Why marginal CO_2 emissions are not decreasing for US electricity: Estimates and implications for climate policy

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Marginal emissions of CO_2 from the electricity sector are critical for evaluating climate policies that rely on shifts in electricity demand or supply. This paper provides estimates of marginal CO_2 emissions from US electricity generation using the most recently available and comprehensive data. The estimates vary by region, hour of the day, and year to year over the last decade. We identify an important and somewhat counterintuitive finding: While average emissions have decreased substantially over the last decade (28% nationally), marginal emissions have increased (7% nationally). We show that underlying these trends is primarily a shift toward greater reliance on coal to satisfy marginal electricity use. We apply our estimates to an analysis of the Biden administration's target of having electric vehicles (EVs) make up 50% of new vehicle purchases by 2030. We find that, without significant and concurrent changes to the electricity sector, the increase in electricity emissions is likely to offset more than half of the emission reductions from having fewer gasoline-powered vehicles on the road. Moreover, using average rather than marginal emissions to predict the impacts significantly overestimates the emission benefits. Overall, we find that the promise of EVs for reducing emissions depends, to a large degree, on complementary policies that decarbonize both average and marginal emissions in the electricity sector.

electricity | emissions | climate policy

Electricity generation accounts for 27% of US greenhouse gas (GHG) emissions (1), and many leading policies that seek to address climate change are closely linked to characteristics of the electricity grid. Examples include the push for more generation from renewable and low-carbon sources of energy, incentives for greater efficiency of electrical systems and appliances, and the growing movement to "electrify everything," especially when it comes to the adoption of electric vehicles (EVs). Indeed, the Biden administration has recently announced an ambitious target of having EVs make up 50% of all new vehicle purchases in the United States by 2030 (2). When it comes to policies or behavioral changes that shift electricity demand and that affect new sources of clean generation, the effect on GHG emissions is highly dependent on the emission rates of the specific sources of generation that are displaced or ramped up in response.

Existing research shows that marginal emission rates, in contrast to average emissions (i.e., carbon intensity), are critical for the evaluation of electricity-shifting climate policies in the United States (3–6). This paper contributes with an important and somewhat counterintuitive finding: Marginal emissions of carbon dioxide (CO_2) have been increasing since 2010, a period over which average emissions have declined substantially. Using the most recently available and comprehensive dataset, we estimate marginal CO_2 emissions due to changes in system-wide electricity use (i.e., load). Our estimates vary by location in the contiguous United States, hour of the day, and year to year over the last decade. Over this time, the US electricity sector has undergone unprecedented changes that affect CO_2 emissions, due, largely, to a shift from coal to natural gas for generation and to greater reliance on renewable sources of energy (e.g., wind and solar) (7–14). Examining how marginal emissions have changed over this period is therefore especially informative, as significant shifts in the sources of electricity generation are also expected over the coming decade.

While changes in the electricity sector since 2010 have caused average emissions to decline 28% nationally, we find that marginal emissions have increased 7% over the same period. We also provide evidence on mechanisms underlying the divergence. Differences between coal and natural gas prices, which operate like a carbon tax in the electricity sector (9), and the coal share of generation capacity explain changes in average but not marginal emissions. One reason is a shift in the order of fuels used to meet electricity demand. Historically, coal has been used to meet base load, and natural gas has been used to follow marginal increases or decreases. More recently, however, changes in the electricity sector have pushed coal, which has the greatest CO_2 intensity, to more frequently be used as the marginal fuel for generation, thereby increasing marginal emissions. Another reason is that the utilization rates of coal generators have been

Significance

Marginal emissions of CO_2 from the electricity sector are critical for evaluating many climate policies. We provide estimates of marginal CO_2 emissions for electricity use in the United States that vary by region, hour of day, and year to year. Despite a decrease in average emissions over the last decade, marginal emissions have increased. We apply our estimates to an analysis of the Biden administration's target of having electric vehicles make up 50% of new vehicle purchases by 2030. We find that, without significant and concurrent changes to the electricity sector far more substantial than those over the last decade, the increase in electricity emissions is likely to offset more than half the emission reductions from having fewer gasoline-powered vehicles.

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falling, which decreases their efficiency and further increases marginal emissions.

Our findings have important implications for evaluating the CO_2 emissions of policies that either directly or indirectly cause shifts in the demand for electricity or in the need for fossil fuel generation, perhaps because of increased generation from renewable sources of energy. Higher marginal emissions means that adding new EVs to the stock of vehicles now causes more CO_2 emissions on the electricity grid than it did 10 y ago. In contrast, new conservation measures that reduce electricity demand will lower emissions more today than they did in 2010. And, similarly, the addition of renewable sources of generation is increasingly displacing higher-emitting fossil generation, thereby increasing the climate benefits of clean energy. An overarching policy implication of our findings is that the move to electrify everything combined with cleaning up the electricity grid is insufficient to maximize the climate benefits of these joint objectives. Policies are needed that lower both average and marginal emissions, and, as we show, eliminating coal-fired generation is the key to both over the next decade.

We illustrate the importance of our findings with an evaluation of the Biden administration's goal of having EVs account for 50% of US new vehicle purchases by 2030. While much of the focus on greater EV adoption is on the emission reductions that will come from burning less gasoline in internal combustion engines, less attention is paid to the increased emissions that will come from greater demand for electricity. Our estimates of marginal emissions are useful for making this calculation, in part because we find that they have not declined over the last decade despite the reduction in average emissions. Accordingly, without significant and concurrent changes to the electricity sector far more substantial that those over the last decade, the increase in electricity sector CO_2 emissions from meeting the Biden EV target would undo more than half of the reductions from reducing the number of gasoline-fueled, light-duty vehicles. Moreover, if one were to use average rather than marginal emissions to make the calculations, the emissions reductions would be overestimated by somewhere between 27% and 114%, depending on alternative assumptions about future trends in electricity emissions and policies that effect vehicle fuel economy. Our analysis underscores how the key to minimizing the undoing effect of electricity sector EV emissions is to link EV targets with clean energy goals to help ensure that increases in electricity demand are met with low-emission sources of energy.

Average Emissions

Over the last decade, total generation in the US electricity sector has remained relatively constant at just over 4,000 TWh per y, but the energy sources of generation have shifted (*SI Appendix*, Fig. S1 and Table S1). From 2010 to 2019, coal-fired generation declined 48%, and natural gas generation increased 58%. These shifts are due, in large part, to lower prices of natural gas brought about by hydraulic fracturing and the shale gas revolution (12, 15). Decreasing costs of renewable generation combined with government subsidies and mandates also caused the amount of wind and solar generation to increase significantly (16). As a share of total generation, wind and solar increased from 2 to 9%, and coal and natural gas decreased from 70 to 62%.

The result has been a decrease in average CO_2 emissions per kilowatt hour of generation in the United States as a whole and in all three grid interconnections, that is, East, West, and Texas (Fig. 1 and *SI Appendix*, Table S2). The interconnections (shown geographically in *SI Appendix*, Fig. S2) are important because they are an aggregation of the electricity system that captures the vast majority of electricity trading. Average emissions are uniformly lowest in the West, followed by the East and then Texas. In 2019, the magnitudes were 0.72 pounds of CO_2 per kWh in the West, 0.88 in the East, and 1.0 in Texas. The national load-weighted average was 0.86 pounds of CO_2 per kWh. Over the period 2010–2019, the average year-to-year decrease in average emissions is 2.2% for the West, 3.6% for Texas, and 3.8% for the East. The average annual decline for the United States is 3.5% per y, which is closest to the East, where the most electricity is generated (*SI Appendix*, Table S1). Underlying these differences in levels is the presence of relatively high-emitting coal generation, and differences in the rates of change are due to fuel shifts from coal to natural gas (13).

