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Location, location, location: The variable value of renewable energy and demand-side efficiency resources

Duncan Callaway, Meredith Fowlie, and Gavin McCormick *

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Abstract

Greenhouse gas mitigation efforts in the electricity sector emphasize accelerated deployment of energy efficiency measures and renewable energy resources. We evaluate renewable energy (RE) and energy efficiency (EE) technologies across regional power systems in the United States in terms of carbon dioxide emissions displaced, operating costs avoided, and capacity value generated. We estimate that external, emissions-related benefits account for between one quarter and one half of the total value generated per MWh over our study period. Regional variation in these emissions benefits gives rise to economically significant, regional differences in second-best production subsidies. This variation is not reflected in the prevailing policy incentives that currently guide new investments.

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1 Introduction

Investments in renewable energy and demand-side energy efficiency improvements are playing a critical role in efforts to reduce domestic greenhouse gas emissions. Renewable energy investment in the U.S. has increased nearly 250 percent since 2004, reaching $36.7 billion in 2013.[1] Domestic investments in energy efficiency are estimated in the range of $90 billion per year.[2] Looking ahead, these investments are expected to continue apace (Barbose et al., 2013; International Energy Agency, 2014).

Over the short to medium-run, returns on these investments in grid-connected renewable energy (RE) and energy efficiency (EE) manifest indirectly in three ways: (1) RE generation and efficiency-induced demand reductions reduce operating costs at marginal electricity generating units; (2) resources can generate "capacity value" if they effectively reduce the costs of maintaining safe and reliable grid operations; (3) RE generation and efficiency-induced demand reductions imply fewer emissions at marginal electricity generating units on the system.

Most – if not all – of the benefits associated with avoided operating costs (1) can be captured privately in the form of revenues earned by renewable electricity producers or reduced energy expenditures in the case of energy efficiency. In restructured regions of the United States, capacity value (2) can also be captured privately via capacity markets, resource adequacy contracts or scarcity pricing in wholesale energy markets. In contrast, a significant share of the emissions-related benefits (3) remain external to electricity market transactions. For example, in much of the domestic power sector, damages associated with greenhouse gas emissions are not currently reflected in operating costs or electricity prices.[3] These external, emissions-related benefits serve as an important justification for policy intervention. Other possible justifications include learning-by-doing, network externalities, and coalition building.(Bollinger and Gillingham, 2014; Meckling et al., 2015)

In principle, policies designed to support socially efficient levels of investment in RE and EE should provide incentives that accurately reflect all external, uncompensated benefits

[1] Michael Liebreich, Bloomberg New Energy Finance Summit (London: Bloomberg New Energy Finance, 2013), available at http://about.bnef.com/summit/content/uploads/ sites/3/2013/12/2013-04-23-BNEF-Summit-2013-keynote- presentation-Michael-Liebreich-BNEF-Chief-Executive.pdf; Pew Charitable Trusts, Whos Winning the Clean Energy Race? (2014), available at http://www.pewenvironment.org/uploadedFiles/PEG/Publications/Report/clen-whos- winning-the-clean-energy-race-2013.pdf.

[2] Laitner, Skip (2013). "Calculating the Nation's Annual Energy Efficiency Investments", ACEEE.

[3] Over the time period we consider, the emissions cap imposed under the Regional Greenhouse Gas Initiative was non-binding. At the time of writing, greenhouse gas emissions from the power sector remain uncapped in much of the country; California and parts of the Northeast are the exception.

and costs. Absent other market failures or distortions, a carbon price equal to the marginal damage caused achieves this objective. However, production and capacity-based subsidies are far more prevalent.[4] Incentives paid on the basis of electricity generated (or energy saved in the case of efficiency) will likely remain an important source of support into the forseeable future.[5]

The prevalence of production-based policy incentives to support investment in RE and EE resources raises some important questions. First, what level of subsidy per unit of electricity generated (or saved) can be rationalized on the basis of uncompensated external benefits? Second, should these incentives be differentiated to reflect differences in external benefits across regions and/or technologies?

As noted above, proponents of RE and EE subsidies point to a number of potential external benefits. This paper focuses on a dominant and central source of these benefits: carbon emissions reductions associated with incremental investments in renewable energy and energy efficiency.[6] We use hourly data from six major independent system operators (ISOs) in the United States over the period 2010-2012, together with site-specific profiles of renewable energy production potential and energy efficiency savings potential, to estimate the impacts of incremental RE and EE investments on regional emissions over the study period. We compare our estimates of external emissions-related benefits with private returns on investment and prevailing policy incentives.

Our primary findings can be summarized as follows. First, we document statistically significant regional variation in the quantity of emissions displaced per MWh of renewable energy generation (or per MWh of energy saved in the case of EE investments). In contrast,

[4]In particular, renewable portfolio standards and tax credits are playing a critical role in driving investment. Twenty-nine states have adopted renewable portfolio standards which mandate minimum levels of renewable generation. Twenty states have efficiency standards which establish specific targets for demand-side energy savings.

[5]Some argue that subsidies targeted at green industries are an essential stepping stone to building political support for other forms of climate policy (including a carbon tax).(Meckling et al., 2015). Recognizing that most U.S. states encourage renewable energy developments through state renewable portfolio standards, the Clean Power Plan allows states to meet the emissions reductions goals of the CPP by leveraging these existing programs and the associated network of regional Renewable Energy Certificate (REC) tracking systems. In the years prior to the CPP start date, states can earn compliance credits for renewable electricity generation and some efficiency investments.

[6]We do not attempt to quantify benefits unrelated to avoided emissions such as learning-by-doing or coalition-building. Moreover, we focus exclusively on CO_2 emissions. Though there are non-CO_2 avoided emissions benefits, on a per MWh basis, CO_2 accounts for a very large fraction of monetized emissions damages using the median marginal damage values for SO_2, NO_x, and particulate matter reported in US National Research Council (2010) and assuming marginal damages of \$38/ton CO_2(U.S. Interagency Working Group on Social Cost of Carbon., 2014). Moreover, most harmful emissions of NO_x and SO_2 were subject to an emissions cap over our study period.

emissions displacement (on a per-MWh basis) does not vary significantly across resources within most of the regions we analyze.

Second, we assess the economic significance of these external benefits estimates. We construct a measure of marginal social value that captures the avoided operating costs (e.g. fuel), capacity value, and the value of avoided CO_2 emissions. Using a social cost of \$38/ton of CO_2, emissions related benefits account for anywhere between one quarter and one half of the estimated social value per MWh. Because emissions-related benefits tend to be negatively correlated with privately captured returns on investment across regions, accounting for external emissions benefits alters the rank-order of returns on investment across regions (but not within technology). This underscores the importance designing policy incentives to accurately capture regional variation in external, emissions-related benefits.

Third, we compare our estimates of emissions-related benefits against estimates of average technology costs. The ratio of technology costs (net of avoided operating costs) and emissions avoided can be approximately interpreted as a marginal abatement cost textitif the benefits or costs omitted from our analysis are small. We document striking variation in these net costs per ton of CO_2 avoided. Utility-scale solar PV costs range from approximately \$50 to \$120 per ton of CO_2 avoided across the regions we consider. In contrast, wind energy costs are in the range of \$20-\$60. Based on engineering estimates of energy savings associated with lighting efficiency improvements, the energy efficiency investments we consider are associated with negative abatement costs. [7]

Finally, we compare our estimates with prevailing production or capacity-based policy incentives (i.e. those conferred by renewable energy portfolio standards and federal tax credits). As noted above, these RE and EE policies can generate benefits that are not captured by our estimates of emissions displacement (inappropriable learning spillovers are one example). Again assuming a social cost of carbon of \$38/to), we subtract the monetized estimate of avoided emissions from the corresponding production-based policy incentive. This residual, plus any costs we have failed to account for, represents the value of other uncompensated benefits that would rationalize the incentive levels we observe. These values are as high as \$450 per MWh for solar PV and up to \$32 per MWh for wind.

This study contributes to a growing literature that investigates the near-term environmental benefits accruing from incremental increases in renewable energy and alternative technology investments (e.g. Cullen (2013), Kaffine et al. (2013), Graff Zivin et al. (2014),

[7] For any reader who wants to understand how these results vary with alternative assumptions, these calculations are presented in a manipulable spreadsheet. See `http://nature.berkeley.edu/~fowlie/papers.html`.

Novan (2015), Siler-Evans et al. (2012)). We extend this line of inquiry in three important ways. First, we characterize the variation in estimated emissions-related benefits along spatial, temporal, and technological dimensions. This analysis of variance is useful for informing policy design trade offs between complexity (i.e. policy differentiation) and efficiency.[8] Second, we put the analysis of short-run benefits associated with emissions displacement, avoided operating costs, and capacity value on the same empirical footing. This facilitates direct and systematic comparison of emissions-related benefits vis a vis private cost savings and prevailing policy incentives. Finally, the paper demonstrates a broadly applicable methodological approach to estimating how incremental increases in RE and EE affect regional operating costs and emissions using public data. The methodology has potential applications in both policy design and commercial settings.[9]

These contributions notwithstanding, our analysis does not eschew some important limitations common across all analyses of marginal emissions impacts. Our methodological approach is not well-suited to evaluating long run impacts, nor should our estimates be used to value returns on very large, non-incremental increases in RE and EE capacity.

The paper proceeds as follows. Section 2 provides a conceptual framework for the analysis. Section 3 summarizes the data. Section 4 estimates marginal operating emissions rates across time and space. Section 5 estimates marginal emissions displacement rates across regions and technologies. Section 6 relates estimates of emissions displacement to a more comprehensive measure of economic value. Section 7 estimates region and resource-specific marginal abatement costs. Section 8 compares the level of carbon benefit we estimate against direct subsidies technologies receive. Section 9 concludes.

2 Conceptual framework

The primary goal of this paper is to estimate the marginal returns on investments in renewable energy and energy efficiency over the short-run, and to summarize the variability in these values along spatial, temporal, and technological dimensions. This is a short-run

[8]States are currently exploring the possibility of tracking emissions avoided from RE generation and EE savings for the purpose of crediting emissions reductions under the proposed Clean Power Plan. If states choose to file compliance plans separately, and then trade RE or EE credits for compliance purposes, it will be important to ensure that the crediting protocol captures significant variation in emissions displacement benefits.

[9]Technology startup WattTime.org has deployed software on select smart devices such as thermostats and electric vehicles to automatically minimize the marginal indirect CO_2 emissions rate of such equipment. The software uses a real-time marginal estimation algorithm that is based on the methods presented in this paper.

analysis in that we condition on the existing infrastructure of regional electric power systems. In this section we organize these steps within a simple conceptual framework.

2.1 Marginal operating emissions rate

We specify an emissions equation, $\mathrm{EM}_r(y_{rt}, x_{rt})$ which defines system-wide emissions in region r as a function of factors we can observe. y_{rt} denotes the total production from generators that respond to marginal changes in production from RE, or changing demand levels, in region r at time t. Other observable factors that affect system operating conditions, such as weather, are captured by x_{rt}. Differentiating with respect to y_{rt}, we obtain an expression for the marginal operating emissions rate (MOER):

$$\phi_{rt} \equiv \frac{\partial \mathrm{EM}_r(y_{rt}, x_{rt})}{\partial y_{rt}} \tag{1}$$

This partial derivative captures the system-wide emissions associated with the last megawatt produced by dispatchable units.

Figure 1 serves to illustrate how these marginal emissions rates can vary across hours within a season (using winter in New York State as a case in point; we will apply this framework across many regions in Section 4). Coal units, which are relatively more carbon intensive, are more likely to be marginal during the evening hours when demand is low. In contrast, less carbon intensive combined cycle gas plants are more often marginal during the mid-day hours when demand is relatively high.[10]

2.2 Marginal emissions displacement rate

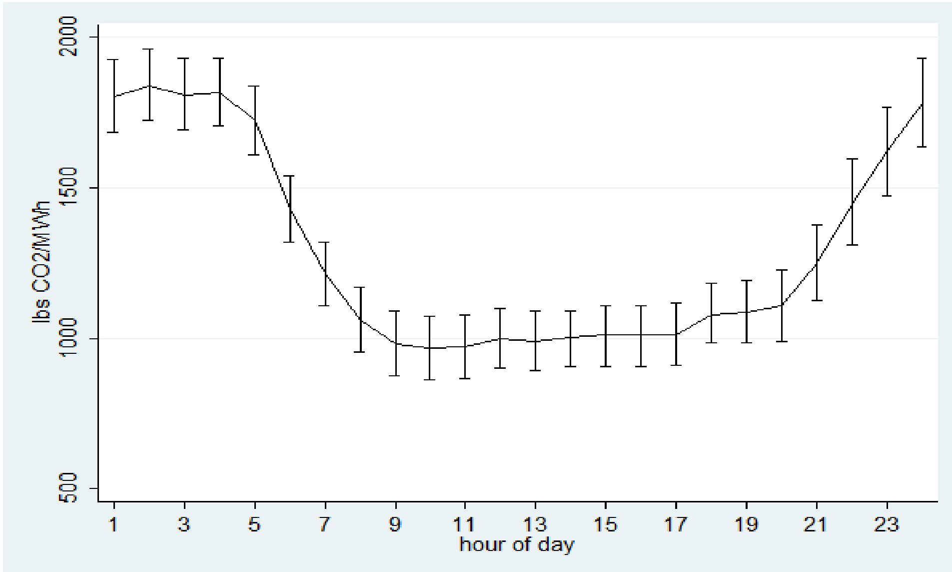
In a second step, We estimate the quantity of emissions displaced by a resource in a given location r at a given hour t as the product of the hourly MOER and the technology's electricity production or savings in that hour.[11]

Our approach is predicated on two features that distinguish grid connected wind, solar, and demand-side efficiency technologies from combustion-based generation resources. First, wind, solar and energy efficiency savings are generally non-dispatchable. Second, because

[10] To put these rates in perspective, using the U.S. Energy Information Administration estimates for prime mover heat rates in 2012 and CO_2 emissions by fuel type, coal plants emit roughly 2075 pounds of CO_2 per MWh (assuming bituminous coal), combined cycle gas turbines (CCGT) emit 892 pounds per MWh and simple cycle gas turbines (SCGT) emit 1346 pounds per MWh.

[11] This neglects changes in transmission and distribution line losses.

Figure 1: Seasonal marginal operating emissions rate profile (NYISO)



Notes: This figure illustrates hour-specific estimates of the marginal operating emissions rate in New York during the winter season. Bars denote 95 percent confidence intervals. Our approach to constructing point estimates and associated confidence intervals is explained in detail in Section 4.

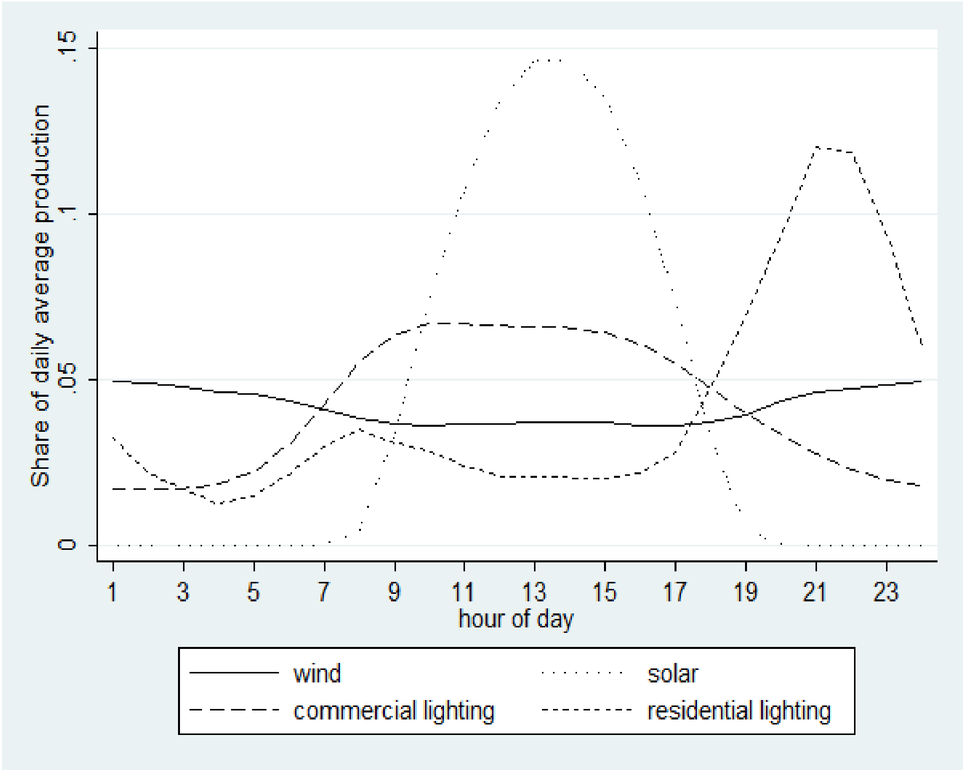
the variable costs of wind, solar are negligible as compared to combustion generators, these resources are typically deployed whenever they are available.[12]

Figure 2 plots average hourly resource availability for a representative wind site, a representative solar PV installation, a generic residential lighting upgrade, and a generic commercial lighting upgrade (all located in New York State). This figure summarizes electricity production or savings during the winter season; realized resource availability or load reduction in any given hour will fluctuate around these average hourly values. Taking Figures 1 and 2 together, one can see how the emissions-displacement benefits can vary across resources with similar overall electricity production (or saving) potential, but different temporal profiles.

