Evaluating Interventions in the U.S. Electricity System: Assessments of Energy Efficiency, Renewable Energy, and Small-Scale Cogeneration

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Abstract

There is growing interest in reducing the environmental and human-health impacts resulting from electricity generation. Renewable energy, energy efficiency, and energy conservation are all commonly suggested solutions. Such interventions may provide health and environmental benefits by displacing emissions from conventional power plants. However, the generation mix varies considerably from region to region and emissions vary by the type and age of a generator. Thus, the benefits of an intervention will depend on the specific generators that are displaced, which vary depending on the timing and location of the intervention.

Marginal emissions factors (MEFs) give a consistent measure of the avoided emissions per megawatt-hour of displaced electricity, which can be used to evaluate the change in emissions resulting from a variety of interventions. This thesis presents the first systematic calculation of MEFs for the U.S. electricity system. Using regressions of hourly generation and emissions data from 2006 through 2011, I estimate regional MEFs for CO_2, NO_x, and SO_2, as well as the share of marginal generation from coal-, gas-, and oil-fired generators. This work highlights significant regional differences in the emissions benefits of displacing a unit of electricity: compared to the West, displacing one megawatt-hour of electricity in the Midwest is expected to avoid roughly 70% more CO_2, 12 times more SO_2, and 3 times more NO_x emissions.

I go on to explore regional variations in the performance of wind turbines and solar panels, where performance is measured relative to three objectives: energy production, avoided CO_2 emissions, and avoided health and environmental

damages from criteria pollutants. For 22 regions of the United States, I use regressions of historic emissions and generation data to estimate *marginal impact factors*, a measure of the avoided health and environmental damages per megawatt-hour of displaced electricity. Marginal impact factors are used to evaluate the effects of an additional wind turbine or solar panel in the U.S. electricity system. I find that the most attractive sites for renewables depend strongly on one's objective. A solar panel in Iowa displaces 20% more CO_2 emissions than a panel in Arizona, though energy production from the Iowa panel is 25% less. Similarly, despite a modest wind resource, a wind turbine in West Virginia is expected to displace 7 times more health and environmental damages than a wind turbine in Oklahoma.

Finally, I shift focus and explore the economics of small-scale cogeneration, which has long been recognized as a more efficient alternative to central-station power. Although the benefits of distributed cogeneration are widely cited, adoption has been slow in the U.S. Adoption could be encouraged by making cogeneration more economically attractive, either by increasing the expected returns or decreasing the risks of such investments. I present a case study of a 300-kilowatt cogeneration unit and evaluate the expected returns from: demand response, capacity markets, regulation markets, accelerated depreciation, a price on CO_2 emissions, and net metering. In addition, I explore the effectiveness of feed-in tariffs at mitigating the energy-price risks to cogeneration projects.

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Chapter 1: Introduction

Modern sources of energy, particularly electricity, provide great benefits to society. Access to affordable and reliable electricity is strongly correlated with per-capita income, life expectancy, and economic growth (1). However, burning fossil fuels to provide electricity results in health and environmental damages that are a growing threat to social wellbeing.

In the United States (U.S.), the electricity sector is responsible for roughly 40% of carbon dioxide (CO_2) emissions (2), the primary driver of global climate change. In the long run, these emissions are expected to result in a wide range of social, economic, and environmental impacts (3). In addition, fossil-fueled power plants emit criteria pollutants, which include sulfur dioxide (SO_2), nitrogen oxides (NO_x), particulate matter (PM), ozone, carbon monoxide, and lead. Criteria pollutants are linked to serious health effects, premature mortality, acid rain, and smog (4). The National Academy of Sciences estimates that SO_2, NO_x, and PM emissions from power plants result in more than $60 billion in health and environmental damages annually in the U.S. (5).

Renewable energy resources, such as wind and solar power, have gained popularity as a means of providing emissions-free electricity. Driven largely by state mandates and federal subsidies, wind capacity grew at an average annual rate of 37% over the past decade (6). Solar is also growing rapidly, though it still represents a very small share of total electricity generation. Alternatively, emissions reductions could also be achieved by increasing the efficiency of end-use applications, thus reducing the demand for electricity. Energy efficiency is widely considered the low-handing fruit for cost-effective CO_2 reductions (7).

Energy efficiency or renewable energy measures may provide health and environmental benefits by displacing emissions from conventional power plants. However, the generation mix varies considerably from region to region and emissions vary by the type and age of a generator. Thus, the social benefits of energy efficiency or renewable energy measures will depend crucially on the specific generators that are displaced.

Chapters 2 and 3 focus on measuring the impacts of energy efficiency and renewable energy measures. In Chapter 2, I present the first systematic assessment of marginal emissions factors (MEF) for the U.S. electricity system. MEFs provide a consistent measure of the avoided emissions per megawatt-hour of displaced electricity. Using regressions of generation and emissions data from 2006 through 2011, I estimate MEFs for CO_2, NO_x, and SO_2 for eight regions of the continental U.S.

Chapter 3 explores regional differences in the performance of wind turbines and solar panels. Because different stakeholders have different objectives, I consider three measures of performance: energy production, avoided CO_2 emissions, and avoided health and environmental damages from criteria pollutants. To perform the analysis, I develop a novel method for estimating the health and environmental benefits that occur when conventional generators are displaced. Results from Chapter 3 provide insight into the regional variations in the impacts of renewables, as well as the tradeoffs between energy production, long-term climate benefits (from avoided CO_2 emissions), and shorter-term health and environmental benefits (from avoided criteria pollutants).

I shift focus in Chapter 4 and explore the economics of small-scale cogeneration, which has long been recognized as a more efficient alternative to central-station power. By generating electricity near customers and utilizing the co-produced heat, cogeneration can achieve net efficiencies in excess of 80% (7). Yet, despite being a mature technology with widely-acknowledged benefits, adoption of cogeneration remains modest in the U.S. With the goal of encouraging broader adoption, Chapter 4 evaluates strategies for increasing the returns and decreasing the risks for cogeneration projects. I present a case study of a 300-kilowatt cogeneration unit and evaluate the expected returns from: demand response, capacity markets, regulation markets, accelerated depreciation, a price on CO_2 emissions, and net metering. In addition, I explore the effectiveness of feed-in tariffs at mitigating the energy-price risks to cogeneration projects.

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Chapter 2: Marginal Emissions Factors for the U.S. Electricity System[1]

2.1 Abstract

There is growing interest in reducing emissions from electricity generation in the United States (U.S.). Renewable energy, energy efficiency, and energy conservation are all commonly suggested solutions. Both supply- and demand-side interventions will displace energy—and emissions—from conventional generators. Marginal emissions factors (MEFs) give a consistent metric for assessing the avoided emissions resulting from such interventions. This work presents the first systematic calculation of MEFs for the U.S. electricity system. Using regressions of hourly generation and emissions data from 2006 through 2011, we estimate regional MEFs for CO_2, NO_x, and SO_2, as well as the share of marginal generation from coal-, gas-, and oil-fired generators. Trends in MEFs with respect to system load, time of day, and month are explored. We compare marginal and average emissions factors (AEFs), finding that AEFs may grossly misestimate the avoided emissions resulting from an intervention. We find significant regional differences in the emissions benefits of avoiding one megawatt-hour of electricity: compared to the

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[1] This chapter is based on the published paper, Siler-Evans, K.; Azevedo, I. L.; Morgan, M. G. Marginal Emissions Factors for the U.S. Electricity System. *Environ. Sci. Technol.* **2012**, 46, 4742–4748.

West, an equivalent energy efficiency measure in the Midwest is expected to avoid roughly 70% more CO_2, 12 times more SO_2, and 3 times more NO_x emissions.

2.2 Introduction

There is growing interest in reducing greenhouse gas and criteria air pollution emissions from electricity generation in the United States (U.S.). Renewable energy, such as wind and solar generation, is a commonly suggested solution. Emissions reductions could also be achieved by increasing the efficiency of end-use applications. In the short term, both supply- and demand-side interventions displace energy—and emissions—from conventional generators. In the long term, interventions in the electricity system may also affect plant retirements and construction. Here we focus on the short-term avoided CO_2, NO_x, and SO_2 resulting from interventions in the U.S. electricity system.

Avoided emissions can be measured using marginal emissions factors (MEFs). MEFs reflect the emissions intensities of the marginal generators in the system—the last generators needed to meet demand at a given time, and the first to respond given an intervention. MEFs constantly change as different generators are dispatched to meet demand. Identifying the marginal generator is difficult due to the many economic and operational constraints on the grid, which is a large and highly interconnected system. Further complicating matters, MEFs depend on the local generation mix and the type and quality of fuels used, which vary considerably from region to region.

Previous studies have developed a range of methods for estimating MEFs. Most commonly, a dispatch model is used to predict the marginal generator for a given time and place (1). These models assume that generators are dispatched in order of marginal cost, where the last generator needed to meet demand sets the marginal emissions rate for the system. Dispatch models have been used to calculate MEFs for various regions, including the United Kingdom, California, and New England (2-5). Dispatch models have also been used to assess the emissions implications of plug-in electric vehicles, wind and solar generation, distributed cogeneration, and various energy efficiency measures (6-8). These analyses vary greatly in their treatment of transmission, generator, and reliability constraints.

Regressions of historical data are a less common method of estimating MEFs. Hawkes estimates marginal CO_2 rates for the United Kingdom using a regression of half-hourly data from 2002 through 2009 (1). More detailed econometric models have been used to study the emissions implications of wind energy and real-time electricity pricing (9, 10). By relying on historical operating data, these studies circumvent the problem of modeling dispatch orders, outage rates, transmissions constraints, etc.

Estimates of marginal CO_2 rates are available for only a few regions in the U.S. Marginal NO_x and SO_2 rates are even harder to come by. As a result, studies may revert to average emissions factors (AEFs) to estimate the emissions implications of an intervention (11). This is problematic because AEFs may result in significant errors, potentially misinforming decision makers (1, 2, 12).

This work presents the first systematic calculation of MEFs for the U.S. electricity system, giving a consistent metric for assessing the emissions benefits of various interventions. Using hourly generation and emissions data from 2006 through 2011, we estimate regional MEFs for CO_2, NO_x, and SO_2 across the continental U.S. We provide a comparison between marginal and average emissions factors, estimate the share of marginal generation from coal-, gas-, and oil-fired plants, and explore trends in MEFs with respect to system load, time of day, and month.

2.3 Data

Our estimates of MEFs are based on an analysis of historic emissions and generation data. We estimate MEFs separately for the eight regions of the North American Electric Reliability Corporation (NERC). NERC regions are as follows: Florida Reliability Coordinating Council (FRCC), Midwest Reliability Organization (MRO), Northeast Power Coordinating Council (NPCC), Reliability First Corporation (RFC), Southeastern Reliability Council (SERC), Southwest Power Pool (SPP), Texas Reliability Entity (TRE), and Western Electricity Coordinating Council (WECC). A map of the NERC regions is included in the Supporting Information (SI).

The generation mix varies considerably from region to region (see SI). Coal accounts for as much as 70% and as little as 15% of regional electricity production, gas accounts for 5% to 49%, and nuclear accounts for 5% to 28%. Oil contributes very little with the exception of FRCC (Florida) and NPCC (Northeast), and hydropower is significant in only two regions—NPCC (Northeast) and WECC (West).

Emissions data are from the Environmental Protection Agency's (EPA) Continuous Emissions Monitoring System (CEMS) (13). CEMS data include hourly, generator-level SO_2, NO_x, and CO_2 emissions as well as gross power output. CEMS data are sorted into NERC regions by cross-referencing generator identification numbers with eGRID, a separate database maintained by the EPA (14).

Unfortunately, the CEMS database is limited to fossil-fueled generators greater than 25 MW (15). As a result, our estimates of MEFs do not account for biomass, wind, nuclear, hydropower, waste-to-power, geothermal, solar, and small fossil-fueled generators. The MEFs presented here are only valid if we assume that these CEMS-exempt generators do not operate on the margin. In other words, we must assume that demand-reducing interventions will not displace nuclear, hydro, etc. These assumptions are discussed in further detail in the SI.

2.4 Method and Example Analysis

2.4.1 Average MEFs

Marginal emissions factors are calculated separately for each NERC region and emissions type (CO_2, SO_2, and NO_x). We use CEMS data to calculate the change in fossil generation (G) and change in emissions (E) between one hour and the next:

$$\Delta G_h = G_h - G_{h+1} \text{ (MWh)} \qquad \Delta E_h = E_h - E_{h+1} \text{ (kg)}$$

From 2006 through 2011, there are more than 50,000 observed changes in emissions corresponding to a change in generation. The slope of a linear regression of ΔE on ΔG estimates the average MEF. For example, Figure 2.1 shows ΔCO_2 plotted against ΔG for the MRO (Midwest) region. In this case, reducing demand by one megawatt-hour is expected to displace, on average, 834 kg of CO_2. Note that we assume that only generators within the MRO region are displaced (i.e., imports and exports between regions are ignored). In addition, interventions that have high variability (e.g., wind and solar) may require conventional generators to cycle more often, or may increase the burden on generators providing regulation and rolling reserves; these impacts are not captured in our analysis. This method was originally demonstrated by Hawkes and used to calculate marginal CO_2 rates for the United Kingdom (1).

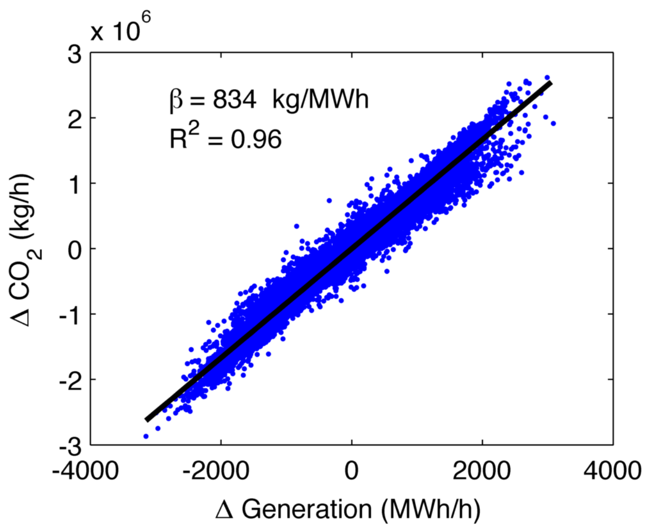

Figure 2.1: Linear regression of ΔCO_2 on ΔG for MRO (Midwest) from 2006 through 2011. The slope of the regression line estimates the marginal CO_2 rate of the system (834 kg/MWh).

2.4.2 Trends in MEFs

Figure 2.1 is an example of the most general result: the average MEF from 2006 through 2011. Trends are explored by applying the above method to subsets of the data. Monthly MEFs are calculated using 12 separate regressions of ΔE on ΔG for all observations in each month. Similarly, time-of-day MEFs are calculated using 24 separate regressions for all observations occurring at a given time (e.g., the MEF for 1 is based on the delta between 1 a.m. and 2 a.m. for each day).

Due to economic dispatch, we expect that the level of electrical demand is a strong predictor of the system MEF. Unfortunately, system demand data are not consistently available. For the remainder of this chapter, we use total fossil generation (based on CEMS data) as a proxy for system demand. In SPP, the correlation between the two is 0.90 with an R^2 of 0.93. In other regions, the correlation may be better or worse depending on the relative shares of fossil and non-fossil generation and the level of interconnection with other regions.

Trends in MEF with respect to system demand are explored by binning data by every fifth percentile. The first bin contains the 5% of data occurring during the lowest-demand hours, and the twentieth bin contains the 5% of data occurring during the highest-demand hours. Separate regressions are used to calculate MEFs for data within each bin.

2.4.3 Marginal fuel source

Using a variation of the method discussed above, we calculate the share of marginal generation from coal-, gas-, and oil-fired generators. We calculate the change in total generation between one hour and the next (ΔX), and the corresponding change in coal-, gas-, and oil-fired generation (ΔY_{coal}, ΔY_{gas}, and ΔY_{oil}). Separate regressions of ΔX on ΔY approximate the share of marginal generation for each fuel type.

Figure 2.2 shows an example of this method applied to coal- and gas-fired generation in MRO (Midwest) for low-demand hours (bottom 5%, shown left) and high-demand hours (top 5%, shown right). Coal is the dominant marginal fuel source when demand is low (β_{coal} = 0.98, β_{gas} = 0.02). During high-demand hours, gas accounts for a larger share of marginal generation (β_{coal} = 0.28, β_{gas} = 0.70).

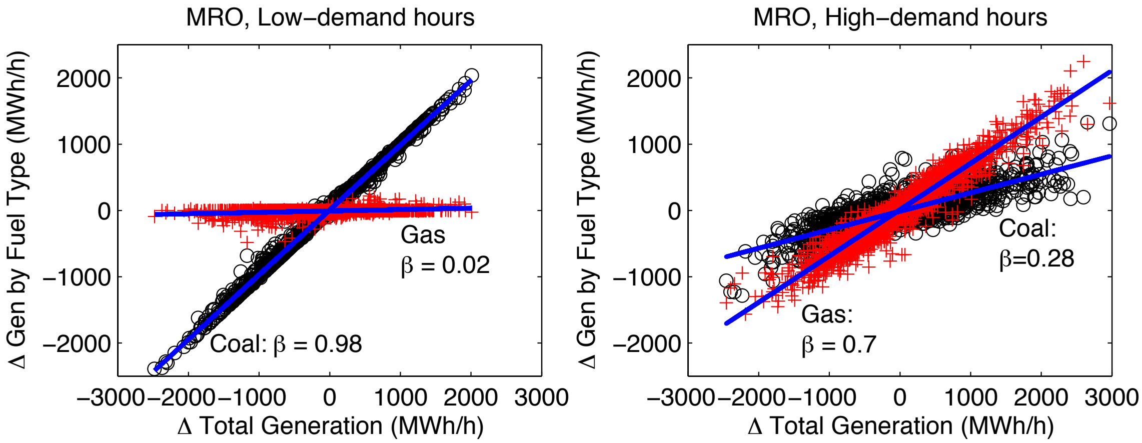

Figure 2.2: Change in coal and gas generation vs. change in total generation in MRO (Midwest). During low demand hours (left), coal is the dominant marginal fuel source (β_{coal} = 0.98, β_{gas} = 0.02). Gas accounts for a larger share of marginal generation during high-demand hours (right; β_{coal} = 0.28, β_{gas} = 0.70).

2.5 Results

2.5.1 Marginal emissions factors and marginal fuel sources: 2006-2011

Table 2.1 presents overall results by region, based on all data from 2006 through 2011. Columns two through four give the marginal fuel source—that is, the extent to which coal-, gas-, and oil-fired generators are expected to respond to interventions in the electricity system. Note that this is a different metric than what is commonly reported by Independent System Operators (ISOs). ISOs report the percentage of time that a fuel source is on the margin, where marginal generators in all balancing areas are weighted equally (see ref 16). Our estimates reflect the degree to which different generators respond to changes in demand. This implicitly weights our results such that marginal generators in areas with greater demand will represent a larger share of the total marginal fuel source. Despite this difference, we find good agreement with our results and those reported by the Southwest Power Pool, as shown in the SI.

Table 2.1: Average marginal fuel source and marginal emissions factors for regional electricity generation from 2006-2011

Region	Marginal Fuel Source			CO_2		SO_2		NO_x [a]	
	Coal	Gas	Oil	MEF±2σ	R^2	MEF±2σ	R^2	MEF±2σ	R^2
FRCC (Florida)	17%	71%	12%	532±1	0.96	1.33±0.01	0.66	0.8±0.01 / 0.76±0.01	0.76/0.67
MRO (Midwest)	79%	20%	0%	834±1.5	0.96	2.11±0.01	0.77	1.07±0.01 / 1.12±0.01	0.79/0.6
NPCC (Northeast)	8%	81%	11%	489±0.8	0.96	0.55±0.01	0.46	0.33±0 / 0.3±0	0.44/0.4
RFC (Mid-Atlantic)	70%	29%	0%	731±0.9	0.98	3.29±0.01	0.78	0.76±0 / 1.19±0.01	0.88/0.79
SERC (Southeast)	55%	45%	0%	680±0.9	0.97	2.01±0.01	0.73	0.53±0 / 0.8±0.01	0.8/0.72
SPP (Southwest)	35%	65%	0%	596±1.3	0.94	0.71±0.01	0.41	0.85±0.01 / 0.95±0.01	0.78/0.73
TRE (Texas)	16%	84%	0%	527±1.1	0.94	0.4±0.01	0.19	0.32±0	0.48
WECC (West)	14%	86%	0%	486±0.8	0.97	0.18±0	0.11	0.32±0	0.48

[a] Summer ozone season (May 1—September 30) / offseason. For the period of interest, TRE and WECC were not affected by seasonal NO_x regulation.

Table 2.1 shows that gas is the dominant marginal fuel source in most regions. Coal accounts for a large share of marginal generation in MRO and RFC (79% and 70%), and oil is significant in NPCC and FRCC (11% and 12%).

Columns four through ten present MEFs (±two standard deviations of the coefficient estimate) and R^2 values. In all cases, the 95% confidence intervals are remarkably narrow, which we believe grossly overstates the precision of this analysis. Errors that arise from data limitations and modeling choices dominate the statistical uncertainty of the regressions.

Across regions, marginal CO_2 rates vary from 486 (WECC) to more than 830 (MRO) kg/MWh. R^2 values range from 94% to 98%, indicating that a change in system generation is a very strong predictor of changes in CO_2 emissions.

Marginal SO_2 rates vary from 0.2 (WECC) to 3.3 (RFC) kg/MWh. In other words, an energy efficiency measure in RFC (Mid-Atlantic) is expected to displace sixteen times more SO_2 than an equivalent measure in WECC (West). In several regions the R^2 values are quite low—11% in WECC, for example. This indicates that changes in demand are a very weak predictor of changes in SO_2 emissions, which is consistent with our finding that coal power plants—the primary source of SO_2—are rarely on the margin in WECC. In coal-heavy regions, such as MRO (Midwest), RFC (Mid-Atlantic), and SERC (Southeast), R^2 values range from 73% to 78%.

In most cases, marginal NO_x rates are shown separately for the summer ozone season (May 1–September 30) and the offseason (the remainder of the year). The majority of the eastern states have stricter NO_x regulations in the summer, affecting all NERC regions except TRE (Texas) and WECC (West). The effect of seasonal NO_x regulation is most pronounced in RFC (Mid-Atlantic), where the ozone-season MEF is approximately 35% lower than that of the off-season.

Overall, there are significant regional differences. Compared to WECC (West), displacing one megawatt-hour in MRO (Midwest) is expected to avoid roughly 70% more CO_2, 12 times more SO_2, and 3 times more NO_x emissions.

2.5.2 Comparison between marginal and average emissions factors

In both scholarly research and policy implementation, average emissions factors (AEFs) are commonly used to assess the avoided emissions resulting from an intervention, though it is widely acknowledged that MEFs are the more appropriate metric for such an analysis (1,2,11,12,17).

Table 2.2 shows a comparison between AEFs and MEFs by NERC region. AEFs are the annual emissions divided by the annual generation, based on 2007 data from the eGRID database (14). For consistency, we also calculate MEFs based on only 2007 data.

AEFs are not consistently higher or lower than MEFs. Average CO_2 rates are 25% lower than marginal in NPCC (Northeast), where hydro and nuclear power significantly lower the average. In SPP (Southwest), large amounts of base-load coal increase the average CO_2 rate to 763 kg/MWh—35% higher than marginal. In the remaining six regions, average and marginal CO_2 rates are within 12%.

Average SO_2 emissions factors are, in some cases, much higher than marginal. In SPP (Southwest), WECC (West), and TRE (Texas), average SO_2 rates are more than 150% higher than marginal. This suggests that using AEFs may significantly overstate the avoided SO_2 resulting from an intervention. FRCC (Florida) is an exception, where marginal SO_2 rates are higher than average due to oil-fired plants operating on the margin, as discussed in the following section.

For regions affected by seasonal NO_x regulations, we report MEFs and AEFs for the summer ozone season, when NO_x emissions are of greater concern. In these cases, both average and marginal NO_x rates were calculated using data from May 1 through September 30, 2007. In seven of the eight regions, average and marginal NO_x rates are within 25%. In WECC (West), average NO_x rates are 160% higher than marginal.

Table 2.2: Comparison between 2007 marginal and average emissions factors[a]

Region	CO_2 (kg/MWh)			SO_2 (kg/MWh)			NO_x (kg/MWh)		
	MEF	AEF	% Diff[b]	MEF	AEF	% Diff[b]	MEF	AEF	% Diff[b]
FRCC (Florida)	577	553	-4%	1.73	1.44	-17%	0.99	0.88	-11%
MRO (Midwest)	786	799	2%	2.13	2.57	21%	1.15	1.39	20%
NPCC (Northeast)	477	357	-25%	0.63	1.09	73%	0.35	0.34	-5%
RFC (Mid-Atlantic)	726	648	-11%	3.96	3.76	-5%	0.81	0.65	-20%
SERC (Southeast)	656	619	-6%	2.3	2.46	7%	0.57	0.56	-2%
SPP (Southwest)	564	763	35%	0.7	1.86	166%	0.86	1.05	22%
TRE (Texas)	506	568	12%	0.29	1.16	295%	0.3	0.33	10%
WECC (West)	464	462	0%	0.14	0.53	280%	0.26	0.68	161%

[a] With the exception of TRE and WECC, average and marginal NO_x rates are based on data from the 2007 summer ozone season (May 1—September 30).
[b] Percent difference = (AEF – MEF)/MEF × 100

2.5.3 Dispatch order, marginal fuel source, and MEFs

Figure 2.3 shows the share of marginal generation by fuel type (top) and MEF (bottom) according to the level of fossil generation, a proxy for system demand. We present results for three regions, discussed below. Results for the remaining regions are included in the SI.

MRO (Midwest): MRO is the most coal-heavy NERC region in the U.S. When demand is low, coal is the dominant marginal fuel, resulting in relatively high MEFs. At higher demand, MEFs fall as gas accounts for a larger share of marginal generation.

TRE (Texas): TRE is the most gas-heavy NERC region in the U.S., where gas-fired generators account for half of all electricity production, and coal accounts for a third. Overall, gas is the dominant marginal fuel source. When demand is low, coal accounts for roughly 60% of marginal generation, falling to roughly 7% at peak demand. As a result, marginal CO_2 and SO_2 rates fall as demand increases.

The marginal NO_x rate increases with demand. We attribute this to the use of older, dirtier gas turbines as peakers. This theory is supported by a comparison of NO_x rates from gas generators in TRE. We sort gas generators by capacity factor, with the assumption that peakers will have a low capacity factor. The average NO_x emissions rate of the bottom quartile (peakers) is six times higher than that of the top quartile (baseload gas generators)(14).

FRCC (Florida): Like TRE, electricity generation in FRCC is dominated by gas (47%) and coal (27%), so it is not surprising that marginal CO_2 rates are nearly identical in the two regions. However, FRCC is unique in that 9% of electricity is supplied from oil-fired generators. As demand increases, oil accounts for a larger share of marginal generation, causing an increase in marginal SO_2 rates.

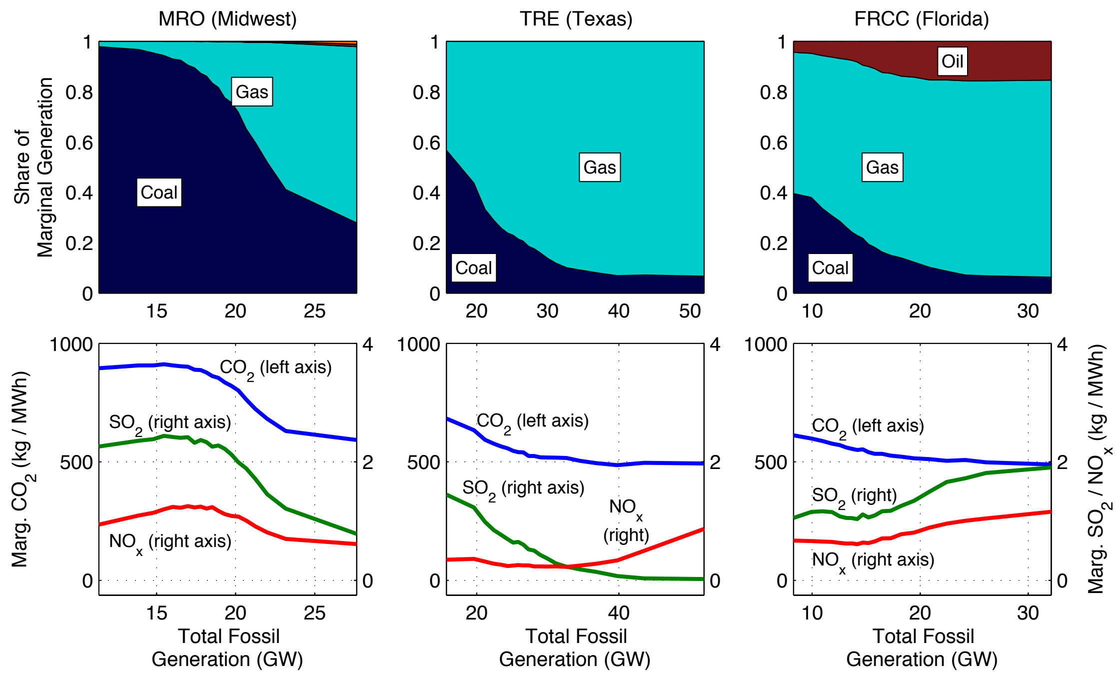

Figure 2.3: Share of marginal generation by fuel type (top) and MEFs (bottom) as a function of total fossil generation, a proxy for system demand. Results are based on data from 2006 through 2011, binned by every fifth percentile of total fossil generation. MEFs have two axes: the left axis applies to CO_2 and right axis applies to NO_x and SO_2.

2.5.4 Temporal trends

Figure 2.4 shows temporal trends in marginal CO_2 factors for MRO (Midwest), TRE (Texas), and FRCC (Florida). Results for the remaining pollutants and regions are included in the SI.

