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From Cradle to Junkyard: Assessing the Life Cycle Greenhouse Gas Benefits of Electric Vehicles

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Abstract

U.S. programs subsidize electric vehicles (EVs) in part to reduce greenhouse gas (GHG) emissions. We model a suite of life cycle GHG emissions considerations to estimate the GHG abatement potential from switching from an internal combustion engine vehicle (ICE) to an EV in the continental U.S. The GHG intensity of EVs hinges on the electricity and ambient temperature when charged and operated. Both have high spatial and temporal heterogeneity, yet are typically modeled inadequately or overlooked entirely. We calculate marginal emissions, including renewables, for electricity by region and test forecasted grid composition to estimate future performance. Location and timing of charging are important GHG determinants, but temperature effects on EV performance can be equally important. On average, EVs slightly reduce GHGs relative to ICEs, but there are many regions where EVs provide a decisive benefit and others where EVs are significantly worse. The forecasted grid shifts from coal towards renewables, improving EV performance; the GHG benefit per EV in western states is roughly $425 today and $2400 in 2040.

JEL: Q48, Q52, R48

Keywords: Electric vehicles; greenhouse gas emissions; life cycle assessment

1 Introduction

Electric vehicles (EVs) are promoted as part of greenhouse gas (GHG) emissions reduction plans by governments nationwide. The Environmental Protection Agency cites EVs as a way to reduce transportation emissions.[1] Some U.S. states, such as California, offer EV subsidies intended to curb GHG emissions.[2]. It seems a foregone conclusion, both in policy and media representations, that EVs are a climate change solution. However, determining the potential GHG benefit from EVs is complicated. While electric powertrains are inherently more efficient, converting approximately 60 percent of energy in electricity to motive power instead of about 20 percent of fuel energy in ICEs [3], GHG savings from this efficiency gain need to be considered from a life cycle perspective, and should consider the real-world operating conditions for vehicles, which can significantly affect their performance. The objective of this research is to quantify the net GHG abatement effect for EVs over ICEs using life cycle metrics and considering the spatial and temporal heterogeneity of operating conditions, namely climate and the emissions intensity of regional electricity grids, and, if EVs do lead to abatement, whether the current subsidies are cost effective relative to the social cost of carbon.[4]

Our research questions emerge from the findings of many antecedents in the literature that have examined the life cycle GHG of passenger cars, and EVs in particular. Assessments for EVs have taken a few different approaches. Some have emphasized the contribution of batteries and other materials and systems unique to EVs to estimate the change in production-related emissions (e.g. Notter et al. [2010]). These studies typically use a life cycle approach and find a modest increase in emissions from EV manufacturing relative to conventional internal combustion engine vehicles (ICEs). Other studies have emphasized the importance of the electricity grid mix on

[1] http://www.epa.gov/climatechange/ghgemissions/sources/transportation.html (accessed 01/13/2015)

[2] California State Assembly Bill 1608, March 8, 2012.

[3] http://www.fueleconomy.gov/feg/evtech.shtml#end-notes (accessed 01/15/2015)

[4] In this research, compare grid-connected battery-electric vehicles (EVs) to gasoline-powered conventional internal combustion engine vehicles (ICEs).

the GHG performance of EVs, sometimes in comparative assessments to other vehicle powertrains (e.g. Hawkins et al. [2012]; Michalek et al. [2011]; Tamayao et al. [2015]; Tessum et al. [2014] and others). These studies generally find that the electricity fuel mix is dominant in the determining the performance of EVs and the preference of EVs over alternatives. For example, in their life cycle assessment study, Hawkins et al. [2013] found that EVs in Europe only outperform conventional internal combustion engine vehicles (ICEs) on a life cycle basis when lower-GHG intensity grids are used for charging.[5] More recently, researchers have begun to study the effects of climate on EV energy efficiency, finding that cold temperatures in particular reduce EV efficiency (Kambly and Bradley [2015]; Meyer et al. [2012]). Yuksel and Michalek [2015] synthesized both climate effects and regional electricity grid composition (using the work of Graff-Zivin et al. [2014] to estimate marginal electricity emissions) in their analysis of EV performance and showed that both factors play important roles in the net environmental benefit that EVs may offer.

Previous studies have relied on Graff-Zivin et al. [2014] and its descendants to estimate marginal emissions. These studies mark something of a paradigm shift in the literature towards using marginal emissions factors to estimate emissions and energy intensity of EVs.[6] However, Graff-Zivin et al. [2014] and its descendants exclude renewables from marginal emissions estimates, due both to technical challenges and the fact that much renewable generation is not marginal. Generally, previous research only estimates marginal emissions rates without identifying the underlying fuel mix, which is unnecessary for their purpose, but is required to estimate total fuel cycle emissions, something our research does. A notable exception, Siler-Evans et al. [2012] does estimate the marginal electricity generation fuel but does not account for non-fossil fuel generation.

[5]Other life cycle studies have compared EVs (including plug-in hybrid electric vehicles) with hybrid electric vehicles as well as conventional ICEs and found that even when EVs perform better than ICEs, they may not outperform hybrid vehicles (e.g. Samaras and Meisterling [2008] and Tessum et al. [2014]).

[6]An alternative approach used by, in particular, Rogers et al. [2013] estimates marginal emissions using locational marginal prices (LMP). Such an approach is less appealing in our situation as identification of marginal emissions relies on assumptions on the competitive landscape and the marginal cost of each generating unit. Further, not every generator in the US participates in a market using LMPs, limiting the geographic scope of any analysis. In fact, Rogers et al. [2013] only estimate marginal emissions for two of the eight NERC regions in the continental US.

To account for the fact that today's electricity grid is becoming ever cleaner, we present the net GHG benefit calculations under different grid mix forecasts. These scenarios are of particular importance since forecasts of the electricity grid include both substantial growth in renewables and persistent reliance on fossil fuels through 2040 and beyond (EIA [2015]). However, these forecasts require us to (methodologically) rely on emissions from the *average* composition of the electric grid, since there is no credible way to estimate the dispatch order of an electric system that does not yet exist. Again, the "average" approach may be justified if a large fraction of electricity demand is derived from EVs. To the extent that policies to promote EVs today are justified via claims that benefits will accrue from a cleaner grid in the future, these results offer quantitative evidence with which to evaluate those claims.

Based on our research questions and the findings and identified limitations of previous studies, we develop a unified, spatially explicit model for protypical midsize EV and ICE vehicles that includes: (1) life cycle emissions for vehicles and fuels, (2) climate effects on the performance of vehicles, and (3) novel modeling of marginal emissions from U.S. regional electricity grids and projections of future grid emissions. Other factors, such as rebound effects on travel distances, and regional differences in travel behavior and vehicle ownership are also considered. Figure 1 provides a general outline of our vehicle life cycle emissions simulation model. We then consider the thought experiment: what is the impact on GHG emissions if a household decided to scrap their current midsize car and replace it with either a new midsize ICE or a comparable EV?

Our analysis leads to several interesting conclusions. If an average household in the US were to buy a new mid-size EV instead of an otherwise-comparable ICE car today, and use the EV for all their vehicle travel, CO_2e emissions in the US would likely decrease by a small amount. However, there is substantial spatial heterogeneity in the emissions benefits. In most states, EVs will yield GHG reductions of up to 20 percent; but in a number of states, replacing an ICE with an EV would lead to an increase in GHG emissions. This result is the sum of many effects. When considering only life cycle emissions (i.e. vehicle production and fuel cycle emissions), and omitting climate effects, EVs are GHG "winners" relative to their ICE counterparts in all regions of the country.

This result is in contrast to Graff-Zivin et al. [2014] due to inclusion of non-fossil fuel generation and total fuel cycle emissions. However, the effects of climate (namely cold temperatures) on EV performance lead to much higher GHG intensity for EV operation in cold regions of the country. In midwestern states the cold weather effects are compounded by a high level of coal generation (the most GHG-intensive electricity fuel) on the margin during winter months. In these cases EVs provide significantly *negative* emissions abatement benefits; that is, they emit more GHGs than their ICE counterparts.

Our prospective calculations use the EIA forecasts of electricity generation through 2040, which incorporate business-as-usual increases in the share of renewables, decreases in coal, and a continued modest increase in natural gas.[7] These forecasts show that EVs powered by a 2040 grid can cut GHG emissions by roughly 50 percent in California, Florida and the west, and 25 percent in the south relative to ICEs. On one hand, these are large GHG reductions, and represent an enormous improvement. On the other hand, 50-75 percent of transportation GHGs will not be eliminated by a switch to EVs barring changes in either vehicle technology or the anticipated trajectory of electricity generation mix. While changes in vehicle technology will certainly occur, it is not ex ante evident whether EV or ICE technologies will improve at a faster rate. For example, Corporate Average Fuel Economy (CAFE) Standards mandate that the average fuel economy of new passenger cars increase from 30 mpg in 2013 to 54 mpg by 2040, which would yield a 44 percent reduction in combustion-related GHG emissions from ICEs. While it falls outside of the scope of this paper to predict technological change in the vehicle fleet, it is important to acknowledge that ICE vehicle technology is not standing still.

Neither the present day results nor the forecasts provide a conclusive basis for claiming that present-day EV policies are or are not justified. Our estimates place the present-day value of net avoided GHG emissions at roughly $425 per EV in clean regions. To put this in perspective, if EV life

[7] Note that the EIA forecasts do not incorporate the impacts of yet-to-be-implemented federal policies such as the Clean Power Plan (Section 111(d) of the Clean Air Act), or of potential future policies. It thus is likely to underestimate the rate of growth of renewable energy sources on the grid. To account for this, in Section 3.2 we discuss how our results would change under more aggressive assumptions about grid reliance on fossil fuels.

cycle GHG emissions were zero in 2015 the net benefit would be $3200 (2015 dollars). However, there are important potential benefits that are excluded from our analysis. First, our analysis omits health improvements from reduced local criteria pollution, which primarily accrue in dense urban areas (see Holland et al. [2015] and Tessum et al. [2014]). Another limitation of this study is the counterfactual against which we compare EVs – a comparable ICE vehicle; we do not consider hybrid electric vehicles (HEVs). Furthermore, one goal of promoting EVs today is to accelerate technological progress and achieve economies of scale. Whether or not one views current policies as optimal for achieving these goals, what is abundantly clear is that policymakers face a complicated landscape in which important linkages exist between the composition of the electric grid and geo-spacial considerations (including climate). The likelihood that EVs achieve the desired pollution abatement objectives depends on how robust policies are to these complexities. For this reason (and others), these authors continue to advocate for policies that assign a price to pollution. A carbon tax or a cap-and-trade program are both cost-effective ways to achieve environmental goals, and are robust to the complexities described above when designed correctly.

The paper proceeds by describing each of the components of the model in sequence. In Section 2, we describe our methodology and data for calculating life cycle ICE vehicle and EV emissions, respectively. Section 3 describes the calculation of marginal emissions associated with electricity generation. Section 4 outlines the behavioral assumptions behind vehicle usage, including how we build the rebound effect into our model.[8] We conclude in Section 5 with a discussion of the implications of these results.

2 Methodology and Data

When considering the net GHG abatement gain from EVs, one must establish a basis for comparison. We pursue a simple thought exercise that is similar in spirit to analogous papers in the

[8] A more detailed description of our methodology, as well as interesting results of secondary importance, will eventually be made available in an online appendix.

literature (e.g. Graff-Zivin et al. [2014], Holland et al. [2015] and Yuksel and Michalek [2015]). Consider an average household in the US scrapping their existing vehicle and choosing to replace each car with either an EV or an ICE with similar attributes. Our methodological approach is to quantify each of the four components of the life cycle GHG emissions associated with these different vehicle types. The four components are 1) emissions from energy used in propulsion, 2) life cycle emissions from the extraction, processing and delivery of the energy used for propulsion (the fuel cycle emissions), 3) emissions associated with the materials and processes relating to the manufacture of the vehicle, and 4) differences in vehicle efficiency and emissions resulting from the location of vehicle use. The first four Methodology and Data subsections that follow describe our process for calculating EV and ICE emissions for each of those components. An additional subsection (2.5) describes the methodology for estimating the net EV GHG savings under different assumptions about the evolution of the electricity grid. Many of the arguments used in favor of intervening on behalf of EVs now have to do with a vision of the grid as being comprised of substantially less coal and substantially more renewable energy sources. Section 2.5 describes the forward-looking scenarios that we model.

2.1 Estimating Emissions from Vehicle Propulsion

There is substantial heterogeneity in household demand for vehicle miles traveled (VMT) across regions of the United States and throughout the year. Since the emissions benefits of EVs vary across the United States (Graff-Zivin et al. [2014]) and throughout the year, it is important to account for the heterogeneous demand for VMT. Our simulation utilizes micro-level data to estimate the distribution of state-level VMT demand. Our preferred estimates of VMT demand also account for changes in VMT demand in response to changes in the operation costs of vehicles (i.e. the rebound effect).

We obtain trip-level travel data for a random sample of households in the United States using the 2009 U.S. Department of Transportation *National Household Travel Survey* (NHTS). We examine the travel habits of individuals driving EPA mid-size cars on weekdays.[9] The NHTS is a stratified random sample of households; so calculations using NHTS data are reweighted using sampling weights provided as part of the survey. A summary of variables used from the NHTS are shown in Table 1.

2.1.1 Fuel Demand from Vehicle-Miles Traveled (VMT)

We derive the distribution of base demand for VMT using the NHTS for EPA mid-sized cars. We estimate the distribution of annual demand for VMT in each state using sample-weighted driver-reported annual VMT for each vehicle in that state. Demand for VMT also varies over the course of the year, so for each state we compute the sample-weighted portion of survey miles per quarter. The distribution of VMT demand for each state in each quarter is the product of the annual VMT demand distribution and the portion of miles driven in each state and quarter of year.

