More recent data

One potential issue with our approach is that we use data starting in 1998. This raises the possibility that due to changes in regulations and technology, these earlier data are less informative of how power plants will respond to the CPP in coming years. To consider this possibility, we restrict our sample to the more recent period, 2007-2012 (recall that in this more recent time period we have data for 2007, 2009, 2010, and 2012). We report these results in Tables 6 and 7.

The results for coal plants show that the elasticity of emissions with respect to output increases substantially for both SO_2 and NO_x when we focus on the more recent data. The elasticity of SO_2 emissions with respect to output rises from 0.61 to 0.78 in coal plants, while for NO_x, it rises from 0.6 to 0.76. The heat rate elasticities both become more positive (less negative); for SO_2 emissions, the negative heat rate elasticity approaches zero (-0.2) and is no longer statistically significant, while for NO_x emissions, the heat rate elasticity becomes larger (1.12) and statistically significant. For gas plants, the elasticity of emissions with respect to output increases only slightly for both SO_2 (0.99 vs 0.95) and NO_x (0.73 vs 0.72) when we focus on the more recent data.

Driven primarily by the larger output elasticities in coal plants, as well as the larger heat rate elasticity for NO_x emissions in coal plants, restricting our analysis to the more recent data yields larger projected reductions in emissions of both SO_2 and NO_x. Using the same approach described above, the results in Table 6 yield a 510,284 ton projected reduction in SO_2 emissions, and in Table 7 a 275,294 ton projected reduction in NO_x emissions. For NO_x a substantial amount of reduction (27,940 tons) comes from improvements on heat rate for coal plants. Without considering those reductions, the total decrease in NOx is 257,108 tons. These projected reductions are substantially larger than those we found using the full sample (389,449 tons and 197,405 tons, respectively). This projected reduction in SO_2 is now roughly 82% larger than the EPA's projected reduction (280,000 tons), while the NO_x projected reduction is about 1% lower than EPA's projection (278,000 tons).

5.4.2 Dirtier plants

Another concern we address is that emissions reductions will not be randomly distributed across plants. In particular, if states implement emissions trading markets or impose a carbon tax, we would expect plants that emit more CO_2 per unit of output to have a stronger incentive to reduce CO_2 emissions.[13] To address this possibility, we restrict our sample to the plants that emitted more than the median level of CO_2 per unit of output in 2012[14,15].

The results in Tables 8 and 9 indicate that when we restrict our analysis to the dirtiest plants (based on CO_2 emissions), the elasticities with respect to output in coal-fired plants are substantially larger for both types of co-pollutants (0.98 vs 0.61 for SO_2 emissions and 0.69 vs 0.6 for NO_x emissions). The elasticity of SO_2 emissions with respect to heat rate is larger in magnitude (-0.86 vs -0.53), but is statistically insignificant, as the standard error is larger in the restricted sample. For NO_x emissions, the heat rate elasticity remains statistically insignificant. In gas plants, we again find that both output

[13] Because output reduction is the primary means of reducing CO_2 emissions, this will be least costly for the most CO_2-intensive plants.
[14] We use the data from all years available for these plants.
[15] We also considered using the 25th and 75th percentiles as cutoffs. Doing so does not greatly change the pattern of results.

elasticities are larger, with a smaller increase for SO_2 emissions (1.00 vs 0.95), and a larger increase for NO_x emissions (1.00 vs 0.72).

When we examine the projected impact on overall emissions, we find that SO_2 emissions would fall by 646,527 tons, while NO_x emissions would fall by about 226,610 tons. These projections are respectively 131% above and 18% below EPA projections. Note, that because the heat rate coefficient is not statistically significant, we do not use it in projecting the reduction in SO_2 emissions. Nonetheless, even if we do include the negative effect of heat rate, we still project that SO_2 emissions fall by about 634,000 tons.

