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Regional Variability and Uncertainty of Electric Vehicle Life Cycle CO_2 Emissions across the United States

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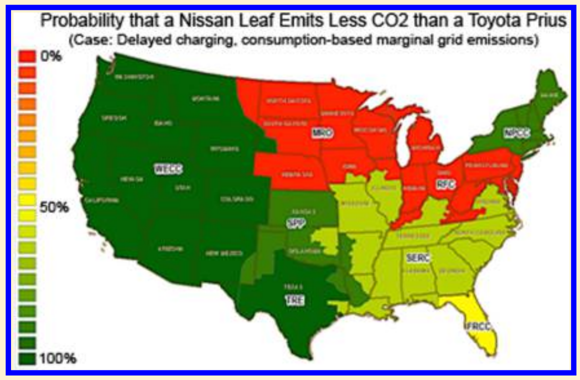
Supporting Information

ABSTRACT: We characterize regionally specific life cycle CO_2 emissions per mile traveled for plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) across the United States under alternative assumptions for regional electricity emission factors, regional boundaries, and charging schemes. We find that estimates based on marginal vs average grid emission factors differ by as much as 50% (using National Electricity Reliability Commission (NERC) regional boundaries). Use of state boundaries versus NERC region boundaries results in estimates that differ by as much as 120% for the same location (using average emission factors). We argue that consumption-based marginal emission factors are conceptually appropriate for evaluating the emissions implications of policies that increase electric vehicle sales or use in a region. We also examine generation-based marginal emission factors to assess robustness. Using these two estimates of NERC region marginal emission factors, we find the following: (1) delayed charging (i.e., starting at midnight) leads to higher emissions in most cases due largely to increased coal in the marginal generation mix at night; (2) the Chevrolet Volt has higher expected life cycle emissions than the Toyota Prius hybrid electric vehicle (the most efficient U.S. gasoline vehicle) across the U.S. in nearly all scenarios; (3) the Nissan Leaf BEV has lower life cycle emissions than the Prius in the western U.S. and in Texas, but the Prius has lower emissions in the northern Midwest regardless of assumed charging scheme and marginal emissions estimation method; (4) in other regions the lowest emitting vehicle depends on charge timing and emission factor estimation assumptions.



1. INTRODUCTION

To address climate change, move toward more sustainable energy systems, and improve the security of energy supply, new technologies and strategies are needed in the transportation sector. In the United States, transportation accounted for about 28% of U.S. greenhouse gas (GHG) emissions[1] and about 28% of total U.S. primary energy consumption[2] in 2012. Vehicle electrification has been proposed as a way to reduce emissions, and much attention has been paid to comparisons of life cycle GHG emissions between plug-in electric vehicles (PEVs) and gasoline vehicles in the United States[4−18,20,21] as well as in Europe[6,22−26] and Asia.[27−29]

Most studies indicate that the key factor when comparing PEVs and gasoline vehicles is the magnitude of emissions associated with electricity production. However, many of these studies rely on a single electricity production emission factor estimate or conduct sensitivity analyses on grid emission factors over a range of power plant types. A more detailed assessment is needed to estimate regionally specific emissions from those power plants that respond to PEV charging.

In Table 1 we summarize recent studies that have focused on a regional comparative analysis of electric and gasoline vehicle CO_2 emissions in the U.S. For illustrative purposes, in the Supporting Information (SI) we provide a set of maps that highlight differences in two of these analyses. These studies vary in life cycle scope, vehicle assumptions, regional boundaries, and grid emission factors. In particular, variation in grid emission factors and regional boundaries are key drivers of differences in the estimates of regional PEV benefits.

We examine how the regional variation in emissions from electrified vehicles differ depending on the assumptions regarding (a) whether marginal emission factors (MEFs) or average emission factors (AEFs) for electricity production are used, (b) whether generation- or consumption-based emission factors are used, (c) regional boundaries of analysis, and (d) charging time. Marginal emission factors represent the emission

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Table 1. Summary of Recent Studies Focusing on Comparative Regional Analysis of Greenhouse Gas Emissions of Electric and Gasoline Vehicles in the U.S.[a]

	Graff Zivin et al. (2014)[3]	Yawitz et al. (2013)[4]	Anair and Mahmassani (2012)[5]	EPRI-NRDC (2007)[15]
institution(s)	UCSD, Yale, Dartmouth, NBER	Climate Central	Union of Concerned Scientists	EPRI and NRDC
publication type	peer-reviewed journal paper	report	report	report
regional definition used	8 NERC regions	50 states	26 eGRID subregions	13 NERC subregions
gasoline or hybrid vehicles considered	avg gasoline (21.7 mpg); avg comparable economy car (31 mpg); 2012 Toyota Prius Hybrid (50 mpg)	Toyota Prius Hybrid (50 mpg); avg new gasoline cars (25 mpg); other gasoline cars in market	Toyota Prius Hybrid (50 mpg); avg new gasoline vehicle (27 mpg); other gasoline cars in market (EPA 2012 combined city/highway)	avg 2010 ICEV: 24.6 mpg avg 2010 HEV: 37.9 mpg
VMT	35 mi/day	50 000 and 100 000 mile/vehicle	166 000 mi/vehicle	12 000 mi/yr
scope of CO_2 emissions covered	gasoline combustion; production of electricity	well-to-wheels (WTW) for gasoline; upstream and production for electricity; life cycle	WTW for gasoline; upstream and production for electricity	WTW for gasoline; upstream and production for electricity
years	2007 to 2009	2010, 2012	2009	2010 to 2050
data sources	CEMS, EPA	EIA, GREET	2009 eGRID, GREET	NEMS, MOBILE6
electricity emission factors	marginal regional consumption	average regional generation	avg regional generation covering transmission and upstream loss (286−983 g CO_2 e/kWh)	regional bottom-up model (573 g CO_2 e/kWh in 2010; 97−412 g CO_2 e/kWh in 2050)
electric vehicles considered	2012 Nissan Leaf (0.34 kWh/mi) and 2012 Chevrolet Volt (0.36 kWh/mi)	2013 Nissan Leaf (0.29 kWh/mi); other PEVs in the market	2012 Nissan Leaf (0.34 kWh/mi); Mitsubishi "i" (0.3 kWh/mi); Chevrolet Volt (0.36 kWh/mi, 37 mpg)	2010 PHEV (10, 20, 40): (0.312 kWh/mi, 37.9 mpg)
electric vehicle utility factor	not stated	PHEV: 0.5	Chevrolet Volt: 0.64	PHEV10:0.12, PHEV20:0.49, PHEV40:0.66
gasoline emission factors	8.9 kg CO_2/mi	11.8 kg CO_2 e/gal	11.2 kg CO_2 e/gal	11.1 CO_2 e/gal
key findings	PEV (Chevrolet Volt) is lower emitting only in WECC and Texas and higher emitting than the Toyota Prius in MRO. PEVs have higher CO_2 emissions when charged from midnight to 5 am	the HEV (Toyota Prius) has lower CO_2 emissions than the BEV (Honda Fit) in 39 states over the first 50 000 miles; over 100 000 miles, the BEV is better in ID, OR, VT, and WA	the BEV (Nissan Leaf) is lower emitting than the average gasoline vehicle throughout the U.S.; the PEV is lower emitting than the Prius in about half of populated America	in low to high GHG grid mix and market penetration levels, PHEVs have lower CO_2 emissions than both hybrid (by 7−46%) and conventional gasoline vehicles (by 40−605%)

[a]ICEV: internal combustion engine vehicle; HEV: hybrid electric vehicle; PHEV: plug-in hybrid electric vehicle; BEV: battery electric vehicle.