We consider the hypothetical scenario where a household replaces their current midsize vehicle with either a midsize ICE or EV. However, using current battery technology, the range of pure EVs can be quite limited. For example, Nissan advertises a range of 135 km for the current model Leaf. Therefore, for some households, an EV would be unable to supply VMT demand placed on their current mid-size ICE. Using household travel survey data we compute histograms of VMT by day in Table 2 and longest trip in Table 3. The vast majority of households (98%) have a longest trip within the range of our prototype electric vehicle (130 km). In fact, 82% of household vehicles could meet their entire survey day of driving with an 130 km range.

Since vehicles could be charged multiple times in one day, our primary specification include all households, regardless of total daily VMT and assumes both ICEs and EVs operate for 257,000 km and are then scrapped. All other variables are functions of distance traveled. Thus, excluding high-VMT households would leave GHG per mile unchanged. As a test of robustness we examined

[9] The EPA defines cars having between 110 and 119 cubic feet of total passenger and cargo volume as mid-size.

an alternative scenario where households utilize EVs only for trips of 130 km or less and a second scenario where the range of trips available to EVs is further limited by the effects of climate on EV performance. While neither of these scenarios qualitatively affect our conclusions on the emissions benefits of EVs, it is important to note the welfare impacts of severely range-limited EVs are less clear. In every state during the period we consider, the marginal cost of operation of EVs is lower than a comparable ICE except under the most extreme operating conditions. Conditional on ownership of an EV, households which choose not to make a particular trip due to range limitations which they would have made in their higher cost-per-mile ICE suffer an explicit welfare loss as the *marginal* benefits of that trip must exceed the *marginal* costs absent the range restriction. These and other test of robustness are described in additional detail in Section 3.1 and more extensively in the Appendix.

Households are likely to alter demand for VMT in response to changes in the marginal cost of operating their vehicle.[10] For ICEs, changes in operating costs are manifested through changes in the price of gasoline over time. We determine the operating cost per mile at the time of the NHTS in each state and quarter of year as the gasoline price on the date of survey times the EPA-labeled standard drive cycle miles per gallon of each household's vehicle from the NHTS. We simulate ICE costs of operation using the the average price of gasoline in each state and quarter during 2011 and 2012.

We obtained retail gasoline prices using EIA's *Weekly retail gasoline and on-highway diesel prices.* These provide monthly average retail gasoline prices by PAD District, for select states, and for select cities. We computed average gasoline prices by state and quarter of year using price data from 2011 and 2012, and assigned the average price for the appropriate PAD District if state-level data are unavailable.

Just as the operating cost of ICEs is directly related to the cost of gasoline, the cost of operating

[10] A household which increases VMT in response to a lower cost of operation realizes a private welfare gain. By choosing to consume VMT over some other good the household reveals each unit of VMT provides as least as much utility as their marginal utility money and their private utility must increase. Borenstein [2013] provides an excellent discussion of how rebound can lead only to private utility gains.

an EV is a function of the price of electricity used to charge the EV. We calculate the average retail electricity price per MWh of electricity for residential customers by state using *Monthly Electric Utility Sales and Revenue Report with State Distributions* (Form EIA-826). These data provide monthly total residential revenues and consumption by state. We compute quantity-weighted average retail price by state and quarter of year from 2011 to 2012.[11] Rational households with electric vehicles should make VMT decisions based on their marginal price of electricity, which often differs from the average price. We employ average price as a reasonable proxy for marginal prices for a number of reasons. Marginal prices will vary by utility, household, and month in ways that are not captured in demographics data provided in the NHTS.[12] Ito [2014] demonstrates households generally make electricity consumption decisions based on average price, not the marginal price. Finally, the average retail price of electricity is available, consistently measured, and easily computed at the state level from 2011 to 2012.

We assume households charge EVs using electricity from their residential electricity connections at home or pay a rate for charging that mirrors the average residential rate. We compute state-level residential electricity prices in each quarter using Form EIA-826 from 2011 and 2012. Our prototype electric vehicle, accounting for inefficiencies of the charger and battery under normal operating temperatures is assumed to require 226.4 Wh per km traveled. Operating cost per mile for EVs is the product of the electricity price and energy consumed per km of travel.

Numerous researchers have examined how household demand for VMT responds to changes in vehicle operating costs. We follow Gillingham et al. [2014] and assume the operating cost elasticity of VMT to be -0.2, implying that a 10 percent decrease in vehicle operating cost per mile results in a 2 percent increase in VMT. For robustness we also consider the case of no rebound and a VMT rebound elasticity of -0.4, covering the range of estimates in the literature. For each state

[11] While residential electricity rates likely do not vary across quarters, many residential households face an increasing block pricing schedule. Prices will tend to be higher when electricity demand is the largest, which is usually the summer months. Computing residential electricity prices by quarter captures the effect seasonal variation in demand on the rate tier.

[12] For example, households on increasing block pricing may face different marginal electricity rates in different months depending on consumption of other appliances. The NHTS does not capture data on use of household appliances.

and quarter we compute the distribution of VMT using the base VMT demand from NHTS and the percentage change in VMT using the percent change in operating cost per mile from the NHTS to our 2011-2012 operating cost measures times the VMT rebound elasticity.

2.1.2 Marginal Emissions from Electricity for Propulsion

After determining the electricity demand for EVs, we estimate the impact of the additional demand for electricity generation on GHG emissions.[13] Our thought experiment considers the the decision of a single household to purchase an EV over a comparable ICE. For such small changes in the composition of the vehicle stock, replacing an ICE with an EV will represent an increase on the margin of electricity generation while the vehicle is charging. Electricity supply is dispatched to minimize the marginal cost of generation, starting with the lowest cost units and adding higher cost units as demand increases. Adding an additional unit of demand does not proportionally increase generation by all operating units. Instead, the additional unit of demand is served by the lowest cost unit that is not already operating at capacity, or the marginal generator. The marginal generator can have an emissions profile that is much different from the grid average.

The electricity generation supply curves and marginal combustion-related CO_2 emissions for two different electricity-generating regions, MRO and WECC , are shown in Figures 2(a) and 2(b), respectively. Note renewable generation technologies, such as wind and solar, have negligible marginal costs and will supply electricity whenever they are available. An increase in demand is unlikely to cause additional solar or wind resources to supply electricity into the grid. In periods of low demand low-cost fossil fuel sources such as coal-fired generation (with high GHG emissions per MWh) are generally marginal. As demand increases higher-cost suppliers, such as combined-cycle gas turbines (CCGTs) burning natural gas will come on-line to serve demand.

When estimating the GHG benefits of replacing an ICE with an EV, one should consider the change in electricity generation emissions caused by the additional electricity demand from charging that

[13] A technical description of our methodology is presented in the Appendix.

EV. Our simulation attributes emissions to the electric vehicle resulting from the *marginal* change in fuel consumption resulting from charging. We find there is substantial heterogeneity in both marginal CO_2e emissions and marginal fuel consumption for electricity generation over space, time of day, and season.

Our estimates of marginal GHG emissions from charging offer a number of unique contributions. First, unlike previous estimates which ignore the non-fossil fuel generation, we compute hourly generation by both fossil fuel and non-fossil fuel sources. We find non-fossil fuel generation can often be the marginal source of generation even in hydro-heavy regions such as the Western and Northeastern US. Second, we decompose marginal CO_2 emissions into the component fuel source. This allows us to compute the full life cycle emissions, including those from fossil fuel extraction, processing, and transportation, per MW of electricity generation.[14] Third, we account for seasonal heterogeneity in electricity generation by computing separate estimates for each quarter of year.

The electricity generating grid in the continental United States is divided into eight distinct regions by the North American Electric Reliability Corporation (NERC) for the purposes of planning and reliability. These NERC regions form three electrical interconnections. The WECC and TRE region each form their own interconnection and the remaining NERC regions form the Eastern Interconnection. Similar to Holland et al. [2015], we assume electricity can flow freely within a NERC region, so demand anywhere withing a given NERC region will have an identical impact on the generation resources deployed regardless of location within the NERC Region.

Electricity may also flow between NERC regions, however, transmission constraints and losses may prevent the free flow of electricity between NERC regions. We model the electric grid in the continental United States as three electrical interconnections (East, Texas, and West). Demand anywhere on an interconnection has the potential to affect generation at any plant on the same interconnection. However, supply on one interconnection cannot serve demand on a different interconnection.

[14] We also account for the full life cycle emissions of gasoline used to power ICEs.

We assign each state to one of the eight electricity-consuming NERC regions as defined in the most recent revision, from 2010. These regions are pictured in Figure 3. A single state can span more than one NERC region. In these cases we assign states to the NERC region with the largest land area in that state. Due to the lack of emissions data, we exclude Alaska and Hawaii from our analyses.

Using a panel dataset of electricity demand and supply in the various regions, it is possible to estimate the marginal source of generation at any moment in time. We describe the procedure briefly here and in more depth in the Appendix. The basic premise is that the electricity grid must remain in balance at all times, such that any increase in demand for electricity must be fulfilled by additional supply. Were this not to be true, either demand would exceed supply (the source of blackouts) or supply would exceed demand (inducing costly damage to the grid infrastructure).

We construct this panel dataset of demand and hourly electricity generation by source fuel type for 2011 and 2012 by combining on a number of data sources and replying on the understanding that electricity demand must balance supply at all times. In each Interconnection the following identity must always hold:

$$\overbrace{\underbrace{\text{Gross FF Generation}}_{(1.\text{A})} + \underbrace{\text{Gross non-FF Generation}}_{(1.\text{B})}}^{\text{Supply}} = \overbrace{\underbrace{\text{Net Load}}_{(1.\text{C})} + \underbrace{\text{Transmission Losses}}_{(1.\text{D})}}^{\text{Demand}} \quad (1)$$

Our primary data source for constructing gross fossil fuel generation (1.A) come from the EPA's Continuous Emissions Monitoring Systems (CEMS) dataset. These data provide hourly gross generation load, fuel consumed (in million BTU), and direct combustion CO_2 emissions for all grid-connected electricity generating units with a nameplate capacity of 50 MW or more in the continental United States from 1997 through the present. The generation mix and dispatch order is constantly evolving, so we limit our estimates to the recent years of 2011 and 2012.[15]

[15] We are unable to use more recent CEMS data as the most recent generation unit data in Form EIA-860

CEMS reports only generation by the combustion turbine part of CCGTs.[16] We scale up generation for CCGTs using a ratio of monthly net generation reported in EIA's Annual Electric Generator Data (Form EIA-860) to obtain gross generation for both components of each CCGTs. Additionally, we use Form EIA-860 to augment plant details not available in CEMS, compute cannibalism at the plant level.

We compute net load in each NERC region (1.C) using the Federal Energy Regulatory Commission's Annual Electric Balancing Authority Area and Planning Area Report (FERC Form 714). These data include net load for every FERC planning area in the United States during the 2011 and 2012 period for which we compute marginal emissions. Some FERC planning areas overlap.[17] We eliminate planning areas that are subsets of other planning areas to create a non-overlapping set of FERC planning areas in each NERC region. We then aggregate up load from each of these planning areas to compute total demand in each NERC region.

As electricity flows within and between NERC regions some energy is lost in the tranmission infrastructure. We compute the transmission losses (1.D) using EIA's Annual Electric Power Industry Report (Form EIA-861). This dataset provides details for every electric utility in the United States including transmission losses from 1990 through the present. We use data from Form EIA-861 from 2011 to 2012 to compute transmission losses for each NERC region.

Finally, we compute gross non-fossil fuel generation (1.B) using the identity in Equation (1) as net load plus transmission losses minus gross fossil fuel generation.

Using these data we estimate a system of equations that yield the marginal contribution of each

(described below) cover 2012.

[16] CCGTs are a common electricity generation technology consisting of two components. The combustion turbine portion burns natural gas (or some other fuel) to directly drive a turbine connected to a generator. The steam turbine portion uses waste heat from the combustion turbine to generate steam which then spins a separate turbine, generating additional electricity. Ignoring the steam turbine portion would overestimate the true heat rate of a CCGT.

[17] For example Pacific Gas and Electric (PG&E) and the California Independent System Operator (CAISO) are both planning areas and report hourly load in Form 714. However, PG&E participates in the CAISO exchange and including both would double-count demand from PG&E.

generation source to an incremental unit of energy demanded during any given hour in any region of the country.[18] Thus, we are able to compute the probability that a given generation type will be the marginal type called upon to meet the demand of an additional EV that plugs into the grid at any hour of the day, for any season of the year anywhere in the country. Importantly, by identifying the marginal generation source, we have determined the corresponding fuel source (coal, gas, petroleum, or non-fossil fuel) as well. The combustion and life cycle GHG footprint can then be calculated.

2.2 Life Cycle Fuel Emissions

Operation emissions are divided between fuel production (well-to-pump or well-to-battery), and fuel combustion (pump-to-wheel) or vehicle operation for EVs. GHG emissions are reported in units of CO_2e based on the most recent 100-year global warming potentials (without climate-carbon feedbacks) from the Intergovernmental Panel on Climate Change (Myhre et al. [2014]).

Vehicle operation emissions for ICEs come from two sources, gasoline fuel production and fuel combustion. The GREET 1 model provides estimates of emissions from gasoline production and combustion. Total operation emissions sum to 248 g CO_2e per km, of which 20 percent is attributable to fuel production.

Operation emissions for electric vehicles are less easily reported, because they depend on the regional electricity grid's marginal combustion emissions and mix of fuels as described in Section 2.1.2. Here we describe life cycle fuel production and delivery emissions only. Electricity fuel production and delivery emissions are taken from GREETnet, a version of GREET 1 which allows a user to more easily extract fuel pathway data (Energy Systems Division of Argonne National Laboratory [2014a]). The pathways extracted include average coal for U.S. electricity, residual oil from petroleum for U.S. electricity, and North American natural gas from shale and regular recovery for U.S. electricity.