6. Health effects (preliminary results)

Having estimated the co-pollutant elasticities for SO_2 and NO_x, the next step is to examine how the CPP will affect human health. The CPP projects a 19% reduction of CO2 in 2030, compared to the 2030 baseline scenario, which amounts to a total reduction of 413 million tons of CO_2. To estimate the reduction in output that will result from a 1% reduction in CO_2 (i.e. 1% of the total amount 413 million tons) we apply the coefficient from Table 3. Because that coefficient (0.998) pertains to the reduction of CO_2 from a 1% reduction in output, we calculate its reciprocal (i.e. 1/.998). The next step is to distribute the output reduction (from the 1% reduction in CO_2) among the coal plants in each state. We develop several alternatives to allocate output reduction amongst coal plants using the following criteria: 1) CO_2 intensity, 2) marginal damages caused by the plant depending on its emissions and the population living in the surrounding area, 3) plant capacity. Once the reductions in output at the plant level of every state have been determined, we calculate the co-pollutant reduction using the coefficient estimates from our main specification (Tables 4 and 5). Alternative specifications are also explored that are based on the coefficient estimates from the two robustness checks described in sections 5.4.1 (more recent data from 2007-2012) and 5.4.2 (dirtier plants). The estimated reductions in co-pollutants from the various plants are aggregated at the county level and are then used as input in the "Estimating Air pollution Social Impact Using Regression" (EASIUR) model. The latter is an integrated assessment model that predicts the marginal damage from an increase in pollution at any point in the continental U.S. The marginal damage estimate is based upon the impact of ambient $PM_{2.5}$ on mortality in both nearby and downwind regions. In addition to varying across geographic space, predicted marginal damages vary with seasonal patterns in pollution transport, stack emission height, and pollutant type ($PM_{2.5}$, SO_2, NO_x, and NH_3). The EASIUR model was developed by Heo (2015). EASIUR is based upon another chemical transport and integrative assessment model, the Comprehensive Air Quality Model with Extensions (CAMx). EASIUR's damage predictions correlate well with the results from other integrated assessment models, including both CAMx and AP2. The results indicate that the reduction in co-pollutants from a 1% decrease in CO_2 will yield avoided damages of \$242,405,620 from SO_2 and \$23,066,212 from NO_x (both numbers are in 2010 dollars)[16].

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[16] Our final paper will include additional estimates of health benefits based on the co-pollutant elasticities estimated in the robustness check section of the paper as well as the different output reduction allocation schemes discussed in section 6.

7. Conclusions

In August 2015, President Obama announced the final version of the Clean Power Plan, which established state limits on CO_2 emissions by power plants. The CPP sets state-specific targets for CO_2 emissions reductions, with the EPA providing states the flexibility to determine the best way to meet these targets. The EPA lists three mechanisms that states can use to achieve the CO_2 reductions: (1) reduce demand for electricity; (2) shift the fuel mix from more carbon-intensive energy sources (coal) to less carbon-intensive source (natural gas) and zero-carbon fuels (renewables); and (3) reduce the plant's heat rate.

In total the EPA projects that US power plants will reduce CO_2 emissions by 19% in 2030 relative to baseline levels. While the primary focus of the CPP is reducing CO_2 emissions to slow climate change, an important element of the plan is that by reducing CO_2 emissions, plants will also reduce emissions of SO_2 and NO_x. These local pollutants have been shown to have a variety of negative health effects including increased respiratory diseases, increased asthma attacks, and greater mortality, among others. The EPA estimates that the health benefits from reducing emissions of these local pollutants are large: roughly as large, or larger than the climate change benefits from reducing CO_2 emissions, the primary target of the plan.

The standard approach for assessing the impact of regulations like the CPP on the behavior of power plants is to use LP models. The EPA itself uses such a model, IPM, to project the impacts of the CPP. In this paper, we consider a different approach to assess the impact of the CPP: we use historical data from power plants to estimate how much the CPP will reduce emissions of local pollutants, SO_2 and NO_x. To do so, we use nine years (spanning 1998-2012) of eGRID data on US power plants to assess how much the EPA's building blocks affect emissions of SO_2 and NO_x. Because our approach is a novel one, we first test its validity by estimating the projected reductions in CO_2 emissions. Our model projects CO_2 emissions reductions within 3% of EPA projections. Using our estimates, we then project how much SO_2 and NO_x emissions would fall if plants reduce output and increase efficiency as projected by the EPA.