To facilitate direct comparisons of emissions displacement across resource profiles, we define δ_{rj} to be the marginal emissions displacement rate (MEDR) specific to each technology

[12]Exceptions to this rule occur when transmission and minimum generation constraints prevent least cost dispatch; these occurrences are relatively rare.

Figure 2: Resource-specific production profiles



Notes: This figure plots the share of energy generated (or saved) on an average winter day in New York by hour of day. See the data appendix for a discussion of data sources.

j and region r over time horizon T:

$$\delta_{rj} \equiv E\left[\sum_{t=1}^{T}\left(\omega_{rjt}\phi_{rt}\right)\right] \tag{2}$$
$$= T \cdot E\left[\omega_{rjt}\right] \cdot E\left[\phi_{rt}\right] + T \cdot cov(\omega_{rj}, \phi_r) \tag{3}$$
$$= \overline{\phi_r} + T \cdot cov(\phi_r, \omega_{rj}) \tag{4}$$

The weights ω_{rjt} represent the energy produced by a wind or solar resource (or saved by an efficiency resource) in time interval t normalized by the total production (savings) from the resource over the time horizon T.[13] The $E[\cdot]$ denotes an expected, or average, value.

A key implication of Equation (4) is that the average quantity of emissions displaced per MWh generated or saved by a resource is determined not only by the average MOER in the region, $\overline{\phi_r}$, but also the correlation between the resource production profile and the marginal operating emissions rate. Intuitively, a resource that is disproportionately displacing electricity production at conventional generators during periods of time when the marginal emissions rate is high will confer larger emissions-related benefits, all else equal. This highlights the importance of capturing both regional and technological variation in our analysis of emissions displacement benefits; we will explore these MEDRs in detail in Section 5.

2.3 Marginal economic value

To put regional and technological variation in emissions displacement benefits into perspective, we introduce a measure of marginal benefit that accounts for both avoided environmental damages and impacts on power system operating costs.

$$E\left[\mathrm{MB}_{rj}\right] = E\left[\sum_{t=1}^{T}\left(\tau\omega_{rjt}\phi_{rt}\right)\right] + E\left[\sum_{t=1}^{T}\left(\omega_{rjt}\lambda_{rt}\right)\right] + CAP_{rj} \tag{5}$$
$$= \underbrace{\tau(\overline{\phi_r} + Tcov(\phi_r, \omega_{rj}))}_{\text{Emissions displacement value}} + \underbrace{\overline{\lambda_r} + Tcov(\lambda_r, \omega_{rj})}_{\text{Avoided operating costs}} + \underbrace{CAP_{rj}}_{\text{Capacity value}} \tag{6}$$

The τ parameter captures the monetary value of the health and environmental damages

[13]For ease of exposition, we ignore variation in resource profiles for each technology within a region. Below we show empirical support for the assumption that within-region variation is not a significant driver of variation in resource value.

avoided per unit of displaced emissions.[14] The λ parameter represents the cost of the last MWh produced by dispatchable units over a particular hour. If ω_{rj} is positively (negatively) correlated with the marginal cost of supplying load, this will positively (negatively) influence the marginal economic value of the renewable or efficiency resource. As we will show in Section 6, decomposing the short-run benefits in this way makes explicit the relative importance of the value of external emissions displacement benefits relative to operating cost reductions.

The final term in the marginal benefit equation, CAP_{rj}, denotes the capacity value generated by technology j in region r. All regional power systems need a certain amount of generation capacity to reliably meet electricity demand, and as peak demand grows (due to changing end-use patterns driven by economic growth or new technologies like air conditioning) new capacity needs to be built to maintain reliability. CAP_{rj} is the cost that would need to be incurred to build conventional generation capacity (e.g. a combustion turbine) in the absence of the renewable or efficiency resource, levelized per MWh of energy produced or avoided by the resource. We will discuss how this quantity is computed in Section 6.

2.4 Marginal abatement cost

In a final step, we combine our estimates of marginal returns on investment with estimates of levelized investment costs. More precisely, we construct a measure of the net costs required to avoid a ton of carbon emissions:

$$E\left[\mathrm{MAC}_{rj}\right] = \frac{LCOE_{rj} - (\overline{\lambda_r} + Tcov(\lambda_r, \omega_{rj}) + CAP_{rj})}{(\overline{\phi_r} + Tcov(\phi_r, \omega_{rj}))} \tag{7}$$

The numerator is the net cost per MWh: the levelized cost of electricity (LCOE) net of avoided fuel costs and capacity value.[15] Dividing this net cost by the quantity of emissions displaced per MWh (in the denominator) yields a cost per ton of emissions avoided. If this value exceeds the social cost of carbon emissions, the investment cannot be rationalized on the basis of the carbon emissions externality alone. We will explore this measure in Section 7.

[14] Because the scale of CO_2 emissions reductions is quite small relative to global emissions, we can safely assume a constant marginal damage value.

[15] The LCOE is a common benchmarking tool used to assess the relative cost-effectiveness of different energy technologies. Conceptually, it measures the constant (in real terms) price per unit of electricity generated that would equate the net present value of revenue from the plant's output with the net present value of the cost of production.

3 Data and empirical strategy

Empirical approaches to estimating the emissions impacts of specific grid-connected renewable energy resources vary in terms of the degree of complexity, data requirements, and identification strategies. The approach we take is data intensive and broadly applicable. We use hourly variation in production at grid-connected thermal power plants to proxy for the effects of adding a new grid-connected renewable energy resource or efficiency improvements. This allows us to estimate the marginal value of grid connected RE and EE resources even in the absence of variation in RE production or changes in EE investments. Inferential statistics are estimated using a block bootstrap.

Before we describe the data, we discuss two research design choices that have direct implications for data construction and interpretation.

3.1 Marginal generating units

At the core of our analysis is the relationship between marginal changes in power system operations and emissions. To implement this empirically, we estimate the relationship between hourly CO_2 emissions in a regional power system and hourly electricity generation at fossil-fueled power plants in the same region. This approach assumes that only fossil fuel production will be affected by an increase in renewable output or energy efficiency. The non-fossil fuel sources we exclude are primarily nuclear and reservoir-based hydroelectric; run-of-river hydro and other non-hydro renewables comprise a much smaller share.

An alternative approach would regress aggregate hourly emissions on total electricity demand. However, if production at non-fossil generators is correlated with changes in net load, marginal emissions rate estimates will be biased. For example, reservoir hydro output may be reduced in response to an increase in renewable output or energy efficiency (which, in the extreme, would give the appearance of a MOER of zero). But a reduction in reservoir hydro leaves water for later use.[16] Because operators will seek to maximize the economic value of a hydro facility, the additional stored water will likely be used at another time with high marginal costs – i.e. when fossil generators are on the margin. Therefore reducing hydro output at one point in time effectively reduces fossil output at a later time. As we will

[16] The circumstances would be different if the hydro operator is forced to spill additional water in this scenario, but we assume this would only occur if thermal generator output cannot be further reduced. Though this sort of spilling – and for that matter curtailment of other renewables – in the face of minimum generation constraints from thermal generators is possible, it is currently sufficiently rare that we assume it will not influence our analysis.

see, because most of our MOERs vary relatively little over a day, this realloction of when fossil generator output is displaced likely results in relatively small errors.

3.2 Regional unit of analysis

We group generating units in our analysis according to the Independent System Operator that oversees their operation.[17] ISOs were created to coordinate large-scale pooled electricity markets. These system operators economically balance load in ISO regions with supply on daily, hourly and sub-hourly time scales.[18] ISOs also coordinate ancillary services – for example frequency regulation and spinning reserves – to balance net load forecast errors on a second-to-second basis, after all electricity markets have cleared.

An alternative approach would aggregate up to the North American Electric Reliability Corporation (NERC) regions (See, for example, Siler-Evans et al. (2012); Graff Zivin et al. (2014)). NERC regions are used for monitoring expansion plans and assessing historical reliability performance. But these regions do not define the footprint of any single pooled market or balancing authority. In recent work, Graff Zivin et al. (2014) regress emissions within an entire interconnection (i.e. an aggregation of ISOs and utilities that interchange power) on load in each sub-region of the interconnection. The advantage of this approach is that it implicitly captures the flow of electricity between areas. A disadvantage, as noted above, is that it captures changes in non-marginal, non-emitting generation that are correlated with load. Moreover, load in neighboring regions tends to be highly collinear, which further complicates the interpretation of the estimated coefficients.

On balance, we find the ISO regions provide a useful way to identify and aggregate the generating units that would most likely respond to incremental RE and EE capacity additions.[19] Our approach is predicated on the assumption that the generators who would respond to an incremental increase in RE or EE investments are located in the same region

[17] Benefits and costs are estimated separately for the six major independent system operators (ISOs) in the United States: ISO New England (ISONE), the New York ISO (NYISO), the PJM Interconnection, the Midcontinent Independent System Operator (MISO), the Electric Reliability Council of Texas (ERCOT) and the California ISO (CAISO). Because the Sacramento Municipal Utility District and Los Angeles Department of Water and Power are surrounded completely by CAISO, we include generators in those footprints in our analysis; therefore we refer to the total region of analysis as California.

[18] On March 1, 2014 the Southwest Power Pool began coordinating daily, hourly and sub-hourly markets via its Integrated Marketplace. At the time of writing this paper there was not yet sufficient historical data to include this region in our analysis.

[19] In some cases NERC regions are larger than ISOs (CAISO is a very small part of the WECC NERC region), and in other cases ISOs straddle multiple NERC regions (for example PJM straddles the MRO, RFC and SERC NERC regions; MISO straddles the MRO and RFC NERC regions).

as the RE or EE resource.

3.3 Data Sources

The data that support the analysis include hourly emissions and electricity generation at fossil-fueled power plants; simulated hourly electricity production across thousands of wind and solar sites; simulated hourly electricity savings from efficiency improvements in the residential and commercial sector; wholesale electricity prices; and estimates of levelized costs for renewable and energy efficiency resources. Except where otherwise noted, the period of analysis is each hour of the period 2010-2012. In light of falling technology costs, we use more recent cost data to construct our MAC estimates. Appendix A describes the data sources and data set construction in detail. Here we provide a brief overview of the data set components.

Hourly electricity production and emissions: We obtain hourly electricity generation and CO_2 emissions for all plants that continuously monitor and report hourly CO_2 mass emissions, heat inputs, and steam and electricity outputs to the U.S. Environmental Protection Agency.[20] We use plant latitude and longitude to locate the plants within ISOs using a spatial database of the footprints of each ISO[21]. We exclude combined heat and power units and co-generation because production these units would presumably be unaffected by an increase in RE or EE capacity.

Marginal operating costs: We use real-time locational marginal prices (LMPs) as a proxy for marginal fuel and operating costs. For most ISOs we use an unweighted spatial average of each region's hourly LMPs.

Wind production: We obtained simulated wind production data from the National Renewable Energy Laboratory's (NREL) Eastern Wind dataset[22] and Western Wind dataset[23]. NREL and its partners produced these datasets with a combination of meso-scale wind speed simulation models and the production characteristics of hypothetical wind farms. The resulting simulated datasets cover more than 30,000 sites across the United States. The meteorological data used to calibrate the simulations cover the years 2004-2006. As we describe below, we use a subset of these sites, and for each site we shift the dates forward by 6 years

[20] Under Part 75, Volume 40 of the Code of Federal Regulations.

[21] `www.ventyx.com/en/solutions/business-operations/business-products/velocity-suite`, last accessed December 28, 2014.

[22] `http://www.nrel.gov/electricity/transmission/eastern_wind_dataset.html`, last accessed December 28, 2014.

[23] `http://www.nrel.gov/electricity/transmission/western_wind.html`, last accessed December 28, 2014.

(e.g. we mapped 2004 to 2010) to match the data with hourly electricity production and emissions data.[24]

Solar production: NRELs PV WATTS simulation tool applies PV performance modeling to typical meteorological year (TMY) weather data to estimate the hourly average production of a solar array at any of thousands of different sites. We use this tool to simulate site-specific hourly output assuming a fixed PV array facing south, with a tilt angle set equal to the sites latitude and PV WATTS default assumptions about system efficiency and ground coverage ratio (see Appendix for details). Because solar production is strongly spatially correlated on hourly time scales we use only one site per region, choosing the TMY3 with the highest production potential from within each region. These sites are listed in the Appendix.

Energy efficiency savings: We focus exclusively on commercial and residential lighting efficiency improvements because these measures are relatively insensitive to climate, which allowed us to use the same consumption profiles in all regions. To estimate savings from lighting efficiency, we began with residential and commercial lighting consumption profiles with seasonal, weekly and diurnal patterns of consumption (Wei et al., 2012). We then assumed lighting efficiency improvements would reduce consumption by the same percentage in each of hour of these profiles, and normalized the hourly savings by total energy saved per year.

Levelized cost of energy (LCOE): Table 1 summarizes the region and technology specific LCOEs.

Levelized cost estimates for wind power are based on power purchase agreements (PPAs) from a large sample of wind installations (Wiser et al., 2014). If we assume the wind industry is competitive, the PPA prices plus the PTC are representative of total developer costs per MWh, and we use this sum to approximate the total LCOE in each region.

Because the price of wind decreased rapidly over the study period, we use the latest available wind price data to generate results most pertinent to the current market environment. For the Northeast, the latest available data are from 2012; for the other regions, PPA data are from 2013. PPA prices are inclusive of energy, capacity and renewable energy certificate (REC) payments. We assume wind developers also received the federal production tax credit (PTC, $22/MWh).

[24] To the extent that wind speed is correlated with other covariates that also influence electricity demand – for example temperature – this shift introduces some error into our analysis. Though these correlations are important for determining wind capacity value and contribution to system peak, they are weak enough that they will not significantly influence our results (Callaway, 2010).

Table 1: LCOEs for all technologies and regions.

technology	CAISO	ERCOT	ISONE	MISO	NYISO	PJM
Utility scale solar	\$90.66	\$91.60	\$132.02	\$106.6	\$133.64	\$138.57
Utility scale wind	\$80.52	\$43.59	\$75.11	\$65.06	\$75.11	\$75.11
Residential lighting	\$26.93	\$26.93	\$26.93	\$26.93	\$26.93	\$26.93
Commercial lighting	\$4.39	\$4.39	\$4.39	\$4.39	\$4.39	\$4.39

Notes: This table lists the estimated levelized cost of energy for each of the four technologies presented in this paper, in dollars per megawatt-hour. Residential and lighting estimates are derived from a national analysis, do not vary by region and reflect the cost to use technology that is incrementally better than code. See appendix for a description of the levelized cost of energy approach.

Solar LCOE estimates are constructed using data summarized by Barbose et al. (2014). We use the 2013 installed cost for >5MW utility scale systems (\$2.97 per watt). These data are reported prior to receipt of any direct financial incentives or tax credits. If we assume the PV industry is competitive, these prices are representative of total social costs per MW. Then, following (Baker et al., 2013), we assume that (i) the inverter is replaced every 10 years at a cost of \$0.20/W but declining at 2% annually in real terms, (ii) a project life of 30 years, (iii) a panel degradation rate of 0.5% per year, and (iv) a real discount rate of 3%. We computed LCOE for each site in our analysis; the resulting LCOEs are in Table 1.

Lighting costs are taken from the US Department of Energy Appliance and Equipment Standard Programs 2011 General Service Fluorescent Lamps rulemaking technical support document. For each appliance efficiency rulemaking under consideration, the DOE releases a technical support document including either a Life Cycle Cost Assessment or a National Impacts Analysis which provide estimates of the energy savings and costs associated with different efficiency levels (EL) under consideration. For both residential and commercial categories, we focused on general service fluorescent lamps (GSFL). DOE estimates that there are more than 2 billion of these lamps in service in the US residential and commercial sectors (Navigant Consulting, 2009). Lighting technologies and associated cost estimates are discussed in detail in the appendix.

Capacity value: We measure capacity value in units of \$/MW as $CAP_{rj} = CC \times P_c$ where CC is a "capacity credit," (in MW per MW) and P_c is a payment for capacity (\$/MW). The capacity credit measures the fraction of a resource's capacity that can be relied on for delivery in high demand conditions. Following Milligan and Parsons (1999), we computed capacity credit by averaging the hourly capacity factor for each resource in the top 30 percent of demand hours for each region.[25] We obtained region-specific capacity prices from a variety of sources (described in the Data Appendix). To convert capacity values to units of \$/MWh, we divided the annual \$/MW numbers by the number of hours in 2010-2012 times the capacity factor of the resource in question. For residential and lighting efficiency, we then multiplied the capacity value by 1.06 to account for the disparity between MWh reduced at the point of use and MWh reduced at the point of generation, due to transmission losses.

4 Marginal operating emissions rates

An important first step in the analysis involves estimating the effect of incremental changes in RE production or EE savings on system-wide CO_2 emissions. We do not observe RE generation or EE savings directly. Instead, we note that incremental investments in RE or EE reduce the quantity of electricity that must be generated by incumbent units on the system to meet demand for energy end uses. To implement equation 1 empirically, we use observable variation in production at grid-connected power plants to proxy for the effects of adding a new grid-connected renewable energy resource or efficiency improvements.