Marginal Emissions and Damages

Average emissions provide clear evidence on how CO_2 emissions per unit of generation are declining across the United States. Some studies use average emissions for policy analysis (17–22). However, it is estimates of marginal emissions that are needed to accurately evaluate the impacts of policies or behaviors that cause changes in the demand or supply of electricity (3–6).

There are two general approaches to estimating marginal emissions. The first uses regression models to determine the relationship between observed emissions and different measures of electricity output, including load (4, 6, 13, 23–27), fossil generation (10, 28–31), and renewable generation (11, 32–36). The second approach uses grid dispatch models, which are built up from theoretical and empirical assumptions (3, 37–40). These models are well suited for making forecasts such as those used to understand the environmental implications of future demand-side management programs (41, 42). Our approach here is to regress hourly emissions on overall hourly load within each interconnection, controlling for month-of-sample and hour-of-day fixed effects. Econometric advantages of this method are that it 1) captures all potential grid responses (ramping, dispatch, imports, etc.), 2) is identified by plausibly exogenous demand shocks, 3) controls for unobserved cost shocks, time trends, and predictable load shapes, and 4) includes an error correction for serial correlation. Moreover, in contrast to the grid dispatch models, our method does not require assumptions about firm behavior (e.g., price taking), information (e.g., potential gains from trade across markets), and grid availability (e.g., transmission capability and power plant outages). Any effects of these issues will be accounted for in our regression coefficients, although we cannot specify the degree to which any of them may play a role in the estimates.

The regression approach that we employ here is especially appropriate when analyzing how marginal emissions have changed over time, because it is based on observed data and can thus capture changes in the actual functioning of the electricity grid. The only directly comparable estimates of marginal CO_2 emissions, which are frequently employed in a broad range of applications, are based on data more than a decade old from 2007 to 2009 (4). We are also not aware of any existing studies that use regression analysis of observed electricity sector data to examine how marginal emissions have changed over time or the underling mechanisms thereof.

Marginal Emissions over Time. In contrast to average emissions, we find that marginal CO_2 emissions are increasing or remaining constant in all three interconnections (Fig. 1 and *SI Appendix*, Table S2). In addition to providing an estimate for each year in each region, we estimate linear trends in marginal emissions over time and find positive and statistically significant effects in the East and West, but not in Texas (Fig. 1 and *SI Appendix*, Table S3). Applying the estimated year-to-year changes, we find that, since 2010, marginal CO_2 emissions increased 6% in the East and 15% in the West. The increase in marginal emissions for the United States as a whole was 7% over the last decade, and this occurs despite the fact that average emissions declined 28% over the same period.

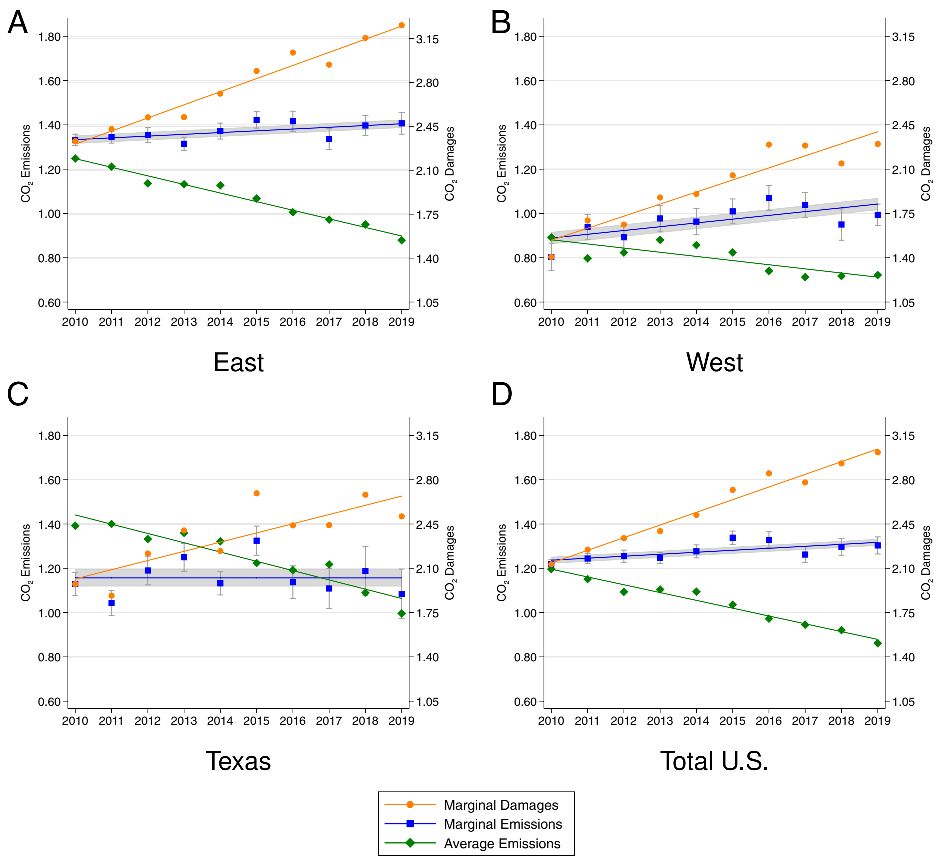

Fig. 1. Average CO_2 emissions, marginal CO_2 emissions, and marginal damages, 2010–2019. Emissions are reported in pounds per kilowatt hour. Damages are reported in cents per kilowatt hour in 2019 dollars. The average emissions trend lines are fitted to the 10 annual estimates in each interconnection. The trend lines for marginal emissions are predictions based on the linear models estimated in Eq. **2**, and the shaded areas represent the 95% CI. Marginal damages are multiplicative adjustments to marginal emissions based on the SCC (43, 44). The total US estimates are load-weighted averages of the estimates for each interconnection. (*A*) East. (*B*) West. (*C*) Texas. (*D*) Total US.

Marginal Economic Damages. We also estimate monetized damages of the marginal emissions (Fig. 1). These estimates are based on the product of marginal CO_2 emissions and the social cost of carbon (SCC) in each year. The SCC represents the economic value of damage caused by an additional ton of CO_2 emitted into the atmosphere in a given year. We value the SCC according to the standard approach adopted by the US government through 2016 (43) and reinstated in 2021 (44), using the central 3% discount rate scenario and converted to 2019 dollars (*SI Appendix*, Table S2). The SCC is increasing over time, in part, because the incremental damages worsen with a greater stock of CO_2 in the atmosphere and therefore greater climate change. The marginal damage curves illustrate that, when viewed from an economics perspective, the increase in marginal emissions over time is even more damaging—having increased 41% since 2010. Indeed, marginal emissions would need to be declining substantially over time for marginal damages to remain constant.

Results by Hour of the Day. Having established spatial and annual heterogeneity of marginal emissions, we now consider heterogeneity by hour of the day. Differences by hour of the day are important because many policies and behaviors intended to reduce emissions seek to encourage or discourage electricity consumption at particular times of day. Examples include technologies and policies designed to shift load to relatively low-emission or low-cost hours of the day (e.g., use of smart meters and time-of-use pricing) and targeting specific hours for EV charging. Indeed, previous studies (4) have shown how the timing of EV charging can have a significant effect on the emissions consequences, and the hour-by-region results reported here can be used to inform charging policy that seeks to minimize the environmental impacts.

