Marginal Emissions Avoided by Solar and Wind Generation in the California Power Grid

By JD PRUETT

I make use of exogenous variation in levels of wind and sun to quantify how the marginal emissions offset by a unit of renewable generation depends on current grid demand. I estimate the average emissions offset by a megawatt of solar and wind energy supplied to the California power grid. I then use these estimates to simulate how the marginal emissions avoided changes depending on the level of current demand. I uncover significant non-linearities, suggesting that the marginal external benefit of renewables is highly conditional on demand level. Given that state and federal programs generally offer fixed incentives in ¢/kWh of generation, regardless of when that generation occurs, these results prompt consideration of how future policies might adapt to the demand-dependency of the marginal external benefits of renewables.

Though emissions can be curbed in various ways, including with new technologies on existing fossil fuel electricity-generation methods, the installation of new renewable capacity has been the preferred method for combating greenhouse gas emissions. Substantial incentives exist at the state and federal level to drive the installation of new solar and wind capacity. As of June 2023, California led the nation with 62.5% of the state's power coming from renewable sources, more than 3x the national average of 19.6%[1]. New incentives suggest that this trend will continue. As a recent illustrative example, the Inflation Reduction Act guarantees an Investment Tax Credit (ITC) of 30% on installations of new renewable capacity between 2022 and 2032. At the state level, programs such as SGIP, California Net Metering, and the California Solar Initiative have propelled California to be the largest producer of solar power, producing 40,494 Gigawatt hours (GWh) in 2022[2].

These incentives apply at a constant rate to generation, regardless of when that generation occurs. The implication of these policies would be that renewable capacity is a homogenous good with constant marginal external benefits, ie. that a MWh of solar is equally beneficial for reducing emissions, regardless of when it's provided to the grid. This implication has largely been left untested, and no state has considered internalizing fluctuating marginal benefits into its renewable installation incentive structure.

A number of papers have sought to quantify the marginal benefits of an additional unit of renewable energy generated (Cullen 2013; Kaffine, McBee, and Lieskovsky 2013). This analysis, however, highlights that paying attention only to average estimates of marginal impact can be misleading. Examining how the marginal external benefit of a

[1]U.S. Energy Information Administration, California 2023 profile, `https://www.eia.gov/state/data.php?sid=CA`

[2]California Energy Commission, `https://www.energy.ca.gov/media/7311`

unit of renewable energy changes with demand uncovers significant nonlinearities in that marginal benefit: the marginal environmental benefit of a given fuel type depends heavily on the current level of overall grid demand.

This demand-dependent effect occurs because an additional unit of renewable energy supplied to the grid naturally has to displace the marginal generating unit. As the demand on the overall grid changes, and as the level of renewable capacity grows, the nonrenewable units operating at the margin for a given level of demand will change. The key implication is that the marginal emissions avoided (MEA) by an additional unit of renewable energy provided to the grid will vary substantially with the level of grid demand because of the composition of generating units on the margin.

To elucidate the interplay between MEA and overall grid demand in California, I use hourly emissions, supply, and demand data provided by the California Independent System Operator (CAISO), the body that coordinates electricity provision to over 80% of the state. I take advantage of exogenous variation in levels of wind and sun to estimate two parameters of interest. First, I quantify the average effect on CO_2 emissions of supplying an additional megawatt (MW) of solar and wind to the CA grid, respectively. Then, I use these estimates to simulate how MEA changes conditional on demand for wind, solar, and renewables in aggregate.

To estimate the average emissions reduction effect, I specify a general fixed-effects regression model that estimates the average change in CA emissions caused by a Mwh of wind or solar generation. A large set of fixed effects controls for correlations between wind generation and electricity consumption as well as seasonal patterns in emissions and wind energy generation. For the simulation, I again use a fixed effects model, this time including an interaction term between hourly generation and overall demand.

I find that on average, a MWh of wind offsets about 0.3278 metric tons (mT) of CO_2 per hour. This is slightly lower than solar, which I esimtat to be 0.3329 mT/h. All renewables in aggregate reduce 0.3784 mT/h on average. Qualitatively, as demand increases, MEA increases for high levels of wind generation and decreases for low levels of wind generation. I find that MEA is also generally increasing in the level of solar generation, but that the overall MEA is higher at lower levels of solar generation.

