Variability in the emissions savings potential of battery electric vehicles across regions and individuals

by

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Abstract

Personal vehicles account for almost 25% of U.S. greenhouse gas emissions, and this share is increasing. The increase is due to several factors, including a growth in transportation demand and the decarbonization of electricity by 30% since 2007. Alternative technologies for road vehicles, such as battery electric, plug-in hybrid, and fuel cell powertrains have the potential to achieve significant emission reductions. Yet questions remain about the emissions and costs of these alternative technologies.

This thesis evaluates the emissions reduction potential of vehicles with electrified powertrains, focusing on battery electric vehicles (BEVs). It evaluates this potential taking into account heterogeneous regional conditions and consumer behavior. Consumers help determine vehicle fleet emissions through their purchasing and driving decisions, which are guided in part by the costs of different options. Therefore, the costs of ownership of BEVs in comparison to conventional vehicles inform the emissions reduction potential of BEVs. Here, we measure the lifecycle greenhouse gas emissions and costs of ownership of BEVs across different vehicle models as a function of travel patterns, driving styles, and properties of the natural, built, and institutional environment. We compare these costs and emissions to gasoline combustion engine vehicles (ICEVs), and then ask whether and under which condition electric vehicle adoption can play a central role in meeting emission targets for the transportation sector.

The current literature does not cover all the interdependent sources of variation in the emissions and costs of BEVs compared to ICEVs. In particular, the effects of annual travel distance and fuel efficiency related to individual travel behavior and the wide variety of available vehicle models have not been assessed. In addition, this variation in emissions and costs of personal vehicles has only been studied across regions, but not across individual vehicles within each region due to vehicle-specific driving patterns. This work addresses these gaps by developing several interlinked models. This includes the construction of a parametrized lifecycle emissions and cost of ownership model (Chapter 2), an algorithm to measure driving style linked to a vehicle energy model (Chapter 3), and a model to quantify the variability in annual travel distance and fuel consumption of different types of vehicles across regions within the United States, encoded as zipcodes, and across individual vehicles within those zipcodes (Chapter 4). Chapter 5 then ties Chapters 2 and 4 together and complements them with additional information to assess the overall heterogeneity in the emissions reduction potential of BEVs.

The central results of the thesis are threefold. First, a rapid decarbonization of electricity in conjunction with an electrification of powertrains will likely be required to meet emission targets for the U.S. transportation sector. Measures that relate to heterogeneous consumer behavior, such

as improving driving style and nudging consumers towards purchasing smaller vehicles, can help to reduce greenhouse gas emissions. Second, the electrification of powertrains can come at little to no additional expense to consumers with today's technology and prices. In most parts of the country, BEVs are substantially cheaper than comparable ICEVs. Within regions, the individuals for which BEVs offer the greatest emissions savings would also tend to experience the largest cost savings, since both emissions savings and cost savings are correlated with annual travel distance. Third, emission reductions achieved by BEVs and their costs relative to ICEVs are highly heterogeneous. The within-region variation in emissions and costs of BEVs compared to ICEVs due to individual driving patterns is at least as large as the variation across regional averages. As a result, a 10% share of BEVs in the fleet can lead to anywhere between 1% and 10% emission reductions, depending on which types of vehicles are being replaced by electric vehicles, by whom, and where.

A key application of this work is to inform tools that provide localized and personalized information about the environmental and economic performance of different vehicle models. In Chapter 6, we discuss such a tool that was built as part of this work, called Carboncounter.com. Results from a survey launched on Carboncounter add to existing evidence that providing such information to consumers can help inform a transition to a cleaner light-duty vehicle fleet. These findings further confirm the importance of understanding heterogeneous human behaviors to inform decarbonization strategies for personal transport.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Motivation

The transportation sector accounts for 13% of greenhouse gas (GHG) emissions through vehicle fuel combustion worldwide, and for 28% of GHG emissions in the U.S. [176, 69]. Light-duty vehicles, which are defined by the U.S. Environmental Protection Agency (EPA) as passenger cars and light trucks with 12 seats or less and a gross vehicle weight rating below 8,500 lbs (10,000 lbs for SUVs and passenger vans) [64], contribute 61% of emissions from the U.S. transportation sector [69]. Most of these light-duty vehicles are personal vehicles, and their relative contribution to overall greenhouse gas emissions is increasing. This increase is in part due to the growing transportation demand and resulting growth in total annual distance traveled [48], and in part due to the decarbonization of the electricity sector by 30% since 2007 [69]. Therefore, personal vehicles are an increasingly crucial element of any comprehensive strategy to reduce U.S. and global GHG emissions [46, 103, 41, 176].

The intergovernmental panel on climate change (IPCC) lists four major ways to reduce greenhouse gas emissions from transport: switching to cleaner fuels, switching to more efficient vehicles, improving driving and maintenance practices, and reducing transportation demand [57]. Alternative powertrain technologies, such as battery electric and fuel cell powertrains, have been suggested as a means of achieving high emission reductions, especially when combined with clean electricity [17, 95, 154, 23, 133]. Yet it remains subject to discussion what factors affect the emissions of those options, how much they cost, and which options suffice to meet climate policy targets.

The majority of newly sold personal vehicles enter the fleet through individual consumers

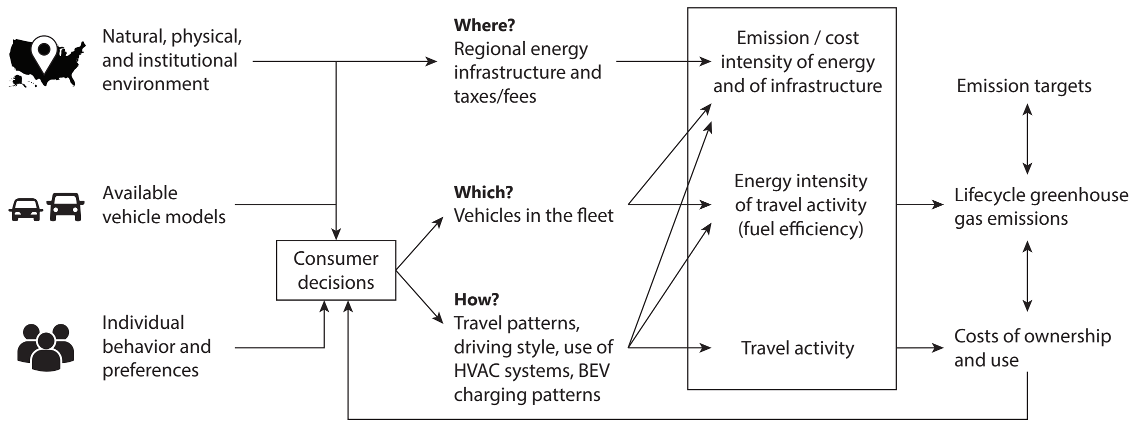

Figure 1-1: Thesis framework, illustrating how properties of the natural, physical, and institutional environment, available vehicle models, and individual behavior and preferences are linked to lifecycle greenhouse gas emissions and costs of ownership and use of personal vehicles. In this thesis, we construct a modeling framework that estimates emissions and costs of any vehicle model on the market as a function of heterogeneous regional properties, vehicle characteristics, and individual behaviors, taking into account relationships between these factors. We then derive implications of this heterogeneity for consumers and policy makers.

purchasing a privately owned vehicle [34]. Therefore, individual purchasing decisions made by consumers on a day-to-day basis shape the personal vehicle fleet of the future. From preferences for different vehicle characteristics [16, 127] to driving styles [143, 27] and travel patterns [88, 15], the behavior of these consumers can vary substantially across individuals in a way that affects emissions and costs of different vehicles (Figure 1-1). Evaluating the emissions reduction potential of technologies from the perspective of individual consumers by tailoring that perspective to their location, travel behavior, and driving style can therefore improve our understanding of the interaction between regional conditions, individual behaviors, and the emissions reduction potential of different personal vehicle technologies. This understanding, in turn, can inform policy, technology development, and consumers themselves about ways to decarbonize transport.

1.2 Background

A variety of studies have evaluated the ability of battery electric vehicles (BEVs) to contribute to the reduction of transportation emissions by measuring their emissions in comparison to a baseline technology, usually gasoline or diesel internal combustion engine vehicles (ICEVs) [126, 172, 17, 62, 194, 95, 96, 198, 22, 131, 154, 23, 133, 204]. These studies have found that BEVs reduce emissions by 20-50% compared to gasoline internal combustion engine vehicles (gasoline ICEVs), mostly depending on the electricity mix and on annual travel distance. In addition, existing studies evaluate the emissions of one representative vehicle, often a compact car, or a few select representative vehicles. In reality, the vehicle market is diverse, with personal vehicles spanning a variety of classes, sizes, and performance levels. In Chapter 2, we address these gaps by evaluating over 100 models currently offered on the U.S. market, covering all major powertrain technologies, against climate policy targets.

Another key factor in determining the emissions reduction potential of a technology is its cost. Studies find that the high sticker prices of BEVs, relative to comparable ICEVs, are one of the major barriers to a higher adoption rate of BEVs [32, 174, 14, 118]. At the same time, BEVs may have lower fuel and maintenance costs. Some researchers have investigated production costs of certain vehicle types (e.g., [133]), and others have studied costs of ownership and use to the consumer [5, 207]. While lifecycle emissions and total costs have been studied simultaneously for power generation technologies to evaluate the trade-off between costs and emissions that decision makers face [190], few studies have conjointly evaluated emissions and costs of personal vehicles. Throughout this work, we include costs of ownership as an additional metric to measure the emissions reduction potential of different powertrain technologies.

Many existing studies that evaluate the emissions and costs of personal vehicles rely on average or typical conditions. However, there is a substantial amount of heterogeneity across locations. Researchers found that within the U.S., the electricity mix [90, 184] and local climate [208] can considerably impact the emission intensity of operating a BEV. One reason why this heterogeneity is important is that sales of electric vehicles are spread unevenly across space. More than 50% of electric vehicle sales in the United States have occurred in California [71], where the combined market share of battery electric vehicles and plug-in hybrids has reached almost 10% [71]. Emission reductions of BEVs in these areas may be higher or lower than the nation-wide average. In addition, location-specific information on the emissions and costs of different vehicles can also be valuable in constructing platforms that provide personalized information to consumers, conditional on the consumer's locations and individual travel habits.

Existing studies have mostly evaluated different factors that cause variation in the emission and costs of BEVs compared to ICEVs in isolation. One recent effort combines heterogeneity in electricity mix with the impact of local climate and urban or rural driving patterns on fuel efficiency to model the variation in emission reductions per km of BEVs [206]. There still is no study, however, that comprehensively addresses the impacts of driving patterns on the emissions savings potential of BEVs, compares the variation in emissions to the variation in costs, or derives quantitative implications of this variation for meeting transportation emission targets. In addition, there is little research covering considers that the impact of heterogeneous driving patterns on the emissions reduction potential of electric vehicles can be expected to not only vary across locations, but also across individual vehicles in a given location (as a result of heterogeneous individual human behavior). In Chapters 4 and 5, we address these gaps by presenting a comprehensive modeling framework to evaluate the heterogeneity in fuel efficiency, annual travel distance, emissions, and costs of ICEV and BEVs across locations within the United States, and across individual vehicles in those locations.

Driving style is another aspect of human travel behavior that affect emissions and costs of personal vehicles. Driving style includes the aggressiveness of acceleration and braking and the driving speed on highways. Studies have found that improving driving style can reduce fuel consumption and emissions by 5–15% [19, 124, 211]. Most of these studies, however, do not use representative drive cycles as a baseline for evaluating the impact of driving style changes on fuel consumption, and they often apply changes that may not be consistent with real-world traffic conditions and behavioral constraints. In Chapter 3, we combine a previously developed model to generate representative drive cycles from travel survey data, which we also use in Chapters 4 and 5, with a newly developed driving style algorithm that operationalizes eco-driving heuristics implementable by the average human driver. This allows us to compare the average emission reductions achievable through wide-spread adoption of better driving style to emission reductions of wide-spread adoption of alternative vehicle technologies.

The results from Chapters 2–5 can inform tools that provide information to consumers about the emissions and costs of different cars. This type of information can affect the perception of the environmental and economic efficacy of different powertrain technologies that consumers have, and therefore, their purchasing decisions [83, 115]. The design of the fuel economy window sticker, for instance, has been found to have an impact on how consumers perceive the emissions and costs of different types of vehicles relative to each other [63, 55]. In Chapter 6, we present a consumer information platform, carboncounter.com, that was developed on the basis of the results presented in Chapter 2. We discuss lessons learned, feedback from users, and potential for further applications of our results.

1.3 Contributions

This thesis helps inform decarbonization strategies for transportation sectors in the U.S. and worldwide by examining the emissions savings potential from electrifying light duty vehicles. We assess the factors that influence the emissions reduction potential of different light-duty vehicle technologies, and evaluate how they depend on individual human travel behavior and on characteristics of the built, natural, and institutional environment. In doing so, we help build understanding of individual behavior and regional conditions are linked to emissions from personal motorized travel. This understanding can improve our capacity to evaluate the effects of individual decisions and policies on fleet-wide emissions of personal transport, and can contribute to designing tools that inform these decisions and policies.

Addressing these research questions requires several new conceptual and mathematical models. In this work, we develop 1) a parametrized emissions and cost model that estimates life-cycle emissions and costs of ownership for any given light-duty vehicle, given a set of publicly available parameters; 2) an algorithm that models the amount of fuel that could have been saved by driving more efficiently based on a given trip speed profile; 3) a fuel economy model, based on TripEnergy [151, 128], that improves the link between ambient conditions and fuel economy and takes into account combustion engine vehicle cold start efficiency losses; 4) a systematic analysis of driving patterns across locations and individual vehicles that yields distributions for annual travel distance and fuel consumption conditional on vehicle technology and location; and 5) a framework that integrates models 1-4 and complements them with other data sources to model the lifecycle emissions and costs of ownership of any light-duty vehicle model on the market, in any location within the U.S., for a given set of individual travel patterns.

By applying above framework to model the lifecycle greenhouse gas emissions and costs to consumers of various light-duty vehicle models subject to regional conditions and individual driving patterns, we show that vehicle technology, vehicle class, location, and individual driving patterns all contribute substantially to the variation in emissions and costs of BEVs compared to ICEVs. From these results, we are also able to evaluate various statements about the environmental and economic efficacy of BEVs that are often presented in public debates. For instance, sources have stated that BEVs perform poorly in cold weather [208, 3]. We find that on average, year-round, BEVs are 10–15% less effective at reducing emissions compared to ICEVs in some of the coldest places within the U.S. compared to warmer climates. Official fuel economy ratings for city and highway cycles suggest that BEVs achieve higher emission reductions in congested city driving because ICEVs experience particularly poor fuel economy in those environments, while other sources have stated that BEVs make more sense in rural areas because of high annual travel distance per vehicle [85]. We find that these two factors balance each other out, leading to an average annual fuel consumption that is consistent across regions. Therefore, emission savings of BEVs compared to ICEVs are only about 10% higher in cities than in rural areas.

The observation that average annual travel distance is negatively correlated with average fuel efficiency, making annual fuel consumption per vehicle homogeneous across regions, means that people tend to have a constant annual fuel budget. This observation is analogous to the notion of a constant travel time budget [102, 140]. One notable outlier is New York City, where average annual fuel consumption per vehicle is 20%-40% lower than for other locations in the same population density bracket. This observation adds to evidence that properties of the built environment, including access to other modes of transport, can strongly affect travel demand for personal vehicle travel and therefore emissions per capita, despite a fixed total travel time budget.

All travel indicators, however, vary considerably across individual vehicles in a given region. The contribution of this variation to the overall heterogeneity in emissions is as large as the contribution of different vehicle classes and sizes and the contribution of region-dependent characteristics. In locations where conditions for BEVs are favorable, such as areas with a clean electricity mix, the impact of individual driving patterns on emission reductions achieved by BEVs is particularly large. This means that individual human behavior is a major determinant of the emissions of personal travel activity, and the emissions savings that a BEV achieves over a comparable ICEV. We find that this behavior can only partially be explained by the natural, built, and institutional environment; there is substantial heterogeneity across people and vehicles in a given region.

Another aspect of individual driving behavior is driving style. This thesis also advances the current understanding of ways to reduce fuel consumption with a more efficient driving style. We provide a simple set of heuristics that human drivers can follow, and evaluate potential fuel savings when these heuristics are applied consistently. We find that accelerating more softly, often emphasized as an important aspect of efficient driving, saves little energy. The most effective way to reduce energy consumption is through softer braking at high speeds, and avoiding braking altogether through coasting at low speeds, both of which can be achieved through anticipatory driving. Overall, driving style improvements, when consistently applied by the majority of drivers, lead to average fuel savings of about 5%. In addition to identifying the specific driving style changes that consistently lead to fuel savings and their impact, the framework developed here can assist the design of measures to reinforce such changes in drivers.

Combining heterogeneity across locations, vehicle classes, and individual driving patterns, we find that a 28% reduction of emissions from cars and SUVs could be reached with a BEV market share of between 12% and 50%. Similarly, an adoption of 10% electric vehicles into the fleet can reduce personal vehicle emissions by anywhere between 1% and 10% compared to a case where all newly sold vehicles are gasoline combustion engine vehicles. Our results also show that electrification can go hand in hand with measures to improve efficiency of all vehicles, such as driving style improvements and vehicle downsizing, to reach decarbonization levels of 50% or more with today's electricity mix. Therefore, we expand the set of factors that policy makers could consider in evaluating past and current light-duty vehicle policies. These results can assist the quantification of impacts of such policies on light-duty vehicle emissions and their changes to travel costs.

Our results allow individuals and regions to better forecast the impacts of BEV adoption on emission and costs, and can provide valuable information for designing corresponding information platforms for consumers. As part of this thesis, we developed one such platform, Carboncounter. It is based on the results from Chapter 2, allowing users to explore the emissions and costs of 1,000 vehicle models currently offered on the U.S. market, and customize parameters to their context. More than 100,000 unique visitors visited the site since fall 2016. A survey launched on carboncounter suggests that the use of the website systematically improved user's perception of the environmental and financial benefits of BEVs, and potentially their future purchasing decisions. Website exemplifies how scientific results can be made accessible to a wider audience by making use of modern interactive visualization tools. Results from Chapters 4 and 5 can inform the development of further tools to provide highly personalized information to consumers.

1.4 Thesis overview

The following chapters address the main research question of this thesis: What is the variation in emissions savings and costs of replacing internal combustion engine vehicles with battery electric vehicles across vehicle models, regions within the U.S., and individual behavior? The chapters are based on a journal paper that has been published [138], and three papers in preparation [134, 135, 139]. Furthermore, we developed Carboncounter, a platform that has been visited by more than 100,000 people since its launch [137].

Chapter 2 The second chapter assesses the emissions and costs to the consumer of 125 currently available personal vehicle models, and compares their emissions to climate targets. We find that alternative powertrain technology vehicles (hybrids, plug-in hybrids, and battery electric vehicles) exhibit systematically lower lifecycle GHG emissions than ICEVs, but do not necessarily cost the consumer more. Many currently available electric vehicles meet the 2030 average GHG intensity target, but none meet the more stringent 2040 and 2050 targets. Therefore, electrification should go hand in hand with decarbonization of the electricity sector and other efforts to meet climate targets in 2040 and beyond.

Chapter 3 The third chapter assesses the impact of driving style changes on fuel consumption, and therefore greenhouse gas emissions from vehicle operation. First, we reformulate commonly proposed eco-driving heuristics into a set of quantitative rules, designed to maximize energy savings while being consistent with realistic traffic and behavioral constraints. Then, we apply those heuristics to a large set of representative speed profiles using, measuring the impact of the heuristics on fuel consumption and trip duration. We find that the average driver in the U.S. can save 5% of fuel an average time loss of 1% by improving their driving style. These savings are consistent across locations, vehicle classes, and vehicle technologies. We conclude that driving style improvements can make a meaningful contribution to personal vehicle emission reductions, but are smaller than reductions achieved by electrifying powertrains.

Chapter 4 The fourth chapter studies the heterogeneity in two key parameters used in the evaluation of emissions and costs of personal vehicles: annual travel distance and vehicle fuel efficiency. In addition, we consider what fraction of annual travel distance is electrifiable with BEVs under certain charging behavior assumptions. We ask how these parameters vary across locations within the United States, and across individual vehicles within those locations. We address these questions by jointly analyzing representative country-wide travel survey data and a detailed, longitudinal dataset that was collected for a specific region. We find that annual travel distance and fuel efficiency vary considerably across locations, but the product of the two, annual fuel consumption, varies less. We show that the fuel efficiency of ICEVs and average annual travel distance are sensitive to urban-rural differences in driving patterns, while the efficiency of BEVs mostly depends on local climate. The fraction of electrifiable distance depends on both. All travel indicators exhibit variation across individual vehicles in a given region. In addition, we find that annual travel distance is negatively correlated with the fraction of distance that is electrifiable and positively correlated with ICEV fuel efficiency. Nonetheless, there are individual vehicles that have a high annual travel distance, a high share of electrifiable trips, and relatively poor ICEV fuel efficiency. For these vehicles, switching to a BEV is particularly effective in terms of emission reductions.

Chapter 5 The fifth chapter evaluates the heterogeneity of the difference in annual emissions and costs of BEVs compared to ICEVs across locations and individual vehicles in those locations. It asks what the distribution in expected emission reductions and costs savings of replacing a randomly chosen ICEV located in the United States with a BEV is, and which factors contribute the most to the resulting heterogeneity. We combine the parametrized model from Chapter 2 with the model developed in Chapter 4 and information on prices, taxes, and the electricity mix in different regions across the country. Our analysis shows that electric vehicles lead to slightly higher emission reductions, at lower costs, in urban areas and in areas with a warm climate, and substantially higher emission reductions in areas with a clean electricity mix. Individual consumer's decisions, reflected in preferences for different vehicle classes and different daily driving patterns, have as large of an impact on the variation in emissions and costs of BEVs compared to ICEVs as regional conditions. Combined, these variations imply that an adoption of 10% electric vehicles into the fleet can reduce personal vehicle emissions by anywhere between 1% and 10% compared to a case where all newly sold vehicles are gasoline combustion engine vehicles, depending on which specific combustion engine vehicles are being replaced by electric vehicles and where. We estimate that BEVs sold in 2018 achieve double the annual emission reductions than estimates based on compact cars operated under average conditions would suggest.

Chapter 6 The sixth chapter discusses Carboncounter.com, a website that lets consumers explore the emissions and costs of different cars, personalize parameter settings, and compare results against climate targets. We developed and launched this website in 2016, and received positive feedback from consumers. A survey launched on Carboncounter suggests that the use of the website has changed users' perception of the environmental and financial benefits of BEVs, and potentially their future purchasing decisions. We discuss the development of this platform, key insights from the survey, and the general potential of such platforms to communicate research results to a wide audience.