Information on marginal emissions by hour of the day is also critical for accurately measuring the emission reductions associated with greater generation from wind and solar energy, which typically follows predictable patterns over a 24-h period. Because these sources of generation are nondispatchable and nonemitting, their effect on emissions is equivalent to a reduction in load. Estimates of hourly marginal emissions can therefore be used to calculate the associated emissions reductions.

Using the same regression approach, we provide estimates of marginal CO_2 emissions for each hour based on models where data are pooled for each 2-y period (Fig. 2 and *SI Appendix*, Tables S4–S7). The intraday marginal emissions vary in ways that do not follow average hourly load, underscoring the way that marginal emissions do not simply track electricity demand. The general trend in the East and West interconnections is one where marginal CO_2 emissions are increasing over time across most hours of the day. Texas is an exception, with marginal emissions showing less of a clear pattern over time and within hours of the day. One factor affecting the Texas results is likely the development of the Competitive Renewable Energy Zones project, which was constructed during the period of study and added significant transmission capacity between wind generators in west Texas and load centers in the rest of the state (35).

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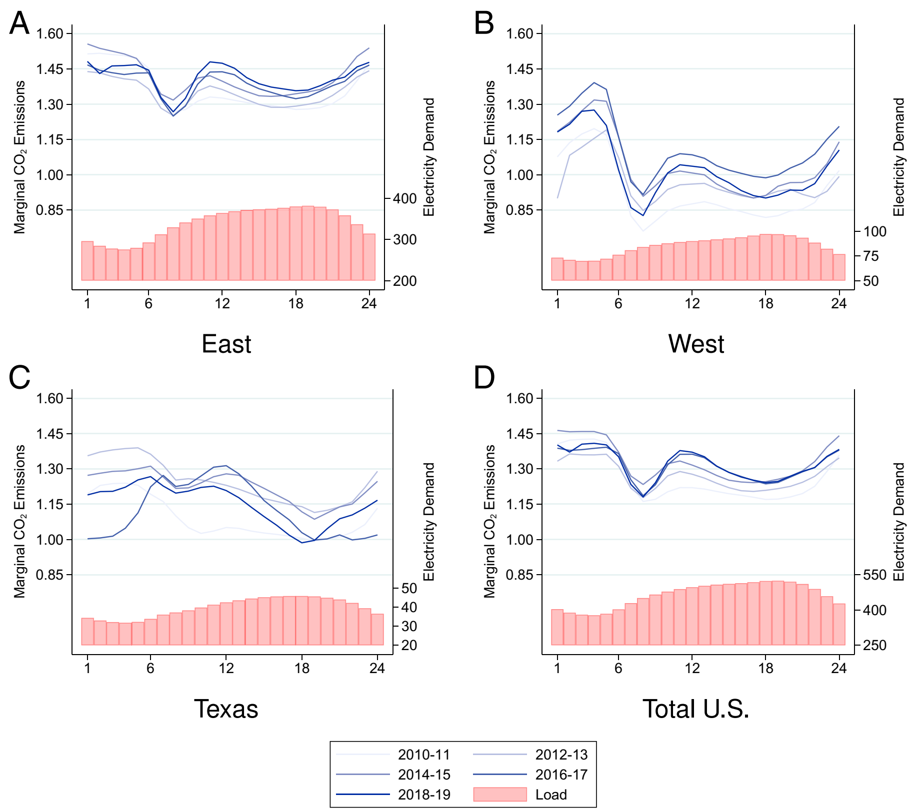

Fig. 2. Hourly marginal CO_2 emissions for each 2-y period, 2010–2019. Emissions are reported in pounds per kilowatt hour. Each panel also reports load by hour averaged over the decade, showing the change in demand for electricity over the course of a day. Load is reported in gigawatts. The total US estimates are load-weighted averages of the estimates for each interconnection. (*A*) East. (*B*) West. (*C*) Texas. (*D*) Total US.

Explaining the Divergence

We now consider two candidate explanations for why average and marginal CO_2 emissions are trending in opposite directions for most of the country. Fig. 3, *Top* shows how average and marginal emissions have changed by month of sample within each interconnection. The only difference between the points in Figs. 1 and 3 is that the latter are monthly rather than annual estimates. The pattern remains the same, with average emissions decreasing and marginal emissions increasing in the East and West. Fig. 3, *Middle* shows the relationship between each measure of emissions and the monthly ratio of coal to natural gas prices. These relative prices are an important determinant of which fuel is used to generate electricity, and previous research shows that the coal–gas price ratio has a useful interpretation as approximating a carbon tax (9). A higher ratio is consistent with a higher carbon tax, and Fig. 3 shows how this is associated with lower average emissions but no change in marginal emissions. Fig. 3, *Bottom* illustrates correlations with coal's share of total generation capacity, which we examine because of coal's high CO_2 emissions intensity. While lower coal-share capacity decreases average emissions, as expected, we again observe no relationship with marginal emissions.

We confirm the observations in Fig. 3 with regression analysis (*SI Appendix*, Table S8). The coefficient estimates are best interpreted as conditional correlations, because fuel prices and capacity shares are equilibrium outcomes rather than variables with plausibly exogenous variation. The results are statistically significant for average emissions only. The change in the coal–gas price ratio over the entire sample period, which has the equivalent effect of a \$37 per t carbon tax in the electricity sector (9), is associated with a 5.3% decrease in average emissions. The change in coal's share of generating capacity over the entire sample period, which dropped from 28.4 to 21.3%, is associated with a 23% decrease in average emissions. Together, these two effects predict nearly the exact reduction of 28% in average emissions that occurred between 2010 and 2019. While the effects on marginal emissions are not statistically significant, it is worth noting that the coefficient estimates, both within interconnections and for the nation as whole, have the opposite sign as those for average emissions.

Mechanisms Affecting Marginal Emissions

What then explains why marginal CO_2 emissions are increasing or remaining constant, despite average emissions decreasing? We consider two reasons for the trends in marginal emissions: changes in the fuel source of marginal generation and changes in the utilization rates of electricity generating units burning coal or natural gas.

Sources of Marginal Generation. While the use of coal has been declining for baseload generation (8–12), marginal emissions would increase if coal generation is becoming the more likely source of electricity for following shifts in load. Our statistical approach for examining this possibility is similar to that for estimating marginal emissions, except we now estimate models where the dependent variable is hourly aggregate generation (rather than emissions) either from all coal units or from all natural gas units. Coefficient estimates can therefore be interpreted as the probability that marginal load is met with generation from the fuel source included in the model.