Excluding Texas, little research examines how MEA varies with demand levels, which may have important implications for future incentive pricing structures. This paper offers one estimation and simulation approach to examine this relationship.

Section I reviews the relevant literature. Section II provides background on the functioning of CAISO. Section III describes the data. Section IV specifies the empirical strategy used to estimate the average effect of different renewable sources on CO_2 emissions. Section V describes the simulation of heterogeneous marginal impacts of renewable generation on CO_2 emissions. Section VI presents results. Section VI offers a brief discussion and concludes.

I. Literature Review

A number of papers document the rising share of wind energy as a percent of the U.S. market and its drivers. Hitaj (2013) finds that in the early 2000s, federal production tax credit and state-level tax credits and incentives – much like the investment tax credit that the Inflation Reduction Act extended in 2022 – were influential in promoting the installation of wind capacity in the early 2000s. In response to this growing production, a number of analyses estimated the average emissions offset by these investments in wind and solar energy, a number of which were skeptical of large installation incentives. For example Cullen (2013) finds that 947 lbs of CO_2 are offset per MWh of wind capacity, a value that could only justify corresponding wind installation incentives for high estimates of the social cost of carbon.

The field has sought for some time to characterize the extent of heterogeneity present in the renewables equation – namely to distinguish pollutants and their respective costs, understand how emissions differ between similar firms, and identify regional differences in pollution patterns. Mendelsohn (1989) was the first to argue that different pollutants had heterogeneous economic costs and should be taxed differently. Zivin, Kitchen, & Mansur (2014) extend this analysis from heterogeneity in individual pollutants to heterogeneity in firm emissions around the U.S. They find significant variation in CO_2 production in electricity plants, sufficient to be concerned about policies that push for the electrification of vehicles, appliances, and other technologies under the broad-based assumption that electricity plants will produce fewer emissions than gas-powered technologies would use directly. Furthermore, they find that within a given region of the country, CO_2 emission rates at plants can vary by more than a factor of 2 at the same time of day.

These results highlight the complexity of estimating the costs of pollution, given the substantial heterogeneity in emissions and plants around the country. Furthermore, they highlight that a body of research has carefully documented the heterogeneity in the costs and emissions levels association with electricity production. Less attention has been paid, however, to heterogeneity in the *benefits* afforded by additional installation of renewable energy capacity.

Castro (2019) also uses random fluctuations in hourly and wind generation in CA to estimate emissions reductions. He considers the dependecy of emissions offset on the displacement of high-cost natural gas generators. he also funds that soler energy tends to displace hydro production afternoon to evening. This approach does not consider how these effects interact with the overall level of demand on the power grid which, as I will demonstrate, is significant. Novan (2015) does consider this interaction with grid-level demand, quantifying heterogeneity in the marginal emissions reduction associated with wind power in the Electric Reliability Council of Texas (ERCOT) grid. Novan's key finding is that when demand is low, an additional MWh of wind energy supplied to the grid has sharply decreasing marginal benefits. As overall demand increases, however, the marginal emissions avoided begins to increase again. The implications of this finding are that depending on how much load is on the grid as a whole, the emissions reduction value of renewable energy varies substantially. Independent System Operators (ISOs) might consider these findings when allocating marginal generating units, and there's relevance for policymakers in considering how to internalize demand-dependent emissions benefits into incentive structures.

This paper borrows methodology from Novan's paper, with a few key changes. First, I apply this analysis to California, making use of CAISO data. Second, I provide average emissions offset for wind, solar, and aggregate renewables to illustrate that on average, emissions offset is relatively similar between energy sources, but that when interaction with demand is considered, much more variation appears. Finally, while Novan only provides MEA estimates for wind, I do for solar, wind, and all renewable sources combined. I make the corresponding adjustments necessary to apply this analysis to solar energy, which has the added quirk of generating 0 MWh during the night.

There are two primary advantages to extending this analysis to California. First, Novan notes in his paper that Texas does not produce enough solar energy to reliably provide MEA estimates for additional units provided to the grid. This is not an issue in California, which has 40% more installed solar capacity.[3] Because such a large portion of California's energy comes from renewable sources, it's possible to perform this analysis for both wind and solar.