Chapter 2

Personal vehicles evaluated against climate targets

Abstract

Meeting global climate change mitigation goals will likely require that transportation-related greenhouse gas emissions begin to decline within the next two decades, and then continue to fall. A variety of vehicle technologies and fuels are commercially available to consumers today that can reduce the emissions of the transportation sector. This chapter asks what the best options are, whether any of these options suffice to meet climate policy targets. We examine the costs and carbon intensities of 125 light-duty vehicle models on the U.S. market today, and evaluate these models against U.S. emission reduction targets for 2030, 2040, and 2050 that are compatible with the goal of limiting mean global temperature rise to 2 °C above pre-industrial levels. Our results show that consumers are not required to pay more for a low carbon emitting vehicle. Across the diverse set of vehicle models and powertrain technologies examined, a clean vehicle is usually a low-cost vehicle. While the average carbon intensity of vehicles sold in 2014 exceeds the climate target for 2030 by more than 50%, we find that most hybrid and battery electric vehicles available today meet this target. By 2050, only electric vehicles supplied with almost completely carbon-free electric power meet climate policy targets.[1]

2.1 Introduction

The transportation sector accounts for 28% of U.S. greenhouse gas (GHG) emissions through vehicle fuel combustion, and 13% worldwide [176, 69]. Light-duty vehicles (LDVs), which are defined by the U.S. Environmental Protection Agency (EPA) as passenger cars and light trucks with 12 seats or less and a gross vehicle weight rating below 8,500 lbs (10,000 lbs for SUVs and passenger

[1] A version of this chapter has been published in *Environmental Science & Technology* [133] with co-authors Geoffrey J. Supran, Ella J. Kim, and Jessika E. Trancik.

vans) [64], contribute about 61% of emissions from the U.S. transportation sector [69]. LDVs are therefore a crucial element of any comprehensive strategy to reduce U.S. and global GHG emissions, particularly under growing transportation demand [46, 103, 41, 176].

Alternative powertrain technologies, such as battery electric and fuel cell powertrains, are potential mitigation technologies for personal LDVs, and a variety of studies have evaluated their capacity to contribute to the reduction of transportation emissions [126, 31, 172, 17, 62, 58, 194, 84, 73, 95, 96, 198, 22, 146, 131, 154, 23, 133, 204]. Most of these studies focus on the comparison of powertrain technologies implemented in a car of single size and body style [126, 31, 172, 62, 58, 194, 84, 73, 96, 198, 22, 146, 204, 23]. Among those studies that consider different vehicle sizes and styles [17, 95, 131, 133], none considers more than three different options. In aggregate, these studies cover a limited set of available vehicles and direct comparisons across studies are complicated by differences in assumed system boundaries, fuel production pathways, and lifetime driving distance, as well as data sources for lifecycle inventories and fuel consumption values.

Here, we address two missing elements in the literature by comparing the diversity of personal vehicle models available to consumers, and by assessing these options against climate change mitigation targets. When comparing personal vehicles against climate targets, it is important to understand the wide range of models available for purchase, as consumer choices are defined by this available set.

In particular, we focus on the tradeoffs between costs and emissions that consumers face in selecting a vehicle model. While cost is not the sole influence on consumer purchasing decisions [32, 158, 142, 94, 174, 97], low-carbon vehicles will only achieve a dominant market share if they are affordable to a majority of the driving population. (Our proxy for affordability is the relative cost of low-carbon vehicles versus popular, conventional vehicles on the market.) Here, we address these issues by examining a comprehensive set of 125 vehicle models on sale today, covering all prominent powertrain technology options: internal combustion engine vehicles (ICEVs); hybrid electric vehicles (HEVs); plug-in hybrid electric vehicles (PHEVs); and battery electric vehicles (BEVs). Our analysis also includes the 2016 Toyota Mirai, one of the first commercially available fuel cell vehicles (FCVs).

We evaluate vehicle models on a cost-carbon plot [190], in order to answer the overarching question: How do the costs and carbon intensities of vehicle models compare across the full diversity of today's LDV market, and what is the potential for various LDV technologies to close the gap between the current fleet and future GHG emission targets? Specifically, we ask: Do consumers face a cost-carbon tradeoff today? Which models, if any, meet 2030 GHG emissions reduction targets? And, longer term, which vehicle technologies would enable emissions targets for 2040 and 2050, designed around a 2 °C limit, to be met? What role can advancements in the carbon intensity of electricity generation, powertrain efficiencies, and production pathways for liquid fuels play? The insights and choices identified in this study may be of interest to car owners, cars manufacturers, and transportation policymakers alike.

This paper is organized as follows. In the next section, we describe the methods used for our analysis. Then, we present a comparison of vehicle models spanning today's LDV market against carbon intensity targets on a cost-carbon curve, before investigating what factors may enable future decarbonization of this sector. Finally, we discuss the significance of our results for key decision-makers.

2.2 Methods

Key steps in our analysis include: (1) estimating LDV lifecycle GHG emission targets (gCO_2eq / km) for the years 2030, 2040, and 2050 consistent with 2 °C climate policy targets; (2) identifying 125 of the most popular LDV models on the market today, across all powertrain technologies; (3) estimating the lifecycle costs and carbon intensities of these vehicles based on today's costs and energy mixes, and comparing these results against the GHG targets; and (4) assessing the potential of different vehicle models and powertrain technologies to meet GHG targets under a number of vehicle improvement and energy market scenarios. Further details are given in Appendix A.

2.2.1 Estimating carbon intensity targets

Based on overall GHG reduction targets, we estimate carbon intensity targets for emissions from personal LDVs, quantified as GHG emissions per unit distance traveled (gCO_2eq / km). The targets are calculated in three steps: (1) define overall annual U.S. GHG emission targets in 2030, 2040, and 2050; (2) allocate a fraction of these emissions to LDVs; and (3) divide these numbers by the total vehicle distance expected to be traveled by LDVs.

In step (1), the U.S. emissions reduction targets correspond to a proposed equitable allocation of GHG emissions across nations to limit global warming to less than 2 °C above pre-industrial temperatures [49]. Under these targets, total U.S. GHG emissions would be reduced by 32% below 1990 levels by 2030, and 80% below 1990 levels by 2050. We also calculate an emission target for 2040, using linear interpolation (56% below 1990 levels). The U.S. had outlined an equivalent emission reduction goal of 42% below 2005 levels (corresponding to 32% below 1990 levels) by 2030 prior to the United Nations Climate Change Conference in Copenhagen. More recently, the U.S. has made less stringent commitments to reduce overall GHG emissions 26-28% below 2005 levels by 2025 as part of the 2014 U.S.-China Joint Announcement on Climate Change [187].

In step (2), we apply equal percent GHG emissions reductions across all end-use sectors. (This is in contrast to the approach applied in step (1) of a differentiated allocation across nations, and is an approach suggested by current policy proposals in the U.S. targeting electricity and transportation end-use sectors. Belowgree, we briefly discuss circumstances below under which different percent emissions reduction targets might be applied across end-use sectors.) We define the share of emissions represented by the LDV end-use sector to include emissions from (a) fuel combustion, (b) emissions from the production, distribution and storage of the fuel, and (c) emissions resulting from the production, shipping and disposal of the vehicles. Using the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation Model (GREET) [11], discussed further in Section 'Estimating Vehicle GHG Emissions', we estimate that on average (a) represents 70.8% of lifecycle emissions, while (b) and (c) represent 18.5% and 10.7% respectively. Including lifecycle emissions based on these estimates raises the share of overall U.S. GHG emissions represented by LDVs from 17% to 24%. (The transportation sector's 28% share [69] of overall GHG emissions cited in this paper's introduction includes only vehicle fuel combustion emissions.) The 24% estimate does not account for the fact that a portion of the vehicle and fuel production emissions may have occurred outside the U.S.

In step (3), we use forecasts of the total vehicle miles traveled (VMT) for personal vehicles from the Annual Energy Outlook [103]. In 2011, the VMT by LDV were 2623 billion miles (4220 billion km), and are projected to grow by 0.9% per year until 2040 [103]. The emissions intensity targets (emissions per km) estimated here assume a continuation of this growth rate until 2050. The resulting targets are 203 gCO_2eq / km for the average vehicle on the road in 2030, 121 gCO_2eq / km in 2040, and 50 gCO_2eq / km in 2050, including well-to-tank emissions of fuel production and distribution, and emissions from the production and disposal of the vehicles. Emission targets are shown as dotted lines in figures 2-1–2-5. The targets are raised relative to a case in which only vehicle fuel combustion emissions are included or to a case where only raw test cycle data is considered, for two reasons: (1) we include well-to-tank emissions of fuel production and distribution, as well as emissions from the production and disposal of the vehicles; and (2) we base fuel consumption estimates on U.S. EPA ratings, which have been adjusted for the use of auxiliaries, driving in cold and hot conditions, aggressive driving patterns, and charging losses of PHEVs and BEVs [64].

A stagnation of VMT has been observed since 2006, meaning that these targets may be somewhat too stringent (although VMT rose again in 2015) [77]. On the other hand, an increase in travel by some modes of transportation for which decarbonization is particularly difficult (such as air travel) may call for the increased decarbonization of others (such as LDVs), offsetting the relaxation of targets due to any long-term reduction in the growth of VMT. Economic efficiency arguments could potentially be used to justify different percent emission reduction targets across sectors, and highlights a potential shortcoming of 'segmental' policies that determine this allocation at the outset rather than letting the market do so [189]. Segmental policies also have some advantages, however, and are the current policy proposals of choice in the U.S.

Indeed these targets are subject to various uncertainties in future demand for LDV travel (or VMT) and the allocation of emissions reductions across sectors (for a quantitative description of the effect of uncertainty see [189]). While the latter is a policy decision, the former will emerge from the decisions of individuals in the population and is more difficult to estimate *ex ante*. These uncertainties and the effect that they can have on the GHG intensity targets are discussed in the Appendix A, section A.1, with the effect of the uncertainty in future VMT estimated in Figures A-1–A-3. Our findings regarding which powertrain technologies can meet mid-century climate targets are robust to these VMT uncertainties, due to the dominant effect of aggressive emissions reduction targets.

2.2.2 Selecting vehicle models

We report the lifecycle carbon intensities and costs to the consumer of a total of 125 LDVs. We define LDVs as all four-wheeled vehicles that are captured by the EPA regulations on light-duty vehicle fuel economy. This includes all passenger cars and light trucks with 12 seats or less and a gross vehicle weight rating below 8,500 lbs (10,000 lbs for SUVs and passenger vans) [64]. We include all internal combustion engine vehicle (ICEV) models that sold more than 50,000 units in 2014 (93 models [33]), all non-plug-in hybrid electric vehicles (HEVs) that sold more than 5,000 units in 2014 (16 models [42]), and all plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) that sold more than 1,000 units in 2014 (4 and 8 models [42]). Combined, these vehicles account for 83% of all personal LDVs sold in 2014 [33]. In addition, we include the recently released Toyota Mirai as the only fuel cell vehicle (FCV), and added Diesel and E85 flex-fuel versions for three of the ICEV models. The Mirai is shown for two different hydrogen production pathways: steam methane reforming of natural gas; and electrolysis using electricity. Except for the Mirai, all data used to calculate emissions and costs are based on the respective 2014 models.

2.2.3 Estimating vehicle GHG emissions

Lifecycle GHG emission intensities are calculated using GREET 1 and 2 [11]. GREET is a widely used, publicly available full vehicle lifecycle model developed by Argonne National Laboratory [11]. GREET 1 models the lifecycle emissions of fuels and of electricity, while GREET 2 models the lifecycle emissions of the vehicles themselves. For each powertrain technology and model, the vehicle class (car, SUV, or pickup), curb weight, fuel consumption, battery power (for HEVs), battery capacity (for PHEVs and BEVs), and fuel cell power (for FCVs) are determined. These parameters are obtained from manufacturers' websites and a car information web portal [38]. The carbon intensity of electricity is modeled as the average U.S. mix, including emissions from infrastructure construction (623 gCO_2eq / kWh). We use a consistent lifetime of 169,400 miles (272,600 km) for all vehicle types, corresponding to the approximate averages for LDVs in the U.S. [76] Other GREET parameters are left at their defaults. Because consistent information could not be obtained for all models, the use of light-weighting materials is not considered; that is, all vehicles are assumed to have the 'baseline' material mix of their respective powertrain technology and vehicle class.

We determine the fuel consumption of each car from the official fuel economy value recorded by the U.S. government (Environmental Protection Agency) based on a standardized test procedure specified by federal law, using the combined city (55%) and highway (45%) rating [64]. These fuel economy ratings are adjusted for the use of air conditioning in warm weather, efficiency losses in cold weather, and driving patterns [64].

While there is public skepticism about the accuracy of these ratings [181], the EPA holds that they are relatively accurate on average [152], and updates test procedures regularly to mitigate biases. Tests found that large cars and diesel cars may yield somewhat higher (better) real-world fuel economies on average than their ratings suggest [181], while certain hybrid models may result in lower fuel economies [45]. Notably, however, these results could be partially explained by biases in driving behavior rather than unrealistic test ratings: hybrids may more often be driven in urban environments with dense traffic (which impacts fuel economy negatively), while large trucks may more often be driven under steady, efficient highway conditions.

For those models where several trims and engine sizes are available, the trim with the best fuel economy is analyzed for each model. In many cases, this trim corresponds to the most affordable trim. However, in some cases, more costly trims improve fuel economies, for example through the use of continuously variable transmissions. While tires are included in the vehicle cycle (3 sets per lifetime for cars, 4 for SUVs and pickups), the GHG emissions of are not modeled, and it is assumed that all components (including the battery) last for a vehicle's entire lifetime. The results' sensitivity to this assumption is provided in Figure A-3 in Appendix A. Further sensitivity analyses, details on how GHG emissions were calculated, and the specific parameters obtained for each of the 125 analyzed vehicle models can also be found in Appendix A, starting from section A.3.

2.2.4 Estimating vehicle costs

The total costs of ownership are calculated as the present value of the costs of purchasing the vehicle, paying for fuel/electricity, tire replacements, and regular maintenance. As with the calculation of GHG emissions, we assume that each vehicle is driven a total distance of 169,400 miles, at 12,100 miles (19,470 km) per year for 14 years of ownership. A discount rate of 8% is applied to future cash flows. The average reported lifetime is slightly longer (15 years) and the average annual driving distance is slightly lower (11,300 miles per year), but decreases with increasing car age [76]. Using a lifetime of 14 years at a constant 12,100 miles per year yields the same discounted cashflows and the same total lifetime distance driven as would using the reported lifetime and vehicle-age-specific annual driving distances. Insurance costs, as well as taxes on vehicle acquisition and ownership, are not included. They depend strongly on the location of the customer, and on additional complicating factors that are specific to each vehicle model. Each vehicle's price is based on its official manufacturer's suggested retail price (MSRP) without tax, for the trim with the best fuel economy. In addition, we evaluate the impact of federal and state tax refunds on the lifecycle costs of PHEVs, BEVs, and FCVs. The federal refund depends on the capacity of the battery, and has a maximum value of $7500 [107]. The state refund, which was assessed for the case of California, is $1500 for PHEVs, $2500 for BEVs, and $5000 for FCVs [54]. Several other states have similar programs, but were not analyzed in detail.

Fuel and electricity prices are based on the 10-year average of the inflation-adjusted prices in the U.S. [59] The resulting prices are $3.14/gal for gasoline, $3.41/gal for premium gasoline,

$3.39/gal for diesel, $2.51/gal for E85, and $0.121/kWh for electricity. Hydrogen prices are estimated to be $4.00/kg for hydrogen from methane and $7.37 for hydrogen from electrolysis, based on average industrial electricity and natural gas prices. A more detailed description of how these values were determined can be found in Appendix A, section A.3. We also investigate the effect of variability in these prices over time and across locations within the U.S.

The costs of tires and regular maintenance are modeled in a simplified manner, assuming a total of $895 per year for sedan ICEVs and HEVs, and $1013 per year for SUVs and pickups [2]. A German study found that regular maintenance costs of BEVs may be a third lower than those of ICEVs [106]; this reduction is applied to BEVs and FCVs. For PHEVs, maintenance costs are lowered by one-sixth. Batteries and fuel cells are assumed to last the entire lifetime of every vehicle, and fuel economies are assumed to stay constant. The sensitivity of the cost estimates and the results to these assumptions is presented in Appendix A, section A.2.

2.2.5 Evaluating vehicle GHG-intensity mitigation pathways

Future prospects for reducing vehicle GHG emissions intensities are assessed based on potential improvements in powertrain efficiency, aerodynamic drag, tire rolling resistance, and weight (without decreasing vehicle size, which is evaluated separately). We base estimates of potential fuel consumption reductions by 2050 on a recent comprehensive report [98]. However, we do not use the projected values for 2050. Rather, we use the arithmetic mean of projections for 2030 and 2050. We do this because (1) some vehicles today may already include some of the projected improvements; and (2) we limit the curb weight reductions (which are also taken into account in calculating vehicle cycle emissions) to 15%, whereas the authors in ref. [98] assume 15% by 2030, and 30% by 2050. Based on this analysis, we apply estimates of maximum possible fuel consumption reductions by 2050 of 40% for ICEVs, 45% for HEVs and PHEVs in charge sustaining mode, 30% for BEVs and PHEVs in charge depleting mode, and 35% for FCVs.

We also examine the effect of changing production pathways for electricity and fuels. We consider changes to lifecycle GHG emissions when a low-carbon electricity mix is used to charge electric vehicles, and when biofuels are used to fuel combustion engines. For the low-carbon electricity mix, we assume a hypothetical energy supply portfolio comprising 50% wind, and 12.5% each of hydro, solar photovoltaic, biomass, and nuclear. Using GREET 2014, this mix results in emissions of 24 gCO_2eq / kWh, including the indirect effects of reducing carbon emissions from manufacturing and constructing power-generation equipment. The electricity mix not only affects the GHG emissions of BEVs and PHEVs (due to charging), but also the carbon intensity of the production of vehicles and fuels for all powertrain technologies.

2.3 Results

2.3.1 GHG emissions and costs of 125 popular cars in the U.S.

We find that GHG emissions and costs vary considerably across popular vehicle models, both within and between powertrain technologies, with lower emissions generally corresponding to lower costs. Alternative powertrain technologies (HEVs, PHEVs, and BEVs) exhibit systematically lower lifecycle GHG emissions than ICEVs, but do not necessarily cost the consumer more (Figure 2-1a). As one example, the most popular BEV, the Nissan Leaf, costs 20% less than the sales-weighted average ICEV in 2014, when considering vehicle, fuel, and maintenance costs. Even before including tax refunds, the compact version of the Nissan Leaf matches the cost of the average compact ICEV sold in 2014 (figures 2-1 and 2-2). At the same time, the Leaf has half the GHG emissions intensity of the average ICEV sold in 2014, and 38% less than the average compact ICEV sold in 2014. In contrast to the tradeoff between costs and GHG emissions reported for electricity [190], where electric utilities are the consumers of energy conversion technologies and fuels, there is no such tradeoff faced by consumers of vehicles.

Among alternative powertrain technologies and fuels, BEVs offer the lowest emissions, followed by PHEVs and HEVs, and then diesel engines and FCVs. Vehicles fueled by diesel are among the lowest-emitting ICEVs in the set examined here, while those using E85 (assuming corn-based ethanol) do not reduce emissions relative to gasoline (Figure 2-1f): the CO_2eq emissions per gallon of E85 fuel are 22% lower than those of gasoline (based on GREET data), but this advantage is offset by the lower fuel economies achieved with E85 in flex-fuel engines. For the one FCV model examined (Toyota Mirai), emissions reductions are only achieved when hydrogen is produced using steam methane reforming (SMR). When using hydrogen from electrolysis, the Toyota Mirai's emissions are almost on par with some of the highest-emitting ICEVs on the market.

The regional variability of the electricity mix has a considerable impact on the emissions reduction potential of BEVs and PHEVs (Figure 2-3a,b). Based on a calculation of regionalized marginal emission factors of electricity [175], we find that under relatively low carbon-intensity electricity conditions, such as the Western Electricity Coordinating Council (WECC) with daytime charging (477 gCO_2eq / kWh, Figure 2-3b), emissions from today's BEVs are reduced by about 50% com-

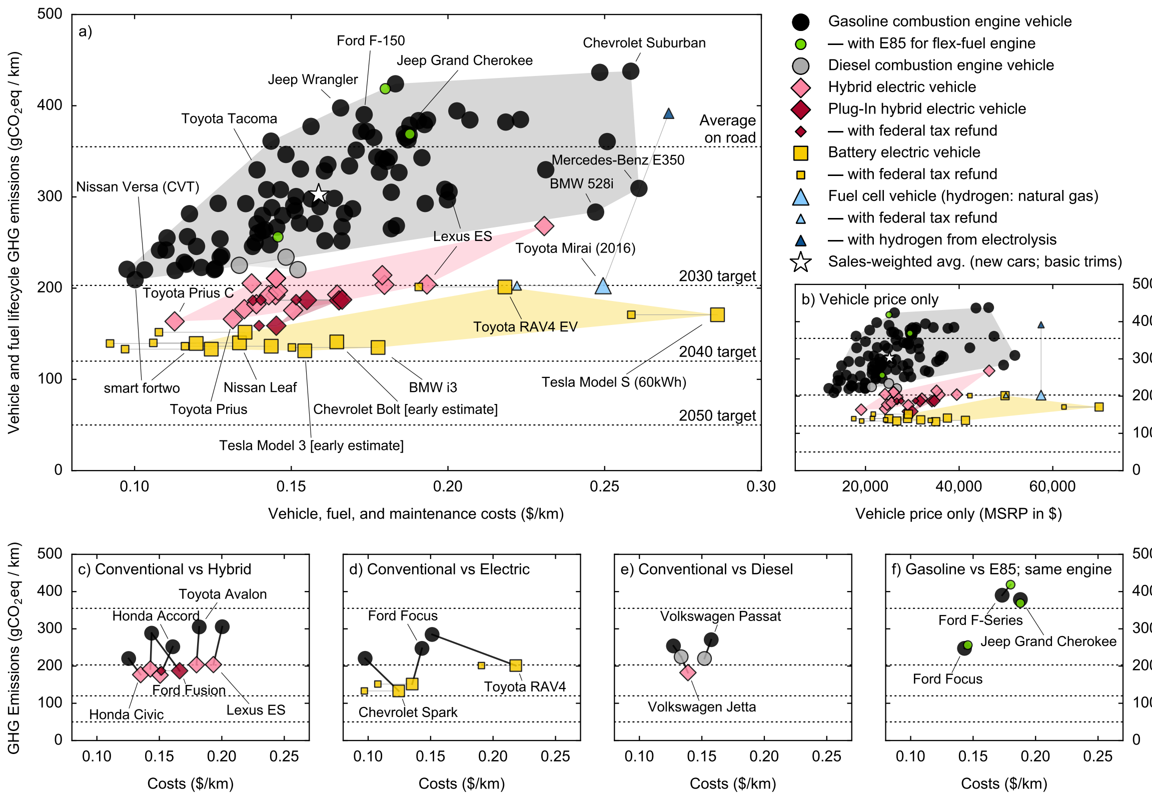

Figure 2-1: (a) Cost-carbon space for light-duty vehicles, assuming a 14 year lifetime, 12,100 miles driven annually, and an 8% discount rate. Shown are the most popular internal combustion engine vehicles (ICEVs; including standard, diesel, and E85 corn-ethanol combustion), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs) in 2014, as well as one of the first fully commercial fuel-cell vehicles (FCVs). For each model, the trim with the best fuel economy is analyzed. The shaded areas are a visual approximation of the space covered by these models. The emission intensity of electricity used assumes the average U.S. electricity mix (623 gCO_2eq / kWh). The FCV is modeled for hydrogen produced either by electrolysis or by steam methane reforming (SMR). Horizontal dotted lines indicate GHG emission targets in 2030, 2040, and 2050 intended to be consistent with holding global warming below 2 °C. (b) Same as (a), but for upfront vehicle prices only, based on MSRPs. (c-f) Comparisons of different powertrain technologies used in the same car models. For PHEVs and BEVs, the impact of tax refunds (federal plus state refund in California) is also shown.