We find that coal generation is indeed becoming more responsive to marginal changes in load over time (Fig. 4). In the West, for example, a 1-kWh increase in load in 2010 was associated with a 0.11-kWh increase in coal generation; however, 10 y later, the same increase in load was associated with a 0.22-kWh increase

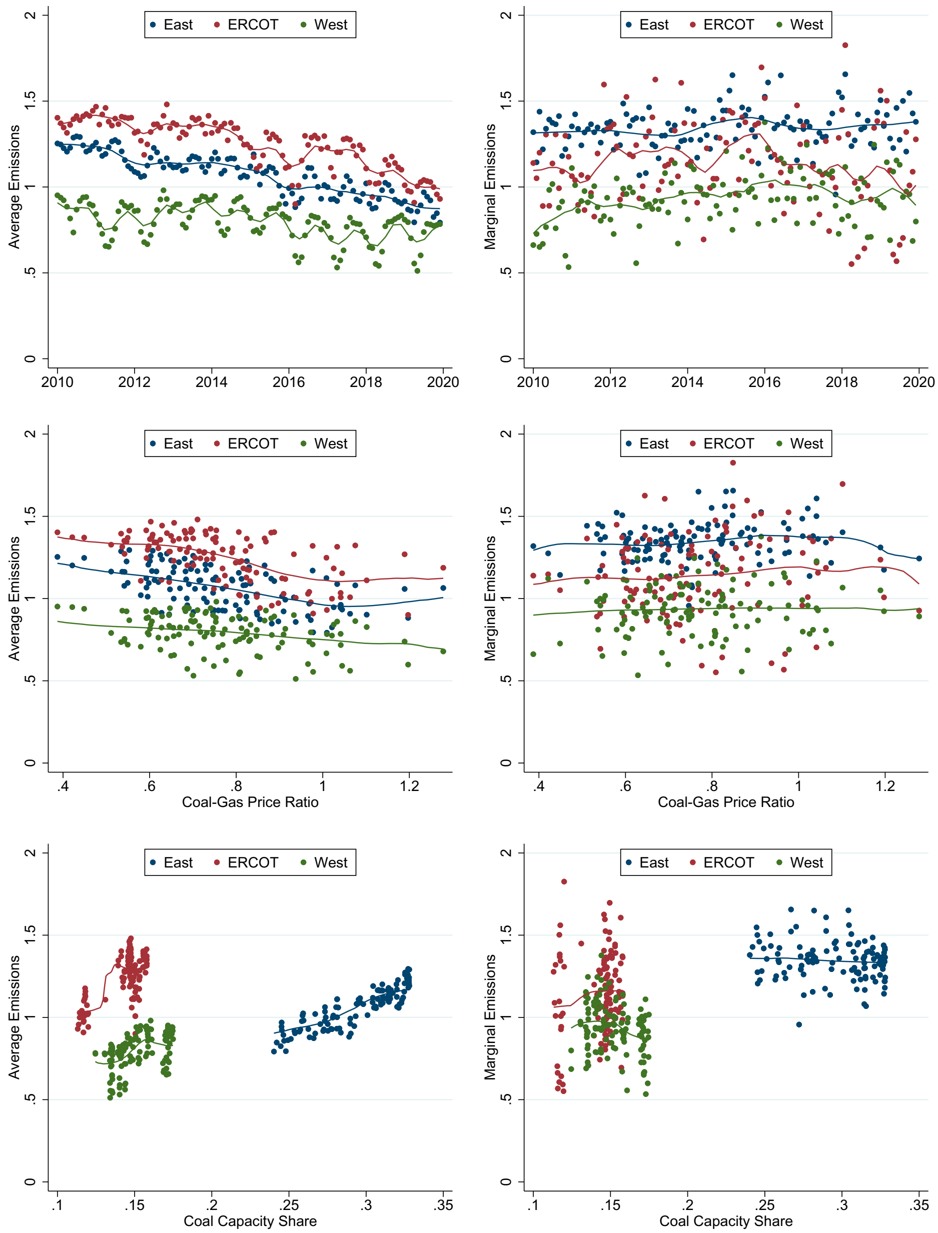

Fig. 3. Explaining the divergence between average and marginal emissions. ERCOT is the Electric Reliability Council of Texas. Monthly estimates by interconnection of average and marginal emissions are plotted against time (*Top*), the coal–gas price ratio (*Middle*), and the coal share of total generating capacity (*Bottom*). Lines are based on kernel-weighted local polynomial regressions.

in coal generation—a 100% increase. While the responsiveness of coal is both positive and statistically significant in all three interconnections, each region differs with respect to the responsiveness of natural gas (Fig. 4). The estimated probability of natural gas being used to follow load is increasing in the East, unchanging in the West, and decreasing in Texas. Natural gas has therefore tended to further increase marginal emissions in the East, have no effect in the West, and offset, to some extent, the effect of coal in Texas.

Utilization, Ramping, and Emission Rates. Utilization rates may further indicate which generating units are likely operating at the margin (45), because units that are operating at full capacity or are limited by ramping constraints may not have the ability to alter generation in response to changes in load. This means that showing less than full utilization rates or nonbinding ramping constraints indicates greater probabilities that generation is taking place at the margin. We find clear differences in the trends of utilization rates between coal and natural gas generation in all three interconnections (Fig. 5). Comparing early and late sample periods, coal and natural gas generation is taking place at lower and higher utilization rates, respectively. This pattern is consistent with an overall shift to coal increasingly being used to meet marginal load and thereby increasing marginal emissions. While the pattern has been demonstrated previously for selected electricity generating units (45), our analysis takes advantage of data across all units (totaling 140 million hourly observations) and illustrates the result across all three interconnections.

Taking ramping constraints into account yields further insight into how coal generation has shifted over the last decade. We identify the fraction of time that coal and natural gas units are unconstrained in the rate at which they can either ramp up or

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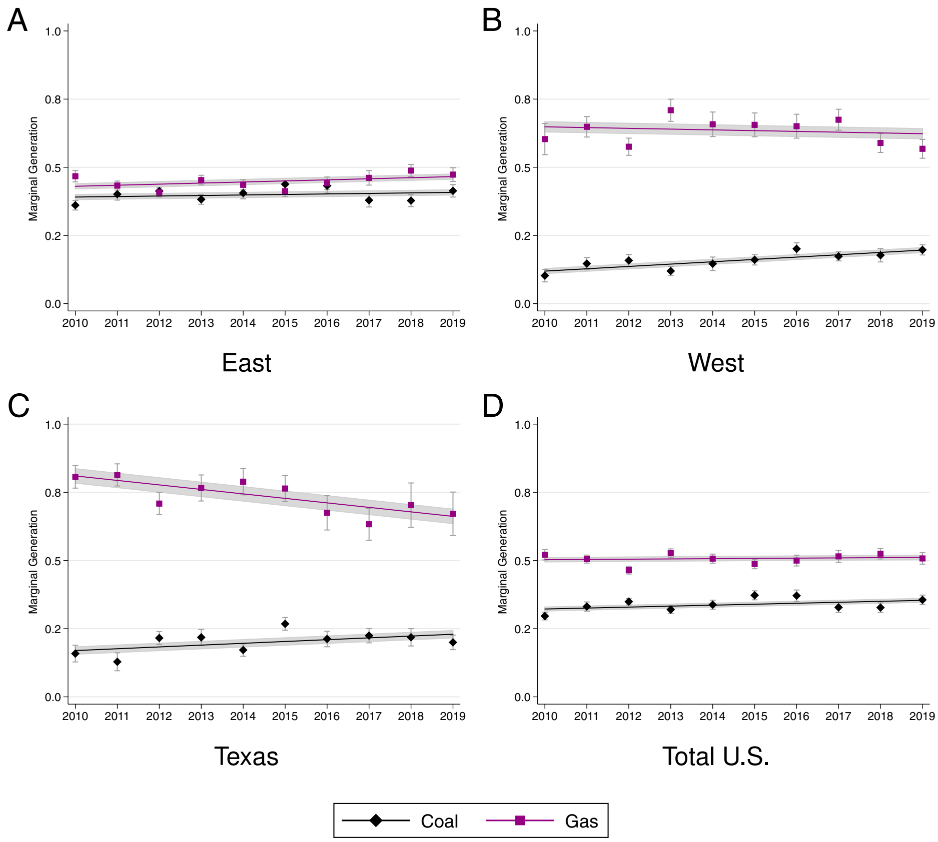

Fig. 4. Marginal coal and natural gas generation in response to load, 2010–2019. Generation is reported as the kilowatt hour response in generation to a kilowatt hour change in load within each hour. The interpretation is therefore the probability that marginal load is met by the corresponding source of generation. The trend lines are for predictions based on the linear models reported in *SI Appendix*, Table S10, and the shaded areas represent the 95% CI. The total US estimates are load-weighted averages of the estimates for each interconnection. (*A*) East. (*B*) West. (*C*) Texas. (*D*) Total US.

ramp down their generation based on unit-level observed rates of change over a decade (Fig. 6). We find little change in the fraction of time natural gas units are unconstrained between the early and late periods in all three interconnections. With respect to coal, however, we find significant changes in the West and Texas interconnections: The fraction of time that coal generation is unconstrained increases 39% in the West and 35% in Texas. These results provide further evidence that coal generation is unconstrained and therefore increasingly being used to follow shifts in electricity load.