The key challenge is to isolate the variation that most closely mimics the variation induced by incremental increases in EE or RE capacity. If we compare system-wide emissions across days with different load profiles, we capture not only the effects of relatively small differences in net load (such as those associated with incremental EE and RE investments), but also the effects of large inter-day differences in how the system is dispatched to meet different load profiles. To isolate the variation that is most relevant to this analysis, we cluster days within a region and season that share similar generation profiles.

We use variation across days with similar load profiles to estimate the ϕ_{rt} parameters introduced in Section 2.1.[26] More precisely, we use a k-means clustering algorithm to cluster daily observations (within a region and season) over the period 2010-2012 into groups of days with very similar load profiles and peak loads. This algorithm, which is explained in more detail in Appendix A.2, gives rise to clusters of days within each season and region denoted by k.

[25]Because hourly demand in CAISO is easy to obtain, we used this in place of hourly load for all of California.

[26]This marginal analysis ignores the intermittency effects of wind on unit commitment. These effects have been demonstrated for large, non-incremental increases in wind penetration. (Dorsey-Palmateer, 2014)

We estimate the following equation:

$$E_{rkt} = \alpha_{rkhs} + \phi_{rkhs} G_{rkt} + e_{rkt}, \tag{8}$$

where E_{rkt} and G_{rkt} measure emissions and electricity production, respectively, at dispatchable fossil-fueled sources in region r and hour t within cluster k.

The α parameter captures the average emissions level observed in region r, season s, hour h, and load profile type k. Differencing out these average values helps to control for the effect of systematic differences in system operating conditions across regions, hours, or seasons that would likely persist with or without an incremental increase in RE or EE investment.

We are primarily interested in the ϕ coefficients which are estimated separately by region and by hour of day to capture systematic variation in marginal operating conditions. To capture seasonal variation in MOERs, these region-hour-specific coefficients are estimated separately for summer and winter seasons (denoted s).[27] The ϕ coefficient values are also allowed to vary across the k clusters to reflect differences in underlying operating conditions that would prevail with or without RE and EE capacity changes.[28]

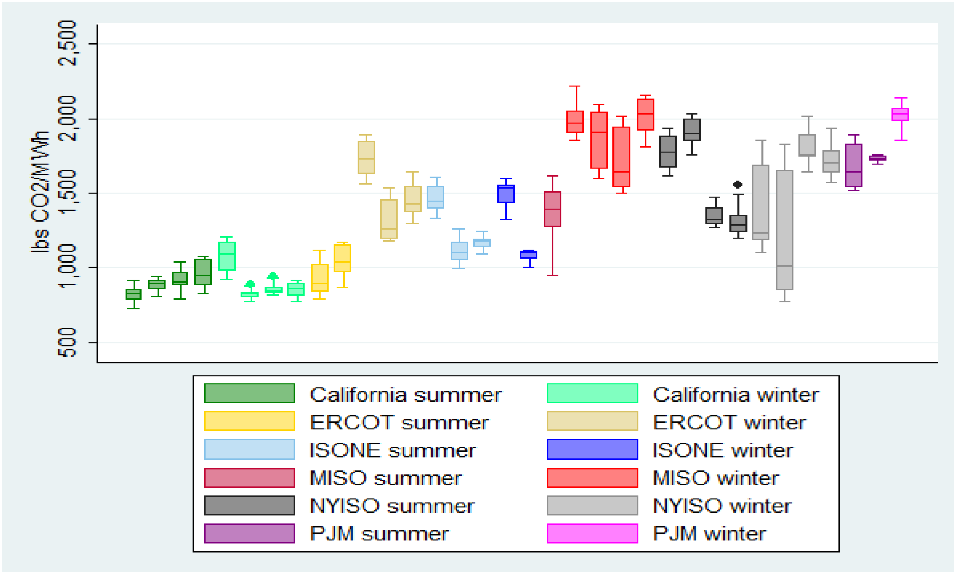
One potential concern with the region-hour-cluster-season fixed effects is that they absorb too much of the variation in net generation, meaning that our estimates capture the emissions implications of only very small changes. To investigate this concern, we examine how much variation in net generation remains once we difference out these region-by-hour-by-cluster-by-season averages. The standard deviation of the residual variation in hourly net generation that is not absorbed by these fixed effects ranges from 1500 MW (New York) to over 9000 MW (ERCOT). To put these numbers into perspective, hourly utility-scale solar and wind generation averaged 348 MW (New York) and 3,732 MW (ERCOT) in 2012. In other words, the variation in generation that we use to identify the ϕ coefficients is the same order of magnitude (and generally greater than) the RE generation we are interested in evaluating.

Throughout the analysis, inferential statistics (such as confidence intervals) are estimated using a block bootstrap. For each each region and season, we select (with replacement) a set of 1000 days which preserves the observed composition of week days and week-end

[27] We define our seasons to match the seasonal NOx emissions regulations which switch on in May and switch off in October and which affect the marginal operating costs of fossil-fueled generating units.

[28] The variation we use to estimate the ϕ coefficients captures both variation in real-time market responses and variation in day-ahead dispatch decisions across days with similar load profiles. It is beyond the scope of our analysis to separate the effects of variation in forecast demand and variation in departures from forecast on system-wide emissions. An incremental increase in RE or EE would presumably affect emissions through both channels.

Figure 3: Seasonal marginal operating emissions rates



Notes: This figure illustrates the range of hour-specific estimates of the marginal operating emissions rate by season and cluster. The top and bottom of each box represent the upper and lower quartile values, respectively. Whiskers denote 1.5 times the interquartile range beyond the 25th and 75th percentile values. Resource profiles for lighting efficiency improvements capture generic seasonal and hourly variation in energy savings. Solar and wind profiles vary within and across days according to simulated meteorological conditions and are site specific. Subsets of sites from each region are used to estimate regional MOERs.

days within that region-season over the study period (2010-2012). We keep 24 hour blocks within each day together because electricity grid operations are optimized day-ahead for the following day.

4.1 Estimation results

With six regions, twenty-four hours, two seasons, and an average of three clusters per region and season, the empirical strategy summarized above yields more than 800 MOER point estimates for each bootstrap repetition. The full set of estimates are reported in the appendix along with bootstrapped confidence intervals.

Figure 3 summarizes the range of variation in these MOER point estimates by region, season, and cluster. Within a region and season, clusters are displayed in increasing order of electricity generation. The patterns of variation, both across and within regions, are intuitive when one considers the generation mix in each. California's electricity sector is dominated by natural gas. Variation in emissions rates is therefore driven primarily by variation in heat rates, with more fuel efficient plants preceding less efficient plants in the merit order. Consequently, we see MOER estimates increasing with generation levels in both the summer and winter. In contrast, MOER estimates are decreasing with generation levels in regions where coal units typically precede cleaner gas units in the merit order. In the case of NYISO, we see a very large range of MOERs in winter, reflecting the diurnal variability in our early example from Fig. 1.

Column (1) in Table 2 summarizes the MOERs by region, averaged across hours in our study period (2010-2012). The numbers in parentheses summarize the variation in our estimates (i.e. 95 percent confidence intervals) of these regional average values. California's average MOER is lowest, near that of a combined cycle gas plant. MISO has the highest average MOER, just below that of an average coal plant (see footnote 10). All other regions lie between the emissions rate for combined cycle gas and coal, suggesting that coal, simple cycle gas and combined cycle gas are marginal in different conditions in these regions.

Table 2: Weighted average MOERs and emissions intensities for each region.

Region	MOER, weighted average (lb/MWh) (1)	Emissions intensity (lb/MWh) (2)
California	896 (870 - 922)	592
ERCOT	1378 (1305 - 1452)	980
ISONE	1262 (1179 - 1346)	605
MISO	1870 (1798 - 1942)	1669
NYISO	1312 (1230 - 1397)	476
PJM	1776 (1706 - 1849)	1077

Notes: Regional MOER values are weighted averages of cluster-specific MOERs, where the weighting is by the number of days in each cluster. MOER values in parenthesis represent the 95 percent confidence interval from the bootstrap results. Emissions intensity is regional CO_2 emissions divided by total regional generation; see Appendix for explanation of data sources.

As a point of comparison, the second column of Table 2 reports the average overall emissions intensity (i.e. the regional sum of CO_2 emissions across 2010-2012, divided by *total* generation within each region over 2010-2012). In all cases the emissions intensities lie below the MOERs, indicating that non-marginal generation is on average cleaner than marginal. In California, ISONE and NYSIO the intensities lie below natural gas, suggesting that hydro power, nuclear and existing renewables play an important part of the fuel mix. In the remaining regions intensities are at or above combined cycle gas.

5 Average Emissions Displacement Rates

In this section, we estimate the region and technology specific emissions displacement rates (δ_{rj}) defined in Equation (4). We estimate these values empirically as:

$$\delta_{rj} = \frac{\sum_{t=1}^{T}\left(\hat{\phi}_{rkhs} \cdot q_{rjt}\right)}{\sum_{t=1}^{T} q_{rjt}}. \tag{9}$$

For each hour in our three year study period (indexed by t), we multiply the quantity of simulated renewable energy production (or energy demand reductions in the case of efficiency) q_{rjt} with the corresponding regional MOER estimate. The numerator in Equation 9 is thus the estimate of the avoided CO_2 over the study period. Dividing by the sum of energy produced (or saved) yields an estimate of the average quantity of emissions avoided per MWh. [29] For each region-technology pairing, confidence intervals are estimated using the block bootstrap described above.

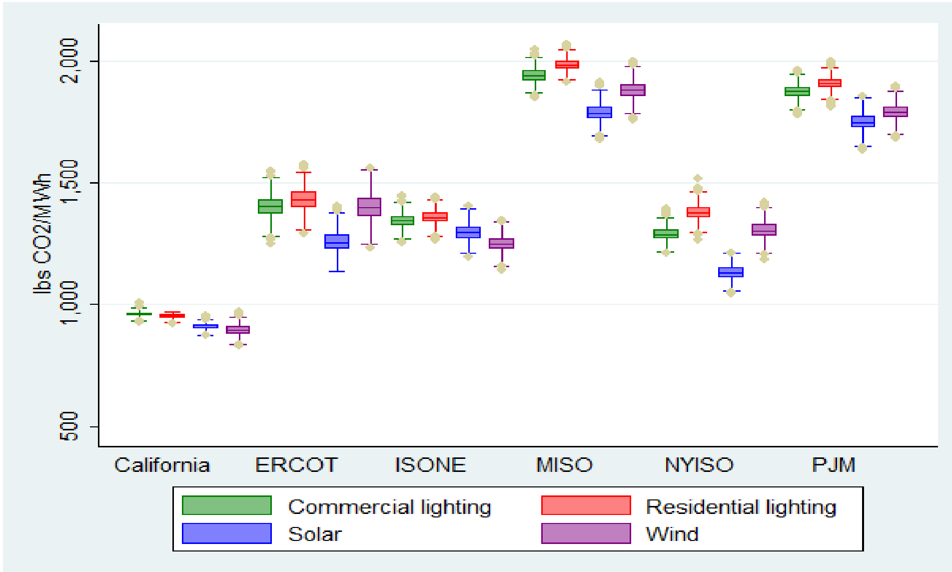
5.1 Estimation results

Figure 4 summarizes the total variation in MEDRs that arises from variation in regional average MOERs (captured by $\overline{\phi_r}$ in Eq. (4)) and correlation between MOER profiles and resource profiles (captured by $T \cdot cov(\phi_r, \omega_{rj})$ in Eq (4)).[30] Consistent with results presented

[29]During the time period of our study, a subset of states participated in the Regional Greenhouse Gas Initiative (RGGI) which imposes a cap on greenhouse gas emissions in the electricity sector. At the end of the first phase, which ran 2009-2012, emissions were well below the cap and many permits went unused. For most of the period we study, the permit price was very close (or at) the reserve price. We take this as evidence that the cap was not binding. Thus, any RE or EE investments in these regions during our study period would displace (versus reallocate) emissions.

[30]Because bootstrapping the full suite of results is a computationally intensive process, we only present results for a representative set of sites. In the case of wind, Figure 4 summarizes the results of 20,000 bootstrap repetitions (20 sites × 1,000 repetitions each) in each region. We use only one time series for all

Figure 4: Marginal emissions displacement rates



Notes: This figure illustrates the range of resource-specific marginal emissions displacement rates estimated by region. The top and bottom of each box represent the upper and lower quartile values, respectively. Whiskers denote 1.5 times the interquartile range beyond the 25th and 75th percentile values. Resource profiles for lighting efficiency improvements capture generic seasonal and hourly variation in energy savings. Solar and wind profiles vary within and across days according to simulated meteorological conditions and are site-specific. Subsets of sites from each region are used to estimate regional MEDRs.

in the previous section, the Figure reveals substantial variation – nearly a factor of two – in MEDRs across regions. Within some regions, we find very limited variation in MEDRs across technology variation (suggesting a small $cov(\phi_r, \omega_{rj})$ from Eq. (4)). In other regions, we find more significant variation across technologies (implying larger $cov(\phi_r, \omega_{rj})$).

Figure 4 is generated using simulated data from *representative* sites in each region. Whereas we observe limited intra-regional variation in solar PV generation or efficiency savings, spatial variation in elevation, topography, and vegetation can generate significant variation in wind patterns across relatively short distances. To assess the importance of intra-regional variation in emissions displacement across wind sites, we generate MEDR point estimates for all wind sites in the data. Results, summarized in Appendix A.4.1, indicate that within-region and within-technology variation in MEDRs is small (bootstrapped differences in MEDRs across extreme sites is 1 to 4 percent). For this reason, we focus on

other technologies. We discuss within region, within technology variation in more detail below.

variation across regions and technologies, but not within regions for a given technology.

5.2 Analysis of variance in emissions displacement rates

In principle, a policy designed to support socially efficient levels of investment in RE and EE should provide incentives that accurately reflect the variation in external emissions benefits summarized by Figure 4 . Absent other market failures or distortions, a carbon tax or emissions trading program that establishes an emissions price equal to the marginal damage caused could achieve this objective. In practice, production-based policy incentives (such as those conferred via renewable portfolio standards, efficiency portfolio standards, and production tax credits) have been far more commonplace. This raises the question: how should production-based incentives be differentiated to reflect differences in emissions-related benefits?

We investigate the extent to which production-based incentives that are regionally differentiated could capture variation in emissions displacement benefits. Let $\overline{\phi}_{ryb}$ denote the average MOER for region r in year y and bootstrap repetition b. We find that 97 percent of the variation in the simulated annual emissions displacement rates, δ_{rjyb}, can be explained by variation in the corresponding average $\overline{\phi}_{ryb}$.[31] In other words, regional average MOERs serve as a reasonably good proxy for the average quantity of emissions displaced per MWh generated or saved.

Recall from Equation (4) that the quantity of emissions displaced per MWh by an RE or EE resource can depart systematically from the regional average MOER if the electricity generation or savings profile is positively or negatively correlated with the MOER profile. To investigate these systematic deviations empirically, we estimate the following:

$$\delta_{rjyb} = \overline{\phi}_{ryb} + \sum_{rj} \Delta_{rjb} d_{rj} + e_{rjyb}. \tag{10}$$

where d_{rj} is a dummy variable for region r and technology j and ϕ_{ryb} is the year- and region-specific weighted average MOER for each bootstrap repetition (taken directly from data,

[31] We computed R-squared for each bootstrap repetition as $R_b^2 = \frac{cov(\delta_b, s_b)^2}{var(\delta_b)var(s_b)}$, where δ_b is a vector of MEDRs, and s_b is a vector of proxy regional emissions measures, each vector containing values for all years, technologies and regions within a bootstrap repetition ($N =$ (number of regions) $\times$ (number of years) $\times$ (number of technologies) $= 6 \times 3 \times 4 = 72$). When a similar calculation is done replacing the average MOER with the the average emissions from all generators in the region, this R-squared drops to 0.83. This suggests that the regional average MOERs serve as a good proxy for emissions displacement rates. It also underscores the importance of using a measure of marginal - versus average- emissions intensity to measure emissions displacement benefits.

not estimated in the regression). The Δ_{rjb} capture the extent to which the regional average MOER measures over or under-estimate actual emissions benefits associated with technology j in region r on average. The results of this regression, reported in Table 3, are consistent with the variation across technologies in Fig. 4.

Deviations from the regional average are relatively small on average in regions like California and MISO where MOER profiles are quite flat. In other regions where MOER profiles are more variable, this regional proxy departs from our estimate of average emissions displacement benefits by a significant margin. The most significant example is NYISO, where the average MOER overestimates emissions displaced by solar PV by roughly 190 lbs/MWh (a 14 percent increase) and underestimates emissions displaced by residential lighting by approximately 38 lbs/MWh (a 3 percent decrease).

Table 3: Estimated differences between MOER and technology-specific MEDR (lb/MWh).

Technology	California	ERCOT	ISONE	MISO	NYISO	PJM
ComLight	14.0	-30.2	14.2	-19.2	-90.8	-10.3
	(7.8)	(12.2)	(11.4)	(16.2)	(13.4)	(16.2)
PV	39.9	-86.6	42.4	-24.4	-190.2	-33.0
	(9.2)	(15.1)	(15.8)	(23.9)	(23.4)	(21.8)
ResLight	2.2	-22.9	15.3	-16.7	37.7	0.5
	(3.3)	(5.9)	(5.8)	(6.4)	(12.3)	(5.8)
Wind	3.3	11.2	-3.5	-13.0	0.3	4.5
	(20.2)	(27.6)	(21.2)	(31.4)	(22.4)	(28.4)

Notes: The table reports results from regressing bootstrapped marginal emissions displacement on regional average marginal operating emissions rates and technology-region fixed effects. The MEDR for residential and lighting efficiency does not include an adjustment for line losses. Positive values indicate the MOER underestimates the MEDR. Bootstrapped standard errors in parentheses.