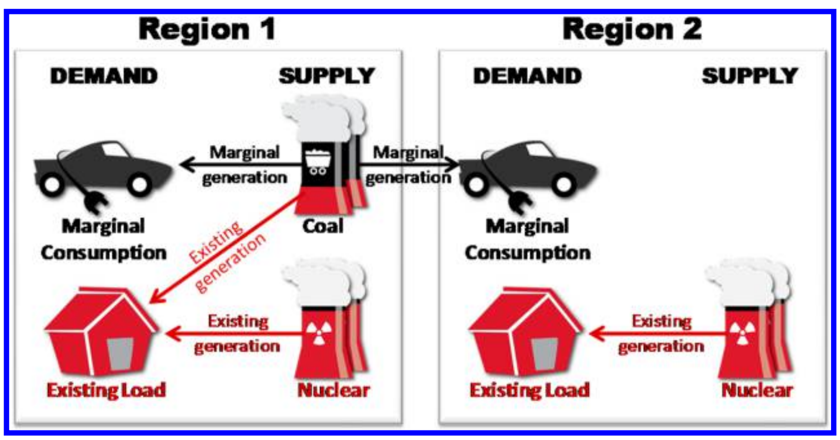

Figure 1. Conceptual illustration of emissions associated with average generation, marginal generation, and marginal consumption.

rates associated with the power plant(s) that would increase generation in response to new load at a particular time and location. Identifying which plants respond on the margin is difficult in practice because the electricity grid is a highly interconnected network, moving supply from geographically diverse generators to geographically diverse demand locations within and between regions dynamically, while responding to economic signals and technical factors such as ramp rates, downtime, frequency regulation, and transmission constraints. It is therefore difficult in practice to know precisely which power plant(s) will ramp up production in response to a new load at a given time and location.

Given this difficulty, several studies of regional PEV emissions employ readily available estimates of average regional generation mix instead, as shown in Table 1. For example, Anair and Mahmassani[5] use average generation emissions within each eGRID subregion, and Yawitz et al.[4] use average generation emissions within each state. Weber et al.[19] emphasize that regional emissions differ substantially under alternative definitions of regional boundaries, accounting for some of the differences between the two studies. Regardless, with any regional definition, average emission rates in a region vary substantially from the change in emissions that a new load will create for two reasons: (1) many baseload plants and nondispatchable renewable generators, which make up a

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substantial portion of average generation, will not change output in response to new load, and (2) electricity is traded across regional boundaries, so the profile of emissions produced in a region is not necessarily a good measure of the emissions produced to satisfy demand in that region.

Figure 1 illustrates these issues. This simplified example includes two regions, each with generators that produce enough supply to satisfy the baseload demand. In region 1 the nuclear generator is fully utilized and the coal generator is partly utilized to satisfy baseload demand. If new PEV load were added in this region, the coal generator would increase production to satisfy the new load. While average generation in this region is a mix of nuclear and coal power sources, the marginal generation associated with supplying new PEV load is 100% coal.

Region 2 has only a nuclear generator that is fully utilized in supplying the baseload demand, so any new PEV load would need to be satisfied by importing electricity from a neighboring region. While region 2's average generation emission factor would be near zero (100% nuclear), marginal emissions associated with supply for new PEV load in the region are those associated with coal generation from the neighboring region. This situation would change over time, depending on demand and supply of electricity generating units. These examples show why emissions associated with marginal consumption in a region may differ substantially from emissions associated with average generation in that region.

There are two broad approaches to estimating marginal consumption emission factors: bottom up and top down. A bottom up approach models power plant operations and computes how generators should normatively behave in response to a load profile to minimize cost. Such studies can range from simple dispatch supply curves to detailed simulation or optimization models to model generator response to load profiles.[9,10,12,20,23,24,58] Such models allow one to model future grid scenarios or large load changes beyond the margin. However, it is difficult to correctly model all of the factors that determine plant behavior in practice (e.g., transmission constraints, ramping constraints, unscheduled maintenance, weather, regulation, contracts, etc.) for a region large enough to capture all relevant factors in such an interconnected system. Furthermore, such modeling approaches generally entail a gap between model predictions and plant operation in practice. Finally, such models are typically developed for one region or interconnect and do not allow for systematic regional comparisons across the United States.

The top-down approach applies regression models using observed data to assess how generation and/or emissions change as a function of changes in load in practice. For example, Graff Zivin et al.[3] regress emissions in each interconnect (Eastern Interconnect, Western Interconnect, and ERCOT) as a function of load in each NERC region for each hour of the day and for multiple seasons. The authors show that the MRO, NPCC, FRCC, WECC, and TRE NERC regions consume more than they produce, while SERC, RFC, and SPP have been net exporters (we define these regions later and provide maps in the SI). This approach has the advantages of accounting for trade across NERC region boundaries and avoiding error in estimating the portion of power generated by each plant that is not sold (e.g., used on site) as well as regional variation in transmission losses. However, using these estimates for prediction risks error from use of noncausal correlations in counterfactual scenarios: The regression captures all changes in generation that co-occur with changes in load, including some nondispatchable renewable units (wind and solar generators), which generally produce the same net output regardless of demand fluctuations, and some buffered renewable units (hydroelectric generators), which can make limited shifts of generation timing in response to changes in load but generally produce the same total output regardless of marginal changes in load. These factors may introduce error in the marginal consumption emission factor estimates by attributing marginal generation to units that would not in practice change net generation in response to new load.

Siler-Evans et al.[30] mitigates this issue by considering only fossil fuel generators (≥25 MW) as marginal generators. The authors rely on the Continuous Emissions Monitoring System (CEMS) from the Environmental Protection Agency and regress change in hourly CO_2 emissions as a function of change hourly fossil generation for each hour and season in each NERC region. The focus is on marginal generation rather than marginal consumption (i.e., plants within the region that respond as regional generation changes, rather than plants across regions that respond as regional consumption changes). The emission factors from Siler-Evans et al.[30] have been estimated for different regional boundaries (NERC and eGRID; see SI for maps). However, those estimates do not account for trade between regions or different transmission losses associated with marginal load in each region. These marginal emissions estimates have been used to assess emissions implications of increasing wind and solar generation,[59] bulk energy storage,[31] lighting systems,[30,32] and building distributed energy resources,[33] among others. Other marginal emission factor estimates exist but with limited geographic scope (California[34] and New England[35−37]) or for regions outside the U.S. (U.K.[38]).