Second, any out-of-state generation, then imported, jeopardizes the relationship between measuring within-state generation and within-state pollution. If a state imports a significant amount of energy but doesn't account for the out-of-state emissions associated with that import, a causal relationship can't be established between generation and emissions. In ERCOT, there are a number of fossil fuel generators outside of Texas that are directly connected to the ERCOT grid. The Kiamichi Energy Facility is one of the largest natural gas plants that feeds into ERCOT and is located in Oklahoma. Additional power lines connect ERCOT to the Southwest Power Pool (SPP), a different ISO, further complicating the tracking of generation and corresponding emissions within ERCOT. Novan accounts for this by including additional emissions data from generating units connected to SPP in the relevant regions of Oklahoma and Texas. Nonetheless, given that generation is measured by ERCOT, emissions by the EPA, and additional controls added with data from SPP, there is room for inconsistencies and unaccounted-for leakage in the Texas setting.

California presents a more tractable analysis. While the EPA collects California emissions data for CO_2, NO_x, and SO_x, CAISO also collects its own hourly emissions data for just CO_2 *and* generation data, from the same sources. Since all the generation and emission data come from the same sources, there is greater reason to trust the causal relationship between energy supplied to the grid and corresponding reductions in emissions. To capitalize on this consistency, I limit my analysis of emissions to just CO_2.

II. CAISO Background and Key Assumptions

In a restructured market like California, an Independent System Operator (ISO) is a federally-regulated entity that is responsible for coordinating the electricity market. With oversight from the board and federal regulaotors, CAISO is tasked with maintaining the reliability of the electric grid, and ensuring market conditions that will ensure reasonable costs for the 80% of Californians who receive electricity via CAISO.

[3]U.S. Energy Information Administration, Texas 2023 Profile, `https://www.eia.gov/state/?sid=TX#tabs-3`

Electricity is provided to the grid by private generating units, which can generally be divided into three classes: baseload, intermittent, and peakers. The baseload units with the lowest marginal cost generally operate at all times near their maximum capacity. Peaker generators have low fixed costs but high marginal costs and are thus only deployed when prices are high because of surging demand on hot days, holidays, etc. Intermittent units, such as wind turbines and solar panels, have no marginal cost but only produce when natural variations in the environment enable them to do so.[4]

The two key observations at the heart of this paper are as follows: First, the short-run variation in hourly generation from wind turbines and solar panels are determined exogenously. The source of this exogenous variation includes random changes in wind speed, direction, and solar irradiation intensity that are uncorrelated with demand. While there are seasonal patterns in these natural variations, I control for these in my specification. This creates a natural source of exogenous variation in the level of renewable energy supplied to the grid that I exploit to understand how changes in solar and wind energy supplied to the grid interact with overall demand and reduce emissions.

Second, because the marginal cost of solar and wind is effectively 0, whenever electricity is available from these sources, it will be supplied to the market. This observation is rooted in the basic operating structure of an ISO. When zero marginal cost electricity flows into the grid, it will necessarily displace a non-zero marginal cost-generating unit currently operating on the margin.

There is the potential concern that if a large amount of zero marginal cost wind or solar energy is supplied to the grid, this would drive down electricity prices overall. While this may be true in the long run as more renewable capacity is installed, consumers face fixed, short-run electricity prices that don't change with hourly generation.

Thus, when wind and solar energy flows into the grid, it necessarily displaces an emissions-generating unit. At the extreme, were California powered by 100% intermittent renewable energy, then a simultaneous surge in wind and solar irradiation could oversupply energy, breaking down this causal link between supply and emissions. This is not a concern now as CAISO has never been exclusively supplied by intermittent sources.

III. Data Identification

The three key variables for this analysis are (1) hourly grid demand (consumption) (2) hourly electricity generation by source and (3) hourly CO_2 emissions. Title 17 §95111 of California regulatory code requires all utilities to report greenhouse gas emissions separately for each type of supplied electricity in metric tons of CO2 equivalent (MT of CO2e).[5]. I obtained these data from CAISO directly for the time period May 10, 2018

[4]E3 Lecture Notes

[5]Cal. Code Regs. Tit. 17, § 95111 - Data Requirements and Calculation Methods for Electric Power Entities, https://www.law.cornell.edu/regulations/california/17-CCR-95111

to December 31, 2022.[6][7]. Hourly generation is provided as total current demand, as well as broken down into the following categories, all reported in MW: renewables, solar, wind, geothermal, biomass, biogas, small hydro, coal, nuclear, natural gas, large hydro, imports, and batteries. Emissions data is a available as an aggregate total and broken down into imports, biogas, biomass, geothermal, natural gas, coal, and other, all reported in metroc tons CO_2 equivalent per hour ($mTCO_2e/hr$).