[18] Details of the estimation procedure are available in the Appendix.

The natural gas mix assumes 77 percent from regular recovery and 23 percent from shale gas. Shale gas is modeled to have 26 percent greater methane emissions during production and processing, but total CO_2e emissions of only 11 percent greater than regular gas due primarily to lower CO_2 emissions. The fuel production and delivery emissions for the electricity fuels on a grams of CO_2e per MJ basis are 6, 11 and 14 for coal, natural gas, and residual oil, respectively.

2.3 Life Cycle Vehicle Emissions

We use Argonne National Laboratory's GREET model series to characterize GHG emissions from the vehicle life cycle. There are two GREET models, GREET 1 which characterizes energy sources for transportation (the GREETnet version was used in this analysis)[19], and GREET 2 which characterizes vehicle production[20] With these two models we are able to attribute life cycle emissions from vehicle production, maintenance and disposal, as well as fuel cycle emissions for gasoline for ICEs, and fuels used in electricity, as decribed above.

GREET 2 includes life cycle GHG analyses for the production of both EVs and ICEs for a number of vehicle classes. GREET 2 model parameters were set so that 2015 model year (MY) midsize vehicles were used. MY selection determines the fuel economy of both vehicle types. Selecting MY 2015 led to the following vehicles; an ICE with a fuel economy of 8.65 L/100 km (27.2 mpg), and an electric vehicle with a gasoline fuel economy equivalence of 2.16 L-equivalent (Le)/100 km (108.8 mpge) before accounting for charging efficiency estimated at 85%, making the effective fuel economy 2.54 Le/100 km (92.5 mpge), or 140.7 Wh/km.[21] The GREET 2 model simulates an EV with a battery capacity of 28 kWh. This modeled vehicle is similar to the Nissan Leaf which has a battery capacity of 24 kWh and a fuel economy of 2.06 Le/100 km (114 mpge) before accounting for charging efficiency.[22]

[19] (a) Energy Systems Division of Argonne National Laboratory [2014c] (b) Energy Systems Division of Argonne National Laboratory [2014a].

[20] Energy Systems Division of Argonne National Laboratory [2014b].

[21] Energy Systems Division of Argonne National Laboratory [2014b]

[22] http://www.nissanusa.com/electric-cars/leaf/versions-specs/ (accessed 1/3/2015).

The GREET 2 model characterizes the life cycle of vehicles, including production, maintenance, operation (as a link to GREET 1) and disposal. For this study we have grouped together all non-operation emissions (vehicle production, maintenance including fluid replacement, and disposal). Vehicle production is broken down into the following categories: components; batteries; assembly, disassembly and recycling; and fluids. ICE vehicles are modeled to have non-operation emissions of 28 g CO_2e per km of travel assuming a 257,400 km (160,000 mi) lifetime. EVs have higher life cycle vehicle non-operation emissions due to traction batteries (assumed to be Li-ion) and due to different vehicle components. This is because the vehicle mass is larger for EVs, increasing the weight of some components, and because of emissions-intensive materials such as copper used in significantly higher quantities. This leads to non-operation emissions of 36 g CO_2e per km assuming a single battery for the entire 257,500 km (160,000 mi) vehicle lifetime. Each battery replacement during that lifetime leads to an increase of approximately 4 g CO_2e per km.

2.4 Cold and Hot Climate Effects

A number of studies have examined the effects of cold ambient temperatures on EVs, illustrating significant reductions in EV range due to increased energy demand for auxiliary loads (namely cabin heating) and decreased discharge efficiency (Kambly and Bradley [2015]). Recognition of these effects has led to cold weather test cycles by the EPA and Environment Canada. Cold weather testing conducted for urban and highway drive cycles by Environment Canada are used in this study to assess the effect of cold temperatures on energy performance of EVs.[23] Two effects are captured; the first is the loss of efficiency in charging and discharging of the battery, and the second is power demand for cabin heating.

Meyer et al. [2012] tested three EVs under cold conditions over a number of drive cycles. Two of the tested EVs were tested over the U.S. city and highway drive cycles at the full range of temperatures considered (referred to as BEV1 and BEV2 in Meyer et al. and referred to as Case 1 and Case 2

[23] Meyer et al. [2012].

here), and those two vehicles' test results are used here.

EV energy efficiency is also affected by hot temperatures, mainly due to air conditioning demands on the battery. Hot weather effects on vehicles were estimated based on Lohse-Busch et al. They tested EVs, plug-in hybrid electric vehicles (PHEVs), HEVs, and ICE vehicles at -6.7 °C (20 °F), 22.2 °C (72 °F), 35 °C (95 °F) (Lohse-Busch et al. [2013]). Hot weather test results for the city and highway drive cycles are used here.

The city and highway drive cycle results for cold and hot weather tests were weighted based on U.S. practices for calculating city-highway average fuel economy (55% city + 45% highway). Because data were only collected at three cold test temperatures; 20, -7, and -18 or -20 °C, and one hot weather temperature, 35 °C, the following logic was used to interpolate between energy use at each test temperatures.

1. Between -40 °C and -7 °C a linear relationship defined by the results of the -20 °C or -18 °C and -7 °C tests with heat on was used.

2. Between -7 °C and 20 °C a linear relationship is used as defined by the results of testing at -7 °C with heat on and 20 °C with heat off.

3. Temperatures above 20 °C are based on the linear relationship between temperature and energy efficiency for the tests at 22.2 °C and 35 °C .

4. The tested alternating current (AC) recharge energy was used in all cold weather cases (rather than the discharge energy of the battery) because AC recharge energy includes losses in charging efficiency at colder temperatures. For hot weather charging efficiency is equal to efficiency measured at 20 °C .

Results were then converted to percent of highway-city average recharge energy use at 20 °C, as shown in Figure 4. These results were used to create two cold weather cases for AC recharge energy demand by region based on climate data.

The loss of efficiency in cold and hot weather leads to reduced range for EVs. Loss of range estimates are derived from Lohse-Busch et al. based on linear interpolation and extrapolation for the three tested temperatures, assuming the combined city-highway drive cycle. This is shown in Figure 4.

Efficiencies of ICEs are also affected in cold and hot temperatures. However, cold temperature effects are less pronounced because ICE vehicles use waste heat from the engine to assist in cabin heating. ICEs are mostly affected by cold temperatures on short trips when engines are cold, and through the use of defrosters and other auxiliary power loads that may be increased. The U.S. EPA cold weather fuel economy tests show that ICEs operated at ambient temperatures of -7 °C leads to approximately 12% less fuel economy, which is most pronounced on short urban trips before the engine is warmed up.[24]

Two cases are developed for climate effects on ICEs; ICE Case 1 and ICE Case 2. ICE Case 1 derives linear relationships between temperature and fuel use, calculating the outcome on a percent basis relative to vehicle operation with no climate control at 22.2 °C for a Ford Focus based on test results from Lohse-Busch et al. [2013].

ICE Case 2 uses the same hot weather effects as ICE Case 1, but uses cold weather test results for Honda as reported in a 2006 EPA report (EPA [2006]). Eight Honda vehicles were tested, all with different fuel economies and different interior cabin space at three temperatures 23.3 °C (75 °F), 10.0 °C (50 °F), and -6.7 °C (20 °F). Results showed a strongly linear relationship between fuel use and temperature for all tested vehicles (R^2 of 0.85-0.99). Using the vehicle model that most closely resembles the ICE vehicle used for this analysis, the Accord L4, we develop a linear relationship between temperature and energy efficiency to estimate the change in fuel consumption on a percent basis as a function of temperature. The Honda Accord results show a larger effect of cold climate on fuel consumption compared to ICE Case 1. Both of these cases are shown in Figure 4.

To determine the impact of cold weather on real-world EV and ICE energy demand, we determine

[24]U.S. Department of Energy [2014].

the probability in each quarter of the year that the average temperature for a household in each NERC Region will fall within a specified range. We employ climate data from the Quality Controlled Local Climatological Data (NOAA [2015]). These data contain daily measurements of climatological data, including daily average temperature, for over 200 climate stations across the United States. We assign each station a weight using the 2010 US Census population of the incorporated unit (e.g., city or town) nearest to the climate station.

Using observed temperatures from 2004 through 2013 and population weights for each station, we compute the population-weighted probability that the daily average temperature will fall within 5 °C bins for each NERC region in each quarter of the year.[25] Each temperature bin is associated with an energy demand factor, shown in or interpolated from Figure 4. Assuming VMT in each quarter and NERC region are uniformly distributed across the quarter, we compute expected quarter-interconnect level energy demand factors and modify EV energy demand by those factors.

2.5 Forecasting Future Grid Emissions

As technology, regulation, and fuel prices change it is reasonable to think electricity grid emissions will change over time. Forecasting life cycle EVs in the future requires accounting for evolution of the grid. When evaluating emissions of vehicles in the future we consider average, not marginal, emissions from electricity generation. Our reasoning is twofold: first, when evaluating the emissions from EVs produced beyond the near future the relevant thought experiment is of the form "What is the change in emissions if we implement a policy that induces, e.g., 1,000,000 vehicle purchasers to choose an EV instead of an ICE by 2040?". In this case, when considering adding a mass of EVs, vehicle charging is inframarginal and average emissions are relevant. Second, forecasting marginal emissions requires determining the marginal generation unit under each forecast scenario which

[25] Daily average temperature is an imprecise measure of temperature when the vehicle is operating. One would expect morning commute temperatures to be below the average and evening commute temperatures to be above the average. Since the relationship between battery charge/discharge efficiency and temperature appears approximately linear over wide temperature bands, we expect the bias from using average temperature to be minimal.

is a function of supply and demand. Any future electricity supply curve would depend critically on the marginal cost of each generation unit, which in turn is a function of fuel prices and the regulatory environment. While the marginal generation unit is quite sensitive to marginal costs, average emissions are much less sensitive.[26]

We compute EV emissions benefits under the following two scenarios.

EIA Electricity Generation Forecast. First, we forecast future average emissions using the Electricity Generation by Electricity Market Module Region and Source from EIA [2015]. It provides forecasts of annual generation by fuel type for each NERC region for each year from the present to 2040. We account for intraday variation in average fuel use by scaling our estimates of hourly average fuel using the change in generation mix from 2012 to the forecast year.

The EIA forecasts small changes in fuel consumption through 2040 relative to 2012. While the penetration of renewables increases over time, nuclear generation is declining over time as nuclear generating stations are decommissioned. This leads to average GHG emissions per MW that are very close to 2012 levels. Forecast generation mix for each NERC region are shown in Figure 5.

It is important to note that the EIA forecasts traditionally underestimate the growth of renewable electricity sources on the grid. This is at least in part because the forecasts do not attempt to incorporate the impact of policies such as the recently-passed Clean Power Plan, which is likely to significantly reduce the GHG footprint of the nation's electricity grid. Our results that rely on the EIA forecasts should be interpreted in light of that drawback. It also motivates our inclusion of a more aggressive grid forecast scenario.

Aggressive Elimination of Coal. As an alternative to EIA's forecast, we model future average emissions assuming the complete replacement of coal-fired electricity generation with less GHG-intensive natural gas generation by 2040. Following Holland et al. [2015], we adjust our EIA

[26] For example, an increase in the price of coal may cause natural gas generation units to be dispatched before coal units, changing the marginal source of generation. However, if demand is sufficiently large to require dispatch of both coal and gas generation, then average emissions per MW would not change.

Electricity Generation Forecast so all coal generation forecast in 2040 is replaced with combined-cycle natural gas generation. We assume constant annual increases in natural gas generation and constant annual reductions in coal-fired generation between 2012 and 2040. Again, we account for intraday variation is average fuel use by scaling our estimates of hourly average fuel use using the change in generation mix from 2012 to the forecast year. Forecast generation mix for each NERC region under this scenario are shown in Figure 6.

3 Results

We model the impact on life cycle emissions of replacing a mid-sized ICE with an EV alternative under a number of assumptions on vehicle performance and driver behavior. The results of these simulations are shown in three different ways. First, Table 4 displays estimates of the net avoided emissions that result from each scenario in each region. Second, Figure 7 display graphically, in maps, the net avoided emissions by state, accounting for variation in vehicle mix and VMT at the state level. Finally, to demonstrate the relative importance of each adjustment factor that we model, Figure 8 is comprised of waterfall charts – one for each NERC region and California – of the net contribution to emissions abatement of each channel. Figure 9 shows the same waterfall charts for the US as a whole. In this section, we describe these results in detail.

As described in Section 2.1.2, the marginal impact of electricity demand on fuel consumption changes throughout the day. We generally consider the average of two charging alternatives: "Day" charging where vehicles charge with uniform probability between 9 AM and 5 PM, consistent with charging while at work, and "Night" charging where vehicles charge with uniform probability from 8 PM to 4 AM, consistent with charing at home after returning from work.[27] Table 5 shows the marginal CO_2e emissions for each NERC region and quarter for both day and night EV charging. These results demonstrate the marginal fuel source (and GHG emissions rate) from electricity

[27] Additional details of our analyses by for day-only and night-only charging are available in the Appendix.

generation varies not only by location and time of day, but also substantially varies throughout the course of the year. The GHG intensity of electricity generation is the highest in the places and times when EVs are the least efficient in converting grid electricity into transportation. Ignoring seasonality could potentially lead to incorrect conclusions on not just the magnitude but the sign of GHG benefits of EVs over ICEs.