In summary, we find that the regional average MOER serves as a reasonable proxy for the average quantity of CO_2 emissions displaced by RE and EE resources in most regions over the time period we study. In some regions, such as New York, the MOER and technology production profiles exhibit enough correlation that the regional MOER deviates more noticeably from emissions displacement.

6 Marginal Economic Value

We have documented statistically significant regional variation in marginal emissions displacement rates among both RE and EE technologies. In this section, we begin to explore the economic implications of this variation. More specifically, we assess how differences in emissions displacement drive differences in a more comprehensive measure of marginal value.

We use a monetary measure of marginal economic benefits, summarized by Equation (6), that includes both the value of avoided emissions (external to market transactions), operating costs (e.g. fuel costs) associated with generation displaced marginal units, and capacity value. We construct this measure as follows:

$$\mathrm{MB}_{rj} = \tau \cdot \delta_{rj} + \frac{\sum_{t=1}^{T} (\lambda_{rjt} \cdot q_{rjt})}{\sum_{t=1}^{T} (q_{rjt})} + CAP_{rj}. \tag{11}$$

The first term on the right hand side multiplies our estimate of emissions displaced per MWh by the social cost of carbon denoted τ. We assume a value of \$38 per ton CO_2 (in 2011 dollars).[32] As noted above, the emissions cap imposed by RGGI during our study period was not binding, and permits cannot be banked for use in subsequent phases. For this reason, we assume that emissions displaced by RE or EE during this period were in fact avoided.[33]

To estimate the second term on the right hand side of Equation 11, we need regional and hourly measures of the variable operating costs at marginal dispatchable generating units (λ_{rjt}). We use real-time locational marginal prices (LMPs) as a proxy. These prices reflect the marginal cost of supplying (at least cost) the next increment of electricity to a particular location given the supply and demand bids submitted by market participants and the physical constraints on the system.[34] Capacity values are estimated separately for each region and technology.

[32] This is approximately equal to the value associated with a 3 percent discount rate in: U.S. Interagency Working Group on Social Cost of Carbon. 2013. Technical Support Document: Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis under Executive Order 12866. `http://www.whitehouse.gov/sites/default/files/omb/inforeg/social_cost_of_carbon_for_ria_2013_update.pdf`, last accessed December 20, 2014.

[33] California's cap and trade program expanded to the electric power sector in 2013, the year after our data end.

[34] In all regions but ISONE we use the unweighted spatial average of each region's hourly LMPs; in ISONE we use the Internal Hub real-time LMP.

6.1 Avoided operating costs

Our approach to estimating the value of avoided operating costs parallels our approach to estimating avoided emissions. In each hour we multiply the megawatt-hours of simulated renewable energy production (or energy demand reductions from efficiency improvements) with the corresponding regional LMP value. Aggregating these avoided costs across all hours and dividing by the sum of energy produced (or saved) yields a region and technology-specific estimate of the average marginal value per MWh. For each region-technology pair, we estimate confidence intervals using the block bootstrap described above.

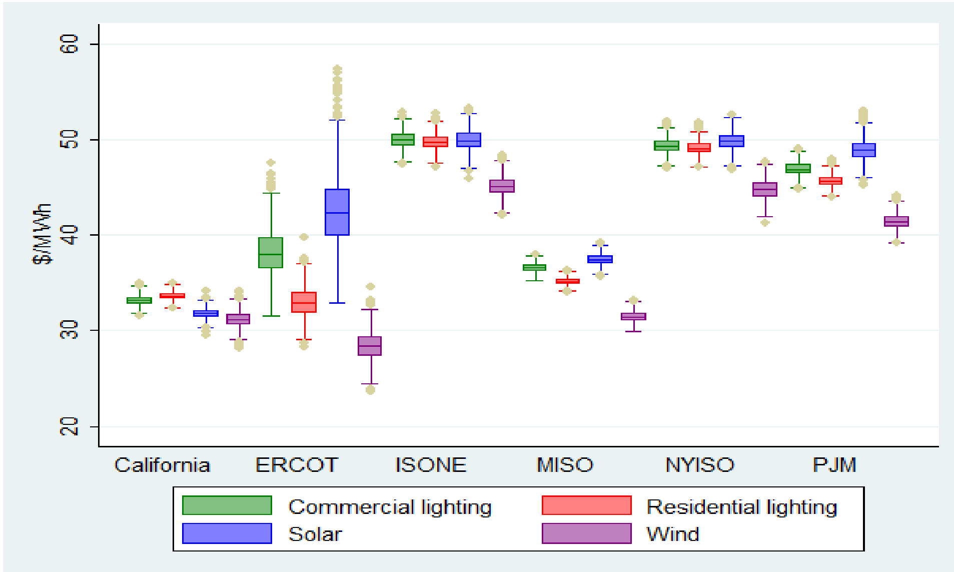
Figure 5 summarizes region and technology-specific estimates of avoided operating costs per MWh. Variation within a region and across technologies is driven by differences in the temporal correlation between resource profiles and marginal operating costs. For example, solar PV, which tends to be correlated with peak demand (and by extension higher LMPs), produces the highest operating cost savings. In contrast wind production, which is slightly negatively correlated with demand, generally has the lowest savings.

Cross-region comparisons of these λ_{rjt} should be made carefully. Differences in marginal prices across regions can reflect, among other factors, differences in market structure and associated incentives that govern the bidding behavior of the market. In our context, there are two institutional considerations that warrant particular consideration.

The first pertains to regional differences in resource adequacy and procurement. Figure 5 shows that estimates of avoided operating costs are relatively more volatile in ERCOT. In contrast to other regions, ERCOT did not have a direct mechanism to procure generation capacity; all generator revenue comes from transactions for energy. In other words, ERCOT prices capture the cost to build new generation capacity in addition to fuel costs. As a consequence, energy prices in ERCOT are allowed to rise to very high levels to reflect scarcity of generation and incentivize construction of new capacity. In the other regions, load serving entities are required to contract with generators solely on the basis of their existing capacity before any energy is transacted. These transactions are intended to ensure that sufficient generation capacity is built (or kept operating) to maintain system reliability. The resulting payments to owners of generation form part of their total revenue, meaning they only need to capture a portion of their revenue in energy markets to be profitable. MEV comparisons between ERCOT and other ISOs should made in this context.

A second consideration pertains to regional differences in emissions regulations. New York, New England, and some states in the PJM participate in the Regional Greenhouse Gas Initiative (RGGI). During our study period, electricity producers under RGGI had to

Figure 5: Avoided operating costs per MWh by technology type and region.



Notes: This figure illustrates the range of cost-related benefits (i.e. operating costs avoided per MWh generated or saved) across regions and technologies. The top and bottom of each box represent the upper and lower quartile values, respectively. Whiskers denote 1.5 times the interquartile range beyond the 25th and 75th percentile values. Resource profiles for lighting efficiency improvements capture generic seasonal and hourly variation in energy savings. Solar and wind profiles vary within and across days according to simulated meteorological conditions and are site specific.

offset emissions with permits. In states subject to RGGI, marginal operating costs - and wholesale electricity prices- reflect the cost of complying with the program. This compliance cost includes both the marginal cost of any abatement activities (a true cost) and the cost of purchasing permits to offset emissions (a transfer). Because the permit price was so low during our study period, the extent to which we over-estimate avoided costs by including the transfer of permit value will be minimal.

6.2 Capacity value

We compute region and technology-specific capacity credits by averaging the hourly capacity factor for each resource in the top 30 percent of demand hours for each region.[35] Table 4 reports these capacity credits as well as capacity factors.

[35]Because hourly demand in CAISO is easy to obtain, we used this in place of hourly load for all of California.

Table 4: Capacity credits and capacity factors by technology and region.

	Wind		Solar		ResLight		CommLight	
	cap. credit	cap. factor	cap. credit	cap. factor	cap. credit	cap. factor	cap. credit	cap. factor
California	0.225	0.217	0.269	0.207	0.114	0.090	0.445	0.392
ERCOT	0.261	0.347	0.260	0.205	0.099	0.090	0.406	0.392
ISONE	0.394	0.385	0.206	0.142	0.108	0.090	0.462	0.392
MISO	0.289	0.327	0.238	0.176	0.105	0.090	0.439	0.392
NYISO	0.350	0.361	0.207	0.140	0.106	0.090	0.453	0.392
PJM	0.361	0.362	0.192	0.135	0.108	0.090	0.447	0.392

Notes: This table lists estimated capacity credits and capacity factors by region.

Table 5: Capacity prices ($/MW-year) for each region.

California	ERCOT	ISONE	MISO	NYISO	PJM
$26,400	$-	$48,600	$39,015	$12,617	$36,591

Notes: This table lists estimated capacity prices in by region in dollars per megawatt.

We obtained capacity prices from a variety of sources (See Appendix). These data are summarized in Table 5. To convert the capacity values to units of $/MWh, we divided the annual $/MW numbers by the number of hours in 2010-2012 times the capacity factor of the resource in question.

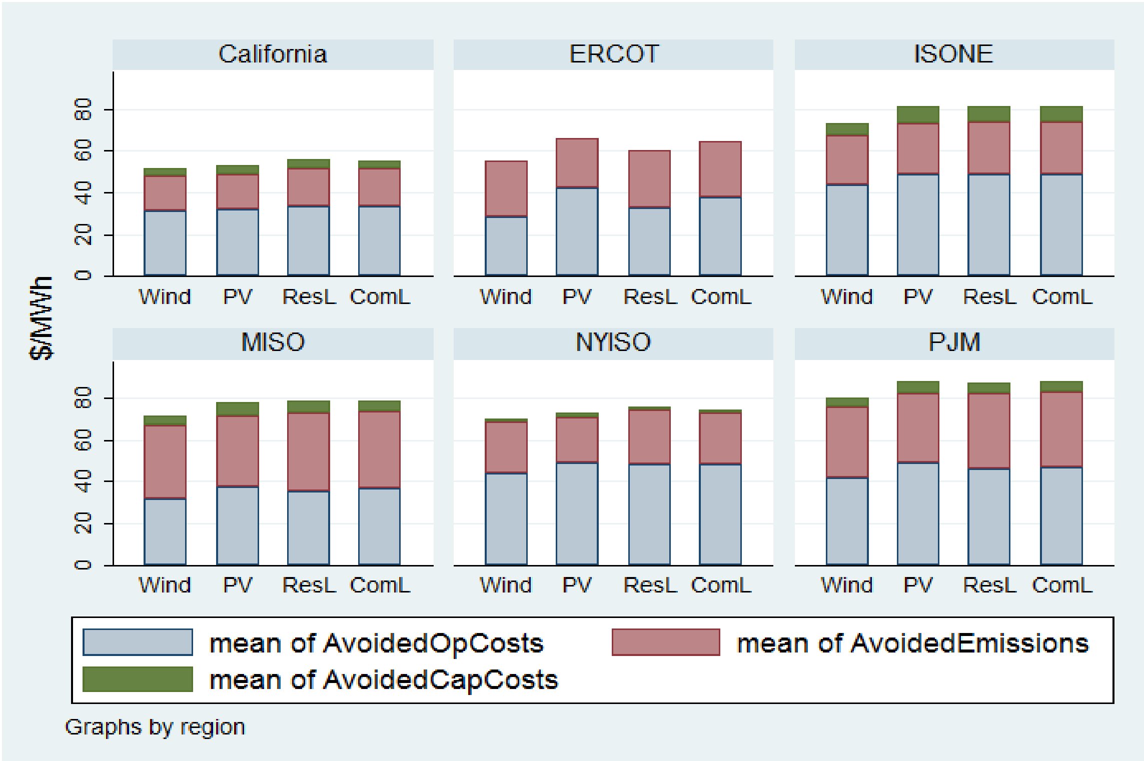
6.3 The marginal value of RE and EE resources

Figure 6 summarizes the point estimates of marginal economic value in terms of emissions displacement benefits (red), the value of avoided operating cost components (blue), and the capacity value (green) by region and technology. Numerical point estimates are reported in Table 11 of the Appendix.

An overarching implication of Figure 6 is that external emissions displacement value comprise an economically significant component of marginal social value. In California, the region with the lowest marginal emissions because natural gas is typically on the margin there, emissions displacement benefits nevertheless comprise approximately a third of marginal social value. In MISO, point estimates of the emissions displacement value exceeds the estimated value of avoided variable operating costs for all technologies except solar PV.

Overall, external benefits associated with avoided emissions are somewhat negatively

Figure 6: Marginal social value by technology type and region.



Notes: This figure summarizes point estimates of operating costs (in blue), emissions (in red; measured in monetary terms), and capacity value (in green) displaced per MWh of renewable energy generated or demand-side electricity saved.

correlated with privately captured benefits. Looking across regions, this is because regions with more coal on the margin are generally associated with lower marginal operating costs, but higher marginal emissions intensities. For example, private returns per MWh are highest in ISONE and lower in ERCOT and MISO (see Figure 6). Once avoided emissions are accounted for, estimates of marginal value in MISO are comparable to those in ISONE.[36]

7 Marginal abatement cost

The analysis thus far has focused exclusively on the benefits generated by RE and EE resources. In this section, we incorporate the cost side of the equation. We compute region-

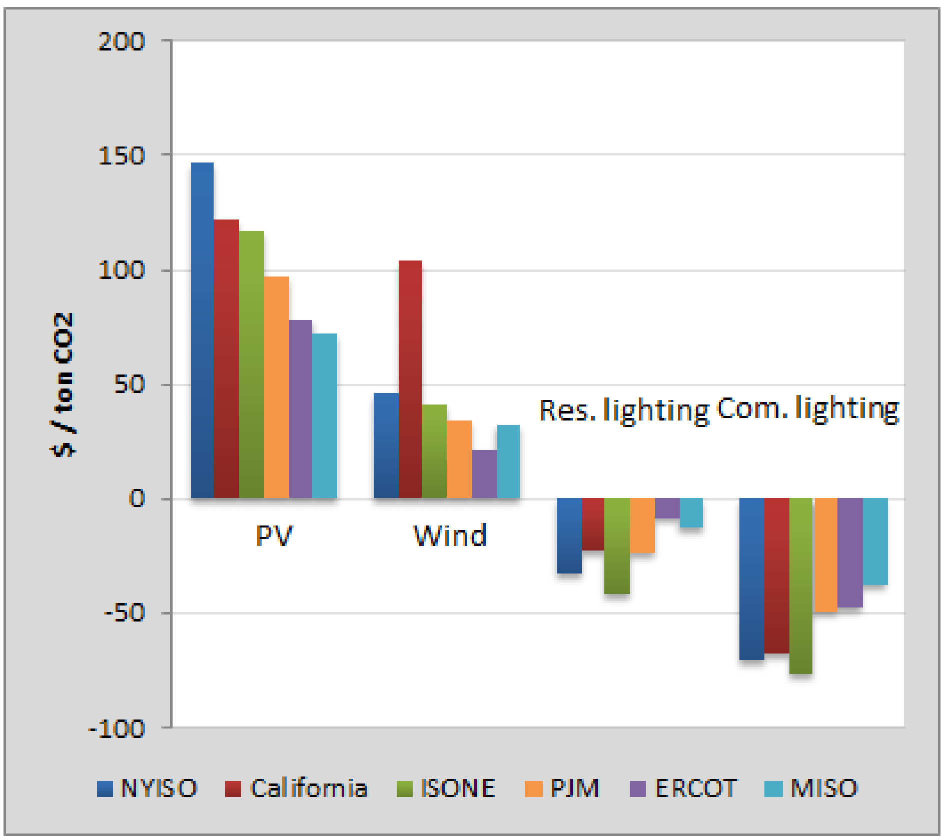
[36]These values are also negatively correlated across time. For example, whereas solar PV ranks last with respect to emissions displacement value in MISO, ERCOT, and PJM, it ranks first in terms of total social value per MWh due to the operating costs displaced during peak hours.

and technology-specific measures of the net cost per ton of CO_2 displaced:

$$\text{MAC}_{rj} = \frac{\text{LCOE}_{rj} - \sum_{t=1}^{T}(\lambda_{rt}\omega_{rjt}) - CAP_{rj}}{\delta_{rj}} \tag{12}$$

The LCOE_{rj} refers to the levelized cost of energy introduced in Section 3. As described in Appendix A.1, wind LCOEs are built from records of region-specific power purchase agreements and solar LCOEs are built from historical installed costs ($/watt) combined with region-specific solar resource potential. Lighting efficiency costs are based on DOE's engineering-economic forecasts of the retail price of and costs to install new technologies, projected power consumption, and projected utilization rates (hours of operation per year).

Figure 7: Marginal abatement costs across technologies and regions



Notes: This figure plots the total marginal abatement cost, in dollars per ton of carbon dioxide, from different region-technology combinations. Regions are ordered from highest to lowest marginal abatement cost for PV.

Figure 7 summarizes the estimated net cost per ton of CO_2 avoided.[37] The data and assumptions used to construct the LCOE estimates and the associated marginal abatement costs in Figure 7 are documented in an interactive spreadsheet.[38] Interested readers can used this tool to investigate how this table varies under alternative assumptions.