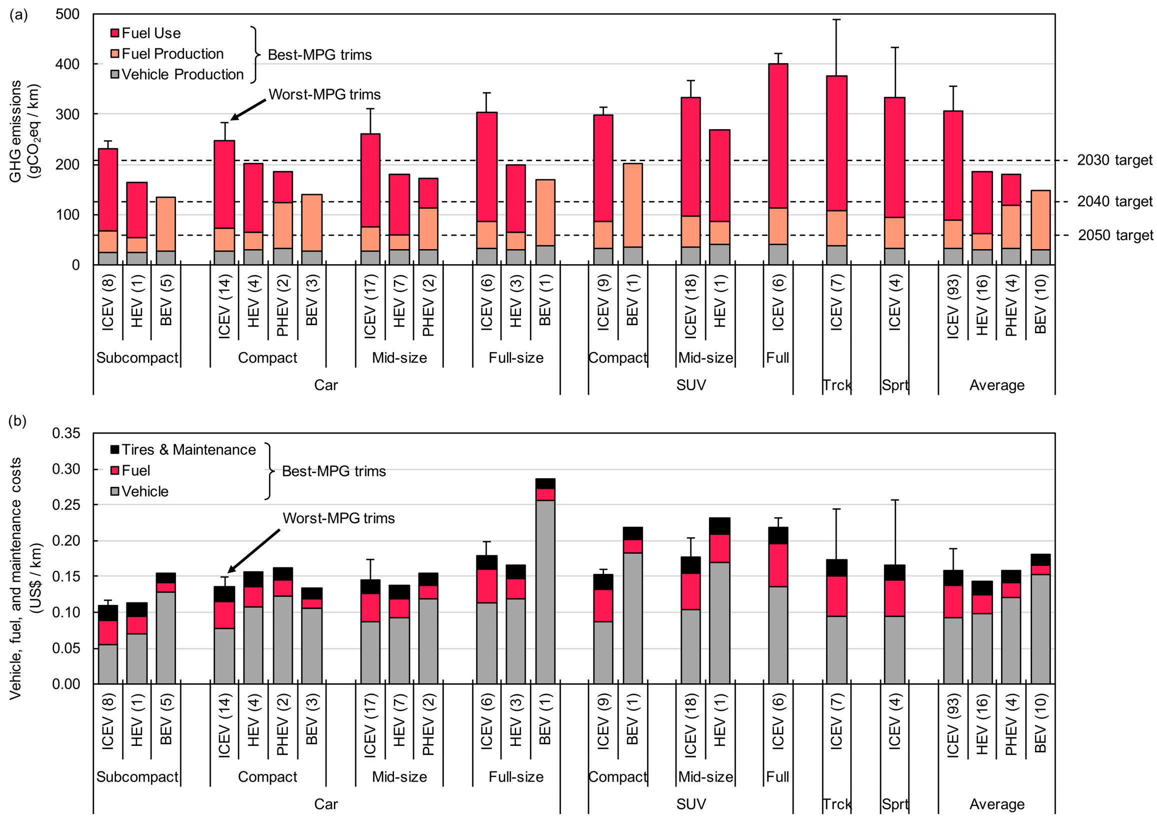

Figure 2-2: Sales-weighted averages by vehicle class, size, and technology of (a) GHG emissions and (b) costs for the data shown in Figure 2-1. The shaded bars represent the averages when analyzing the trim with the best fuel economy for each model, as in Figure 2-1. The error bars represent the averages when analyzing the trim with the worst fuel economy for each model (only ICEVs have trims with substantially different fuel economies for each model). The numbers in brackets represent the number of vehicle models considered for each group. SUV = Sport Utility Vehicle; Trck = Pickup truck; Sprt = Sports car.

pared to ICEVs, and by about 25% compared to HEVs. In regions with high carbon-intensities of electricity, for example the Midwest Reliability Organization (MRO) with nighttime charging (857 gCO$_2$eq / kWh, Figure 2-3a), BEVs do not outperform (P)HEVs, and emit only about 25% less than comparable ICEVs.

A comparison of the costs and GHG emissions of various powertrain technology and fuel options for the same vehicle model provides further perspective. We find that alternative powertrain technologies often do not cost more for the same vehicle model (Figure 2-1c-f). Most HEVs do not result in higher costs to the consumer than their ICEV counterparts (Figure 2-1c). Only the smallest HEVs for which direct comparisons to ICEVs exist (the Honda Civic and the VW Jetta) come at a slight cost penalty. For PHEVs and BEVs, there is a cost penalty on the order of 20-30%, with the exception of the Ford Focus Electric, which was found to be cheaper overall than the combustion engine version (Figure 2-1a,b). However, a combined federal and California state tax refund currently offered can remove a large portion of the difference between the lifecycle costs of plug-in electric vehicles (PHEVs, BEVs) and vehicles that cannot be plugged into a power outlet (ICEVs, HEVs).

When only the purchasing prices (upfront costs) of the vehicles are considered, the comparison, based on current costs, shifts in favor of ICEVs (Figure 2-1b). If consumers are more sensitive to the vehicle purchasing price than to overall lifecycle costs, due to a limited budget for purchasing a vehicle and limited access to financing, they may perceive ICEVs to be more affordable. In addition, some studies suggest that consumers do not fully account for fuel costs when making vehicle purchasing decisions [92].

One consequence of the higher upfront costs and lower fuel costs of alternative powertrains, particularly BEVs, can be a more stable driving cost over time. Because of the higher fuel cost contribution to the per-distance cost of driving an ICEV (Figure 2-2), a changing fuel price can cause the cost of driving to fluctuate more, leaving consumers with a less predictable driving cost over the lifetime of the vehicle. The difference can be considerable, with fuel costs contributing 31% to total costs in the case of ICEVs and only 9% in the case of BEVs, based on a sales-weighted average (Figure 2-2). The effect can be amplified by the fact that gasoline prices tend to vary more than (consumer) electricity prices over time. Across geographical locations, on the other hand, electricity prices vary more than gasoline prices. In Figure 2-3c and d, we examine the combined impact of spatial and temporal variation in fuel costs by comparing a strongly ICEV-friendly price scenario (Figure 2-3c) against a strongly BEV-friendly scenario (Figure 2-3d) price scenarios, based on inflation-adjusted annual average prices in the lower 48 U.S. states between 2003 and 2015 [59]. We find that in going from the ICEV-friendly to the BEV-friendly scenario, the average ICEV becomes 15% more expensive, the average HEV becomes 9% more expensive, the average PHEV stays the same, and the average BEV becomes 6% less expensive. While these changes do not substantially shift the relative position of the different technologies in the cost-carbon space, they can have a considerable impact on the cost-competitiveness of specific models.

2.3.2 Vehicles evaluated against climate targets

Several currently available vehicles meet the 2030 average GHG intensity target, while none meet the more stringent 2040 and 2050 targets (figures 2-1 and 2-2). Those vehicles meeting the 2030 target include several HEVs, PHEVs, and BEVs, as well as the Toyota Mirai FCV when operated

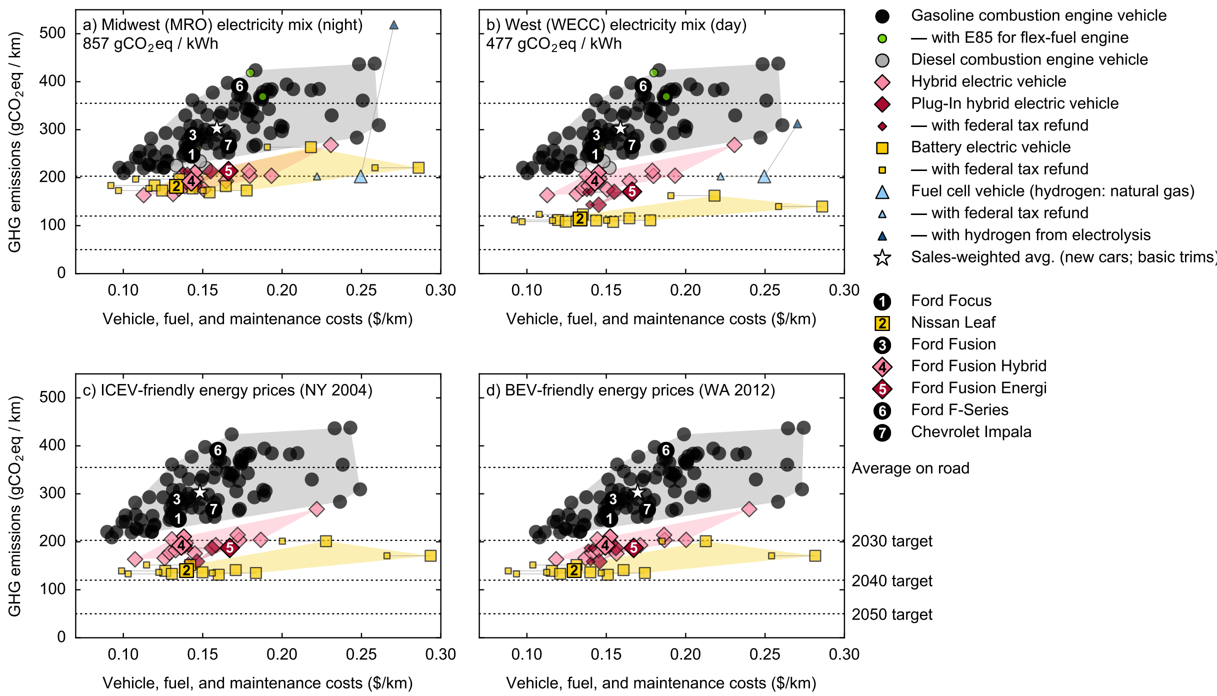

Figure 2-3: The cost-carbon space of light-duty vehicles as in Figure 2-1a, shown for four different cases: (a) a lower carbon intensity electricity mix, using the emissions intensity of electricity of the Midwest during nighttime charging [175]; (b) a higher carbon intensity electricity mix, using the emissions intensity of electricity of the West during daytime charging (note that the region has a larger impact on the emission intensity of electricity generation than the time of day of charging) [175]; (c) an ICEV-friendly energy price scenario, using average inflation-adjusted prices from New York State in 2004 ($2.43/gal for gasoline and $0.178/kWh for electricity); and (d) a BEV-friendly energy price scenario, using average inflation-adjusted prices from Washington State in 2012 ($3.88/gal for gasoline, and $0.086/kWh for electricity).

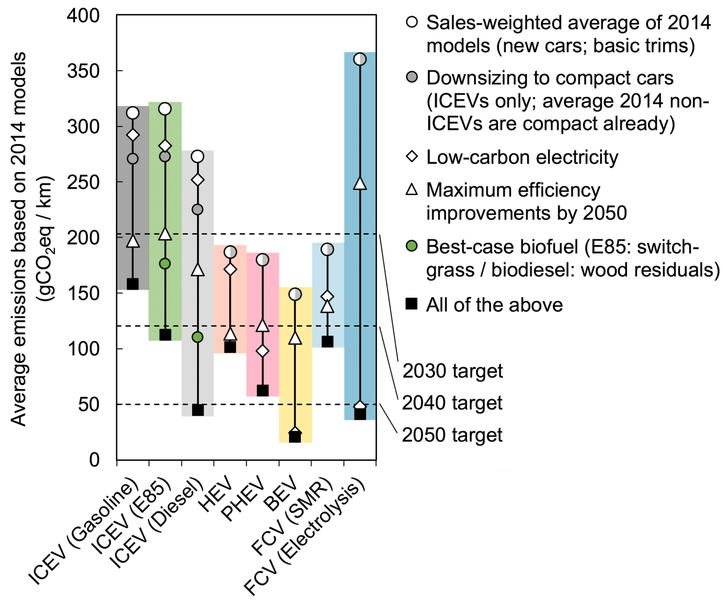

Figure 2-4: The average GHG emissions intensities of each powertrain technology in response to vehicle downsizing, a low-carbon (zero fossil fuel) electricity supply mix (24 gCO_2eq / kWh), efficiency improvements, the use of future biofuels (for ICEVs), and the combination of all factors. Efficiency improvements include a 15% weight reduction and reduced fuel consumptions of 40% (ICEVs), 45% (HEV and PHEVs in charge sustaining mode), 30% (BEV and PHEVs in charge depleting mode), and 35% (FCV) [98].

with hydrogen from SMR (Figure 2-1a). None of the ICEV vehicles meet the 2030 target, although some come very close. Meeting the 2030 target would therefore require that consumer choices change well in advance of 2030 (likely by 2025 or earlier) given the time required for the operating fleet to mirror the average carbon intensity of new vehicles. Alternatively, major improvements to ICEV efficiencies and substantial downsizing could allow gasoline-fueled ICEVs to fall below the 2030 target, but not 2040 and 2050 targets (Figure 2-4).

As shown in Figure 2-4, emission reductions due to estimated improvement potentials of fuel economies [98] are higher for combustion-engine vehicles (ICEVs and HEVs) than for electric vehicles (PHEVs, BEVs, and FCVs). Even if these fuel economy improvements and other emissions-reducing changes are achieved, however, gasoline-powered non-hybrid ICEVs may never be able to drop below the emission intensities of today's BEVs (charged with electricity at the current U.S. average GHG emissions intensity).

Some of the 'best-case' *second* generation biofuels promise greater emission reductions for ICEVs. The average 2014 ICEV, equipped with an E85-capable combustion engine and operated with E85 from switchgrass, would reach the 2040 target. The same average car, equipped with a

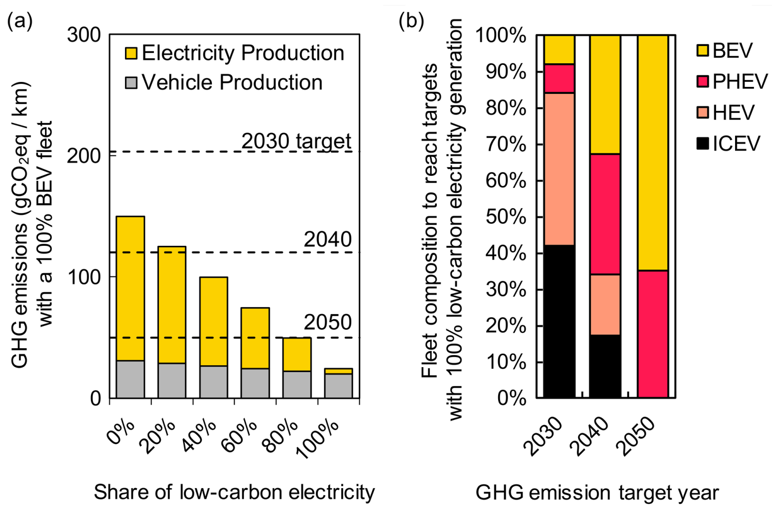

Figure 2-5: (a) Share of low-carbon (24 gCO_2eq / kWh) and fossil fuel-based (840 gCO_2eq / kWh) electricity generation necessary to reach the GHG emission targets for climate mitigation, if the entire fleet consists of the average 2014 BEV model (see Figure 2-4). (b) Examples of powertrain technology shares that meet the GHG emission targets if the electricity is generated from 100% low-carbon sources, using the average emissions of the 2014 models (see Figure 2-4).

diesel engine and operated with biodiesel from wood residuals, would surpass it.

The greatest emissions savings, however, are expected from decarbonizing the electricity mix, and only technologies that can benefit most from this are able to reach the 2050 GHG emissions intensity target (Figure 2-4). The lowest GHG emissions are achieved by BEVs, at 32 gCO_2eq / km. The Toyota Mirai FCV operated with hydrogen from electrolysis results in GHG emissions that are nearly comparable to BEVs under this scenario. However, the overall electricity consumption per distance driven is almost three times higher for the Mirai. This is the reason why the GHG emissions of the Mirai, when driven with hydrogen from electrolysis, are so sensitive to the carbon intensity of the electricity mix.

To illustrate a possible scenario for reaching the 2040 and 2050 targets, we consider the effects of the electrification of transportation and the simultaneous decarbonization of electricity. Figure 2-5a depicts the average emission intensity of a hypothetical LDV fleet consisting entirely of BEVs, based on the sales-weighted average of 2014's BEV models. Under this scenario, no improvements to the carbon intensity of electricity production would be necessary to meet the 2030 target, as the average 2014 BEV surpasses that target with the current average U.S. electricity mix. In fact, as Figure 2-3a shows, even in regions of the U.S. with very high carbon-intensities of electricity, many BEVs and (P)HEVs meet the 2030 target. Later targets do require reductions, however. To meet the 2040 target, the share of low-carbon electricity generation technologies would need to reach about 40%. To meet the 2050 target, a share of more than 80% would be necessary. In Appendix A, Figure A-2, we show the vehicle cost-carbon space when using a fully decarbonized electricity mix, considering different electricity price scenarios.

Interestingly, these emissions reduction targets for electricity are less stringent than they would be for the electricity sector when applying a similar approach to that used here, as previously reported [190]. This is because electric vehicles have a higher efficiency of conversion from primary energy to energy at the wheel than dominant vehicle technologies used today. The implication is that if the electricity end-use sector meets its targets, the decarbonization would be more than enough to achieve LDV transportation targets under a full electrification of transportation.

Another scenario that meets the 2050 target is a partial electrification of transportation, but a full decarbonization of electricity. In Figure 2-5b, we analyze the powertrain technology mix required to meet a target if electricity were to be generated using low-carbon technologies only. The 2030 target could be reached with a fleet consisting almost entirely of ICEVs and HEVs, even if no improvements in efficiency are assumed. To meet the 2040 target, however, a considerable share of PHEVs and BEVs would be necessary. The 2050 target is only met with a large share of BEVs and PHEVs.

2.4 Discussion

This paper presents an approach to quantifying the diversity of carbon emissions across the U.S. LDV market against climate mitigation targets, with the goal of better informing three categories of decision-makers: car owners, car manufacturers, and transportation policymakers. Our analysis identifies choices available to consumers of vehicles, and insights that can inform directed innovation efforts by policy makers and car manufacturers. Together, these stakeholders will dictate progress in decarbonizing the transportation sector, and whether a transition occurs at a speed and scale commensurate with climate policy goals.

Despite the broad spectrum of vehicle costs and carbon intensities on offer — within the 125 vehicles examined, there is a 400% spread between the lowest- and highest-emitting cars, and a 250% spread between the cheapest and most expensive — several clear patterns emerge. We find that the least emitting cars also tend to be the most affordable ones within and, in many cases, even across different powertrain technologies. And while the average carbon intensity of vehicles sold in 2014 exceeds the 2030 climate target by more than 50%, most available (P)HEVs and BEVs meet this goal.

A primary takeaway for car buyers is that vehicle decarbonization compatible with future climate targets can only be achieved by transitioning away from ICEVs, principally to hybrid and battery EVs. We find that with today's options, the average consumer is able to choose (P)HEVs and BEVs at little to no additional cost over similarly-sized ICEVs once the existing tax refunds for PHEVs and BEVs are taken into account. Our analysis helps highlight the extent of cost-carbon savings that car buyers forego by opting for traditional ICEVs over alternative lower cost, lower carbon technologies.

Meeting the 2030 climate target requires that by well before 2030, the emissions intensity of the average new car must be as low as that of today's average HEVs and PHEVs. Thereafter, sufficient vehicle emissions reductions will likely require both electrification of the vehicle fleet and a large and rapid decarbonization of the electricity generation sector (40% by 2040, 80% by 2050). This finding corroborates previously proposed climate mitigation scenarios at state [201, 199, 108], national [202], and global scales [169]. But by examining technology choices from the perspective of consumers—key decision makers in any future low-carbon transition—our study goes a step further in illuminating technological development and policy pathways that might reach these goals.

An all-electric fleet would increase 2050 electricity consumption in the U.S. by an estimated 1315 TWh per year, or about 28%, if all cars were replaced by today's Ford Focus Electric. This figure would increase to 73% if all cars were replaced by a Toyota Mirai FCV (with an efficiency of electrolysis, compression, and storage of 62% [11]). Accordingly, it will be important for public and private actors to address infrastructure integration challenges such as charging stations and demands on the electricity supply system [191, 94, 165], monitor materials scalability [196, 119, 113], avoid environmental burden shifting [95, 132, 50], and identify alternative road infrastructure revenue streams to today's per-gallon taxes on liquid fuels like gasoline and diesel [110]. One of the most important technological developments may be an increase in the vehicle range of affordable BEVs, though recent research has shown that the typical daily transportation energy needs of most drivers in the U.S. would be met by a relatively low-cost electric vehicle available on the market today [151].

In addressing the greenhouse gas emission challenge of the personal transportation sector, consumer behavior should be taken into account when designing government policies. Policies designed to nudge car buyers towards carbon-saving powertrain technologies and vehicle sizes and classes will likely be important. Additionally, strategies for reducing travel demand can play a critical role, and might include discouraging rebound effects [40], implementing road pricing [111, 9] and information feedback traffic management systems [82, 209], and ensuring that any eventual proliferation of autonomous vehicles helps lower - rather than raise - miles travelled [205, 91].

Even with the most beneficial behavioral changes, however, a fundamental transition away from ICEVs will be required to meet future GHG emission targets. Overall, we conclude that there are already cost incentives in many contexts for consumers to begin this transition. Further reducing costs (especially vehicle manufacturing costs) of BEVs and other low-carbon technologies (for example through learning-by-doing, research and development, and economies of scale [145, 74, 25]), providing favorable financing, and also better informing consumers of the lifecycle cost benefits of more efficient technologies, will likely all be important measures. Given the unprecedented speed and scale of the simultaneous transformations in energy and transportation needed, the joint support of government energy and climate policy, manufacturing innovation, and conscientious consumer decision-making will be key.

Chapter 3

The impact of driving style changes on vehicle fuel consumption

Abstract

Changing driving styles can reduce the energy use and emissions of personal vehicles. These reductions can come at no monetary cost to drivers and do not require changes to infrastructure or vehicle technology. Due in part to different definitions of an eco-friendly driving style, there is disagreement on energy savings achievable through improved driving style. Another reason for this disagreement is that the fuel savings from most driving style improvements depend on what types of drive cycles are being used as a baseline. In this paper, we propose a set of heuristics implementable by human drivers: limiting top speeds on highways, smoothing acceleration and deceleration in suburban and highway driving, and increasing the amount of coasting in urban driving. We apply these heuristics to a large set of representative drive cycles, obtained by combining travel survey data with GPS drive cycles. We evaluate energy consumption and duration of the entire trip before and after the modifications. We find that these four driving-style improvements can combine to provide the average US driver fuel savings of 5% with a 1% average increase in travel time. Braking early and coasting contribute the most to fuel savings. Accelerating more softly, often emphasized as an important aspect of efficient driving, contributes the least. We also find that percentage fuel savings are consistent across different locations and vehicle classes. This work can inform drivers about behaviors that reduce fuel consumption and their impact on travel time, policy makers about population-wide emissions savings achievable through driving style improvements, and car manufacturers or software developers about how to provide meaningful driving style feedback to drivers.[1]

[1]A version of this chapter is in preparation for submission with co-authors Zachary A. Needell, Sankaran Ramakrishnan, John B. Heywood, and Jessika E. Trancik. [134]

3.1 Introduction

Lowering light-duty vehicle greenhouse gas emissions is a crucial element of proposed strategies to meet climate targets [46, 103, 41, 176]. Existing technological approaches can lower vehicle emissions per distance traveled, including switching to more efficient and electrified powertrains [203]. An overall reduction in demand for light-duty vehicle travel can also reduce transportation emissions [141]. While potentially powerful in their impact, these types of changes require a change in stock of the light-duty vehicle fleet, which is time consuming [116], or a change in transportation patterns, which can be expensive to achieve through policy measures [141].