In summary, to properly assess the CO_2 emissions implications of adding new PEV charging demand in a particular region, one should estimate and use marginal consumption emission factors. Graff Zivin et al.[3] attempt to do this directly for each interconnect, with some potential for error due to renewable generators, and Siler-Evans et al.[30] avoid renewable generators but focus on marginal generation rather than marginal consumption, ignoring interregional trade and regional variation in transmission losses. Both estimates suggest significant differences between marginal and average emission factors in a region. Both estimates have potential sources of error, and we apply both to assess robustness of findings and compare to implications of prior studies that use average generation emission factors. In this work, we assess regional variation in electric and conventional vehicle CO_2 emissions under a range of assumptions for regional boundaries of analysis, electricity emission factors, and charging patterns.

2. DATA AND METHODS

Because we focus on comparative life cycle assessment, we include only components of the vehicle life cycle that differ across vehicle types. These include vehicle emissions associated with parts assembly and manufacturing, lithium-ion battery emissions associated with manufacturing (we excluded lead-acid batteries, which are present in all of the examined powertrains), emissions associated with producing, transporting, and combusting gasoline, and emissions associated with producing, transmitting, and distributing electricity. These components represent the overwhelming majority of life cycle vehicle CO_2 emissions. We focus here on our method for

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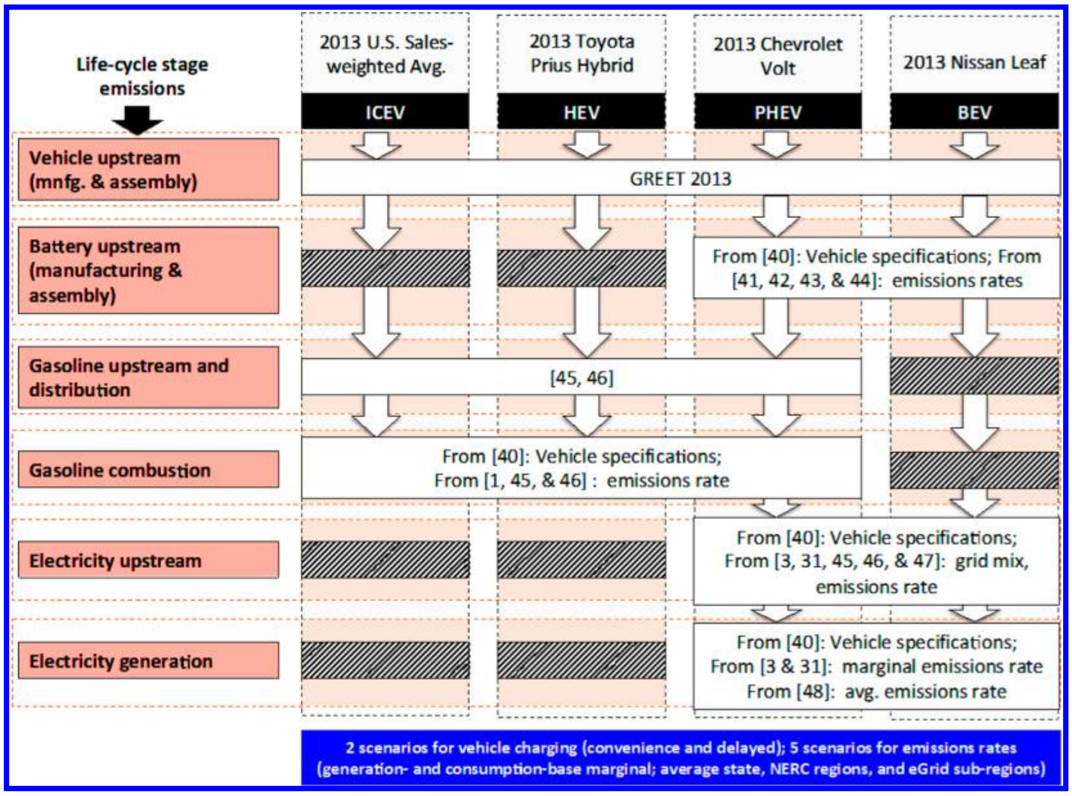

Figure 2. Vehicle life cycle emissions framework and data sources.

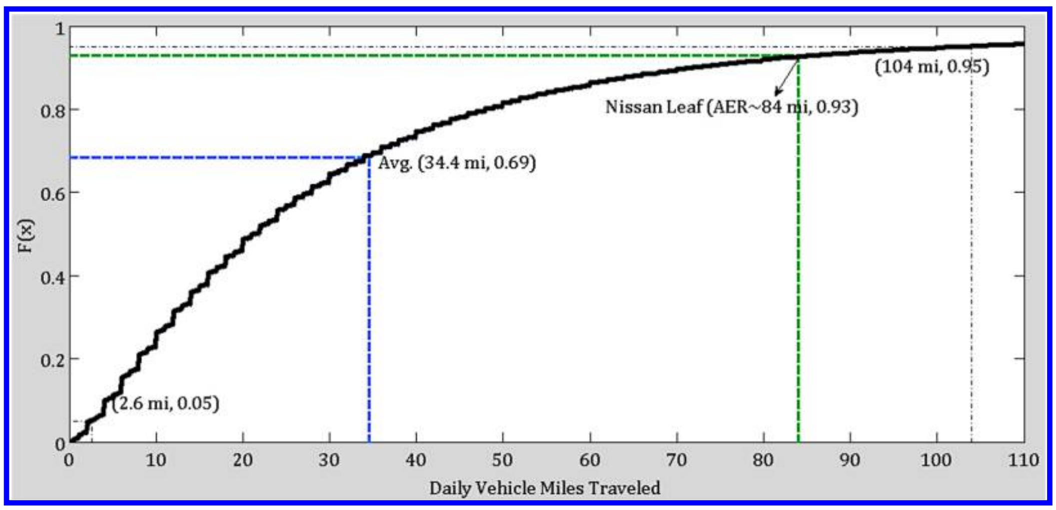

Figure 3. Empirical cumulative distribution function of daily vehicle miles traveled. Data source is ref 50.

estimating vehicle operation emissions, using a functional unit of vehicle miles traveled. For other life cycle stages, we use data from published sources identified in the SI. Additional details regarding the assumptions and respective data sources are also provided in the SI. Figure 2 illustrates the framework we use in estimating and comparing vehicle emissions showing different vehicle types and data sources for key parameters under each life cycle module.

2.1. Vehicles Considered and Key Vehicle Parameters. We use selected representative vehicles for the analysis. For PEVs, we focus on the Nissan Leaf (BEV) and Chevrolet Volt (PHEV). These vehicles are the highest selling in their categories as of 2013, constituting 23% and 12% of all 2013 PEV sales, respectively. They have also been in the market the longest.[48] The Nissan Leaf also has the highest electric-mode energy efficiency among PEVs in the market, at 0.29 kWh/mi.[39] We compare these vehicles with the Toyota Prius HEV, the most efficient gasoline vehicle (at 50 mpg) and highest selling HEV (constituting more than 40% of 2013 HEV sales).[48] We also compare the PEVs to the 2013 sales-weighted average new car with fuel economy of 24.6 mpg.[49] Relevant vehicle parameters such as all-electric range (AER) and energy use as well as battery charge acceptance rate and capacity are summarized in the SI.