The figure shows striking variation in estimated abatement costs across technologies. Owing to its relatively high installed technology cost, solar PV is associated with the highest cost per ton of CO_2 across all regions.[39] Using the average PPA prices we observe, wind resources are not yet cost effective (on average) from a private perspective. Importantly, in several of the regions we consider, our point estimates of abatement costs are in the range of values typically used to approximate the social cost of carbon.

Turning to the investments in lighting efficiency, marginal abatement cost estimates are *negative*. One interpretation of negative MAC is that lighting efficiency standards should be more stringent in order to equate marginal costs with marginal social returns. However it is important to note that these estimates are predicated upon engineering estimates of energy savings – which are based on a specific utilization rate of the technology – and technology costs.[40] In Appendix A.6 we reproduce Fig. 7 cutting the assumed utilization rates in half. Using these more conservative assumptions, commercial lighting remains strongly cost effective (negative MAC). However residential lighting MAC values cease to be negative in regions other than ISONE, though they remain below the social cost of carbon.

Although technology rankings are consistent across regions, regional rankings vary within technologies. For solar PV, MAC estimates are higher in New York and New England where the solar resource is low relative to sunnier regions like ERCOT. Somewhat surprisingly, MISO has the lowest solar PV abatement costs; this is driven by both high MEDRs and an excellent solar resource on the western side of the ISO. Furthermore PV in California does not rank as well as NYISO; though its solar resource is excellent, the MEDRs we estimated

[37] Although our bootstrap approach captures the variability from marginal operating emissions rates and wind, solar and lighting profiles, we cannot fully characterize the remaining sources of uncertainty in the MAC calculations, especially with respect to the LCOE. The latter uncertainty may well dominate any uncertainty we are able to capture. Therefore we present our results as point estimates only, with strong caveats on interpreting small differences in MAC values.

[38] `http://nature.berkeley.edu/~fowlie/papers.html`

[39] It is worth noting that recent estimates of signed, but not completed, utility scale solar PPAs suggest that the cost of utility scale solar is falling, in some cases to that of wind or even lower Bolinger and Weaver (2014).

[40] We are using a 3% discount rate to calculate the LCOE, reflecting our focus on total social costs rather than private consumer costs. A higher discount rate would be more realistic for private decisions and would push residential lighting to have positive cost in some regions. For example, a 7 percent discount rate would raise the LCOE by roughly 20 percent.

there are low. The ranking of regions changes modestly for wind. In particular, due to historically high PPA prices there, California overtakes New York as the highest cost region.

Variation in negative cost estimates (i.e. lighting estimates) is driven predominantly by regional variation in the MEDR, with lower MEDR regions having more negative MAC values. This result is mathematically intuitive – smaller emissions reductions in the denominator results in a larger (in absolute value) fraction. In other words, relatively few tons of CO_2 are avoided for each unit of electricity saved.

8 Policy context

In theory, subsidies paid to RE and EE should reflect the value of external, uncompensated benefits generated over the life of the project. Our analysis does not attempt to capture all of the external benefits that renewable energy investments might generate. As noted above, advocates of existing RE and EE policies cite additional benefits that we do not attempt to quantify, such as economic development opportunities, health benefits unrelated to climate change, and learning by doing. There are also costs, such as the costs of dealing with increased ramping and cycling requirements, that we do not account for. These omitted factors notwithstanding, it is instructive to examine the extent to which the policy incentives that prevailed during our study period can be rationalized by the carbon emissions benefits we estimate.

8.1 Interpreting MEDRs in context of state- and federal subsidies

With respect to RE policy incentives, the states in our analysis fall into two categories. The first includes states that have renewable portfolio standards (RPS) with supporting markets for renewable energy certificates (RECs). In these states, we can compute the total subsidy to wind and solar producers as the combination of federal tax credits and renewable energy certificates [41] A second category includes states where compliance with an RPS is achieved via bilateral contracts between load serving entities and renewable generation. In these states, additional costs incurred to procure renewables are less transparent, and therefore we do not include them here.

Table 6 summarizes the production based subsidies that prevailed in 2010-2012 for states falling into the first category. Column (4) reports the total subsidy per MWh generated (i.e.

[41] see Appendix A.1 for a description of the sources of the REC data and a discussion of how the investment tax credit was converted to a \$/MWh metric.

REC price plus tax credit) for solar PV and wind technologies, respectively. Column (5) divides the region and technology specific production subsidy (measured in \$/MWh) by our estimate of the corresponding MEDR (i.e. the quantity of carbon emissions displaced per MWh). If we assume that RE generation receives these subsidy payments (in real terms) over the life of the project, and we ignore (for now) the costs and benefits that our analysis does not capture, we can interpret the values in Column (5) as the subsidy paid per ton of CO_2 abated. Because solar REC prices are significantly higher than wind REC prices, and because the ITC gives solar a larger levelized subsidy than the PTC does for wind, the implied carbon cost is much larger for solar than it is for wind.[42]

As noted earlier, our analysis captures only one dimension of the external benefits generated by these policies – emissions reductions. Other possible external benefits, such as uncompensated health co-benefits and learning, tend to be harder to quantify. The final column of the table provides a measure of how large these additional external benefits would have to be – after subtracting a \$38/ton social cost of carbon – to justify the federal- and state-level policy incentives we observe.[43] One can interpret this residual as the energy-levelized value of all external benefits that would need to accrue from the production of each kWh to rationalize the policy incentive.

The variation in these residual external benefit estimates is striking. For all solar locations, these values exceeds the current installed cost of utility-scale solar (roughly \$3,000/kW). [44] Wind's valuation is lower on account of lower installed cost and higher capacity factors. Indeed in some states we see *negative* non-carbon valuation, implying the estimated carbon benefits exceed the total subsidy amount. If we assume that any external costs we have neglected to account for are small, these results imply that wind resource development in these regions is a socially cost effective investment even absent emissions-unrelated external

[42]In the case of solar PV, our estimates of the implied cost of carbon in Table 6 significantly exceed our MAC estimates reported in Figure 7. There are a couple of potential explanations for this . First, under regulatory uncertainty, investors may demand higher payments per unit of generation to compensate for the risk that the RPS will be dismantled during the life of the project. Second, we use national estimates for the costs of utility scale solar in our analysis; these costs may be significantly higher in some regions of the country.

[43]We computed this measure as $(S - \mathrm{C}_{\mathrm{CO}_2} \times \mathrm{MEDR}) \times (\text{annual production}) \times (\text{annuity factor})$, where S is the total subsidy per MWh and $\mathrm{C}_{\mathrm{CO}_2}$ is the cost of carbon. We set $\mathrm{C}_{\mathrm{CO}_2}$ =\$38/ton. Annual production for solar is based on a 14.2 percent capacity factor in ISONE and 13.5 percent capacity factor in PJM (taken from the NREL data described in the Appendix). For simplicity we used a 40 percent wind capacity factor in all regions. This analysis assumes that

[44]Variation across states suggests a range of political support of renewable energy policy. There is one interesting case of variation *within* a state, in the case of solar in Ohio. Ohio's non-carbon valuation of solar capacity built within the state is nearly double that of solar built anywhere – this could be a result of the presence of a major solar manufacturer in state (FirstSolar, founded in Toledo).

benefits.

Table 6 shows that regional variation in subsidy levels is poorly – if not negatively – correlated with external benefits generated on a per MWh basis. This has implications for allocative efficiency if prevailing policy incentives are failing to direct RE investments to locations where external net benefits are largest.

8.2 Interpreting MEDRs in context of regional cap-and-trade programs

With respect to both EE and RE, overlapping policies are commonplace. Within a given state or region, there are typically multiple policies in place to offer concurrent support for RE and EE resources. The current practice of deploying regional emissions trading programs alongside renewable and/or efficiency portfolio standards is likely to continue under the Clean Power Plan as states look to leverage and augment their existing programs and policies for compliance purposes.

During the time period we study, ten Northeastern states imposed a non-binding cap on CO_2 emissions in the electricity sector. All ten states had also imposed an RPS. The marginal cost of complying with the emissions trading program was less than \$2 per ton of CO_2 over the time period we consider (2010-2012). In contrast, we estimate marginal abatement costs for solar that exceed \$110/ton CO_2 in the RGGI region. These costs are closer to \$40/ton CO_2 for wind. In other words, marginal abatement costs in the RGGI region were not set equal across RPS and cap-and-trade policies during the time period we study. External benefits unique to RE, and separate from avoided carbon emissions, would need to be substantive in order to rationalize the differences in marginal abatement costs across the emissions trading and RPS policies, respectively.

9 Conclusion

Increasing levels of investment in renewable energy and energy efficiency resources lie at the heart of most climate change mitigation strategies. Policy incentives have been – and will continue to be – a driving force behind this increased investment. In principle, these policy incentives should accurately reflect external, uncompensated costs and benefits in order to efficiently allocate investment across technologies and across regions.

This paper estimates the impacts of increased deployment of grid-connected renewable

Table 6: Comparison between emissions displacement and subsidy levels.

Location	Region	MEDR, (lbs/MWh)	REC price, ($/MWh)	PTC or ITC ($/MWh)	total subsidy ($/MWh)	subsidy paid per ton of CO_2, ($/ton)	susbsidy for non-carbon benefits ($/MWh)
		(1)	(2)	(3)	(4)	(5)	(6)
				Solar			
Massachusetts	ISONE	1295	$433	$37.70	$470	$726	$446
Delaware	PJM	1746	$154	$39.57	$194	$222	$160
Maryland	PJM	1746	$260	$39.57	$300	$344	$267
New Jersey	PJM	1746	$386	$39.57	$426	$488	$393
Ohio	PJM	1746	$157	$39.57	$196	$225	$163
Ohio (in state)	PJM	1746	$255	$39.57	$295	$338	$262
Pennsylvania	PJM	1746	$147	$39.57	$186	$213	$153
Wash., DC	PJM	1746	$218	$39.57	$257	$294	$224
				Wind			
Texas	ERCOT	1400	$1.58	$22	$23.58	$33.69	$(3.85)
Connecticut	ISONE	1248	$27.68	$22	$49.68	$79.62	$25.97
Maine	ISONE	1248	$21.60	$22	$43.60	$69.87	$19.88
Massachusetts	ISONE	1248	$32.32	$22	$54.32	$87.05	$30.61
New Hampsh.	ISONE	1248	$32.39	$22	$54.39	$87.16	$30.68
Rhode Island	ISONE	1248	$33.55	$22	$55.55	$89.02	$31.84
Illinois	MISO	1878	$2.07	$22	$24.07	$25.63	$(11.61)
Delaware	PJM	1788	$3.54	$22	$25.54	$28.57	$(8.43)
Maryland	PJM	1788	$1.69	$22	$23.69	$26.50	$(10.28)
New Jersey	PJM	1788	$1.84	$22	$23.84	$26.67	$(10.13)
Ohio	PJM	1788	$18.95	$22	$40.95	$45.81	$6.97
Pennsylvania	PJM	1788	$2.52	$22	$24.52	$27.43	$(9.45)
Wash., DC	PJM	1788	$2.54	$22	$24.54	$27.45	$(9.44)

Notes: This table lists inputs and results to different calculations of subsidies per megawatt-hour to technologies in given states. The total subsidy is the total dollar per megawatt-hour subsidy. The implied carbon valuation is the total subsidy divided by the marginal emissions displacement rate. The subsidy for non-carbon benefits is the positive externality per megawatt-hour of production from this technology which would rationalize this subsidy level. Each state is given along with its corresponding region. See Section 9 for a description of subsidy calculations.

energy capacity and energy efficiency on short-run outcomes. We are particularly interested in estimating impacts on CO_2 emissions across several regions in the United States. Within each region, we find limited variation in these emissions impacts across technologies over our study period (2010-2012). In contrast, we find statistically and economically significant variation in emissions-related benefits *across* regions. For example, on a per MWh basis, the quantity of emissions displaced by RE and EE resources in the Midwest is more than double that in California. We also find that emissions-related benefits generated by RE and EE resources can comprise a significant fraction of the short run marginal returns on RE and EE investment. In regions where power sector emissions are not capped, emissions displacement value can equal or exceed the value of avoided operating costs.

Although our analysis focuses on a key source of external benefits, it is not exhaustive. External benefits of RE and EE investments can extend beyond short-run emissions reductions. On the benefits side, support for RE policy is often rooted in the potential for learning-by-doing and network effects. On the cost side, we do not attempt to estimate potential integration costs imposed by increased RE or EE investment. Subtracting our estimates of CO_2 emissions benefits (valued at the social cost of carbon) from the corresponding, production-based RE incentives provides a sense of how large these omitted external benefits (net of any omitted external costs) would need to be to rationalize the policy incentives we observe. These 'residual benefits' estimates are as high as \$450/MWh (in the case of solar PV) and vary significantly across regions and technologies.

These results should be interpreted with some caveats. First, this is a short-run analysis that conditions on the power system structure, energy prices, the policy environment, and the technology characteristics that prevailed during our study period. As fuel prices change, new resources get added to the system, and the policy environment changes, our estimates will no longer apply, although our methodological approach can be readily re-applied using more current data. Our approach is not well suited to evaluating long run impacts, nor should our estimates be used to value returns on very large, non-incremental increases in RE and EE capacity.

These caveats notwithstanding, our findings have implications for policy implementation. Production-based incentives will continue play an important role in accelerating and supporting new RE and EE investments. Given the extent of regional differences in existing generation portfolios, regional variation in marginal emissions rate profiles will persist for some time. Designing policy incentives that reflect the value of – and the variation in – emissions-related benefits will help to steer future investments towards regions and technologies that can provide the greatest social returns.

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A Appendix

A.1 Data

Hourly electricity production and emissions

Almost all combustion-based electricity generating units in 22 states in the Eastern United States are required to participate in a regional Nitrogen Oxide emissions trading program. During "ozone season" (May-September), these units must continuously monitor and report hourly CO_2 mass emissions, heat inputs, and steam and electricity outputs to the U.S. Environmental Protection Agency.[45]

We sum boiler-level data within regional markets in each hour of the analysis period to estimate market-level production from thermal units and market-level CO_2 emissions. Not all generators in California, MISO, Texas, New York and New England are required to report emissions. Specifically, small capacity plants and plants that are not covered by the NOX or SO2 trading programs are exempt from reporting during this time period.

Marginal operating costs We collected real-time locational marginal prices for each region[46]. In ISONE, we set λ_r equal to the Internal Hub real-time LMP in ISONE. For all other regions, we set λ_r equal to the unweighted spatial average of each region's hourly LMPs. Note that ERCOT's nodal market began on December 1, 2010; we drop all preceding dates from our analysis of ERCOT.

Wind production data. We obtained simulated wind production data from the National Renewable Energy Laboratory's (NREL) Eastern Wind dataset[47] and Western Wind dataset[48]. These data span 3 years from 2004-2006. Data of this extent are not available in

[45] Under Part 75, Volume 40 of the Code of Federal Regulations.

[46] http://www.gdfsuezenergyresources.com/index.php?id=712 and http://oasis.caiso.com/, both last accessed December 28 2014.

[47] http://www.nrel.gov/electricity/transmission/eastern_wind_dataset.html, last accessed December 28, 2014.

[48] http://www.nrel.gov/electricity/transmission/western_wind.html, last accessed December 28, 2014.

the years that we collected combustion generator data (2010-2012). Though correlation between wind speed and electricity load is very weak, using wind data from different years than those used to construct MOERs could introduce small errors in our analysis. We used the latitude and longitude of each simulated wind site to locate the production within each ISO, and normalized these data to hourly energy production per megawatt of installed capacity for each site.

Solar production data are from NRELs PV WATTS simulation tool [49]. This software applies PV performance modeling to typical meteorological year (TMY3) weather data to estimate the hourly average production of a solar array installed at thousands of different sites. We replicate this typical year for each year in our analysis. We used the default assumptions: fixed open rack system facing south, tilt angle set equal to the sites latitude, total system losses of 14%, ground coverage ratio of 0.3. As with the wind data, we normalized the solar data to be energy production per megawatt of installed capacity. Because solar production is highly spatially correlated on hourly time scales, we restricted our analysis to only one location per ISO. We used NREL's Solar Prospector to chose the TMY3 site with the best solar resource within each region, as follows: China Lake, CA (California); Marfa, TX (ERCOT); Boston, MA (ISONE), Rapid City, SD (MISO); New York, NY (NYISO); Virginia Beach, VA (PJM).