Our full-sample estimates indicate that if coal and gas plants reduce output by the amounts that the EPA projects, and if coal plants reduce heat rate as projected by EPA, then relative to the base case scenario, SO_2 emissions will fall by 389,449 tons in 2030, or 39 percent more than EPA projections, while NO_x emissions will fall by 197,405 tons, which is about 29 percent less than EPA projections. Additional analysis suggests that the EPA may be substantially underestimating the reductions in SO_2 emissions, while overestimating the reductions in NO_x emissions by a smaller amount.

This is important from a public health perspective, because of the negative health effects associated with these co-pollutants. Our preliminary analysis on the health effects of emissions reductions suggests that the health benefits of the CPP may be different than what the EPA projects, assuming that plants behave as EPA expects. More generally, our results suggest that, in the absence of strong evidence that the effects of mechanisms under power plant control have changed markedly, there is value in using an empirical approach to project the regulatory impacts of EPA interventions, rather than relying exclusively on engineering-based, integrated planning models.

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Table 1

Total Annual Generation: Plants with Observed Emissions vs Plants with Imputed Emissions

	Total Generation (GWh)	
Year	**Plants with Observed Emissions**	**Plants with Imputed Emissions**
1998	1,623,711	1,954,085
1999	1,524,171	2,133,085
2000	1,538,793	2,230,741
2004	1,972,511	1,949,731
2005	2,183,049	1,860,369
2007	2,326,383	1,822,433
2009	2,293,367	1,644,650
2010	2,448,960	1,663,162
2012	2,404,131	1,641,387

Table 2

Summary Statistics for Coal and Gas Plants

		Coal Plants		**Gas Plants**	
Variable	**units**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Net generation	MWh	5,395,054	4,744,456	1,116,361	1,703,507
CO_2 emissions	tons	5,954,211	5,091,476	541,143.5	786,862
SO_2 emissions	tons	22,083.82	27,979.01	5.41	79.59
NO_x emissions	tons	9,484.72	10,908.46	272.59	893.25
Heat rate	Btu/kWh	11,093.83	1,339.78	NA	NA
SO_2 control devices	% plant operating hours	0.41	0.46	0	0
NO_x control devices	% plant operating hours	0.88	0.29	0.87	0.32
N	plant-years	2,077		3,640	

Table 3
The effect of output and heat rate on CO_2 emissions

	Coal Plants		**Natural Gas Plants**	
	Coefficient (elasticity)	**Marginal Effect of One MWh of Output (tons)**	**Coefficient (elasticity)**	**Marginal Effect of One MWh of Output (tons)**
lnOutput	0.998** (0.002)	1.100	0.924** (0.011)	0.427
lnHeat rate	0.979** (0.013)			
Number of Plants (plant-years)	319 (2077)		709 (3638)	

All models include plant and state-year fixed effects. In all models we weight each observation by plant output (MWh of electricity produced). *p<.05 **p<.01.

Table 4
The effect of output and heat rate on SO_2 emissions

	Coal Plants		**Natural Gas Plants**	
	Coefficient	**Marginal Effect of Output (pounds)**	**Coefficient (elasticity)**	**Marginal Effect of Output (pounds)**
lnOutput	0.612** (0.148)	2.600	0.954** (0.021)	0.006
lnHeat rate	-0.532† (0.295)			
SO_2 control device(s)	-1.811** (0.120)			
Number of Plants (plant-years)	319 (2077)		708 (3630)	

All models include plant and state-year fixed effects. In all models we weight each observation by plant output (MWh of electricity produced). †p<.10 *p<.05 **p<.01.

Table 5

The effect of output and heat rate on NO_x emissions

	Coal Plants		**Natural Gas Plants**	
	Coefficient	**Marginal Effect of Output (pounds)**	**Coefficient (elasticity)**	**Marginal Effect of Output (pounds)**
lnOutput	0.604** (0.099)	1.183	0.717** (0.044)	0.162
lnHeat rate	0.436 (0.307)			
NO_x control device(s)	0.067 (0.146)		-0.321 (0.305)	
Number of Plants (plant-years)	319 (2077)		709 (3640)	

All models include plant and state-year fixed effects. In all models we weight each observation by plant output (MWh of electricity produced). *p<.05 **p<.01.