2.2. Assumptions Regarding Vehicle Miles Traveled. We assume lifetime vehicle miles traveled ranges from 100k to 150k miles with a best estimate of 125k miles used for the base case analysis using estimates of battery and vehicle lifetime from

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various sources as summarized in the SI. In practice, vehicle and battery lifetime depend on several factors such as use intensity, operating temperature conditions, and charging frequency.[9]

We obtain daily vehicle miles traveled (DVMT) from the National Household Travel Survey (NHTS) 2009 data set.[50] These data are obtained through a sample of 26 000 households throughout the U.S. who were surveyed between March 2008 and May 2009. We extract the DVMTs for over 76 800 automobile entries and treat the full set of entries as being representative of driving in all locations (i.e., we ignore regional differences in driving patterns). In Figure 3, we provide an empirical cumulative probability distribution (ECDF) and the all electric range (AER) of the electric vehicles considered. The NHTS DVMT data set has an average of 34.5 mi with a 5th and 95th percentile of 2.6 and 104 mi, respectively, among automobiles that traveled on the day surveyed. As shown, about 93% of the data have DVMT less than or equal to the Nissan Leaf AER (~84 mi). Vehicles with zero travel were excluded.

2.3. Use Phase Emissions: Emissions of CO_2 per Mile Driven for Different Vehicles. The use-phase CO_2 emissions per vehicle mile traveled, $\hat{\Upsilon}_{jrv}$, (g CO_2 per mile) of vehicle type v using emission factors data set j in region r is computed as a function of vehicle efficiency, emission factors for gasoline and electricity, and the distance traveled on gasoline versus electricity (eq 1):

Average Vehicle Emissions

$$\hat{\Upsilon}_{jrv} = \frac{\sum_i \left(d_{iv}^{\mathrm{ELEC}} \frac{\hat{\Phi}_{ijrv}^{\mathrm{W\_ELEC}}}{\eta_v^{\mathrm{ELEC}}} + (d_i - d_{iv}^{\mathrm{ELEC}}) \frac{\hat{\Phi}^{\mathrm{GAS}}}{\eta_v^{\mathrm{GAS}}} \right)}{\sum_i d_i} \quad (1)$$

where $\hat{\Phi}_{ijrv}^{\mathrm{W\_ELEC}}$ [in g CO_2/kWh] is the hourly weighted electricity emission factors for NHTS vehicle travel entry i under vehicle type v using an electricity emission factors j in region r, $\hat{\Phi}^{\mathrm{GAS}}$ [in g CO_2/gal] is the emission factors for gasoline, d_i is the distance traveled by vehicle entry i, d_{iv}^{ELEC} is the distance [in miles] that vehicle entry i under vehicle type v travels using electric power, η_v^{ELEC} is the energy efficiency of vehicle v when driving on electricity [in mi/kWh], η_v^{GAS} is the fuel efficiency of vehicle v when driving on gasoline [in miles per gallon], and the $\wedge$ symbol is used to indicate a random variable. For gasoline vehicles $d_{iv}^{\mathrm{ELEC}} = 0 \ \forall \ v$.

Miles traveled on electricity, d_{iv}^{ELEC}, for vehicle entry i of vehicle type v depends on the distance traveled and the vehicle's AER:

Miles Traveled on Electricity

$$d_{iv}^{\mathrm{ELEC}} = \begin{cases} d_i \geq d_v^{\mathrm{AER}} & d_v^{\mathrm{AER}} \\ d_i < d_v^{\mathrm{AER}} & d_i \end{cases} \quad (2)$$

where d_v^{AER} is the AER for vehicle type v and d_i is the DVMT for vehicle entry i.

2.4. Electricity CO_2 Emission Factors. We consider several emission factor estimates for electricity and discuss how these assumptions affect our results. These are as follows: (1) hourly consumption-based MEFs adapted from Graff Zivin et al.;[3] (2) hourly generation-based marginal emission factors (MEF) from Siler-Evans et al.;[30] (3) 2009 NERC regional average annual emission factors (AEF); (4) 2009 eGRID subregion average emission factors (eGRID subregions are subsets of NERC regions,[47] and details are provided in the SI); (5) 2009 state average emission factors. We obtain all AEFs from EPA data[47] and aggregate at the needed regional boundary levels (see Table 2).

Table 2. Summary of Scenarios Considered

scenario	MEF versus AEF for electricity	consumption versus generation MEFs	region	MEF/AEF ref source	charging scheme
1	MEF	consumption	NERC	3	convenience
2	MEF	consumption	NERC	3	delayed
3	MEF	generation	NERC	30	convenience
4	MEF	generation	NERC	30	delayed
5	AEF	generation	NERC	47	NA
6	AEF	generation	eGRID	47	NA
7	AEF	generation	state	47	NA

We emphasize that AEFs are conceptually inappropriate for assessing the implications of new PEV adoption and use, but we include AEF scenarios for comparison due to their common use in the literature. We also emphasize that, while consumption-based MEFs are the conceptually appropriate estimates, we compare generation-based MEFs because of the potential sources of error in estimating causal relationships using the consumption-based MEF estimation approach, as described previously.

NERC has defined eight regional entities that are responsible to manage reliability of the U.S. bulk power system. These entities are Florida Reliability Coordinating Council (FRCC), Midwest Reliability Organization (MRO), Northeast Power Coordinating Council (NPCC), ReliabilityFirst (RF), SERC Reliability Corporation (SERC), Southwest Power Pool (SPP), Texas Reliability Entity (TRE), and the Western Electricity Coordinating Council (WECC). These eight regional entities are further divided into subregions (see NERC subregion map in the SI), and regional boundaries of these subregions have changed and will continue to change over time to accommodate changes in resource and reliability planning. Another regional boundary to consider is provided by the Environmental Protection Agency (EPA) in what is called the eGRID subregions. These regions have been defined by the EPA for analysis of environmental aspects of power generation, as state boundaries frequently do not correspond to meaningful partitioning of the power grid. The amount of trade among regions depends on the regional boundaries used (e.g., state, eGRID, or NERC), but average interregional trade is not necessarily a good indicator of marginal trade, so it is not known which regional definitions induce greater error to marginal emissions estimates when ignoring trade.

We provide maps of NERC and eGRID regions as well as a comparison of the electricity emission factors by time of day and for each NERC region in the SI. Figure S4 in the SI highlights that, for most regions, MEFs are lower than AEFs during peak load times, where natural gas is often the fuel used at the margin.[30] Also, hourly estimates for the consumption-based MEFs[3] vary more by hour and have wider statistical uncertainty ranges from the regressions, especially for the regions within the eastern interconnect, than the generation-based MEFs.[30]

Discrepancies between generation- and consumption-based MEF values are small in the WECC and TRE regions where trading with other regions is limited. In MRO, consumption-based values are much higher than generation-based values (by