Eco-driving, that is, optimizing driving style for fuel efficiency, can also lower vehicle fuel consumption and therefore emissions [19]. In addition to being implementable quickly, applying eco-driving does not require infrastructure investment, and can be financially beneficial for drivers by lowering their fuel costs [19]. Energy and greenhouse gas emission reductions from eco-driving have been estimated to be on the order of 5–15% [19, 18, 124, 177, 211]. Further research is required, however, to characterize efficient driving styles, effectively promote the adaption of such driving styles, and evaluate the potential aggregate benefits of changes in driving style [6].

Although some studies include routing choice optimization and proper vehicle maintenance in its definition [178, 211], eco-driving usually involves making small modifications to a trip's time-speed trajectory—its drive cycle—to reduce vehicle energy consumption and emissions per distance traveled [19]. Assuming a constant powertrain efficiency and no traffic, an energy-optimal trajectory can be derived analytically for a trip with a given distance and duration. This trajectory consists of strong acceleration, followed by cruising at constant speed, followed by decelerating slowly without active braking (coasting), followed by moderate active braking towards a full stop at the end [99, 182]. Traffic and road network conditions, however, imply that the set of feasible drive cycles is constrained by the position and motion of other vehicles on the road as well as by legal and practical limits imposed by road geometry [129]. In addition, combustion engine powertrains yield low efficiency at low power outputs, complicating the search for an ideal driving style [170].

Methods have been proposed that optimize drive cycles considering realistic powertrain behavior [171] and constraints defined by stop-and-go driving patterns [129]. Results from applying these methods suggest that optimal vehicle control could allow for energy savings of 15–20%. These estimates do not necessarily reflect average savings achievable by the majority of human drivers under real-world driving conditions, however. They have been derived from models applied to specific drive cycles that are not necessarily representative of typical driving patterns. In addition, arriving at mathematically optimal trajectories is not feasible for the majority of human drivers [21]. Instead, a set of heuristics informed by optimal trajectories could allow drivers to achieve significant reductions in energy use and emissions without having to complex optimization strategies [192, 159]. Examples for such heuristics are: accelerate firmly but not too hard, maintain reasonable highway speeds, and anticipate traffic conditions to minimize hard braking [19]. These heuristics can be taught in classes, and have been adopted in some countries as a mandatory part of driver's education [186, 183]. Studies show that such driving style classes can lead to sustained reductions in fuel consumption of around 5% [26, 18, 167].

Another approach to promoting eco-driving is to provide real-time driving style feedback to drivers while operating a vehicle [124, 6, 167]. Such feedback systems were implemented in commercial cars as early as in the 2010 Honda Insight [180], and are also available as mobile phone apps (e.g. Geco [105]). Initial efforts focused on providing instantaneous fuel consumption readings to drivers. Because trip duration influences fuel consumption, however, lowering instantaneous fuel consumption does not necessarily reduce trip fuel consumption. To alleviate this issue, some vehicles, including recent Mercedes-Benz models, can be configured to provide an aggregate eco-driving scores in the gauge cluster [130]. While these scores are more representative of trip-wide fuel efficiency than instantaneous information, they neither indicate what specific rules the drivers would have to follow in order to achieve a higher score, nor what the impact on fuel economy of better driving behavior would be.

Here, we evaluate the impact of applying a set of driving style heuristics on average trip fuel consumption and duration. We consider four specific heuristics: (1) limiting maximum travel speed; (2) limiting the intensity of acceleration; (3) limiting the intensity of braking by braking earlier; and (4) reducing the number of acceleration and braking phases by encouraging coasting, that is, letting vehicles decelerate slowly without using the brake pedal. These modifications are based on suggestions for driving style modifications found in literature [19] and vehicles [130], reformulated here to be quantitative and to maximize energy savings while being consistent with realistic behavioral constraints. We develop an algorithm to apply these heuristics to a large sample of representative speed profiles, yielding eco-driving versions of the same profiles. We then use a vehicle energy estimation model (TripEnergy, [150]) to estimate energy consumption for the original and the modified profiles across different trip types, vehicle types, and locations. Finally,

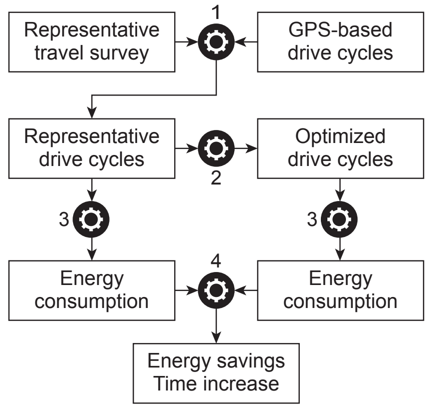

Figure 3-1: Schematic overview of the modeling approach to estimate energy savings and time losses resulting from driving style improvements. The four steps of analysis are: (1) obtaining a set of drive cycles using TripEnergy [150] that are representative for a given region (entire U.S., urban New York City, or rural Wisconsin), (2) optimizing those drive cycles for fuel economy using the algorithm discussed in section 2.2; (3) simulating vehicle energy consumption for both the unmodified and the modified profiles using TripEnergy; and (4) comparing the energy consumption between the original and the modified profiles across different trip types, vehicle classes, and region-specific travel patterns.

we examine the sensitivity of trip energy consumption and trip duration to behavioral parameters from the four heuristics and to road grade.

3.2 Methods

The analysis consists of four key steps: (1) obtaining a set of representative speed profiles (drive cycles), (2) modifying those speed profiles into profiles that were optimized for fuel consumption by four applying eco-driving heuristics; (3) simulating vehicle energy consumption for both the unmodified and the modified profiles; and (4) calculating differences in energy consumption and trip duration between the original and the modified profiles across different trip types, vehicle classes, and region-specific travel patterns (Figure 3-1). Steps (1) and (3) are based on a previously developed model called TripEnergy [150]. Step (2), the modification of speed profiles to reflect eco-driving, uses a new algorithm that we developed for this work.

3.2.1 Deriving representative drive cycles

We use a model called TripEnergy [151, 128] to obtain representative drive cycles for a given region. First, we sample trips from the 2017 National Household Travel Survey (NHTS, [78]), and collect information on trip distance and trip duration for each of those NHTS trips. We then probabilistically assign second-by-second speed profiles from a dataset of about 121,497 drive cycles collected over several regional travel studies [185, 13, 155] to each NHTS trip, based on each trip's distance and average speed. This assignment procedure has been shown to yield an error of less than 5% in resulting calculated energy consumption compared to a case where the true speed profile of a trip is known [128].

To assign GPS drive cycles to NHTS trips, we bin each NHTS trips into 10 bins for trip distance and 10 bins for average trip speed. Distance bin intervals are 5 km, while speed bin intervals are 10 km/h (2.8 m/s). Trips longer than 50 km or faster, on average, than 95 km/h are allocated to the corresponding highest bins (50+ km or 95+ km/h). We then randomly select a GPS trip that falls within the same bin, after having filtered GPS trips to exclude trips that contain acceleration values of larger than 8 m/s^2.

We sample trips from NHTS for three locations (Table 3.1). For the default case, we sample trips from across the entire United States, representing U.S. average driving. For the second case, only trips in the state of New York and the highest population density bracket for the household of the vehicle owner (25,000 people/mi^2 or higher) are selected. For the third case, only NHTS trips in the state of Wisconsin and the lowest population density bracket (0-100 people/mi^2) are selected. The second and third case represent the breath in U.S. driving behavior in terms of trip distance and trip speed distributions, with rural Wisconsin being chosen because it yields a larger sample size than other rural areas in the country. A summary of characteristics of the different locations is shown in Table 3.1.

Since energy savings can be expected to depend on trip characteristics, in particular trip distance and speed, we analyze results not only across all drive cycles that have been matched to NHTS trips, but also for each of the distance and speed bins described above. The bin sizes were chosen to balance the resolution of the analysis with the number of trips falling into each bin. Bins with fewer than 50 profiles are not assessed, and left blank in the Results section.

3.2.2 Modifying speed profiles

Modifying speed profiles while keeping total trip distance constant can lead to energy savings because the energy consumption per distance of a road vehicle depends on their speed and current acceleration [19, 128]. Driving at constant speed, for instance, is most energy efficient around 70 km/h (44 mph) for an average vehicle (Figure 3-2a).

Aggressive driving, such as intensely accelerating and decelerating, can decrease instanta-

Table 3.1: Basic driving patterns characteristics for each of the three locations used in the analysis. NHTS = 2017 National Household Travel Survey. Urban NY = New York with population density of 25,000 people/mi^2 or higher; Rural WI = Wisconsin with population density of 100 people/mi^2 or lower.

		United States	Urban NY	Rural WI
Number of trips in NHTS		603,718	1,081	11,608
Average trip distance	km	14.4	13.8	20.3
Average trip speed	km/h	42.2	28.7	56.3
Average trip duration	min	20.4	28.8	21.7
Average annual travel distance	km	18,480	14,060	12,500

neous fuel economy by increasing the total amount of work the engine must do and the amount of kinetic energy wasted in the brakes. Limiting the intensity of acceleration and braking, however, does not necessarily lead to trip-wide energy savings. If a vehicle accelerates firmly from 0 km/h to 50 km/h, it will spend less time accelerating than if it accelerated more slowly to the same speed, and it will require less time to get to a certain point in space, thus shortening the duration of that trip segment. For these two reasons, curbing the intensity of acceleration at low speeds only leads to energy savings for extremely high values of acceleration (Figure 3-2b). This is consistent with previous findings on the optimal speed trajectory of road and rail vehicles, where accelerating or braking slowly at low speeds prolongs trip time and thus total energy consumption [99, 182]. At high speeds, on the other hand, the benefits of reducing energy consumption during the accelerating phase outweigh the disadvantages of a longer acceleration phase and increased trip duration (Figure 3-2d). For braking, a similar pattern emerges, with curbing the intensity of braking only leading to energy savings at high speeds (Figure 3-2c,e).

The observation that softer braking does save fuel at low speeds assumes that it does not substantially reduce the energy consumption of a subsequent segment of the trip. Softer braking could, however, lead to a traffic light clearing before the car has to come to a full stop, or an obstacle on the road ahead clearing before the vehicle comes so close that it has to slow down considerably. In these situations, coasting can save fuel because phases of braking immediately followed by acceleration, or phases of acceleration immediately followed by braking, are avoided or mitigated (Figure 3-2f). We show that this type of smoothing provides energy consumption benefits down to very small acceleration and deceleration values of 0.15 m/s^2. Below that threshold, decelerating does not require active braking, thus not wasting energy that had previously been spent accelerating. Therefore, the energy consumption of the segment shown in Figure 3-2f remains flat for acceleration values of less than 0.15 m/s^2.

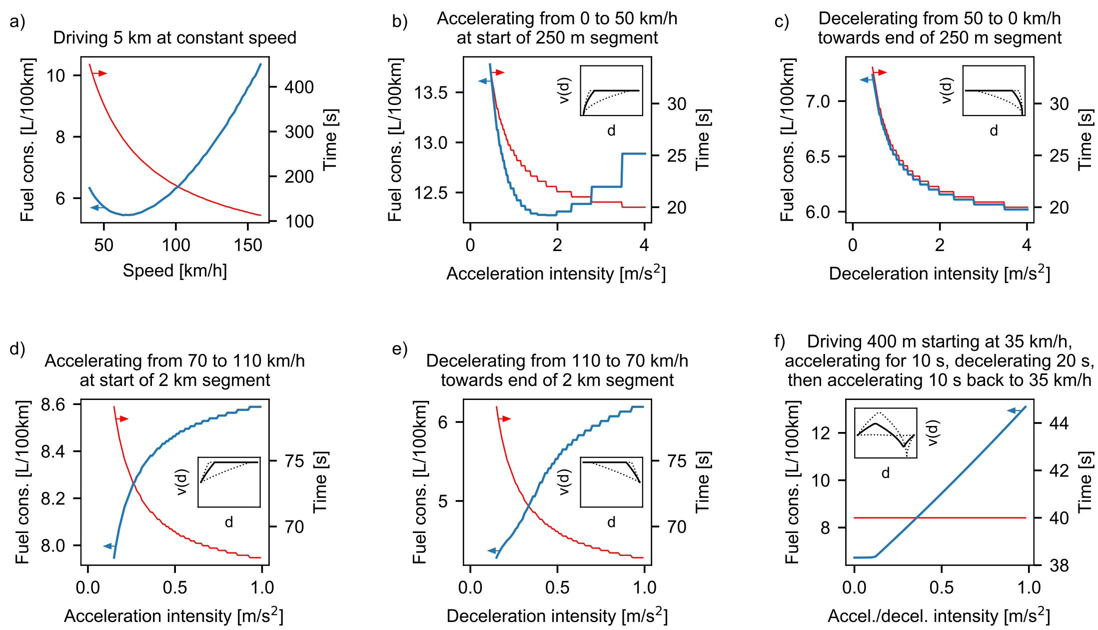

Figure 3-2: Examples illustrating the impact on fuel consumption of an average 2018 internal combustion engine vehicle (blue) and trip time (red) of changes in a) continuous driving speed; b) the intensity of acceleration at low speeds; c) the intensity of deceleration at low speeds; d) the intensity of acceleration at high speeds; e) the intensity of deceleration at high speeds; and f) the intensity of acceleration and braking in a trip segment consisting of acceleration, followed by deceleration, followed again by acceleration. For each figure, the distance of the drive cycle segment is constant across the entire range of x-axis values. Some of the lines are not smooth because of the 1 hz resolution in time used for the drive cycles and fuel consumption calculations. The inset figures show examples of speed profiles as a function of distance for three different values on the x-axis of the corresponding larger figure: the center value (solid black line in the inset), and the left-most and right-most values (dotted lines).

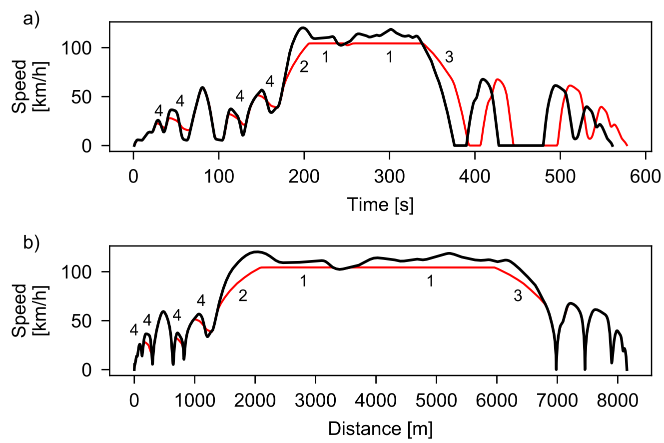

Figure 3-3: Illustration of driving style modifications applied to a real-world drive cycle, shown as speed over time (above) and speed over distance (below). The modifications are 1: reducing speed; 2: reducing the intensity of acceleration at high speeds; 3: reducing the intensity of braking at high speeds; and 4: adding coasting. Modifications 1, 2, 3 cause a dilution in the time vector, increasing trip time. None of the modifications cause a change in trip distance.

Based on the observations from Figure 3-2, we evaluate the impact of eco-driving on fuel economy using four eco-driving heuristics: (a) limiting maximum travel speed; (b) limiting the intensity of acceleration at high speeds; (c) limiting the intensity of braking at high speeds by braking earlier; and (d) reducing the need for subsequent phases of braking and acceleration altogether by letting vehicles coast towards obstacles and intersections. For each modification, three constraints are kept: (1) the total trip distance must remain constant; (2) using the modified speed profile, the car is never ahead of where it would have been using the original profile; and (3) the intensity of modifications is kept to levels that are implementable for human drivers and are unlikely to result in safety issues. Figure 3-3) illustrates the four modifications using a real-world trip profile. In the subsequent sections, we explain each heuristic and its quantitative implementation in more detail.

Curbing high speeds

At high speeds, excessive aerodynamic drag can lead to decreased fuel economy. To reduce this effect, we modify the speed profiles to limit their top speed to v_{max}. By default, v_{max} is set to 105 km/h (65 mph or 29 m/s), corresponding to the general federal highway speed limit in the U.S. [1]. To apply the modification to a given 1 Hz speed profile, the time step $\Delta t_i = t_i - t_{i-1}$ is extended at each time step t_i if the speed v_i is higher than v_{max}, such that $v_i = (d_i - d_{i-1})/\Delta t_i = v_{max}$. Based on the resulting speed and time step vectors, a new 1 Hz speed profile is created using linear interpolation.

In locations where the highway speed limit is higher than 105 km/h, but typical driving speeds on those highways are higher as well, limiting speeds to the corresponding speed limit will achieve higher energy savings, because the energy consumption per distance increases non-linearly above 70 km/h (Figure 3-2a).

Curbing acceleration and braking

To simulate the effect of less aggressive driving, we modify the speed profiles to limit the intensity of acceleration and deceleration (braking). We achieve this by reducing speeds during and after moments of high positive acceleration and decreasing speeds before moments of hard braking. Speeds are reduced by dilating the time vector as in the previous method, in order to ensure that total distance traveled remains constant. Note that when a profile section of acceleration above the acceleration limit is immediately followed by a section of deceleration (braking), the top speed that is reached in that section can be reduced as well.

We implement the acceleration and braking limits as speed-dependent percentiles of typical acceleration and braking values across the 121,497 drive cycles we use (Figure 3-4a). At speeds of 50 km/h or lower, the limits are set to the 100th percentiles for acceleration and braking, thus not imposing any limits. At speeds of 70 km/h or higher, we reduce acceleration intensity to the 90th percentile of acceleration values at that given speed, and braking intensity of the 80th percentile of braking values at that given speed (Figure 3-4b). In between 50 km/h and 70 km/h, we use linear interpolation to determine the corresponding percentile. We limit curing acceleration to the 90th percentile because a stricter limit (that is, softer acceleration) at those speeds may interfere with safe merging from on-ramps onto highways. Different percentile values, both at low speeds and at high speeds, are explored in the sensitivity analysis.

Adding coasting

Actively braking with a vehicle following a period of positive engine power wastes energy compared to a flat speed profile. In such cases, a functionally equivalent trajectory could have been followed by replacing the period of engine use and braking with a period of coasting. We modify the speed profiles to reduce the need for braking by adding coasting in suitable sections (Figure 3-3, modification 4). This reflects anticipatory driving for energy saving purposes, where drivers stop accelerating, step off the gas pedal, and let their car coast towards an obstacle, such as an intersection or a slow car.

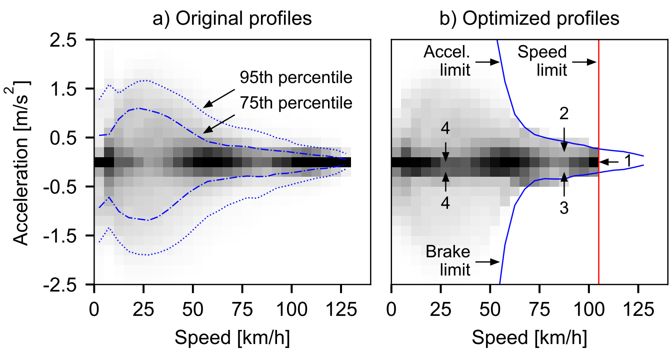

Figure 3-4: Distribution of acceleration and speed values for average U.S. driving before (a, left) and after (b, right) the application of driving style optimizations. In the left figure, the dashed and dotted lines show the 75th and 95th percentiles, respectively, of acceleration and braking values. In the right figure, the solid blue lines show where acceleration and braking were cut off; the red line shows where speed was cut off. The arrows indicate changes to the frequency distribution compared to the original distribution on the left as a result of (1) speed reduction; (2) curbing acceleration; (3) curbing braking; and (4) adding coasting.

To add coasting segments to an existing speed profile, a coasting trajectory is determined at each step in time, given the current speed, the vehicle's aerodynamic drag, and its rolling resistance. Then, the algorithm compares the original trajectory with the possible coasting trajectory between the point in time and space where coasting would start, and the point in time and space where the two trajectories would meet again. If such a point exists, and if both trajectories share the same starting speed, ending speed, average speed, and duration, coasting is possible, and the segment of the initial trajectory is replaced by a coasting trajectory. These constraints ensure that the final trajectory maintains the same total distance and, unlike for the acceleration and speed curbing components, total duration as the original trajectory.

Applying the algorithm to a specific speed profile requires choosing the maximum duration of coasting. Here, we apply 30 seconds as the default value, estimated to be the largest feasible maximum duration. The impact of changing this parameter is explored in the sensitivity analysis.

3.2.3 Simulating energy consumption

To estimate energy savings from optimizing driving style for a given speed profile, we calculate vehicle energy consumption in MJ-equivalents of gasoline or electricity for both the original and the modified profile, and compare the two. Calculations are based on TripEnergy [151, 128], which allows a reliable estimation of the energy consumption of any light-duty vehicle for a given speed profile and a small set of public vehicle parameters. These parameters include the vehicle's powertrain type, its curb weight, its coastdown coefficients from the EPA fuel economy test, and its official (unadjusted) EPA fuel economy ratings. The TripEnergy model has been found to yield errors of less than 3% compared to a sophisticated bottom-up vehicle energy simulator [128]. A more detailed discussion of TripEnergy's vehicle energy model follows in Chapter 4, where we further refine the model to account for engine cold starts and the impact of ambient conditions on fuel consumption. Here, we use the original, unmodified version of TripEnergy [151, 128].

TripEnergy's vehicle energy model estimates vehicle energy consumption for a given trip using a linear model based on tractive power, $\mathscr{P}_{tr}$. $\mathscr{P}_{tr}$ corresponds to the total amount of energy per second required to overcome inertia, rolling resistance, and drag, and can be negative when inertia is negative, that is, when the vehicle is braking. When $\mathscr{P}_{tr} > 0$, energy is required from the vehicle's tank or battery, corresponding to the driver using the gas pedal. When $\mathscr{P}_{tr} < 0$, the driver is using the brakes, and energy can be recuperated if the vehicle is a hybrid or a battery electric vehicle. When $\mathscr{P}_{tr} = 0$, the vehicle is coasting.

Defining the drive energy $\mathscr{E}_{drive}$ as the time integral of the positive portion of the tractive power and the braking energy $\mathscr{E}_{brake}$ as the time integral of the negative portion, a vehicle's net energy consumption on a given trip, E_{use}, is expressed as $E_{use} = a\,T + b\,\mathscr{E}_{drive} - c\,\mathscr{E}_{brake}$. Here, a is a constant related to the vehicle's baseline (idle) fuel consumption, T is the trip duration in seconds, b is related to the vehicle's peak powertrain efficiency, and c is related to the vehicle's overall recuperation efficiency. For regular internal combustion engine vehicles, $c = 0$. The coefficients a, b, and c are estimated for a given vehicle based on that vehicle's curb weight, coastdown coefficients, and unadjusted fuel economy ratings. Specifically, the coefficients are calibrated to reproduce the vehicle's unadjusted fuel economy ratings for the city (FTP), highway (HWFET), and high speed (US06, where available) tests, given that vehicle's curb weight and coastdown coefficients. This model has been shown to provide reliable estimates for trip energy consumption in comparison to more comprehensive vehicle energy simulators [151, 150].

In addition to estimating the energy required to move the vehicle forward, we apply a consumption of 800 W electrical in order to power dashboard, lights, fans, air-conditioning, entertainment systems, and other vehicle auxiliaries. Setting this auxiliary consumption penalizes modifications to the speed profile that increase the total trip duration. This is because the electricity consumption of auxiliaries can be assumed a constant rate per time, and a longer trip duration leads to higher total energy consumption by auxiliaries.

By default, parameters of an average internal combustion engine light-duty vehicle are used,

Table 3.2: Curb weight, coastdown coefficients, and powertrain model coefficients for each of the five vehicles used in the analysis. 'Average vehicle', 'compact car', and 'pickup' refer to typical values for 2018 models sold in the U.S. The hybrid and battery electric vehicles have the same weight and coastdown coefficients as the average internal combustion engine vehicle (ICEV), but with adjusted powertrain coefficients typical for those technologies. 'Rated EPA fuel consumption' refers to the official fuel economy ratings following the Environmental Production Agency (EPA) standard in the U.S.