Limited Effects Scenario: The Limited Effects Scenario considers life cycle emissions from fuels and vehicles, but omits climate effects on vehicles, and rebound effects on VMT. This allows us to highlight the net emissions changes attributable to powertrain efficiency and the life cycle GHG footprint of the energy used to manufacture and propel the vehicles. Table 4 shows the average emissions benefits of replacing a mid-size ICE with a comparable EV in each NERC region.[28] The majority of emissions benefits from EVs come from fuel combustion, particularly in NERC regions where natural gas is frequently the marginal fuel source.

Under this scenario, life cycle CO_2e emissions from EVs are lower than ICEs regardless of the geographic region (i.e. fuel mix), season, or time of day. In coal generation-heavy NERC regions, such as MRO, the benefits are substantially smaller than in NERC regions, such as NPCC, where natural gas is more often the marginal fuel. The emissions benefits of replacing and ICE with an EV by state are shown graphically in Figure 7.

Complete Effects Scenario: This scenario is our preferred, due to the inclusion of all relevant effects that we build into the simulation estimates. It includes each of the channels from the Limited Effects Scenario, along with household VMT response to changes in vehicle operating costs and the effect of operating in cold or hot ambient temperatures on the efficiency of ICEs and EVs. Inefficiency in cold weather has a particularly large effect on EV emissions because coal is more often the marginal electricity generation fuel both in the winter and in states with cold climates.

[28] We provide breakdowns of average manufacturing, fuel production, and fuel combustion emissions for EVs and ICEs in each NERC region in the Appendix.

Our analysis of marginal fuel use for electricity generation shows that in MRO, which includes Minnesota, Wisconsin, and the Dakotas, coal is the primary marginal fuel in the winter months. Contrast this with WECC, which comprises warmer states in the western US, where coal is much less likely to be the marginal fuel supplying electricity demand.[29]

Additionally, EVs generally have a lower cost of operation per mile traveled than ICEs. In this scenario we also account for the possibility that, in the face of lower operation costs, households will drive more. Gillingham et al. [2014] compiles the most credible estimates of price elasticity of VMT, leading us to choose -0.2 as our preferred measure of rebound.[30]

Figure 10 shows the reduction in CO_2e emissions in tons per year from replacing a ICE with an EV in each NERC region accounting for VMT response and the impacts of climate on vehicle performance. These effects (and the seasonal mix of fuels used to supply the marginal megawatt) substantially reduce the emissions benefits of EVs in cold portions of the country, particularly New England (NPCC), the upper midwest (MRO), and the Great Lakes (RFC). For many states in these regions, replacing an ICE with an EV may actually increase CO_2e emissions. The impacts of climate in warmer states such as Florida (FRCC) and Texas (TRE) are much smaller. The emissions benefits of replacing an ICE with an EV by state in Complete Effects Scenario are shown graphically in Figure 7.

For each NERC region and California, Figure 8 compares the annualized expected life cycle CO_2e emissions from (Column 1) an ICE and (Column 6) an EV. Columns 2 through 5 show the decrease (blue) or increase (red) in each component of expected annualized CO_2e emissions from replacing an ICE with an EV. For NERC regions with particularly cold weather (MRO and RFC) fuel combustion emissions are near identical or larger for EVs as opposed to ICEs. Moreover, in these NERC regions, reduced battery performance and energy demand due to climate effects far outweigh any emissions benefits of EVs in fuel production and combustion. A similar graph aggregating over

[29] Detailed marginal fuel use by hour is available in the Appendix.

[30] Our conclusions are robust to larger or zero rebound effects. We describe tests of robustness in Section 3.1.

the entire US is shown in Figure 9.

3.1 Tests of Alternate Assumptions and Robustness

We conduct a number of additional tests of the robustness of our results. Details of the results are available in the Appendix.

Vehicle Life: Our primary specification assumes both ICEs and EVs operate for 257,000 km and are then scrapped. As alternatives, we assume both EVs and ICEs have a fixed life measured in years. We model vehicle scrappage occurring after either 12 or 16 years. EVs tend to have larger manufacturing emissions than ICEs, thus increasing the life of the vehicle spreads those emissions over more VMT, improving EVs relative to ICEs. Direct combustion emissions account for the majority of life cycle emissions and the effect of the lifespan assumption is small.

Accelerated Battery Wear: There is strong evidence that prolonged exposure to high temperatures can substantially shorten the life of EV batteries (e.g., Eddahech et al. [2015], Gu et al. [2014], and Ecker et al. [2014] among others). However, our review of the literature has not found research that estimates the calendar life of batteries under real-world high-heat conditions. As a test of robustness, we compute life cycle CO_2e emissions assuming each EV would require three, as opposed to two, battery replacements during its lifetime. This implies an expected 85,000 km life for each battery. Additional battery replacements have small impacts on life cycle CO_2e emissions, on the order of 0.08 tons per year which is small relative to the difference between EVs and ICEs in fuel procurement and combustion-related reductions in CO_2e emissions.

VMT Response: Our primary specification assumes households have a price elasticity of VMT of -0.2. Electric vehicles have lower marginal costs of operation than gasoline-powered ICEs, so any price response of households in VMT will tend to reduce the GHG benefits of EVs. As a test of robustness, we consider alternative VMT response elasticities of zero (no response) and -0.4, consistent with the range of elasticities identified in the literature by Gillingham et al. [2014]. We find these alternative assumptions have the expected effect on the quantitative output of the simulation; EVs, with lower marginal costs of operation tend to increase emissions more than ICEs when the VMT response elasticity is larger. However, under the range of elasticities consistent with the literature our qualitative results are unchanged.

Average Grid Emissions: Other research examining the emissions benefits of EVs (e.g., Hawkins et al. [2013]) have considered average and not marginal emissions from electricity generation. While the relevant metric when considering the benefits of replacing an ICE with an EV is marginal change in GHG emissions from charging, as a test of robustness we compute the GHG reduction using average grid emissions for comparison. Using average instead of marginal emissions tends to make low-GHG grids, such as renewables-heavy WECC, look cleaner but high GHG grids, such as MRO with significant inframarginal coal, look much more GHG-intensive. We reach identical qualitative conclusions – compared to an ICE, an EV would lead to more GHG emissions in cold, coal-heavy regions of the US – as when using marginal emissions, but the differences are much more pronounced.

EV Range Limitations: Not only is the maximum range of an EV on a single charge shorter than the range of a typical ICE on a single tank of gasoline, but the range of an EV depends critically on ambient temperature. As described further in Section 2.4, EVs may expend additional energy for each kilometer driven when operating in cold or hot temperatures, depleting the battery faster, and reducing range. If a potential trip falls outside of the range of an EV a household may chose to make the trip in an ICE, modify the trip route, or to not take the trip at all. As a test of robustness, we compute the probability that any trip in the NHTS would fall within the range of our prototype EV within that NERC Region and quarter given climate conditions in that region. We then reestimate our preferred Complete Effects Scenario, downweighting the probability of any trip occurring by the probability it is within the range of the EV.[31] We find adjusting for the limited range of EVs does not alter our qualitative conclusions.

3.2 Forecasting EV benefits in the future

The analysis presented so far considers the change in GHG benefits from replacing an ICE with an EV at a snapshot in time. Namely, direct and indirect fuel emissions of EVs are tied to the fuel type of the marginal electricity generating unit when and where the EV owner decides to charge. Policy encouraging adoption of EVs should not only consider the present benefits of EVs, but the benefits EVs may provide in the future as well. In this section we forecast the emissions benefits of EVs forward to 2040.

Forecasting into the future is an inherently speculative process. The technological, political, and economic factors underlying any forecast are all changing over time. The analysis presented here holds the policy environment, technology, and economic factors constant. We assume the relative prices of gasoline and residential electricity are unchanged, and the relative prices of electricity fuels do not change over time,[32] the technology for powering both ICEs and EVs remains constant,[33] and the policy environment is unchanged.

Instead, we forecast the emissions benefits of EVs compared to ICEs as the generation mix of the electric grid changes over time. We forecast under two scenarios. First, we model evolution in the composition of the electric grid using forecasts from EIA [2015]. The change in generation mix for each NERC region from 2012 to 2040 are shown in Figure 5. EIA forecasts increases in renewable

[31] This assumes households will substitute VMT in an ICE for VMT in an EV when the trip length exceeds the range of the EV. If households instead reduced VMT in response to range restrictions this assumption would understate the emissions benefits of EVs. However, if households responded to reduced range by making more, shorter trips (for example, returning home to charge in what would be the middle of a longer trip absent range restrictions and then resuming the trip later) EV emissions benefits would be overstated.

[32] For example, a large increase in the price of coal could make it infeasible as an electricity fuel, changing the calculation of emissions from electricity generation.

[33] In reality one expects both EVs and ICEs may become more efficient in converting fuel into transportation as time passes.

and a decline in nuclear generation over the next 25 years, however, there is little overall change in generation mix.

The emissions benefits of replacing an ICE with an EV forecast through 2040 are shown in Table 6. Under this forecast, the emissions benefits of EVs increase steadily across the US through 2040. By 2040, on average, replacing an ICE with an EV in the US would reduce GHG emissions by 1.13 tons CO_2e/year. However, even in 2040 EVs still have higher emissions than ICEs in the coal-heavy MRO and RFC NERC regions. These results are shown graphically in Figure 12.

3.2.1 An Optimistic Scenario

As an alternative to the EIA forecast, we assume aggressive reduction in coal-fired generation across the US. Specifically, we assume all NERC regions replace all coal-fired generation with combined-cycle natural gas generation by 2040. The change in generation mix from 2012 to 2040 under this aggressive scenario are shown in Figure 5.

In addition to elimination of coal-fired generation, we make additional assumptions favorable to EVs in this forecast. First, we assume households exhibit zero VMT price response and, second, we assume households charge during the daytime (with lower average emissions). The emissions benefits of replacing an ICE with an EV forecast through 2040 are shown in Table 6. Under this scenario, EVs have lower emissions than ICEs in every NERC region by 2030. By 2040, replacing an ICE with an EV would reduce GHG emissions by 3.32 tons CO_2e/year. These results are shown graphically in Figure 12.

3.3 Implications for EV Policy

Our analysis places an upper bound level of EV subsidy that can be rationalized by GHG abatement alone. If that were to be the only objective (which it is not), an efficient policy would require that the per-unit subsidy be smaller than the present discounted value of damages avoided, or the social cost of GHGs times the emissions avoided over the life of the vehicle.[34] Currently, replacing a midsize ICE with an EV in the WECC reduces GHG emissions by 0.74 tons CO_2e per year. Assuming a vehicle life of 16 years, the present value of avoided damages is $427. Even if EVs resulted in zero life cycle emissions, the damages avoided by replacing an ICE with an EV in the WECC region are $3182.[35]

Looking to the future, using forecasts of electricity generation from EIA [2015], replacing an ICE with an EV in the WECC NERC region will reduce GHG emissions by 2.7 tons per year in 2040.[36] In 2040, replacing an ICE with an EV in will avoid $2380 of damages in 2040 dollars. Alternatively, supposing life cycle emissions of an EV are zero, replacing an ICE with an EV in the WECC NERC region in 2040 will avoid $4866 of damages in 2040 dollars.

4 Conclusions and Implications

The impressive efficiency of the EV powertrain led many to hope that EVs would provide a path to transportation sector GHG emissions reductions. However, powertrain efficiency alone does not guarantee GHG emissions reductions. Electricity fuel source and performance under real-world conditions are the determinants of life cycle GHG emissions. This study is the first comparative analysis that presents an integrated model of life cycle emissions for both the manufacture and use of ICEs and EVs that also considers the effects of climate conditions on vehicle efficiency and non-fossil power sources used for marginal electricity. This contribution builds on work from several other scientists who have examined these factors mostly in isolation. There are two benefits

[34] In the calculations that follow we discount avoided damages at 3% and assume a $38/ton CO_2e social cost of carbon in 2015 which grows linearly over time, following Interagency Working Group on Social Cost of Carbon, United States Government [2013].

[35] This would require not only that the EV be powered entirely by non-fossil fuel generation but that no GHGs are emitted during the manufacturing, maintenance, and scrapping of the vehicle.

[36] Again, we follow Interagency Working Group on Social Cost of Carbon, United States Government [2013] and assume the social cost of carbon is $62/ton CO_2e in 2040 which grows over time.

of taking the integrated approach. First, we are able to estimate the cumulative net effect, and, second, our approach reveals the relative magnitude of the different sources and causes of emissions.

Our results show that net abatement benefits from EVs depend primarily on two key factors: 1) the marginal source of electricity generation, which depends on the composition of the electricity grid; and 2) the effect of ambient temperatures have on the efficiency of charging and discharging batteries. In areas with warm temperatures and a relatively clean electricity grid, like California and Florida, EVs provide substantial GHG abatement gains relative to a comparable ICE. But in regions with cold temperatures and dirty marginal electricity generation technology, EVs will provide little GHG abatement gains, and can even cause emissions to increase. Other factors also contribute to the emissions balance of EVs, such as battery life (which shortens in hot temperatures) and differences in the manufacturing footprint of EVs vs ICEs. However, these effects are smaller and relatively similar across regions.

These results help to inform policymakers about whether and where to promote EVs for the goal of abating GHG emissions. Much is already known about optimal policy in the presence of externalities such as the damage arising from GHGs. The so-called "first best" approach is to increase the price of emissions, which can be accomplished either by imposing a tax equal to the marginal damages associated with them, or by creating a tradable permit system. The inability or unwillingness of the political system to implement these optimal policies has left governments with more problematic alternatives. One such alternative is to subsidize "clean" technologies. In the US, a federal electric vehicle credit reduces the price of EVs by up to $7500, irrespective of location of purchase. Some states add incentives of their own. Figure 13 displays a map of states that offer some sort of EV subsidy program. Were we to assume that the goal of these EV incentive policies is to reduce GHG emissions, a measure of the effectiveness of the policies is gained by seeing whether EVs should be expected to produce such benefits. A simple comparison of Figure 7(b) with Figure 13 reveals that there is a misalignment, and implies that some states that subsidize EVs should not do so on the basis of GHG abatement (e.g. states in the Midwest). Further, our analysis is able to place bound on the welfare-improving subsidy intended to reduce GHG emissions.