Over the course of the sample, solar supplied about 14% of all energy to grid, slightly more than wind at 8%. Natural gas and imported energy were the largest sources of energy in the four year sample.

All units are in ($mTCO_2/h$)

	N	Mean	StdDev	Min	Max	Share (%)
Imports	36360	2720.81	1131.02	0.00	5755.00	40.67
Biogas	36360	113.10	10.68	68.00	152.00	1.69
Biomass	36360	139.62	24.05	68.00	233.00	2.09
Natural Gas	36360	3703.32	1469.31	0.00	10286.00	55.35
Geothermal	36360	8.46	1.10	2.00	12.00	0.13
Coal	36360	10.58	4.31	0.00	25.00	0.16

Table 1—: Hourly CAISO Emissions by Fuel Source

Other includes biogas, hydro, coal, and batteries. All units are in MWh.

	N	Mean	StdDev	Min	Max	Share (%)
Solar	36360	3500.17	4460.67	0	14258	13.78
Wind	36360	2097.49	1342.32	0	6324	8.26
Geothermal	36360	895.74	103.43	0	1133	3.53
Biomass	36360	311.12	49.16	157	481	1.23
Nuclear	36360	1937.26	535.69	0	2289	7.63
Natural Gas	36360	8338.64	3372.44	0	21860	32.84
Large Hydro	36360	1770.74	1116.94	0	6231	6.97
Imports	36360	6082.22	2528.68	0	11806	23.95
Other	36360	112.25	0.07	0	2	3.34

Table 2—: Hourly CAISO Supply by Fuel Source

[6]CAISO publishes daily profiles of electricity generation, broken down by the hour. However, data is only available to download one day at a time, so I used a privately developed API available for limited free use on RapidAPI to aggregate hourly data.

[7]Similarly, hourly emissions data are only available for download at the daily level no API was available for emissions data. I wrote a webscraper in Python that extracted encoded data from the network request for the same timeframe for which generation data was available. Script available upon request

IV. Average Emissions Offset

I specify a general linear model with fixed effects to estimate the average CO_2 offset by solar and wind generation.

$$E_t = \beta \cdot W_t + \phi \cdot \mathbf{Z}_t + \varepsilon \tag{1}$$

where t is each hour's observation during the four year sample and

$$\begin{aligned} E_t &= \text{Hourly emissions of } CO_2 \text{ in metric tonnes} \\ W_t &= \text{Aggregate hourly CAISO renewables generation in MWh} \\ Z_t &= \text{Vector of controls} \end{aligned}$$

β estimates the average change in emissions caused by a MWh of solar or wind generation. To address correlation between generation and consumption, I control for electricity demanded in hour t. To allow for a non-linear relationship between consumptions and emissions, I include the squares and cubes of hourly demand.

Numerous versions of seasonal, hourly, monthly, and day-of-week patterns could be present. For example, people consume more electricity on Fridays, in cold months, and on certain hours of weekends. To address these patterns, I include every permutation of fixed effects for day, week, hour, and month, resulting in 9,576 fixed effects (24 hours x 7 days per week x 57 months in sample). The full model is then

$$E_t = \beta \cdot W_t + \sum_{n=1}^{3} (\phi \cdot D^n) + \alpha_{h,w,m,y} + \varepsilon_t \tag{2}$$

where

$$\begin{aligned} E_t &= \text{Hourly emissions of } CO_2 \text{ in metric tonnes} \\ W_t &= \text{Aggregate hourly CAISO renewables generation (MWh)} \\ D^n &= \text{Hourly demand (MWh) raised to } n = [1,2,3] \\ \alpha_{h,w,m,y} &= \text{hour-of-week fixed effect across whole sample} \end{aligned}$$

The results suggest that the average hourly emissions reduced by a MWh of wind and solar generation is quite similar, around 0.33 metric tons per MWh. Across all types of renewable generation – wind, solar, biogas, biomass, and geothermal – the effect is a reduction of 0.378 mT of CO_2. While solar has a small edge over wind on emissions avoided, the important thing to note is that between the two sources, the average effect is quite similar. But as the next section will demonstrate, that effect varies widely as demand fluctuates.