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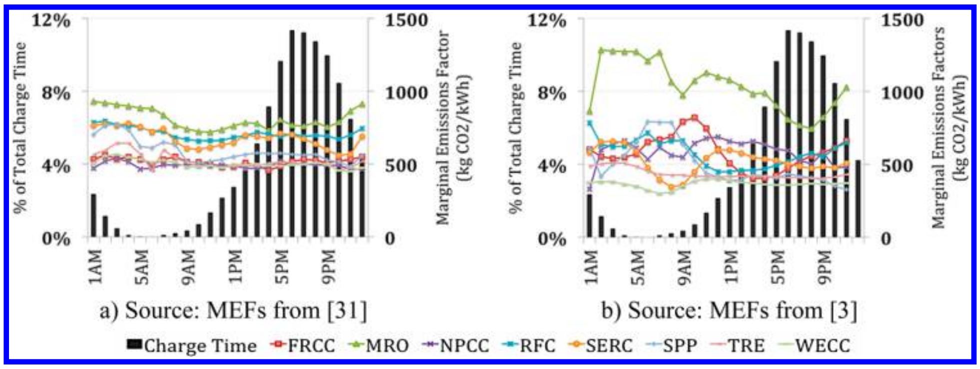

Figure 4. Convenience charging profile and hourly marginal emission factors. Figure 4(a) uses MEFs from ref 30 whereas Figure 4(b) uses MEFs from ref 3. Lines correspond to the emission factors for different NERC regions, and the black bars show the percentage of total charge time per hour.

up to 66%) even though MRO is a net importer from regions that are less carbon-intensive. A potential explanation is that the majority of the energy that MRO imports is supplied by coal power plants in neighboring regions.[3] Table 2 highlights key differences in the different emission factors used.

Using the MEFs, we compute the hourly weighted MEFs (WMEF) for both convenience- and delayed-charging. The WMEF takes into account the time of the day and the duration that an PEV is charged. To determine the WMEFs, $\Phi_{ijrv}^{\mathrm{W\_ELEC}}$, we performed a Monte Carlo simulation (N = 10 000) using eq 3 and the marginal emission factor distribution summarized in the SI:

Weighted Marginal Emission Factors

$$\hat{\Phi}_{ijrv}^{\mathrm{W\_ELEC}} = \frac{\sum_t h_{tiv}\hat{\Phi}_{tjr}^{\mathrm{ELEC}}}{t_{iv}^{\mathrm{CHG}}} \tag{3}$$

where h_{tiv} is the fraction of hour t that vehicle entry i of vehicle type v charges, $\hat{\Phi}_{tjr}^{\mathrm{ELEC}}$ is the MEF for hour t, region r, using MEF data source j, including both direct and upstream emissions, and t_{iv}^{CHG} is the total charge time for vehicle entry i under vehicle type v.

Both sets of MEFs estimate CO_2 emissions during power plant operation. To estimate upstream emissions, we extrapolate hourly marginal grid mix from Siler-Evans et al.[30] and used associated upstream emission rates from Argonne National Laboratory[44] and Venkatesh et al.[46] Marginal grid mix was not available for consumption-based MEFs, so we estimate upstream emissions using generation-based marginal grid mix. We provide details of this calculation in the SI.

2.5. Charging Schemes and Charge Times. The vehicle charge time, t_{iv}^{CHG}, for vehicle type v if it were to travel the same distance as vehicle entry i, is given by eq 4:

Vehicle Charge Time

$$t_{iv}^{\mathrm{CHG}} = \begin{cases} d_i \geq d_v^{\mathrm{AER}} & t_v^{\mathrm{CHG}} \\ d_i < d_v^{\mathrm{AER}} & \dfrac{d_i}{d_v^{\mathrm{AER}}} t_v^{\mathrm{CHG}} \end{cases} \tag{4}$$

where t_v^{CHG} is the time it takes to fully recharge vehicle type v, assuming combined (45% city, 55% highway) vehicle fuel efficiency.[39]

We consider two charging schemes: convenience and delayed charging. Under the convenience-charging scheme, we assume that vehicles start charging upon arrival to the home after the last trip of the day. We obtain data on arrival time t_i^{E} for each vehicle entry i from the NHTS data[50] and compute the fraction of time h_{tiv} spent charging in each hour $t \in \{0,1,2,...,23\}$ using eq 5:

Charge Time Fraction per Hour (convenience charging)

$$h_{tiv} = \sum_{n=0}^{1} \begin{cases} 1 \text{ if } t_i^{\mathrm{E}} \leq t_n \text{ and } t_i^{\mathrm{E}} + t_{iv}^{\mathrm{CHG}} \geq t_n + 1 \\ 0 \text{ if } t_i^{\mathrm{E}} \geq t_n + 1 \text{ or } t_i^{\mathrm{E}} + t_{iv}^{\mathrm{CHG}} \leq t \\ \min(t_n + 1,\, t_\tau^{\mathrm{E}} + t_{iv}^{\mathrm{CHG}}) - \max(t_n,\, t_\tau^{\mathrm{E}}) \\ \quad \text{otherwise} \end{cases} \tag{5}$$

where $t_n = t + 24n$ to account for charging that takes place the day following a trip. For the delayed charging scenario, we assume that the vehicles start charging at 12 am, so that

Charge Time Fraction per Hour (delayed charging)

$$h_{tiv} = \begin{cases} 1 \text{ if } t_{iv}^{\mathrm{CHG}} \geq t + 1 \\ 0 \text{ if } t_{iv}^{\mathrm{CHG}} \leq t \\ \min(t + 1,\, t_{iv}^{\mathrm{CHG}}) - t \text{ otherwise} \end{cases} \tag{6}$$

where midnight is $t = 0$.

The national distribution of charging times under the convenience charging scheme assumption and the corresponding hourly MEFs are shown in Figure 4. The left y-axis shows the percentage of charge time that occurs within each hour, and the right y-axis shows the MEFs in kg CO_2/kWh. Under the convenience charging scenario, most of the charging (~80%) would occur within the period of 4:00 pm to 11:00 pm.

2.6. Scenarios Considered. We perform a Monte Carlo simulation (N = 10 000) by taking random draws for each of the random variables to estimate the vehicle CO_2 emissions under each scenario of emission factor estimation methodologies, charging schemes, and regional boundary definitions. We summarize these scenarios in Table 2.

3. RESULTS AND DISCUSSION

Figure 5 shows, for each NERC region, the life cycle estimates for the Nissan Leaf CO_2 emissions per mile traveled under different scenarios (colored bars), compared to that of Toyota Prius HEV (green line) and the sales-weighted average ICEV (red line) (in the SI we provide similar results for the Volt emissions). Each bar represents the mean Leaf life-cycle