Future research is required to build upon key aspects of the setting that we did not build into our model and analysis. There are three, in particular, that we expect may alter the qualitative and/or quantitative results. First, EVs provide a potentially large benefit in the form of shifting the location of criteria pollutant emissions from the tailpipe to the electricity generating facility. To the extent that the former is in a dense urban area and the latter is more rural, health benefits will accrue to society at large (although this will likely not be Pareto improving, since people living near the electricity generating facilities may still be worse off). Recent work by Holland et al. [2015] focus on quantifying these benefits.

The second major caveat relates to the thought exercise that underpins our modeling of the vehicle choice decision. We are essentially asking the question "what would happen to CO_2e emissions if the average US household were to scrap their existing vehicle and choose instead to purchase either a mid-size EV or an equivalent ICE vehicle?". Our model does not account for HEVs and PHEVs, which inherently offer margins of adjustment that may be CO_2e-advantageous (such as running on gasoline in low temperatures).

Finally, policies to promote EVs are not motivated exclusively by environmental improvement from todays fleet. They are also intended to give a boost to a nascent technology, which may presently be hindered by low scale economies, appropriable learning-by-doing, network effect obstacles, and potentially other market inefficiencies. There would be great value to identifying and quantifying the magnitude of these effects so that policymakers are equipped with full information as they determine how much to promote the EV technology.

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Tables and Figures

Table 1: Summary statistics for 2009 National Household Travel Survey (NHTS)

Grid Interconnection	Annual Miles	EPA-Estimated Miles Per Gallon	Gasoline Price $/gal	# Households
CA	10,732	33.04	3.31	3,670
	(171)	(0.20)	(0.00)	
FRCC	10,143	30.50	3.06	2,511
	(220)	(0.16)	(0.00)	
MRO	10,104	29.63	2.94	1,519
	(265)	(0.19)	(0.00)	
NPCC	10,765	30.98	3.17	3,345
	(139)	(0.16)	(0.00)	
RFC	10,898	29.96	2.98	1,143
	(314)	(0.23)	(0.00)	
SERC	11,474	30.11	3.02	7,329
	(132)	(0.09)	(0.00)	
SPP	9,649	31.64	2.96	74
	(833)	(1.25)	(0.00)	
TRE	11,663	30.47	2.90	3,083
	(177)	(0.13)	(0.00)	
WECC	10,343	31.17	3.12	1,533
	(212)	(0.24)	(0.00)	
US	10,959	30.80	3.07	24,207
	(66)	(0.06)	(0.00)	

Summary statistics from the NHTS limited to drivers of EPA midsized cars making trips on weekdays. Standard errors shown in parentheses. Means and standard errors computed using NHTS sampling weights.

Table 2: Total distance per day by household

Total Day Distance (km)	Proportion of Observations	Cumulative Proportion
0-10	0.140	0.140
10-20	0.134	0.273
20-30	0.120	0.393
30-40	0.087	0.481
40-50	0.079	0.560
50-60	0.055	0.615
60-70	0.043	0.658
70-80	0.043	0.701
80-90	0.033	0.733
90-100	0.024	0.757
100-110	0.021	0.778
110-120	0.021	0.800
120-130	0.016	0.816
130-140	0.013	0.829
140-150	0.023	0.851
150-160	0.008	0.860
160-170	0.011	0.871
170-180	0.012	0.882
180-190	0.008	0.891
190+	0.109	1.000

Total distance driven in km on weekdays by NHTS households with EPA midsize vehicles. Proportions computed using NHTS sampling weights.

Table 3: Longest trip distance by household

Longest Trip Distance (km)	Proportion of Observations	Cumulative Proportion
0-20	0.648	0.648
20-40	0.194	0.842
40-60	0.086	0.928
60-80	0.029	0.957
80-100	0.014	0.971
100-120	0.005	0.976
120-140	0.005	0.981
140-160	0.003	0.983
160-180	0.003	0.987
180+	0.013	1.000

Longest trip distance in km on weekdays by EPA midsize vehicles in the NHTS. Proportions computed using NHTS sampling weights.

Table 4: GHG emissions benefits of replacing a midsize ICE with an EV

Region	Limited Scope Day Charging	Limited Scope Night Charging	Complete Scope Day Charging	Complete Scope Night Charging	Complete Scope Avgerage
FRCC	1.86	1.69	1.20	0.99	1.09
	[0.85 - 2.33]	[0.79 - 2.23]	[0.27 - 1.64]	[0.32 - 1.35]	[0.31 - 1.53]
MRO	1.33	0.44	0.01	-1.27	-0.63
	[0.39 - 1.81]	[0.08 - 0.78]	[0.01 - 0.67]	[-1.56 - -0.11]	[-0.66 - 0.10]
NPCC	1.29	1.66	0.20	0.70	0.45
	[0.64 - 1.66]	[0.85 - 2.11]	[-0.18 - 0.58]	[0.04 - 1.23]	[-0.04 - 0.91]
RFC	1.05	1.01	-0.18	-0.23	-0.21
	[0.48 - 1.43]	[0.46 - 1.32]	[-0.45 - 0.09]	[-0.50 - 0.08]	[-0.48 - 0.08]
SERC	1.46	1.28	0.32	0.11	0.22
	[0.64 - 1.90]	[0.51 - 1.63]	[0.03 - 0.50]	[-0.03 - 0.18]	[0.04 - 0.28]
SPP	1.26	0.62	0.29	-0.54	-0.12
	[0.44 - 1.78]	[0.25 - 0.89]	[-0.07 - 0.80]	[-0.71 - -0.14]	[-0.09 - 0.11]
TRE	1.99	1.86	1.19	1.03	1.11
	[0.97 - 2.57]	[0.90 - 2.39]	[0.57 - 1.53]	[0.49 - 1.33]	[0.53 - 1.43]
WECC w/o CA	1.86	1.59	0.93	0.56	0.74
	[0.92 - 2.27]	[0.83 - 1.99]	[0.37 - 1.22]	[0.20 - 0.69]	[0.29 - 1.01]
CA	1.94	1.67	1.18	0.84	1.01
	[0.91 - 2.36]	[0.80 - 2.08]	[0.54 - 1.47]	[0.34 - 1.04]	[0.45 - 1.26]
US	1.47	1.30	0.41	0.18	0.29
	[0.62 - 1.91]	[0.51 - 1.70]	[0.01 - 0.76]	[-0.09 - 0.48]	[0.00 - 0.60]
Charge Time	Day	Night	Day	Night	Avg
Climate Effects	No	No	Yes	Yes	Yes
Battery Replacements	2	2	2	2	2
Rebound Elasticity	0	0	-.2	-.2	-.2
Emissions Calculation	Marginal	Marginal	Marginal	Marginal	Marginal
Assumed Vehicle Life	257k km	257k km	257k km	257k km	257k km
Forecast Model	N/A	N/A	N/A	N/A	N/A
Foreast Year					

Expected life cycle tons of CO_2e avoided per year by replacing a midsized ICE with an EV. Day charging assumes EV charging is uniformly distributed from 9 AM to 5 PM. Night Charging assumes EV charging is uniformly distributed from 8 PM to 4 AM. Effects for the 25th and 75th percentile of the VMT distribution from NHTS shown in square brackets. Limited Scope assumes a midsize ICE is replaced with an EV with identical driver behavior. Complete Scope also accounts for the impact of ambient temperature on vehicle efficiency and assumes households alter demand for VMT in response to changes in vehicle operating costs.

Table 5: Marginal CO_2e emissions from EV charging

NERC Region	Emissions Source	Day Charging Q1	Day Charging Q2	Day Charging Q3	Day Charging Q4	Night Charging Q1	Night Charging Q2	Night Charging Q3	Night Charging Q4
FRCC	Combustion	0.732	0.435	0.605	0.590	0.730	0.553	0.770	0.538
	Procurement	0.110	0.078	0.105	0.088	0.078	0.089	0.087	0.073
	Total	0.843	0.513	0.710	0.677	0.808	0.643	0.857	0.611
MRO	Combustion	0.594	0.762	0.603	0.998	0.856	0.987	0.845	1.157
	Procurement	0.063	0.081	0.109	0.081	0.084	0.075	0.078	0.101
	Total	0.656	0.843	0.712	1.079	0.940	1.062	0.923	1.258
NPCC	Combustion	0.779	0.771	0.691	0.579	0.748	0.748	0.575	0.473
	Procurement	0.080	0.128	0.150	0.069	0.075	0.104	0.114	0.045
	Total	0.859	0.899	0.840	0.648	0.823	0.852	0.689	0.517
RFC	Combustion	0.812	0.820	0.744	0.716	0.843	0.860	0.791	0.717
	Procurement	0.079	0.123	0.143	0.078	0.079	0.094	0.104	0.074
	Total	0.891	0.943	0.887	0.794	0.922	0.953	0.895	0.791
SERC	Combustion	0.749	0.713	0.749	0.772	0.721	0.846	0.876	0.740
	Procurement	0.064	0.083	0.070	0.053	0.061	0.066	0.062	0.062
	Total	0.813	0.797	0.819	0.825	0.782	0.912	0.938	0.802
SPP	Combustion	0.649	0.732	0.706	0.877	0.828	0.978	0.936	0.954
	Procurement	0.060	0.035	0.057	0.076	0.080	0.013	0.046	0.077
	Total	0.709	0.767	0.763	0.954	0.908	0.991	0.982	1.031
TRE	Combustion	0.578	0.612	0.611	0.619	0.607	0.679	0.664	0.647
	Procurement	0.096	0.097	0.110	0.083	0.100	0.065	0.079	0.086
	Total	0.675	0.709	0.721	0.702	0.707	0.743	0.743	0.733
WECC	Combustion	0.665	0.615	0.580	0.596	0.685	0.707	0.644	0.693
	Procurement	0.065	0.077	0.084	0.078	0.080	0.057	0.074	0.080
	Total	0.731	0.691	0.664	0.674	0.765	0.763	0.717	0.773

Marginal tons of CO_2e emissions from fuel combustion per MWh of electricity generated. Day charging assumes eight hours of charging from 9 AM until 5 PM. Night charging assumes eight hours of charging from 8 PM until 4 AM.

Table 6: Forecast GHG emissions benefits of replacing a midsize ICE with an EV through 2040

Region	Current Average Emissions	2030 Forecast EIA	2040 Forecast EIA	2030 Forecast Optimistic	2040 Forecast Optimistic
FRCC	2.63	2.76	2.95	3.40	3.70
	[1.25 - 3.37]	[1.32 - 3.55]	[1.40 - 3.78]	[1.64 - 4.33]	[1.78 - 4.66]
MRO	-1.85	-1.63	-1.34	1.62	3.37
	[-2.25 - -0.64]	[-2.00 - -0.54]	[-1.64 - -0.42]	[0.65 - 1.96]	[1.32 - 3.88]
NPCC	2.97	3.05	3.05	3.59	3.70
	[1.57 - 3.71]	[1.62 - 3.82]	[1.63 - 3.82]	[1.95 - 4.52]	[2.01 - 4.61]
RFC	-0.67	-0.87	-0.74	1.62	2.88
	[-0.91 - -0.26]	[-1.17 - -0.38]	[-0.99 - -0.30]	[0.75 - 2.10]	[1.33 - 3.83]
SERC	1.11	1.10	1.18	2.48	2.97
	[0.46 - 1.50]	[0.46 - 1.50]	[0.49 - 1.60]	[1.06 - 3.19]	[1.26 - 3.80]
SPP	0.88	1.35	1.56	2.42	2.95
	[0.35 - 1.22]	[0.53 - 1.99]	[0.66 - 2.35]	[0.98 - 3.55]	[1.12 - 4.12]
TRE	1.00	1.01	1.13	2.60	3.26
	[0.47 - 1.32]	[0.48 - 1.33]	[0.54 - 1.50]	[1.29 - 3.22]	[1.58 - 4.15]
WECC w/o CA	2.28	2.55	2.70	3.54	3.97
	[1.17 - 2.89]	[1.30 - 3.15]	[1.35 - 3.30]	[1.84 - 4.41]	[2.12 - 4.85]
CA	2.48	2.72	2.87	3.62	4.03
	[1.19 - 3.10]	[1.28 - 3.38]	[1.34 - 3.56]	[1.73 - 4.57]	[1.93 - 5.04]
US	0.96	1.00	1.13	2.60	3.32
	[-0.29 - 1.90]	[-0.38 - 2.02]	[-0.31 - 2.15]	[1.10 - 3.35]	[1.54 - 4.27]
Charge Time	Avg	Avg	Avg	Avg	Avg
Climate Effects	Yes	Yes	Yes	Yes	Yes
Battery Replacements	2	2	2	2	2
Rebound Elasticity	-.2	-.2	-.2	0	0
Emissions Calculation	Average	Average	Average	Average	Average
Assumed Vehicle Life	257k km	257k km	257k km	257k km	257k km
Forecast Model	N/A	EIA	EIA	Optimistic	Optimistic
Foreast Year		2030	2040	2030	2040

Expected life cycle tons of CO_2e avoided per year by replacing a midsized ICE with an EV. Effects for the 25th and 75th percentile of the VMT distribution from NHTS shown in square brackets. EIA forecast emissions forecast using the 2015 EIA Annual Energy Outlook. Optimistic forecast emissions forecast assuming generation mix in each NERC region evolves at a constant rate from 2012 to 2040 to replace all coal-fired generation with CCGTs in 2040. The optimistic forecast also assumes zero VMT rebound. Accounts for the impact of ambient temperature on vehicle efficiency.