Table 3 – Average Emissions Offset per MWh of Generation

	Hourly CO_2 Emissions (mTCO2/h)		
	All Renewables	Wind	Solar
Renewable Generation (MWh)	-0.3784***	-0.3278***	-0.3329***
	(0.0025)	(0.0032)	(0.0041)
Controls			
Squared Hourly Consumption	✓	✓	✓
Cubed Hourly Consumption	✓	✓	✓
Time-Month-Year-Weekday FE	✓	✓	✓
Observations	40,402	40,402	40,402
R^2	0.98416	0.96618	0.96415
Within R^2	0.91403	0.81647	0.80547

V. Heterogeneity Simulation

I've established that the nature of intermittent energy is such that a unit of solar or wind power necessarily displaces the marginal generating plant. Furthermore, as discussed in sections I and II, plants vary significantly in their emissions. Depending on the level of overall CAISO consumption at a given hour t, the composition of the nonrenewable generating units on the margin when a given unit of solar or wind power flows into the CAISO grid will vary. With this simulation, I illustrate the extent to which the marginal emissions avoided by a unit of wind or solar generation depends on when that generation occurs.

Borrowing from Novan (2013), I again use a general fixed effects linear model, with a key change that captures the relationship between demand, generation, and emissions offset. I include an interaction term between hourly generation raised to the ith power and CAISO demand to the jth. Notice that when $j = 0$ we recover the average effects model, simply regressing emissions on hourly renewables generation. However, by including every permutation of non-linearity between demand and generation, this term captures how the emissions reduced *changes* at different levels of demand. The model is

$$E_t = \sum_{i=1}^{3} \sum_{j=0}^{3} \beta_i j W_t^i D_t^j + \sum_{n=1}^{3} (\phi \cdot D^n) + \alpha_{h,w,m,y} + \varepsilon_t \tag{3}$$

where $(W_t^i \cdot D_t^j)$ is the interaction between hourly renewables generation and CAISO demand. Levels, squares, and cubes of current demand alone are again included as controls, as are hour-of-week fixed and month-of-year effects that are allowed to vary across the whole sample. β, then, is the change in emissions for a given level of generation W and total grid demand D, interacted. I estimate this model, creating a grid of β_{ij} for every i and j to capture the full interaction. With these values of β_{ij}, I simulate the marginal emissions avoided at different levels of W and D. Intuitively, the marginal emissions avoided by additional generation is the change in E_t with respect to W. Taking the partial derivative:

$$MEA(W,D) = \frac{-\partial E(W,D)}{\partial W} = \sum_{i=1}^{3} \sum_{j=0}^{3} i \cdot \beta_{ij} \cdot W^{i-1} \cdot D^j \tag{4}$$

Equation (4) gives the MEA for every non-linear interaction permutation, the sum of which gives the MEA for a given W and D. I perform a continuous simulation over the 5th to 95th percentile of total CAISO demand to avoid outlier values at the extremes when the grid goes down or rare weather events occur. For values of W, I used the 5th, 25th, 50th, and 75th percentiles of generation for wind, solar, and aggregate renewables, respectively. For MEA with solar, I restricted the simulation to include positive generation values. Because solar generates 0 MW throughout the night, both the 5th and 25th quartiles are 0 MWh. If W is always 0, the interaction term doesn't capture non-linear effects and the result wouldn't tell us anything useful about how MEA changes with overall grid demand. For these reasons I only simulated with positive values.

The sample regression output below illustrates the estimation strategy for all non-linearity combinations. These variables are highly correlated so the standard errors are likely inaccurate, but this is meant to aid in understanding how the summation of all non-linear interactions contributes to the overall effect. In the case of wind, multiple non-linear combinations are significant, illustrating the importance of exponentiating the predictors.