The final set of results illustrate how lower utilization rates further increase marginal emissions. The engineering literature shows evidence that generating units that run at low capacity typically run less efficiently (46–49). Our data provide empirical evidence on the relationship between CO_2 emission rates and utilization (Fig. 7). We report the coal and natural gas results separately for each interconnection. The pattern is clear: When the hourly utilization rate is lower within a unit, its emission rate is higher (see also *SI Appendix*, Fig. S3 and Table S15). The observation that coal units are growing more likely to generate at the margin, and with lower utilization rates, provides two reinforcing explanations for why marginal emissions are increasing. At the same time, the observation that natural gas units are growing more likely to generate base load, and with higher utilization rates, provides a further explanation for why average emissions are decreasing. Decomposing the change in marginal emissions between a probability effect and a utilization effect, we find that the probability effect explains the vast majority of the change in marginal emissions that we estimate over the entire sample period.

Biden's 2030 EV Target

Estimates of marginal emissions are a key input for evaluating the emission impacts of electricity-shifting climate policies. Take, for example, the Biden administration's new target for EVs to make up half of all new vehicle sales by 2030 (2). How will achieving this target affect US CO_2 emissions? The answer depends on the net effect of two impacts. First is the emissions avoided by displacing sales of vehicles with internal combustion engines. Second is the increase in emissions due to the need for greater electricity generation, and the magnitude of this effect depends critically on marginal emissions.

Fig. 8 summarizes results for a range of scenarios in 2030. The avoided emissions from gasoline-powered vehicles will depend on the future fuel economy of new vehicles sold, yet there is uncertainty about what regulations will be implemented over the next decade. We thus consider a range of scenarios that span plausible outcomes, from a baseline of no change in the fuel economy of light-duty vehicles to a scenario where it improves 5% per y. Accordingly, we estimate that, in 2030, the emission reduction associated with the displacement of gasoline-powered vehicles from having just under 60 million EVs on the road (i.e., the number consistent with reaching the Biden target on a linear trend) will range between 171 million metric tons and 235 million metric tons of CO_2. At the same time, powering the fleet of EVs will require an increase in electricity generation. By 2030, the cumulative total of new generation required is ~176 million kWh, a quantity equal to 4% of total generation in 2019.

Using our estimates of marginal emissions—either the most recent estimate for 2019 (*SI Appendix*, Table S2) or a case where it increases 0.9% per y (*SI Appendix*, Table S3)—we find that

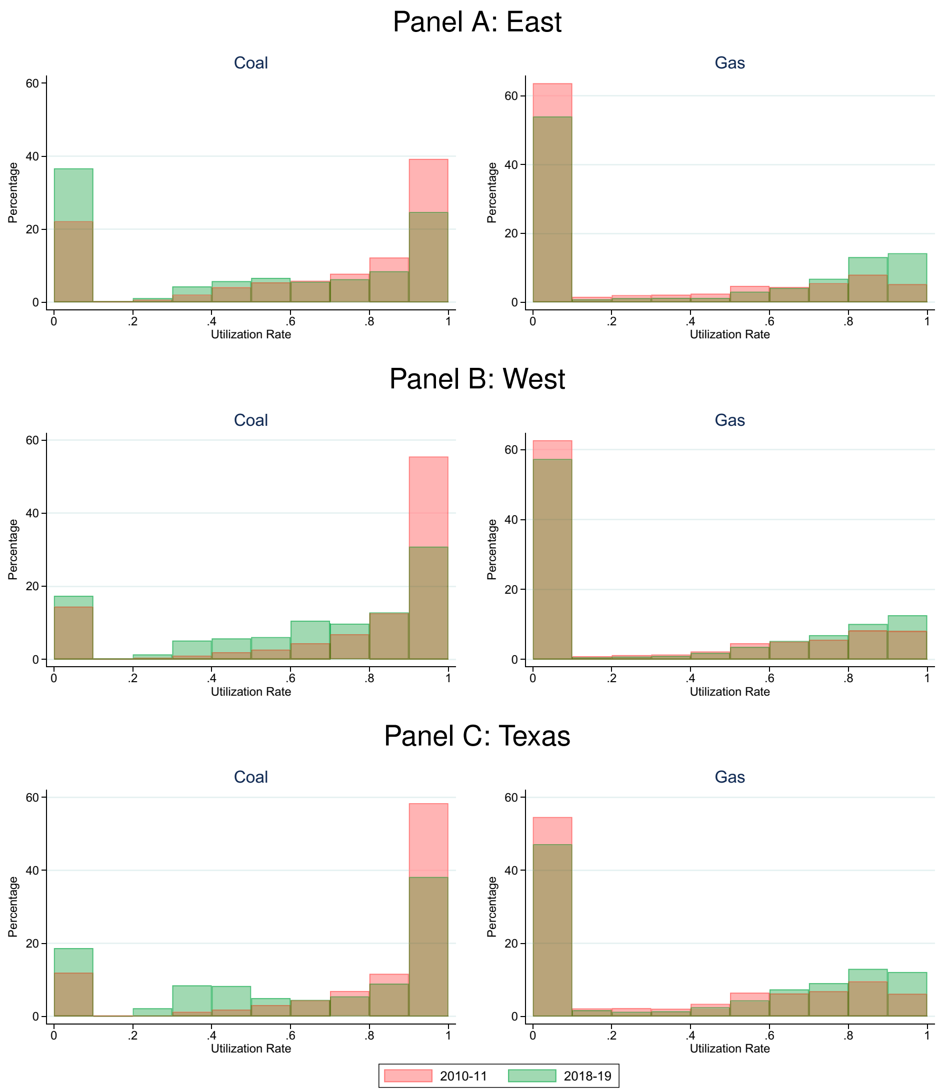

Fig. 5. Change in utilization rates of coal and natural gas generation within interconnections from 2010–2011 to 2018–2019. Each panel indicates the shift in the density function of generation over utilization rates. Utilization rate is defined as the ratio of hourly generation to capacity. We measure capacity as the 99th percentile of each generating unit's hourly generation over the entire 10-y sample period. Utilization rates are weighted by unit capacity. Data for the intermediate set of time periods are included in *SI Appendix*, Tables S11 and S12. (*A*) East. (*B*) West. (*C*) Texas.

the increase in electricity demand will increase CO_2 emissions between 104 and 114 million metric tons in 2030. Accounting for this undoing effect, the net reduction in emissions across scenarios ranges between 57 million metric tons and 131 million metric tons (Fig. 8). Importantly, these net reductions, which take account of shifts in the electricity sector, are, in most scenarios, less than 50% of the emissions reduction in the transportation sector alone.