Figure 1: Vehicle life cycle emissions simulation model outline

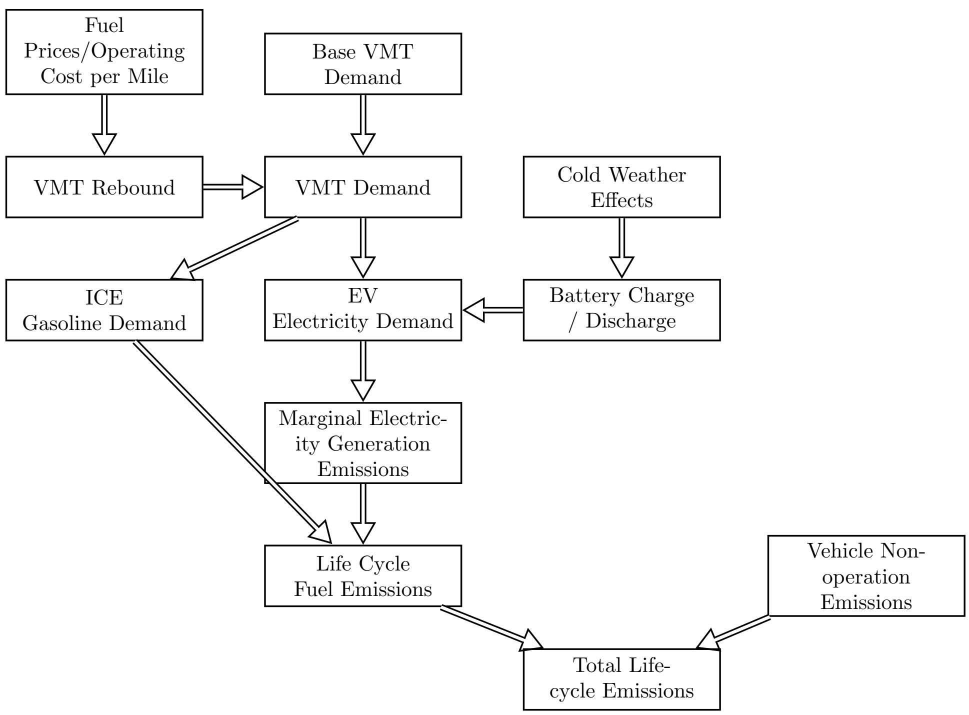
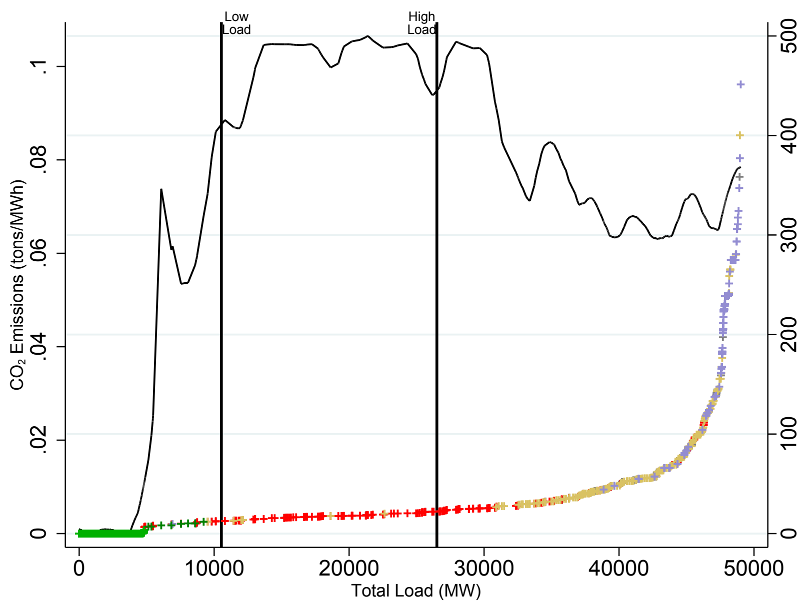
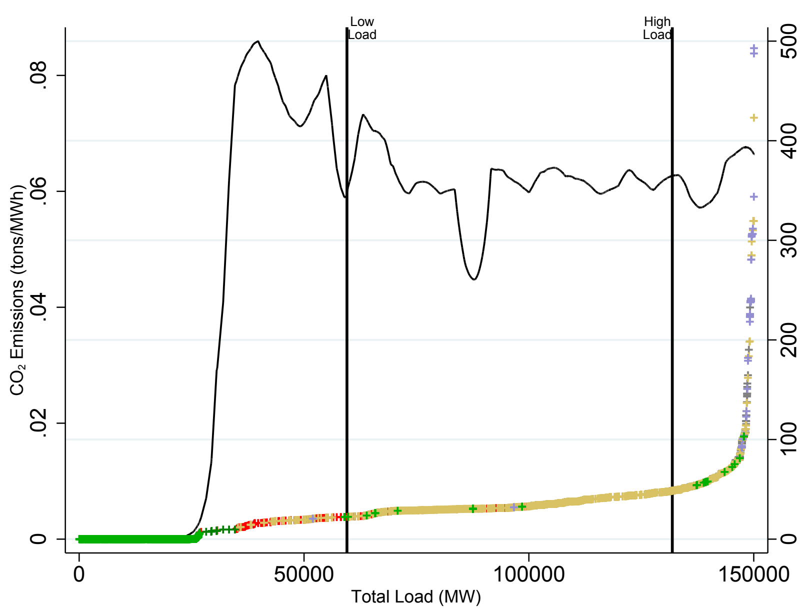


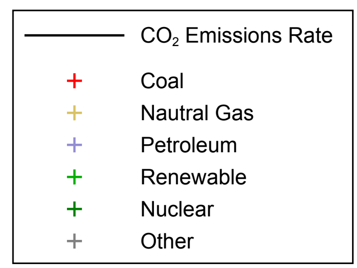
Figure 2: Electricity generation supply curves

(a) NERC Region: MRO



(b) NERC Region: WECC





Supply curves generated by rank-ordering generating units in each NERC region by average variable input costs as reported in EIA Form 860. Generating unit capacities represent summer nameplate capacity adjusted by the capacity factor computed from Summer 2012 net generation. CO_2/MWh represent direct combustion emissions estimated using locally-weighted linear regression and the Epanechnikov kernel and bandwidths 500 MW for MRO and 1800 MW for WECC.

Figure 3: Map of 2010 eGRID NERC regions

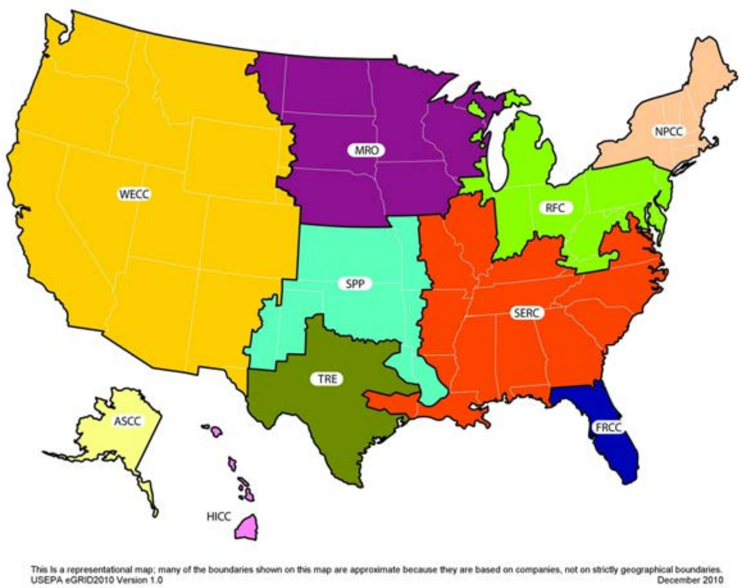
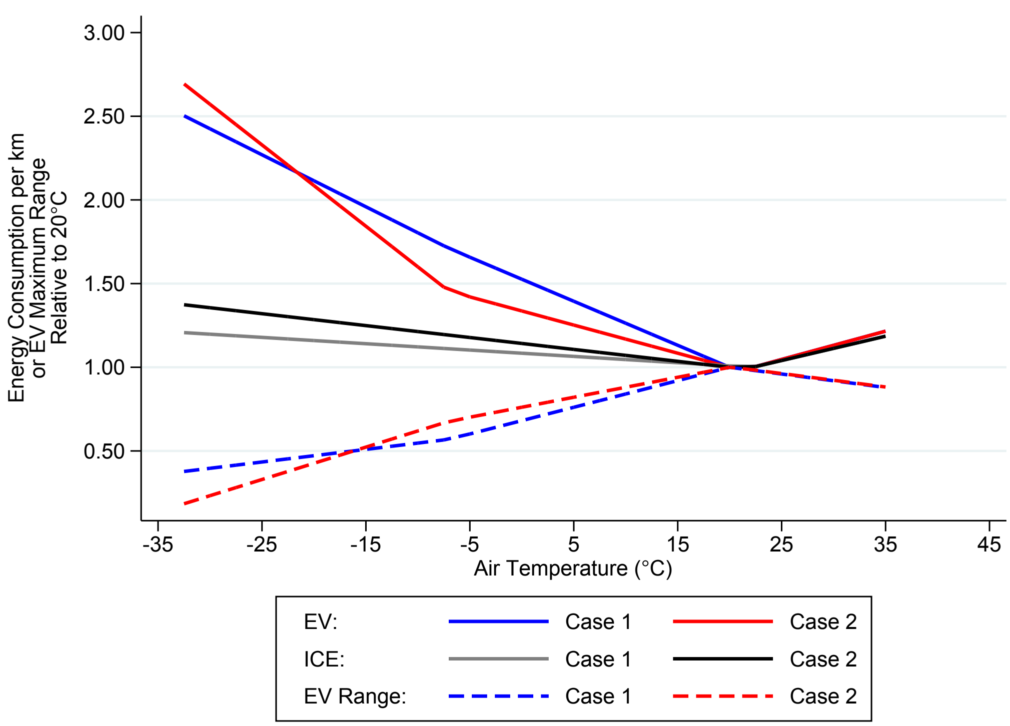


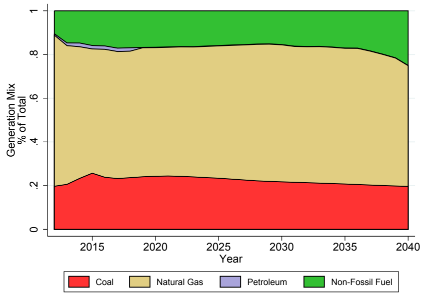
Figure 4: Relative vehicle energy and range



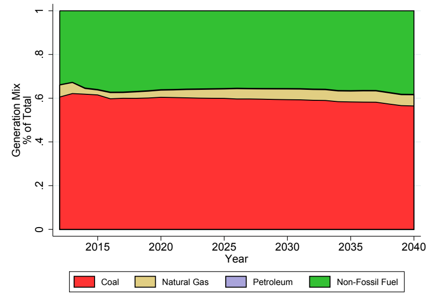
Energy consumption of EVs and ICEs per km relative to operation at 20 °C. EV Case 1 and Case 2 use cold-weather performance data from Meyer et al. [2012] cases BEV1 and BEV2, respectively. ICE energy consumption and hot weather effects derived using Lohse-Busch et al. [2013].

Figure 5: Forecast electricity generation mix from 2012 to 2040, EIA forecast

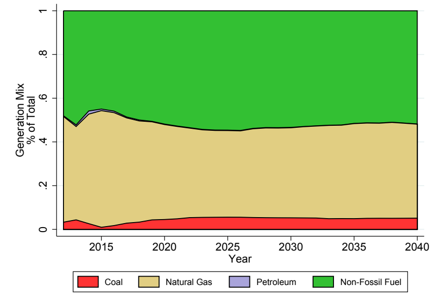
(a) NERC Region: FRCC



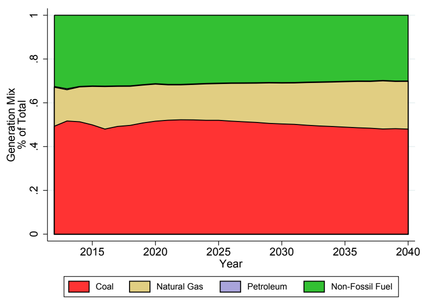
(b) NERC Region: MRO



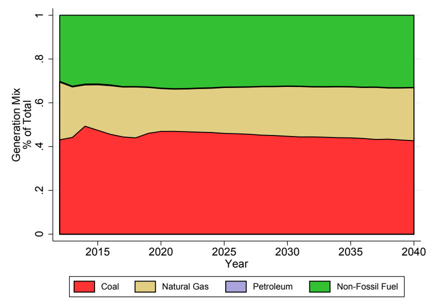
(c) NERC Region: NPCC



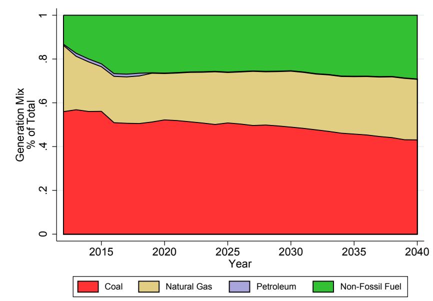
(d) NERC Region: RFC



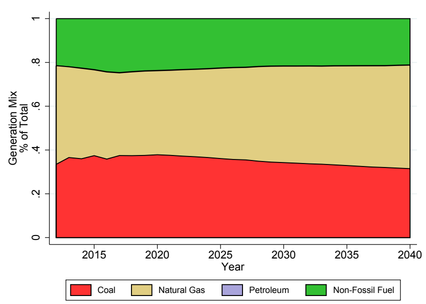
(e) NERC Region: SERC



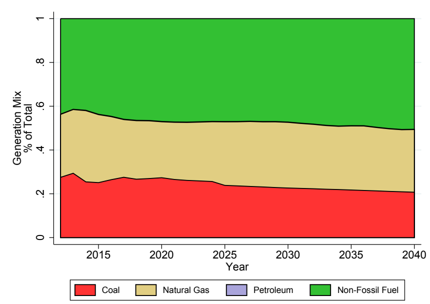
(f) NERC Region: SPP



(g) NERC Region: TRE



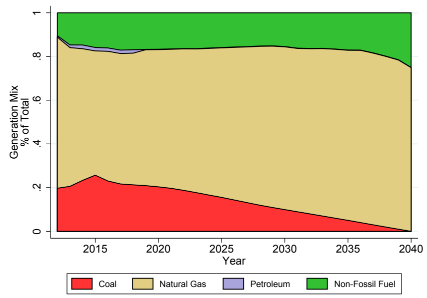
(h) NERC Region: WECC



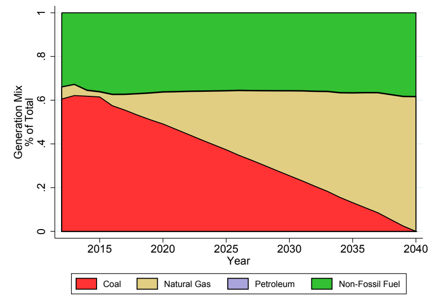
Forecast electricity generation mix from 2012 to 2040 from EIA [2015].