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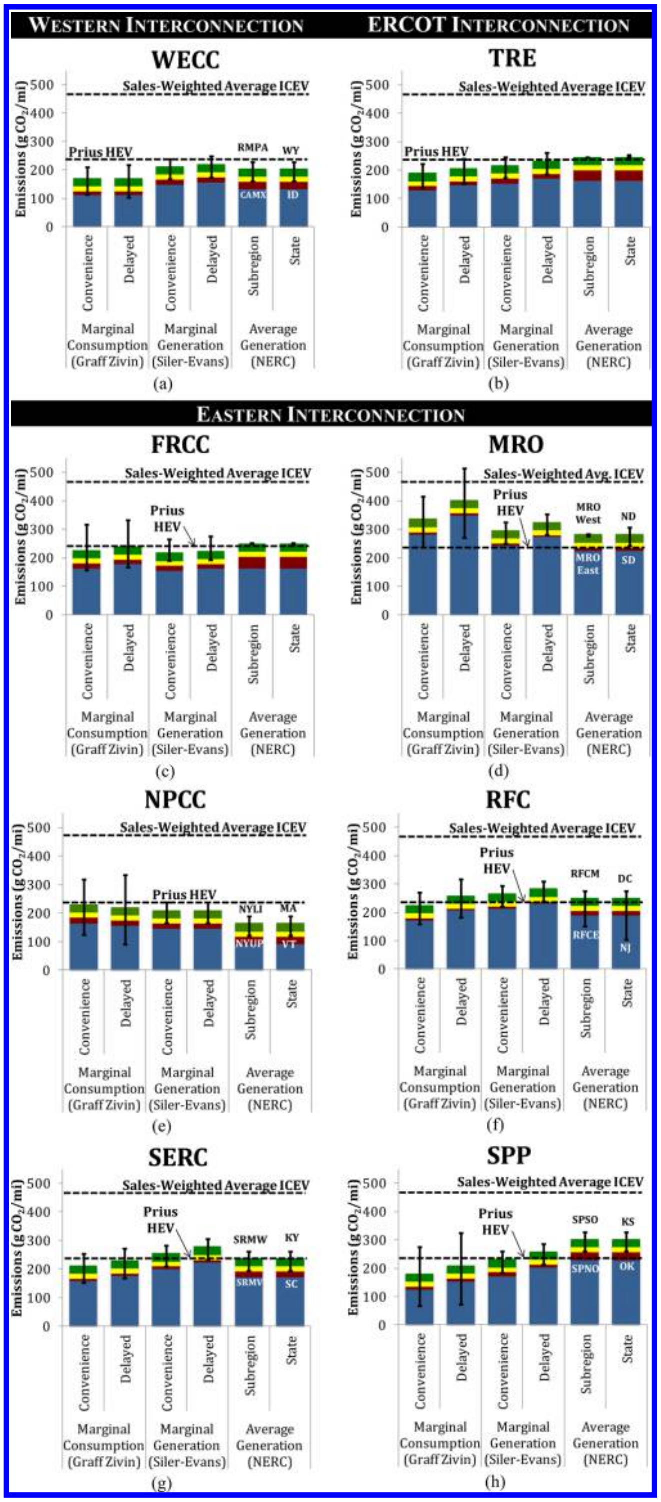

Figure 5. Nissan Leaf life cycle emissions (g CO_2/mile) using alternative grid emission factors by region and different scenarios for vehicle charging. The life cycle stages included are as follows: electricity production (blue); electricity upstream (red); vehicle assembly and manufacturing (yellow); battery upstream and production (green). The marginal emission cases show expected marginal emissions estimates with error bars for the 5th and 95th percentile values. Average generation estimates show NERC region average emissions estimates with error bars that represent the lowest and highest eGRID subregion or state emissions estimates within each NERC region, respectively. Horizontal lines show expected Toyota Prius hybrid and sales-weighted average vehicle emissions estimates. Combined driving pattern (45% city and 55% highway) energy use

Figure 5. continued

from ref 39 was used for all vehicles. FRCC = Florida Reliability Coordinating Council; MRO = Midwest Reliability Organization; NPCC = Northeast Power Coordinating Council; RFC = Reliability First Corporation; SERC = SERC Reliability Corporation; SPP = Southwest Power Pool, RE; TRE = Texas Reliability Entity; WECC = Western Electricity Coordinating Council; ERCOT = Electric Reliability Council of Texas.

emissions using different scenarios and assumptions for electricity emission factors and charging times. The error bars for the marginal emissions estimates show the 5th and 95th percentile emissions estimates. Error bars for state and subregion values are the lowest and highest average state or subregion emissions estimates in each region, respectively. Mean Nissan Leaf life-cycle CO_2 emissions estimates range from 157 to 219 g CO_2/mi in WECC, and from 295 to 395 g CO_2/mi in MRO. These values are comparable to results for low and high carbon intensity scenarios investigated in ref 14. The Toyota Prius HEV average emissions are about 238 g CO_2/mi, the emissions from the sales-weighted average ICEV are 468 g CO_2/mi, and these do not vary by region.

We find that the Nissan Leaf has lower expected life cycle emissions than the average internal combustion engine vehicle in all regions and across all scenarios. In addition, expected MEF-based life cycle GHG emissions estimates for the Nissan Leaf are lower than those of the Prius in western states (WECC), Texas (TRE), New England (NPCC), and Florida (FRCC), while the Leaf is higher emitting in the Northern Midwest (MRO) regardless of charging scenario or MEF estimation method. In the remaining regions (RFC, SPP, and SERC) the Leaf's expected emissions may be higher or lower than the Prius, depending on which charging scenario and MEFs estimates are used. Further, due to statistical uncertainty in MEF estimates one cannot rule out the possibility that the Leaf may be higher or lower emitting than the Prius in each region. Comparisons with the Chevrolet Volt are provided in the Supporting Information.

Next we discuss the implications of key assumptions and scenarios used in this analysis, in particular the use of marginal versus average emissions, the consumption- versus generation-based marginal emission factors, the charging scheme assumed, and regional boundary definitions. We perform *t* tests to ensure sufficient Monte Carlo draws to determine which estimates have larger expected value (see the SI).

3.1. Marginal versus Average Emissions. Results indicate that marginal estimates differ from average estimates in all regions, and the magnitude and direction of the difference vary across regions. The expected value of marginal estimates are higher in the MRO (7−34%) and NPCC (39−46%) regions and lower in SPP (11−87%) than average estimates. In other regions, marginal emissions may be as much as 24% higher (SERC) or 28% lower (TRE) than average emissions estimates, depending on assumptions for charging scheme and marginal emissions estimation method. Both average and marginal estimates account for regional variation in grid mix, but only marginal estimates account for temporal variation due to incremental changes in power demand over time. This difference is large enough in several regions to change which vehicle is expected to be lower emitting.

3.2. Consumption-Based versus Generation-Based MEFs Estimates. Table 3 summarizes the median emissions

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Table 3. Median CO_2 Emissions Difference by Region and Estimation Method Computed as Vehicle Emissions Difference Divided by Gasoline Vehicle Emissions[a]

	Nissan Leaf − Toyota Prius HEV (%)				Nissan Leaf − avg ICEV (%)			
NERC region	Cons_Conv	Cons_Del	Gen_Conv	Gen_Del	Cons_Conv	Cons_Del	Gen_Conv	Gen_Del
FRCC	−12	0	−11	−6	−55	−49	−55	−52
MRO	46	69	24	43	−26	−14	−37	−27
NPCC	1	−17	−13	−15	−48	−58	−56	−57
RFC	−12	15	14	23	−55	−42	−42	−37
SERC	−10	−2	10	19	−54	−50	−44	−40
SPP	−24	−19	−4	7	−61	−59	−51	−45
TRE	−24	−15	−12	−6	−61	−57	−55	−52
WECC	−30	−29	−13	−12	−64	−64	−56	−55

[a]Note: The headings are as follows: Cons_ = consumption-based MEF; Gen_ = generation-based MEF; _Conv = convenience charging; _Del = delayed charging.