While marginal emissions are the key to making the calculations accurately, it is useful to contrast the results with those that would arise if one were to employ average emissions instead. For, as noted previously, average emissions are sometimes used for policy evaluation despite the fact that shifts in electricity demand are associated with different sources of generation than what characterizes the grid on average. Using the average emission rate compared to the marginal emissions rate in 2019, one would estimate increases in emissions due to electricity generation that are 34% less (Fig. 8). Alternatively, assuming average emissions continue to decrease 3.5% per y while marginal emissions increase 0.9% per y, one would underestimate the increase in electricity sector emissions by 58% (Fig. 8), thereby making the EV target appear substantially more beneficial for reducing US CO_2 emissions. In terms of the overall net effects, the overestimates would range between 27% and 114%.

These results underscore the importance of using marginal emissions to evaluate electricity-shifting policies, especially while coal and natural gas remain a substantial portion of the electricity-generating fuel mix. And evidence suggests this is likely to be the case for quite some time without significant policy interventions. For example, the US Energy Information Administration (EIA) predicts that, even in a scenario with low costs of renewable sources of generation, coal and natural gas generation will account for 15% and 32% of total generation in 2030 and 12% and 30% in 2050 (50). This suggests that the last decade, which itself was subject to significant shifts in the sources of electricity generation, is likely to provide reasonable estimates of marginal emissions over the coming decade.

Concluding Remarks

We provide annual and hourly estimates of marginal CO_2 emissions from electricity generation in the United States using the most recently available and comprehensive set of data. The

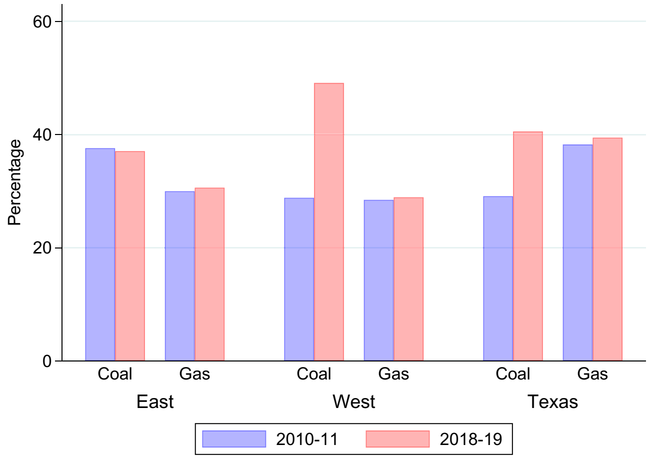

Fig. 6. Percentage of time coal and natural gas generation is unconstrained, 2010–2011 and 2018–2019. A unit is considered unconstrained if its utilization rate is greater than 0 and less than 0.9 of its capacity, and its ramping rate (up or down) is less than 90% of the maximum ramping rate, as defined in *Materials and Methods*. The hourly observations are weighted by unit capacity. Data for the intermediate set of time periods are included in *SI Appendix*, Tables S13 and S14.

estimates, which are available by grid interconnection and for the contiguous United States overall, are a critical input for evaluating climate policies that directly or indirectly shift electricity demand, supply, or both. Researchers seeking to evaluate the climate impacts of electricity-shifting policies or behaviors can readily employ the estimates reported here. Possible applications include detailed evaluations of the emissions impacts of expanding the fleet of EVs, greater electricity generation from renewable sources of energy, and time-of-use incentives for load shifting.

We also identify a widening gap between average and marginal emissions on the US electricity grid. The significant drop in CO_2 emissions from the US electricity sector over the last decade is reflected in decreasing average emissions. However, we show that marginal emissions have been increasing over the same period. Coal-fired units are increasingly being used to meet marginal load, and this trend has increased marginal emissions for the United States as a whole and for the East and West interconnections in particular. When converted into the economic impacts of these emissions, valuing them with the SCC, marginal damages are increasing at an even faster rate.

Our particular application of marginal emissions to analysis of the Biden administration's 2030 EV target highlights two important points. First, without significant and concurrent changes to the electricity sector (i.e., far more substantial that those over the last decade), the increase in electricity emissions is likely to offset more than half of the emission reductions from having fewer gasoline-powered vehicles on the road. Second, using estimates of average rather than marginal emissions to predict the intended impacts will produce a significantly overoptimistic forecast about the potential benefits for reducing CO_2 emissions.

More generally, the promise of many electricity-shifting policies for reducing emissions depends, to a large extent, on how electricity generation will change in the future, and the success of many policies is highly dependent on a transition to more low-emission sources of generation. Our reduced form approach thus accords with the results of recent structural approaches showing how the effectiveness of EV targets for reducing emissions is closely tied to complementary policies in the electricity sector (51). Moreover, our results underscore the particular need for policies that effectively lower both average and marginal emissions. With current technologies, the obvious approach for meeting this dual objective is to eliminate coal-fired generation over the next decade.

Materials and Methods

Average Emissions. We obtained data on hourly CO_2 emissions of electricity generating units from the US Environmental Protection Agency's (EPA) Continuous Emission Monitoring System (CEMS) (52). This includes most fossil fuel generating units with at least 25 MW of generating capacity. Data on hourly system-wide electricity use (i.e., load) were obtained from the Federal Energy Regulatory Commission's form 714, which is reported at the level of grid planning areas across the United States (53). Both the emissions and load data were aggregated up to the grid interconnection level, producing a dataset of matched emissions and load for all hours 2010–2019 in the East, West, and Texas interconnections. The average annual emission rate in each interconnection is simply the ratio of the annual sum of emissions divided by the annual sum of load, and the US total is a load-weighted average across the three interconnections (*SI Appendix*, Table S2).

Marginal Emissions and Damages. Building on the methods in previous studies (4, 6), our econometric model for producing an annual estimate of marginal emissions for each interconnection is specified as

$$CO2_t = \beta Load_t + \alpha_{mh} + \epsilon_t, \qquad [1]$$

where $CO2_t$ is emissions (in million pounds) in hour t, $Load_t$ is electricity usage (in million kilowatt hours) in hour t, and α_{mh} represents month-of-sample m by hour-of-day h fixed effects (i.e., 1 y $\times$ 12 mo $\times$ 24 h). The coefficient β is interpreted as the hourly change in emissions given a change in load, averaged across all hours of the year, taking account of monthly differences by hour of day. We estimate Eq. **1** separately for each year and interconnection. The coefficients are reported in Fig. 1, along with the load-weighted averages for the US total. The full set of coefficient estimates are reported in *SI Appendix*, Table S2, along with the Newey–West SEs using 48-h lags.

We examine linearity of the relationship between emissions and load. To do this, we separately regress emissions and load on hour-of-day with month-of-sample fixed effects and retain the residuals. We then compare a local polynomial regression of the residuals for emissions on the residuals for load and the fitted line from a linear regression of the residual for emissions on the residuals for load. The local polynomial is very close to our fitted line over the range of observed data (*SI Appendix*, Fig. S4).

We estimate the trend in marginal emissions over time using the entire sample period from 2010 to 2019. Specifically, we estimate the following equation for each interconnection:

$$CO2_t = \beta Load_t + \gamma Load_t \times Year_t + \alpha_{mh} + \epsilon_t, \qquad [2]$$

where $Year_t$ is a time trend that starts at zero in 2010, and α_{mh} are month-of-sample by hour-of-day fixed effects (i.e., 10 y $\times$ 12 mo $\times$ 24 h). The coefficient β is an estimate of marginal emissions in 2010, and the coefficient of primary interest γ is a linear estimate of the annual change in marginal emissions over the whole sample period. These are the trend lines for marginal emissions shown in Fig. 1, with a weighted average across interconnections for the US total. The coefficient estimates and SEs are reported in *SI Appendix*, Table S3.