Energy efficiency

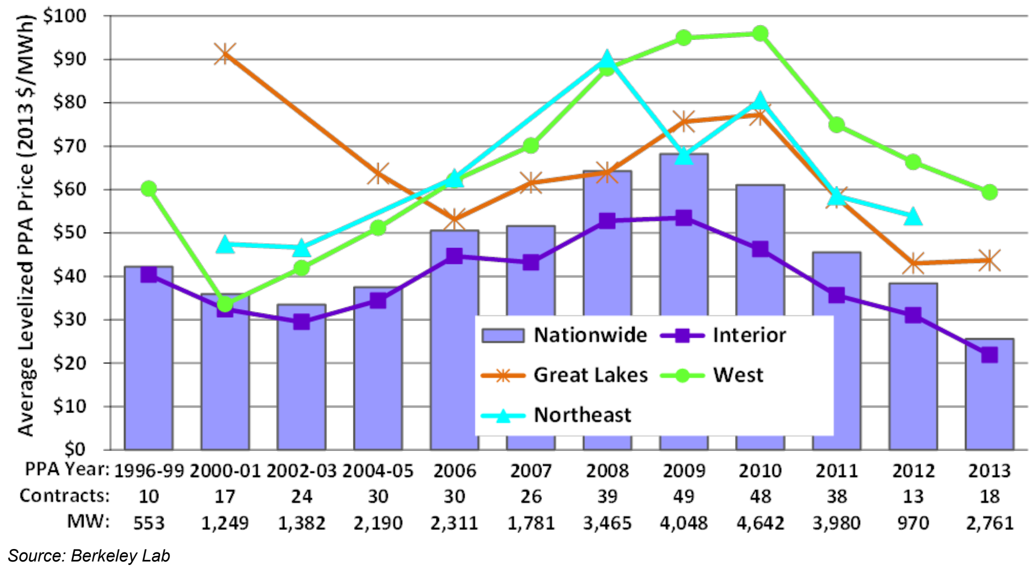
We obtained a year of simulated hourly consumption data for typical residential and commercial buildings in California (details on the data are can be found in (Wei et al., 2012)). We focus on lighting efficiency as opposed to other forms of energy efficiency such as heating and cooling loads in part because lighting is more consistent across different climate regions. These consumption profiles vary by hour of day, weekdays/weekends and season. Commercial lighting consumption is concentrated in business hours and residential lighting energy is concentrated in evening hours.

We used these data to obtain a temporal profile for energy savings from increased lighting efficiency. Specifically, we assumed that each MWh of energy saved from increased lighting efficiency would be distributed in proportion to these hourly consumption data, and treat those saved units of energy in a given hour as equivalent to energy produced from a wind or solar generator. We assumed the hourly consumption profiles, conditioned on season, and weekend / weekday, would be the same in each year of our analysis.

Levelized cost of wind energy (LCOE) are constructed from data provided by

[49] `http://pvwatts.nrel.gov`, last accessed December 28, 2014.

Figure 8: Wind Power Purchase Prices: 1996-2013



Lawrence Berkeley National Laboratory (LBNL) Wiser et al. (2014). This report analyzes power purchase agreements (PPAs) from a large sample of wind installations to produce annual average levelized prices per megawatt-hour of wind. We used the latest data for each of four regions: 2013 for Great Lakes, Interior, and West, and 2012 for the Northeast. Prices and ISOs that we assigned to each region are in the Appendix.

In the 2013 Wind Technology Market Report, LBNL reports on a data set of 343 power purchase agreements (PPAs) totalling nearly 30 GW of installed wind capacity. LBNL collected these data from multiple sources, including FERCs Electronic Quarterly Reports, FERC Form 1, avoided-cost data filed by utilities, pre-offering research conducted by bond rating agencies, and a Berkeley Lab collection of PPAs. Figure 8 shows a summary of the full data set. There is a clear downward trend in wind prices following the 2009 peak. Though there are relatively few data in 2012-2013, their averages fall in line with the overall trends in the data set.

These PPAs bundle together the sale of electricity, capacity and renewable energy certificates and the receipt of federal incentives (e.g. the production tax credit, investment tax credit or treasury grant). ecause all projects should have received the federal production tax credit (PTC) we set the total LCOE equal to the sum of PPA prices and the 2012 PTC ($22/MWh). Neglecting the influence of policies at the state and local level as well as local market characteristics on PPAs, and assuming a competitive wind market, the PPA plus federal incentives will be representative of the levelized cost of wind power, and we treat them as such in this paper.

Solar LCOE data are constructed from data from LBNL Barbose et al. (2014). We used the 2013 installed cost for >5MW utility scale systems ($2.97 per watt).[50] The LBNL data are reported prior to receipt of any direct financial incentives or tax credits, therefore assuming the PV industry is competitive, these prices are representative of total social costs per MWh. We use the same cost model as in (Baker et al., 2013), namely: we assume that the inverter is replaced every 10 years at a cost of $0.20/W but declining at 2% annually in real terms; assume a project life of 30 years; assume a panel degradation rate of 0.5% per year; and assume a real discount rate of 3%. We computed LCOE for each of the two sites per region and averaged the result within each region; the resulting LCOE are in Table 1.

Energy efficiency LCOE data are from the US Department of Energy Appliance and Equipment Standard Programs 2011 General Service Fluorescent Lamps rulemaking. For each appliance efficiency rulemaking under consideration, the DOE releases a technical support document including either a Life Cycle Cost Assessment or a National Impacts Analysis which provide estimates of the energy savings and costs associated with different efficiency levels (EL) under consideration. For both residential and commercial categories, we focused on general service fluorescent lamps (GSFL). DOE estimates that there are more than 2 billion of these lamps in service in the US residential and commercial sectors (DOE, 2009), with most (92%) in the commercial sector [51]. DOE documents GSFL lamp characteristics extensively for rulemaking purposes. The current DOE standard is 88 lumens per watt for the lamp-ballast system (DOE, 2009). For each sector, we chose the baseline as the technology with the lowest installed cost in that sector that also meets the standard. We defined the efficiency option as the technology with the second lowest installed cost that also meets the standard and is more efficient than the baseline. The resulting technology choices were different for the residential and commercial sectors. We calculated a levelized cost of energy saved by the efficiency option over a fifteen-year period (to reflect ballast lifetimes Navigant Consulting (2009)) at a 3% discount rate. Further detail on efficiency calculations, including the chosen technologies and their costs, in the appendix.

We used DOE estimates of technology costs and energy consumption to compute ef-

[50] We note that residential scale solar installed prices vary systematically across the country, and large-scale systems likely do as well, however the data available comprise only a single nation-wide number. However, local resource potential drives levelized cost, and this was factored into our analysis.

[51] Though this suggests the number in the residential sector is relatively small, at roughly 35 W per lamp, the residential sector alone has over 6.5 GW of lamps installed. DOE estimates these lamps are used 791 hours per year, suggesting roughly 5 TWh of end-use electricity consumption per year

Table 7: Data used to calculate efficiency LCOE.

	residential	commercial
baseline technology	0.75 ballast factor, 32 watt	0.78 ballast factor, 32 watt
efficiency option	0.75 ballast factor, 30 watt	0.75 ballast factor, 32 watt
baseline cost	$52.96	$62.87
baseline energy	39.2 kWh	224.1 kWh
efficiency cost	$53.55	$63.31
efficiency energy	37.3 kWh	215.4 kWh
LCOE	$26.93	$4.39

Notes: (1) All lamps are electronic ballast. (2) We assumed a lamp and ballast replacement (due to failure of existing lamp and ballast) for both residential and commercial. (3) All lamps are T8. (4) Levelized cost computed by dividing cost difference between baseline and efficient option by the energy saved times an annuity factor for 15 years at 3% discount rate (=12.3).

ficiency LCOEs. The key assumptions are in Table 7, taken from the DOE's Technical Support Document for the General Service Fluorescent and Incandescent Reflector Lamps Energy Conservation Standard (Navigant Consulting, 2009).

The current DOE standard for general service fluorescent lamps is 88 lumens per watt for the lamp-ballast system (DOE, 2009). We gathered data on technology costs and energy consumption from the National Impacts Analysis for the current standard . In addition to technical assessments of the lumens per watt and installed cost (including retail price to consumer, taxes and installation labor) for each technology, DOE assumes residential lamps will be operated 791 hours per year, and commercial lamps for 3,435 hours per year. For each sector, we chose the baseline as the technology with the lowest installed cost in that sector that also meets the current standard. We defined the efficiency option as the technology with the lowest installed cost from among technologies that are more efficient than the baseline. We calculated a levelized cost of energy saved by the efficiency option over a fifteen-year period (per DOE's estimates that ballast lifetime is 15 years (DOE, 2009)), at a 3% discount rate.

Capacity value: We constructed capacity value in units of \$/MW as $CAP_{rj} = CC \times P_c$ where CC is a "capacity credit," (in MW per MW) and P_c is a payment for capacity (\$/MW).

We obtained capacity prices from a variety of sources. Where possible we averaged pricing data over 2010-2012 though circumstances did not permit in all cases. For California, we used the median price for resources delivering between 2010 and 2012, as published in the California Public Utility Commission's 2011 annual resource adequacy report (Brooks and Gannon, 2013). ERCOT does not have a capacity market so we set the price to zero there. For ISONE, we averaged the results of the 2010-2011 and 2011-2012 Forward Capacity

Auctions.[52] For MISO, we noted that it's state of the market report in 2012 argued that very low capacity prices there are the result of market distortions that suppress prices (Potomac Economics, 2013). Rather than use these prices we used the annualized cost of a new combustion turbine, based on \$650/kW installed cost (Black and Veatch, 2012), 3 percent real discount rate, 30 year project life (yielding an annualization factor of 19.6 years) and 85 percent availability. For NYISO we used the Unforced Capacity spot auction prices averaged over all months in 2010-2012. For PJM we used the RTO Base Residual Auction prices and averaged across results from 2010/2011, 2011/2012 and 2012/2013 auction years. The data are shown in Table 5.

Regional emissions intensities are computed as the ratio of regional CO_2 emissions to *total* regional generation. For all regions but California we used CEMS CO_2 emissions; California CO_2 emissions were taken from EIA's state electricity profiles (non-dispatchable cogeneration plants comprise a substantial fraction of California emissions, but are not reported in CEMS). Total regional generation for California was also taken from EIA. We assumed negligible imports in ERCOT and used historical load data, available from ERCOT's website, as a proxy for total generation. We calculated generation in ISONE, MISO and NYISO as historical load minus net imports (all data from each ISO's website). For PJM, we took generation data directly from its state of the market reports.

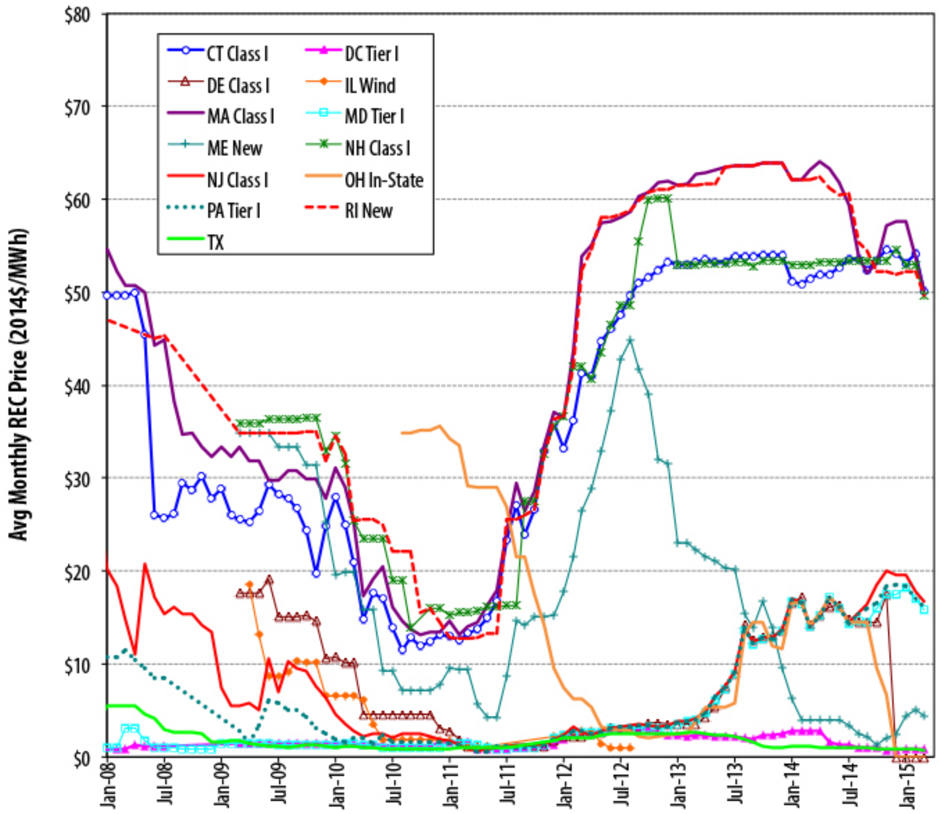
Renewable energy certificate data were retrieved from the website of the US Department of Energy's Office of Energy Efficiency and Renewable Energy[53]. Figure 9 shows REC prices used for wind power (originally sourced from Spectron) and Figure 10 shows solar-REC (SREC) prices (originally sourced from SECTrade). We digitized the datapoints from 2010-2012 and took a simple average of the data.

Investment Tax Credit. Renewable energy developers in the United States can claim either the production tax credit (\$22/MWh) or an investment tax credit (equal to 30 percent of the installed cost of the system). Typical wind plant capacity factors favor the production tax credit. However most solar developers claim the investment tax credit and we assume so here. To levelize this credit on a per-unit energy basis, we used the same parameters as those used for the LCOE calculations described above (including the assumption that utility-scale solar PV costs \$2.97/W and selecting the best solar site from within each ISO) to levelize 30 percent of the system cost over 30 years of energy production.

[52]ISONE disaggregates its auctions into resources that deliver to Maine and those that deliver to the rest of the pool; prices were identical for both.

[53]`http://apps3.eere.energy.gov/greenpower/markets/certificates.shtml?page=5`

Figure 9: REC prices



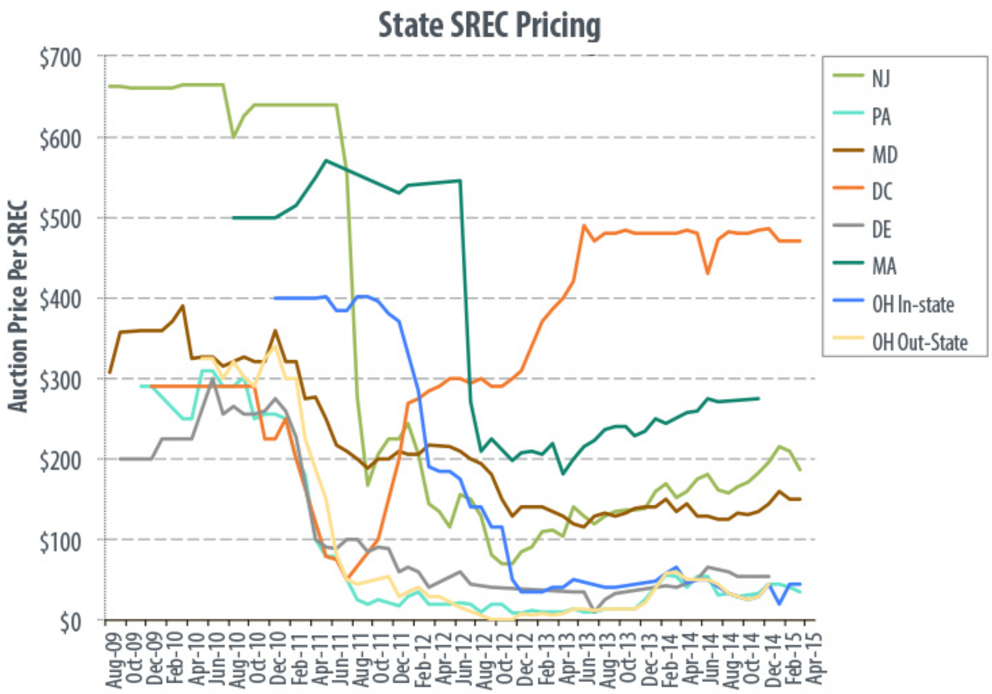
Credit: US Department of Energy

A.2 k-means clustering

We cluster calendar days in our data using a k-means clustering algorithm. Within a given region and season, every day of the period 2010-2012 is given a 24-dimensional value based on the megawatt-hours per hour of fossil fuel generation in that hour. An additional value is added for the megawatt-hours per hour at peak that day (which may occur at different times). We then use a k-means clustering algorithm that matches days along these 25-dimensions. Thus, we are matching days on both the shape of electricity demand and the quantity in that day. We seed the clusters by initially matching entirely based on peak load in that day.

We determine the number of clusters using the following algorithm. For each region and season combination, we construct 12 clusters. We calculate the corresponding MOERs and check for a significant difference (which we define as non-overlapping 95% confidence

Figure 10: SREC prices



Credit: US Department of Energy

intervals) between any of the MOERs that result. If there are no significant differences between any of the clusters, we drop to the next lowest number of clusters. Thus, we use the smallest number of clusters which provides more informational content than the next smallest number of clusters.

Figure 11 and Figure 12 summarize the results of this exercise. Each figure plots the average generation profile for each season-region-cluster triad. Bars denote 95-percentile confidence intervals. These graphs illustrate significant variation in load profiles even within a region-season. The average number of clusters is 2.8.

A simpler approach to capturing this variation in load profiles would be to use the calendar month to proxy for intra-seasonal variation in load profiles. Figure 13 illustrates how our season-specific cluster composition varies in space and time over a single year, 2011. In each region and season, green denotes the first cluster associated with low load levels. Higher numbered clusters correspond with higher average load profile days. The figures show how our approach leads to a very different grouping of days as compared to a by-month grouping. Our approach is designed to more directly control for the effects of load profile differences across days within a region-season.

A.3 Marginal Operating Emissions Rates

Detailed hourly MOER results are in Fig. 14 and Tables 8 and 9.

A.4 Marginal Emissions Displacement Rates

A.4.1 Intra-regional variation in emissions displacement across wind sites

We are interested in assessing the potential significance of variation in wind energy production profiles within a region. We start by estimating marginal emissions displacement rates for the over 30,000 wind sites in the data. Figure 15 arranges these sites in ascending order of estimated MEDR values. The figure suggests minimal variation in emissions displacement across sites within a given region. This is not altogether surprising given the limited variation in MOERs within most regions.