		Gasoline ICEV			Hybrid	Electric
		Average vehicle	Compact car	Pickup truck		
Curb weight	kg	1752	1275	2394	1752	1752
Coastdown coeff. A	N	147	108	171	147	147
Coastdown coeff. B	Ns/m	2.73	2.06	5.27	2.73	2.73
Coastdown coeff. C	Ns^2/m^2	0.524	0.382	0.740	0.524	0.524
Powertrain coeff. a (P_{idle})	W	14,585	10,465	22,355	2,500	100
Powertrain coeff. b (η_{max})	-	0.43	0.38	0.45	0.35	0.85
Powertrain coeff. c (η_r)	-	0	0	0	0.6	0.6
Auxiliary power cons.	W	800	600	1000	800	800
Rated EPA fuel consumption	L/100km	10.1	7.6	14.0	-	-

corresponding approximately to a compact crossover sport-utility vehicle (Table 3.2). To compare energy savings from eco-driving across different vehicle types, four additional vehicles are being evaluated: a compact car, a large SUV, a hybrid, and a battery electric vehicle. The hybrid and the battery electric vehicle are assumed to have the same size, weight, and aerodynamic properties as the default vehicle (Table 3.2).

3.3 Results

3.3.1 Fuel savings potential for typical internal combustion engine vehicles

We estimate fuel consumption reductions for an average combustion engine vehicle from the combined application of all four eco-driving heuristics to be 5.00% (Figure 3-5, top right). This corresponds to about 1.8 MJ or 0.057 L (0.016 gal) of gasoline saved per trip, or 73 L/year for an average of 1290 individual trips per year. Contributions to these savings are spread evenly across speed reductions, braking intensity reductions, and adding coasting. Reducing the intensity of acceleration only leads to energy savings of 0.18%. Time losses across all modifications are found to be 1.15% on average, with about two thirds of these losses coming from speed reductions.

Contributions of the four heuristics vary considerably across trip distance and speed. The impact of highway speed reductions, unsurprisingly, is highest for trips with high average speed. The impact of adding coasting is highest for short, presumably urban trips at low to medium speeds. The impact of curbing acceleration and deceleration is highest for relatively short trips with high

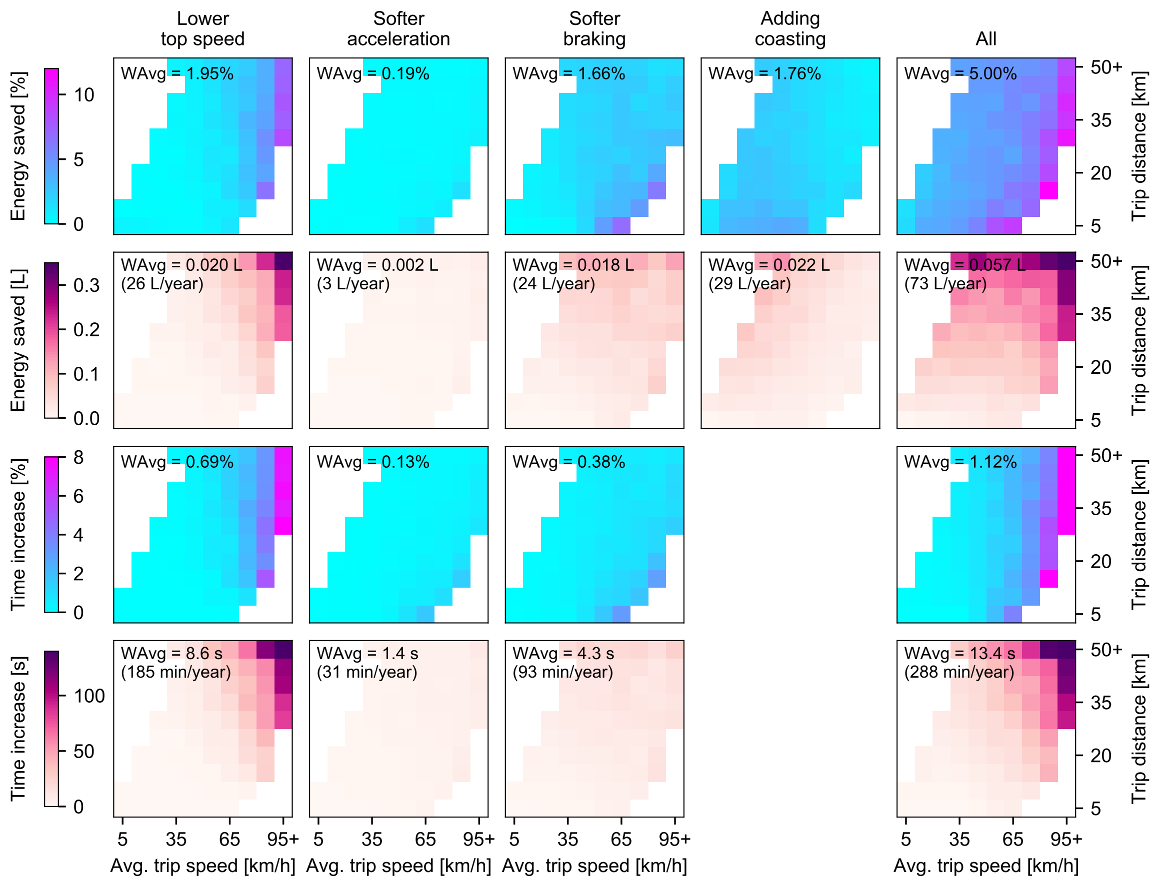

Figure 3-5: Per-trip energy savings achieved and travel time increase resulting from four types of eco-driving modifications to real-world drive cycles, binned by trip distance and average trip speed. Energy savings are calculated for the average 2018 gasoline internal combustion engine vehicle. The averages indicated in the top left corner of each subplot are weighted with the frequency of occurrence of that particular bin for U.S. driving. Absolute savings in L of gasoline (second row) and seconds (fourth row) are indicated per year. The number of trips per year is estimated by dividing annual travel distance by average trip distance (see Table 3.1). Adding coasting, as modeled here, does not change the total trip duration.

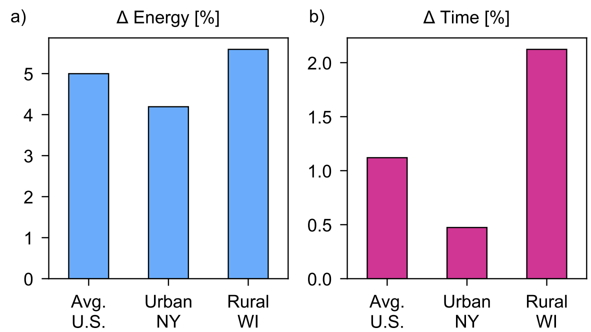

Figure 3-6: Average energy savings and time increase based on typical distribution for trip length and time in 3 geographical areas: all of U.S., New York with population density of 25,000 people/mi^2 or higher, and Wisconsin with population density of 100 people/mi^2 or lower (see Table 3.1).

average speed. Overall, the four modifications complement each other across the different speed and distance bins, resulting in relatively homogeneous savings across much of the trip distance-speed map when all three contributions are combined.

3.3.2 Expected savings by location

We find that energy savings (in %) from eco-driving are consistent across different locations in the U.S., ranging from 4.1% in congested urban areas to 5.6% in rural areas (Figure 3-6). Time losses, on the other hand, vary considerably across regions. In rural areas, where curbing top speeds on highways occurs more often than for U.S. average driving, the average time lost from applying the four eco-driving heuristics increases from 1.1% to 2.0%. In urban areas, conversely, where anticipatory braking and adding coasting dominate savings, the average time loss decreases to 0.5%.

3.3.3 Fuel savings across different vehicle technologies and classes

We find that energy savings from eco-driving are consistent across different vehicle classes from compact cars to large pickup trucks, implying that vehicle mass and aerodynamic properties do not strongly affect fuel use reductions achievable from eco-driving (Figure 3-7). Vehicles that recuperate braking energy, such as hybrids and battery electric vehicles, exhibit a 30% higher percentage energy savings potential from eco-driving than vehicles that cannot recuperate braking energy. This is because hybrid powertrains have a lower baseline (idle) fuel consumption than regular internal combustion engine vehicles (powertrain coefficient a in Table 3.2). A lower idle fuel consumption implies that prolonging the trip duration has a smaller impact on total trip energy

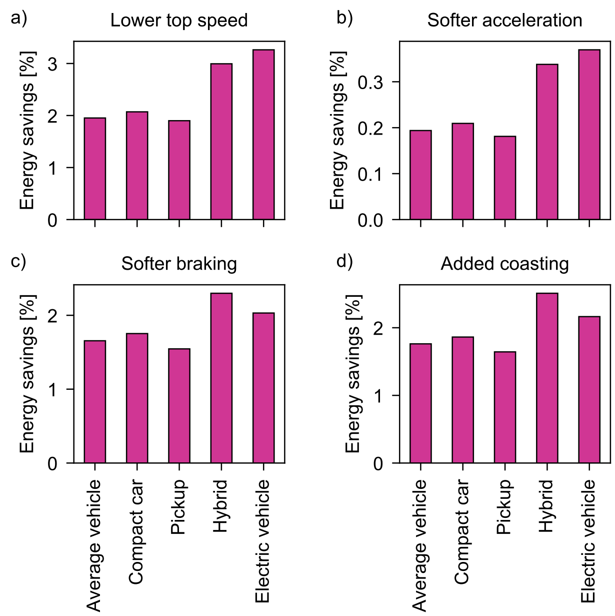

Figure 3-7: Average energy savings for five different vehicle types from different driving style modifications.

consumption (increasing savings from curbing top speeds and acceleration or braking intensity), and that the energy consumption while the vehicle is coasting is lower (increasing savings from adding coasting). For battery electric vehicles, the advantages of a lower idle fuel consumption are partially mitigated by their high powertrain efficiency (powertrain coefficient b in Table 3.2), meaning that they benefit slightly less from reducing the need for and amount of braking than hybrids.

3.3.4 Sensitivity to behavioral parameters

The magnitude of energy savings is sensitive to the different behavioral parameters underlying the quantitative implementations of the four eco-driving heuristics evaluated here. Reducing highway speeds from 105 km/h (65 mph) to 90 km/h increases average energy savings due to speed reduction to over 5% (Figure 3-8a). At the same time, the trip duration penalty rises from to 4%. Notably, it can be unsafe to drive below the speed limit on highways when conditions are good, meaning that the choice of speed is not up to the driver. Lifting the highway speed cap to 125 km/h reduces both energy savings and time loss to almost zero, because hardly any trips in the trip databases we use have speeds above that value (see also Figure 3-4a).

The maximum coasting time describes how far ahead the driver is able to plan speed and

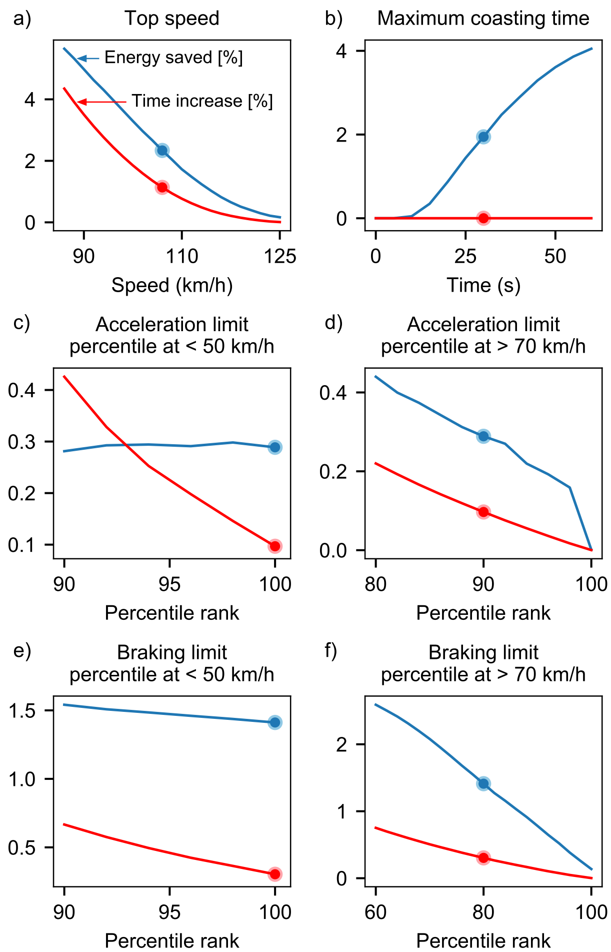

Figure 3-8: Sensitivity of average energy savings and time increase in response to eight behavioral parameters: top speed limit, maximum coasting time, acceleration limit below 50 km/h, acceleration limit above 70 km/h, braking limit below 50 km/h, and braking above 70 km/h. Dots represent default values used to calculated results shown in Figures 3-5–3-7. Energy savings and time losses reflect only the effect from the corresponding type of modification: curbing top speed (a), adding coasting (b), limiting acceleration (c and d), and limiting braking (e and f).

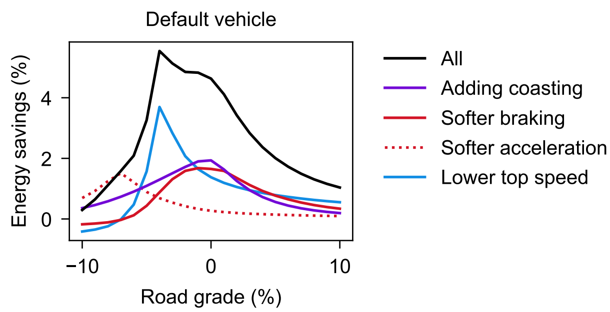

Figure 3-9: Estimated energy savings from eco-driving as a function of road grade.

braking of the vehicle. With a window of 60 s instead of 30 s, energy savings from coasting are increased to 4% (Figure 3-8b). However, anticipation of traffic and road conditions this far ahead is likely unfeasible. Reducing the maximum coasting time from 30 s to 20 s cuts average energy savings from coasting in half, from 1.9% to 0.9%. In reality, the maximum forward-looking time window will depend on the current speed, visibility, and the unpredictable movements of other vehicles.

Modifying the acceleration limit percentile for speeds below 50 km/h does not change energy savings of curbing acceleration, because on average, the positive effects of reducing instantaneous fuel consumption and the negative effects of prolonging trip distance cancel each other out (Figure 3-8c). Imposing a stronger limit at high speeds, on the other hand, does lead to higher energy savings from curbing acceleration (Figure 3-8d). However, this may lead to unsafe behavior, for instance when merging from on-ramps onto highway lanes. Decreasing the braking limit at high speeds to the 60th percentile can almost double energy savings from reducing braking intensity, but as with stronger acceleration curbing, may lead to unsafe driving behavior (Figure 3-8f). In addition, the resulting time loss would double as well.

Overall, greater energy savings could be achieved than the ones shown in Figures 3-5 and 3-6, given the appropriate behavioral parameters. However, such modifications would lead to substantially higher time losses. In addition, they would often lead to unsafe or unfeasible driving behavior. Therefore, these results illustrate the importance of considering feasible behavioral heuristics when modeling the potential energy savings from a more eco-friendly driving style.

3.3.5 Sensitivity to road grade

The results shown in Figures 3-5–3-8 assume that the road is flat, that is, that there is no potential energy gained or lost during each trips. We find that an incline of higher than 3% or a decline of lower than -5% has a substantial impact on the energy savings achieved from more eco-friendly driving (Figure 3-9). While most drivers in the U.S. will not experience road grades larger than ±2% on a regular basis, these results can be meaningful for drivers living in mountainous areas or particularly hilly cities.

The relative contributions of the four individual types of modifications shift considerably as the road grade changes. Reducing speed and the intensity of acceleration is even more important on a declining road than on a flat road. Once the decline becomes larger than -6%, however, the decline is so strong that even high speeds can be achieved without consuming fuel at all, at which point reducing speed stops saving fuel (although the combination of high speed limits and road grades below -6% is rare). On inclining roads, on the other hand, emphasis shifts onto smoother and earlier braking.

3.4 Discussion

This study estimates potential average energy savings from eco-friendly driving to be between 4 and 7% across all vehicle classes, vehicle technologies, and locations within the U.S. This implies that eco-friendly driving, whether entirely driver-driven or assisted through low-level autonomy features, can make a meaningful contribution to emissions reduction from light-duty vehicles without requiring any changes in vehicle technology or investments in infrastructure. Eco-friendly driving can cause an additional cost to the passengers in the form of a time loss, but we estimate this loss to be small, at an average of about 1% (less than 15 seconds per trip).

At a real-world vehicle fuel economy of 20 MPG, a typical annual driving distance of 11,000 miles, and a gasoline price of $3/gallon, eco-driving can save about $85 in fuel costs (5.2%) per year. At a typical average speed of 12 m/s (43 km/h), about 0.8 minutes per day or 5 hours per year (1.2%) would be lost because of increased trip duration. Combined, this implies that drivers who value their time at $18/h or less should choose to apply eco-driving out of financial considerations alone (if they're driving alone). Notably, savings from anticipatory driving (braking early and coasting) come at little to no time loss, meaning that those savings should always be applied. For reducing speeds on highways and reducing acceleration intensity, the trade-off between energy savings and time loss is more salient (see Figure 3-8a). At the same time, this exemplary calculation does not consider additional monetary benefits from reduced wear on brakes and transmission systems and additional time savings from fewer required stops at gas stations (about 2 per year).

Our estimated average fuel savings of 5% falls within the range of previous estimates for savings achievable through modest changes in driving style, although at the lower end [19, 18, 124, 177, 211]. It does match, however, most estimates found by studies that use an experimental approach [26, 18, 167]. We suspect there are three reasons for why our modeled estimate is closer to experiment-based estimates than to model-based estimates, despite using a model-based approach. First, we use representative drive cycles to estimate fuel savings from eco-driving. This is important because some measures, such as reducing top speeds on highways, may save a large amount of fuel for specific trips (long highway trips), but less across all trips that people typically make across a year. Second, we evaluate the impact of driving style changes at a given point in time in the context of the entire trip. As we show, curbing the intensity of acceleration and braking may reduce instantaneous fuel consumption, but it also prolongs trip duration, which can offset those savings. And third, we use a set of eco-driving heuristics aimed to be applicable by the majority of human drivers. Previous studies have found a difference in modeled estimates and experimental estimates for fuel savings if the eco-driving rules require expert knowledge in order to be applied consistently [21].

While reducing the intensity and frequency of braking through anticipatory driving may be one of the largest contributors to energy savings from eco-friendly driving, it may also be the most difficult factor to drivers, and the one that requires the most practice to find its way into daily driving habits. Certain countries have already incorporated eco-efficient driving in general, and anticipatory driving in particular, into driving schools. Knowledge about energy efficient and environmentally friendly driving is a mandatory part for driving schools in the European Union [186]. Similarly, anticipatory driving for energy-saving purposes is taught during a mandatory 'driving camp' that new driving license holders have to attend within two years of receiving their initial license in Switzerland [183].

Smartphone apps and in-vehicle software that educate the drivers about driving style optimization and provide feedback about their current performance may substitute or supplement formal education. While both in-vehicle feedback on eco-driving performance [180] as well as smartphone apps (e.g., [101, 105]) have existed for some time, this study lays some of the groundwork to develop software that maximizes the efficacy of live and post-trip feedback provided to drivers with regards to their eco-driving performance. Therefore, the results presented here can form a useful basis for reinforcing effective behaviors for drivers by 1) identifying key behavioral aspects that contribute the most to fuel economy savings; 2) showcasing how trip speed profiles can be analyzed to derive eco-driving performance; and 3) offering a consistent rating of driving style that is independent of the traffic conditions of any specific trip.

Chapter 4

Variation in fuel efficiency and annual travel distance in personal vehicles

Abstract

Annual travel distance and fuel efficiency are two key parameters for assessing the environmental and economic performance of battery electric vehicles (BEVs) in comparison to internal combustion engine vehicles (ICEVs). Most existing studies that evaluate emissions or costs of personal vehicles use a country-specific average for annual travel distance, and officially rated fuel consumption values—an approach we have also used in Chapter 2. In reality, however, annual travel distance and fuel efficiency vary across regions and across individual vehicles within those regions. In addition, the fraction of trips that is electrifiable with BEVs under certain charging behavior assumptions may vary as well. Here, we model the variability in these travel indicators in the U.S. by combining several travel survey datasets, a meterological dataset, vehicle model properties, a trip matching and vehicle energy model called TripEnergy, an ambient temperature model, and a trip pattern adjustment algorithm for BEVs. We find that annual travel distance and fuel consumption per distance vary considerably across locations, but the product of the two, annual fuel consumption, varies less. We show that the fuel efficiency of ICEVs and average annual travel distance are sensitive to urban-rural differences in driving patterns, while the efficiency of BEVs mostly depends on local climate. The fraction of electrifiable distance depends on both aspects. All travel indicators exhibit variation across individual vehicles in a given region. In addition, we find that annual travel distance is negatively correlated with the fraction of distance that is electrifiable and positively correlated with ICEV fuel consumption per distance. Nonetheless, there are individual vehicles that have a high annual travel distance, a high share of electrifiable trips, and relatively poor ICEV fuel efficiency. For these vehicles, switching to a BEV is particularly effective in terms of emission reductions. These results improve our understanding of how individual behavior and regional conditions are linked to energy use from personal motorized travel, and how these links might change with electrification of vehicles. They also enable the estimation of emissions and costs of BEVs compared to ICEVs across regions and individual vehicles, covered in Chapter 5.[1]

[1]A version of this chapter is in preparation for submission with co-authors Sankaran Ramakrishnan and Jessika E. Trancik [135]

4.1 Introduction

Personal human mobility, especially automotive travel, contributes substantially to greenhouse gas emissions [176, 69]. Common measures suggested to reduce these emissions include a switch to electric vehicles, such as battery electric vehicles (BEVs) [95, 23, 138], and a reduction in personal vehicle travel demand through mode substitution or increased occupancy [57]. Two key parameters required to determine emissions form personal vehicle travel and analyze the environmental and financial performance of BEVs in comparison to internal combustion engine vehicles (ICEVs) are each vehicle's average annual travel distance and average fuel consumption per distance.

Most existing studies that evaluate the emissions and costs of different personal vehicles use a country-specific average for annual travel distance, and officially rated economy values (e.g., [95, 23, 138]). In reality, however, annual travel distance and fuel consumption per distance vary systematically across different regions within a country, such as between urban and rural areas (e.g., [48]). In addition, these two parameters can be expected to vary substantially across individual vehicles in a given region, due to the heterogeneous travel patterns of the individuals using each vehicle [88, 15, 188]. Finally, there may be systematic differences in travel patterns between BEVs and ICEVs, resulting from the limited range and long recharging times of BEVs that may decrease their usability for long trips[151]. The combined heterogeneity in annual travel distance and fuel efficiency across regions and individual vehicles within those regions implies that emissions and cost savings of replacing an ICEV with a BEV can vary substantially.