Time of Day: In MRO (Midwest), marginal emissions rates are consistently higher during late-night and early-morning hours: the marginal CO_2 factor is approximately 30% higher at midnight compared to noon. In TRE (Texas), marginal CO_2 rates are highest in the early-morning hours. There is a notable drop at 7 a.m. (based on the delta between 7 and 8 a.m.). We attribute this to the morning ramp. On average, there is a 2000 MW increase in demand between 7 and 8 a.m., giving an average ramp rate of 33 MW/min. It is likely that gas-fired generators, which are more amenable to such ramp rates, are disproportionately on the margin during these times, resulting in lower marginal CO_2 factors. In FRCC (Florida), time-of-day differences are very minor. In the SI, we include time-of-day trends by season, which show that time-of-day differences are, in the majority of cases, most pronounced in the summer.

Monthly: In both TRE (Texas) and FRCC (Florida), monthly differences in marginal CO_2 factors are insignificant. In MRO (Midwest), marginal CO_2 rates are highest in spring and fall, when demand is low and coal is more often on the margin. Generally, marginal SO_2 factors have more pronounced temporal variations, particularly in coal-heavy regions (see SI).

Annual: From 2006 through 2011, marginal CO_2 rates have been relatively stable. In both TRE (Texas) and MRO (Midwest), the net difference between 2006 and 2011 is a few percent, and the maximum difference is less than 10%, which is consistent with the five regions not shown (see SI). FRCC (Florida) is the exception, with a 20% drop in the marginal CO_2 rate between 2006 and 2009. As shown in the SI, marginal SO_2 rates have dropped significantly (>45%) in FRCC (Florida), RFC

(Mid-Atlantic), and SERC (Southeast). In five of the eight regions, marginal NO_x rates have dropped by more than 25% between 2006 and 2011.

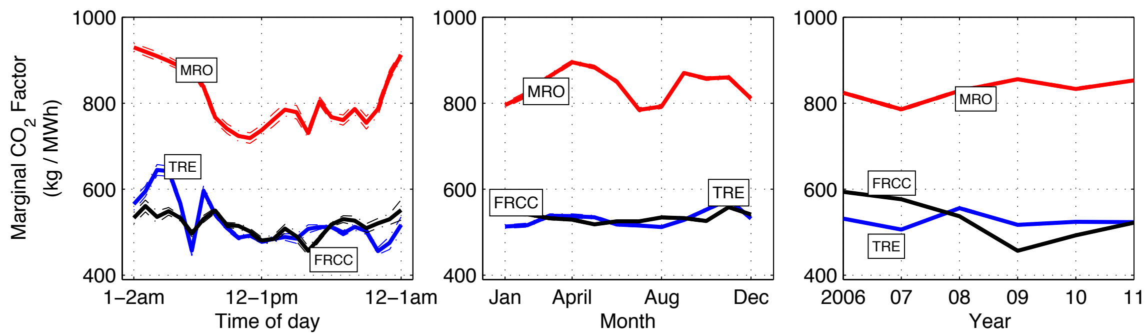

Figure 2.4: Temporal variations in marginal CO_2 factors for MRO (Midwest), TRE (Texas), and FRCC (Florida) based on data from 2006 through 2011. Dashed lines give the 95% confidence intervals, which are so narrow that they are not visible in most cases.

2.5.5 Application of MEFs

To illustrate an application of MEFs, we consider efficiency improvements in (1) a lighting system that operates from 8 a.m. to 5 p.m. Monday through Friday (e.g., interior lighting in an office) and (2) a lighting system that operates from 7 p.m. to 7 a.m. every day (e.g., exterior lighting). While it would be straightforward to use time-of-day MEFs to calculate the avoided emissions, the level of electrical demand better reflects the underlying operation of the system (generator dispatch). We calculate avoided emissions by determining the avoided energy in each hour of the year, then applying the appropriate MEF based on the level of demand at that hour (using total fossil generation as a proxy for demand; see Figure 2.3).

For each NERC region, we calculate the avoided CO_2, SO_2, and NO_x resulting from the two interventions. Results highlight three important points. First, there are significant regional differences in the avoided emissions resulting from the same intervention. Second, assessing the interventions using AEFs would, in some regions, grossly misestimate the avoided emissions. Third, surprisingly, the temporal differences between the two interventions have a modest impact on avoided emissions. Simply using the average MEF, thus ignoring temporal differences, is within 7% of the more detailed assessment for CO_2, 20% for NO_x, and 30% for SO_2 (see SI).

2.6 Discussion and Conclusions

The avoided emissions resulting from an intervention in the electricity system will depend on the generators that are displaced, which vary depending on the timing and location of the intervention. Marginal emissions factors give a consistent metric for assessing avoided emissions.

Lacking a database of MEFs, studies may revert to using system-average emissions factors, which can significantly misestimate the avoided emissions resulting from an intervention. AEFs may misestimate avoided CO_2 emissions by as much as 35% (in SPP), SO_2 by nearly 300% (in TRE), and NO_x emissions by more than 150% (in WECC).

On average, coal-fired generators emit more CO_2, NO_x, and SO_2 than other generators. As a result, displacing demand in coal-heavy regions will have greater emissions savings. Compared to WECC (West), displacing one megawatt-hour of electricity in MRO (Midwest) is expected to avoid roughly 70% more CO_2, 12 times more SO_2, and 3 times more NO_x emissions.

Several regions show consistent temporal differences in marginal emissions factors. In coal-heavy regions, MEFs tend to be higher during the spring, fall, and late-night hours—when demand is low and coal is more often on the margin. Temporal differences in marginal CO_2 factors are modest, and using an average MEF is reasonable for most applications. When considering avoided NO_x and SO_2 emissions, analysts must weight the need for accuracy with the simplicity offered by average MEFs.

We note that existing set-aside programs for NO_x allowances err on the side of simplicity. These programs credit energy efficiency and renewable energy projects for avoiding NO_x emissions. Existing set-aside programs assume that 1 kg of NO_x is avoided for every megawatt-hour displaced (17,18). By neglecting temporal and regional differences in avoided emissions, these policies risk incentivizing inefficient investments in renewable energy and energy efficiency.

From 2006 through 2011, marginal CO_2 rates have changed very little. Given the long life of the electricity infrastructure, it is likely that the marginal CO_2 factors presented here will remain reasonably valid for the next several years. Rapid changes in the generation fleet or new environmental regulations may warrant more frequent updates. In several regions, marginal SO_2 and NO_x rates have decreased substantially in the past six years. In such cases, practitioners should be cautious when applying MEFs to future scenarios. We recommend that a database of MEFs be maintained so as to facilitate effective policy and investment decisions. Independent System Operators (ISO) and Regional Transmissions Organizations (RTO)—the entities responsible for dispatching generators—could greatly help by publishing MEFs for their systems. However, much of the U.S. is not covered by an ISO or RTO. Therefore, an agreed-upon method is needed to estimate MEFs consistently across the U.S. electricity system.

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2.8 Supporting Information

2.8.1 Map and generation mix of NERC regions

Figure 2.5 shows the eight regions of the North American Electric Reliability Corporation (NERC) that encompass the continental U.S. NERC regions are as follows: Florida Reliability Coordinating Council (FRCC), Midwest Reliability Organization (MRO), Northeast Power Coordinating Council (NPCC), Reliability First Corporation (RFC), Southeastern Reliability Council (SERC), Southwest Power Pool (SPP), Texas Reliability Entity (TRE), and Western Electricity Coordinating Council (WECC).

There was a significant change to NERC region boundaries on January 1st, 2006. We therefore limit our analysis to 2006 through 2011.

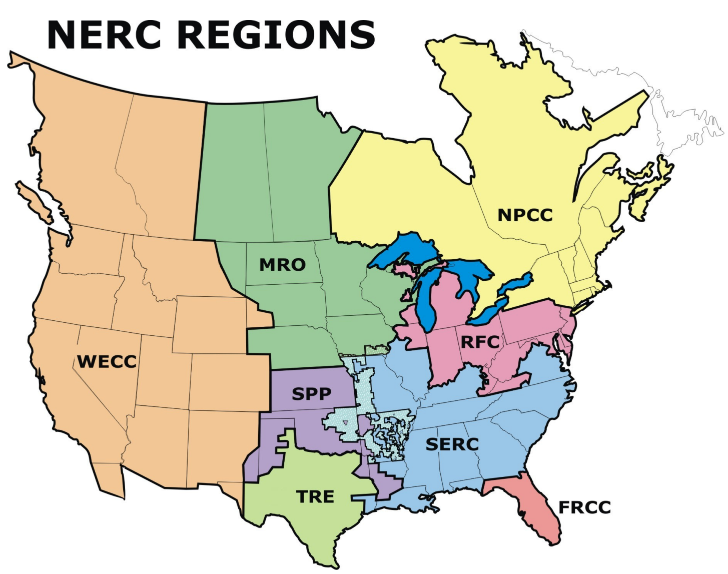

Figure 2.5: Map of NERC regions (source: http://www.nerc.com)

Table 2.3 gives the share of electricity generation by fuel source for each NERC region, based on 2007 eGRID data (*1*). Coal and gas are the dominant fossil-fuel sources; oil accounts for a very minor share with the exception of FRCC (Florida) and NPCC (Northeast); nuclear contributes between 5% and 28%; and hydropower is significant in only two regions—NPCC (Northeast) and WECC (West).

Table 2.3: Generation mix in 2007 by NERC region

	Total (TWh)	Coal	Gas	Oil	Nuclear	Hydro
FRCC (Florida)	218	27%	47%	9%	13%	0%
MRO (Midwest)	215	70%	5%	1%	15%	3%
NPCC (Northeast)	282	15%	37%	5%	28%	11%
RFC (Mid-Atlantic)	1005	64%	7%	1%	26%	1%
SERC (Southeast)	1133	57%	14%	1%	24%	2%
SPP (Southwest)	212	62%	26%	0%	5%	3%
TRE (Texas)	342	34%	49%	0%	12%	0%
WECC (West)	735	30%	31%	0%	10%	23%

2.8.2 Data limitations

Our estimates of MEFs are based on the CEMS database, which is limited to fossil-fueled power plants larger than 25 MW (*2*). The MEFs presented here are only valid if we assume that CEMS-exempt generators do not operate on the margin. In most cases, this assumption is reasonable. Nuclear and wind generation do not generally respond to changes in demand, and as a result, would not affect MEFs. The impact of hydropower on MEFs is difficult to assess without higher time-resolution data. If hydropower is on the margin and an energy efficiency measure reduces demand, hydropower may be scaled back. If this is accomplished by diverting water to the spillway, then the efficiency measure achieves no emissions benefits. However, this scenario is unlikely because diverting water to the spillway is essentially throwing away free electricity. It is more likely that an energy efficiency measure would shift the use of hydro, rather than displacing it. Under normal circumstances, if hydropower scales back in response to an energy efficiency measure, the reservoir will fill with a little extra water, which will be used to generate power at some future time, thus displacing some other generator (e.g. a gas turbine). In other words, an energy efficiency measure in hour A may shift the use of hydropower and displace the marginal unit in hour B. By excluding hydropower from our analysis, we do not account for this shifting effect. In WECC (West) and NPCC (Northeast)—the only regions with a significant share of hydro—temporal variations in MEFs are very small (see Figure 2.9), indicating that any shifting effect from hydro will have a minor impact on marginal emissions factors.

In several regions, CEMS-exempt fossil-fueled generators make up a significant share of total generation. In TRE (Texas), for example, CEMS-exempt gas plants account for roughly 10% of total generation. However, the majority (35 of 45) are combined heat and power (CHP) generators, which are unlikely to affect marginal emissions rates (*3*).

Of some concern are non-CHP biomass and fossil-fueled generators that are excluded from the CEMS database. Table 2.4 gives the share of generation from these plants, which account for 0.2% to 2.8% of regional power generation.

We also note that in recent years wind generation has frequently been on the margin in west Texas (*4*). In such cases, an energy efficiency measure would cause wind energy to be curtailed, thus resulting in zero avoided emissions.

Our estimates of MEFs do not account for wind generators being on the margin, and as such, our estimates of MEFs for TRE are likely high. Planned additions to the transmission system, which will connect wind plants in west Texas with metropolitan areas, will reduce the frequency that wind is on the margin.

Table 2.4: Share of total electricity production by non-CHP biomass and fossil-fueled generators that are excluded from the CEMS database. Values are based on a comparison between CEMS and eGRID data from 2007.

Region	Total Generation (TWh)	Non-CHP generation excluded from CEMS				
		Biomass	Coal	Gas	Oil	**Totals**
FRCC (Florida)	218	1.2%	0%	0.1%	0.1%	**1.4%**
MRO (Midwest)	215	0.4%	2.0%	0.2%	0.1%	**2.7%**
NPCC (Northeast)	282	2.5%	0%	0%	0%	**2.5%**
RFC (Mid-Atlantic)	1005	0.5%	0.1%	0%	0%	**0.6%**
SERC (Southeast)	1133	0.2%	0%	0.3%	0%	**0.6%**
SPP (Southwest)	212	0%	0%	0.1%	0%	**0.2%**
TRE (Texas)	342	0.1%	0%	1.4%	0%	**1.5%**
WECC (West)	735	0.5%	1.4%	0.8%	0.1%	**2.8%**

2.8.3 Verification of marginal fuel estimates

Figure 2.6 shows a monthly comparison of the share of marginal generation by fuel type in the Southwest Power Pool (SPP). The solid line gives the percentage of time that coal and gas were on the margin, as reported by the annual SPP State of the Market Reports (*5*).

Our estimate (dashed line) is based on a linear regression of the change in total generation between one hour and the next (ΔX), and the corresponding change in coal, gas, and oil-fired generation (ΔY_{coal}, ΔY_{gas}, ΔY_{oil}). Regressions are performed separately for each month.

From February 2007 through December 2010, SPP estimates that gas is on the margin 68% of the time, and coal is on the margin the remaining 32% of the time (*5*). Over the same time period, we estimate the share of marginal generation from gas and coal to be 63% and 37%, respectively.

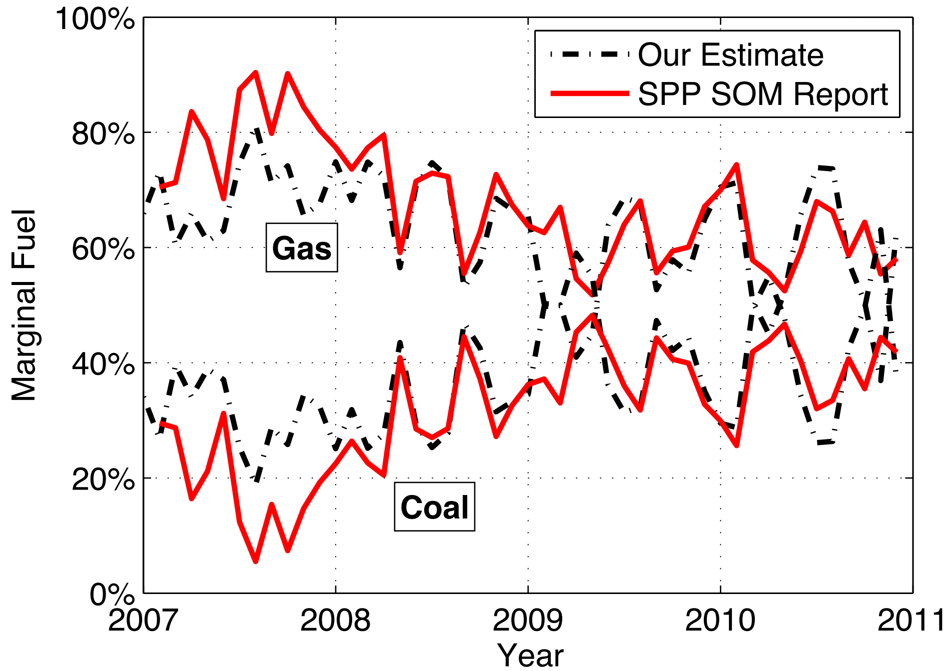

Figure 2.6: Marginal fuel source in SPP from 2007 through 2010. The solid line is the percentage of time the coal or gas was on the margin, as reported by the SPP state of the market reports. The dashed line gives our estimate of the share of marginal generation from coal- and gas-fired generators.

While this provides some indication as to the reliability of our estimates, note that the metrics being compared are not identical. SPP reports the percentage of time that a fuel source is on the margin, where marginal generators in all balancing areas are weighted equally. Our estimates reflect the degree to which different generators respond to changes in demand. This implicitly weights our results such that the marginal generators in balancing areas with greater demand represent a larger share of the total marginal fuel source.

2.8.4 Application of MEFs

In the main text, we describe a method for estimating the avoided emissions resulting from efficiency improvements in (1) a lighting system that operates from 8 a.m. to 5 p.m. Monday through Friday (e.g. interior lighting in an office) and (2) a lighting system that operates from 7 p.m. to 7 a.m. every day (e.g. exterior lighting). Results from this analysis are shown in Table 2.5, along with the average MEF and AEF.

In terms of CO_2, simply using the average MEF, thus ignoring temporal differences, is within 7% of the more detailed assessment. Using AEFs may over or underestimate the avoided CO_2 by approximately 30% in SPP and NPCC.

With the exception of FRCC and NPCC, the nighttime lighting intervention is expected to displace more SO_2 compared to the daytime lighting intervention—66% more in TRE and 38% more in WECC. Simply using average MEFs may misestimate the avoided SO_2 by as much as 30%. Using AEFs may overstate the avoided SO_2 by more than 150% (SPP, TRE & WECC).

In terms of NO_x, the difference between the two interventions is no more than 25%. Average MEFs may misestimate avoided NO_x by as much as 20% and AEFs may overstate avoided NO_x by as much as 150% (in WECC).

Table 2.5: Avoided emissions resulting from an efficiency improvement in daytime and nighttime lighting systems. Results presented in columns 3 and 4 account for temporal differences of the two interventions. Columns 5 and 6 give the average MEF and AEF, which do not account for temporal differences.

		Daytime	Nighttime	MEF	AEF
CO_2 (kg/MWh)	FRCC	523	555	532	553
	MRO	804	857	834	799
	NPCC	492	487	489	357
	RFC	706	735	731	648
	SERC	662	706	680	619
	SPP	598	640	596	763
	TRE	518	545	527	568
	WECC	477	483	486	462
SO_2 (kg/MWh)	FRCC	1.40	1.21	1.33	1.44
	MRO	1.99	2.21	2.11	2.57
	NPCC	0.59	0.53	0.55	1.09
	RFC	3.08	3.38	3.29	3.76
	SERC	1.90	2.23	2.01	2.46
	SPP	0.72	0.95	0.71	1.86
	TRE	0.35	0.58	0.40	1.16
	WECC	0.14	0.19	0.18	0.53
NO_x (kg/MWh)	FRCC	0.83	0.71	0.78	0.90
	MRO	1.06	1.13	1.09	1.41
	NPCC	0.38	0.28	0.32	0.36
	RFC	0.90	0.95	0.94	1.00
	SERC	0.60	0.66	0.62	0.78
	SPP	0.89	0.91	0.89	1.12
	TRE	0.29	0.27	0.32	0.33
	WECC	0.27	0.32	0.32	0.68

2.8.5 Full results by region

For each of the eight NERC regions, Figures 2.7-2.8 show the marginal fuel type and marginal emissions factors (CO_2, SO_2, and NO_x) as a function of total fossil generation, a proxy for system demand.

Time-of-day trends in MEFs are shown in Figure 2.9 and time-of-day trends by season are shown in Figures 2.10-2.11. Figure 2.12 shows monthly trends and Figure 2.13 shows annual MEFs from 2006 through 2011. Example regressions for each region and pollutant are shown in Figures 2.14-2.15. All results are based on generation and emissions data from 2006 through 2011.

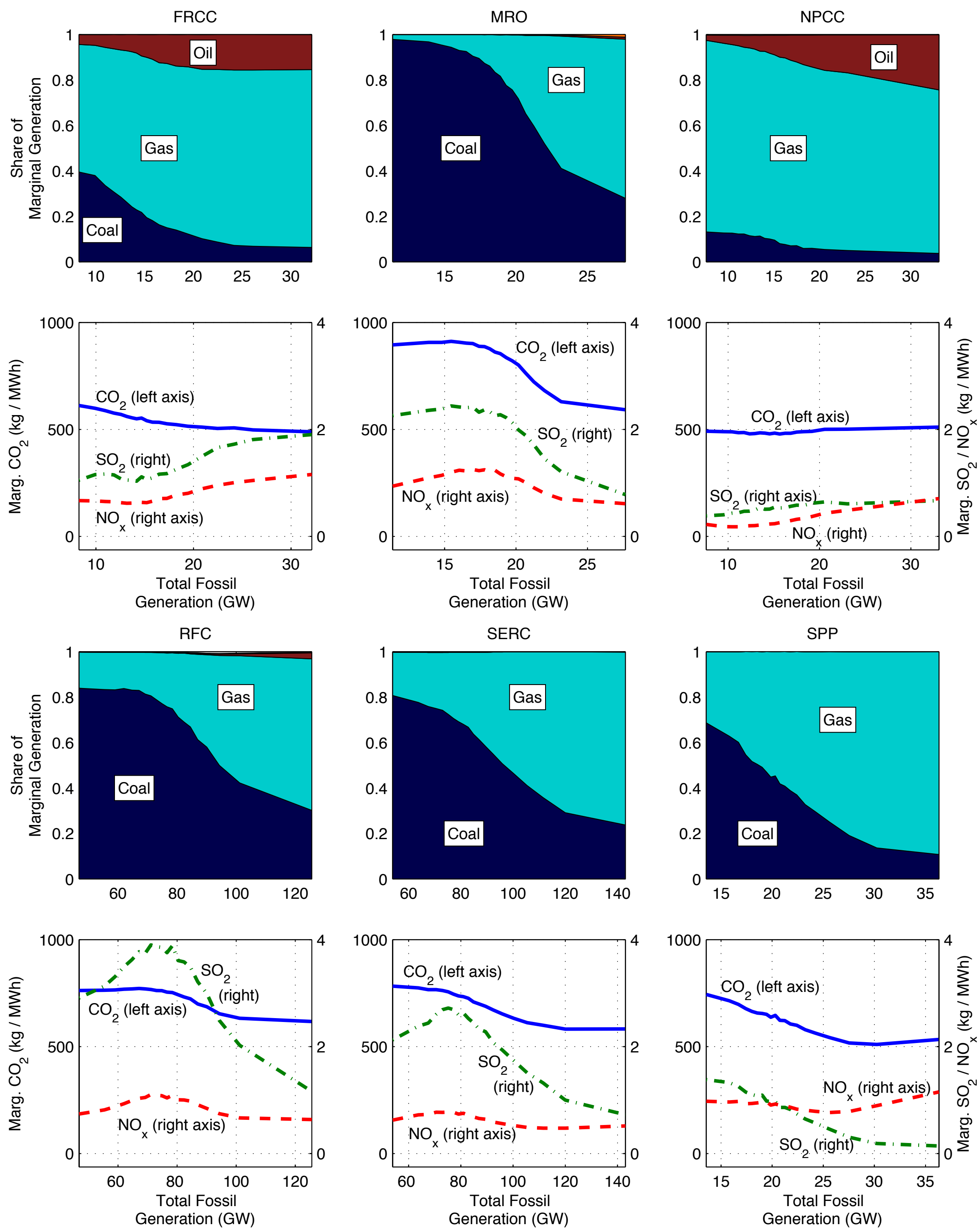

Figure 2.7: Share of marginal generation by fuel type (top) and MEFs (bottom) for FRCC (Florida), MRO (Midwest), NPCC (Northeast), RFC (Mid-Atlantic), SERC (Southeast), and SPP (Southwest). Results are based on data from 2006 through 2011, binned by every 5th percentile of total fossil generation, a proxy for system demand. MEFs have two axes: left axis applies to CO_2 and right axis applies to NO_x and SO_2.

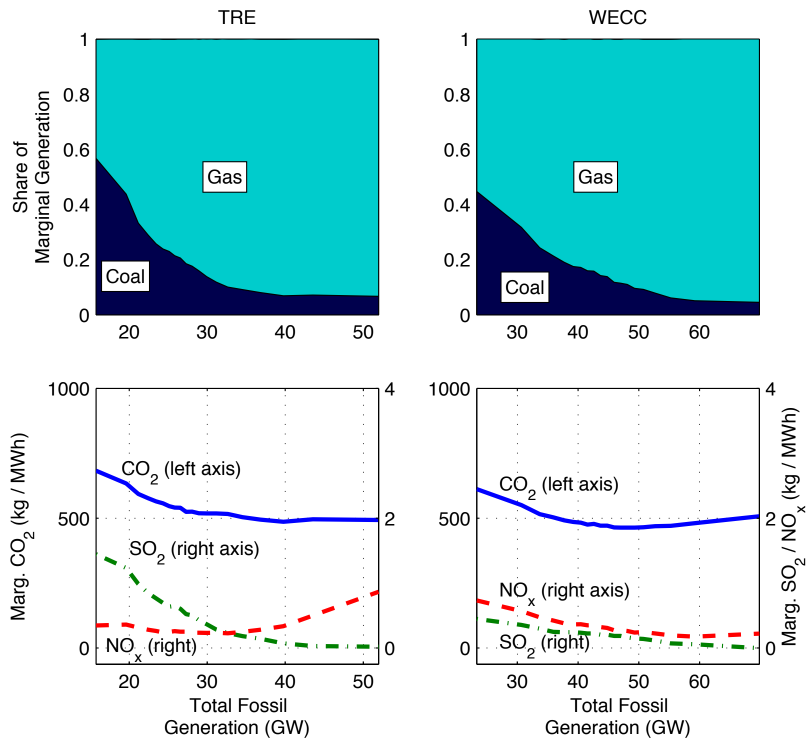

Figure 2.8: Share of marginal generation by fuel type (top) and MEFs (bottom) for TRE (Texas) and WECC (West) regions. Results are based on data from 2006 through 2011, binned by every 5th percentile of total fossil generation, a proxy for system demand. MEFs have two axes: left axis applies to CO_2 and right axis applies to NO_x and SO_2.

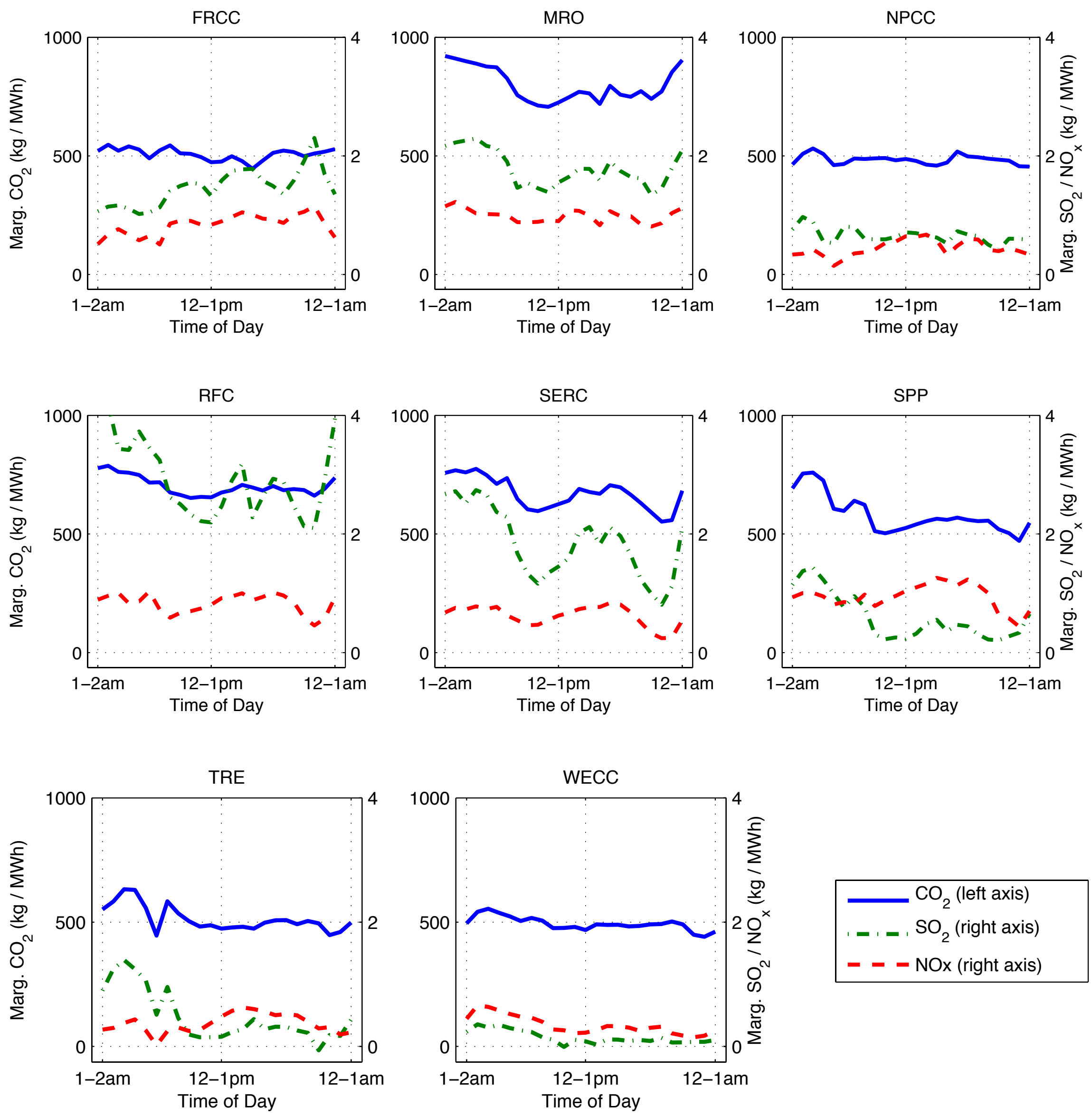

Figure 2.9: Time-of-day trends in marginal emissions factors. Left axis applies to CO_2 and right axis applies to NO_x and SO_2.