Figure 6: Forecast electricity generation mix from 2012 to 2040, aggressive elimination of coal

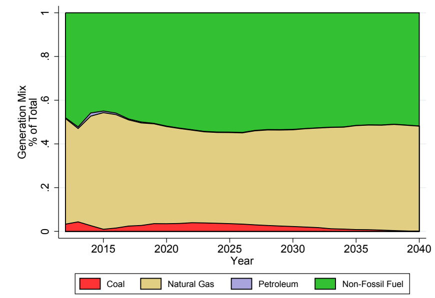
(a) NERC Region: FRCC



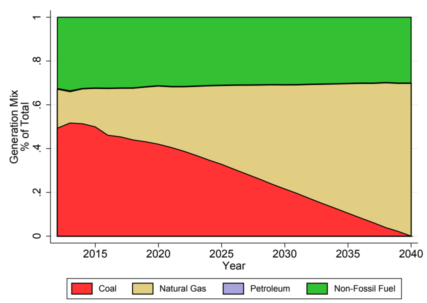
(b) NERC Region: MRO



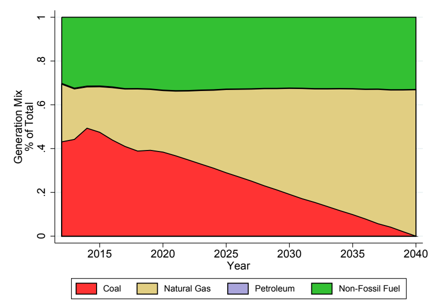
(c) NERC Region: NPCC



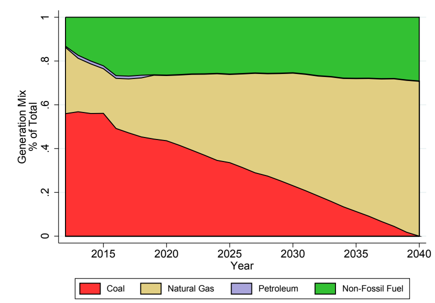
(d) NERC Region: RFC



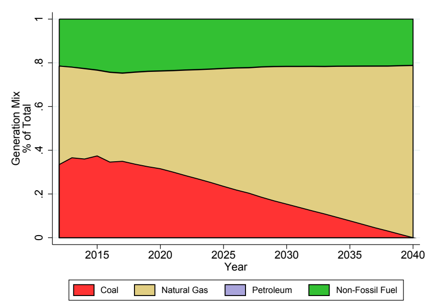
(e) NERC Region: SERC



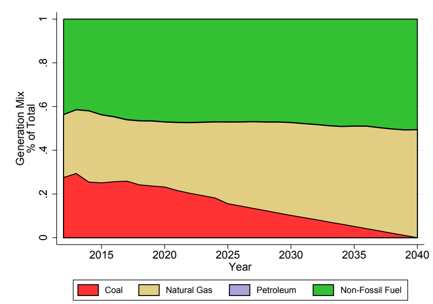
(f) NERC Region: SPP



(g) NERC Region: TRE



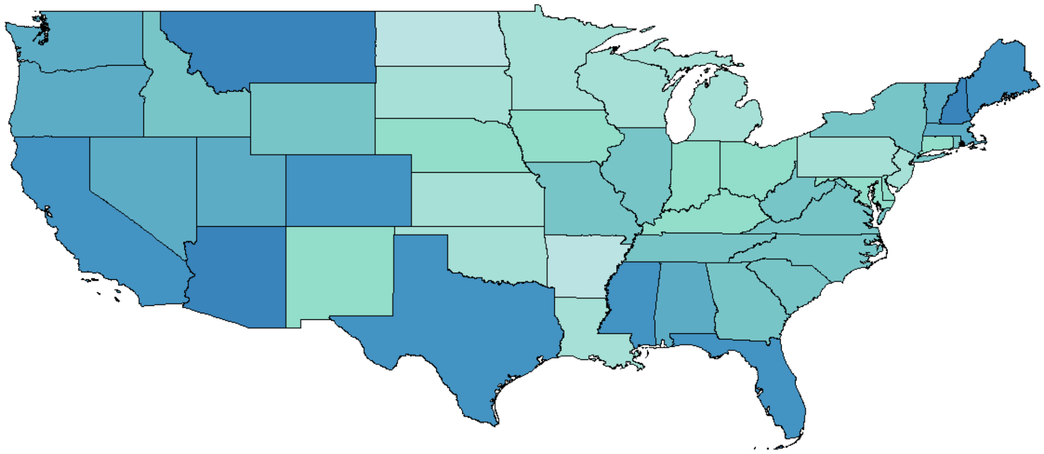
(h) NERC Region: WECC

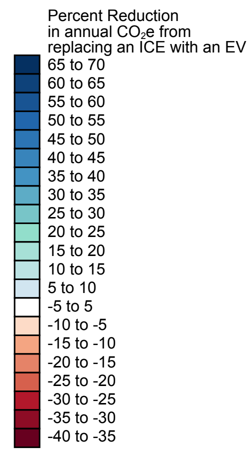


Forecast electricity generation fuel mix assuming aggressive elimination of coal. All coal-fired generation from fuel mix forecasts in EIA [2015] is assumed to be replaced with combined-cycle natural gas generation in 2040. Natural gas and coal generation change at a constant rate over time.

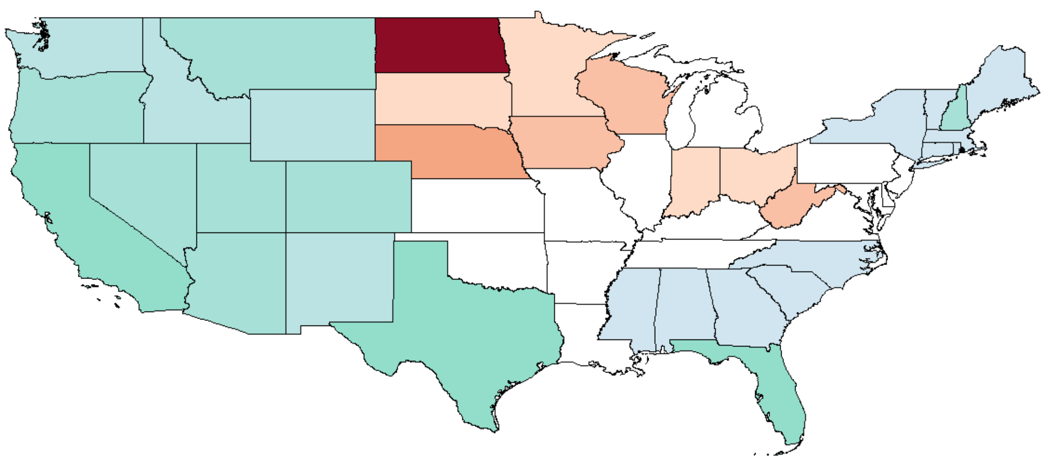
Figure 7: Expected annual CO_2e emissions from replacing an ICE with an EV

(a) Limited Scope



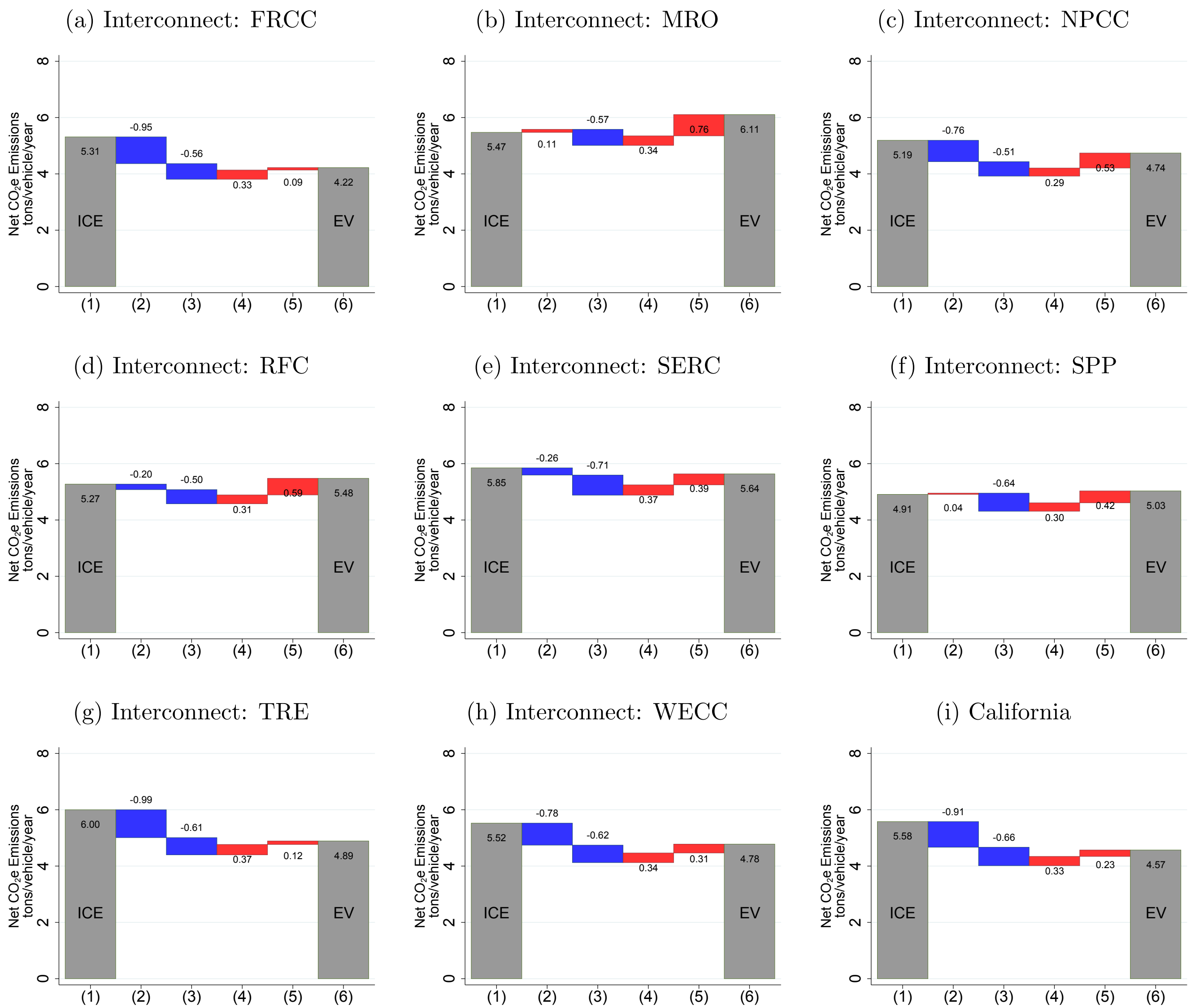


(b) Complete Scope



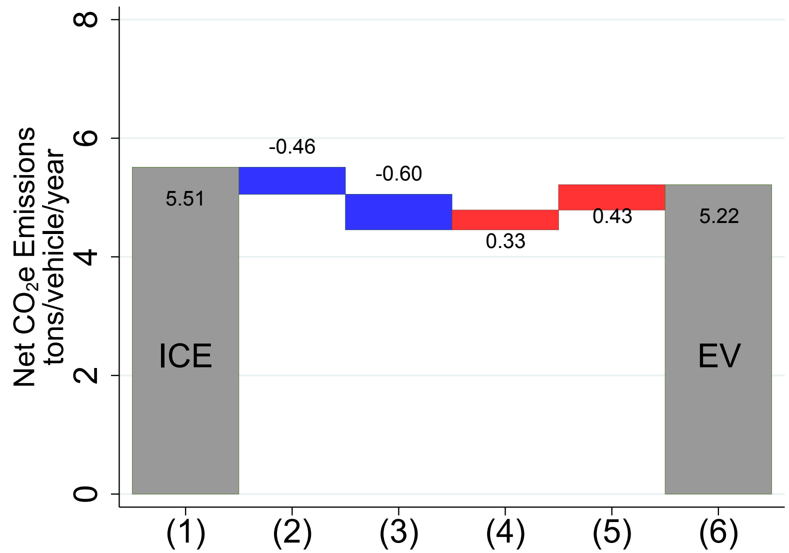
Expected emissions reduction in tons of CO_2e per year from replacing a midsized ICE with an EV. Color scales are identical across maps. Limited Scope assumes a midsize ICE is replaced with an EV with identical driver behavior. Complete Scope also accounts for the impact of ambient temperature on vehicle efficiency and assumes households alter demand for VMT in response to changes in vehicle operating costs. EV charging emissions are the average of day and night charing emissions.