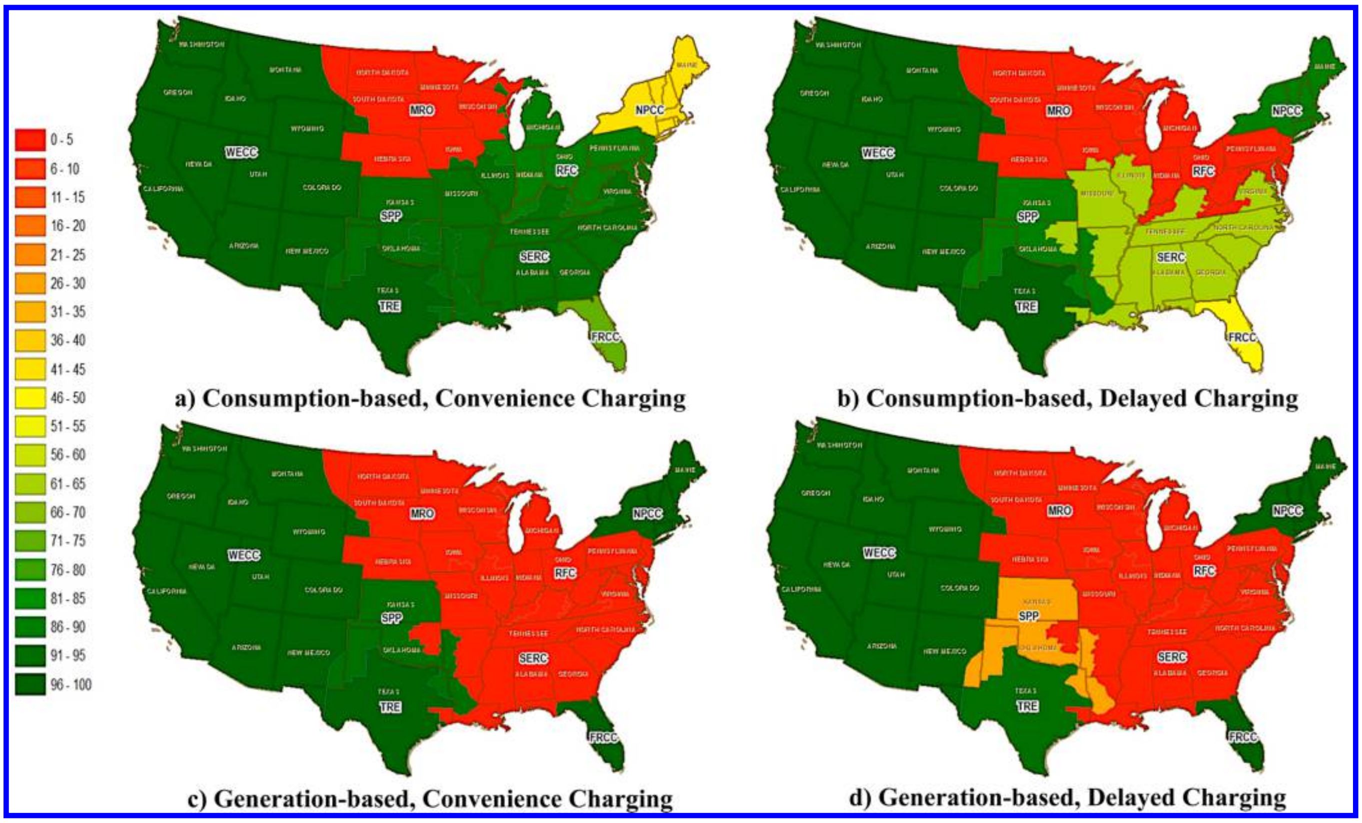

Figure 6. Probability that the Nissan Leaf is lower CO_2 emitting than the Toyota Prius Hybrid by region and charging scheme. Green indicates that the Nissan Leaf is lower emitting than the gasoline vehicle (Toyota Prius Hybrid or sales-weighted ICEV), while red means that the opposite holds.

difference between the Nissan Leaf and the Toyota Prius and between the Nissan Leaf and the sales-weighted average ICEV. This table shows the differences by region and by estimation method (see the SI for similar results for the Chevy Volt). In SERC, for example, the Prius HEV has higher median emissions estimates than the Leaf when using generation-based MEFs, but the Leaf has higher median emissions when using consumption-based MEFs.

3.3. Convenience versus Delayed Charging. Results also show that conclusions depend on the charging scheme. Under convenience charging, most charging occurs during peak system load times when more expensive but cleaner energy sources are on the margin. Delayed charging (i.e., starting at 12 am and until vehicle is fully charged) results in higher Nissan Leaf emissions (higher by 6−20% for generation-based and 3−29% for consumption-based), with the exception of the NPCC region (where delayed charging has lower emissions by up to 13%).

3.4. Regional Boundary Definition. We also find that average emissions estimates are substantially different under different regional boundary definitions. This observation is congruent to the conclusion of Weber et al.[19] on the substantial difference in average electricity emission factors under different regional boundary definitions. For example, state-based Leaf emissions in WECC vary from 16 to 288 g CO_2/mi for Idaho and Wyoming, respectively, compared to NERC region average emissions estimate of 130 kg CO_2/mi. Similarly, eGRID subregion average emissions estimates of 90 to 248 g CO_2/mi in CAMX and RMPA, respectively, vary significantly from NERC region estimates. This is a key reason why conclusions from existing regional comparisons of PEVs and gasoline vehicles vary significantly. For example, Yawitz et al.,[4] which

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uses 2010 state emission factors, indicates that the Leaf is lower emitting than the Prius in 14 states, while Anair et al.,[5] which uses eGRID subregion 2009 emission rates, declares the Prius to be lower emitting in more but sometimes different states.

3.5. Robustness of Vehicle Comparisons. Comparison of expected marginal CO_2 emissions estimates in Figure 6 indicates that the Leaf is lower emitting than the most efficient gasoline vehicle (Toyota Prius HEV) in the FRCC, NPCC, TRE, and WECC regions and higher emitting in the MRO region, regardless of the estimation method (i.e., consumption- or generation-based MEF, convenience or delayed charging). In ref Anair et al.,[5] which estimates Leaf emissions using AEFs by eGRID subregion, the Leaf is lower emitting in SERC eGRID subregions, whereas we find that results in these regions are uncertain.

To account for uncertainty in MEF values, we estimate the probability that the Nissan Leaf is lower emitting than the Prius Hybrid by region and estimation method, as shown in Figure 6. As shown, the probabilities are different under different estimation methods and charging schemes, but some findings are robust: there is high probability that the Leaf is lower emitting in WECC and TRE and the Prius is lower emitting in MRO regardless of MEF estimation method or charge timing. Similar values for the Chevrolet Volt are provided in the SI.

These comparisons differ from Graff Zivin et al.[3] because of the inclusion of manufacturing and life cycle components rather than only tailpipe and power plant emissions, they differ from Yawitz et al.[4] and Anair et al.[5] because of the use of marginal rather than average emission factors, and they differ from EPRI/NRDC's analysis,[15] which uses assumptions for future grid characteristics and does not report regional differences.