Table 6

SO_2 emissions: 2007-2012

	Coal Plants	**Gas Plants**
lnOutput	0.775** (0.123)	0.986** (0.042)
lnHeat rate	-0.196 (0.529)	
SO_2 control device(s)	-1.753** (0.145)	
Number of Plants (plant-years)	275 (1027)	666 (2496)

All models include plant and state-year fixed effects. In all models we weight each observation by plant output (MWh of electricity produced). *p<.05 **p<.01.

Table 7

NO_x emissions: 2007-2012

	Coal Plants	**Gas Plants**
lnOutput	0.761** (0.088)	0.730** (0.041)
lnHeat rate	1.115** (0.322)	
SO_2 control device(s)		
NO_x control device(s)	0.184 (0.243)	-1.204** (0.371)
Number of Plants (plant-years)	275 (1027)	666 (2496)

All models include plant and state-year fixed effects. In all models we weight each observation by plant output (MWh of electricity produced). *p<.05 **p<.01.

Table 8

SO_2 emissions: More CO_2-intensive plants

	Coal Plants	**Gas Plants**
lnOutput	0.983** (0.118)	0.996** (0.044)
lnHeat rate	-0.857 (0.863)	
SO_2 control device(s)	-1.702** (0.304)	
Number of Plants (plant-years)	116 (801)	316 (1713)

All models include plant and state-year fixed effects. In all models we weight each observation by plant output (MWh of electricity produced). *p<.05 **p<.01.

Table 9

NO_x emissions: More CO_2-intensive plants

	Coal Plants	**Gas Plants**
lnOutput	0.689** (0.167)	0.999** (0.120)
lnHeat rate	0.101 (0.555)	
NO_x control device(s)	-0.134 (0.117)	-0.482** 0.105)
Number of Plants (plant-years)	116 (801)	316 (1721)

All models include plant and state-year fixed effects. In all models we weight each observation by plant output (MWh of electricity produced). **p*<.05 ***p*<.01.