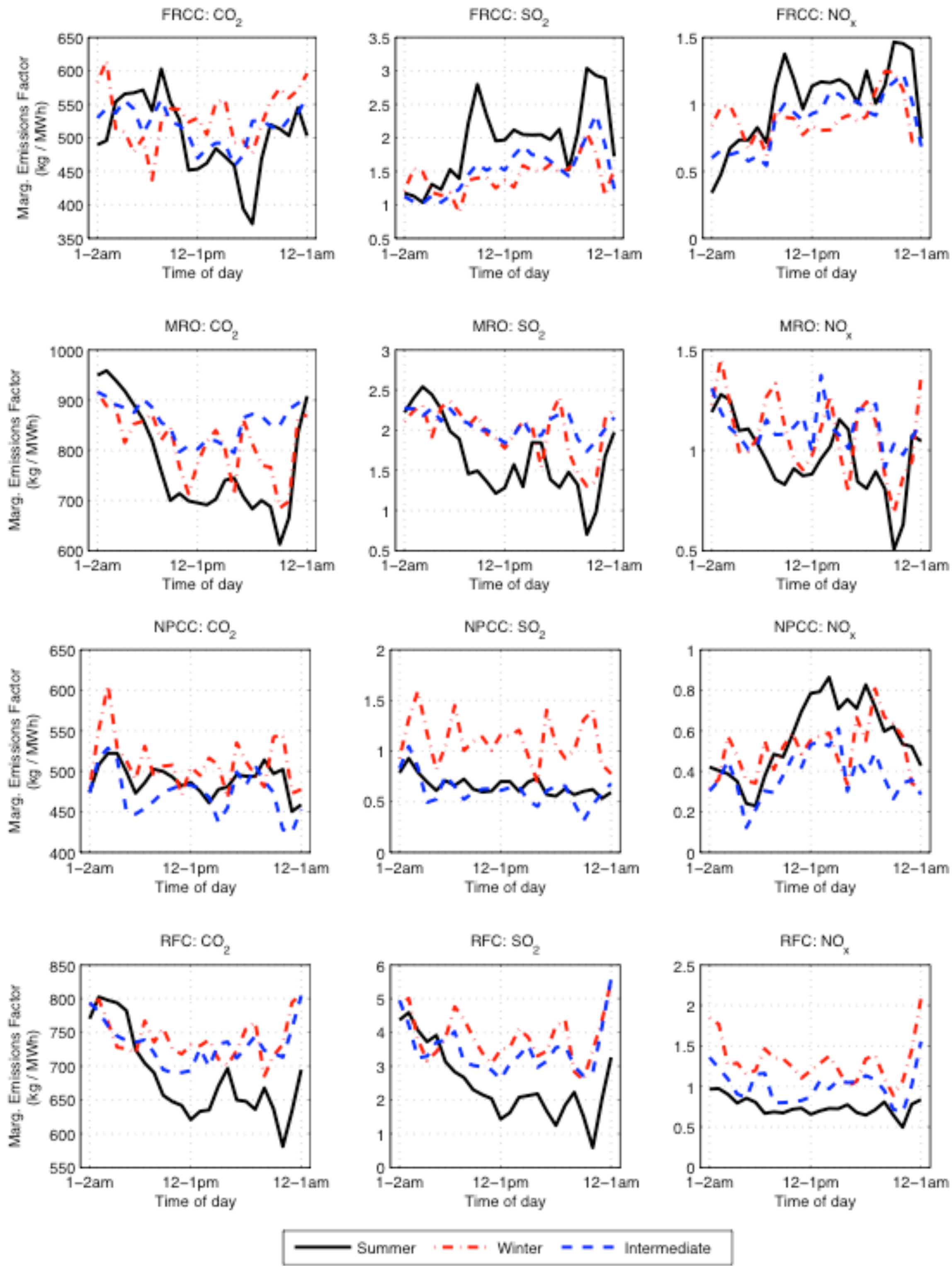

Figure 2.10: Time-of-day trends by season. Summer months are May through August; winter months are December through February; intermediate months are March, April, September, and November.

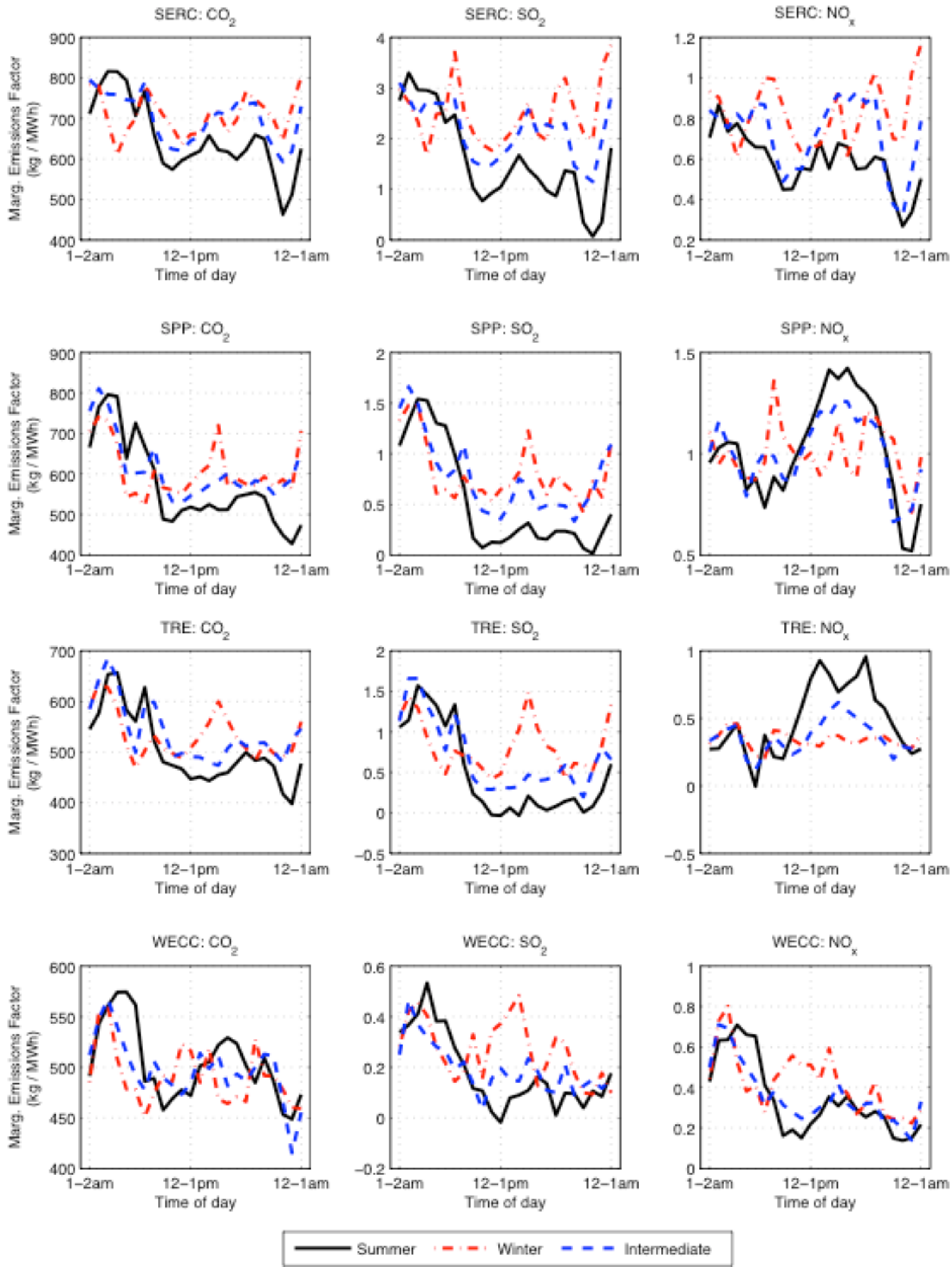

Figure 2.11: Time-of-day trends by season. Summer months are May through August; winter months are December through February; intermediate months are March, April, September, and November.

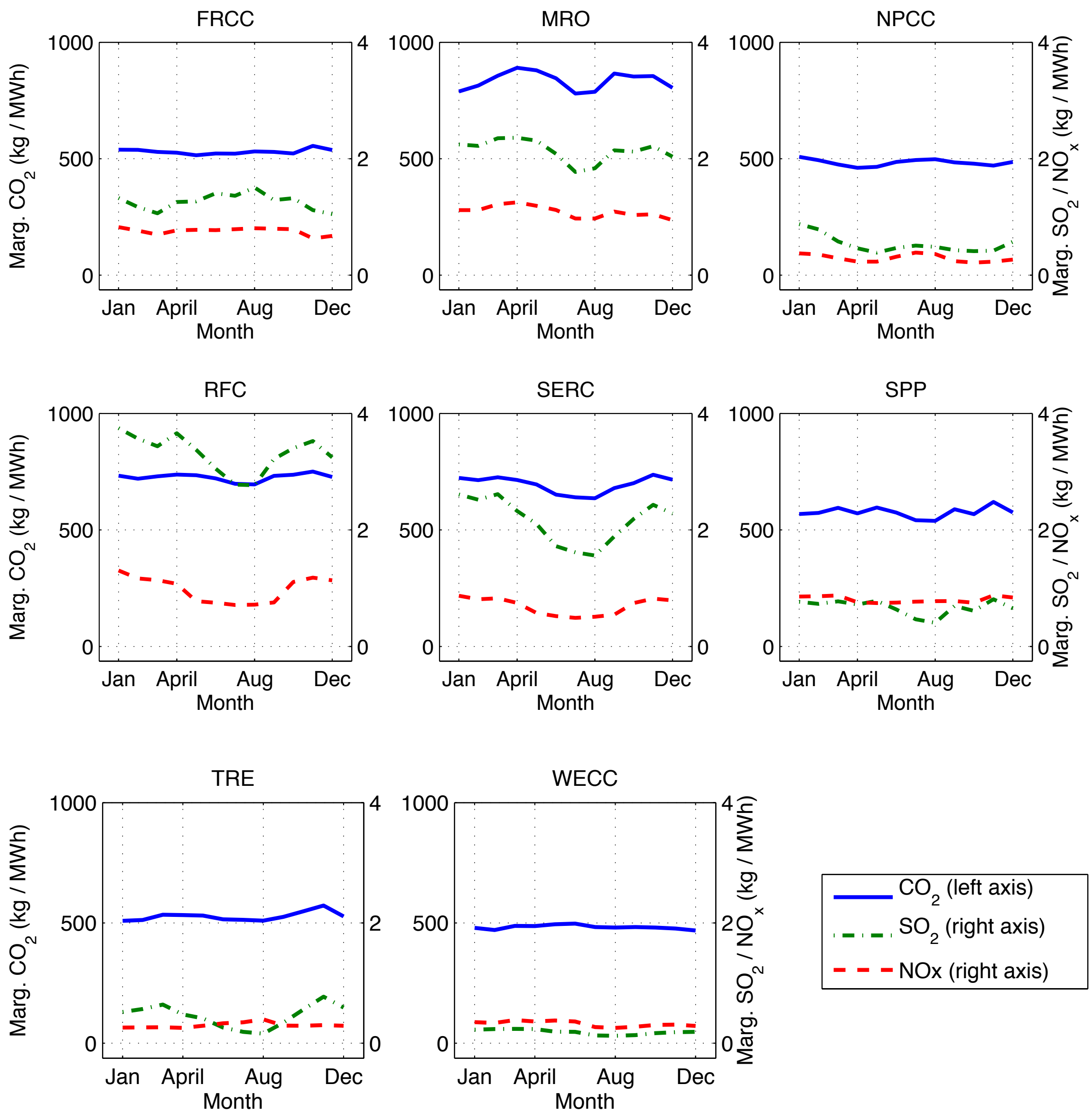

Figure 2.12: Monthly trends in marginal emissions factors. Left axis applies to CO_2 and right axis applies to NO_x and SO_2.

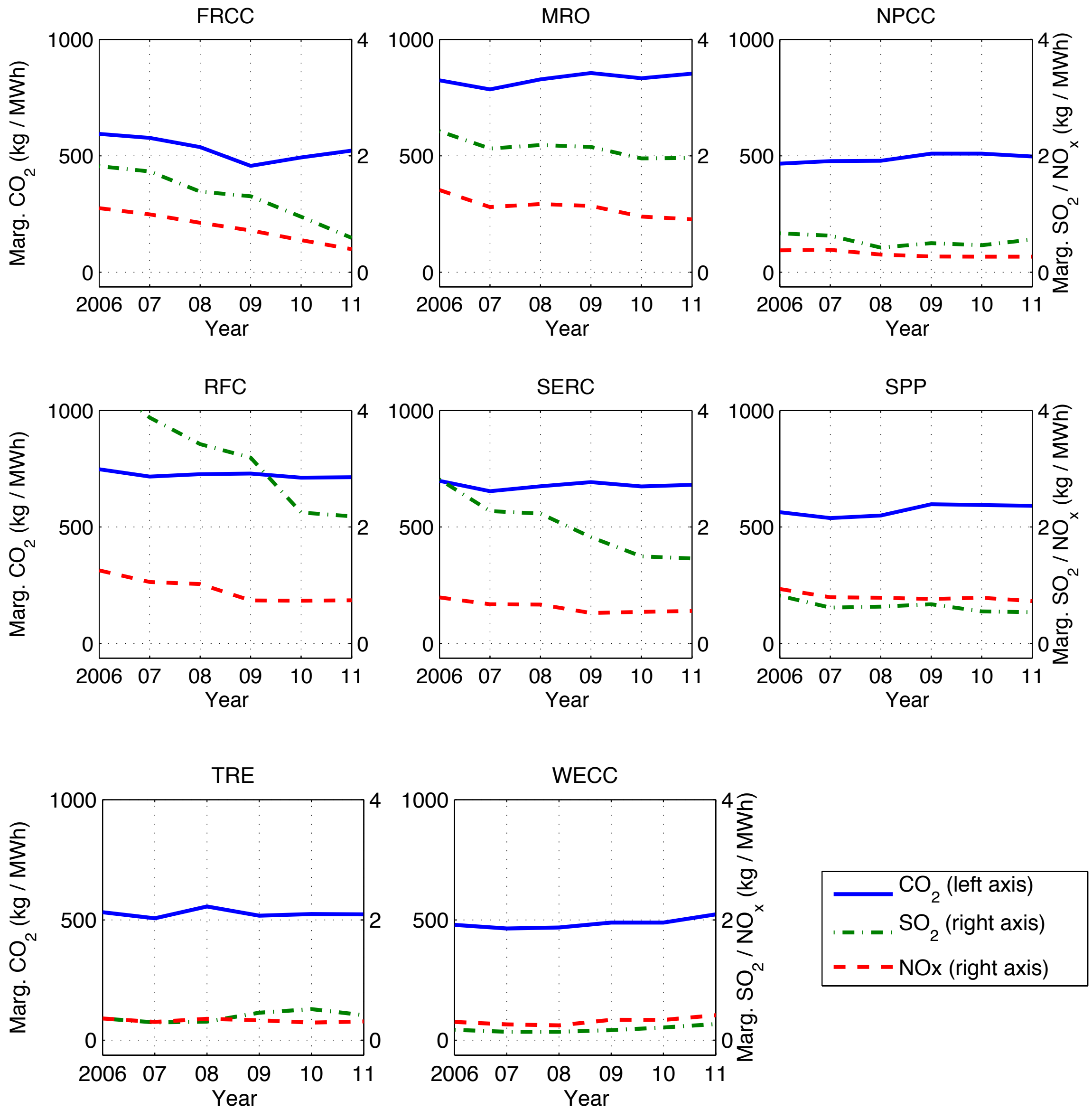

Figure 2.13: Annual marginal emissions factors from 2006 through 2011. Left axis applies to CO_2 and right axis applies to NO_x and SO_2.

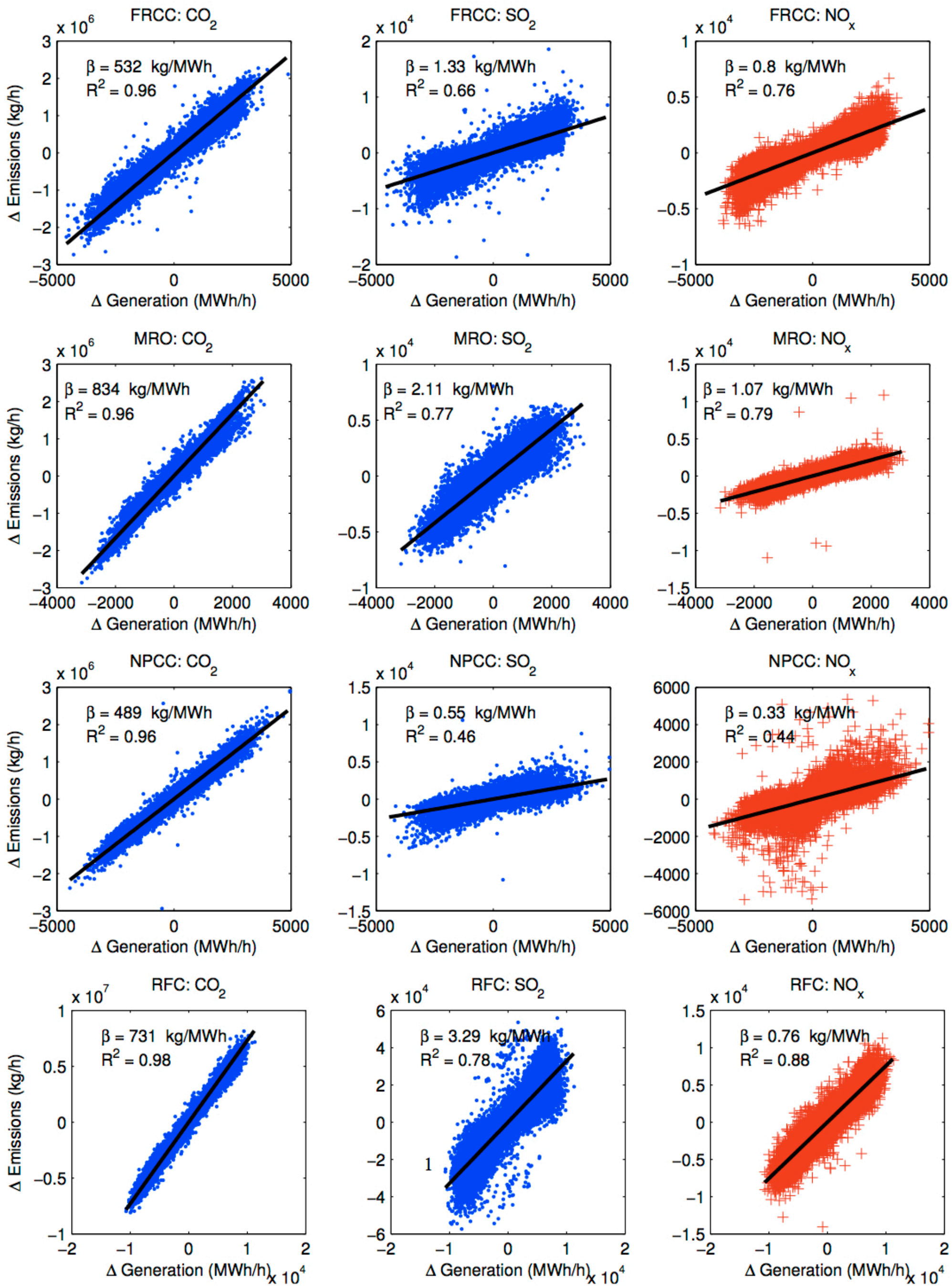

Figure 2.14: Estimates of average MEFs using data from 2006 through 2011. Each point is the difference in emissions and generation between one hour and the next. Results for NO_x emissions are limited to hours occurring in the summer ozone season (May 1st through September 30th).

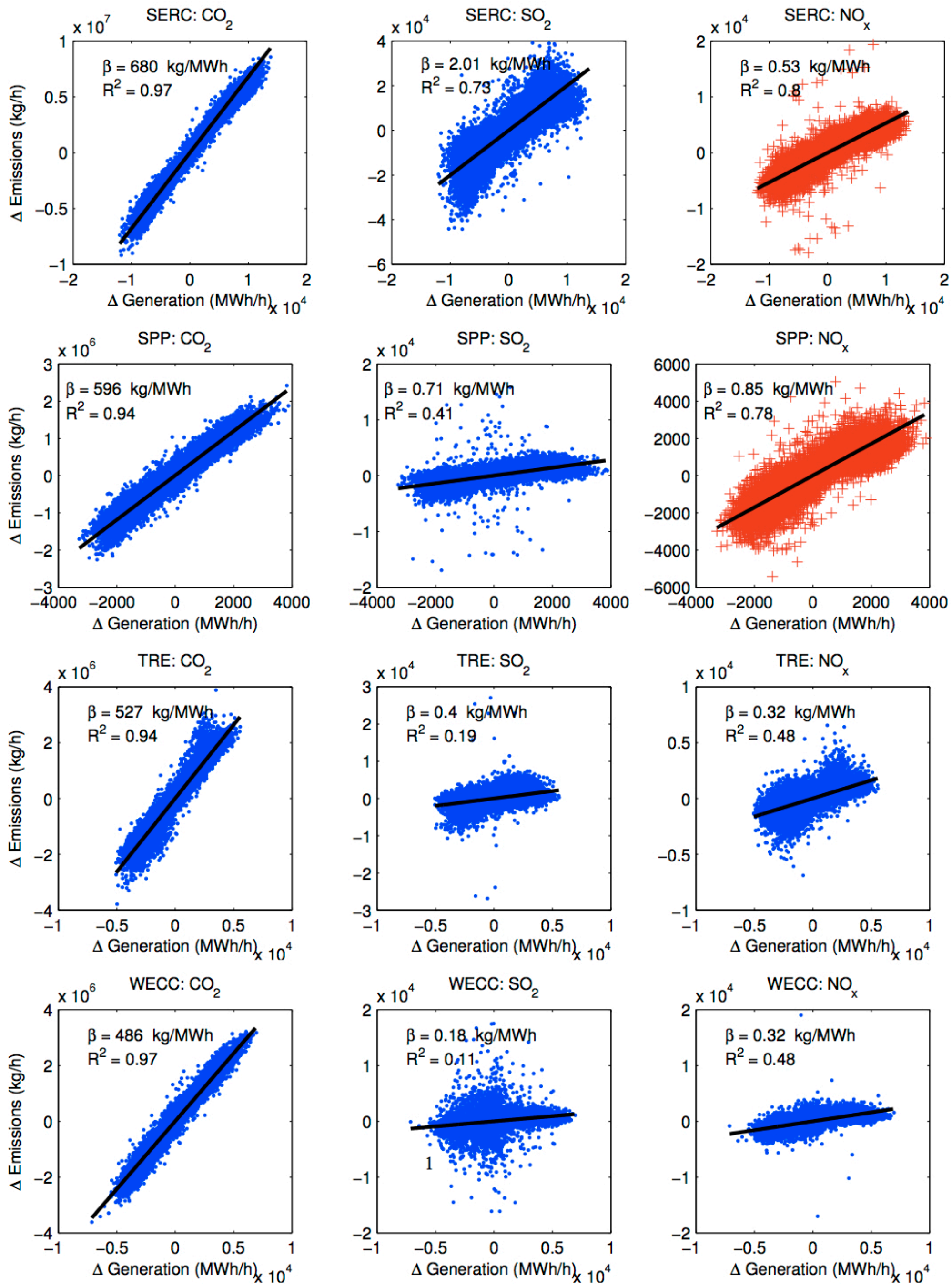

Figure 2.15: Estimates of average MEFs using data from 2006 through 2011. Each point is the difference in emissions and generation between one hour and the next. With the exception of TRE (Texas) and WECC (West), results for NO_x emissions are limited to hours occurring in the summer ozone season (May 1st through September 30th).

2.8.6 References for the supporting information

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Chapter 3: Regional Variations in the Health and Environmental Benefits from Wind and Solar Generation

3.1 Abstract

This work explores regional differences in the performance of wind turbines and solar panels. Because different stakeholders have different objectives, we consider three measures of performance: energy production, avoided CO_2 emissions, and avoided health and environmental damages arising from criteria pollutants. For 22 regions of the United States, we use regressions of historic emissions and generation data to estimate *marginal impact factors*, a measure of the avoided health and environmental damages per megawatt-hour of displaced electricity. Marginal impact factors are used to evaluate the impacts of an additional wind turbine or solar panel in the U.S. electricity system. We find that the most attractive sites for renewables depend strongly on one's objective. A solar panel in Iowa displaces 20% more CO_2 emissions than a panel in Arizona, though energy production from the Iowa panel is 25% less. Similarly, despite a modest wind resource, a wind turbine in West Virginia is expected to provide 7 times more health and environmental benefits than a wind turbine in Oklahoma. We estimate the social benefits from existing wind farms and find that, on aggregate, the costs of the production tax credit for wind are justified.

3.2 Introduction

In the United States (U.S.), the electricity sector is responsible for roughly 40% of carbon dioxide (CO_2) emissions (*1*), the primary driver of global climate change. In the long run, these emissions are expected to result in a wide range of social, economic, and environmental impacts (*2*). In addition, fossil-fueled power plants emit criteria pollutants, which include sulfur dioxide (SO_2), nitrogen oxides (NO_x), particulate matter (PM), ozone, carbon monoxide, and lead. Criteria pollutants cause serious health effects, premature mortality, acid rain, and smog (*3*).

Renewable energy resources, such as wind and solar, have gained popularity as a means of providing emissions-free electricity. Common sense suggests that renewables should be located in regions where the resource is most abundant: solar panels should be installed in the sunny deserts of the Southwest and wind turbines should be located in the open, windy plains of middle America. However, this rationale assumes that the objective of renewables is to maximize energy output. Policy makers and the general public may support renewables for different reasons, and different objectives require different measures of performance. Those concerned with long-term climate change should look at *avoided carbon dioxide emissions*—that is, the CO_2 emissions from conventional generators that are displaced when renewables are introduced. Those concerned with shorter-term health and environmental impacts should look at the *avoided emissions of criteria air pollutants*, along with the benefits of reducing those emissions.

This work explores regional differences in the performance of wind turbines and solar panels. Because different stakeholders have different objectives, we consider three measures of performance: energy production, avoided CO_2 emissions, and avoided health and environmental damages from criteria pollutants.

Past studies have estimated the emissions benefits of wind and solar generation in the U.S. These studies cover a range of geographical areas, including the entire county (*4*), the Eastern U.S. (*5*), the Western U.S (*6*), the Southwest (*7*), Illinois (*8*), California (*9*), and Texas (*10*, *11*). The vast majority of studies rely on economic dispatch models to predict the conventional generators that are displaced by renewables, though the details of these models vary widely. By contrast, Cullen uses regressions of historic market data to estimate the substitution between wind energy and conventional generators (*10*). Some studies are limited to estimating avoided CO_2 emissions (5,7,9,11), others include NO_x and SO_2 (4,6,10), and Valenteno et al. include a more complete list of criteria pollutants (*8*). Due to variations in the methods and assumptions used, there are limited opportunities to compare results across studies.

This work contributes to the literature in three ways. First, we develop a novel method for estimating the health and environmental benefits that occur when conventional generators are displaced. For more than 1,400 fossil-fueled generators, we estimate social damages resulting from emissions of CO_2, SO_2, NO_x, and $PM_{2.5}$; we then use regressions to estimate the change in damages corresponding to a change in the supply or demand of electricity (e.g. due to renewables). The result is what we call *marginal impact factors*, a measure of the avoided health and environmental damages per megawatt-hour of displaced electricity. Second, we use marginal impact factors to provide a systematic assessment of the regional differences in the impacts of renewables across the U.S. Third, we consider tradeoffs between the objectives of energy production, long-term climate benefits (from avoided CO_2 emissions), and shorter-term health and environmental benefits (from avoided criteria pollutants).

The remainder of this chapter is organized as follows. The methods are discussed in Section 3.3, results are presented in Section 3.4, and a sensitivity analysis is presented in Section 3.5. In Section 3.6, we estimate the social benefits from existing wind farms and compare those benefits to the costs of the production tax credit, an important subsidy for wind energy. We conclude in Section 3.7.

3.3 Methods and Analysis

This analysis consists of two steps. First, we estimate marginal impact factors for CO_2 and criteria pollutants. Marginal impact factors provide a measure of the avoided health and environmental damages per megawatt-hour of displaced electricity. Second, we apply marginal impact factors to estimate the effects of an additional wind turbine or solar panel in the U.S. electricity system.

3.3.1 Marginal impact factors for criteria pollutants

To calculate marginal impact factors, we (1) gather emissions data for U.S. power plants, (2) estimate the health and environmental damages associated with those emissions, and (3) use regressions to estimate the change in damages corresponding to a change in the supply or demand of electricity (e.g. due to renewables). Each step is discussed below.

Data: Emissions data are from the Environmental Protection Agency's (EPA) Continuous Emissions Monitoring System (CEMS) (*12*). CEMS data include hourly, generator-level SO_2, NO_x, and CO_2 emissions as well as gross power output. CEMS data is limited to fossil-fueled generators greater than 25 MW (*13*). This analysis uses the three most recent years of CEMS data, from 2009 through 2011. $PM_{2.5}$ emissions data are from the 2005 National Emissions Inventory (NEI) (*14*). We assume that emissions are proportional to power output, allowing us to estimate hourly $PM_{2.5}$ emissions from each plant. Plant locations and primary fuel types are from the eGRID database (*15*).

Health & Environmental Damages: Damages from pollutants are estimated using the Air Pollution Emissions Experiment and Policy (APEEP) analysis model (*16*). APEEP estimates the damages from emissions of SO_2, NO_x, $PM_{2.5}$, PM_{10}, VOCs, and NH_3 on a dollar-per-ton basis (*16-18*). Damages include human-health impacts (e.g. lung cancer, bronchitis, asthma, and cardiopulmonary diseases), reduced crop and timber yields, reduced visibility, degradation of materials, and lost recreational services.

For each source location, APEEP uses a Gaussian plume model to estimate the dispersion of emissions and the resulting concentrations in each county. Dose-response functions are used to estimate physical impacts of affected populations and other receptors (crops, forests, materials, etc.). Physical impacts are translated to monetary values using market prices for lost commodities, costs of illnesses, a value of a statistical life (VSL), and other non-market valuations from the literature.

Results from the APEEP model give dollar-per-ton damages for each pollutant (SO_2, NO_x, $PM_{2.5}$, PM_{10}, VOC_s, and NH_3) emitted in each U.S. county. In addition, APEEP differentiates damages by the height at which pollutants are emitted. We match location-specific damages from APEEP with power-plant locations and stack heights to estimate damages from more than 1,400 power plants in the U.S. VOCs, NH_3, and PM_{10} are excluded from this analysis because they result in damages that are, on average, more than two orders of magnitude lower than damages from other pollutants.