To put the variation summarized in the figure above into context, we systematically compare the MEDR estimates in either tail of these regional distributions. More precisely, in each region we select the ten sites straddling the 2.5 percentile value and ten sites straddling the 97.5th percentile value. We bootstrap within region differences in MEDR across all possible pairwise comparisons between low and high ranked sites.

Table 10 summarizes these differences. The average pairwise difference between sites with high and low emissions displacement estimates, normalized by the average MEDR across all sites in the region, varies from 1 to 4 percent. We also report a more extreme difference. We take the two most different sites in each region, bootstrap the difference, and report the 95th percentile difference in MEDRs. The table shows that even this extreme measure of the difference in emissions displacement rates across sites within a region is small relative to the average MEDR (averaged across all sites in the region).

Based on these results, we conclude that intra-regional variation in emissions displacement rates across wind sites can be neglected for further analyses. We instead use only a subset of the sites (twenty wind sites from each region, ten from the 2.5th and ten from the 97.5th percentile of MEDRs) to summarize the variation in emissions displacement values across regions and technologies.

A.4.2 Variation in marginal emissions displacement rates

The paper reports the average deviation of simulated marginal emissions displacement rates from regional and annual averages by technology. These interaction terms mask some regional variation. The table below reports the coefficient estimates from a fully saturated model (i.e. one including technology-region interactions).

A.5 Marginal Economic Value

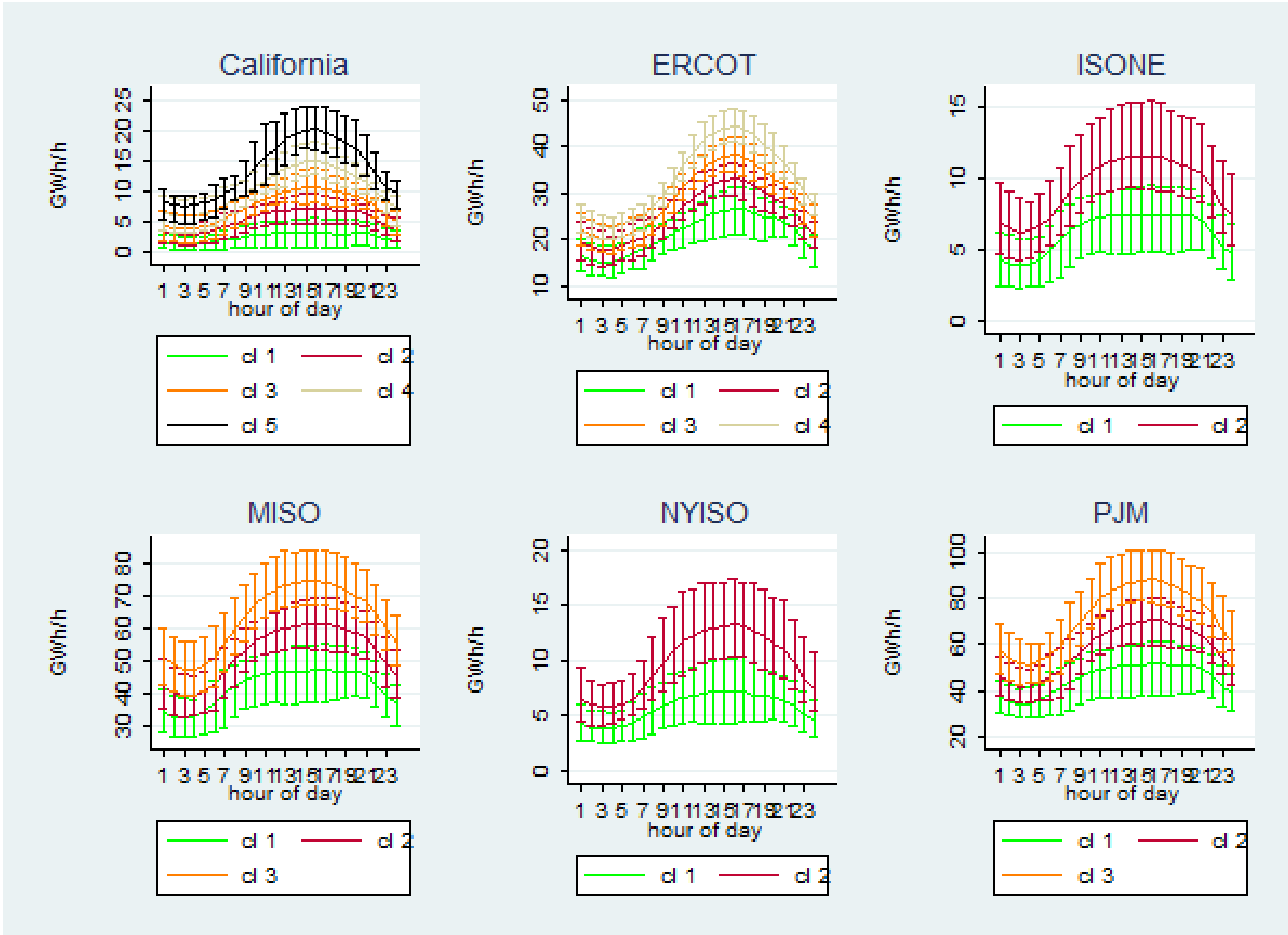
The data used to generate Fig. 6 are in Table 11.

A.6 Marginal Abatement Cost

50% energy efficiency realization rate sensitivity analysis

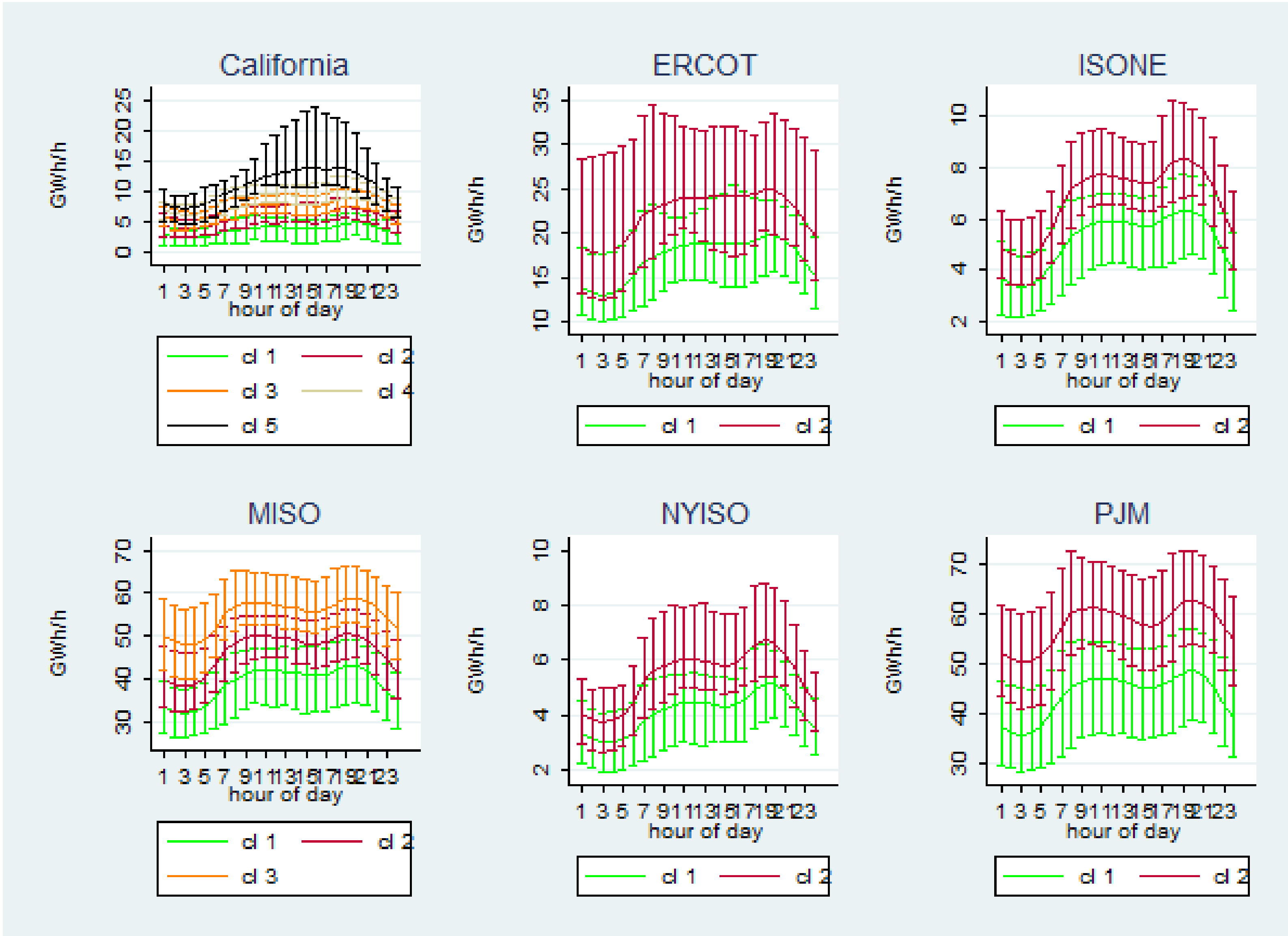
We performed an additional sensitivity analysis to examine the possibility that energy efficiency technologies do not achieve as great a level of energy savings in practice as their engineering characteristics would suggest. To model this possible behavioral factor, we rerun the marginal abatement cost analysis with a 50% realization rate for lighting efficiency. The 50% rate is equally applied across all hours of the 2010-2012 period, i.e. the load shape is unchanged. The figure below demonstrates how marginal abatement costs are different if lighting efficiency technologies assuming that our lighting efficiency technologies achieve 50% less energy savings.

Figure 11: K-means clustering: Summer generation profiles



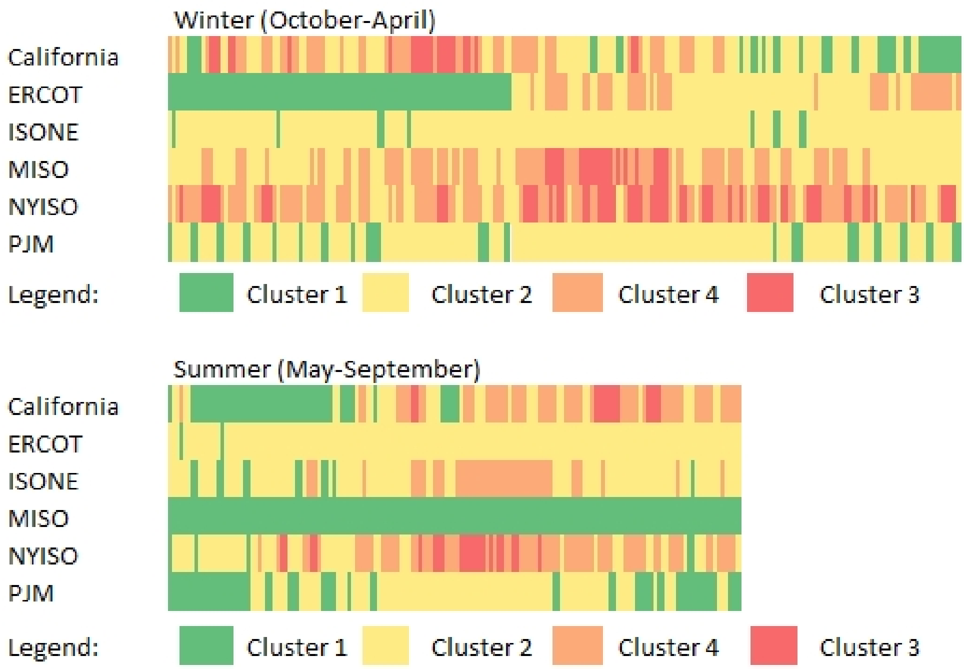
Notes: This figure plots the total generation from fossil fuels by region at each hour of the day for an average day of each k-means cluster, of the final clusters we keep for each region in the summer. Bars denote 2.5th and 97.5th percentile observations within each hour for a given cluster. See Appendix for a description of k-means clustering approach.

Figure 12: K-means clustering: Winter generation profiles



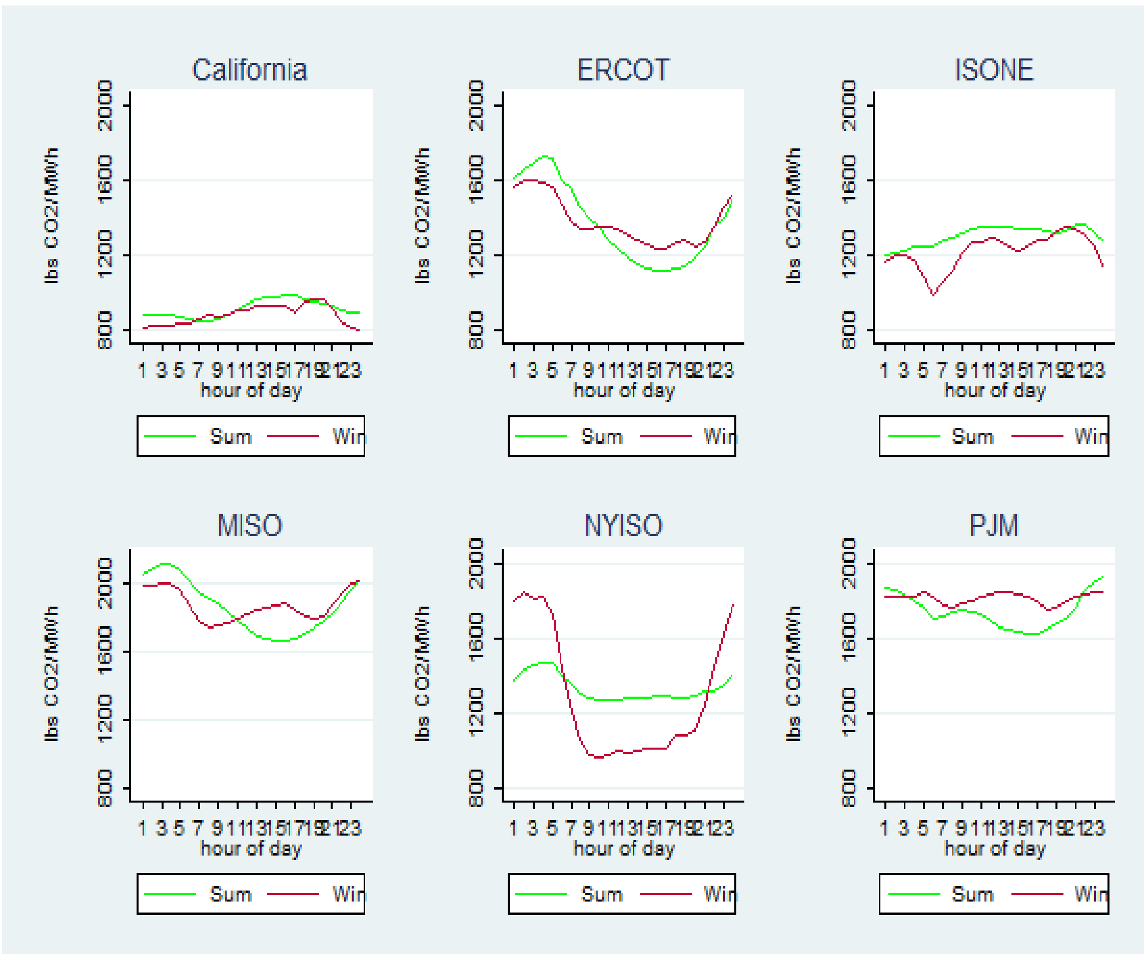
Notes: This figure plots the total generation from fossil fuels by region at each hour of the day for an average day of each k-means cluster, of the final clusters we keep for each region in the winter. Bars denote 2.5th and 97.5th percentile observations within each hour for a given cluster. See Appendix for a description of k-means clustering approach.

Figure 13: Cluster composition over the time period



Notes: This figure displays the occurrence of different clusters over time for a representative year (2011). Each region and season is represented as a series of colored blocks depending on the cluster that the algorithm assigned to that day. Higher number clusters represent higher levels of electricity generation. Winter and summer are displayed separately to emphasize that the clusters are defined separately by region and season, i.e. cluster 3 represents two different levels of electricity generation in two different seasons. See Appendix for a description of k-means clustering approach.

Figure 14: Marginal operating emissions rates



Notes: This figure displays the average marginal operating emissions rates, in pounds of carbon dioxide per megawatt-hour, in each hour of the day for different regions. Summer and winter are displayed separately. See Section 4 for a description of marginal operation emissions approach.