Figure 1

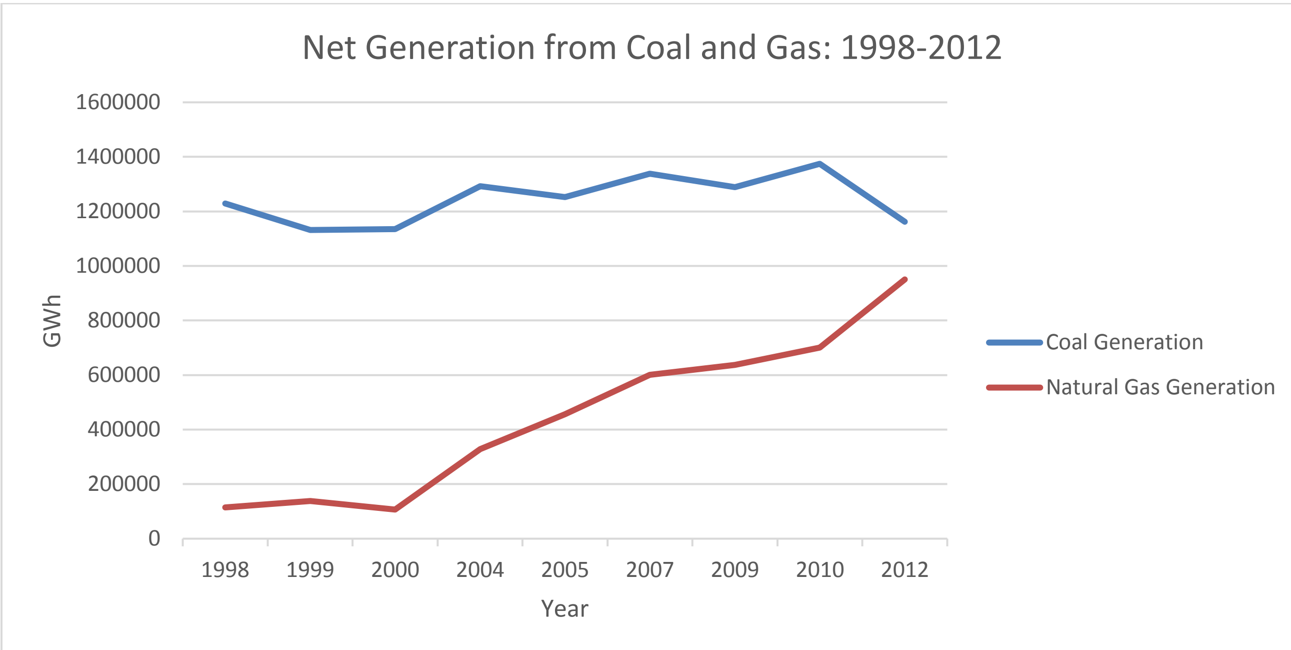
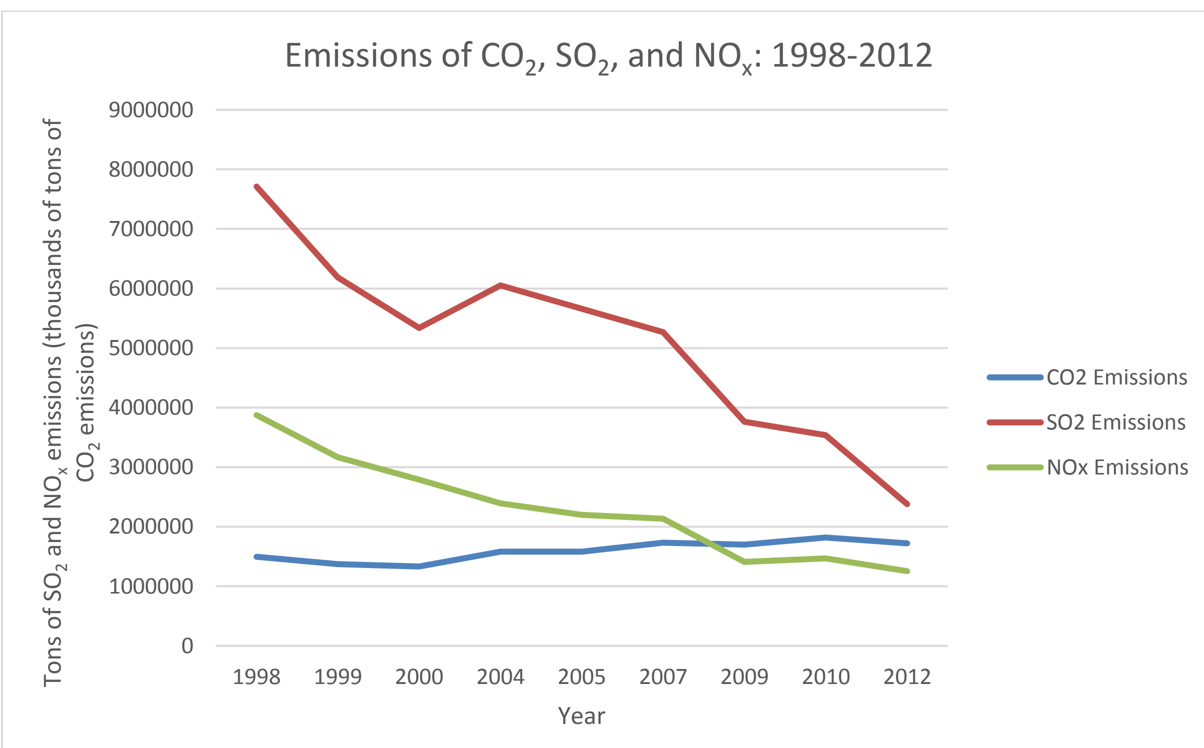


Figure 2



Appendix 1

List of SO_2 and NO_x control Devices in eGRID Source: EPA (2008)

List of SO_2 control devices	List of NO_x control devices
Jet bubbling reactor	Advanced overfire air
Circulating dry scrubber	Biased firing
Dual alkali	Fluidized bed combustor
Dry lime flue gas desulfurization unit	Combustion modification/fuel reburning
Fluidized bed	Dry low NO_x premixed technology
Mechanically aided type	Flue gas recirculation
Magnesium oxide	Fuel reburning
Other	Water injection
Packed type	Low excess air
Sodium based	Low NO_x burner
Spray dryer type	Low NO_x burner with overfire air
Spray type	Low NO_x burner technology with close-coupled overfire air
Tray type	Low NO_x burner technology with separated OFA
Venturi type	Low NO_x burner technology with close-coupled and separated overfire air
Wet lime flue gas desulfurization unit	Low NO_x burner technology for cell burners
Wet limestone	Ammonia injection
	Overfire air
	Slagging
	Selective catalytic reduction
	Selective noncatalytic reduction
	Steam injection