Vehicle operation constitutes the largest part of life cycle CO_2 emissions for all vehicles, as shown in the SI. However, lithium-ion battery production emissions are also significant for BEVs, constituting about 12% of life cycle emissions, on average. Our range of life cycle estimates is comparable to past estimates.[8,14,22]

3.6. Limitations. Our analysis examines only GHG emissions and does not estimate marginal changes in air pollutants due to PEV charging nor other potential benefits of reducing gasoline consumption. Given that, in several locations across the United States, vehicle life cycle air pollution externalities can be larger than greenhouse gas emissions externalities, particularly when coal-fired power plants operate on the margin[8,52] and the emissions affect densely populated areas, future work on air pollutants would be needed to understand social costs of PEVs more broadly.

The marginal emissions estimates used are based on regression models that estimate marginal grid emission factors by hour and season using historical data on power plant operations and emissions. These estimates capture the electricity grid historically but do not capture the potential and expected changes in the grid over time (including during the life of the vehicle). However, the data sets used will be regularly updated by the Environmental Protection Agency, so it is possible to update the analysis as changes in the electricity sector occur. While average emission factors are expected to decrease over time in response to policy, marginal emission factors may increase in some regions and decrease in other regions as the change in power plant fleets and feedstock prices modify which plants operate on the margin at different seasons and times of day.

Second, marginal emissions estimates have known potential sources of bias, as discussed previously, including the potential of our consumption-based estimates to count renewable plants that, by chance, happen to ramp production at a time when demand increases as though they would produce less in the absence of such demand. In practice, most renewables sell nearly all of the electricity they can produce regardless of the existence of new PEV load.

Additionally, the generation-based estimates used ignore interregional trade, plant energy consumption, and variation in transmission efficiency. We should also note that the MEFs in Graff Zivin et al.[3] and in Siler-Evans et al.[30] use different years of analysis. The two MEF estimates we use have different benefits and disadvantages with respect to mitigating sources of error, and we use both to assess robustness. Future work estimating interregional trade in the generation-based approach could improve MEF estimates and resolve some of the discrepancy between consumption- and generation-based estimates.

Additionally, our maps suggest that all locations within a NERC region have identical marginal emission factors. In practice, marginal emissions may vary within each region, but we lack the resolution to differentiate sub-NERC-region variation.

Finally, we estimate only the immediate life cycle emissions implications of electric vehicles versus gasoline vehicles but do not include the systems effects of policies such as the corporate average fuel economy standards, which may lead to changes in vehicle fleet mix and net emissions each time an electric vehicle is sold in place of a gasoline vehicle.[51] We also ignore changes in fuel prices, which could lead to different driving patters between ICV and PEVs, and we ignore other factors that vary regionally, such as driving patterns[53−55] and climate.[56] Extensions of our study that incorporate regional climate and driving patterns could more fully characterize regional difference in PEV implications.

3.7. Implications. In summary, there is significant regional variation and uncertainty in the CO_2 emissions reduction potential of PEVs because of the temporal and regional differences in electricity grid mix and because there is uncertainty regarding marginal emissions associated with electricity consumption in each region. Nevertheless, some comparisons are robust: The Nissan Leaf BEV is lower emitting than the Toyota Prius HEV in western states (WECC) and Texas (TRE), and the Prius is lower emitting than the Leaf in the northern Midwest (MRO) regardless of charge timing or MEF estimation approach. Additionally, the Chevy Volt PHEV is higher emitting than the Toyota Prius in the Eastern Interconnect.

Use of marginal emission factors, rather than average emission factors, is appropriate for estimating the emissions implications resulting from new PEV adoption, and consumption-based marginal emissions estimates that account for interregional trade are conceptually more appropriate than generation-based emissions estimates within NERC regions. However, because of potential sources of error in the estimation approach, we compare both consumption-based and generation-based MEF estimates. Use of average emission factors is incorrect for understanding emissions implications of new PEV adoption; however, the question of what emissions PEV charging is "responsible for" is a less-straightforward question of allocation, where use of AEFs is one possible value judgment.

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Temporal variation should also be taken into consideration when formulating policies that encourage consumers to charge at certain times of the day (e.g., when electricity demand and prices are lowest). For example, emissions using delayed charging (starting at midnight) are higher in most regions due to more carbon-intensive marginal grid mix during nonpeak hours.

Given substantial regional differences in PEV GHG emissions implications, differential regional policy may be warranted, but current differences in state subsidies[57] do not align particularly well with regions where PEVs provide the largest GHG emissions benefits. For example, the state with the largest state subsidies ($7500) for BEVs is West Virginia, which is under the RFC region, where the Nissan Leaf and the Chevy Volt are likely higher emitting than the Toyota Prius. Under the Clean Power Plan Proposal, West Virginia is expected to bring down its carbon rate to about 730 kg/MWh, but that level is not yet low enough for PEVs to be lower emitting than the Prius, and the effect of average emissions reductions on marginal emissions has not yet been characterized. The second highest state subsidies ($6000) are in Colorado, part of the WECC region where the Leaf is likely lower emitting than the Prius and the Volt may be higher or lower. The third highest state subsidies ($5000) are in Georgia, where the comparison of the Leaf and Prius is inconclusive and the Volt is higher emitting. Of course, GHG benefits must be balanced against other goals, including reduction of air pollution and oil dependency as well as economic factors.

In sum, we offer the following recommendations for policymakers: (1) Be wary of regional claims about electric vehicle air emissions implications based only on regional electricity generation mix, since the emissions associated with new PEV charging in a region can differ substantially from the average generation mix in that region. (2) Consider federal and regional strategies for promoting electric vehicle adoption most strongly in the regions where they can do the most good. When considering GHG reductions alone, this would mean the western U.S. and Texas (where there is high confidence that GHG emissions of the Nissan Leaf are lower than the best gasoline vehicles) and in Florida and New England (where the Leaf also likely has lower GHG emissions). However, other factors beyond the scope of this analysis, such as air quality implications, should be considered as well. (3) Continue to reduce the emissions intensity of the electricity grid. When electricity generation is sufficiently clean, electric vehicles have lower GHG emissions than the most efficient gasoline vehicles. (4) Avoid treating PEVs as though they are all the same. While the Nissan Leaf has lower GHG emissions than the gasoline Toyota Prius in several regions, the Chevy Volt has higher GHG emissions than the Toyota Prius across much of the U.S. Policies that target outcomes (e.g., GHG emissions reduction) rather than specific technologies are generally preferred. (5) Finally, incentivizing nighttime charging should be avoided: while night charging can be preferred by grid operators and can lower costs, in most regions nighttime charging increases GHG emissions, and nighttime charging can also increase health costs in some regions due primarily to increased air pollution from coal-fired power plants.[58]

■ ASSOCIATED CONTENT

Supporting Information

Additional detail on geographical boundaries of NERC and eGRID regions, data sources and values, comparisons of results in prior studies, comparisons of emission factors, emissions estimates by life cycle stage, statistical tests, and comparisons with the Chevrolet Volt are provided in a supplemental document. This material is available free of charge via the Internet at http://pubs.acs.org/.The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.est.5b00815.

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Notes

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