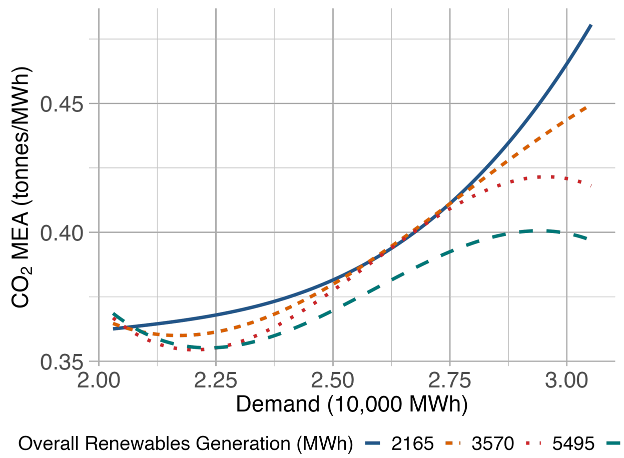
Table 4 – Wind Generation-CAISO Demand Interaction

	Hourly CO2 Emissions (mTCO2/h)	
	Wind Generation (MWh)	(Standard Error)
wind_power1_demand_power0	-47.94**	(22.36)
wind_power2_demand_power0	0.0174*	(0.0096)
wind_power3_demand_power0	-2×10^{-6}	(1.22×10^{-6})
wind_power1_demand_power1	0.0059**	(0.0027)
wind_power2_demand_power1	$-2.16 \times 10^{-6*}$	(1.17×10^{-6})
wind_power3_demand_power1	$2.51 \times 10^{-10*}$	(1.48×10^{-10})
wind_power1_demand_power2	$-2.38 \times 10^{-7**}$	(1.09×10^{-7})
wind_power2_demand_power2	$8.86 \times 10^{-11*}$	(4.72×10^{-11})
wind_power3_demand_power2	$-1.04 \times 10^{-14*}$	(5.94×10^{-15})
wind_power1_demand_power3	$3.2 \times 10^{-12**}$	(1.46×10^{-12})
wind_power2_demand_power3	$-1.2 \times 10^{-15*}$	(6.29×10^{-16})
wind_power3_demand_power3	$1.42 \times 10^{-19*}$	(7.92×10^{-20})
Hourly CAISO Demand (MWh)	-5.699***	(1.779)
Squared Hourly Consumption	0.0003***	(7.16×10^{-5})
Cubed Hourly Consumption	$-3.38 \times 10^{-9***}$	(9.56×10^{-10})
Observations	29,454	
R^2	0.95567	
Within R^2	0.71034	
time-month-year-weekday fixed effects	✓	

VI. Results

Starting with figure 1, the general shape for demand-dependent MEA for aggregate renewables resembles the parabolic shape from Novan's analysis of ERCOT wind generation. The primary difference is the intercept. In the ERCOT analysis, MEA was greater at low demand for all levels of wind, before decreasing and then increasing again. While we still see increasing marginal emissions avoidance at high demand, overall MEA increases in demand. From this simulation, we would generally predict MEA to be increasing in overall grid demand, with reductions around 0.35 mT in the low-demand regime

Figure 1. : Marginal Emissions Avoided by Renewable Generation – All Renewables



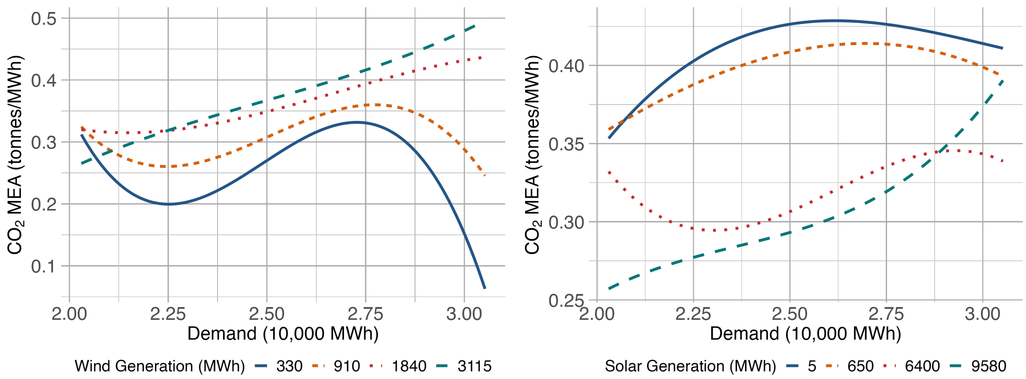
and increasing around 30% to 0.45 metric tons in the high-demand regime. The important qualitative result is that when averaged across all technologies, MEA seems fairly homogenous. However, figure 2 suggests that further decomposition reveals differences between energy sources.