Additional regression models are used to estimate marginal emissions by hour of day for each 2-y interval over the sample period (Fig. 2). For each interconnection and 2-y period, we estimate

$$CO2_t = \sum_{h=1}^{24} \beta_h Hour_h \times Load_t + \alpha_{mh} + \epsilon_t, \qquad [3]$$

where $Hour_h$ is an indicator variable for each hour of the day and the fixed effects span 2 y (i.e., 2 y $\times$ 12 mo $\times$ 24 h). The key feature of Eq. **3** is that β_h is an estimate of marginal emissions for each hour of the day, and our estimation of the model over 2-y intervals enables a comparison of how the hourly estimates change over time. The full set of coefficients for each interconnection and the weighted averages for the US total are reported in *SI Appendix*, Tables S4–S7.

Explaining the Divergence. We create the coal–gas price ratio and the coal share of generation capacity variables as follows: We use EIA data on weekly coal spot prices for five types of coal (50). We calculate the monthly average (in dollars per metric million British thermal units). These prices are compared with the delivered coal prices from EIA form 423 to determine an average delivery fee (~65 cents per metric million British thermal units).

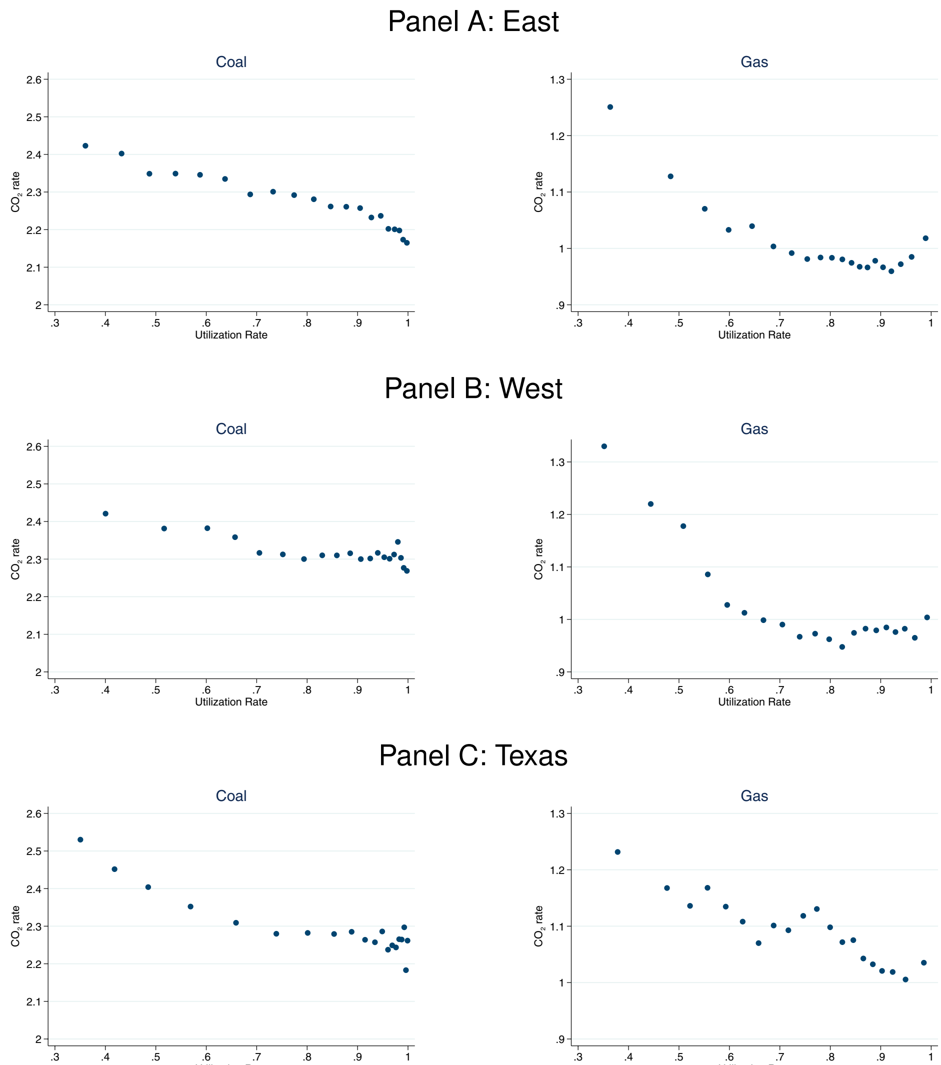

Fig. 7. CO_2 emission rates vs. utilization rates, 2010–2019. The figure shows a binned scatterplot based on data by hour and generating unit. The emission rate is reported as pounds per kilowatt hour. *SI Appendix*, Fig. S3 is a companion figure that shows the relationship between emission rates and utilization rates based on within-unit variation only. (*A*) East. (*B*) West. (*C*) Texas.

The monthly averaged coal prices plus the average delivery fee are divided by the monthly spot price of natural gas at the Henry Hub, and this produces our measure of the coal–gas price ratio. For the coal share of generation capacity, we use EIA form 860, which reports the amount of capacity by generation source for each month of the sample within each interconnection.

The regression results reported in *SI Appendix*, Table S8 as based on the following specifications. For average emissions by month of sample, $CO2_m/Load_m$, we first estimate

$$\frac{CO2_{mi}}{Load_{mi}} = \gamma Ratio_m + \psi Share_m + \alpha_m + \mu_i + \epsilon_{mi}, \quad [4]$$

where identification is based on within-interconnection variation, because we include interconnection fixed effects μ_i. The total US results are based on taking the national average and dropping μ_i. Both models include Newey–West SEs with a 2-mo lag. Models examining the effects on marginal emissions follow the same progression, with the left-hand variable being the only difference. The dependent variable in the first set of results is the estimate of marginal emissions by interconnection and month of sample (i.e., those shown in Fig. 3, *Top*). The second set of results for the nation as a whole use a load-weighted average of the marginal emission estimate for each interconnection in each month of sample.

Mechanisms Affecting Marginal Emissions. CEMS provides hourly gross generation for electricity generating units that the EPA identifies as primarily burning coal or natural gas. We convert gross generation to net generation (production less power used at the plant) using the ratio of each plant's annual net generation from EIA form 923 over the annual gross generation from CEMS. The annual estimates for each interconnection shown in Fig. 4 are based on specification Eq. **1**, where the only difference is that the dependent variable is hourly aggregate generation either from all coal units or from all natural gas units, with a separate model estimated in each case. The full set of results are reported in *SI Appendix*, Table S9.

We calculate utilization rates for electricity generating units based on each unit's observed CEMS generation data. In particular, the utilization rate for any given period is the average hourly generation over capacity, where, to eliminate outliers, capacity is defined as the 99th percentile of each unit's hourly generation over the 10-y sample period. For the comparisons in Fig. 5, utilization is weighted by unit capacity, and this means that a shift in the density function indicates whether overall coal generation is more or less likely to occur at different utilization rates over time.