Regressions: Damages from power production are quite varied: the health impacts from the worst coal plant are 10,000 times higher than those of the best gas plant (*19*). Therefore, the benefits of displacing one megawatt-hour of electricity may vary enormously depending on the specific plants that are displaced. We use regressions of historic data to estimate the response of the electricity system to changes in supply or demand (e.g. due to renewables).

Regressions are performed separately for 22 regions, which were defined by the EPA for use in the eGRID database (*15*). A map of the regions is included in the Supporting Information (SI). eGRID subregions, as they are called, are the best estimates for the group of plants serving loads within a region (*20*). However, errors arise because imports and exports between regions are ignored. Larger regions would reduce these errors, but may mask variations in the generation mix. The 22 eGRID subregions provide a reasonable balance between these competing effects. We have verified that our conclusions hold when using a coarser level of aggregation (see SI).

For each region (r) and each pollutant (p), we calculate the change in total generation (G) and change in damages (D) between one hour (h) and the next for all hours from 2009 through 2011:

$$\Delta G_{r,h} = G_{r,h+1} - G_{r,h} \quad \text{(MWh)} \qquad\qquad \Delta D_{r,p,h} = D_{r,p,h+1} - D_{r,p} \quad (\$)$$

Total generation is the sum of the electrical output from all plants in a given region. Total damages are the product of the emissions from a plant times the appropriate dollar-per-ton damages from the APEEP model, totaled across all plants within a region.

Using hourly data from 2009 through 2011, there are more than 25,000 observed changes in damages corresponding to a change in generation. The slope of a linear regression of ΔD on ΔG estimates the marginal impact factor of the system—that is, the avoided health and environmental damages per megawatt-hour of displaced electricity. For example, Figure 3.1 shows ΔD plotted against ΔG for SO_2, NO_x, and $PM_{2.5}$ emissions in the RFCM region (Michigan). In this case, reducing demand by one megawatt-hour is expected to displace, on average, \$38 of damages from SO_2 emissions and \$2 of damages from both NO_x and $PM_{2.5}$.

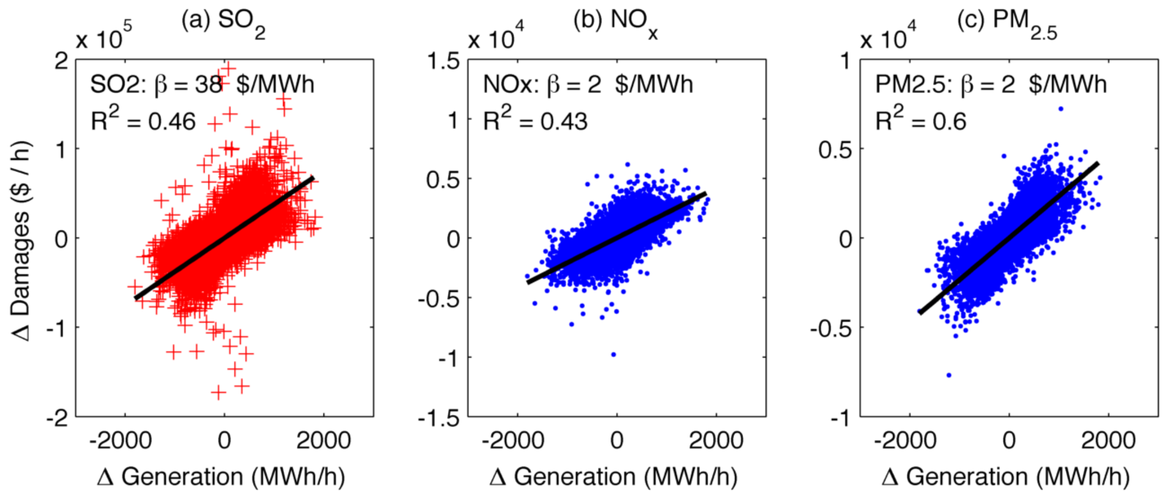

Figure 3.1: Example regressions of ΔDamages vs. ΔGeneration for SO_2, NO_x, and $PM_{2.5}$ emissions in the RFCM region (Michigan). The slope of the regression line estimates the marginal impact factor for the region ($38/MWh for SO_2 and $2/MWh for NO_x and $PM_{2.5}$).

<u>*Temporal Variations In Marginal Impact Factors*</u>: The marginal generator constantly changes as different plants are dispatched to meet demand. As a result, there are temporal trends in marginal impact factors. These trends are important for an evaluation of wind and solar, both of which have strong seasonal and time-of-day patterns. To account for temporal differences, we calculate marginal impact factors as a function of system demand, which is a strong predictor of the marginal emissions rates of an electricity system (*21*). Due to data limitations, we used total fossil generation (based on CEMS data) as a proxy for system demand. Hourly data are binned by every 5th percentile, where the first bin contains the 5% of data occurring during the lowest-demand hours, and the twentieth bin contains the 5% of data occurring during the highest-demand hours. An example of this method is shown in Figure 3.2a for the ERCT region (Texas). During low-demand hours

(bottom 5%), displacing a megawatt-hour of electricity is expected to reduce $19 in damages from SO_2 emissions. Reducing demand has a negligible effect on SO_2 emissions during high-demand hours (top 5%). For each pollutant, separate regressions are used to calculate marginal impact factors using data within each bin. For the ERCT region (Texas), Figure 3.2b shows an example of marginal impact factors as a function of total fossil generation, a proxy for system demand.

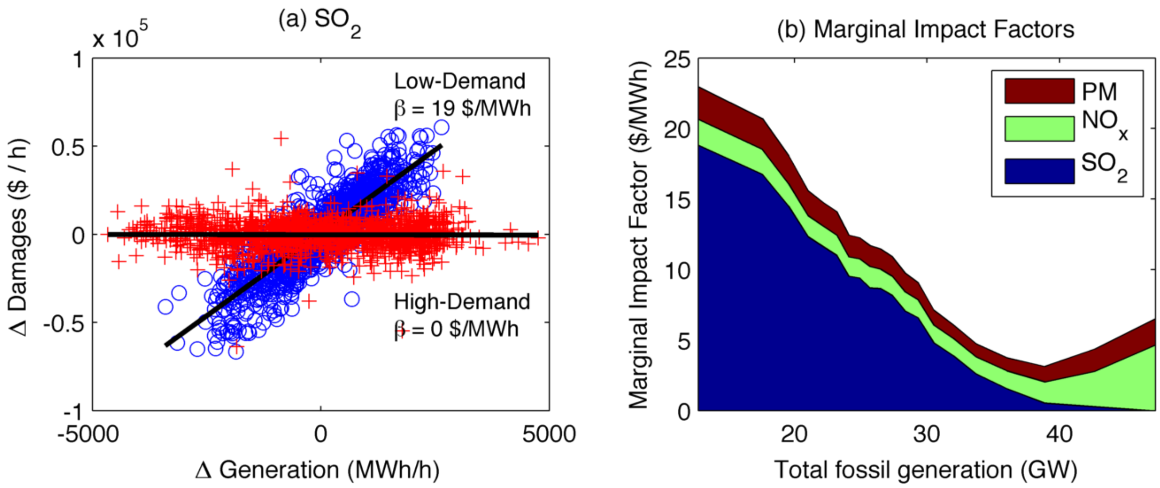

Figure 3.2: Example regressions for low- and high-demand hours for SO_2 (left) and marginal impact factors as a function of system demand (right). Both figures are based on data from 2009 through 2011 for the ERCT region (Texas).

By disaggregating the data in this way, we account for temporal variations in the electricity system. For example, coal-fired generators are more likely to be on the margin when demand is low (e.g. in the spring, fall, and late at night) (*21*). Note, however, that dollar-per-ton damages from the APEEP model are not temporally differentiated (*17*). In some cases, there are seasonal differences in the impacts of pollutants. NO_x is more likely to cause ground-level ozone in the summer, resulting in higher damages. Seasonal differences are accounted for in the APEEP model but are rolled into an annual-average damage value.

3.3.2 Marginal impact factors for CO_2

Avoided CO_2 emissions are measured using marginal emissions factors, which reflect the emissions intensities of the marginal generators in the system. Marginal emissions factors are calculated using a method that is analogous to the one described above. The method and data are described in detail in Chapter 2.

Damages from CO_2 emissions are valued using a social cost of carbon (SCC), which reflects the present value of economic and environmental damages resulting from CO_2 emissions. We assume an SCC of $20 per ton, which is based on a recent study by the Interagency Working Group on Social Cost of Carbon (*22*). Using a collection of integrated assessment models and discount rates ranging from 2.5% to 5%, the study reports four values for the SCC in 2010: $4.7, $21.4, $35.1 and $64.9 per ton of CO_2. We select $20 per ton as the more conservative central value (rounded to one significant figure due to the uncertainty in these estimates).

3.3.3 Evaluating wind turbines and solar panels

We evaluate a photovoltaic (PV) solar panel at more than 1,300 locations across the U.S. Solar insoluation data for 2005 are from the National Solar Radiation Database, which provides hourly solar intensities (*23*). Solar panels are assumed to have a nameplate capacity of one kilowatt and an efficiency of 13%. Panels are installed facing true south with a tilt equal to the latitude of the installation site.

Similarly, we evaluate wind turbines at more than 33,000 locations. Wind data for 2006 are from the Eastern Wind Integration and Transmissions Study (EWITS) and the Western Wind and Solar Integration Study (WWSIS), which model wind power output from Vesta-3 turbines (*5*, *6*). For each site, power output data are available at 10-minute temporal resolution, which we average to find the hourly power output for each site. A map of the wind and solar sites is included in the SI.

Note that there are year-to-year differences in renewable resources that are not captured in this analysis (*24*). We assume that solar output from 2005 and wind output from 2006 repeat in future years.

Marginal impact factors are used to estimate the avoided health and environmental damages for each wind farm and solar panel. We determine the displaced energy in a given hour and apply the appropriate marginal impact factor based on the level of demand at that hour. For example, consider a wind turbine in Texas that produces 2 MWh between midnight and 1 a.m. on January 1st, 2009. During this hour, total fossil generation in the ERCT region is 21 GW and the corresponding marginal impact factor is $16/MWh (see Figure 3.2). Thus, the wind turbine displaces $32 in health and environmental damages from criteria pollutants. The process is repeated for each hour of the year from 2009 through 2011. Hourly avoided damages are summed and divided by three to find the annual impact of the wind turbine. The approach is applied separately for CO_2 emissions and criteria pollutants (limited to SO_2, NO_x, and $PM_{2.5}$).

3.3.4 A caveat to valuing displaced emissions

Throughout this analysis, we value emissions using social costs, or damages. In doing so, we assume that renewables achieve a net reduction in emissions, and therefore a reduction in damages. However, for pollutants regulated under a cap-and-trade program, emissions displaced from one generator free up allowance permits that can be used elsewhere. As long as pollution caps are binding, renewables will put downward pressure on allowance prices but will not achieve a net reduction in emissions.

In much of the eastern U.S., SO_2 and NO_x are regulated by cap-and-trade programs. In such cases, some argue that emissions should be valued using allowance prices when the cap is binding (*10*). Doing so implies that there are zero environmental and health benefits related to SO_2 and NO_x displacements because net emissions remain unchanged. Rather, by freeing up NO_x and SO_2 allowances, renewables reduce the costs for conventional generators to meet a pollution cap.

If pollution caps are not binding, then social damages are the appropriate metric for valuing displaced emissions. Emissions caps have not been binding in recent years for both NO_x (2010) and SO_2 (2008 and 2009) (*25*). The EPA has proposed aggressively lower caps, though the future of these regulations is uncertain. A stay has been issued on the Cross-State Air Pollution Rule (CSAPR), the EPA's latest revision to cap-and-trade regulation, which was scheduled to begin in 2012. The Clean Air Interstate Rule (CAIR) remains in place until a new program takes effect, though CAIR was vacated by the courts in 2008 (*25*).

We proceed in this analysis by valuing all emissions using social costs. In a sensitivity analysis, we explore valuing NO_x and SO_2 emissions using allowance prices.

3.4 Results

3.4.1 Marginal impact factors

Figure 3.3 shows marginal impact factors for criteria pollutants (left) and CO_2 emissions (right). Based on regressions of hourly data from 2009 through 2011, marginal impact factors are a measure of the health and environmental benefits per megawatt-hour of displaced electricity.

Criteria Pollutants (SO_2, NO_x, $PM_{2.5}$): Results are based on a VSL of $6 million (2010 dollars). Damages from criteria pollutants are dominated by SO_2 emissions, which are primarily from coal-fired power plants. Marginal impact factors are more than $85 per megawatt-hour in Indiana, Ohio, and West Virginia, where coal-fired plants account for roughly 70% of marginal generation (21). Marginal impact factors are lower in the Midwest—between $35 and $50 per megawatt-hour—though the Midwest is a more coal-heavy region. This discrepancy is explained by (1) relatively low population densities in the Midwest, resulting in lower damages per ton emitted, and (2) lower SO_2 emissions from coal-fired plants due to greater use of sub-bituminous coal, which has a relatively low sulfur content.

In much of the West, population densities are low and natural gas is the dominant marginal fuel. As a result, marginal impact factors are low—ranging from $3 to $9 per megawatt-hour. In both Texas and Florida, coal accounts for roughly 15% of marginal generation. Yet, the marginal impact factor in Florida is nearly twice as high, which is due to higher population densities and oil-fired plants operating on the margin. Marginal impact factors are approximately \$8/MWh in New England, \$30/MWh in New York, and \$30 to \$50/MWh throughout the South.

Overall, there are significant regional differences. For one megawatt-hour of displaced electricity, the avoided health and environmental damages in Ohio are 25 times greater than those in Arizona or California.

CO_2 emissions: Figure 3.3 (right) shows marginal emissions factors for CO_2, in kilograms per megawatt-hour. A second scale gives the marginal impacts based on an SCC of \$20 per ton. Marginal CO_2 factors range from 425 to 850 kg/MWh. In other words, displacing a megawatt-hour of electricity in Iowa is expected to displace twice as much CO_2 than in California. Again, this range is driven by regional differences in the generation mix. The average CO_2 rate of coal-fired plants is roughly double that of gas-fired plants. Therefore, marginal CO_2 rates are highest in regions where coal accounts for a large share of marginal generation (e.g., Midwest and mid-Atlantic).

Assuming an SCC of \$20 per ton, marginal impact factors for CO_2 range from \$10 to \$19 per megawatt-hour. Though the SCC is highly uncertain, a sensitivity analysis is simple because marginal impact factors for CO_2 are linearly related to the social cost of carbon. Therefore, doubling the SCC to \$40 per ton doubles the marginal impact factor for CO_2. Similarly, marginal impact factors are cut in half if we assume an SCC of \$10 per ton.

Total Impacts: Damages from criteria pollutants and CO_2 emissions can be added together to find the total benefits of displacing one megawatt-hour of electricity. Total marginal impact factors range from \$13/MWh in California to more than \$100/MWh in Indiana, Ohio, and West Virginia. CO_2 accounts for roughly 80% of total impacts in the former and less than 20% in the latter. A map of total marginal impact factors is included in the SI.

While total impacts are a useful measure, bear in mind that the damages from criteria pollutants are very different than those from CO_2 emissions. Criteria pollutants result in localized damages that occur relatively quickly. By contrast, the bulk of the damages caused by CO_2 emissions will occur many decades from now and will disproportionately affect developing countries (*2*). Due to these differences, we report impacts separately for CO_2 and criteria pollutants for the majority of this analysis.

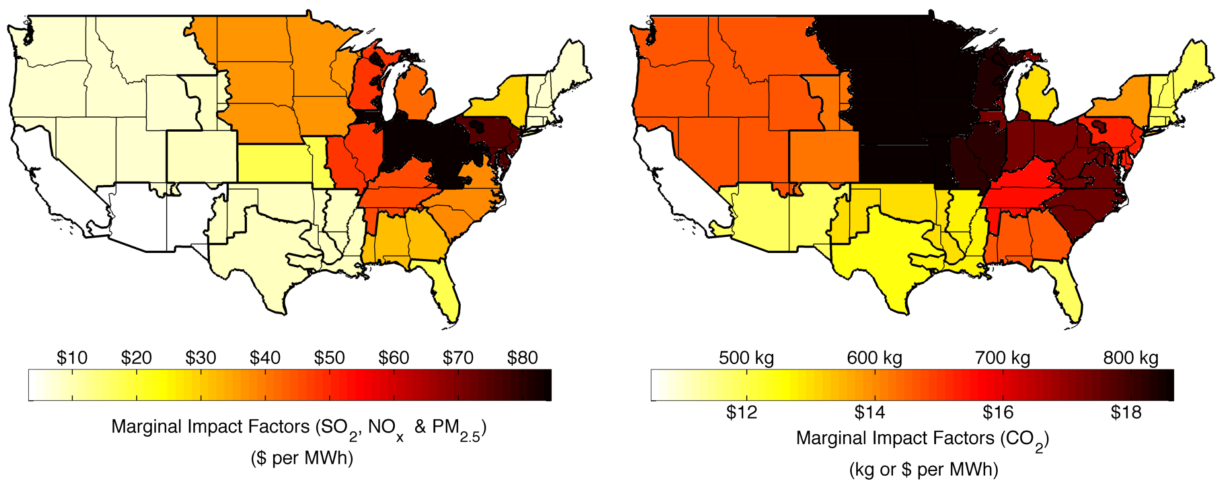

Figure 3.3: Marginal impact factors for SO_2, NO_x, and $PM_{2.5}$ (left) and CO_2 (right). Impacts from criteria pollutants assume a value of a statistical life of \$6 million. Results for CO_2 include two scales: kilograms of CO_2 per MWh and dollars per megawatt-hour. The latter is based on a social cost of carbon of \$20 per ton. All monetary values are expressed in 2010 dollars.

3.4.2 Regional performance of wind and solar

We explore regional differences in the performance of wind turbines and solar panels, where performance is measured relative to three objectives: energy production, long-term climate benefits from displaced CO_2 emissions, and shorter-term health and environmental benefits from displaced emissions of SO_2, NO_x, and $PM_{2.5}$.

__Solar:__ Figure 3.4 (top left) shows the expected performance of a 1 kW PV solar panel in terms of energy output, measured by the annual capacity factor[2]. Results are based on an evaluation of more than 1,300 sites across the U.S. As expected, energy output is highest for solar panels in the Southwest, where capacity factors peak near 28%. Texas, the West, and the Great Plains offer moderate solar intensities. Energy output is lowest in New England, where capacity factors are roughly 18%. A typical solar panel in Arizona is expected to produce 45% more energy than a panel in Maine.

Figure 3.4 (middle left) shows the annual avoided CO_2 emissions resulting from the same solar panel. Avoided emissions depend on the generators that are displaced by solar energy. In California, natural gas is the dominant marginal fuel and, as a result, solar panels displace relatively little CO_2. Avoided emissions are highest in Western Nebraska and the Dakotas, where there is a moderate solar resource and a carbon-intensive supply of electricity. On average, a solar panel in

[2] Capacity factor is the annual power output divided by the annual power output when operating at nameplate capacity.

Nebraska is expected to displace 30% more CO_2 than a panel in Arizona, though energy output from the Nebraska panel is 15% less. Assuming an SCC of $20 per ton, the value of displaced CO_2 emissions ranges from $20 to $36 annually, equivalent to $12 to $18 per megawatt-hour (in Massachusetts and Kansas, respectively).

For the same solar panel, Figure 3.4 (bottom left) shows the avoided health and environmental damages from SO_2, NO_x, and $PM_{2.5}$. Solar panels that displace coal-fired plants in populated regions have the greatest impact. For example, despite the poor solar resource, a solar panel in Ohio provides $120 in health and environmental benefits per year ($75/MWh)—17 times more than a solar panel in Arizona.

Under the assumptions used here, solar panels in Indiana provide the greatest combined benefit (CO_2 plus criteria)—more than $150 per year or $92 per megawatt-hour. Note that displaced CO_2 emissions account for only 20% of the total benefits for a solar panel in Indiana. By contrast, the combined benefits from the average solar panel in California are $29 per year ($14/MWh) and displaced CO_2 emissions account for 75% of the total.

Wind: Figure 3.4 (right) shows an analogous evaluation based on more than 32,000 wind sites. Wind data from EWITS does not cover Florida, much of the South, and parts of Texas (*5*). These areas are excluded from this analysis.

From an energy standpoint, wind turbines perform best in the Great Plains down through west Texas. In these areas, Vesta-3 turbines are expected to operate with capacity factors up to 40%. A handful of sites along the western edge of the Rocky Mountains are even better, yielding capacity factors of 45%. The wind resource is poor in much of the Western U.S. and moderate in much of the Eastern U.S.

In terms of avoided CO_2 emissions, the best sites are concentrated in the Midwest, where the wind resource is excellent and coal accounts for a large share of marginal generation. Sites in Oklahoma and Texas become less attractive because gas-fired plants, with relatively low CO_2 rates, are predominantly on the margin. In terms of avoided CO_2 emissions, wind turbines in California are among the worst in the country. For example, a wind turbine at the best site in California displaces 30% less CO_2 than the average turbine in Pennsylvania. The annual value of displaced CO_2 emissions ranges from roughly \$25 to \$70 per kW installed, equivalent to \$11 to \$19 per megawatt-hour (Rhode Island and Kansas, respectively).

Health and environmental benefits from wind turbines are highest in Indiana, Ohio, and West Virginia due to the concentration of coal-fired plants with high SO_2 output. Despite a moderate wind resource, a wind turbine in West Virginia is expected to displace \$230 in health and environmental damages per kW per year (\$82/MWh)—7 times more than a wind turbine in Oklahoma and 27 times more than a wind turbine in California. It is worth emphasizing that the results presented in Figure 3.4 assume that NO_x and SO_2 caps are not binding. The importance of this assumption is discussed in the following section.

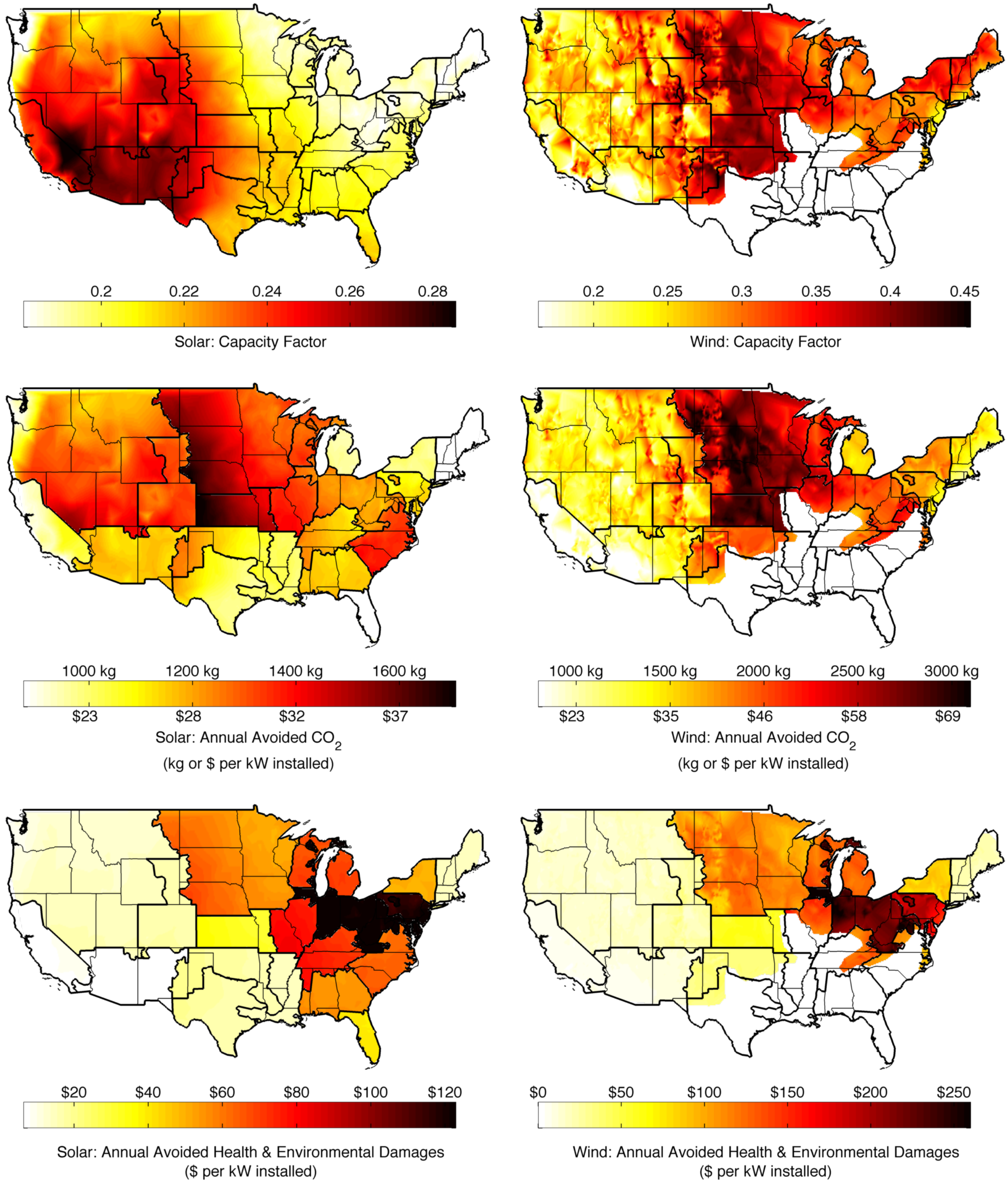

Figure 3.4: Performance of solar panels (left) and wind turbines (right) relative to three objectives: energy output (measured by capacity factor), avoided CO_2 emissions, and avoided health and environmental damages from SO_2, NO_x & $PM_{2.5}$. Due to data limitations, parts of Texas and the South are excluded from our assessment of wind energy. Monetary values are in 2010 dollars.

3.5 Sensitivity Analysis

We conduct a sensitivity analysis to explore (1) valuing displaced NO_x and SO_2 emissions using allowance prices and (2) key assumptions in the APEEP model. Two additional assumptions are explored in the SI. First, we repeat our calculation of marginal impact factors using eight regions of the North American Electric Reliability Corporation (NERC), rather than 22 eGRID subregions. Second, we explore the relevance of marginal impact factors for assessing large-scale interventions.

3.5.1 Valuing displaced emissions using allowance prices

Perhaps the most important assumption in this analysis is our treatment of displaced emissions in the Eastern U.S., where NO_x and SO_2 are regulated under cap-and-trade programs. Assuming pollution caps are binding, total emissions remain fixed. Renewables will put downward pressure on allowance prices but will not achieve a net reduction in SO_2 and NO_x. In such cases, some argue that displaced emissions should be valued using allowance prices rather than social damages.

To explore the implications of cap-and-trade programs, we examine the Cross-State Air Pollution Rule (CSAPR), the EPA's latest revision to cap-and-trade regulation. CSAPR was scheduled to begin in 2012, though a stay has been issued by the U.S. Court of Appeals and the Clean Air Interstate Rule remains active until new regulation takes effect (25). Under CSAPR, SO_2 and NO_x emissions are capped in 23 eastern states, 7 of which are classified as "Group 1" for SO_2 trading. Twenty-five states have a separate cap-and-trade program for ozone-season NO_x, which only applies to emissions occurring between May 1st and September 30th. A map of the affected states is included in the SI. Assumed allowance prices, based on EPA projections for 2014, are shown in Table 3.1.

Table 3.1: Assumed allowance prices ($2010 per ton)(*26*).

Trading Program	Allowance Price	States Covered
Group 1 SO_2	$1,155	16
Group 2 SO_2	$735	7
Annual NO_x	$630	23
Ozone-Season NO_x	$1,575	25

For the relevant states and pollutants, we value displaced emissions using allowance prices. Note that this approach changes the interpretation of the results. Rather than measuring the health and environmental benefits of renewables, we are estimating the cost-savings of meeting the CSAPR pollution cap. For regions and pollutants unaffected by cap-and-trade regulation, we maintain the original method of valuing displaced emissions using health and environmental damages. Results are shown in Figure 3.5, which can be compared with the original results from the bottom of Figure 3.4.

This approach significantly lowers the estimated benefits of renewables in certain regions. In the absence of a binding cap-and-trade program, a 1 kW solar panel in Ohio is expected to yield nearly $120 in annual benefits from displaced criteria pollutants (Figure 3.4), equivalent to $75 per megawatt-hour. With CSPAR in effect, the estimated benefits fall to $25 per year or $15 per megawatt-hour. This difference arises because health and environmental damages from SO_2 emissions are roughly 10 times higher than allowance prices, suggesting that the SO_2 cap is too lax. In theory, social welfare is maximized when abatement costs equal social damages.

Regional variations persist even given binding cap-and-trade programs for NO_x and SO_2. For example, the impacts of a solar panel in New Jersey are seven times greater than a solar panel in Arizona.

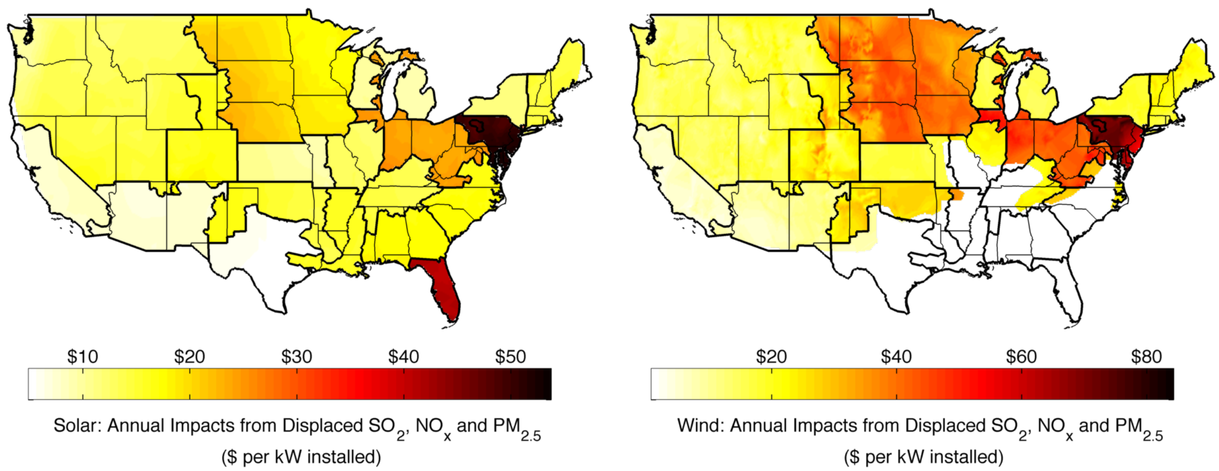

Figure 3.5: Impacts from displaced SO_2, NO_x and $PM_{2.5}$ emissions resulting from solar (left) or wind (right). For states covered by CSAPR, displaced SO_2 and NO_x emissions are valued using allowance prices rather than health and environmental damages.