Figure 8: Net impact on CO_2e emissions by source



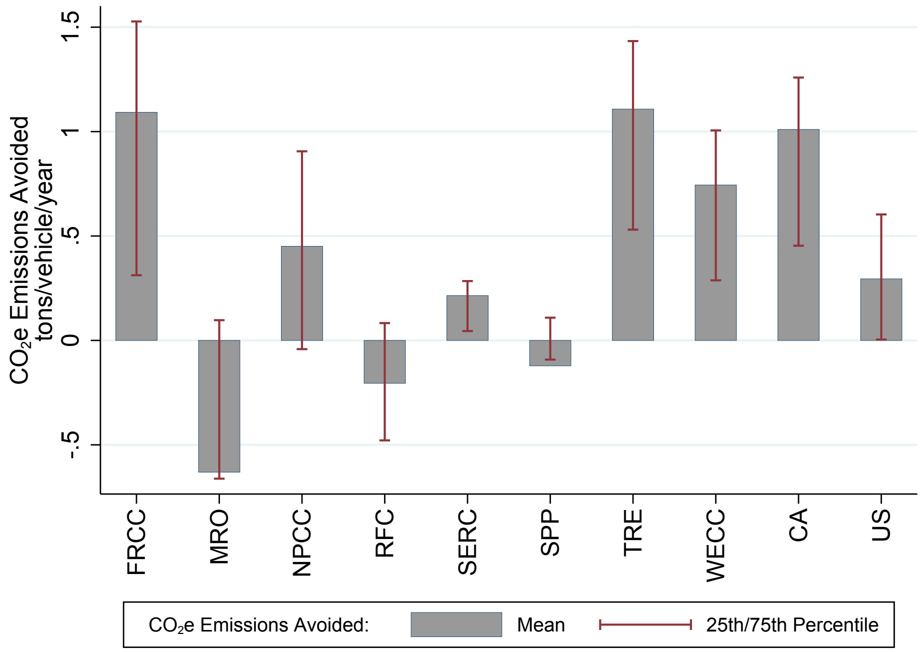
Blue (red) bars represent net CO_2e emissions reduction (increase) in tons per year by replacing (1) a midsize ICE with (6) an EV. Assumes a VMT rebound elasticity of -0.2. EV batteries are assumed to be replaced twice during the life of the vehicle, after about 80,000 miles. Emissions sources are categorized as follows: (2) Fuel Combustion - direct emissions from combustion of fuel to power ICEs or electricity generation; (3) Fuel Production - other emissions associated with the extraction, processing, transport, and storage of fossil fuels for combustion; (4) Manufacturing Emissions - emissions associated with manufacturing and maintenance of the vehicle over its lifetime; (5) Climate - emissions attributable to the impact of climate on the efficient operation of EVs and ICEs.

Figure 9: Net impact on CO_2e emissions by source, United States



Blue (red) bars represent net CO_2e emissions reduction (increase) in tons per year by replacing (1) a midsize ICE with (6) an EV. Assumes a VMT rebound elasticity of -0.2. EV batteries are assumed to be replaced twice during the life of the vehicle, after about 80,000 miles. Emissions sources are categorized as follows: (2) Fuel Combustion - direct emissions from combustion of fuel to power ICEs or electricity generation; (3) Fuel Production - other emissions associated with the extraction, processing, transport, and storage of fossil fuels for combustion; (4) Manufacturing Emissions - emissions associated with manufacturing and maintenance of the vehicle over its lifetime; (5) Climate - emissions attributable to the impact of climate on the efficient operation of EVs and ICEs.

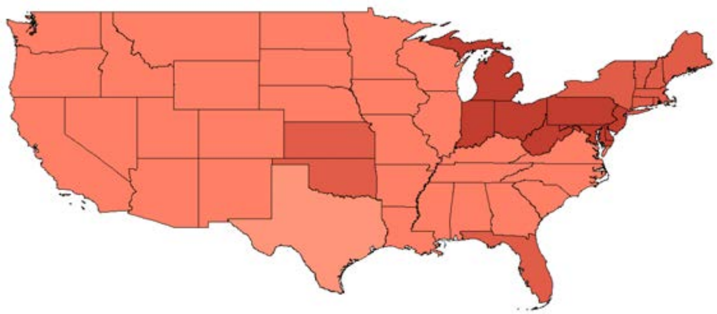
Figure 10: Overall CO_2e emissions reduction from replacing an ICE with an EV



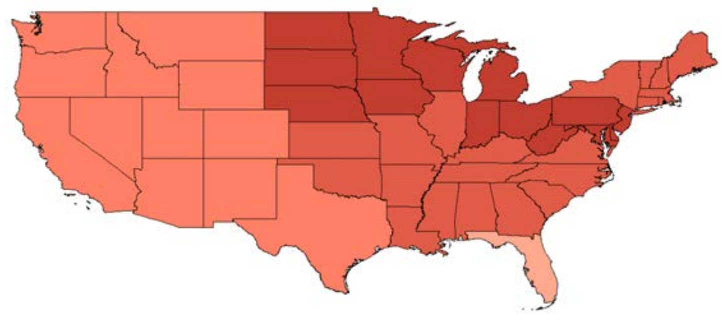
Mean (bars) and 25th/75th percentile (ranges) emissions reduction in tons of CO_2e per year from replacing a midsized ICE with an EV. EV Charging emissions are the average of day and night charging emissions. Accounts for the impact of ambient temperature on vehicle efficiency and assumes a VMT rebound elasticity of -0.2.

Figure 11: Marginal emissions from EV charging

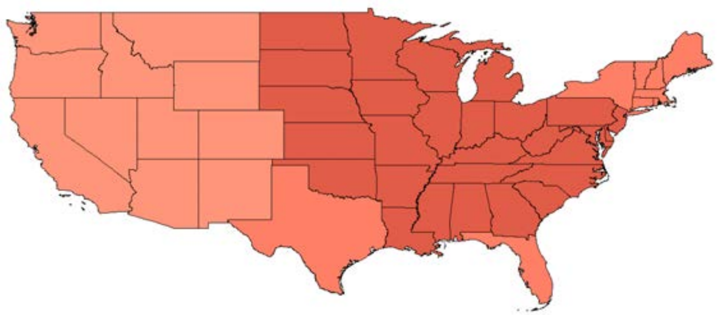
(a) January to March



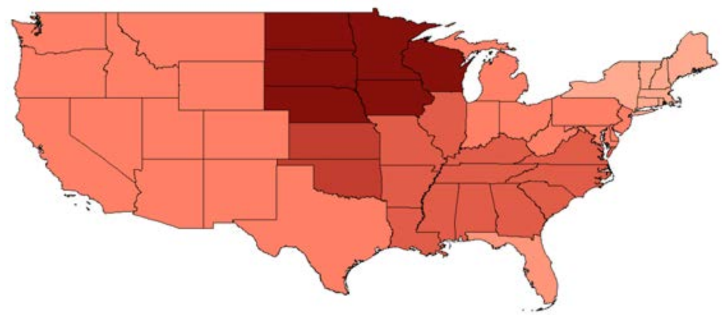
(b) April to June

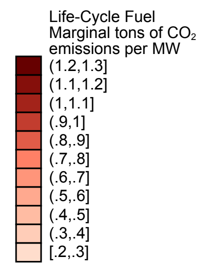


(c) July to September



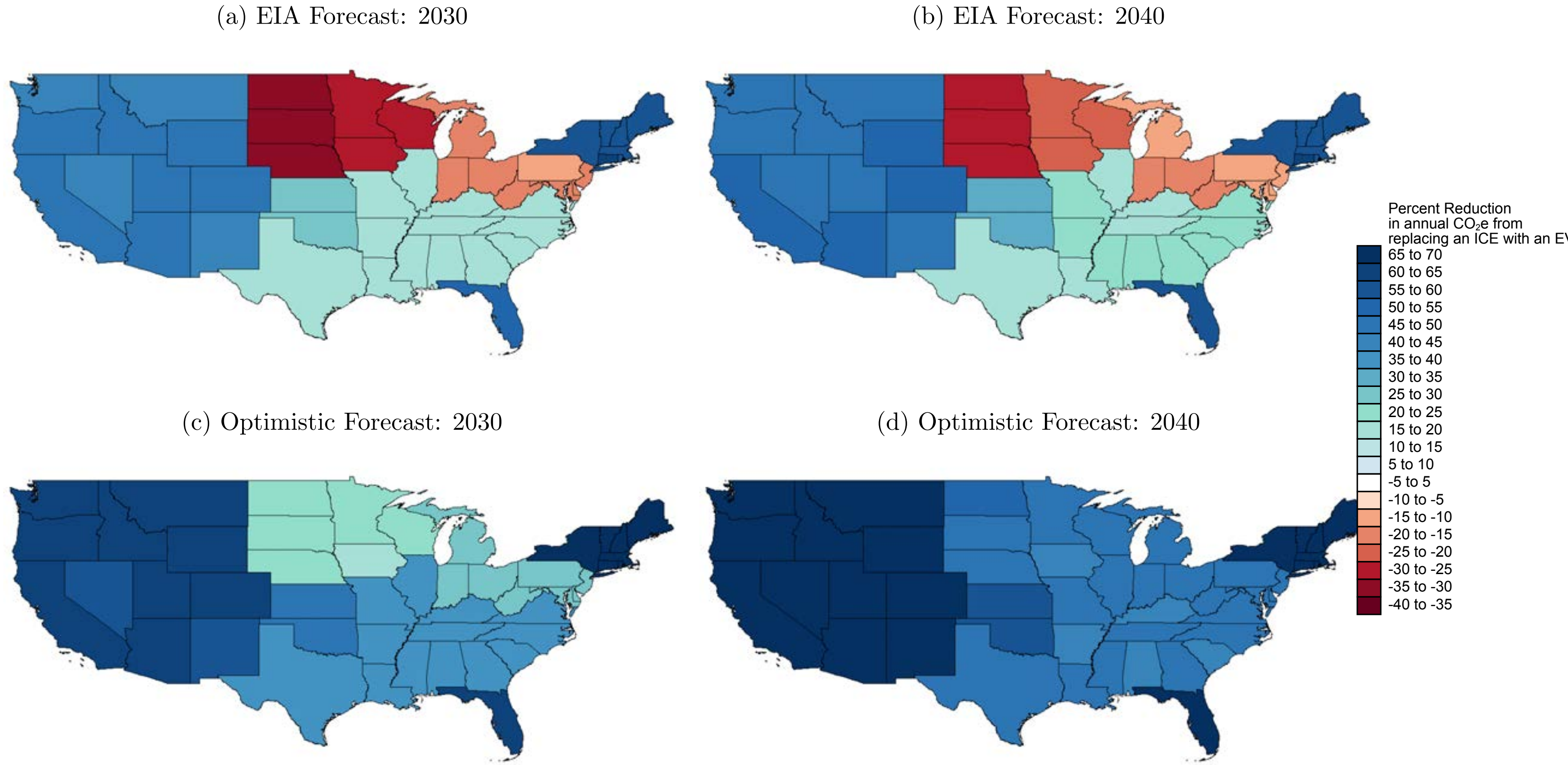
(d) October to December





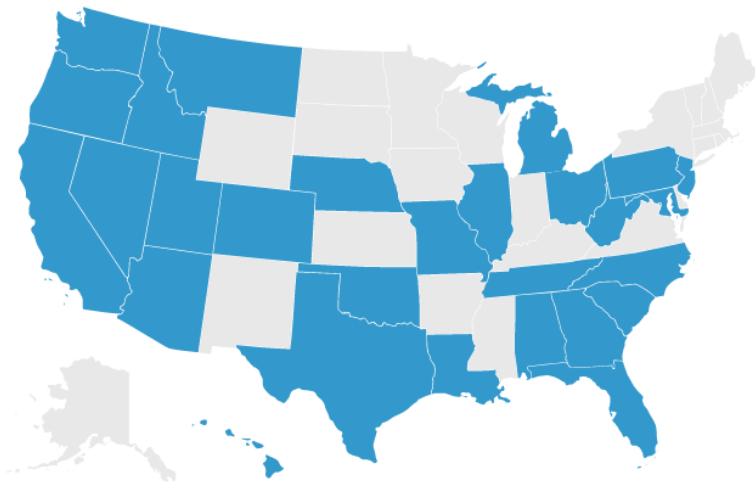
Expected marginal emissions in tons of CO_2e by grid NERC region from direct fuel combustion and indirect GHG emissions per MWh of EV charging. Estimated using CEMS and FERC Form 714 data from 2011 and 2012. Color scales are identical across quarters and darker colors indicate higher emissions. Average of day and night charging emissions.

Figure 12: Forecast annual GHG emissions benefits of replacing an ICE with an EV



Forecast expected percentage reduction in CO_2e emissions from replacing a midsize ICE with a comparable EV. Color scales are identical across maps. Accounts for impact of climate on vehicle operating efficiency. Forecasts assume EVs are inframarginal load and use average emissions in each NERC Region. EIA forecast computes grid emissions in each NERC region using EIA [2015]. Optimistic forecast assumes VMT rebound elasticity of zero and generation mix in each NERC region changes at a constant rate from 2012 to 2015 to meet California's goal of 50% non-fossil fuel generation in 2030.

Figure 13: States with EV incentives



Source: http://www.pluginamerica.org/incentives (accessed 01/13/2015).