Researchers have investigated the relationship between travel indicators, such as annual travel distance or annual fuel consumption, and characteristics of the vehicle owners' households and the built environment around them (e.g., [72, 121, 173, 195]). These studies intend to identify the drivers behind travel energy consumption and emissions. Most of these studies, however, focus on relating the average of a travel behavior indicator, such as annual travel distance, to environmental factors [195]. There is less existing research on how these indicators are distributed, either systematically across locations or across individual vehicles in a given location. One recent study considers the combined impact of local climate and urban or rural driving patterns on fuel efficiency of different types of vehicles [206]. The spatial resolution and the number of ways in which driving patterns affect the emissions reduction potential of BEVs is still limited, however. Furthermore, to our knowledge, there is not study to date that models the variation in time-average fuel efficiency across individual vehicles that are located in the same region. One likely reason for this gap is that trip-specific or annual fuel consumption is not usually reported in travel surveys. Therefore, their study requires the use of additional models and tools.

Another limitation of estimating travel indicator variables directly from widely available representative travel survey data is that this type of data is usually collected once for each vehicle (yielding, for instance, one sample for annual travel distance), or for a limited amount of time (yielding, for instance, trip distance and time for each single trip made on one specific travel day). Therefore, only population-average indicators can be derived for a given subset of the data, corresponding to a region. This data cannot be used directly to model the distribution in indicators across multiple individual vehicles in that subset.

Here, we present an approach to model the heterogeneity in average annual distance traveled and fuel efficiency, or fuel consumption per distance, across regions in the U.S., and across individual vehicles within those regions. This model allows us to quantify and compare different determinants of annual emissions from personal vehicle travel, including vehicle technology, vehicle class, the built environment, local climate, and individual travel behavior. To do so, we combine a trip matching and vehicle energy model called TripEnergy (NHTS, [78]) to model population-average annual travel distance and fuel efficiency for BEVs and ICEVs. We combine these results with meterological data from the Typical Meterological Year dataset [156] and an ambient temperature model to reflect the impact of local climate on fuel consumption per distance. Finally, we combine these models with data tracking the behavior of individual vehicles over time to model the heterogeneity in annual travel distance and fuel efficiency across individual vehicles.

Due to their limited range and recharging times, BEVs may exhibit systematically different travel patterns compared to ICEVs. We construct two scenarios for modeling the travel patterns of BEVs. In the first scenario (Scenario A), BEV travel patterns are identical to those of ICEVs. In the second scenario, the frequency of long trips is reduced as a result of the limited range and long recharging times of BEVs, and these long trips are allocated to an ICEV instead (Scenario B).

This chapter is organized as follows. In the next section, we describe in detail the method used for analyzing the heterogeneity in key travel indicators across regions within the United States and across individual vehicles. We also discuss the two scenarios for travel patterns of BEVs. We then apply the modeling framework to evaluate the heterogeneity in annual travel distance and fuel consumption per distance of 5 ICEVs and 5 BEVs, covering 5 vehicle classes ranging from compact hatchbacks to mid-size SUVs. Finally, we discuss the significance of our results for modeling emissions and costs of personal vehicles, and the relationship of our results to the fundamentals of human travel behavior.

4.2 Method

We model how annual travel distance and fuel consumption per distance of gasoline internal combustion engine vehicles (g-ICEV) and battery electric vehicles (BEVs) vary across locations and across individual vehicles in those locations. First, we describe the specific indicators whose variability is assessed. We also describe two charging scenarios for modeling the travel patterns of battery electric vehicles. Second, we describe how we split the National Household Travel Survey (NHTS) into subsets covering specific regions to calculation population-average indicators for each region. We also explain how we match this information to data on local climate by matching both types of data with each zipcode in the U.S. the model used to estimate the fuel efficiency of vehicles conditional on regional drive cycles and climatic conditions. Third, we describe how we obtain region-specific drive cycles (speed profile) by combining National Household Travel Survey (NHTS) data with a dataset containing GPS-measured second-by-second speed profiles. Fourth, we describe how we obtain region-specific climatic conditions. Finally, we describe how we obtain distributions of all indicators across individual vehicles in a given location, and combine these distributions with region-specific values for each indicator.

4.2.1 Indicators and scenarios

Fuel efficiency (consumption per distance, F) Fuel efficiency, measured here as the fuel consumption per distance, represents the amount of energy used by a given vehicle per distance. The fuel consumption of ICEVs is measured in L of gasoline per 100 km, whereas the fuel consumption of BEVs is measured in kWh of electricity per 100 km. The BEV fuel consumption includes losses from charging.

Annual travel distance (M) The annual travel distance describes the cumulative distance of all trips a vehicle makes during a given year. While most data sets only provide the annual travel distance for a given vehicle of a given age in a single year, M_a, we are interested in the average annual travel distance across a vehicle's life. The average annual travel distance of a given vehicle corresponds to the sum of annual travel distances for vehicles of age a, divided by the vehicle's lifetime A:

$$M_{\text{avg},A} = \frac{1}{A} \sum_{a=1}^{A} M_a \tag{4.1}$$

To calculate the population-average annual travel distance across ages 1 through A, we calculate the average annual travel distance for all vehicles with age a first, summing over each of N individual vehicles i with age $a_i = a$:

$$M_{\text{avg},A,pop} = \frac{1}{A} \sum_{a=1}^{A} \left(\frac{1}{N} \sum_{i:a_i=a}^{N} M_i \right) \tag{4.2}$$

In the U.S., the average vehicle lifetime A is 15 years [48]. Therefore, we use $A = 15$ years to calculate the population-average annual travel distance during a vehicle's life and duration of first ownership, respectively. For individual vehicles, we can expect that vehicle lifetime is negatively correlated with annual travel distance. Therefore, we model annual travel distance and vehicle lifetime jointly. This model is explained in detail in section 4.2.5.

Fraction of electrifiable distance (β) and Scenarios A and B The battery capacity of BEVs is a concern to many consumers, especially in conjunction with long recharging times and limited density of recharging stations [160, 80]. Therefore, BEVs may not be ideal to make particularly long trips [151]. While the trips whose energy consumption exceeds the battery capacity of a BEV only comprise a small fraction of all trips, they can account for a considerable fraction of total distance traveled [151]. If the frequency, length, and duration of all trips that a given person makes are assumed to be fixed, that person may make fewer total trips with a newly acquired BEV than if they had bought an ICEV instead, shifting some long trips to other vehicles or other modes.

To take this into account, we calculate the fraction of the annual travel distance that is electrifiable if BEVs are only being charged at night, β. We do so by summing up the distance of all trips i for which the energy consumption of corresponding daytrips j exceeds 80% of the battery capacity of the BEV, $c_{E,\text{BEV}}$. We call this set of daytrips J. Here, a daytrip represents the cumulative sum of all trips i made by the same vehicle during a given travel day.

$$\beta = 1 - \frac{\sum_{i \in J} d_i}{\sum_i d_i} \mid J = \{j : \sum_{i \in j} F_i \, d_i > 0.8 \, c_{E,\text{BEV}}\} \tag{4.3}$$

We then show results of indicators M and F adjusted for the reduction in the frequency of long trips. M is adjusted by multiplying it with β. F is adjusted by calculating average fuel consumption

Table 4.1: The two scenarios used to model BEV charging and their impact on travel indicators. Where applicable, the vehicle travel days that are not electrifiable in Scenario B are assumed to be made with an ICEV that is comparable to the corresponding BEV in terms of vehicle class. This allows us to compare total emissions from travel activity if a BEV is purchased instead of an ICEV for all trips that would have been made with that ICEV.

Scenario A	All trips from the sample (population sample or sample for individual vehicle, depending on dataset) are included. This reflects a case where extensive charging infrastructure and fast charging technology allow BEVs to be used for any trip of any distance.
Scenario B	Only trips are included for which the energy consumption of the corresponing daytrips (cumulative sum of trips made during a given travel day) don't exceed 80% of the BEV's battery capacity. The total fraction of annual travel distance excluded this way is labeled β. This reflects a case where BEVs are only charged overnight.

per distance only over the set of trips $i \in J$ instead of all trips. We name this adjustment Scenario B (see Table 4.1). In addition, we report unadjusted values for all indicators, named Scenario A. We validate the feasibility of Scenario B and the corresponding β against data for BEVs from the 2017 National Household Travel Survey (NHTS) data.

Average trip speed (v_{avg}) The average trip speed determines how strongly the consumption of electric vehicle auxiliary systems, such as lightning, fans, power steering, and HVAC (heating, ventilation, and air conditioning), affect fuel efficiency. A higher average speed implies a lower impact of auxiliaries, whose power consumption is modeled to be constant with time (in W), on fuel consumption per distance. We only report this metric in the expanded results contained in the appendix (Figure B-3).

4.2.2 Modeling heterogeneity of indicators across regions

We model the heterogeneity of all indicators across regions in the United States using data from the 2017 National Household Travel Survey (NHTS) data [78]. In addition, we consider how local climate affects fuel efficiency, and therefore β, using data from the Typical Meteorological Year (TMY) dataset [156].

NHTS provides information on 129,696 randomly sampled households, their vehicles, and trips made on a single travel day of a randomly selected date in the collection year. Using this data, we are able to calculate annual travel distance, $M_{\text{avg},A,pop}$, and average trip speed, v_{avg}, directly. To calculate F and β, however, additional analysis is required.

Table 4.2: Combinations of population density brackets (in people/mi^2) and state used in the analysis, and the number of travel days present for each combination. The combinations shown are used to sample trips and vehicles to calculate indicators M, F, and v. To calculate β, data is only stratified by population density (column on the right) to achieve a higher sample size. Further data for each population density-state combination, such as the number of individual trips and the number of vehicles, is available in Appendix C (Table B.3).

	State							
Population density	CA	NY	TX	WI	NC	GA	OTHERS	ALL
50	2,219	3,500	2,385	3,066	1,804	1,041	5,208	8,053
300	2,541	4,224	2,849	2,678	3,065	2,218	6,772	12,055
750	1,716	1,507	2,065	1,461	1,567	1,357	4,489	7,413
1500	2,555	2,458	3,645	1,809	1,726	2,146	5,608	9,480
3000	4,526	3,026	7,118	2,434	1,708	2,326	7,649	11,683
7000	10,620	2,471	10,219	2,409	438	806	6,811	8,055
17000	3,827	850					2,419	2,419
30000	566	295					395	395

We estimate the fuel efficiency, or fuel consumption per distance, of each individual trip using a model called TripEnergy [151, 128]. First, the model probabilistically assigns a GPS-measured speed profile to each individual trip, based on that trip's distance and average speed. Then, the model estimates vehicle fuel efficiency for that speed profile, based on the vehicle's mass, aerodynamic properties, and calibrated powertrain parameters. This model allows us to effectively estimate fuel efficiency for a given vehicle and a given trip given a limited set of trip and vehicle information. It has been found to yield average errors of about 7% compared to detailed vehicle simulators given full drive cycle data [128]. Here, we develop an extended version of this vehicle energy model that takes into account combustion engine cold start losses, models electric vehicle charging losses explicitly, and uses a more sophisticated approach to modeling the impact of meteorological conditions on fuel consumption per distance. Once fuel efficiency is calculated for each individual trip, we calculate the average fuel efficiency of that set of trips, weighted by each trip's distance, as well as β (Equation 4.3).

To match the trip distance and average speed to GPS profiles, we use the same binning approach described in Chapter 3. However, instead of using 10 bins for trip distance and 10 bins for average speed, we bin trips into 24 distance bins, ranging from 0-1 km to 500+ km, and 12 bins for average speed, ranging from 0-2 m/s (0-7.2 km/h) to 25+ m/s (90 km/h+). The increased bin resolution for trip distance ensures that the tail end of the distribution in trip energy consumption is modeled accurately. This tail is important for evaluating the number of trips that would not

Table 4.3: Data structure used to calculate the average value for each indicator in 32,989 zipcodes. The NHTS data matching determines the vehicle information (including M) and trip patterns (which influence fuel consumption per distance F and the fraction of electrifiable trips β). The meterological stations determine the local climate, which affects fuel consumption per distance F and therefore also β. For each zipcode, the 3 closest stations are assigned. The vehicle count in each zipcode is used to calculate weighted probability distributions of the indicators across the country based on where people live. An asterisk (*) below S_{NHTS} indicates 'other' states (not one of the 6 considered explicitly).

	NHTS data selection				Vehicle count estimation			TMY meterological station selection			
Zipcode	PD	S	PD_{NHTS}	S_{NHTS}	Pop.	Veh/cap	Count	Lon	Lat	Stations	Distances
43451	39	OH	50	*	952	1.13	1077	-83.62	41.32	700637, ...	0.1, ...
76354	144	TX	300	TX	11308	0.90	10207	-98.62	34.1	722637, ...	1.7, ...
94112	24999	CA	17000	CA	84145	0.77	64584	-122.44	37.72	737321, ...	5.1, ...
14827	1467	NY	1500	NY	132	0.78	103	-77.14	42.18	700901, ...	1.1, ...
74044	93	OK	50	*	7533	1.13	8521	-96.38	36.1	703100, ...	13.5, ...
...	...	...	...	...	...	...	...	...	...	...	...

be electrifiable with a BEV in Scenario B. If no GPS is found for a given bin, adjacent speed bins are searched (but not change is allowed for the distance bin). If no GPS trip is found in adjacent bins either, the NHTS trip is discarded. About 0.2% of NHTS trips are discarded this way, mostly consisting of trips that have a long distance (100+ km) but low average speed (<10 m/s).

To model how annual travel distance and trip distance-speed distributions (used to calculate F and β) vary across location, we split the NHTS data into subsections, and then calculate the population-average indicators for each of these subsets. First, we split the data along the 8 population density brackets of the household's location present in NHTS: 30, 300, 750, 1500, 3000, 7500, 17000, and 30000 people/mi^2. Exploratory analysis suggests that the population density is the location-related variable with the strongest systematic impact on the travel indicator variables modeled here. Then, we split those subsets of the data by U.S. states for which there is a sufficient amount of data available to estimate the travel indicator variables with less than a 5% error, based on a 95% confidence interval derived using the bootstrap. Estimating β requires a larger sample size than all other indicators, because β is highly sensitive to the long tails of the trip distance distributions. Therefore, we do not consider individual states to determine β, and use only the population density instead. Table 4.2 shows a summary of the combinations of population density and state used in this analysis, and the number of travel day samples present for each combination. Further data for each population density-state combination, such as the number of individual trips and the number of vehicles, is available in the Appendix (Table B.3).

The selection of NHTS subsets shown in Table 4.2 lets us model the population-average of each travel indicator η as a function of population density and state: $\eta_{\text{pop}}(PD, S)$. Local climate, on the other hand, is defined by the latitude and longitude of each meteorological station in the TMY dataset. To combine heterogeneity in travel patterns from NHTS data with the heterogeneity of local climate from TMY data, we map both datasets to each of the 32,989 zipcodes in the 50 U.S. states and the District of Columbia, and estimate the number of vehicles present in each zipcode. To do so, we map each zipcode's population density and state to a subset of NHTS data, and each zipcode's latitude and longitude to the three closest meteorological stations in the TMY dataset (Table 4.3). For each zipcode, we then calculate the value of each indicator $\eta_{\text{pop,zip}}\left(PD_{\text{NHTS,zip}}, S_{\text{NHTS,zip}}, lat_{\text{zip}}, lon_{\text{zip}}\right)$. Finally, to obtain representative distributions of the indicators across the country, we estimate the number of vehicles present in each zipcode. We do so by multiplying the zipcode's population with the average number of vehicles per capita, as indicated by the NHTS data subset for the zipcode's population density and state.

4.2.3 Modeling fuel consumption per distance

Instantaneous fuel consumption

To evaluate the impact of driving patterns and local climate on fuel consumption per distance of different types of vehicles, we use a vehicle energy model adopted from TripEnergy [151, 128]. Here, we extend this model by adding or modifying three components: First, we introduce an explicit parameter for the charging efficiency of BEVs, instead of considering charging efficiency implicitly through other coefficients. This allows us to use different charging efficiencies for the EPA test cycles and for real-world use. Second, we introduce an efficiency adjustment factor for the cold start of combustion engines. This allows us to estimate fuel efficiency of ICEVs more precisely for short trips. Third, we extend the method to estimate the impact of how ambient temperature on fuel efficiency. We take into account solar irradiation, humidity, and wind speed in addition to the ambient dry-bulb temperature, and we consider the effects of cold temperatures on both ICEVs and BEVs, rather than just BEVs.

The fuel consumption per distance, F, can be calculated by dividing the fuel consumption per time, P_{fuel}, by the traveling speed v. P_{fuel} can be expressed as:

$$P_{fuel} = F \times v = \left(P_{idle} + \frac{\mathscr{P}_{gas} - \mathscr{P}_{brake}\,\eta_r}{\eta_{max}} + \frac{P_{aux}}{\eta_{aux}\,\eta_{max}}\right)\frac{1}{\eta_{coldstart}\,\eta_{charge}} \tag{4.4}$$

where P_{idle} is the idle power consumption of the powertrain in W; $\mathscr{P}_{gas}$ is the tractive power in

W whenever tractive power is positive, and 0 otherwise; $\mathscr{P}_{brake}$ is the tractive power in W whenever tractive power is negative, and 0 otherwise; η_r is the efficiency of the energy recuperation system; η_{max} is the marginal efficiency of the powertrain for each additional W of tractive load; P_{aux} is the electrical energy consumption of auxiliary devices such as the A/C and headlights; η_{aux} is the efficiency of delivering power to those auxiliary devices; and $\eta_{coldstart}$ is a factor that accounts for lower efficiency of combustion engines while they have not yet reached equilibrium operating temperature. Compared to the original TripEnergy model [128], η_{charge} and $\eta_{coldstart}$ have been added, and P_{aux} is calculated differently based on meteorological conditions.

For ICEVs and HEVs, η_{aux} considers losses incurred by converting mechanical energy to electric energy through an alternator. For PHEVs, BEVs, and FCVs, η_{aux} only represents losses from the power system, such as the power converter. η_r, the recuperation efficiency, is 0 for ICEVs. Notably, the amount of energy recuperated from braking (P_{brake}) is divided by η_{max} as well, since the recuperated energy replaces energy coming from the tank or battery.

The tractive power, P_{gas} (when positive) or P_{brake} (when negative), can be expressed as the sum of road load and vehicle inertia:

$$\mathscr{P}_{tractive} = \left(\mathscr{C}_A + \mathscr{C}_B v + \mathscr{C}_C v^2 + m\delta a\right) v$$

where v is the current speed in m/s, m is the vehicle mass, a is the acceleration in m/s^2, δ is a mass correction factor accounting for simultaneous angular and linear rotation of the vehicle wheels ($\delta = 1.04$), and $\mathscr{C}_A$, $\mathscr{C}_B$, and $\mathscr{C}_C$ are the EPA coastdown coefficients in N, Nm/s, and Nm^2/s^2. $\mathscr{C}_A$ comes in part from the rolling resistance of the tires, in part from necessary accessory loads that do not scale with velocity and that are turned on in the EPA coastdown test, and in part from drag from the brake pads and wheel bearings [24]. $\mathscr{C}_B$ includes part of the rolling resistance from the tires, but also the power used by the various pumps and similar accessories of the vehicle [24]. $\mathscr{C}_C$ represents aerodynamic drag including the frontal area and the density of air [24, 125]. We obtain the coastdown coefficients as well as the vehicle curb weight M from EPA certification data. We add 300 lbs (136 kg) of load to the curb weight to determine the final mass of the vehicle, in accordance with EPA certification procedures.

We calibrate the vehicle parameters P_{idle}, η_{max}, and η_r to reproduce the unadjusted EPA fuel economy estimates for the city (FTP) and highway (HWFET) cycles. For internal combustion engine vehicles, we set η_r to 0, and obtain P_{idle} and η_{max} by fitting the two parameters to the two unadjusted fuel economy measurements. For electric vehicles, we set P_{idle} to 0 W, and obtain η_{max} and η_r by fitting the two parameters to the two unadjusted fuel economy measurements. Once calibrated against the EPA fuel economy ratings, this model has been evaluated against detailed, bottom-up fuel economy simulators, and shown to yield an error of less than 5% in estimating a vehicle's fuel consumption per distance for a given trip [128]. The original calibration model, however, did not consider that the FTP75 cycle is based on a cold start, while the HWFET is based on a warm start. Therefore, we extend the original vehicle energy model here to include the impact of engine cold start on combustion engine vehicle fuel efficiency through an additional parameter, $\eta_{coldstart}$ (see Equation 4.4).

Finally, for calibrating BEV parameters, we assume that charging efficiency is 92% during the official certification tests ($\eta_{charge} = 0.92$). For calculating modeled BEV fuel consumption, we assume that charging efficiency is 89%, and add an additional 3% loss for battery self-discharging over time when the BEV is not used.

Cold start efficiency loss

The cold start efficiency, $\eta_{coldstart}$ (see Equation 4.4), accounts for the lowered efficiency of combustion engines while they are reaching equilibrium operating temperature [117, 10]. We express the instantaneous cold start efficiency correction at time t for a given trip (that started with the engine being cold), $\eta_{coldstart}(t)$, as a function of a coefficient α:

$$\eta_{coldstart}(t) = 0.4 + 0.6\frac{t}{t + \alpha} \tag{4.5}$$

where α represents the time t at which efficiency reaches 70% (0.4 + 0.6/2). To apply cold start losses to the fuel consumption of an entire trip, we can calculate the average impact of the engine cold start on fuel efficiency across a trip:

$$\eta_{coldstart,avg} = \frac{1}{T}\int_{t=1}^{T} \eta_{coldstart}(t) = 1 + 0.6\ \frac{\alpha}{T}\ ln\left(\frac{\alpha}{\alpha + T}\right) \tag{4.6}$$

In a test conducted for a midsize gasoline passenger car in the New European Drive Cycle (NEDC) [117], researchers found that the cumulative fuel consumption per distance for a warm start after 200s is 30% lower than the fuel consumption per distance up to the same point in time after a cold start, 23% lower after 300s, 16% after 600s, and 10% after 1200s [10]. Using equation 4.6, an average efficiency of 0.77 after 300s implies $\alpha = 68$. This, in turns, predicts an average efficiency of 0.72 after 200s, 0.84 after 600s, and 0.90 after 1200s. These predicted values are close to the measured values of 0.70, 0.84, and 0.90, indicating that the equation used to approximate instantaneous cold start efficiency (equation 4.5) is close to real-world behavior.

Notably, α could also be estimated using bag 1 and bag 3 of the EPA city cycle (FTP75). In that test, bag 1 represents the cold start phase and bag 3 represents the hot start phase of an otherwise identical, 505 seconds long speed profile [65, 149]. We can then solve for α numerically:

$$\frac{FE_{bag1}}{FE_{bag3}} = 1 + 0.6\,\frac{\alpha}{505}\,ln\left(\frac{\alpha}{\alpha + 505}\right) \tag{4.7}$$

where FE_{bag1} and FE_{bag3} are the fuel economy values in miles per gallon (MPG) measured in part 1 and part 3 of the FTP 75 test cycle. Typical α values for vehicles in the EPA database range from 20 to 70 and are therefore consistent with the value found for the NEDC using a lab test [117]. Here, we use a value of $\alpha = 50$ for ICEVs.

Total trip consumption

Given a calibrated set of vehicle coefficients (P_{idle}, η_{max}, η_r, P_{aux}, α, A, B, C, and M), we can now calculate the fuel consumption per distance F for a given trip i with speed profile $v(t)$, average speed $\overline{v}$, and duration T:

$$F_i = \frac{1}{\overline{v}} \int_{t=1}^{T} P_{fuel}(v(t))\, dt \tag{4.8}$$

The last coefficient that needs to be determined is auxiliary consumption P_{aux}, which depends on ambient conditions.