3.5.2 Key assumption in the APEEP model

Figure 3.6 shows marginal impact factors for SO_2, NO_x and $PM_{2.5}$ emissions for four cases. For brevity, we have selected seven of the twenty-two regions to illustrate the full range of results. Results for the remaining regions are included in the SI.

Base-case results (Case 1) assume a VSL of $6 million, where the full value is applied to each premature fatality. A life-year method is used in Case 2, where the

VSL is discounted according to the expected years of life remaining. This approach places a relatively low value on elderly people, who make up a large share of the population affected by air pollution (*17*). Using the life-year method reduces marginal impact factors by roughly 60%. Case 3 uses the life-year method with an alternative dose-response function for mortalities from $PM_{2.5}$, the dominant source of damages (damages attributed to SO_2 are primarily from sulfate, a form of $PM_{2.5}$, which is a secondary pollutant of SO_2). With the alternative dose-response function, based on a study by Laden et al. (*27*), mortality rates are almost three times more sensitive to $PM_{2.5}$ concentrations.

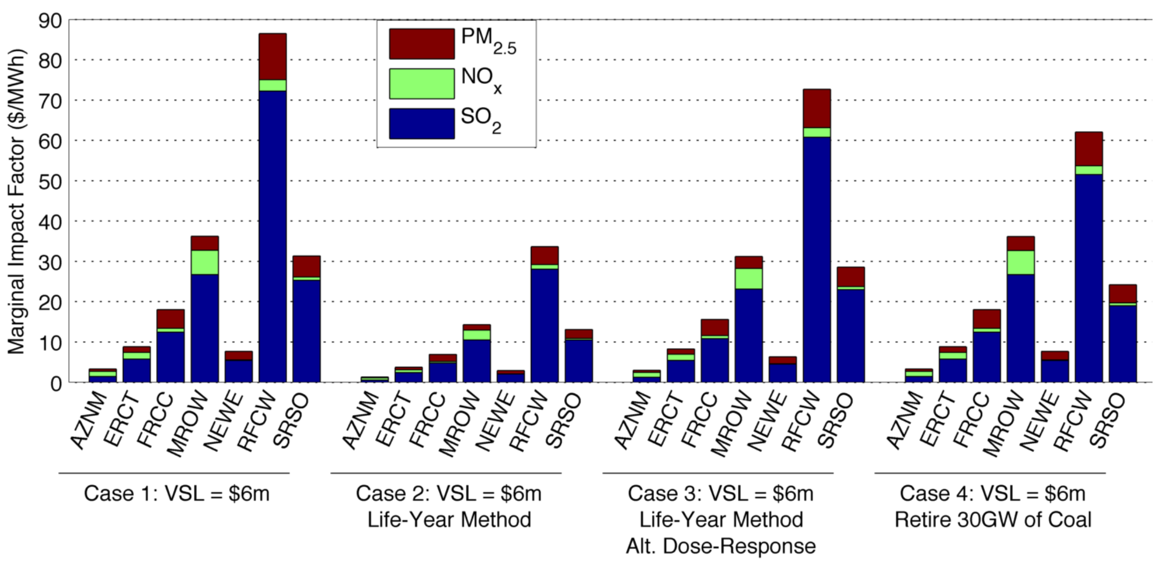

Figure 3.6: Sensitivity analysis for marginal impact factors for SO_2, NO_x, and $PM_{2.5}$ emissions. Four cases are presented for seven of the twenty-two eGRID subregions. The selected regions are: AZNM (Arizona and New Mexico), ERCT (Texas), FRCC (Florida), MROW (Western Midwest, which includes Nebraska, the Dakotas, Minnesota, and Iowa), NEWE (New England), RFCW (Indiana, Ohio, and West Virginia), and SRSO (Alabama and Georgia).

Case 4 assumes that 30 GW of the coal plants are retired. This scenario was motivated by the fact that a significant number of coal-fired generators are expected to retire in response to new EPA regulations (*28*). We rank coal plants according to the rate of SO_2 emissions and the worst 30 GW of capacity—92 plants—are removed from the dataset. Retired plants are replaced with new gas-fired generators[3], which are assumed to provide the same electricity as the retired plant.

In Case 4, 37 plants with a combined capacity of 13 GW are retired from the RFCW region (Illinois, Ohio, & West Virginia), causing a 30% decrease in the marginal impact factor relative to the base case. In SRSO (Georgia and Alabama), 2.3 GW of coal-fired generators are retired, causing a 20% decrease in the marginal impact factor. The retirement scenario has a negligible effect on the remaining five regions shown.

There are three general takeaways from Figure 3.6. First, marginal impact factors for criteria pollutants are driven largely by mortalities from fine particulates (SO_2 and direct emissions of $PM_{2.5}$); therefore, results are sensitive to the number of mortalities attributed to $PM_{2.5}$ and the method used to value those mortalities. Second, the ranking of the regions is consistent in all four cases. Third, regional variations span at least a factor of 25 in all four cases. This supports the general conclusion that there are significant regional differences in the social benefits of displacing a unit of electricity.

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[3] Assumed emissions rates are for combined cycle natural gas turbines: SO_2=0.0006 lb/mmBtu; NO_x=0.02 lb/mmBtu; CO_2=33.3 lb/mmBtu (4).

3.6 Implications for Renewable Energy Subsidies

Given that private investments in renewables are significantly bolstered by public subsidies, it is important to understand the social benefits achieved by renewable energy measures. Arguably, the renewable electricity production tax credit (PTC) is the biggest driver of renewables in the U.S. The PTC is a per-kilowatt-hour subsidy for electricity generated by qualifying technologies. We focus our discussion on wind, which accounts for the bulk of new renewable energy capacity. The PTC guarantees wind energy an inflation-adjusted tax credit of $22 per megawatt-hour, which can represent more than half of the revenue for a wind farm (*10*).

As of 2009, there was approximately 34,000 MW of installed wind generation producing more than 74 million megawatt-hours of electricity annually (*15*). Based on a VSL of $6 million and an SCC of $20 per ton, we estimate that these wind farms provide $2.6 billion in health and environmental benefits annually (see SI). The benefits are primarily from avoided CO_2 emissions (40%) and avoided SO_2 emissions (44%). Assuming all wind farms receive the PTC, the annual cost of the subsidy is approximately $1.6 million. This suggests that the PTC is a good value for taxpayers—the social benefits of existing wind farms are roughly 60% higher than the cost of the subsidy.

However, we argue that the PTC is poorly designed for two reasons. First, energy production is, in our opinion, the wrong measure of performance for policy makers and the general public. As this analysis has shown, energy output is poorly aligned with health and environmental benefits. Private developers already have a strong incentive to seek high-energy sites, as much of the revenue for a wind farm is tied to energy production. This incentive is reinforced by production-based subsidies. Our second concern with the PTC is that it fails to reflect regional differences in the performance of renewables. Per megawatt-hour, wind energy in Ohio offers seven times more social benefits than wind energy in New Mexico, yet the two receive the same subsidy under the PTC.

3.7 Conclusions

This work investigates regional differences in the performance of wind turbines and solar panels, where performance is measured relative to three objectives: energy production, avoided CO_2 emissions, and avoided health and environmental damages.

We challenge the conventional wisdom for siting renewables. If the goal is to mitigate climate change or reduce human-health impacts, then the sites with the greatest energy output may not be the best choice. For example, we find that a solar panel in Iowa displaces 20% more CO_2 emissions than a panel in Arizona, though energy production from the Iowa panel is 25% lower. Similarly, despite a modest wind resource, a wind turbine in West Virginia is expected to displace $230 in health and environmental damages per kW per year ($82/MWh)—7 times more than a wind turbine in Oklahoma and 27 times more than a wind turbine in California.

We estimate the social benefits from existing wind farms and find that, on aggregate, the costs of the PTC subsidy are justified. However, we argue that production-based subsidies are a crude policy instrument. This analysis shows that energy output from renewables is a poor measure of broader social benefits. Production-based subsidies, such as the PTC, encourage developers to seek sites with high energy potential rather than those that offer the greatest social benefits. Policy makers should be explicit about the goals for renewable energy, and subsidies should be better targeted to achieve those goals.

It is worth emphasizing three caveats to this analysis. First, we have estimated the impacts of a marginal increase in wind or solar generation. Numerous states have plans to aggressively expand the use of renewables, which will fundamentally change the electricity system. Further work is needed to understand the long-term implications of widespread deployment of wind and solar energy. Second, this is not a comprehensive benefit-cost analysis. Private costs are outside the scope of this analysis and a range of social costs and benefits have not been explored. Third, this analysis is based on a single year of simulated wind and solar data. Actual performance may deviate from the simulated performance and year-to-year variability is not captured in this analysis.

Given that private investments in renewables are significantly bolstered by public subsidies, it is important to understand the social benefits achieved by such investments. This work provides insight into the regional variations in the health and environmental benefits offered by renewables, as well as the tradeoffs between energy production, long-term climate benefits from avoided CO_2 emissions, and shorter-term health and environmental benefits from avoided criteria pollutants.

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3.9 Supporting Information

3.9.1 eGRID subregions, summary of data, and marginal impact factors by region

Figure 3.7 shows the eGRID subregions used in this analysis. For each region, Table 3.2 shows marginal impact factors for SO_2, NO_x, $PM_{2.5}$, and CO_2. Table 3.3 shows average emissions rates for coal- and gas-fired generators by region, based on eGRID data from 2007. Table 3.4 presents dollar-per-ton damages for emissions of SO_2, NO_x and $PM_{2.5}$; values are based on results from the APEEP model and are the weighted average from fossil-fueled generators in each region.

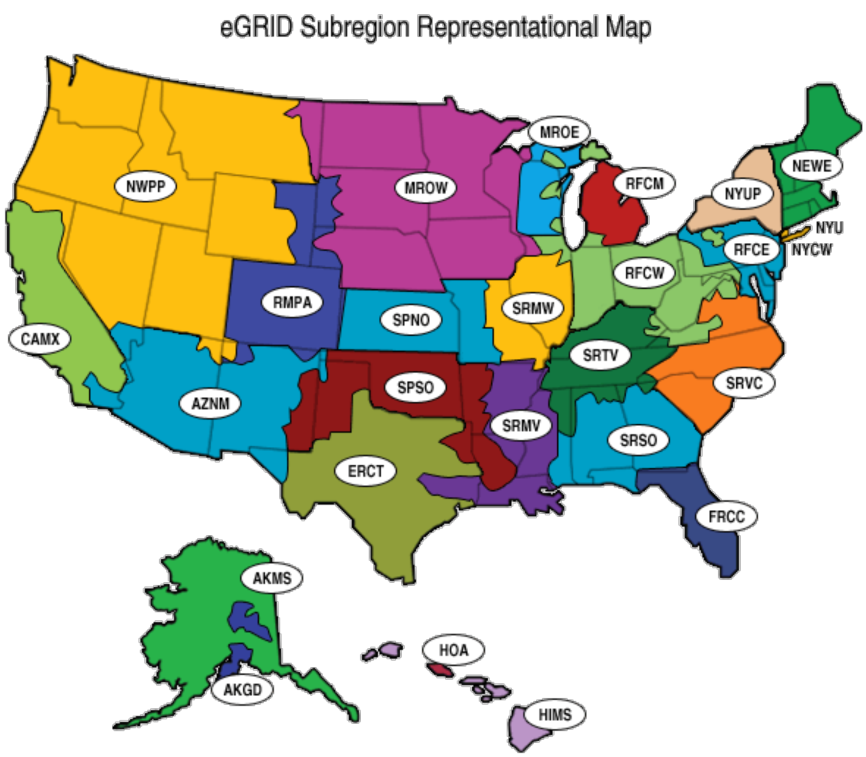

Figure 3.7: eGRID subregions (*1*).

Table 3.2: Marginal impact factors by region

Region	SO_2	NO_x	$PM_{2.5}$	Total	CO_2	CO_2[a]	Grand Total
	($/MWh)				(kg/MWh)	($/MWh)	($/MWh)
AZNM	1.5	1.3	0.5	3.3	494	11.4	14.7
CAMX	0.3	0.3	2.7	3.2	424	9.8	13.0
ERCT	5.8	1.7	1.4	8.8	522	12.1	20.9
FRCC	12.5	0.9	4.6	18.0	489	11.3	29.3
MORE	43.3	2.8	2.0	48.2	819	18.9	67.1
MROW	26.7	6.0	3.4	36.2	849	19.6	55.8
NEWE	5.5	0.1	2.1	7.7	493	11.4	19.1
NWPP	4.3	2.1	1.0	7.4	630	14.6	22.0
NYCW	5.8	5.6	20.0	31.4	385	8.9	40.3
NYLI	5.3	1.7	5.8	12.7	577	13.3	26.1
NYUP	24.3	0.7	4.0	29.0	592	13.7	42.7
RFCE	48.8	2.6	22.7	74.0	666	15.4	89.4
RFCM	37.7	2.1	2.3	42.2	549	12.7	54.9
RFCW	72.2	2.8	11.2	86.2	764	17.6	103.9
RMPA	4.5	3.4	0.8	8.7	615	14.2	22.9
SPNO	8.6	5.6	3.1	17.3	828	19.1	36.5
SPSO	4.2	3.6	0.9	8.7	548	12.6	21.3
SRMV	5.9	1.5	0.8	8.3	538	12.4	20.7
SRMW	40.8	2.4	4.3	47.5	811	18.7	66.3
SRSO	25.3	0.9	5.1	31.3	633	14.6	45.9
SRTV	39.2	1.8	4.9	45.9	680	15.7	61.6
SRVC	30.4	0.6	7.3	38.4	774	17.9	56.3

[a] monetized CO_2 values are based on a social cost of carbon of $20/ton

Table 3.3: Average health and environmental damages per ton emitted (weighted average of all fossil-fueled generators in a region, adapted from (*2*)).

Region	SO_2 (\$/ton)	NO_x (\$/ton)	$PM_{2.5}$ (\$/ton)
AZNM	6050	2473	6548
CAMX	5542	1573	30611
ERCT	8213	3838	15952
FRCC	9499	1251	24137
MROE	13047	3548	16650
MROW	9333	3642	12196
NEWE	9486	457	29123
NWPP	6040	2289	6609
NYCW	42598	8960	251208
NYLI	8681	2273	60182
NYUP	12278	1026	20664
RFCE	19142	2117	51999
RFCM	17655	2125	27329
RFCW	16591	2295	29436
RMPA	5952	3246	9565
SPNO	6515	3841	11597
SPSO	6821	3530	11676
SRMV	8807	2014	10273
SRMW	12863	3949	23939
SRSO	10094	1346	18130
SRTV	13887	2127	20157
SRVC	13851	985	23497

Table 3.4: Average emissions rates by fuel type and region (*1*).

	Coal-Fired Generators (lbs/MWh)					Gas-Fired Generators (lbs/MWh)				
	N[a]	CO_2	SO_2	NO_x	$PM_{2.5}$	N[a]	CO_2	SO_2	NO_x	$PM_{2.5}$
AZNM	14	2003	1.28	2.89	0.54	38	911	0.00	0.22	0.02
CAMX	14	1862	0.71	3.63	0.29	88	941	0.01	0.10	0.03
ERCT	15	2096	5.50	1.29	0.36	77	999	0.01	0.30	0.06
FRCC	14	2138	3.00	1.22	0.48	45	1139	0.09	0.39	0.22
MROE	14	2066	5.88	1.56	0.22	14	875	0.01	0.25	0.01
MROW	50	2166	4.85	2.56	0.44	33	975	0.01	0.55	0.00
NEWE	14	2013	11.93	1.84	0.74	43	1001	0.01	0.14	0.05
NWPP	14	2085	2.49	2.65	0.44	26	896	0.01	0.15	0.08
NYCW	0					18	996	0.02	0.33	0.05
NYLI	0					15	1259	0.11	0.71	0.11
NYUP	14	2112	7.62	3.01	0.79	27	968	0.01	0.18	0.02
RFCE	45	2155	5.45	2.75	1.08	47	1108	0.01	0.21	0.06
RFCM	20	2287	7.99	2.35	0.26	20	661	0.08	0.67	0.02
RFCW	94	2000	6.58	1.97	0.65	73	937	0.00	0.14	0.06
RMPA	14	2099	2.32	2.62	0.29	16	993	0.01	0.30	0.03
SPNO	15	2091	2.81	1.95	0.38	20	1193	0.01	1.19	0.31
SPSO	15	2059	4.80	2.40	0.31	46	1125	0.01	1.09	0.09
SRMV	14	2067	5.59	2.25	0.45	44	1095	0.01	0.86	0.06
SRMW	25	2078	4.65	1.35	0.37	25	929	0.00	0.26	0.03
SRSO	24	1905	5.18	1.63	0.76	38	919	0.01	0.15	0.01
SRTV	30	2015	4.80	1.67	0.51	17	868	0.00	0.12	0.02
SRVC	51	2168	3.55	1.74	0.79	29	1007	0.03	0.26	0.04

[a] Number of plants with coal or gas as the primary fuel type

3.9.2 Location of wind and solar sites

Solar data for 2005 are from the National Solar Radiation Database (*3*); the location of solar sites is shown in Figure 3.8 (left). Wind data for 2006 are from the Western Wind and Solar Integration Study (WWSIS) and the Eastern Wind Integration and Transmission Study (EWITS); the location of wind sites is shown in Figure 3.8 (right) (*4*, *5*).

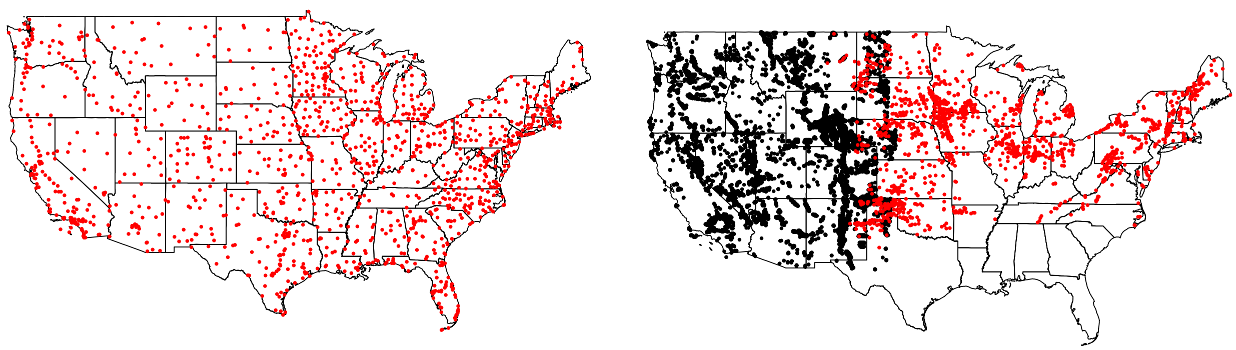

Figure 3.8: Location of solar (left) and wind (right) sites.

3.9.3 Total impacts (criteria pollutants plus CO_2)

Because CO_2 and criteria pollutants affect different populations and occur on different time scales, we keep the two separate for the majority of this analysis. Nonetheless, the combined impacts from CO_2 and criteria pollutants are a useful measure. Figure 3.9 shows the total marginal impact factor by region. Figure 3.10 shows the total annual impacts from solar (left) and wind (right). Impacts from criteria pollutants assume a value of a statistical life of \$6 million and CO_2 emissions are monetized using a social cost of carbon of \$20 per ton.

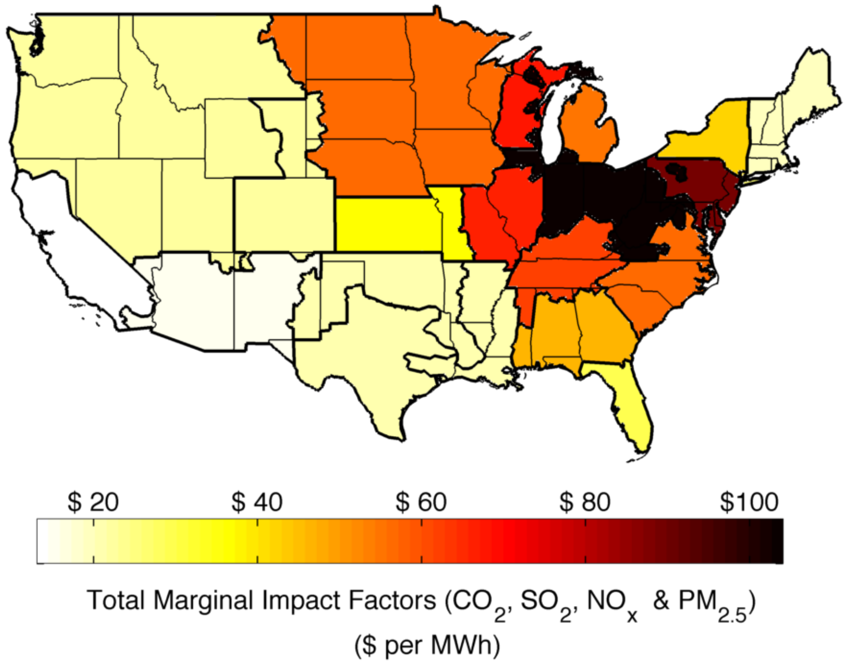

Figure 3.9: Total marginal impact factors. Impacts from criteria pollutants assume a value of a statistical life of \$6 million; CO_2 emissions are monetized using a social cost of carbon of \$20 per ton.

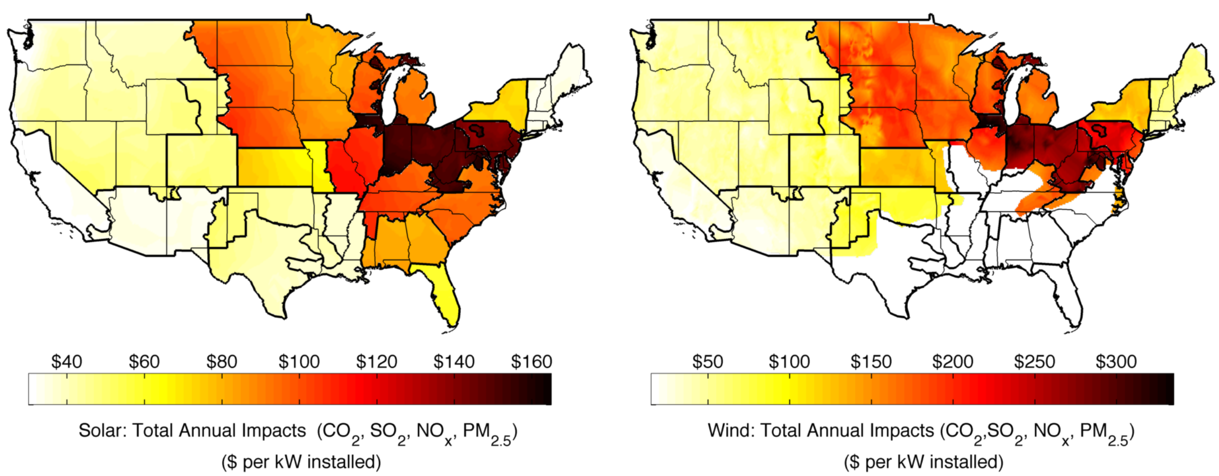

Figure 3.10: Total annual impacts from solar (left) and wind (right). Total impacts are the combined value of displaced criteria pollutants and displaced CO_2 emissions. Impacts from criteria pollutants assume a value of a statistical life of \$6 million. Avoided CO_2 emissions are valued using a social cost of carbon of \$20 per ton.

3.9.4 Sensitivity of marginal impact factors

Figures 3.11 – 3.17 show marginal impact factors for SO_2, NO_x, and $PM_{2.5}$ under a range of assumptions. Figure 3.11 assumes a value of statistical life (VSL) of \$6 million, where the full value is applied to each premature mortality. Figure 3.12 applies a life-year method, where the VSL is discounted according to the expected years of life remaining. Figure 3.13 is based on a life-year method and a VSL of \$2 million. Figure 3.14 is based on a life-year method, a VSL of \$6 million, and a dose-response function for health impacts of $PM_{2.5}$ from Laden et al. (*6*). Figure 3.15 assumes that 30 GW of coal plants are retired. In Figure 3.16, for regions covered by the Cross-State Air Pollution Rule, NO_x and SO_2 are valued using allowance prices. Figure 3.17 shows the states affected by the Cross-State Air Pollution Rule. Finally, Figure 3.18 shows marginal impact factors for CO_2 based on a social cost of carbon (SCC) ranging from \$20 to \$80 per ton.

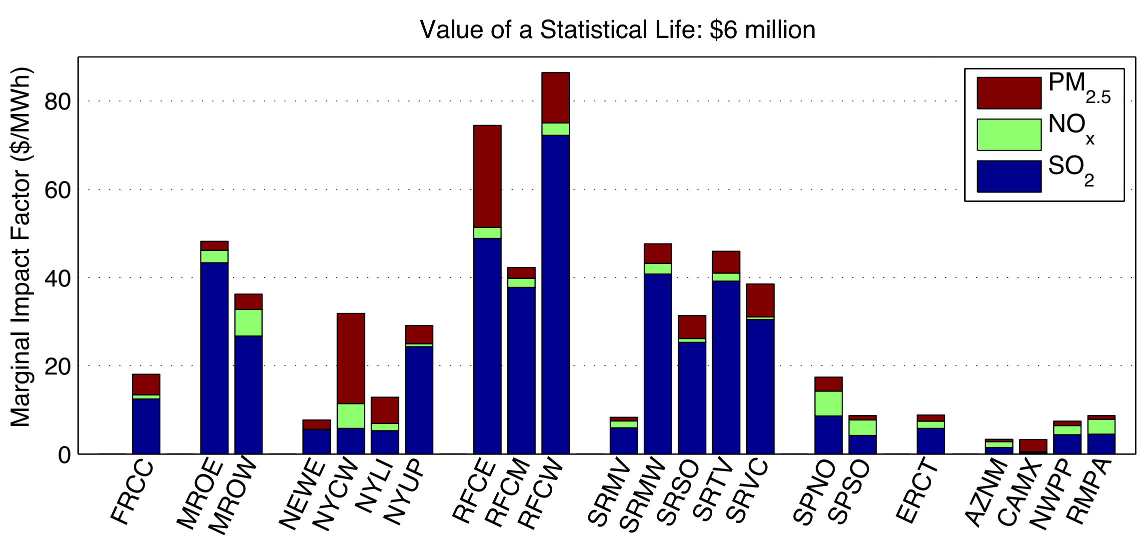

Figure 3.11: Marginal impact factors for SO_2, NO_x, and $PM_{2.5}$. Results are based on a VSL of \$6 million.

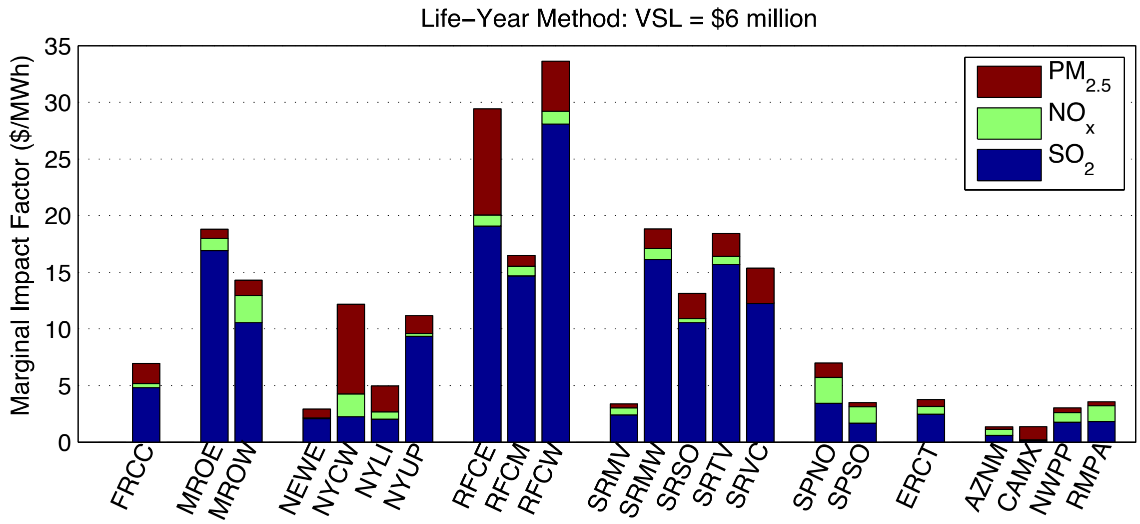

Figure 3.12: Marginal impact factors for SO_2, NO_x, and $PM_{2.5}$. Results are based on a life-year method and a VSL of $6 million.

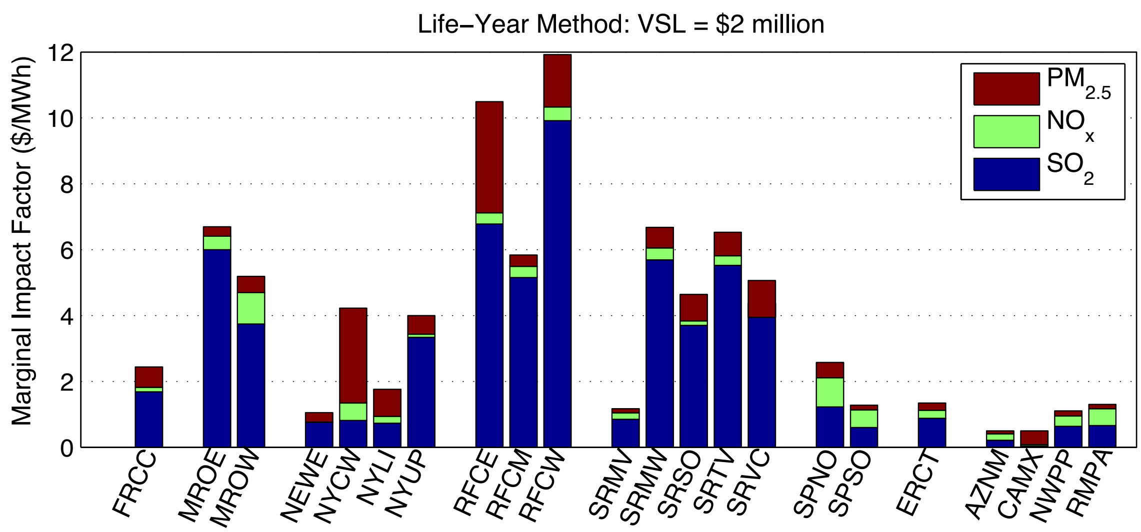

Figure 3.13: Marginal impact factors for SO_2, NO_x, and $PM_{2.5}$. Results are based on a life-year method and a VSL of $2 million.