Table 8: Summer MOERs and bootstrapped 95 percent confidence intervals.

hour	California	ERCOT	ISONE	MISO	NYISO	PJM
1	878	1615	1204	2051	1371	1868
	(858-899)	(1528-1698)	(1136-1276)	(1978-2119)	(1312-1432)	(1786-1957)
2	880	1659	1210	2082	1432	1851
	(860-900)	(1566-1750)	(1137-1288)	(2008-2144)	(1371-1499)	(1769-1944)
3	883	1690	1226	2110	1455	1832
	(863-904)	(1594-1780)	(1151-1305)	(2037-2172)	(1392-1525)	(1736-1934)
4	881	1726	1249	2117	1469	1800
	(859-903)	(1628-1818)	(1165-1330)	(2047-2183)	(1405-1537)	(1706-1909)
5	868	1716	1241	2077	1468	1761
	(849-888)	(1621-1815)	(1159-1321)	(2016-2137)	(1404-1537)	(1671-1856)
6	856	1593	1250	2008	1402	1705
	(838-877)	(1500-1677)	(1179-1321)	(1952-2065)	(1342-1464)	(1632-1784)
7	851	1549	1280	1951	1353	1712
	(831-872)	(1467-1624)	(1211-1354)	(1890-2012)	(1293-1413)	(1647-1781)
8	847	1460	1294	1911	1300	1738
	(823-870)	(1359-1556)	(1220-1372)	(1840-1985)	(1243-1354)	(1671-1809)
9	855	1394	1317	1885	1277	1752
	(829-880)	(1296-1495)	(1241-1398)	(1796-1973)	(1225-1329)	(1681-1824)
10	878	1353	1337	1836	1263	1740
	(851-903)	(1263-1448)	(1263-1413)	(1739-1935)	(1213-1315)	(1672-1810)
11	908	1282	1347	1783	1264	1725
	(878-935)	(1208-1362)	(1275-1423)	(1685-1884)	(1215-1316)	(1661-1796)
12	944	1235	1355	1736	1265	1693
	(916-972)	(1171-1299)	(1284-1427)	(1640-1833)	(1220-1315)	(1632-1760)
13	962	1188	1352	1691	1279	1655
	(934-990)	(1127-1247)	(1285-1419)	(1601-1786)	(1235-1324)	(1594-1722)
14	971	1153	1346	1674	1281	1640
	(944-999)	(1095-1210)	(1280-1414)	(1587-1765)	(1239-1323)	(1583-1703)
15	980	1126	1342	1665	1280	1627
	(952-1008)	(1073-1178)	(1275-1410)	(1582-1754)	(1240-1322)	(1573-1686)
16	984	1122	1340	1663	1291	1622
	(957-1011)	(1072-1175)	(1271-1405)	(1581-1754)	(1251-1331)	(1570-1681)
17	982	1117	1340	1672	1288	1622
	(956-1008)	(1069-1168)	(1272-1405)	(1588-1763)	(1245-1328)	(1568-1679)
18	966	1123	1330	1699	1280	1643
	(940-991)	(1073-1172)	(1258-1400)	(1610-1792)	(1235-1322)	(1588-1703)
19	948	1146	1317	1744	1278	1673
	(923-974)	(1093-1202)	(1243-1389)	(1648-1839)	(1230-1330)	(1615-1737)
20	942	1185	1324	1783	1289	1699
	(918-966)	(1128-1249)	(1251-1400)	(1681-1879)	(1234-1347)	(1630-1769)
21	925	1241	1364	1823	1320	1766
	(903-948)	(1177-1307)	(1289-1441)	(1723-1919)	(1264-1377)	(1696-1839)
22	909	1351	1358	1887	1320	1852
	(885-934)	(1276-1427)	(1280-1441)	(1798-1975)	(1263-1380)	(1783-1927)
23	898	1398	1312	1962	1352	1906
	(872-924)	(1318-1476)	(1232-1390)	(1882-2040)	(1294-1419)	(1828-1992)
24	893	1506	1274	2026	1405	1924
	(871-916)	(1413-1596)	(1200-1354)	(1950-2099)	(1344-1470)	(1840-2013)

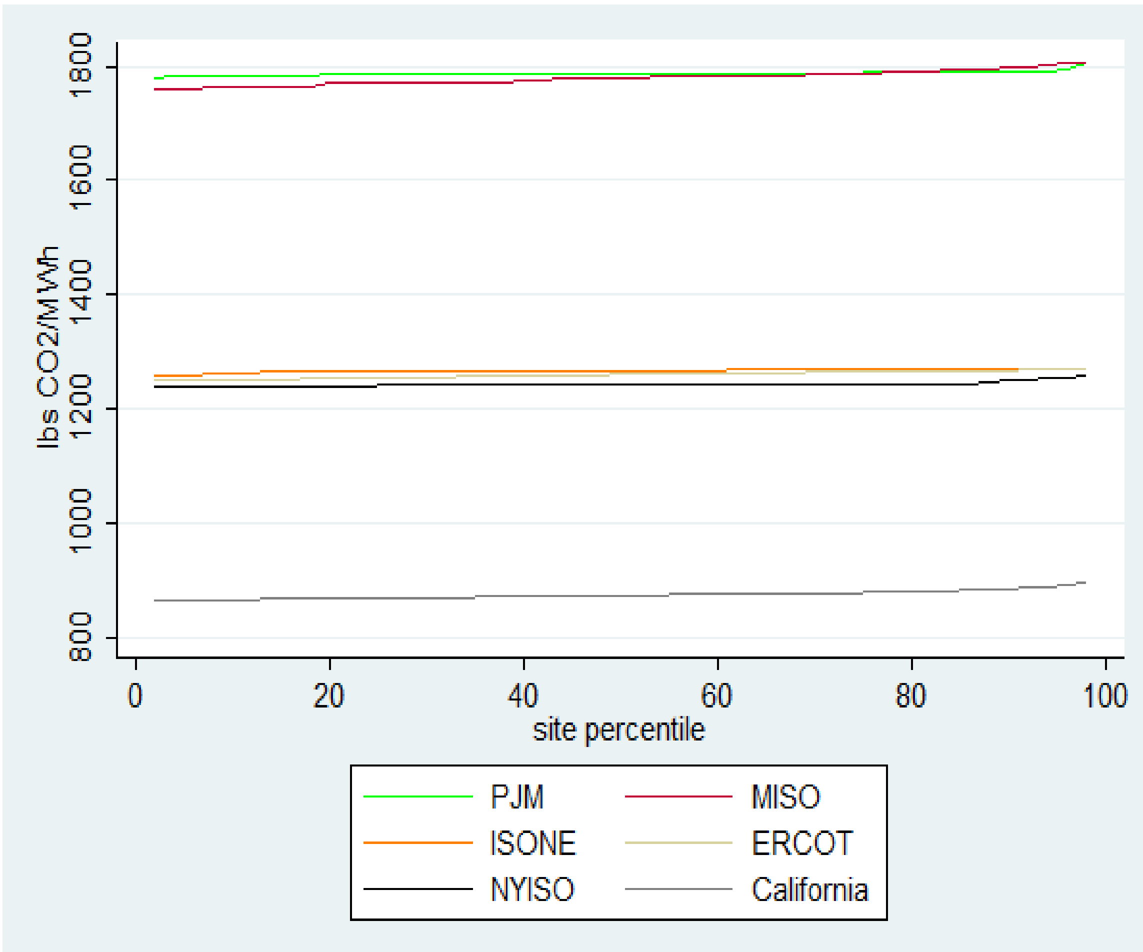
Notes: This table displays the average marginal operating emissions rates, in pounds of carbon dioxide per megawatt-hour, in each hour of a summer day for different regions. Bootstrapped 95 percent confidence intervals in parentheses. See Section 4 for a description of marginal operation emissions approach.

Table 9: Winter MOERs and bootstrapped 95 percent confidence intervals.

hour	California	ERCOT	ISONE	MISO	NYISO	PJM
1	813	1565	1160	1984	1800	1824
	(792-833)	(1499-1633)	(1058-1259)	(1937-2032)	(1682-1926)	(1755-1897)
2	826	1597	1195	1981	1838	1820
	(802-847)	(1528-1668)	(1090-1298)	(1928-2029)	(1723-1961)	(1753-1893)
3	827	1595	1199	1994	1808	1817
	(804-849)	(1525-1665)	(1101-1299)	(1946-2040)	(1694-1929)	(1750-1891)
4	826	1591	1176	1991	1814	1820
	(802-851)	(1524-1661)	(1075-1274)	(1943-2036)	(1703-1930)	(1749-1893)
5	834	1565	1082	1960	1724	1842
	(813-859)	(1499-1635)	(982-1178)	(1904-2008)	(1607-1838)	(1767-1916)
6	838	1468	991	1868	1428	1818
	(815-864)	(1405-1537)	(893-1087)	(1810-1920)	(1320-1540)	(1751-1886)
7	864	1378	1057	1778	1212	1772
	(841-889)	(1320-1441)	(968-1142)	(1722-1833)	(1106-1319)	(1711-1836)
8	878	1335	1119	1736	1057	1757
	(857-902)	(1277-1400)	(1029-1209)	(1679-1793)	(955-1167)	(1694-1818)
9	871	1341	1206	1747	978	1787
	(846-896)	(1276-1411)	(1115-1294)	(1686-1812)	(875-1088)	(1716-1856)
10	883	1353	1268	1762	968	1802
	(855-911)	(1279-1430)	(1183-1355)	(1695-1832)	(860-1071)	(1726-1874)
11	907	1351	1273	1795	970	1818
	(878-936)	(1273-1432)	(1186-1361)	(1725-1867)	(865-1076)	(1743-1888)
12	907	1343	1293	1818	999	1826
	(876-937)	(1255-1429)	(1201-1384)	(1750-1895)	(900-1097)	(1752-1895)
13	925	1310	1277	1842	991	1838
	(895-955)	(1223-1395)	(1178-1374)	(1772-1915)	(890-1089)	(1766-1906)
14	924	1277	1244	1851	1001	1838
	(891-955)	(1193-1359)	(1142-1346)	(1781-1926)	(906-1091)	(1769-1903)
15	925	1255	1220	1873	1010	1834
	(893-955)	(1179-1332)	(1117-1324)	(1805-1944)	(908-1108)	(1768-1898)
16	924	1239	1243	1876	1009	1820
	(890-955)	(1170-1311)	(1140-1350)	(1809-1949)	(904-1109)	(1756-1883)
17	893	1237	1281	1836	1011	1801
	(860-924)	(1168-1313)	(1193-1371)	(1767-1913)	(909-1116)	(1730-1870)
18	947	1269	1283	1806	1078	1750
	(918-977)	(1198-1347)	(1205-1366)	(1739-1880)	(985-1184)	(1678-1818)
19	968	1277	1330	1785	1084	1760
	(933-1005)	(1213-1346)	(1255-1411)	(1715-1858)	(987-1192)	(1689-1831)
20	965	1242	1347	1809	1106	1791
	(933-1001)	(1171-1311)	(1269-1432)	(1736-1881)	(989-1227)	(1714-1867)
21	916	1274	1342	1867	1250	1818
	(883-949)	(1206-1342)	(1258-1429)	(1800-1934)	(1126-1377)	(1742-1892)
22	847	1357	1305	1932	1447	1831
	(820-874)	(1294-1430)	(1221-1392)	(1874-1992)	(1308-1593)	(1756-1906)
23	807	1456	1242	1999	1623	1839
	(783-833)	(1389-1532)	(1154-1332)	(1948-2054)	(1474-1769)	(1764-1917)
24	805	1523	1131	2012	1781	1840
	(779-832)	(1450-1599)	(1032-1230)	(1967-2062)	(1635-1928)	(1763-1918)

Notes: This table displays the average marginal operating emissions rates, in pounds of carbon dioxide per megawatt-hour, in each hour of a winter day for different regions. Bootstrapped 95 percent confidence intervals in parentheses. See Section 4 for a description of marginal operation emissions approach.

Figure 15: Site-specific marginal emissions displacement



Notes: This figure displays the average marginal emissions displacement rates of individual sites over the entire study period within each region. Sites are arranged from lowest marginal emissions displacement on the left rate to highest on the right. See Section 5 for a description of marginal operation emissions approach.

Table 10: Summary of pairwise MEDR differences between wind sites with high and low emissions displacement estimates

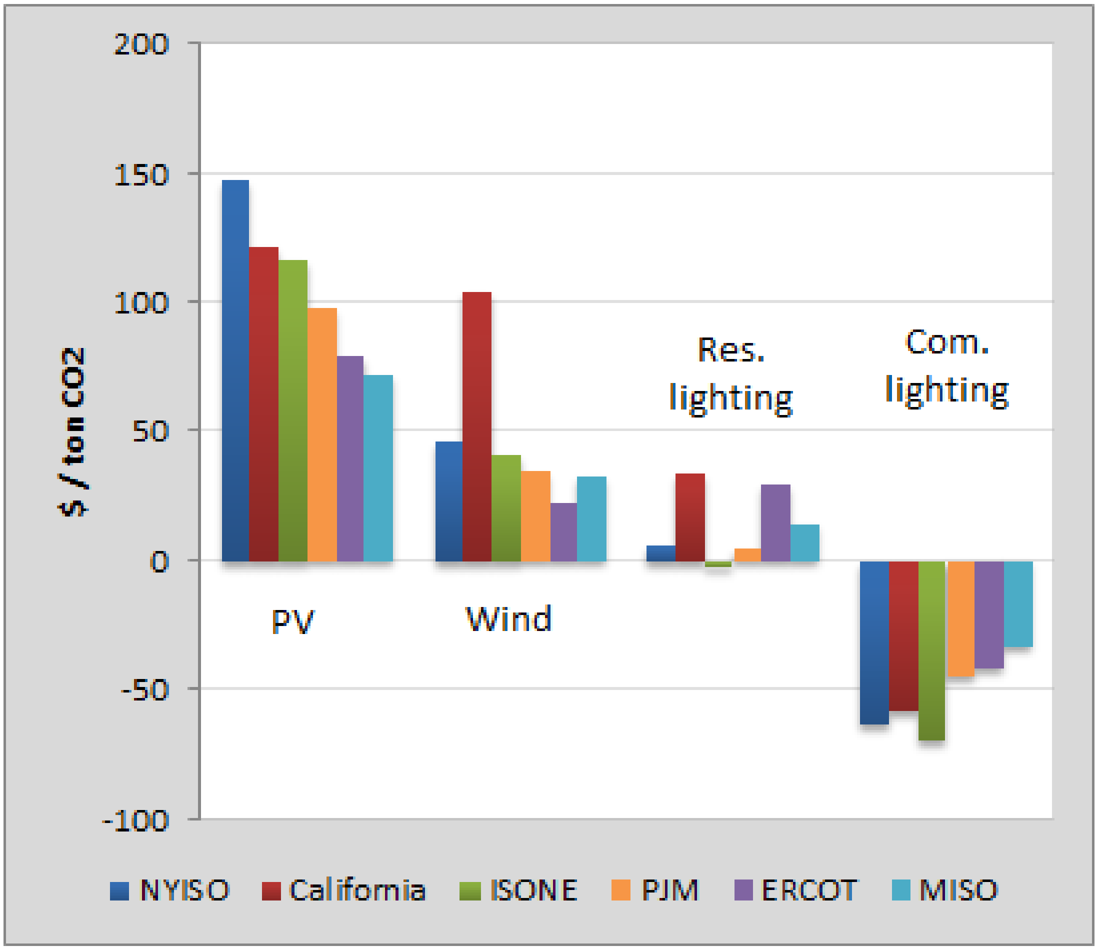
Region	Mean difference (lbs/MWh)	Extreme difference (lbs/MWh)	Mean difference as share of regional average	Extreme difference as share of regional average
ISONE	14	60	1%	5%
ERCOT	32	145	2%	10%
MISO	14	123	1%	7%
NYISO	26	91	2%	7%
PJM	12	95	1%	5%
California	34	153	4%	17

Notes: This table displays differences between the mean MEDR of 20 representative high- and 20 representative low-MEDR sites. High sites are at the 97.5th percentiles distribution within each region and low sites are at the 2.5th percentile. The mean difference represents the bootstrapped mean of this difference. The extreme difference represents the 97.5th percentile difference between the mean of these representative sites. Mean and extreme difference are also presented as a share of the average regional average MEDRs. See Section 5 for a description of marginal operation emissions approach.

Table 11: Marginal social values used in Fig. 6

Region	Technology	Avoided operating costs per MWh	Avoided emissions value per MWh	Capacity value per MWh
California	Com Light	$33.15	$18.23	$3.63
	Solar	$31.79	$17.20	$3.93
	Res Light	$33.61	$18.05	$4.02
	Wind	$31.14	$16.96	$3.13
ERCOT	Com Light	$37.98	$26.64	-
	Solar	$42.36	$23.83	-
	Res Light	$32.89	$27.15	-
	Wind	$28.35	$26.60	-
ISONE	Com Light	$49.95	$25.51	$6.93
	Solar	$49.87	$24.60	$8.04
	Res Light	$49.96	$25.74	$7.04
	Wind	$45.02	$23.72	$5.68
MISO	Com Light	$36.55	$36.85	$5.29
	Solar	$37.40	$33.93	$6.04
	Res Light	$35.17	$37.66	$5.50
	Wind	$31.45	$35.67	$3.94
NYISO	Com Light	$49.32	$24.47	$1.76
	Solar	$49.81	$21.46	$2.13
	Res Light	$49.08	$26.18	$1.79
	Wind	$44.75	$24.75	$1.40
PJM	Com Light	$46.89	$35.60	$5.05
	Solar	$48.89	$33.18	$5.95
	Res Light	$45.69	$36.24	$5.28
	Wind	$41.39	$33.97	$4.17

Figure 16: Marginal abatement costs at 50% energy efficiency realization rate



Notes: This figure plots the total marginal abatement cost, in dollars per ton of carbon dioxide, from different region-technology combinations under the assumption that only 50% of the estimated energy savings from lighting efficiency measures actually take place. See Section 7 for a description of marginal abatement cost calculations.