4.2.4 Modeling the impact of local climate on fuel consumption

Impact of ambient temperature on fuel economy

The fuel efficiency of light-duty vehicles depends on ambient temperature in various ways. Most importantly, the air conditioning system of cars is usually active at high ambient temperatures [75, 210]. At cold temperatures, the heating system is usually active [4]. For electric vehicles, this represents a considerable additional load, as there is no waste heat available from a combustion engine to heat the cabin [4]. However, the fuel economy of combustion engine vehicles decreases at low temperatures as well [157, 68]. While the source of the heat is free in combustion engine

Table 4.4: List of vehicle models used in this chapter and their properties. To calculate the difference in emissions between BEVs and ICEVs, the five comparisons are weighted by the class shares indicated in the last row, normalized to 100%. Properties below the horizontal line in the center of the table are calibrated using the TripEnergy vehicle model. Unless annotated otherwise, properties above that line are obtained from publicly available certification data [67] and manufacturer websites.

	Comparison 1 (compact car)		Comparison 2 (mid-size or compact executive car)		Comparison 3 (large car)		Comparison 4 (compact crossover sport-utility vehicle)		Comparison 5 (mid-size sport-utility vehicle)	
	Honda Civic	Nissan Leaf	BMW 3-series	Tesla Model 3	Mercedes S-Class	Tesla Model S	Chevrolet Equinox	Hyundai Kona	Audi Q7 55 SE Prem.	Jaguar i-Pace
Trim	Hatchback 2.0L CVT	Base	330i	Standard plus	S450 4matic	75D	2.0L FWD		3.0L Auto AWD	
Technology	ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV
Model year	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019
Curb weight (kg)	1332	1557	1625	1645	2125	2163	1564	1685	2145	2170
Rated power (hp)	158	214	255	282	362	398	252	201	333	400
Rated fuel econ.[a]	34	112	28	131	22	111	25	120	21	76
—L or kWh/100 km	7.1	18.8	8.3	16.0	10.8	18.9	9.2	17.5	11.2	27.6
Battery capacity (kWh)		40		50		75		65		75
Avg. share of class[b]	10%		18%		8%		21%		9%	
Coastdown A (N)	121.7	117.0	213.8	160.2	204.9	184.2	142.2	110.6	216.0	158.6
Coastdown B (Ns/m)	2.970	2.854	-1.318	-1.283	2.554	1.584	2.605	-1.994	2.555	6.878
Coastdown C (Ns^2/m^2)	0.403	0.446	0.452	0.371	0.351	0.364	0.467	0.527	0.564	0.408
P_{idle} (W)	7791	100	8474	100	13899	100	10062	100	10667	100
$\eta_{\max}$	0.40	0.87	0.41	0.85	0.40	0.88	0.38	0.78	0.38	0.81
η_r	0	0.92	0	0.93	0	0.88	0	0.94	0	0.73
η_{aux}	0.55	0.90	0.55	0.90	0.55	0.90	0.55	0.90	0.55	0.90
P_{aux} (W)	400	400	600	600	800	800	600	600	800	800
$P_{H,+}$ (W)	30	160	32	171	36	192	32	170	37	197
$P_{H,-}$ (W)	80	80	86	86	96	96	85	85	98	98
η_{charge}		0.86		0.86		0.86		0.86		0.86
$\alpha_{\text{coldstart}}$	50		50		50		50		50	

[a] U.S. fuel economy ratings are adjusted for aggressive driving, cold starts, air conditioning use, and electric vehicle charging losses, and may differ from fuel efficiency rating for the same vehicle models in other countries; [b] Average share of vehicle class, as per 2017 NHTS. Shares have been obtained by matching make and model codes in NHTS to EPA vehicle class definitions. Classes not covered in this analysis, because there are no corresponding BEVs, include pickup trucks (27% of vehicles), vans (6%), and 2-seater sports cars (1%).

vehicles, fans still have to work to pump air into the cabin, heated seats and window defrosters may consume additional power, and the efficiency of powertrain components can decrease [157, 68].

The ambient temperature therefore affects auxiliary power consumption, powertrain efficiency, and cold-start losses in different ways. Since we do not have sufficient data to model these effects separately for each vehicle type, we group all effects of ambient temperature on fuel efficiency into a single number for additional power consumption, $P_{aux,amb}$, which affects P_{aux} in Equation 4.4:

$$P_{aux} = P_{aux,const} + P_{H+}\,(T_{amb} - T_{ref})_{+} + P_{H-}\,(T_{ref} - T_{amb})_{+} \tag{4.9}$$

where P_{H+} is the additional load in W per °C when the ambient temperature is higher than T_{ref}, P_{H-} is the additional load in W per °C when the ambient temperature is lower than T_{ref}, T_{amb} is an ambient temperature index, and T_{ref} is the reference temperature. Positive and negative differences compared to T_{amb} are modeled separately because P_{H+} and P_{H-} can be different both for BEVs as well as for ICEVs. While the relationship between P_{aux} and $T_{amb} - T_{ref}$ is not necessarily linear in reality [120, 4, 3], we approximate the impact of deviations from T_{ref} on P_{aux} as a linear relationship.

The reference temperature, T_{ref}, is related to the desired comfort temperature. In reality, the perceived comfort temperature depends on ambient temperature, humidity, and cultural aspects[153]. Here, we use a fixed comfort temperature of 20°C. The common range in literature on A/C systems is 20-25°C [153, 35, 100]; the temperature in the EPA SC03 test schedule is 72°C (22°C) for automated systems [65].

Determining the electrical load per degree of temperature difference

For vehicles whose fuel economy has been tested using the EPA 5-cycle method, we can infer P_{H+} and P_{H-} from the test data. The EPA 5-cycle test contains five test cycles: the FTP75 test schedule, consisting of the UDDS schedule conducted with an engine cold start followed by an additional 505 seconds of the UDDS schedule with a warm engine start; the HWFET highway schedule, the US06 aggressive driving schedule, the SC03 air conditioning schedule; and the cold temperature schedule, an FTP75 test cycle performed at -7°C. To obtain P_{H+}, we calculate the fuel economy for the SC03 test cycle with P_{aux} set to 0 W using equation 4.4, and compare that value to the measured fuel economy for the SC03 test cycle. The difference between these two fuel consumption values, divided by the temperature difference of 13°C, yields P_{H+}.

$$P_{H+} = \frac{P_{\text{SC03,measured}} - P_{\text{SC03,calculated,noaux}}}{13} \tag{4.10}$$

To estimate P_{H-} for ICEVs, we follow a similar procedure, but using the difference between in measured fuel consumption per distance between the measured cold temperature FTP75 test cycle fuel economy and measured regular FTP75 value.

$$P_{H-} = \frac{P_{\text{FTP75Cold,measured}} - P_{\text{FTP75,measured}}}{29} \tag{4.11}$$

Using this method, we obtain values around 70-120 W/°C for P_{H+} for the 2018 ICEV models for which the 5-cycle data is available, assuming $\eta_{aux} = 0.55$ [30]. For P_{H-}, we obtain 20-40 W/°C. As discussed earlier, η_{aux} reflects the efficiency to convert energy delivered by the powertrain into electric energy for auxiliary devices, and reflects the efficiency of the alternator in ICEVs. For PHEVs, BEVs, and FCVs, η_{aux} only represents losses from the power system, such as the power converter, and is higher. Here, we set $\eta_{aux,BEV} = 0.9$. Since the conversion efficiency to provide electrical energy for auxiliaries by the powertrain is accounted for separately, we expect P_{H+} to be the same for ICEVs and BEVs. P_{H-}, on the other hand, is expected to differ between ICEVs and BEVs, since the heat required to warm up the cabin in cold temperatures is free in ICEVs, but not in BEVs.

Unfortunately, the 5-cycle test data is currently not available for any BEV. A fuel economy calculator on the Tesla website that allows to estimate fuel economy of a Tesla Model S as a function of ambient temperature and current speed suggested a P_{H+} of 80-100 W/°C, and P_{H-} of 100-250 W/°C, depending on driving speed, and assuming $\eta_{aux} = 0.9$. Unfortunately, this calculator has since been removed from the Tesla website. A recent study by the AAA [3] for the BMW i3 suggests a P_{H+} of about 100 W/°C, and P_{H-} of about 180 W/°C, mostly independent on driving speed, and assuming $\eta_{aux} = 0.9$. Both sources distinguish the impact of temperature on fuel consumption per distance if the HWAC system is turned off (thus predominantly measuring the impact of ambient temperature on powertrain efficiency and friction losses) and when the HVAC system is turned on. A majority of the impact, about 75%, comes from the HVAC system [3].

Combining all of the information above, we use $P_{H+} = 100$ W/°C for compact vehicles of both powertrain technologies, $P_{H-,\text{ICEV}} = 30$ W/°C, and $P_{H-,\text{BEV}} = 180$ W/°C. For larger vehicles, we scale all values based on the relative floor area of each vehicle compared to a typical compact car.

Determining temperature difference

We determine the difference between T_{amb} and T_{ref} at a given time of day and given day in the year using meterological information from the Typical Meteorological Year (TMY3) dataset [200, 156]. One of the most straight-forward ways to estimate this difference is to use the dry-bulb temperature T_{db}. The dry-bulb temperature is, however, not necessarily representative of the HVAC system load. It does not account for humidity, which affects A/C efficiency [100] as well as desired comfort temperature [153]. It also does not account for additional heating due to direct solar irradiation and cooling due to wind. This can be critical, as vehicles exposed to direct sunlight can get much warmer than the dry-bulb temperature would suggest [112].

To take into account these factors, we calculate two temperature indices in addition to the dry-bulb temperature T_{db}: the humidity-adjusted heat index, T_{HI}, and the black globe temperature T_g. We then calculate the final ambient temperature index, $T_{amb,index}$, as the average between the three individual temperatures:

$$T_{amb,index} = 0.34\ T_{db} + 0.33\ T_g + 0.33\ T_{HI} \tag{4.12}$$

The heat index, T_{HI} is a measure of the dry-bulb temperature T_{db} adjusted for the amount of relative humidity, R. It provides a measure of the perceived (sensed) temperature by humans. We use an empirical equation to estimate T_{HI} [168]:

$$\begin{aligned} T_{HI} = & -42.379 + 2.04901523\ T_{db,F} + 10.14333127\ R - 0.22475541\ T_{db}R - 6.83783 \times 10^{-3}\ T_{db,F}^2 \\ & - 5.481717 \times 10^{-2}\ R^2 + 1.22874 \times 10^{-3}\ T_{db,F}^2 R + 8.5282 \times 10^{-4}\ T_{db,F} R^2 - 1.99 \times 10^{-6}\ T_{db,F}^2 R^2 \end{aligned} \tag{4.13}$$

where $T_{db,F}$ is the dry-bulb temperature in degrees F, and RH is the relative humidity in % (integer percentage). This equation applies when $T_{db,F} > 80$ [168]. Below that temperature, we set $T_{HI} = T_{db}$. The impact of T_{HI} on the ambient index temperature is most noticeable in hot, humid climates, such as Florida (4-1).

The globe temperature T_g is the temperature of a black globe with a thermometer inserted in the center reaches in the open environment, taking into account direct and indirect irradiation as well as wind speed [51]. It is often used as part of the WetBulb Globe Temperature (WBGT) to measure heat stress for humans and animals [51, 148]. Since it is not usually available from meteorological data, it has to be estimated empirically [51, 122]. To calculate the globe temperature T_g, we use series of empirical equations[51]:

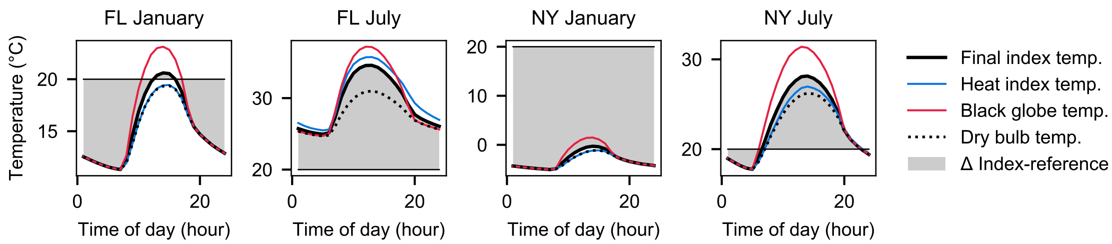

Figure 4-1: Average temperature profiles across all meteorological stations in Florida (FL) and New York (NY) in January and July. The shaded area between the temperature index T_{index} and the reference temperature (20°C) reflect the corresponding cooling (above the line) and heating (below the line) loads at the corresponding time of day. Note that daily temperature profiles in a given month vary beyond the monthly mean, implying the shaded areas don't necessarily corresponding exactly to the average heating and cooling loads in the respective locations and the corresponding months and times of day.

$$f_{\text{diff}} = \frac{\text{DHI}_{W/m^2}}{\text{GWI}_{W/m^2}} \text{ if } \text{GWI}_{W/m^2} > 0 \text{ else } 1 \tag{4.14}$$

$$f_{\text{dir}} = 1 - f_{\text{diff}} \tag{4.15}$$

$$e_a = \exp\left(\frac{17.67\,(T_{C,dew} - T_{C,db})}{243.5 + T_{C,dew}}\right)(1.0007 + 3.46\;10^{-6}\;P_{mbar})\;6.112\exp\left(\frac{7.502\;T_{C,db}}{240.97 + T_{C,db}}\right) \tag{4.16}$$

$$\eta_a = 0.575\;e_a^{1/7} \tag{4.17}$$

$$\alpha = \arccos\left(\frac{\text{GHI}_{W/m^2} - \text{DHI}_{W/m^2}}{\text{DNI}_{W/m^2}}\right) \text{ if } \text{DNI}_{W/m^2} > 0 \text{ else } 0 \tag{4.18}$$

$$B = \text{GWI}_{W/m^2}\,(f_{\text{dir}}/(4\;\sigma\;cos(\alpha)) + 1.2/\sigma\;f_{\text{diff}}) + \eta_a\;T_{C,db}^4 \tag{4.19}$$

$$v = 3600\;\text{Wspd}_{m/s} \tag{4.20}$$

$$C = 0.315\;v^{0.58}(5.3865\;10^8) \tag{4.21}$$

$$T_g = \frac{B + C\;T_{C,db} + 7680000}{C + 256000} \tag{4.22}$$

where DHI is the diffuse horizontal irradiance, GWI is the global horizontal irradiance, DNI is the Direct normal irradiance, T_{dew} is the dew-point temperature, T_{db} is the dry-bulb temperature, P_{mbar} is the station pressure, σ is the Stephan-Boltzman constant (5.67×10^{-8}), α is the solar zenith angle, and Wspd is the wind speed. The impact of T_g on the ambient index temperature is noticeable in all climates (Figure 4-1), but most pronounced in locations with a substantial amount of sunshine hours per year.

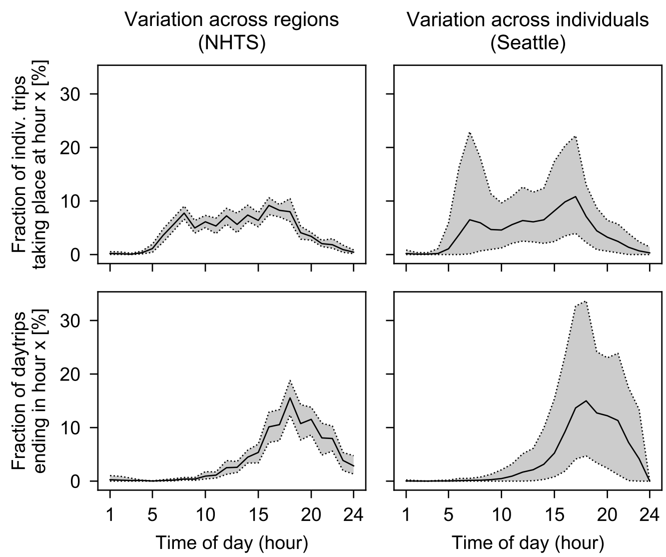

Figure 4-2: Typical time of day of driving in NHTS data (left) and Seattle data (right). The top row shows the distribution of the average midpoint time each individual trip, rounded up (for instance, if a trip starts at 9am and ends at 11am, the value is 10am). This information is used to calculate the average impact of ambient temperatures on fuel consumption per distance. The bottom row shows the average end time of each daytrip (or instance, if the last trip on a given day ends at 10pm, the value is 10pm). This information will be used in Chapter 5 to calculate the average electricity mix for charging BEVs. The shaded areas represent the range from the 5th to the 95th percentile across region averages (left) and across individual people (right).

Determining average temperature loads

Next, we combine the difference between T_{amb} and T_{ref} as a function of time of day and day of year with information with data on when people drive. We assume that there is an equivalent amount of driving throughout the year, but take into account at what time of day people drive. We calculate the average distribution for time of day of driving for each NHTS subset listed in Table 4.2 (Figure 4-2). The distribution is similar across different locations.

For model the heterogeneity of individual driving patterns in a given location, we use a separate dataset, described in more detail later in this chapter. We find that the heterogeneity in time of day of driving across individual trips in a given location is substantially larger than the heterogeneity in time of day across the NHTS regions considered here (Figure 4-2).

4.2.5 Modeling heterogeneity across individual vehicles in given region

NHTS only contains a single travel day per vehicle. Therefore, we can only estimate population-average indicator values, but not distributions for F, AF, v, and β across individual vehicles without making strong assumptions. Instead, we employ a separate dataset, providing longitudinal trip data across more than a year, between fall 2004 and spring 2006, for 441 vehicles in the Seattle area [162]. We use a subset of 309 vehicles from this data, covering vehicles that made at least one trip per week in 2006, and whose household is located in suburban areas of Seattle with a population density of between 2,500 and 8,000 people/mi^2. The selection of vehicles for a specific population density bracket ensures that the observed heterogeneity in travel patterns is not caused by varying population density. For each of the 309 individual vehicles, we calculate the value of each indicator. For this calculation, we do not consider the impact of climate on fuel efficiency, since the distribution in fuel efficiency across individual vehicles will be scaled to a corresponding regional average, which takes into account the local climate in that region.

We then combine the distribution of indicators among individual vehicles in the Seattle dataset, k, with the distribution across regions by scaling the distribution across individuals to the population-average of the corresponding location $\eta_{\text{pop,zip}}$. The value for a given indicator η for a randomly sampled vehicle k assigned to zipcode pop,zip is calculated as:

$$\eta_{\text{zip},k\in\text{zip}} = \eta_{\text{Seattle},k} \frac{\eta_{\text{pop,zip}}\left(PD_{\text{NHTS,zip}}, S_{\text{NHTS,zip}}, lat_{\text{zip}}, lon_{\text{zip}}\right)}{\eta_{\text{pop,Seattle}}} \tag{4.23}$$

where $\eta_{\text{pop,Seattle}}$ is the population-average of indicator η in the Seattle dataset. Unfortunately, longitudinal information on annual travel distance M or vehicle lifetime A is not available in the Seattle data. Therefore, for each individual vehicle k, we first sample average annual travel distance M_{avg} and vehicle lifetime A from NHTS using an auto-regressive model, and then match values for the other travel indicators from the Seattle data to that vehicle, given M_{avg}.

Sampling average annual travel distance and vehicle lifetime for individual vehicles

Annual travel distance for vehicles of a given age are approximately lognormally distributed (Figure 4-3, left), and the mean of that distribution changes with each year. First, we transform the data so that the distribution of annual travel distance among vehicles of age a follows a normal distribution with mean 0. To do so, we take the natural logarithm of each data point, and then subtract the mean of vehicles of age a:

$$\omega_{i,a} = \log\left(M_{i,a}\right) - \sum_{j\in a} \log\left(M_{j,a}\right) \tag{4.24}$$

Next, we apply an Auto-regressive model with time lag 1 (AR1) to the data:

$$\omega_{i,a} = \rho \times \omega_{i,a-1} + \epsilon_a \tag{4.25}$$

where ϵ_a is a normally distributed noise term with mean 0, and ρ is the correlation between the annual travel distance in year a and the distance in the previous year. We cannot estimate ρ from the data, since longitudinal data (containing data on annual travel distance across multiple years for the same vehicle) is unavailable. Assuming a specific ρ, however, we can estimate the variance of ϵ_a so that sampled values for $\omega_{i,a}$ match the variance of the distribution of ω among vehicles of age a in NHTS, σ_a^2:

$$\epsilon_a \sim \mathcal{N}\left(0, \sigma_a^2\left(1-\rho^2\right)\right) \tag{4.26}$$

To apply the model, we first estimate ϵ_a for each year a from the data, using Equation 4.26. We then sample a distribution of $\omega_{i,1}$ (the annual travel distance in the first year of each vehicle's life) for K vehicles directly from NHTS data. Next, we sample the annual travel distance in each consecutive year up to age A using Equation 4.25. Finally, we transform the sampled data back to annual travel distance M, using the inverse of Equation 4.24:

$$M_{\text{sampled},a,k} = \exp\left(\omega_{\text{sampled},k,a} + \sum_{j\in a} \log\left(M_{j,a}\right)\right) \tag{4.27}$$

Once annual travel distance in each year a is sampled for a given vehicle k using equation 4.27, we determine each vehicle k's lifetime. For each vehicle, we apply a lifetime travel distance threshold of 250,000 km, and a maximum age of 30 years. The vehicle is then assumed to leave the fleet after the year that exceeds either of the two thresholds. For example, if a given vehicle's cumulative annual travel distance up to year $q-1$ is 240,000 km, and the sampled annual travel distance in year q is 30,000 km, the vehicle's lifetime is set to q years, its lifetime travel distance is 270,000 km, and its average annual travel distance is $270000/q$ km. Because vehicles are allowed to exceed 250,000 km in their final year, or become 30 years old before they reach that threshold, there is variation in the lifetime travel distance across individual vehicles. The resulting average lifetime travel distance across all vehicles is 261,000 km. Figures B-1 and B-2 in Appendix B show additional details on the resulting distributions in annual travel distance, lifetime travel distance, and vehicle lifetime across individual vehicles.

Once vehicle lifetime is sampled for each vehicle, we calculate the average annual travel distance up to age A using Equation 4.1.

$$M_{\text{avg},A,k} = \frac{1}{A} \sum_{a}^{A} M_{\text{sampled},a,k} \tag{4.28}$$

With correlation coefficient ρ set to 0, this model corresponds to sampling each value $M_{\text{sampled},a,k}$ directly from the corresponding distribution of M_a in NHTS, assuming that annual travel distances for a given vehicle in different years are independent. With correlation coefficient ρ set to 1, the resulting distribution in $M_{\text{avg},A,k}$ has a similar coefficient of variance as the distribution of M_1 in the data, but a different mean. $\rho = 0$ and $\rho = 1$ therefore represent boundary cases for the unknown real distribution of $M_{\text{avg},A,k}$, given an unknown correlation across time ρ (Figure 4-3). The reality likely is somewhere in the middle. Here, we use $\rho = 0.5$, producing a distribution in $M_{\text{avg},A,k}$ whose standard deviation is closer to the lower bound ($\rho = 0$) than the upper bound ($\rho = 1$).