We calculate ramping constraints using the same CEMS generation data. For each unit, we use adjacent hours to calculate the distribution of ramping rates (up and down) over the entire 10-y sample period. We define the maximum ramp up rate as the 99th percentile of the distribution and the maximum ramp-down rate as the first percentile of the distribution. We then define hourly generation as unconstrained if utilization is greater than 0 and less than 0.9 and the ramp-up is less than 90% of the ramp-up maximum or the ramp-down is less than 90% of the ramp-down maximum. Aggregating these hours across all units and weighting by unit capacity (defined above)

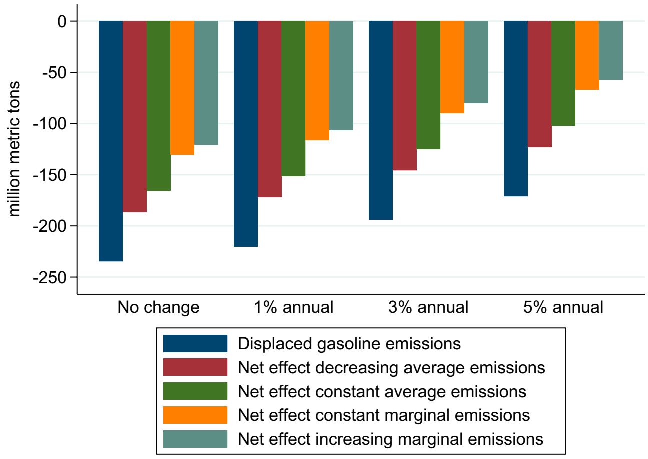

Fig. 8. The CO_2 emissions consequences in 2030 of EVs making up 50% of new vehicle purchases by that same year. The analysis assumes a linear trend of increased EV purchases (see *Materials and Methods*). Displaced gasoline emissions show the reduction in emissions due to fewer gasoline-fueled vehicles in 2030 under four scenarios: no change in fuel economy standards (No change) and cases with 1%, 3%, or 5% annual improvements to 2030. The other bars indicate the net effect after taking account of increased emissions from greater electricity generation under four different assumptions. Average emissions are used for purposes of comparison at the constant 2019 level and assuming a 3.5% annual decrease. The preferred estimates are based on marginal emissions using the 2019 estimate and assuming a 0.9% annual increase.

produces the unconstrained percentage of time estimates in Fig. 6. One caveat to the approach is that unconstrained units may still face network transmissions constraints, which are unobservable, but we do not believe taking account of these would materially change the findings. Another caveat is that units may be constrained by minimum load requirements that limit them from reducing generation; these vary by technology and vintage and are not included in our data.

Next, we examine the relationship between CO_2 emission rates and utilization rates using hourly data for all coal and natural gas units over the 2010–2019 sample period. Fig. 7 reports binned scatterplots of these rates in levels. For purposes of comparison, *SI Appendix*, Fig. S3 uses data that are demeaned within each unit, and this implies that variation is based on within-unit differences and therefore takes account of technical differences between electricity generating units. The lines included in each panel of the figure are from a regression of the CO_2 emission rates on utilization rates with fixed effects at the unit level. *SI Appendix*, Table S15 shows the coefficient estimates.

We have considered two explanations for the change in marginal emissions over time: changes in the probability that coal or natural gas generation is operating at the margin and changes in coal and natural gas utilization rates that affect efficiency. We now consider a decomposition of changes in marginal emissions to provide a sense for the relative magnitudes of these effects. The estimate of marginal emissions at any given point in time can be expanded as

$$\beta = \beta_c \times p_c + \beta_g \times p_g + \beta_o \times (1 - p_c - p_g), \qquad [5]$$

where β_c, β_g, and β_o are the marginal emissions from coal, natural gas, and other sources operating at the margin, and p_c and p_g are the probabilities that coal and natural gas are operating at the margin. Totally differentiating Eq. **5**, and recognizing that the other dispatchable generation is primarily hydro with zero emissions so that $\beta_o \approx 0$, we can write

$$\Delta\beta = [\beta_c \Delta p_c + \beta_g \Delta p_g] + [\Delta\beta_c p_c + \Delta\beta_g p_g], \qquad [6]$$

where we denote the first term surrounded by brackets as the "probability effect," and the second term as the "utilization effect." The probability effect captures the net change in marginal emissions due to the change in probabilities of operating at the margin, holding marginal emissions constant. The utilization effect captures the change in marginal emissions due to the change in coal and gas utilization rates, holding the probabilities of operating at the margin constant.

To quantify the effects, we estimate the probability effect in Eq. **6** and compare it to our estimate of how β changes over the sample period for all three interconnections. Estimates of Δp_c and Δp_g for each interconnection are the load trend coefficients in *SI Appendix*, Table S10. We approximate β_c and β_g with the average emissions for coal and natural gas units during hours when they are operating unconstrained as defined for Fig. 6. Estimates of the probability effects are then as follows:

- East: $2.215 \times 0.002 + 0.952 \times 0.004 = 0.008$;
- West: $2.272 \times 0.009 - 0.944 \times 0.003 = 0.018$; and
- Texas: $2.329 \times 0.007 - 1.013 \times 0.016 = -0.000$.

These estimates can be compared with the estimates of $\Delta\beta$ over the sample period, which are the load trend coefficients in *SI Appendix*, Table S3. These are 0.008 for the East, 0.017 for the West, and -0.000 for Texas, which are virtually identical to estimates of the probability effects. We thus conclude that the probability effect explains the vast majority of the change in marginal emissions from 2010 to 2019.

Biden's 2030 EV Target. Many assumptions are needed to provide estimates of the CO_2 emissions consequences of having EVs make up 50% of new vehicle purchases by 2030. However, given our focus on comparisons across scenarios, where many of the key assumptions remain constant, the assumptions themselves are less critical, and the analysis can readily accommodate alternatives.

We assume new, light-duty vehicle sales of 16 million in 2030. This number is less than the 17 million sold in 2019 and more than the 14.5 million sold in 2020 (54). We assume a linear path to the 2030 target of 8 million EV purchases. *SI Appendix*, Table S16 provides the sales and cumulative stock of EVs for each year. The predicted total stock of EVs in 2030 is 50.9 million, which accounts for 20% of all operating light-duty vehicles, assuming the total number remains constant at the 2019 number of 253.8 million (55). Assuming, further, that total vehicle miles traveled (VMT) remains constant at 2,924 billion miles and is the same for EVs and non-EVs (56), the total EV VMT in 2030 is projected to be 586.8 billion miles (*SI Appendix*, Table S16). Finally, assuming 0.3 kWh per mi (57), this implies an EV-induced increase in electricity demand of 176 TWh in 2030, an amount equal to 4.3% of total generation in 2019. See *SI Appendix*, Table S16 for annual estimates of the cumulative EV VMT and electricity demand.

To estimate the reduction in emissions from displaced gasoline-fueled vehicles, we consider four different scenarios because of uncertainty in future fuel economy regulations. The first is no change in the average fuel economy of light-duty vehicles. In this case, the reduction is based simply on the product of EV VMT and the estimate of 4.6 t of CO_2 per 11,500 VMT (58). The other three scenarios are based on assumptions of a 1%, 3%, and 5% increase in fuel economy per year. In these cases, the fuel economy of the gasoline-powered vehicles that are displaced in each year has lower emissions per VMT corresponding with the different rates of each scenario.

We also consider four different scenarios for estimates of the increase in electricity emissions. The first assumes our 2019 estimate of marginal emissions for the nation at 1.303 pounds per kWh (*SI Appendix*, Table S2). The second assumes the estimate increases at 0.9% per y out to 2030 (*SI Appendix*, Table S3). The other two scenarios, for purposes of comparison, are based on average emissions. The first uses the 2019 estimate for the nation at 0.862 pounds per kWh. The second assumes the estimate follows the same path of decreasing at 3.5% per y out to 2030.

Data Availability. All data used in this study are publicly available and can be found through the referenced sources.

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