For example, the marginal emissions avoided of wind and solar feature opposite trends with respect to demand. At low to medium levels of generation, MEA_{wind} generally decreases with demand while MEA_{solar} is generally increasing in demand. Wind also seems like a more homogenous good in the low-demand demand regime, while levels of solar converge in the high-demand regime. MEA_{wind} is relatively similar for all levels of wind generation. As CAISO demand increases, however, these results diverge; lower levels of wind generation experience sharply decreasing MEA while higher levels generally increase smoothly. Solar demonstrates the opposite effect: the different levels of solar generation are reasonably differentiated in the low-demand regime, but begin to converge in the high-demand regime.

In both cases, the range on MEA for a give value of demand is much larger than one might predict just looking at figure 1. Around 20,000 MWh, MEA_{solar} ranges from 0.25 to 0.35, a much larger range than the tight band of MEA values suggested at the same level of demand in figure 1. Approaxhing maximum capacity D = 30,000 MWh, MEA_{wind} is simulated to occupy values between 0.15 to 0.5, a larger range than the 0.4 to 0.5 predicted in aggregate. Again, the quantitative results would need to be probed further, but qualitatively, there's evidence that the marginal benefit of renewable capacity is not constant and depends on overall demand.

The final important observation is that the convexity of these MEA estimations changes at different levels of wind and solar generation. In the solar figure, as solar generation increases from the 5th to the 75th quartile, the general convexity of the curves shifts from concave to convex. This highlights the interaction between grid demand and solar avail-

Figure 2. : Marginal Emissions Avoided by Renewable Generation



Wind Solar

ability, specifically that at higher levels of generation, emissions avoidance increases in demand. A similar effect is observed for wind. As the level of wind generation increases from 330 to 3115 MWh, marginal emissions shifts from negatively to positively sloped, again suggesting that as demand on the CAISO grid increases, the relative environmental benefit of additional units of wind energy is increasing, rather than decreasing.

VII. Conclusion

The purpose of this analysis is to begin to elucidate how the marginal environmental benefits attained from renewables sources like wind and solar change conditional on overall demand and natural environmental variability. These preliminary results suggest that significant variation occurs at the margin and we should not assume constant benefits of an hour of renewable energy without considering when it was generated.

The primary limitations of this analysis are twofold. The first is the absence non-fixed-effect controls. Ideally, weather data would be factored in to ensure robustness in the assumption of exogenous variation in wind and solar energy supply. Furthermore, while less of an issue with wind energy, there's possible correlation between the amount of solar energy supplied to the grid and energy demanded, because people use A/C on hot days. I controlled for this by including the level, square, and cube of current demand, as well as fixed effects for day, month, week, and year across the sample. Nonetheless, further testing could be done to see what happens when fixed effects are varied and controls for level of current demand are excluded to further clarify this relationship.

Second, this simulation assumes a functional form of the relationship between MEA and demand. In this case, the relationship was constrained to be cubic, but there is reasonable debate about the validity of assuming functional forms for such relationships. Further modeling should be conducted with alternate specifications to see if the results remain consistent. Furthermore, these simulation figures are based on just a single estimate of β_{ij}. In future simulations, confidence intervals should be calculated and plotted to emphasize and highlight the uncertainty in the estimations.

There's much room for improvement in this implementation of modeling MEA. Nonetheless, should further research agree with these findings that grind-dependent heterogeneity exists in the marginal benefits of renewable generation, consideration should be paid to how this heterogeneity can be exploited for maximum environmental benefit. If the marginal composition of generating units in California is such that a reallocation of capacity could further reduce emissions, this would certainly have implications for CAISO and other ISOs. Additionally, if we understand the relationship between grid demand and MEA, incentive structures can internalize this heterogeneity, offering higher incentives for new renewable technologies that generate at times when demand is known to reach certain levels and MEA is high. These results in conjunction with Novan's ERCOT findings are a strong starting point for exploring how policy might more effectively internalize and capitalize on variation in the marginal emissions avoided by solar, wind, or other renewables generation.

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