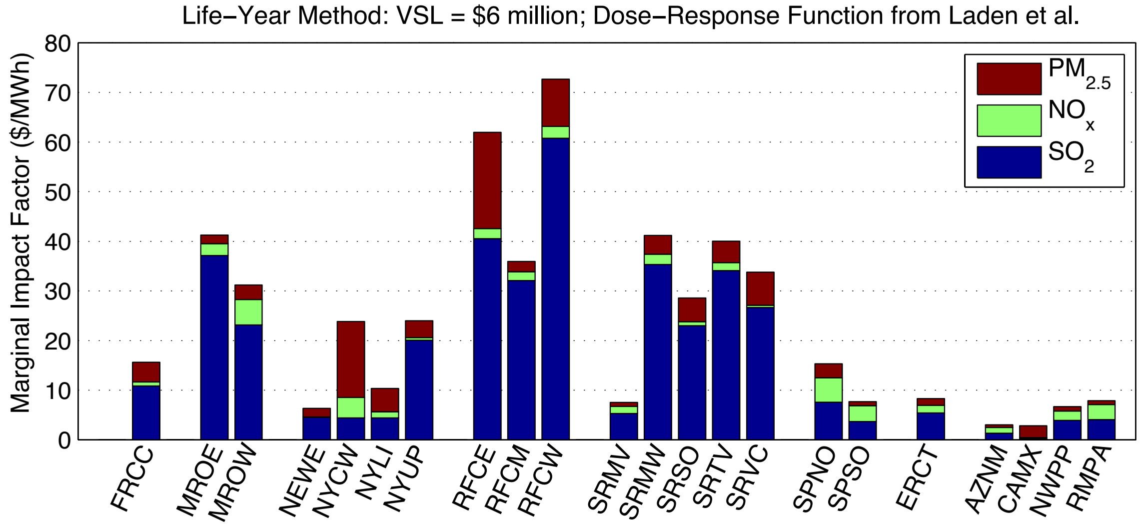

Figure 3.14: Marginal impact factors for SO_2, NO_x, and $PM_{2.5}$. Results are based on a life-year method, VSL of $2 million, and a dose-response function for the health impacts of $PM_{2.5}$ from Laden et al. (*6*).

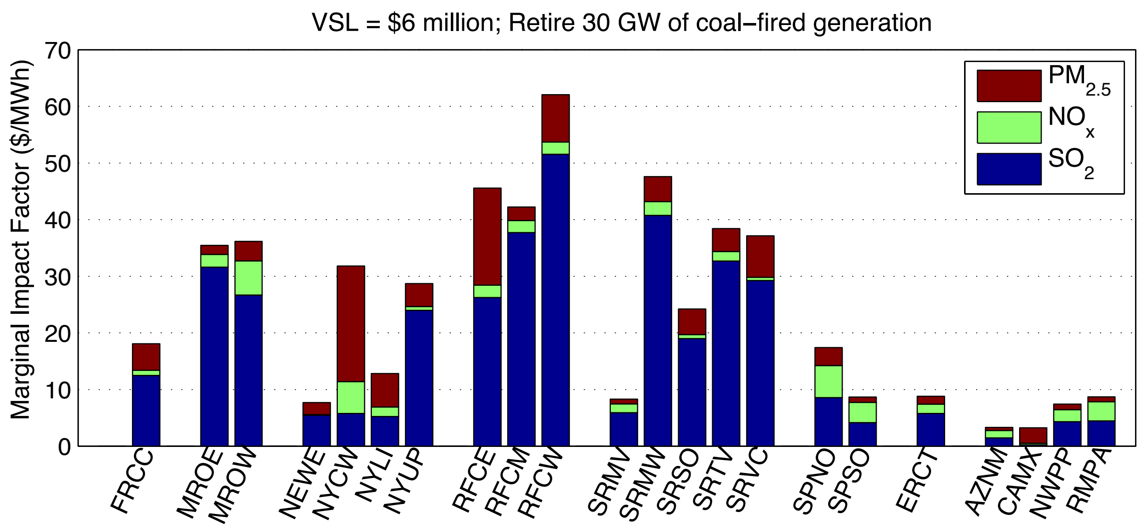

Figure 3.15: Marginal impact factors for SO_2, NO_x, and $PM_{2.5}$. Results are based on a VSL of $6 million. Under this scenario, 30 GW of coal-fired plants are retired (removed from the dataset) and replaced with combined-cycle gas turbines.

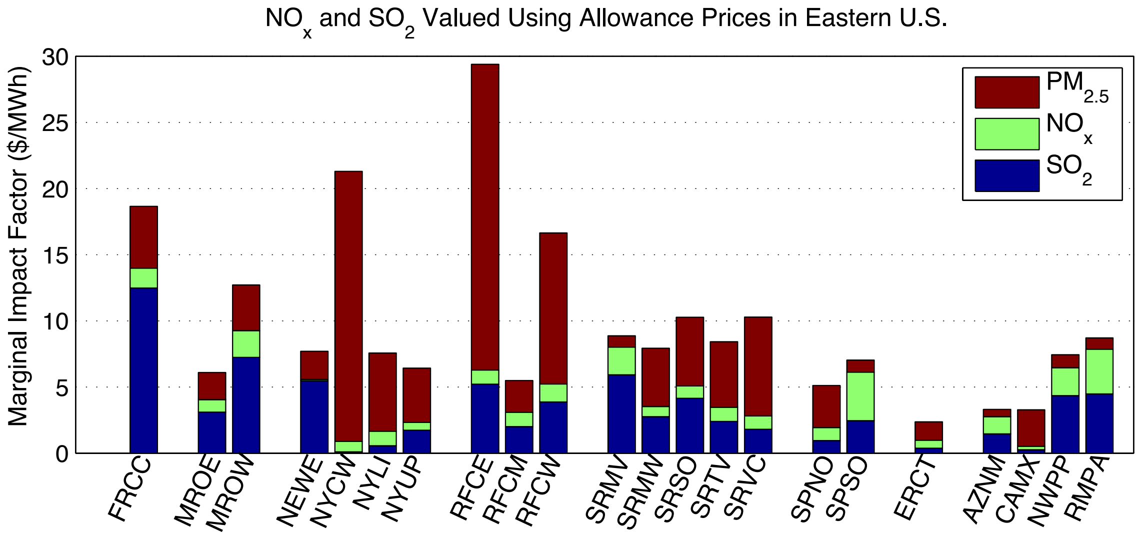

Figure 3.16: Marginal impact factors for SO_2, NO_x, and $PM_{2.5}$. For states coved by the Cross-State Air Pollution Rule (CSAPR), SO_2 and NO_x are valued using projected allowance prices for 2014. In regions and pollutants unaffected by CSAPR, emissions are valued using health and environmental damages (VSL = $6 million).

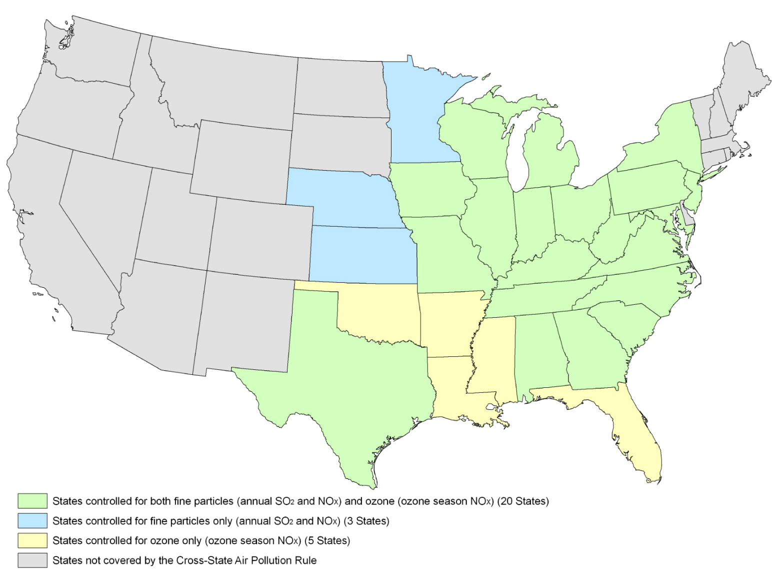

Figure 3.17: Coverage of the Cross-State Air Pollution Rule (*7*).

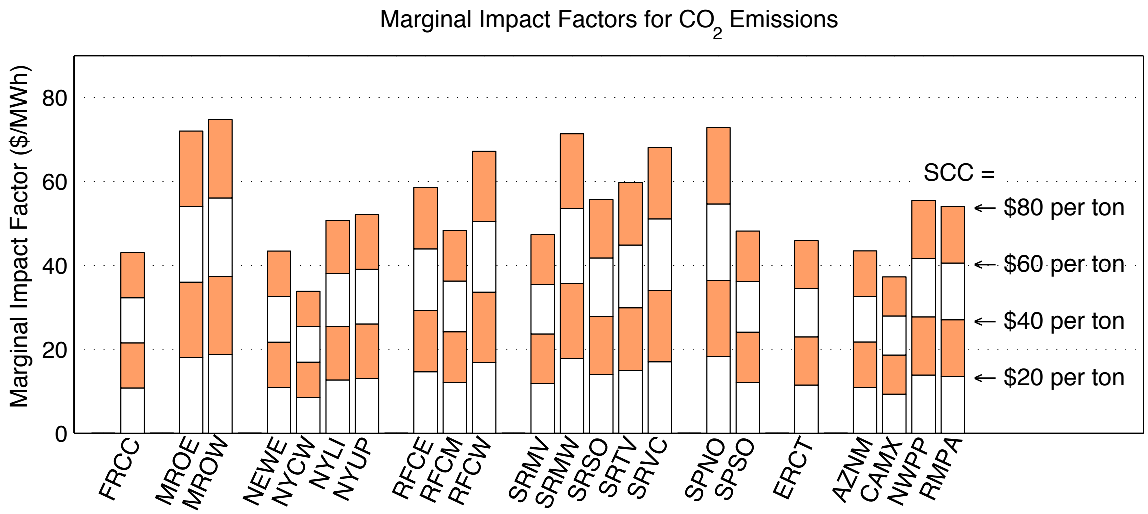

Figure 3.18: Marginal impact factors for CO_2. Impacts from CO_2 are proportional to the assumed social cost of carbon (SCC). This figure shows impact factors for an SCC of $20, $40, $60, and $80 per ton.

3.9.5 Choice of regional boundaries

The method described in Section 3.3 assumes that interventions only affect generators within the same region. For example, a wind farm in Nebraska is assumed to displace generators in the MROW region, but imports and exports from neighboring regions are ignored. We can reduce the errors associated with this assumption by defining larger regions. However, larger regions also reduce the accuracy of marginal impact factors by masking variations in the generation mix.

Figure 3.19 shows marginal impact factors for 22 eGRID subregions (top) and eight NERC regions (bottom). Differences between the two are most pronounced in the West and the South. In the West, California is a single eGRID subregion with a marginal CO_2 factor of 424 kg/MWh, the lowest in the country. This is likely an underestimate because roughly 40% of California's electricity is imported (*8*). Using the larger NERC regions, the marginal CO_2 factor in WECC, which includes California, is roughly 500 kg/MWh.

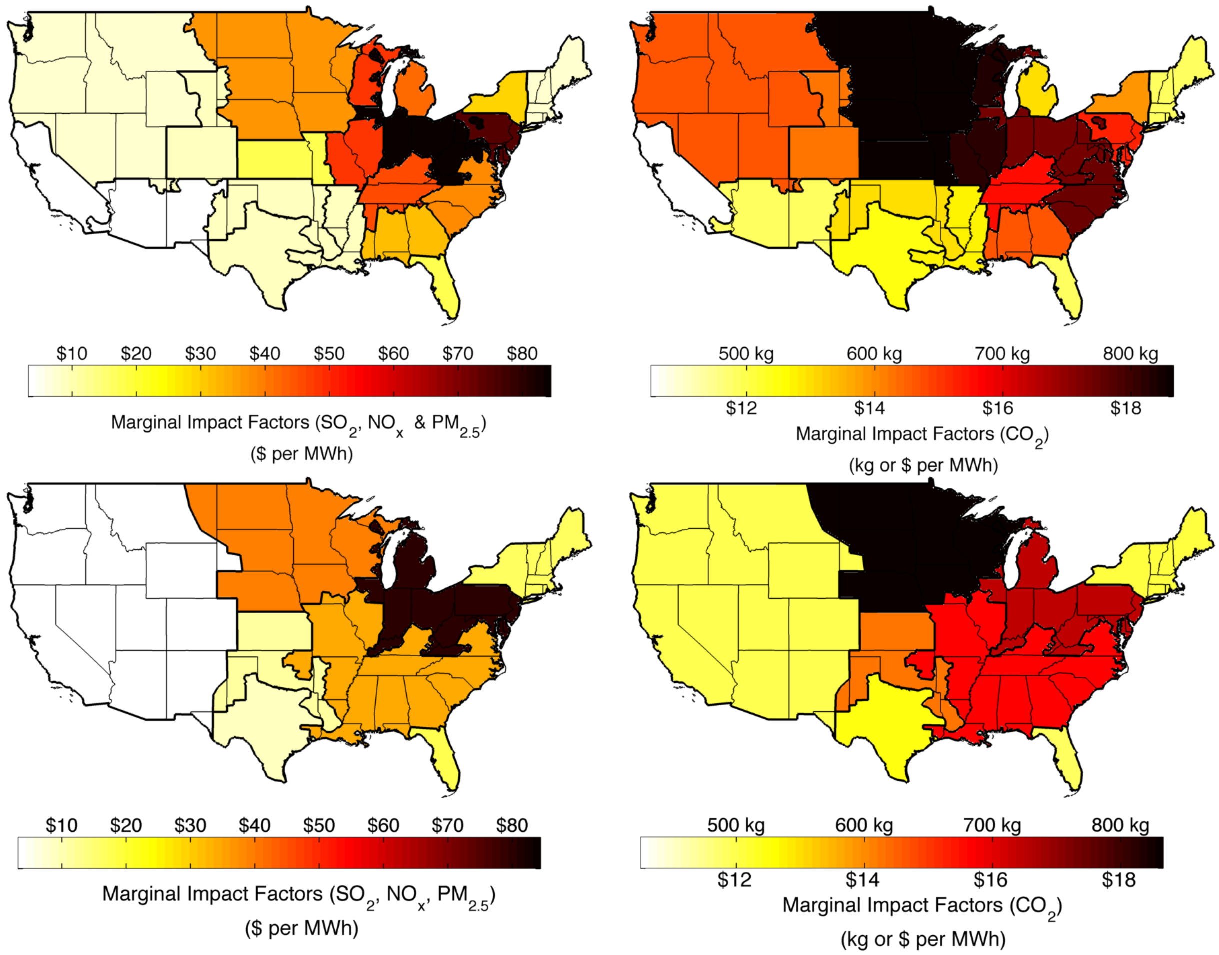

Figure 3.19: Marginal impact factors for 22 eGRID subregions (top) and 8 NERC regions (bottom). Impacts from criteria pollutants assume a value of a statistical life of $6 million. Results for CO_2 include two scales: kilograms of CO_2 per MWh and dollars per megawatt-hour. The latter is based on a social cost of carbon of $20 per ton.

In the South, there are five eGRID subregions that are roughly equal to a single NERC region (SERC). Using eGRID subregions, marginal CO_2 factors range from 540 to 810 kg/MWh and marginal impact factors for criteria pollutants range from $8 to $48/MWh. Using the larger NERC region gives a marginal CO_2 factor of 680 kg/MWh and a marginal impact factor of $34/MWh.

Despite these differences, regional variations are qualitatively consistent. In both cases, marginal CO_2 factors are highest in the Midwest, followed by the mid-Atlantic and the South; marginal impact factors for criteria pollutants are highest in the mid-Atlantic and are significantly lower throughout the West.

3.9.6 Broad adoption of renewables and long-term implications

This analysis relies on regressions of historic data to estimate marginal impact factors for the U.S. electricity system. Such measures are appropriate for estimating the health and environmental benefits of near-term, small-scale interventions. However, we are also interested in the impacts of large-scale investments in renewables.

Short-term effects: In the short term, before construction and retirement decisions take place, large-scale adoption of wind or solar will result in deep displacements from existing power plants. Here we describe the process for estimating avoided CO_2 emissions resulting from large-scale interventions; an equivalent method applies to estimating avoided health and environmental damages from criteria pollutants.

Figure 3.20 shows the marginal CO_2 factor for the MROW region as a function of total fossil generation, a proxy for system demand. For a particular hour when total fossil generation is 1.8 GW, the marginal CO_2 factor is 735 kg/MWh. However, this rate is not valid for large-scale interventions because the emissions factor changes with each additional megawatt displaced. For a large-scale intervention, displaced emissions are the integral under the curve. As illustrated in Figure 3.7, a

2,000 MW intervention displaces 1.7 million kg of CO_2 emissions, or 865 kg/MWh. By repeating this calculation for every hour of the year, we can estimate the annual avoided CO_2 emissions resulting from a large-scale intervention.

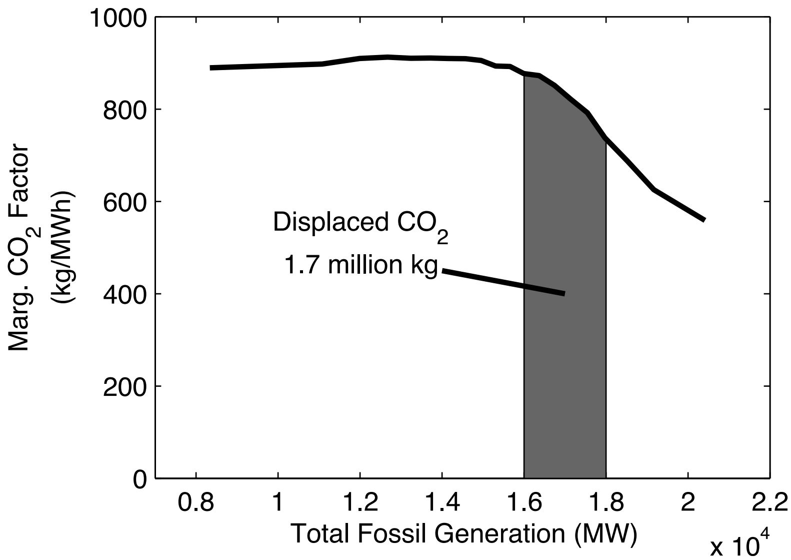

Figure 3.20: Example calculation of avoided CO_2 emissions resulting from a large-scale intervention in the MROW region. For a particular hour when total fossil generation is 18,000 MW, the marginal CO_2 factor is 735 kg/MWh. For a 2000 MW intervention, the avoided emissions are 1.7 million kg, or 865 kg/MWh.

To test the sensitivity of our results to the size of an intervention, we apply this approach to wind generation in each eGRID subregion. We begin by estimating the avoided CO_2 emissions resulting from a single wind farm, assuming that the site offering the highest capacity factor is selected first. We then add the next best site and calculate the avoided CO_2 emissions resulting from the two wind farms. The process is repeated until wind generation accounts for 15% of electricity production.

Results for four regions are shown in Figure 3.21. The x-axis is the size of the intervention, measured by the share of electricity from wind generation. The y-axis gives the avoided CO_2 emissions (left) and avoided health and environmental damages (right) per megawatt-hour of wind generation. Differences between small- and large-scale interventions are generally modest. These results suggest that marginal impact factors will, in most regions, provide a conservative estimate when applied to large-scale interventions.

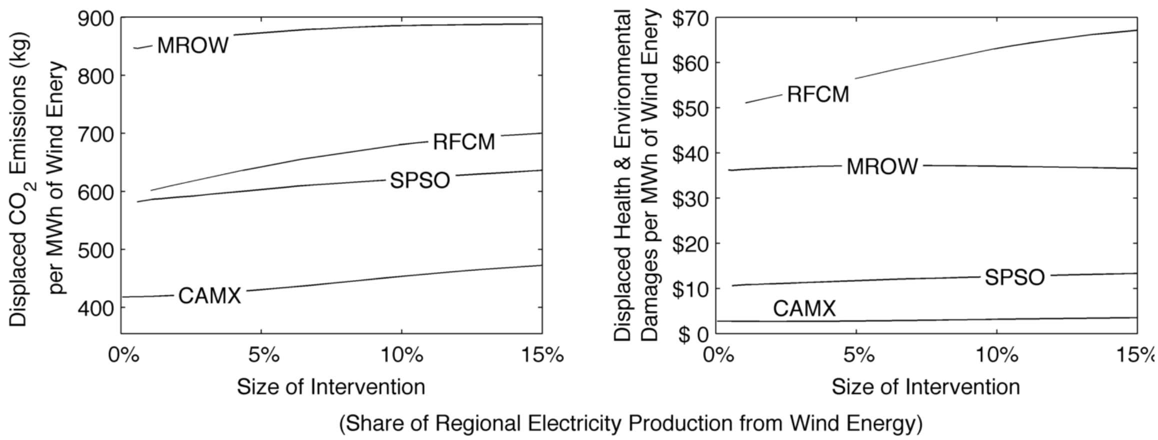

Figure 3.21: Displaced CO_2 emissions (left) and displaced health and environmental damages from SO_2, NO_x, and $PM_{2.5}$ emissions (right) per megawatt-hour of wind energy. The x-axis is the size of the intervention, measured by the share of electricity production from wind energy. Regions are MROW (Western Midwest, which includes Nebraska, the Dakotas, Minnesota, and Iowa), RFCM (Michigan), SRMV (portions of Louisiana, Mississippi, and Arkansas) and CAMX (California).

Note that additional short-term effects may also influence emissions. Wind and solar power are highly variable and may require conventional generators to cycle more often, which will likely increase emissions (*9*, *10*). On the other hand, high penetration of wind or solar may increase the need for flexible generation. To meet this need, gas generators may be dispatched before coal units to meet reliability standards, which will tend to decrease the overall emissions from the system (*11*).

Long-term effects: In the long run, broad adoption of renewables will affect investment and retirement decisions for conventional generators. Attributing emissions savings to these decisions is very uncertain, but the effects are potentially large. Using a model of the Texas electricity system, Cullen finds that new wind capacity reduces the profitability of coal plants while increasing the profitability of gas plants (*12*). If investments in wind and gas generation crowd out investments in coal plants, the avoided emissions could be significant over the lifetime of a plant. While marginal impact factors likely underestimate the long-run social benefits of renewable energy measures, a full analysis of these issues is beyond the scope of this work.

3.9.7 Estimating social benefits from existing wind farms

34,000 MW of installed wind generation producing more than 74 million megawatt-hours of electricity annually (*1*). The location of existing wind capacity is shown in Figure 3.22, where the height of each bar is proportional to the size of a wind farm.

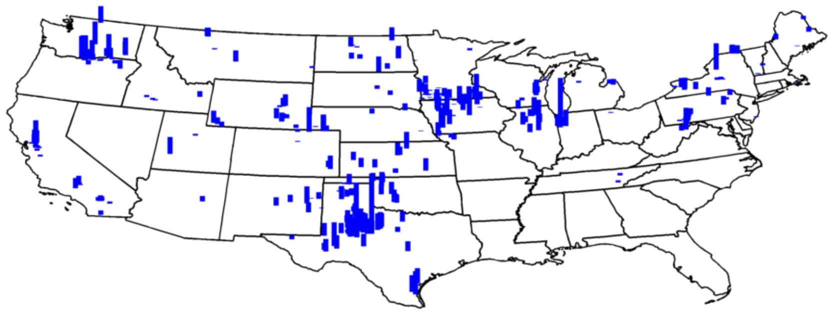

Figure 3.22: Location of existing wind farms as of 2009 (*1*).

We use marginal impact factors to estimate the social benefits resulting from existing wind farms. While eGRID reports annual power output, data with higher time resolution are not consistently available for existing wind farms. To account for temporal patterns, we find the average hourly power output from wind farms in the EWITS and WWSIS databases. Wind power profiles are calculated separately for each eGRID subregion. The profile is scaled to match the annual power output from existing wind farms in a given region. We then apply marginal impact factors to estimate the avoided health and environmental damages resulting from the wind farms (as described in Section 3.3.3).

Results are summarized in Table 3.5. Impacts from criteria pollutants are based on a VSL of $6 million and displaced CO_2 emissions are valued using a SCC of $20 per ton. Under these assumptions, existing wind farms provide $2.6 billion in health and environmental benefits annually. The benefits are primarily from avoided CO_2 emissions (40%) and avoided SO_2 emissions (44%). Assuming all wind farms receive the PTC, the annual cost of the subsidy is approximately $1.6 billion.

Table 3.5: Estimated benefits from existing wind farms by region.

Region	Installed Capacity (MW)	Energy Produced (GWh)	Displaced CO_2 (thousand tons)	Value of Displaced Emissions (Thousand 2010-Dollars)			
				CO_2	SO_2	NO_x	$PM_{2.5}$
AZNM	502	1055	590	11799	1961	1683	678
CAMX	2407	5184	2381	47620	1586	1799	10629
ERCT	8522	17688	10584	211676	146989	28676	26583
MROE	449	1052	937	18749	44262	2944	2189
MROW	6708	16291	14895	297904	422651	97133	53293
NEWE	201	373	203	4057	2020	38	788
NWPP	5242	10053	6710	134206	38778	19545	9154
NYUP	1274	2266	1473	29454	54013	1540	8923
RFCE	655	869	638	12752	44400	2088	19001
RFCM	143	300	195	3904	13270	660	783
RFCW	1915	2795	2338	46765	198157	7827	30785
RMPA	1327	3385	2311	46213	15802	11733	2880
SPNO	1320	3363	3091	61822	29272	19059	10511
SPSO	2150	6122	3905	78090	35538	21793	6680
SRMW	1145	2390	2085	41700	94517	5650	10079
SRTV	54	59	45	897	2409	114	293
Totals	34012	73244	52380	1047608	1145626	222283	193251
				Total Social Benefits = $2.6 Billion			

3.9.8 References for the supporting information

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Chapter 4: Distributed Cogeneration for Commercial Buildings: Can We Make the Economics Work?[1]

4.1 Abstract

Although the benefits of distributed cogeneration are widely cited, adoption has been slow in the United States. Adoption could be encouraged by making cogeneration more economically attractive, either by increasing the expected returns or decreasing the risks of such investments. We evaluate the expected returns from demand response, capacity markets, regulation markets, accelerated depreciation, pricing CO_2 emissions, and net metering. We find that (1) there is an incentive to overcommit in the capacity market due to lenient non-response penalties, (2) there is significant revenue potential in the regulation market, though demand-side resources are yet to participate, (3) a price on CO_2 emissions will make cogeneration more attractive relative to conventional, utility-supplied energy, and (4) accelerated depreciation is an easy and effective mechanism for improving the economics of cogeneration. We go on to argue that uncertainty in fuel and electricity prices present a significant risk to cogeneration projects, and we evaluate the effectiveness of feed-in tariffs at mitigating these risks. We find that guaranteeing a fixed electricity payment is not effective. A two-part feed-in tariff, with an annual capacity payment and an energy payment that adjusts with fuel costs, can eliminate

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[1] This chapter is based on the published paper, Siler-Evans, K.; Morgan, M. G.; Azevedo, I. L. Distributed cogeneration for commercial buildings: Can we make the economics work? *Energy Policy* **2012**, 42, 580–590.

energy-price risks.

4.2 Introduction

Concerns over emissions and natural resources are causing many to rethink the century-old paradigm of centralized electricity generation. On average, fossil-fueled power plants in the U.S. have an efficiency of only 35%, with roughly 6% of the electricity lost across the transmission and distribution (T&D) lines (*1*, *2*).

Cogeneration, or combined heat and power generation (CHP), has long been recognized as a more efficient alternative to central-station power. By generating electricity near customers and utilizing the co-produced heat, cogeneration can achieve net efficiencies in excess of 80% (*3*). Heat from cogeneration can also run an absorptive chiller to provide air conditioning. These combined cooling, heat and power (CCHP or *trigeneration*) generators have the flexibility to provide heating in the winter and cooling in the summer.

Recognizing the potential for efficiency gains, the U.S. Congress passed the Public Utilities Regulatory Act of 1978 (PURPA), clearing many of the regulatory barriers to cogeneration. Since then, cogeneration capacity grew four times faster than total U.S. capacity—from approximately 11 GW_e (gigawatt electric) in 1978 to 84 GW_e in 2010 (*4*-*6*). Despite steady growth, cogeneration plays a relatively minor role in the U.S., accounting for roughly 7.5% of total electricity supply (*7*). Industrial cogeneration in the U.S. is estimated to be only one-half to one-third of the economical market potential (*6*, *8*). Adoption is also well short of levels demonstrated in several European countries. For example, cogeneration accounts for more than 50% of electricity production in Denmark and 30% in the Netherlands (*9*).

Studies commonly cite regulatory and utility barriers as reasons for lower–than–expected adoption in the U.S. (*10*). Alternatively, adoption of cogeneration may be low simply because it is not economically attractive. Some argue that this is the case because the benefits of cogeneration are not properly valued. For example, cogeneration may reduce CO_2 emissions and ease the burden on T&D networks, but these benefits are generally not rewarded (*11*, *12*).