Appendix 2: Output and Emissions Using Full eGRID Sample

Figure 1a

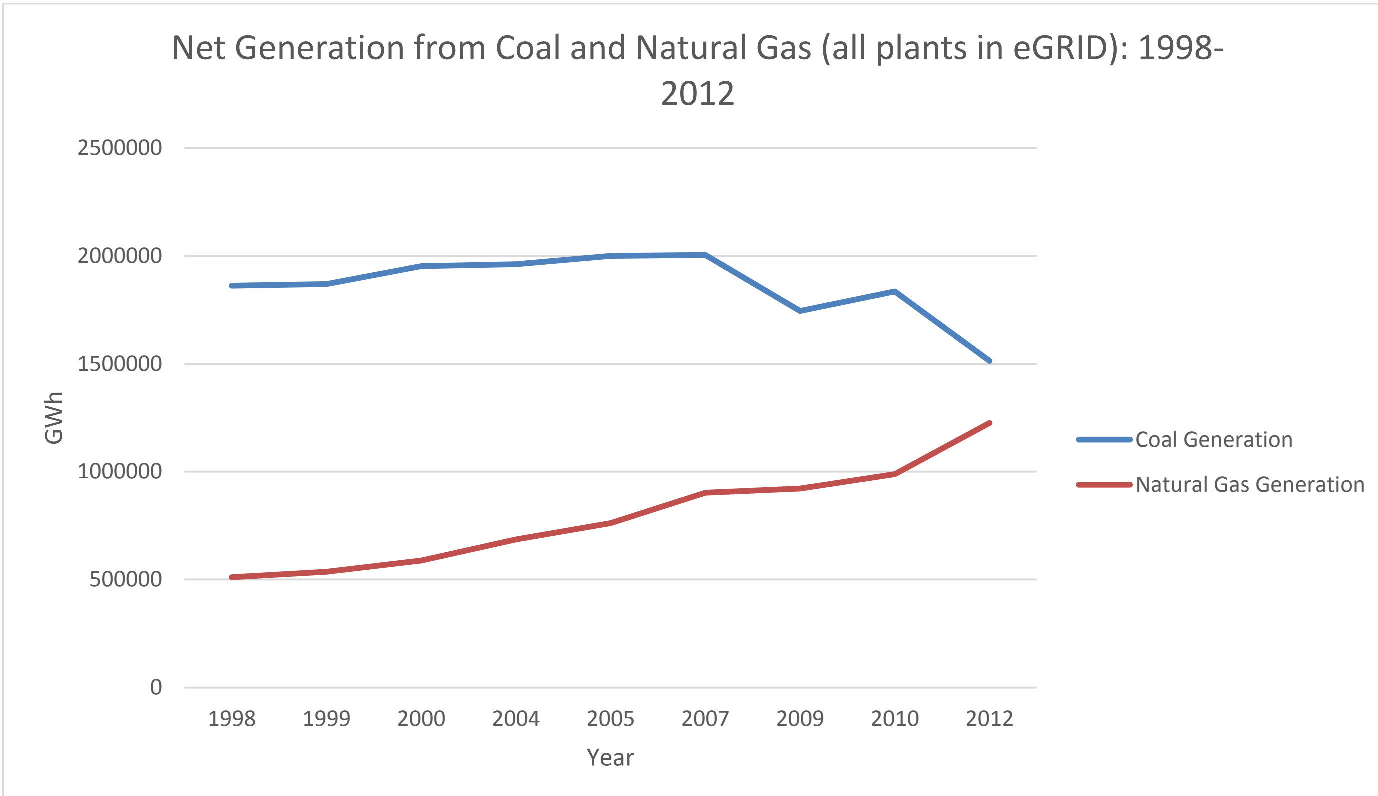
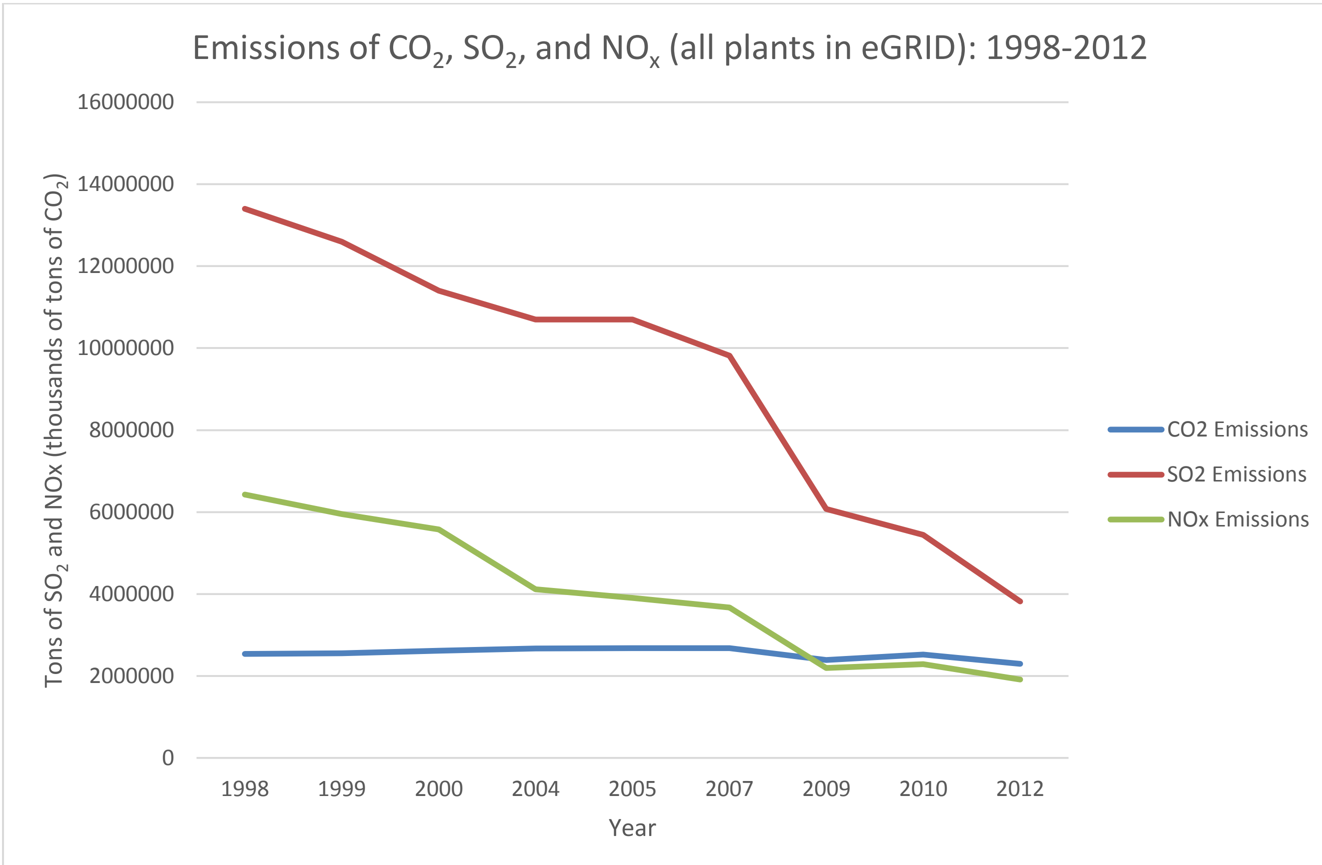


Figure 2a



Emissions of CO_2, SO_2, and NO_x (all plants in eGRID): 1998-2012
Tons of SO_2 and NOx (thousands of tons of CO_2)
16000000
14000000
12000000
10000000
8000000
6000000
4000000
2000000
0
1998
1999
2000
2004
2005
2007
2009
2010
2012
Year
CO2 Emissions
SO2 Emissions
NOx Emissions