Several previous studies have evaluated the economics—and strategies for improving the economics—of cogeneration. In a comparison of distributed generation (DG) options across a range of building types, Medrano et al. found that absorptive chillers improved both the efficiency and the economics of CHP systems (*13*). Siddiqui et al. found that the value of CHP projects could be improved with low-grade heat storage (*14*). Lemar explores how different public policies and programs affect CHP adoption, estimating that aggressive policies could induce 70 GW_e of new cogeneration over 20 years (*6*). Strachan and Dowlatabadi compare CHP adoption in the Netherlands with that of the UK (*15*). While both governments had policies to promote DG, Strachan found that the Netherlands was much more successful due to high buy-back rate for excess electricity (i.e., net metering) and adoption of larger DG units that benefited from economies of scale. King and Morgan found that using cogeneration to serve small aggregates of customers, in what is called a ‘‘microgrid’’, has significant advantages compared to single-customer applications; these microgrids would be cost effective for many customer classes, under existing rate structures, in several regions of the U.S. (*16*).

Building on the above literature, the goal of this work is to evaluate additional strategies for making cogeneration more attractive to potential adopters, either by increasing the expected revenue to decreasing the risks of such investments. Using a case study of a hypothetical hospital in New Jersey, we explore the value of: demand response, capacity markets, regulation markets, accelerated depreciation, pricing CO_2 emissions, and net metering. We go on to examine the effectiveness of feed-in tariffs at mitigating the risks resulting from uncertain energy prices.

The organization of this chapter is as follows. Section 4.3 describes the case-study hospital and cogeneration equipment, Section 4.4 introduces several mechanisms for improving the economics of cogeneration, and Section 4.5 summarizes the mathematical model and key assumptions used in the analysis. Base-case results and a sensitivity analysis are presented in Section 4.6, strategies for increasing the revenue to cogeneration are presented in Section 4.7, and Section 4.8 evaluates the use of feed-in tariffs for mitigating energy-price risks. We conclude in Section 4.9.

4.3 Description of the Case Study

This analysis focuses on a case study of a hypothetical hospital in Newark, New Jersey. We evaluate the use of a 300 kW_e reciprocating engine for CHP and, in the case of CCHP, the same generator paired with a 260 kW_{th} (75 ton) absorptive chiller.

The location was chosen because it has a relatively high spark-spread (the difference between electricity and fuel prices), which is favorable for cogeneration. Previous analyses have shown that hospitals are good candidates for cogeneration (*16*). Medrano et al. note that hospitals are both ubiquitous and energy intensive, representing 3% of all commercial floor space and more than 11% of commercial building energy use (*13*).

Currently there are approximately 320 cogeneration projects operating in the health services industry (Standard Industry Classification (SIC) code 80), 75% of which use reciprocating engines. Total CHP capacity in this industry is 730 MW_e, or about 10% of the estimated market potential (*4*, *17*).

4.3.1 Building energy demands

We use the Building–CHP screening tool (BCHP), developed by Oak Ridge National Lab, to generate hourly thermal and electrical demand profiles for the hospital (*18*). The BCHP tool estimates energy demands based on user inputs, such as building dimensions, location, and type (e.g. hospital, office, hotel, etc.). The peak and average energy demands for the simulated hospital are shown in Table 4.1. Thermal demand includes both space and water heating.

Table 4.1 also shows a comparison of energy intensities from the BCHP model and those from the Commercial Buildings Energy Consumption Survey (CBECS). The CBECS data are based on a 2003 nation-wide survey, which includes approximately 8000 inpatient hospitals (*19*). While the comparison shows close agreement for electrical and cooling demands, the heat intensity from the BCHP model is about half of the CBECS value. If in fact the BCHP model underestimates the buildings' heat demand, then results presented here will tend to underestimate the value of the cogeneration project.

Table 4.1: Energy demands of a hypothetical 22,300 m^2 (240,000 ft^2) hospital in Newark, New Jersey. The bottom half of the table compares the energy intensities from the BCHP model with values from the Commercial Buildings Energy Consumption Survey (*19*).

	Electrical Demand	Thermal Demand	
	(non-cooling) (kW_e)	Heating (kW_{th})	Cooling (kW_{th})
Average	712	312	490
Peak	993	1127	2209
	Electrical Intensity ($kWh_e/m^2/yr$)	Thermal Intensity ($kWh_{th}/m^2/yr$)	
BCHP Model	280	122	192
CBECS	255	242[a]	160[b]

[a] CBECS Table E7A. Natural gas use was converted to thermal demand assuming a boiler/furnace efficiency of 0.8
[b] CBECS Table E6A. Electrical use for cooling was converted to thermal demand for cooling assuming an electrically driven air conditioner with a coefficient of performance of 4

4.3.2 Characteristics of the CHP unit

We select a 300 kW_e reciprocating engine for the case study. The generator was sized for base-load operation, where the unit runs at a high capacity factor with minimal load following.

Performance and cost characteristics for the generator are shown in Table 4.2. Note that the capital costs include interconnection costs, heat recovery equipment, and other installation costs. Variable operation and maintenance (O&M) does not include fuel costs, which are discussed in a later section.

Table 4.2: Performance and cost characteristics of 300 kW_e reciprocating engine (*20*). Costs in 2010 dollars.

Capital Cost ($/$kW_e$)	2,040
O&M Variable ($/$MWh_e$)	16
O&M Fixed ($/$kW_e$/yr)	7.4
Electrical Efficiency	0.35
Thermal Efficiency	0.44

4.3.3 Characteristics of the absorptive chiller

Heat from cogeneration can run an absorptive chiller—a heat-driven refrigeration cycle—to provide air conditioning. The cost and performance characteristics for the single-stage absorptive chiller are shown in Table 4.3. Also shown are the characteristics of a conventional, direct-expansion air conditioner, which we assume is displaced when CCHP used. The costs of the two cooling technologies are comparable, though electrically driven air conditioners have a much higher coefficient of performance (COP).

Table 4.3: Performance and cost characteristics for conventional air conditioners and absorptive chillers. Costs in 2010 dollars. (adapted from (*8*)).

Size (kW_{th})	Type	Capital Cost ($\$/kW_{th}$)	O&M ($\$/kW_{th}/yr$)	COP
260	Conventional[a]	230	15	3.4
	Absorption	290	14	0.7

[a] Values for conventional air conditioners are the average of three technology types: air-cooled reciprocating, water-cooled reciprocating and centrifugal

4.4 Mechanisms for Improving the Economics of Cogeneration

We use our case study to explore several existing and possible future mechanisms for increasing the revenue to cogeneration projects. A brief description of each follows.

4.4.1 Demand response (FERC Order 745)

In the spring of 2011, the Federal Energy Regulatory Commissions (FERC) issued Order 745, allowing ‘‘negawatts’’, or demand reductions, to compete with traditional sources of supply in wholesale energy markets (*21*).

Order 745 requires Independent System Operators (ISO) and Regional Transmission Organizations (RTO) to compensate demand-side reductions at the marginal cost of energy. This requirement holds only in cases when demand response provides a net benefit to customers (i.e. reduced cost of electricity). The PJM interconnection, the ISO serving New Jersey, found that customers would benefit from demand response when locational marginal prices (LMP) exceed some threshold value—$35 to $40 per MWh depending on the month (*22*). Based on these threshold values and day-ahead LMPs, we estimate the benefit of demand response to a cogeneration project. Note that only excess generation capacity—beyond normal CHP/CCHP use—counts toward demand response.

4.4.2 Capacity markets

PJM operates a three-year forward capacity market, the *Reliability Pricing Model*, to ensure that there is sufficient generation to meet peak demand. Participating demand-side resources, such as cogeneration, are paid the auction-clearing price and are contracted to reduce load up to 6 hours for no more than ten events during the contracted performance period (June through September three years following the initial auction). As with demand response, normal CHP/CCHP use is not considered a load reduction in the PJM capacity market; only excess generation capacity should be committed into the market.

We estimate the expected value of PJM's capacity market based on historic prices and the duration and frequency of historic reliability events (see SI).

4.4.3 Regulation markets

Generators providing regulation must accommodate the small imbalances between dispatched generators and the constantly changing load. Demand-side resources, such as cogeneration, are allowed to participate in PJM's regulation market if they are capable of responding to a regulation control signal from the system operator. We calculate the revenue from regulation services based on 2008 regulation market-clearing prices, which range from $8 to $590 per MW per hour (*23*).

4.4.4 Accelerated depreciation

The capital costs of a cogeneration unit would typically be depreciated over the useful lifetime of the generator, which we assume to be 15 years. Under the Energy Improvement and Extension Act of 2008, cogeneration now qualifies for 5-year depreciation, accelerating the tax benefit to the project owner.

4.4.5 Pricing CO_2 emissions

Lower CO_2 emissions are one of the commonly cited benefits of cogeneration. In most of the U.S., however, there is currently no financial reward for being a low-carbon technology. With a price on CO_2 emissions (e.g. a tax or cap-and-trade market), dirtier sources of energy will be penalized, giving a relative advantage to cleaner ones.

Europe implemented a CO_2 cap-and-trade program in 2005, with (Phase II) allowance prices averaging around €20 per tonne (metric ton) of CO_2 (*24*). In the U.S., a coalition of Northeast and mid-Atlantic states, including New Jersey, formed the Regional Greenhouse Gas Initiative (RGGI). The RGGI implemented a cap-and-trade program for CO_2 emissions in 2008. Prices from the RGGI auctions have been quite low, averaging around $2.40 per tonne of CO_2 (*25*). Similarly, the price of CO_2

in the Chicago Climate Exchange was so low that the market closed in 2010.

We assume a hypothetical policy that prices CO_2 emissions at $20 per tonne, approximately the present price in the EU. Based on the average CO_2 emissions rate from PJM generators (0.6 t CO_2 per MWh_e) we estimate that the retail rate of electricity would increase by approximately $12 per MWh_e. This estimate is quite simplistic. In reality the change in retail rates would depend on the marginal generators, which set the wholesale market price, and on the price elasticity of demand, which has generally been estimated as being very inelastic (*26*, *27*).

Under RGGI, generators smaller than 20 MW_e are exempt, giving small-scale cogeneration an advantage over large power plants. To level the playing field, we assume that a comprehensive CO_2 policy would also increase the price of natural gas to end-use customers. Based on an emissions rate of 181 kg per MWh_{th}, we estimate that natural gas prices would increase by approximately $3.60 per MWh_{th}.

4.4.6 Net metering (NM)

NM allows excess electricity from qualifying DG sources to be sold back to the utility. Previous studies have noted the benefits of net metering. For example, Carley found that NM programs "have a significant marginal effect on distributed generation adoption and deployment", though this study did not include cogeneration (*28*). Strachan and Dowlatabadi credit much of the Netherlands' success with cogeneration to their generous NM rates (*15*).

In New Jersey, and most of the U.S., natural gas-fired cogeneration does not qualify for NM (*29*). We evaluate the benefit of net metering assuming that excess electricity from cogeneration is credited at the full retail rate.

4.5 Model Description & Assumptions

Results presented here are the output of a Matlab model that estimates the cost-savings of cogeneration, which are assessed relative to conventionally supplied energy (i.e. utility-supplied electricity and natural gas-fired systems for space and water heating). An hourly optimization is used to minimize the cost of meeting the customer's energy demands, either through cogeneration, conventionally supplied energy, or a combination of the two.

Results are given in terms of the lifetime net present value (NPV) of the cogeneration project, based on a 15-year lifetime. The details of the optimization model are included in the SI.

4.5.1 Fuel & electricity prices

Previous work has shown that the economics of cogeneration are heavily dependent on fuel and electricity prices, both of which are highly uncertain over the lifetime of a cogeneration project. We explore the implications of three different energy-price scenarios:

1. Electricity and gas prices are assumed to follow forecast values from 2011 to 2026. Forecast values are taken from the Annual Energy Outlook for commercial customers in the mid-Atlantic region (*30*).
2. Electricity and gas prices from a single sample year are assumed to repeat for

the life of the cogeneration project. Prices are based on monthly-averaged rates for commercial customers in New Jersey, as reported by the Energy Information Administration (EIA) (*2*).

3. A range of energy prices are explored using a Monte Carlo approach, which is based on a random sampling of historic natural gas and electricity prices from 1990 to 2009.

The intention with the Monte Carlo approach is to explore a wide but realistic range of energy prices. The simulation consists of the following steps: (1) fifteen years between 1990 and 2009 are randomly sampled (years are sampled independently with replacement), (2) energy prices from the sampled years are used to calculate the 15-year NPV for a cogeneration project, and (3) the process is repeated hundreds of times.

While samples are taken on a yearly basis, monthly fuel and electricity prices are used so as to capture seasonal fluctuations. Fuel and electricity prices are sampled as a pair so as to account for the cross-correlation between the two (e.g. high electricity prices are correlated with high fuel prices). Figure 4.1 shows an example of fuel and electricity prices from one run of the Monte Carlo method (dashed line).

Each of the above approaches has some drawbacks. Projections of future energy prices are notoriously poor. Smil notes that energy forecasts have ''missed every major shift of the past two generations'' (*31*). Forecasts also fail to capture the seasonal fluctuations and the volatility seen in historic prices (Figure 4.1). Using actual energy prices from a recent year accounts for seasonal fluctuations but fails to capture year-to-year variations and long-term trends, which could be significant over a 15-year lifetime.

The shortcomings of the Monte Carlo approach are the assumptions that (1) the range of historic energy prices is representative of the range of future prices, (2) prices from any year between 1990 and 2009 are equally likely to occur in the future, and (3) prices in a given year are independent of prices in any other year. Due to obvious concerns with these assumptions, we also explored forecasting future energy prices with autoregressive models (which have their own shortcomings), finding that results from the two methods agreed relatively well. We also note that energy prices from the Monte Carlo method are reasonably consistent with past values and, in our opinion, give a plausible range for future prices.[4]

Historic and projected electricity prices from the EIA are reported as flat-rate energy charges (e.g. ¢/kWh). However, electricity tariffs for large commercial customers are not so simple. Prices generally have seasonal and time of day adjustments, as well as monthly capacity charges. We adjust the EIA flat-rate

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[4] Our sampling method gives mean electricity prices ranging from 120 to 140 $/MWhe and gas prices ranging from 25 to 39 $/MWhth (lowest and highest lifetime-average prices from 500 runs of the Monte Carlo approach). Using standard deviation as a measure of variability, we find reasonable agreement between the variability of historical prices and those from our sampling method. Based on 500 runs of the Monte Carlo approach, we find standard deviations in lifetime gas prices ranging from 4 to 13 $MWhth. The low end of this range matches the standard deviation of gas prices from 1990 to 1997, a period of stable prices. The high end of our range matches the standard deviation of fuel prices over the past decade.

electricity prices to construct a more realistic electricity tariff, which is modeled after the 2008 Public Service Electric and Gas Company (PSEG) tariff for large commercial customers in Newark, New Jersey. Details on the adjusted tariff are included in SI.

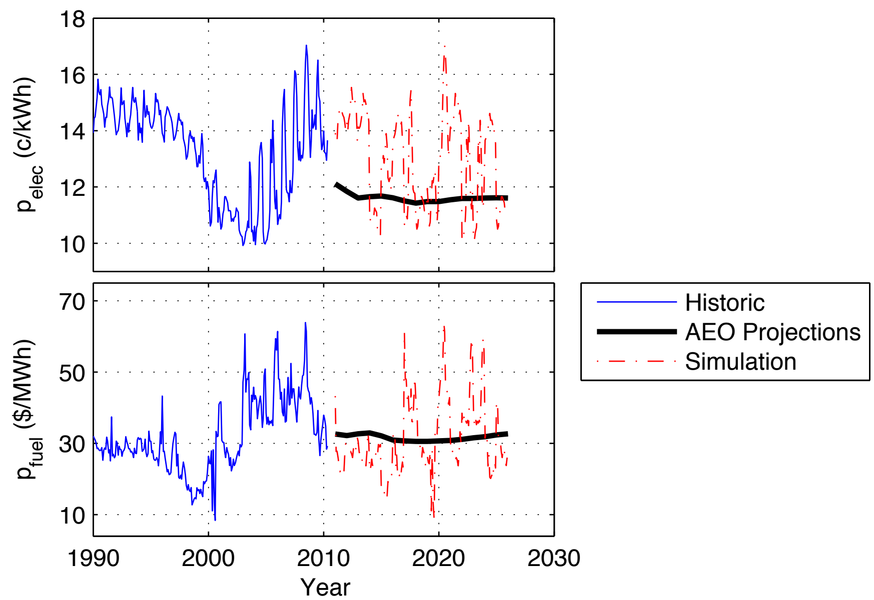

Figure 4.1: Natural gas and electricity prices for New Jersey commercial customers from 1990 to 2010 (thin solid line), forecast energy prices for the mid-Atlantic region (thick solid line), and simulated energy prices based on a random sampling of historic energy prices (dashed line). All prices are in 2010 dollars.

4.5.2 Financial parameters

Financial parameters are shown in Table 4.4. The discount rate is based on a weighted cost of capital, assuming an 80% debt fraction at 7% interest rate and a 20% equity fraction with a 30% return expected (0.8 x 7% + 0.2 x 30% = 11.6%). In a sensitivity analysis we consider discount rates ranging from 6% to 30%.

Table 4.4: Financial parameters

(values adapted from (6))

Project lifetime	15 yr
Federal income tax	35%
State income tax	5%
Property tax	1.5%
Depreciation (straight line)	15 yr
Insurance rate	0.5%
Discount rate	11.6%

4.6 Results: Economic Performance of Cogeneration

Figure 4.2 shows results for the base-case cogeneration project (i.e. without demand response, capacity markets, NM, etc.). Results from the Monte Carlo sampling of historic energy prices are shown as a cumulative distribution function (CDF). The expected value of the CHP and CCHP projects are \$13 and \$280 per kW_e with a 44% and 9% probability of a negative NPV.

On the low end of the CDFs are the cases when cogeneration is least attractive, when fuel prices are high and electricity prices are low. The worst-case scenario is an NPV of -\$620 and -\$537 per kW_e for the CHP and CCHP projects. At the high end, when fuel prices are low and electricity prices are high, the NPVs are \$623 and \$1,023 per kW_e. In all cases, the absorptive chiller is a cost-effective addition to the cogeneration project.

Also shown are results based on energy prices from a single sample year—either 2008 or 2009—with the assumption that first-year savings would be achieved annually for the life of the project. There is a wide difference in NPV depending on the base-year chosen for the analysis (from -\$620 to \$164 per kW_e for the CHP project). This emphasizes (1) the sensitivity of cogeneration to energy prices, which vary widely from year to year, and (2) the limitations of using a single sample year to calculate lifetime savings. The latter is a common practice. For example, Medrano et al. calculate payback periods assuming that "first year savings are achieved every year", and King and Morgan use an analysis of 2003 to calculate energy savings over a 25-year lifetime (*13*, *16*).

Using AEO projected energy prices, the NPV of the CHP project is -\$500/kW_e. Overall, the base-case results show the expected returns are questionable and the energy-price risks are high, as evident by the wide range of the CDFs.

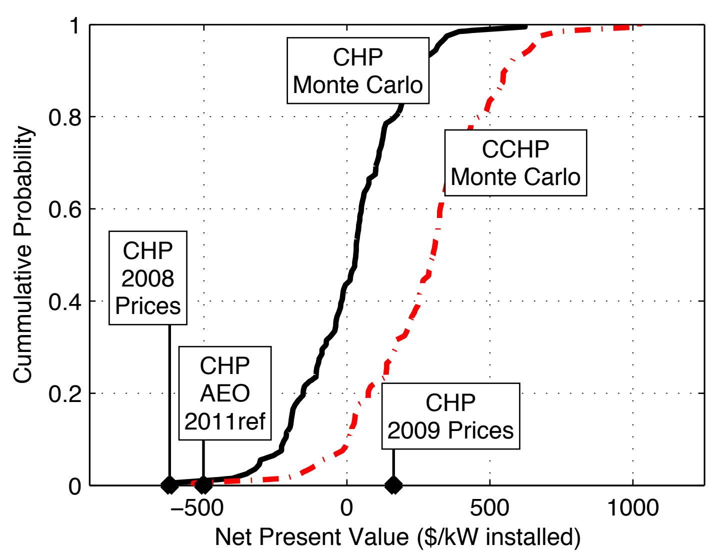

Figure 4.2: Cumulative distribution function for the net present value of the 300 kW_e cogeneration project.

Results are based on (1) a Monte Carlo sampling of historic energy prices, (2) AEO energy price projections, and (3) energy prices from a single sample year—either 2008 or 2009—with the assumption that first-year savings will repeat for the life of the project.

Note that the economics of cogeneration are case-specific because building energy demands, energy prices, and tariff structures differ widely across regions and customer types. Results from this analysis may not be representative of other cogeneration projects. Rather, this case study is intended to provide a starting point for evaluating strategies for improving the economics of small-scale cogeneration.

4.6.1 Sensitivity

Results from a sensitivity analysis are shown in Figure 4.3. We use the CCHP unit with 2009 energy prices as the base case, giving an NPV of \$490/kW_e. Parameters were varied individually to find the corresponding impact on NPV. From the base-case values, the thermal and electrical efficiency of the generator and the COP of the absorptive chiller were varied ±25%. The hospital size, capital cost of the generator, and capital cost of the absorptive chiller were varied ±50%.

A wide range was selected for the discount rate, reflecting different ownership scenarios. At the low end, a 6% discount rate may be appropriate for a cogeneration project owned by a utility, which will typically have a low cost of capital (*32*). At the high end, a 30% discount rate reflects an internally financed cogeneration project for a customer with a high hurdle rate. With a similar rational, we consider project lifetimes from 5 to 25 years.

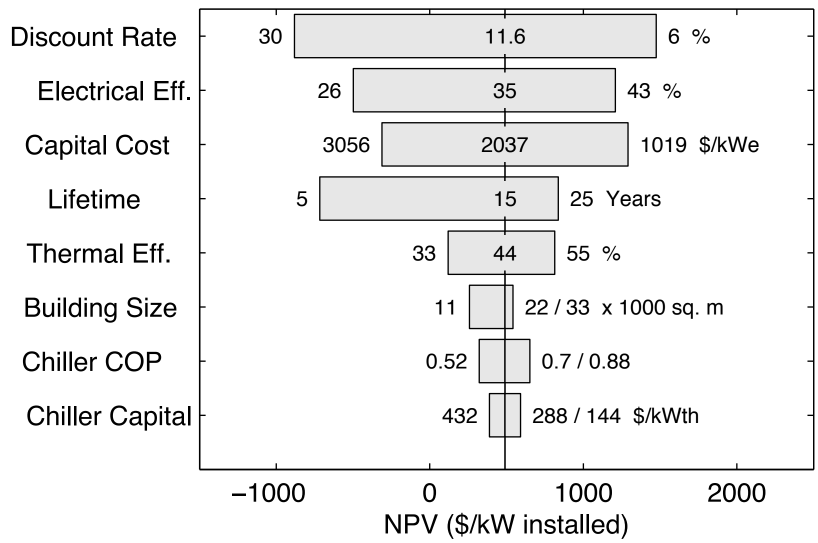

Figure 4.3: Sensitivity analysis for CCHP unit with 2009 energy prices.

Under these assumptions, the discount rate, electrical efficiency, capital cost of the generator, and project lifetime are the most important parameters. Improving the COP of the chiller by 25% significantly outweighs a 50% cost increase, suggesting that a more efficient—and more expensive—two-stage chiller may be worthwhile.

Also of concern is the effect of energy prices. According to the EIA, supply from the Marcellus shale is expected to keep up with growing demand for natural gas, resulting in stable prices in the mid-Atlantic region (Figure 4.1). However, we note that when natural gas prices were at a historic low in 1998, the EIA had a similarly sanguine forecast, which was followed by a decade of rising prices and high volatility. In the future, a regulatory intervention to shale gas could limit supply and drive prices up. Alternatively, gas production could exceed demand, putting downward pressure on prices. Reflecting these possible extremes, we consider a wide range of gas prices.

Figure 4.4 shows the NPV of the CCHP project for gas prices ranging ±75% relative to 2009 prices (8.5 to 60 $/MWh_{th}$). Because electricity prices are often influenced by gas prices, we show scenarios where (1) electricity and gas prices change at the same rate (100%), (2) electricity prices change at half the rate of natural gas prices (50%), and (3) electricity prices do not change in response to gas prices (0%). We assume that only the energy charge for electricity changes, while the demand charge remains constant.

Historically, the correlation between commercial electricity and gas prices in New Jersey has been roughly 30% (dash-dot line). If this relationship continues, a 75% increase in gas prices will result in a 22.5% increase in electricity prices (75% x 30%), causing the NPV to fall from $490 to -$212 per kW_e. Similarly, a 75% decrease in gas prices would increase the NPV to $1390/$kW_e$. The economics of the CCHP project remain steady if electricity prices increase or decrease at approximately 50% the rate of gas prices.

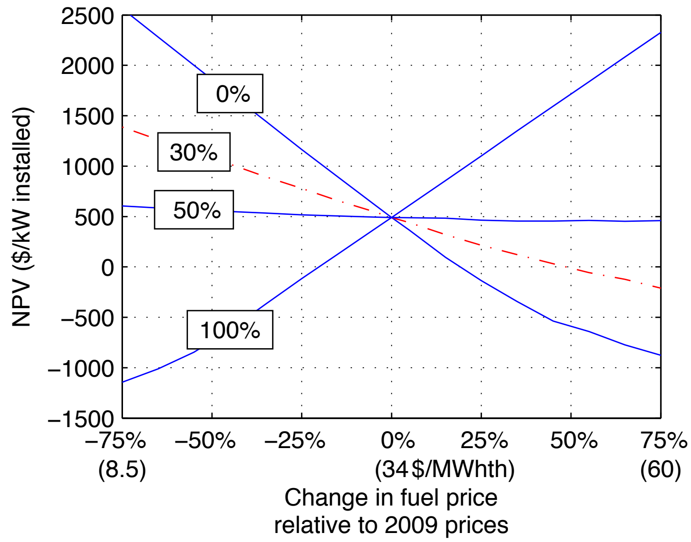

Figure 4.4: Sensitivity of CCHP project to changes in fuel and electricity prices. Changes in fuel price are relative to 2009 (average gas and electricity prices of 34 $/MWh$_{th}$ and 124 $/MWh$_e$). Historically, the correlation between electricity and gas prices has been roughly 30% (dashed line). Also shown are scenarios where (1) electricity and gas prices change at the same rate (100%), (2) electricity prices change at half the rate of natural gas prices (50%), and (3) electricity prices do not change in response to gas prices (0%).

4.7 Increasing Revenue to Cogeneration

Figure 4.5 illustrates the value of five mechanisms for increasing the revenue to a cogeneration project. Using 2009 energy prices, the base-case NPVs are $165 and $490 per kW for the CHP and CCHP projects, respectively.

In this case, adding an absorptive chiller to the CHP project adds $325/kW$_e$ to the lifetime NPV. This result is strongly dependent on the assumption the hospital would avoid the capital cost of a conventional air conditioner when adopting CCHP; without this assumption, the benefit of an absorptive chiller drops to $164/kW$_e$.

The value of demand response is \$101 and \$64 per kW_e for the CHP and CCHP projects. The benefit to the CHP unit is greater because the generator operates at a lower capacity factor, leaving more capacity available for demand response.

Demand reductions are measured relative to a baseline, which we calculate as the net electrical demand after normal CHP/CCHP use but before the demand response incentives. This baseline is consistent with the spirit of FERC Order 745. In practice, however, the baseline is calculated from historical demand data for the customer, and changes in the baseline will affect demand response payments.

Our case study understates the revenue potential of demand response, which is significant following FERC Order 745. The cogeneration unit in this analysis was sized for base-load operation; as a result, there is limited capacity available for demand response. It is likely that over sizing the generator and using excess capacity for demand response could further improve the economics of the cogeneration project.

Similarly, there is limited excess capacity available for the capacity market. However, demand-side resources are rarely called on (see SI) and non-response penalties are lenient. As a result, we find that there is an incentive to overcommit in the capacity market. For our case study, it is most profitable to bid the full 300 kW_e into the market and incur non-response penalties when called on. Based on this strategy, the PJM capacity market adds about \$250/kW_e to the lifetime NPV. The benefit of the capacity market is essentially zero if the customer takes the honest strategy, committing only what they are able to deliver.

Our assessment of regulation markets warrant a few caveats. First, our analysis does not account for the effect of ramping the cogeneration unit up and down, which likely reduces the efficiency of the generator. Second, we constrained the amount of regulation to no more than 20% of the generator capacity; it is technically feasible to provide more regulation, but doing so may interfere with the use of cogeneration to meet the hospitals' energy demands. Third, our analysis does not account for the cost of an automated generation controller (AGC), which allows the generator to receive control signals from the system operator. Fourth, previous work suggests that regulation markets may quickly become saturated (*33*). Advances in grid-scale battery technology, vehicle-to-grid power, or broad adoption of cogeneration could drive regulation prices down. On the other hand, increased use of intermittent renewables, such as wind and solar power, will likely increase the demand for regulation services.

That said, we find that the revenue potential from regulation markets is substantial—adding \$379 and \$337 per kW_e. However, not a single demand-side resource has bid into the PJM regulation market as of April 2011, though the market has allowed demand-side participation since May 2006. This suggests that there remains significant barriers to using cogeneration in the PJM regulation market.

Accelerated depreciation increases the NPV by roughly \$205 per kW_e, though the benefit varies with the assumed discount rate. Based on a 6% discount rate, the value of accelerated depreciation is about \$150/kW_e. We believe that accelerated depreciation is a simple and effective mechanism for improving the economics of cogeneration. See Kranz and Worrell for a detailed analysis of the effect of depreciation schedules on CHP investments (*34*).

At $20 per tonne, the benefit of pricing CO_2 emissions is $193 and $226 per kW_e for the CHP and CCHP unit. However, there is a negligible benefit to cogeneration if carbon prices remain at a few dollars per tonne CO_2, as currently seen in the RGGI market.

In this case, net metering was not beneficial, though this is not generally true. Strachan and Dowlatabadi found that net metering in the Netherlands "extended DG use to the much larger set of sites with limited electricity base-loads" (*15*). We found that NM was beneficial for cogeneration when running the analysis with low-rise office and retail commercial buildings.

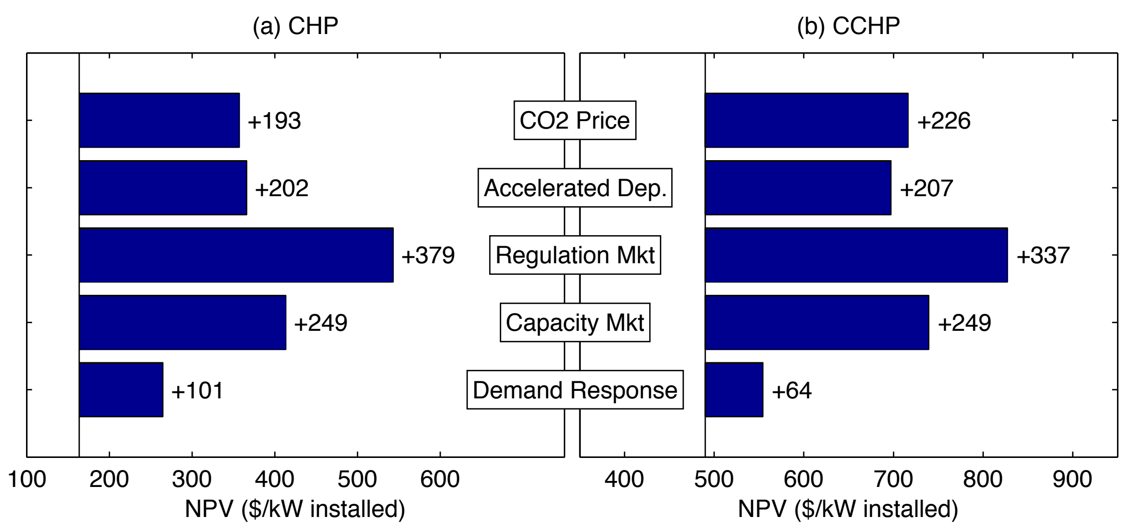

Figure 4.5: Net present value of CHP (left) and CCHP (right) with the added benefit of demand response revenue, capacity market revenue, regulation market revenue, accelerated depreciation, and a $20-per-ton price on CO_2 emissions.

4.7.1 Economies of scale

We now expand the analysis to include generators of different types and sizes. Table 4.5 lists eleven generators—turbines, microturbines, and reciprocating engines—ranging in size from 30 kW_e to 40 MW_e. For each generator, the base-case hospital was scaled such that the cogeneration unit was sized for the base-load thermal demand, consistent with above analysis. The assumed hospital sizes are also shown in Table 4.5.

Aside from the generator and building size, the base-case assumptions are unchanged. Results, based on 2009 energy prices, are shown in Figure 4.6 as a function of generator size (log axis).

Table 4.5: Size and type of generators and assumed hospital sizes.

	Generator Size (kW_e)	Hospital Size (1000 m^2)
Turbines	5,000	394
	10,000	787
	25,000	1580
	40,000	2257
Micro-Turbines	30	2.5
	65	5.2
	250	17.8
Recip. Engines	100	9.8
	300	22.3
	800	60
	3,000	184
	5,000	268

There is a clear trend favoring larger generators, which tend to have lower unit costs and higher efficiencies. However, it should be noted that some of the generators are far too large for a single hospital. The average hospital in the U.S. is approximately 7000 m^2 (75,000 ft^2)—appropriate for a baseload cogeneration unit of less than one hundred kilowatts. A very large hospital may exceed 100,000 m^2 (~ one million ft^2), which could accommodate a generator of one megawatt or more.

Under the assumptions used here, a 5 MWe reciprocating engine would operate in a building of approximately 270,000 m^2 (~ 3 million ft^2), which is unreasonably large for a single hospital.

One proposed strategy to expand the market for larger cogeneration projects is to allow a single generator to serve aggregates of multiple end-users, in what is called a microgrid. King and Morgan found that microgrids have a significant advantage over single-customer CHP, both because of economies of scale and because aggregating different building types helped smooth the demand profiles (*16*). Our analysis simply scales the demand profile for a single hospital. As illustrated in Figure 4.6, larger generators outperform smaller ones even without the benefit of aggregating different building types.

These results suggest that microgrids may improve the economics of cogeneration. However, legacy distribution utilities enjoy ‘‘exclusive service territories’’ and as a result, microgrids are currently illegal, or their legal status is ambiguous, in most of the U.S. (*35*).

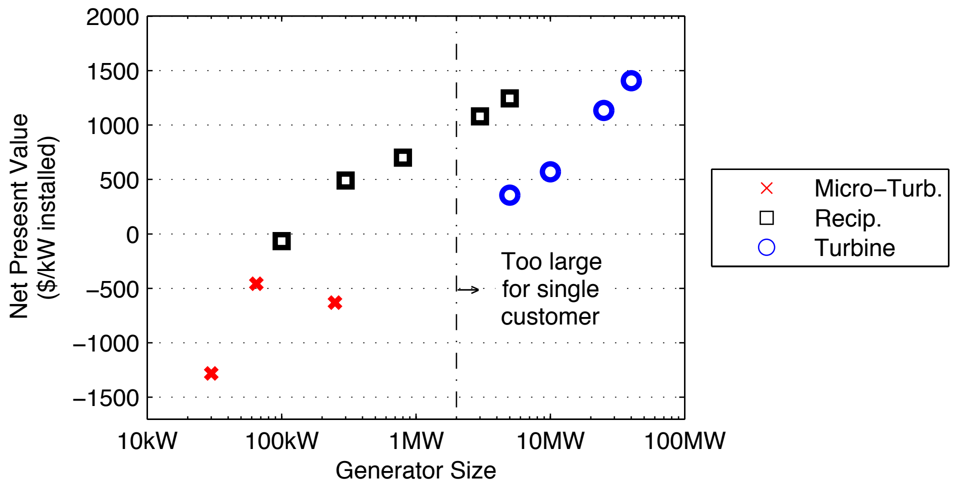

Figure 4.6: Economies of scale for CCHP. Results are given as a function of generator size (log scale). Generators of more than several megawatts are unreasonably large for a single hospital but may be appropriate for a microgrid, which would serve a small aggregate of end users.

4.8 Mitigating Energy-Price Risks

In the previous section, we evaluated mechanisms for increasing the revenue to cogeneration projects. Many of these mechanisms would add to the expected value, thus making cogeneration more attractive to potential adopters. However, we believe that energy-price risks remain a significant deterrent to broader adoption of cogeneration.

Using a range of fuel and electricity prices, we found that the NPV of the CHP project ranges from -$619/kW to +623/kW (Figure 4.2). This indicates that uncertain energy prices make cogeneration a very uncertain investment. In this section, we evaluate the use of feed-in tariffs for mitigating the energy-price risks to a cogeneration project.

Feed-in tariffs are a per kilowatt-hour payment for energy produced from qualifying sources. Payments are usually guaranteed for extended periods, thus protecting energy projects from price volatility (*36*). Feed-in tariffs have been widely used to encourage renewable energy resources such as wind and solar generation. While they have been successful, they are also controversial.

Opponents argue that feed-in tariffs are expensive and economically inefficient, requiring ratepayers or taxpayers to subsidize expensive energy projects. For example, German feed-in tariffs for solar are exceptionally lavish, paying six to eight times the market price of electricity (*37*). On the other hand, advocates argue that fossil fuel sources have high externality costs, which society pays indirectly. For example, the health impacts from the dirtiest power plants cost an estimated 25 ¢/kWh (*38*). Better to fund clean energy, it is argued, than pay the health and environmental costs resulting from conventional energy sources.

Evaluating the costs, benefits, and efficiency of feed-in tariffs is beyond the scope of this study. Rather, we evaluate the effectiveness of feed-in tariffs at reducing the risks to a cogeneration project. We compare two feed-in tariff designs. The first is a fixed-rate tariff, which guarantees a per kilowatt-hour payment for all electricity produced from a cogeneration unit. The second is a two-part tariff that includes an energy payment, which adjusts with fuel prices, as well as an annual capacity payment.

4.8.1 Fixed-rate FIT

We set the first FIT to 12 ¢/kWh for the life of the project. The rate was chosen so as to equal the average retail rate from the sample period used in the Monte Carlo analysis (this is the average energy charge, which does not include the demand charge, as discussed in the SI). While the two rates do not have to be equal, this allows a fair comparison against the base-case results.

While the fixed-rate FIT eliminates all uncertainty with regard to electricity prices, it does nothing to account for volatile fuel prices. As shown in Figure 4.7, the fixed-rate FIT does not effectively reduce the risks to the cogeneration project.

The FIT could be increased so as to guarantee a positive NPV. For our case study, this would require a FIT of roughly 15 ¢/kWh. Such a generous FIT is above the marginal operating cost of the generator, making it attractive to run cogeneration for straight electricity. Doing so reduces the net efficiency of the cogeneration unit. For example, the net efficiency of the generator is 79% (35% electrical + 44% thermal); with a FIT of 15 ¢/kWh, the net efficiency drops to 64% (35% electrical + 29% thermal). At such efficiencies, combined-cycle power plants and high-efficiency furnaces would better achieve the goals of reducing emissions and increasing efficiency (*39*).

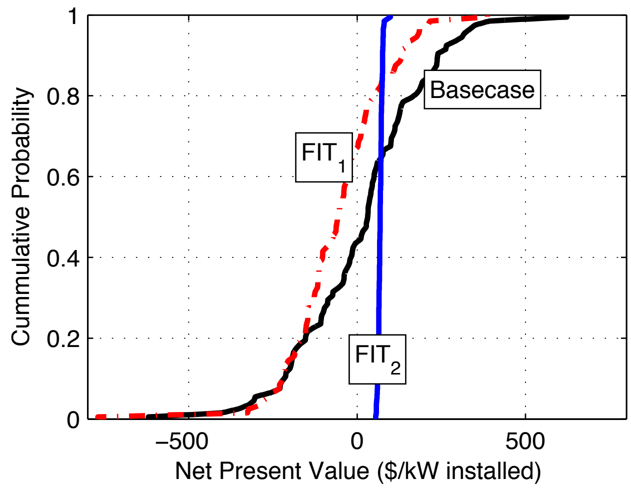

Figure 4.7: Comparison of feed-in tariffs for cogeneration. FIT_1 is a fixed-rate tariff, which guarantees 12 ¢/kWh for the life of the project. FIT_2 is a two-part tariff that includes an annual capacity payment and an energy payment that adjusts with fuel price.

4.8.2 Two-part FIT

The second FIT we consider is a two-part tariff designed to eliminate the risks of volatile fuel prices. The FIT consists of an energy and capacity payment:

$$p_{FIT\_2} = \left(\frac{p_{fuel}}{\eta_{cogen}} - \frac{HPR}{\eta_{boiler}} \cdot p_{fuel} + V_{O\&M} \right) \cdot 1.1 \quad (\$ / kWh) \tag{4.1}$$

$$\text{Payment(rate, lifetime, CapEx)+F}_{O\&M} \qquad (\$/\text{kW/yr}) \tag{4.2}$$

Eq. (4.1) gives the energy payment, where p_{fuel} is the cost of natural gas to commercial customers ($/MWh), η_{cogen} is the electrical efficiency of the generator, HPR is the heat-to-power ratio of the generator, η_{boiler} is the efficiency of the displaced boiler, and $V_{O\&M}$ is the variable operation and maintenance cost.

The energy payment is set 10% above the cost of running the generator if the co-produced heat can be used (i.e. the marginal cost minus the value of the co-produced heat). This gives a relatively low energy payment so as to discourage running cogeneration for straight electricity. The capacity payment (Eq. (4.2)) covers the fixed costs of the generator. The capacity payment is a function of the discount rate, project lifetime, capital cost of the generator, and the fixed O&M costs ($F_{O\&M}$).

With the two-part FIT, the NPV is unaffected by volatility in fuel and electricity prices, as shown in Figure 4.7. The NPV is slightly above zero, meaning that the cogeneration owner gets a small profit beyond the 30% return on equity that was assumed in the discount rate. The two-part FIT also results in much higher efficiencies. With the two-part FIT, the average net efficiency is roughly 78%, compared to 65% for the other two cases shown.

For the two-part FIT, the average energy payment is 7 ¢/kWh and the fixed payment is \$340/kW_e annually. By dividing the fixed cost by the annual electricity production, we get an equivalent electricity cost of 12.8 ¢/kWh_e (including the energy payment).

In this case, the equivalent energy cost of the two-part FIT is slightly higher than the other two cases shown. However, the cost of the FIT is strongly dependent on the discount rate used in the analysis. If a FIT can greatly reduce the risk of a cogeneration investment, then the cost of capital should decrease; banks may be willing to lend money at a lower interest rate and the project owner may be willing to accept lower returns. Thus, a lower discount rate may be appropriate. The equivalent energy cost would also decrease with higher capacity factors because the fixed costs are spread over a greater number of kilowatt-hours.

Figure 4.8 shows the equivalent energy cost for the two-part FIT across a range of capacity factors and discount rates. Our case study has a 67% capacity factor and a 11.6% discount rate, resulting in an equivalent energy cost of approximately 13 ¢/ kWh_e, roughly equal to the current retail rate. Figure 4.8 shows that equivalent energy costs could quite reasonably drop below the retail price of electricity at higher capacity factors and lower discount rates.

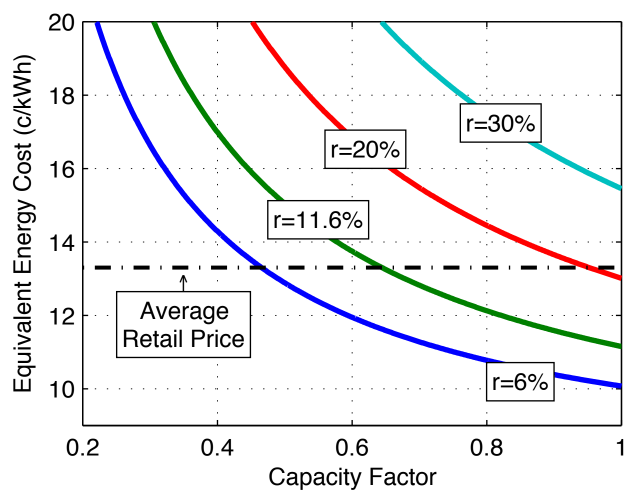

Figure 4.8: Equivalent energy cost of two-part FIT for 300 kW_e CHP unit. Results are given across a range of discount rates and capacity factors. Fixed payments were converted to energy costs by dividing the fixed payments by the energy produced. Average retail price is that paid by commercial customers in New Jersey.

4.8.3 Designing feed-in tariffs for cogeneration

The two preceding sections provided illustrative examples of two FITs applied to a single cogeneration project. In general, we offer the following suggestions for designing feed-in tariffs for cogeneration.

First, energy payments should adjust with fuel prices; without this adjustment, a FIT will not effectively reduce the risks to a cogeneration project.

Second, energy payments should not be too generous. Excessive energy payments may encourage the use of cogeneration for straight electricity, or encourage the adoption of low-efficiency cogeneration units. On the other hand, a FIT with low energy payments will be less effective at spurring adoption. The parameters in Eq. (1)—specifically HPR and η_{cogen}—could be adjusted to find a suitable balance.

Third, with low energy payments, a fixed capacity payment will be needed to make cogeneration economically attractive. The combination of an adjustable energy payment and fixed capacity payment can, if properly designed, completely eliminate the energy-price risks to a cogeneration project.

4.9 Conclusions

Based on a case study of a hospital in New Jersey, this work evaluates strategies for improving the economics of small-scale cogeneration. We find that (1) an absorptive chiller was a cost- effective addition to the CHP project, (2) there is an incentive to overcommit in the capacity market due to lenient non-response penalties, (3) there is significant revenue potential in new demand-response programs (following FERC Order 745), though sizing cogeneration for base-load operation limits the excess capacity available for such programs, (4) there is significant revenue potential in the PJM regulation market, though demand-side resources are yet to participate, (5) a price on CO_2 emissions will make cogeneration more attractive relative to conventional, utility-supplied energy, and (6) accelerated depreciation is an easy and effective mechanism for improving the economics of cogeneration.

We argue that uncertainty in fuel and electricity prices present a significant risk to cogeneration projects. Feed-in tariffs are one proposed strategy for mitigating these risks. We find that guaranteeing a fixed electricity payment does not effectively mitigate energy-price risks. Further, an excessively generous feed-in tariff may encourage cogeneration to operate for straight electricity, potentially reducing the efficiency to the point that there is no longer a social-benefit argument for cogeneration. We show that a two-part feed-in tariff, with an annual capacity payment and an energy payment that adjusts with fuel costs, can eliminate energy-price risks.

4.10 References

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4.11 Supporting Information

4.11.1 Expected value of revenue from capacity markets

Table 4.6 shows annual auction revenues (AAR) from the PJM's capacity market, the *Reliability Pricing Model*. The weighted average AAR is approximately \$52,000 per MW per year. Demand-side resources that fail to respond to a reliability event are penalized one-fifth of the ARR per failure, but not more than the total AAR. We calculate the expected value of the ARR as follows:

$$EV(AAR) = \sum_{k=0}^{5}\left[P(\text{non-respose} = \text{k})\cdot\frac{5-k}{5}\right]\cdot AAR \tag{4.3}$$

where k is the number of reliability events that the customer fails to fulfill their committed demand reduction. P(non-response) is the probability of such a failure, which we calculate based on the frequency and duration of historic reliability events (Table 4.7).

Table 4.6: Annual auction revenue (AAR) from PJM's capacity market (1)

Delivery Year	Capacity Region	AAR ($/MW-yr)	Percent of Annual Total
2008-09	RTO	41,300	61%
	EMAAC	53,000	27%
	SWMAAC	66,800	12%
2009-10	RTO	37,200	43%
	MAAC+APS	68,800	45%
	SWMAAC	79,600	12%
2010-11	RTO	63,600	97%

	DPL	65,100	3%
2011-12	RTO	40,200	100%
Weighted Average		52,000	

Table 4.7: Historic reliability events in PJM (2). Note that these events did not necessarily apply to the entire PJM interconnection, so the actual probability of DG being called on is less than estimated here

Year	Emergency events in PJM	Event Durations
2000	2 (May 8th and May 9th)	5:10, 6
2001	4 (July 25th, August 8th, 9th and 10th)	3:56,5:30,6:30,3:40
2002	3 (July 3rd, 29th, 30th)	6,4:50,6
2003	None	0
2004	None	0
2005	2 (July 27th, Aug 4th)	5:10, 2:45
2006	2 (Aug 2nd, 3rd)	6:33, 5:00
2007	1 (Aug 8th)	5:15
2008	None	0

4.11.2 Optimization of cogeneration use

We optimize the dispatch of the cogeneration unit to maximize the lifetime net present value (Eq. 4.4), which is assessed relative to the cost of conventional, utility-supplied energy:

$$NPV = -CapEx + \sum_{yr=0}^{14} \frac{\overbrace{TC_{conventional,yr} - TC_{cogen,yr}}^{\text{annual cost savings from cogen}}}{(1+r)^{yr}} \tag{4.4}$$

$$\begin{aligned} TC_{conventional,yr} = \sum_{m=1}^{12} \sum_{h=1}^{n} \Bigg[\frac{p_{fuel,m}}{\eta_{boiler}} \cdot H_{demand,m,h} + \cdots \\ + p_{elec,m,h} \cdot \left(E_{demand,m,h} + \frac{C_{demand,m,h}}{COP_{AC}} \right) \Bigg] + DemandCharge_{yr} \end{aligned} \tag{4.5}$$

$$\begin{aligned} TC_{cogen,yr} = min. \sum_{m=1}^{12} \sum_{h=1}^{n} \Bigg[\overbrace{E_{cogen,m,h} \left(\frac{p_{fuel,m}}{\eta_{cogen,m,h}} + V_{O\&M} \right)}^{\text{generator operating cost}} + \overbrace{\frac{p_{fuel,m} \cdot H_{boiler,m,h}}{\eta_{boiler}}}^{\text{boiler operating cost}} + \cdots \\ + p_{elec,m,h} \cdot \underbrace{\left(E_{buy,m,h} + E_{buyAC,m,h} - E_{sell,m,h} \right)}_{\text{utility-supplied electricity after NM}} - \cdots \\ \underbrace{p_{reg,m,h} \cdot (R_{up,m,h} + R_{down,m,h})}_{\text{regulation payment}} \Bigg] + DemandCharge_{yr} - CapPMT_{yr} \end{aligned} \tag{4.6}$$

where

$$\eta_{cogen,m,h} = \eta_{peak} \left[\beta_0 + \beta_1 \left(\frac{E_{cogen,m,h}}{E_{max}} \right) + \beta_2 \left(\frac{E_{cogen,m,h}}{E_{max}} \right)^2 \right] \tag{4.7}$$

$$DemandCharge_{yr} = \sum_{m=1}^{12} \underbrace{max(E_{buy,m,\forall h} + E_{buyAC,m,\forall h})}_{\text{monthly peak electricity demand}} \cdot DC_m \tag{4.8}$$

subject to:

$$\mathrm{E}_{cogen,m,h} + E_{buy,m,h} - E_{sell,m,h} = E_{demand,m,h} \tag{4.9}$$

$$\underbrace{HPR \cdot E_{cogen,m,h}}_{\text{heat from cogen}} + \underbrace{H_{boiler,m,h} \cdot \eta_{boiler}}_{\text{supplemental heat from boiler}} \geq H_{demand,m,h} \tag{4.10}$$

$$\underbrace{HPR \cdot E_{cogen,m,h} \cdot COP_{chiller}}_{\text{cooling from cogen}} + \underbrace{COP_{AC} \cdot E_{buyAC,m,h}}_{\text{supplemental cooling from AC}} \geq C_{demand,m,h} \tag{4.11}$$

$$E_{cogen,m,h} + R_{up,m,h} \leq E_{max} \tag{4.12}$$

$$E_{cogen,m,h} - R_{down,m,h} \geq E_{min} \tag{4.13}$$

$$\left[E_{cogen,m,h}, R_{up,m,h}, R_{down,m,h}, H_{boiler,m,h}\right] \geq \mathbf{0} \tag{4.14}$$

Eq. 4.5 is the annual cost of meeting the hospital's energy demands with conventional, utility-supplied energy. Eq. 4.6 is the minimized cost of meeting the customer's energy demands with cogeneration. Eq. 4.7 gives the electrical efficiency of the generator ($Z_{cogen,m,h}$), which is adjusted from its peak efficiency (Z_{peak}) when the generator operates at partial load (3).

Eq. 4.8 gives the annual demand charge, based on the hospitals monthly peak power demand and the utility demand charge.

Eqs. 4.9–4.14 give the constrains of the optimization problem. Eqs. 4.9–4.11 ensure that the customers' demand for electricity (E_{demand}), heating (H_{demand}), and cooling (C_{demand}) are met, either through cogeneration or conventional boilers or air conditioners.

Eqs. 4.12 and 4.13 ensure that the electrical output of the generator does not exceed the nameplate capacity or fall below some minimum threshold. Eq. 4.14 simply ensures that variables are non-negative.

The optimization problem is solved for each hour for a fifteen- year lifetime (more than 130,000 h). Because the objective function is nearly always monotonic within regions of the feasible domain, we find the optimal solution by checking the transition points between regions. These points include (1) where the thermal output of the generator is equal to the thermal demand of the customer, (2) where the electrical output of the generator is equal to the electrical demand of the customer, (3) a constraint boundary, or (4) the generator is off. We verified a sample of the results using a mixed integer nonlinear programming method and found that the two methods agreed within a fraction of a percent. Each hour was solved independently and startup and shutdown costs were not accounted for.

Nomenclature:

$CapEx$ = capital costs ($)

$CapPMT$ = annual auction revenue from PJM capacity market ($/MW/yr)

C_{demand} = cooling demand (MWh_{th})

COP = coefficient of performance (conventional AC unit or absorptive chiller)

E_{buy} & E_{sell} = electricity bought from and sold to the utility (MWh_e)

E_{buyAC} = electricity bought for running conventional air conditioner (MWh_e)

E_{cogen} = electrical output of cogeneration unit (MWh_e)

E_{demand} = non-cooling electrical demand (MWh_e)

E_{min} = minimum operating load of generator (MW_e)

E_{max} = maximum generator output (MW_e)

h, m, yr = hour, month, year

H_{boiler} = heat output from conventional boiler (MWh_{th})

H_{demand} = heating demand (MWh_{th})

HPR = heat-to-power ratio of generator

p_{fuel} & p_{elec} = natural gas and electricity prices ($/$MWh_{th}$ & $/$MWh_e$)

p_{reg} = regulation market-clearing price ($/$MW_e$-h)

r = discount rate

R_{up} & R_{down} = generation dedicated into the regulation market (MW_e per hour)

$V_{O\&M}$ = variable, non-fuel operation and maintenance costs ($/$MWh_e$)

β = coefficients for part-load efficiency curve

η_{boiler} = efficiency of conventional boiler

η_{peak} = peak electrical efficiency of cogeneration unit

4.11.3 Time-of-use and demand charges for utility-supplied electricity

Historic and projected electricity prices from the EIA are reported as flat-rate energy charges (e.g. ¢/kWh), which we adjust to construct a more realistic electricity tariff. The adjusted tariff is shown in Table 4.8, where p_{EIA} is the energy-only electricity price reported by the EIA. Capacity charges were adopted directly from the 2008 Public Services Electric and Gas Company (PSEG) tariff for large commercial customers in Newark, New Jersey. Two adjustment factors are applied to the EIA energy price. The first adjustment factor (0.91) reduces the energy price to account for the addition of the capacity charges; the second factor adjusts the average price for time-of-use and seasonal differences.

As a check, we compare the adjusted EIA electricity prices with those from past PSEG tariffs. The adjusted EIA electricity prices based on this method are within 5% of the 2008 PSEG rates and within 1% of 2009 PSEG rates.

Table 4.8: Assumed electricity tariff. p_{EIA} is the energy-only price reported by the EIA, which is adjusted to account for the added demand charge as well as seasonal and time-of-use differences. The tariff was modeled after the 2008 PSEG tariff for large commercial customers.

	October-May		June-September	
	Energy (¢/kWh)	Demand ($/kW$_{peak}$)	Energy (¢/kWh)	Demand ($/kW$_{peak}$)
On-Peak	$p_{EIA} \times 0.91 \times 1.03$	3.9	$p_{EIA} \times 0.91 \times 1.32$	7.2
Off-Peak	$p_{EIA} \times 0.91 \times 0.77$		$p_{EIA} \times 0.91 \times 0.88$	

4.11.4 References for the supporting information

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Chapter 5: Conclusions

There is growing interest in reducing the environmental and human-health impacts resulting from electricity generation. Renewables, energy efficiency, and energy conservation are commonly suggested solutions. Chapters 2 and 3 in this thesis further our understanding of the avoided emissions and the avoided health and environmental damages resulting from such interventions. Chapter 4 explores the economics of small-scale cogeneration, a more efficient alternative to conventional power plants.

5.1 Summary of Results and Policy Implications

Chapter 2 presents the first systematic assessment of marginal emissions factors (MEFs) for the U.S. electricity system. MEFs give a consistent measure of the avoided emissions per megawatt-hour of displaced electricity (e.g. due to renewables or energy efficiency). I find that energy efficiency measures in the Midwest and parts of the mid-Atlantic will primarily displace coal-fired generators. By contrast, energy efficiency measures in Texas, New England and the West will primarily displace gas-fired generators, yielding much smaller reductions in CO_2, NO_x and SO_2. Regional differences are significant. Compared to the West, displacing a unit of electricity in the Midwest is expected to avoid roughly 70% more CO_2, 12 times more SO_2, and 3 times more NO_x emissions.

These regional differences, I believe, are underappreciated in policy discussions. If the goal is to reduce emissions, investments in energy efficiency should be focused in places like Wisconsin, Iowa, or Pennsylvania. In California, given how clean the electricity mix is, additional investments in energy efficiency yield relatively little emissions savings.

I compare marginal and average emissions factors (AEFs), finding that AEFs may grossly misestimate the avoided emissions resulting from an intervention. Despite these errors, average emissions factors are commonly used because they are readily available and marginal emissions factors are not.

I recommend that a database of MEFs be maintained so as to facilitate effective policy and investment decisions. As a first step, the Federal Energy Regulatory Commission should direct Independent System Operators (ISO) and Regional Transmission Organizations (RTO) to publish marginal emissions factors for their systems. However, much of the U.S. is not covered by an ISO or RTO. Therefore, I recommend that the Environmental Protection Agency develop, and periodically update, a nation-wide database of marginal emissions factors.

Chapter 3 investigates regional differences in the performance of wind turbines and solar panels, where performance is measured relative to three objectives: energy production, avoided CO_2 emissions, and avoided health and environmental damages from criteria pollutants. I find that the most attractive sites for renewables depend strongly on one's objective. If the goal is to mitigate climate change or reduce human-health impacts, then the sites with the greatest energy output may not be the best choice. A solar panel in Iowa displaces 20% more CO_2

emissions than a panel in Arizona, though energy production from the Iowa panel is 25% lower. Similarly, despite a modest wind resource, a wind turbine in West Virginia is expected to displace 7 times more health and environmental damages than a wind turbine in Oklahoma, and 27 times more damages than a wind turbine in California.

I estimate the social benefits from existing wind farms and find that, on aggregate, the costs of the production tax credit are justified. However, production-based subsidies incentivize energy production rather than social benefits. If the goal is to mitigate climate change or improve human health, then energy production is the wrong measure of performance. Thus, I recommend that policy makers reconsider their reliance on production-based subsidies for supporting renewables.

In Chapter 4, I evaluate strategies for improving the economics of small-scale cogeneration using a case study of a hospital in New Jersey. I explore mechanism for increasing the revenue to a cogeneration project, finding that (1) an absorptive chiller is a cost-effective addition to the project, (2) there is significant revenue potential in new demand-response programs (following FERC Order 745), though sizing cogeneration for base-load operation limits the excess capacity available for such programs, (3) there is significant revenue potential in the PJM regulation market, though demand-side resources are yet to participate, (4) a price on CO_2 emissions will make cogeneration more attractive relative to conventional, utility-supplied energy, (5) there is an incentive to overcommit in the capacity market due to lenient non-response penalties, and (6) accelerated depreciation is an easy and effective mechanism for improving the economics of cogeneration.

I evaluate the effectiveness of feed-in tariffs at mitigating the energy-prices risks of a cogeneration project, finding that a fixed feed-in tariff for electricity accomplishes very little. Further, an excessively generous feed-in tariff may encourage cogeneration to operate for straight electricity, which significantly reduces the net efficiency of a cogeneration unit. I show that a two-part feed-in tariff, with an annual capacity payment and an energy payment that adjusts with fuel costs, can eliminate energy-price risks. While this is clearly desirable for the owner of a cogeneration project, further work is needed to understand if two-part feed-in tariffs are an effective and efficient policy mechanism.