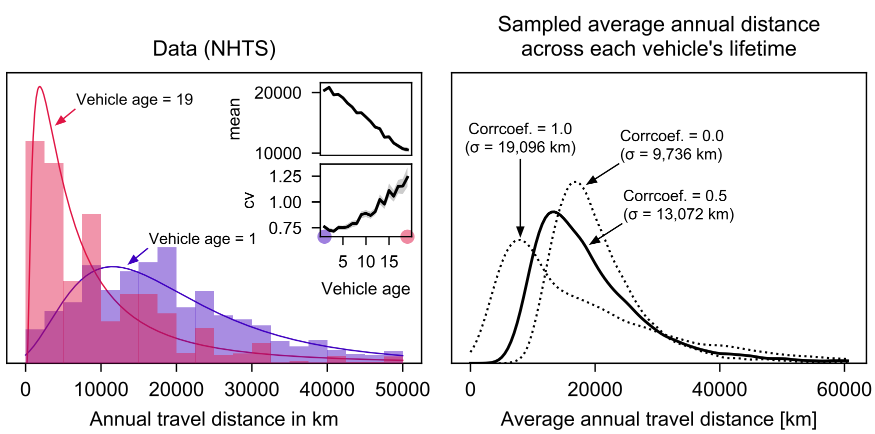

Figure 4-3: (left) Distribution of annual travel distance as a function of vehicle age in NHTS. (right) Resulting distribution of sampled average annual travel distances across each vehicle's lifetime for individual vehicles using an Auto-regressive (AR1) model with imposed correlation coefficient ρ, age-specific noise ϵ_a estimated from NHTS data, a cutoff lifetime travel distance of 250,000 km, and a maximum lifetime of 30 years. Three cases are shown, imposing a correlation coefficient between the annual travel distance in one year and annual travel distance in the next year of either 0 (implying sampled values are independent), 0.5, or 1 (implying that only travel distance in the first year of a vehicle's age is random, and follows a fixed annual trend afterwards). Note that the left and the right subplot have matching y-axis limits.

Finally, to sample values for average annual travel distance for a vehicle k assigned to a specific zipcode with population-average annual travel distance $M_{\text{avg,A,zip,pop}}$ and of a given vehicle class, we scale the sampled distribution of average annual travel distances across individual vehicles to the corresponding population-average average travel distance in that zipcode, and adjust the distribution based on vehicle k's class:

$$M_{\text{avg},A,k\in\text{zip}} = M_{\text{avg},A,k} \frac{M_{\text{avg,A,zip,pop}}}{M_{\text{avg,A,sampled,pop}}} \frac{M_{avg,A,pop,class,PD}}{M_{avg,A,pop,class}} \tag{4.29}$$

where $M_{\text{avg},A,k}$ is the sampled average annual travel distance of vehicle k, $M_{\text{avg,A,zip,pop}}$ is the population-average annual travel distance in zipcode zip, $M_{\text{avg,A,sampled,pop}}$ is the population-average annual travel distance across all sampled vehicles k, $M_{avg,A,pop,class,PD}$ is the population-average annual travel distance for vehicles belonging to class class in locations with population density PD, and $M_{avg,A,pop,class}$ is the same population-average across all vehicle classes. Class-specific average annual travel distance values for each population density bracket are shown in Figure B-8 in Appendix B.

The scaling procedure to match the mean indicator value in the corresponding zipcode in Equation 4.29 is equivalent to how the other indicators are scaled to each zipcode's population-average indicator values, as shown in Equation 4.23. This approach implies the assumption that annual travel distance is distributed in a similar shape and with a similar coefficient of variation across different locations.

Combining sampled annual travel distance with Seattle data

For each sampled vehicle k and corresponding sampled average annual travel distance $M_{\text{avg},k}$, we select vehicle i in the Seattle dataset among all 309 vehicles whose annual travel distance in 2005 as measured in that data matches the most closely with annual travel distance to obtain rest of metrics. This corresponds to weighing Seattle data for indicators other than M according to each vehicle's annual travel distance. Matching M with other indicators is necessary because all other indicators are strongly correlated with M (see Figure 4-8 in the results section).

$$\eta_{\text{zip},k\in\text{zip}} = \eta_{\text{Seattle},i_k} \frac{\eta_{\text{pop,zip}}\left(PD_{\text{NHTS,zip}}, S_{\text{NHTS,zip}}, lat_{\text{zip}}, lon_{\text{zip}}\right)}{\eta_{\text{pop,Seattle}}} \tag{4.30}$$

$$i_k = i \in [0, 309] \,:\, \min\left(\text{abs}(M_{\text{avg},15,i} - M_{\text{avg,15,zip,pop}})\right) \tag{4.31}$$

As was the case with scaling the distribution in average annual travel distance to a given location-specific average, we again assume that the distribution of other metrics, as indicated by the Seattle data, is the same across different locations, relative to each location's mean, and conditional on the distribution of annual travel distance.

4.2.6 Calculating lifecycle greenhouse gas emissions

Based on the modeled fuel consumption per distance, annual travel distance, and fraction of electrifiable distance, we calculate lifecycle greenhouse gas emissions using an existing, parametrized model that estimates emissions and costs as a function of key vehicle characteristics [138]. Here, we calculate emissions and costs on a per-vehicle-year basis, rather than the per-vehicle-km unit used in Chapter 2. We argue that the former more closely reflects the total emissions savings achievable by replacing one internal combustion engine vehicle with one electric vehicle. If per-distance emissions savings are high in a certain region, but the annual travel distance is low, overall emissions reductions achieved can be lower than in a region where per-distance savings are slightly higher, but the annual travel distance is much higher.

The greenhouse gas emission parameters are based on the lifecycle inventories of Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET), developed at the Argonne National Laboratory (ANL) [12]. It takes into account emissions from the fuel cycle, including fuel production and distribution, and the vehicle cycle. For this study, we update the previous model from Chapter 2 [138] to reflect the 2018 inventories of GREET. These updates are described in appendix section B.1. In addition, we adjust the emission intensity of electricity used to charge electric vehicles. We use emission factors from the eGRID database [66]. Average emissions amount to 474 gCO_2eq/kWh, including losses from transmission and distribution. We also consider the lowest-carbon and highest-carbon grids, NYUP (Upstate New York) and HIOA (Oahu / Hawaii), with emission factors of 140 gCO_2eq/kWh and 797 gCO_2eq/kWh, respectively.

4.2.7 Summary of key modeling assumptions

The first key assumption is that the variation in travel indicators across individual vehicles relative to their location-specific mean value is same in all regions within the country. This implies that the distributions of travel indicators across regions and across individual vehicles in those regions are independent. Under this assumption, we evaluate the variations in travel indicators based on variations observed in the Seattle dataset, and adjust it for location-specific mean values.

Another assumption is that the correlation of annual travel distance between one year and the next is 0.5. A lower correlation would imply a higher amount of variation in annual travel distance across individual vehicles and a higher correlation would imply a lower amount of variation, as shown in Figure 4-3.

Third, we implicitly assume that the population density bracket and the state are sufficient proxy variables to model the heterogeneity in the trip distance and time distributions across regions in the U.S. Since a sufficiently large sample size from NHTS data must be maintained to estimate the trip distance and time distributions based on population density and state, the spatial resolution of our analysis is limited. A higher spatial resolution would likely mean that some of the heterogeneity in travel indicators across individual vehicles is shifted to the heterogeneity across regions.

Fourth, we make assumptions regarding BEV trip patterns, depending on the scenario (A or B). In Scenario A, charging speed and density of charging stations are high enough so that BEVs can comfortably be used for any trip that would have been made with ICEV. In Scenario B, charging only occurs overnight. In both Scenarios, we assume that only long trips are affected by switching from an ICEV to a BEV. The trip patterns of BEVs remain identical to those of ICEVs for trips that are electrificable in each of the two scenarios. This means that we assume that there is no rebound effect, for instance due to lower operating costs of BEVs compared to ICEVs.

Finally, for the calculation of annual greenhouse gas emissions of BEVs, we assume that trips that cannot be electrified in Scenario B are made with an ICEV that corresponds to the baseline ICEV of the comparison shown in Table 4.4. Operating emissions for those trips are then calculated using that baseline ICEV, and allocated to the BEV. Additional vehicle production emissions are not considered.

Most of these assumptions are difficult to verify with existing data. If more data was available, these assumptions could either be tested, or they could be relaxed based on additional information. The assumption on BEV trip patterns compared to ICEV trip patterns (assumption 4), however, can be tested by using data from NHTS that has been collected by BEV owners. In the results section, we show this comparison against NHTS data.

4.3 Results

4.3.1 Variation in travel indicators across regions and individual vehicles

We find that the average fuel consumption per distance of ICEVs varies by 20% across locations due to urban-rural differences in driving patterns and by 5% across locations due to differences in local climate (Figure 4-4). Within a given region, average fuel consumption per distance varies by

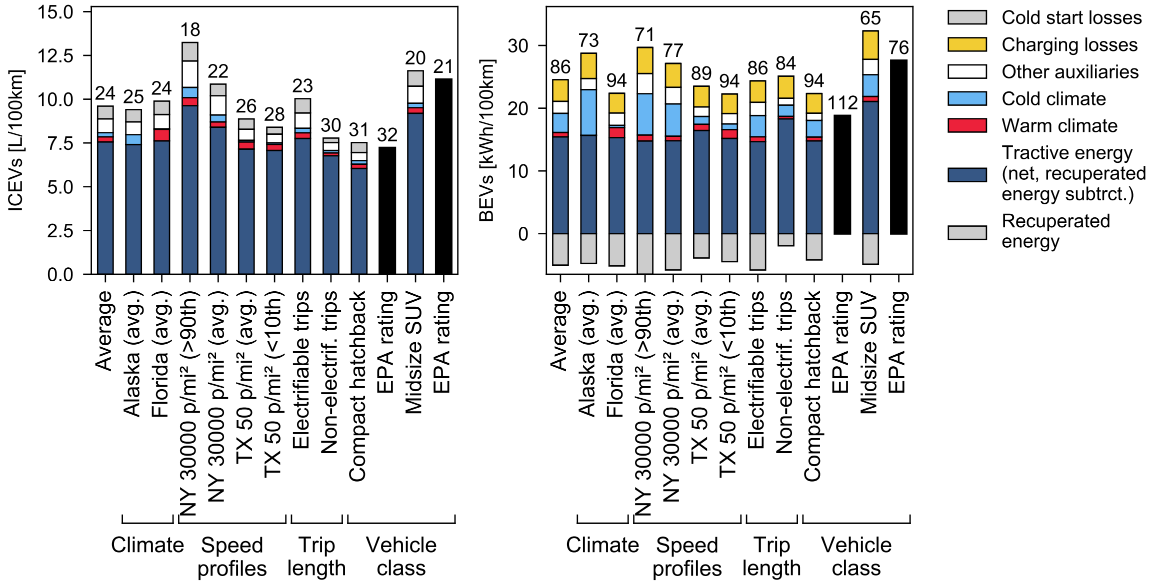

Figure 4-4: Composition and variation ICEV (left) and BEV (right) fuel consumption due to local climate, typical trip speed profiles, trip length, and vehicle class. The different aspects are not independent. For instance, the climate in NY is colder on average than in TX, affecting the contribution of cold climate to fuel consumption (which is amplified by the slow average travel speed in urban NY, see Figure B-3). 'Electrifiable trips' refer to trips whose corresponding vehicle travel days (the cumulative sum of trips made during a given day) do not exceed 80% of the BEV's battery capacity (see Scenario B in Table 4.1). 'Non-electrif. trips' are all other trips. Unless indicated otherwise, results apply to the average across the five classes shown in Table 4.4, weighted by their average relative share (see Figure B-8 in Appendix B). '>90th' and '<10th' refer to all vehicles whose fuel consumption is above the 90th and below the 10th percentile among all vehicles in the corresponding region due to individual driving patterns, respectively (still weighted across multiple vehicle classes). The 'EPA rating' refers to the official combined fuel economy rating of the corresponding vehicle model belonging to the vehicle class indicated on the left. Details on how travel patterns vary across all 49 regions shown in Table 4.2 can be found in Appendix B, Figures B-3–B-8.

50% across the five vehicle classes in Table 4.4, and by an additional 30% for a given class across individual driving patterns.

The average fuel consumption per distance of BEVs varies less across locations due to driving patterns than the fuel consumption per distance of ICEVs (15%), but more due to local climate (30%; Figure 4-4). Within a given region, average fuel consumption per distance of BEVs varies by about 40% across the five vehicle classes in Table 4.4, and by 15% for a given class across individual driving patterns. This observed variation is smaller for BEVs than for ICEVs.

The reason why the electricity consumption of BEVs varies more with location due to local climatic conditions than the gasoline consumption of ICEVs is that the fraction of energy consumption per distance due to cold climate represents a higher share of total energy consumption of BEVs (Figure 4-4). Warm climate and the increased HVAC use, on the other hand, represent similar relative fractions of total energy consumption for the two vehicles. While BEVs have a more efficient powertrain, and therefore only consumers about 40% of the energy per distance as ICEVs, they are also more efficient at providing electricity to its electrical auxiliary systems than the ICEVs. For the latter, electricity has to be produced by an alternator, whose typical efficiency is only 55% [30]. Notably, cold start losses of ICEVs, are mostly related to the average length of a trip, not ambient temperature. On average, they account for about 5% of fuel consumption. For vehicles with particularly short average trips, the contribution can be as high as 10%.

We find that using our bottom-up vehicle energy model, the resulting U.S. average fuel consumption per distance of the Honda Civic (a compact hatchback) and the Audi Q7 (a mid-size SUV) closely resemble the official EPA rating for combined city and highway driving (Figure 4-4). The estimated average fuel consumption per distance of the Nissan leaf and Jaguar i-Pace, on the other hand, is 20% higher than the rating indicates. There are two likely reasons for this observation: First, charging efficiency in the EPA test cycles is higher (above 90%) than assumed here (89%), and battery self-discharge over time (here: 3%) is not accounted for in the official rating. And second, while the EPA rating does reflect the impact of warm climate on HVAC use and on fuel efficiency, it does not consider the impact of cold climate on HVAC use, which increases fuel consumption per distance of the BEV by 10% on average.

Average annual travel distance varies between 15,000 and 20,000 km/year across locations, and by 5-10% across vehicle classes (Figure 4-5). Across individual vehicles in a given region, annual travel distance varies substantially. We estimate that even in urban New York, where the average annual travel distance is 15,000 km/year, about 10% of vehicles are being driven over 40,000 km/year. Similarly, 10% of vehicles in rural Texas are being driven less than 10,000 km/year.

The fraction of electrifiable distance depends slightly on both local driving patterns and on climate, both due to the differences in on fuel efficiency across locations observed in Figure 4-4. Across individual driving patterns, there is a large amount of heterogeneity: while the average fraction of electrifiable distance is about 80%, 10% of vehicles make long trips so frequently that only 30% of their annual travel distance would be electrifiable in Scenario B. Conversely, all trips are electrifiable for at least 10% of vehicles. Further details on how the fraction of electrifiable trips varies across regions and vehicle classes are available in Appendix B, Figure B-6.

The combined variation in fuel consumption per distance, annual travel distance, and the fraction of electrifiable trips means that annual greenhouse gas emissions are highly heterogeneous

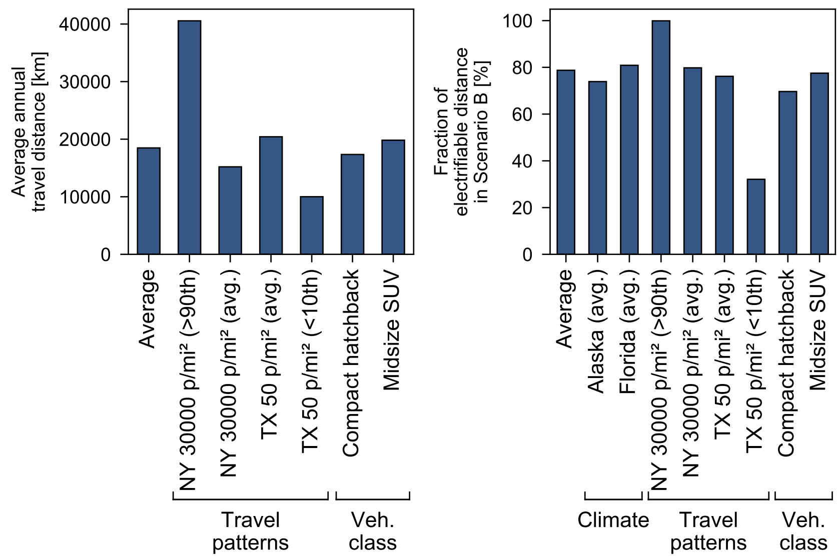

Figure 4-5: Variation in annual travel distance (left) and the fraction of annual travel distance that is electrifiable by BEVs in Scenario B (right; see Table 4.1) across individual travel patterns and across vehicle classes. BEVs belonging to different vehicle classes have different battery capacities (see Table 4.4), which affect the fraction of electrifiable trip distance. '>90th' and '<10th' refer to all vehicles whose corresponding indicator value is above the 90th and below the 10th percentile among all vehicles in the corresponding region due to individual driving patterns, respectively (still weighted across multiple vehicle classes). Details on how travel patterns vary across all 49 regions shown in Table 4.2 can be found in Appendix B, Figures B-3–B-8.

across individual vehicles, even averaged across different classes, with the top 10% and the bottom 10% differing by a factor 4 or more (Figure 4-6). Differences between different vehicle classes further amplify this variation. Population-average annual emissions per vehicles, on the other hand, only exhibit a small amount of heterogeneity across regions. The reason is that annual travel distance and fuel consumption per distance are negatively correlated: in urban areas, annual travel distance is lower, but average fuel consumption per distance is higher. This is particularly true for ICEVs (see also Figures 4-4 and 4-5).

Even though the average fraction of electrifiable distance in Scenario B is relatively high at 80%, using a baseline ICEV for the remaining 20% can raise total BEV emissions (Figure 4-6, center). In Scenario B, average emissions of BEVs (plus emissions from ICEVs for the non-electrifiable trips) are almost 20% than in Scenario A. For those individual vehicles for which the fraction of electrifiable distance is particularly low (see Figure 4-5, right), ICEV trips make up the majority of emissions. Another notable source of variation for BEV emissions is the electricity mix: lifecycle emissions of BEVs vary by a factor of 2 in Scenario B and a factor of 3 in Scenario A between the

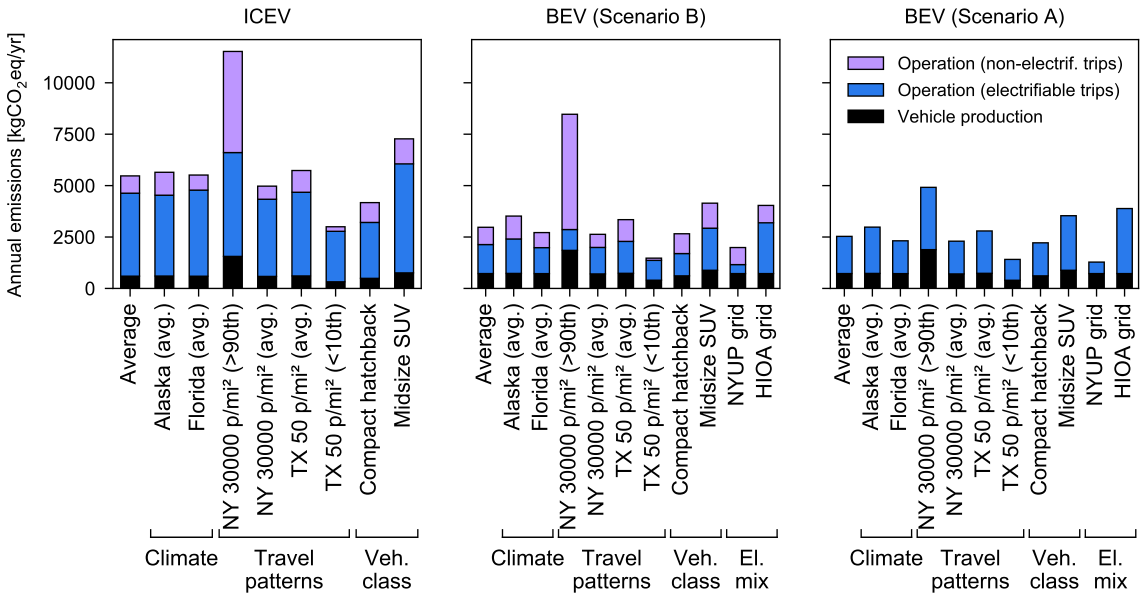

Figure 4-6: Variation in annual emissions of ICEVs and BEVs across local climates, driving patterns, vehicle classes, and electricity mixes. In Scenario B, certain travel days that are not electrifiable with BEVs are made with the corresponding baseline ICEV listed in Table 4.4 instead (see Table 4.1). In Scenario A, all travel days are assumed to be made with the BEV. Electrifiable and non-electrifiable trips are shown separately for the ICEV for purposes of comparison; ICEV emissions are equivalent in the two scenarios. Unless indicated otherwise, results apply to the average across the five classes shown in Table 4.4, weighted by their average relative share (see Figure B-8) in Appendix B). '>90th' and '<10th' refer to all vehicles whose annual emissions are above the 90th and below the 10th percentile among all vehicles in the corresponding region due to individual driving patterns, respectively (still weighted across multiple vehicle classes).

lowest-carbon subgrid and the highest-carbon subgrid in the U.S.

Finally, we investigate the correlation between fuel consumption per distance and annual emissions of ICEVs and BEVs (Figure 4-7). We find that energy consumption per distance between the two vehicles is largely uncorrelated. This is because energy consumption of the Leaf depends mostly on local climate, while energy consumption of the Civic depends mostly on population density and corresponding traffic density. Annual emissions, on the other hand, are strongly correlated, because annual travel distance is the same for an individual vehicle of either technology. There still is, however, a substantial amount of variation between the annual fuel of the ICEV and annual fuel consumption of the BEV.

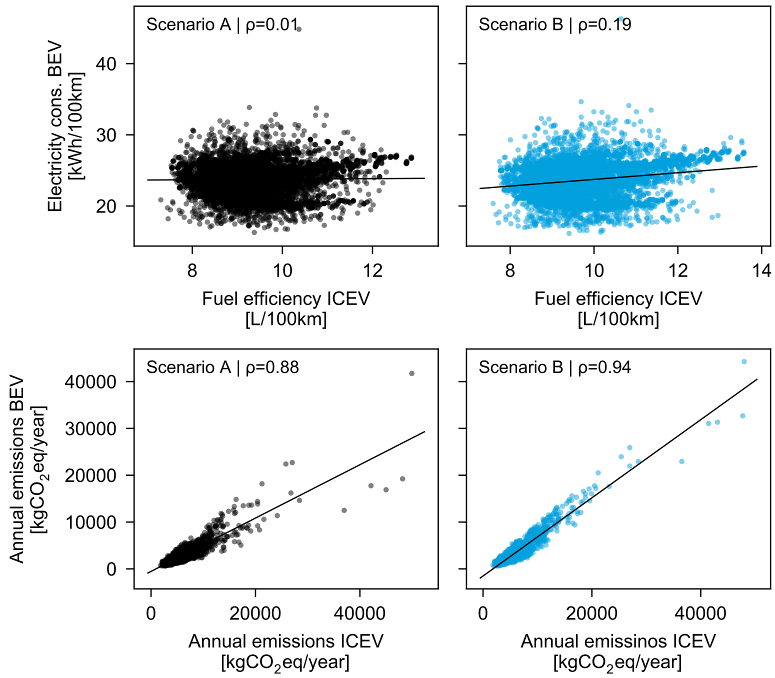

Figure 4-7: Correlation between fuel consumption per distance (top row) and annual fuel consumption (bottom row) across individual vehicles if they were either an ICEV or a BEV, for Scenario A (left side) and Scenario B (right side). For the correlation between fuel consumption values in Scenario B (top right), only electrifiable trips are considered. Results are weighted across the five classes shown in Table 4.4). The heterogeneity shown represents the aggregate heterogeneity across locations and across individual vehicles. Each vehicle shown has the same annual travel distance for both vehicle types. The numbers next to ρ indicate the Pearson correlation coefficient.

4.3.2 Heterogeneity in travel patterns across individual vehicles

There is substantial variation across individual vehicles for all travel indicator variables (Figure 4-8). The variation is particularly large for annual travel distance and the fraction of non-electrifiable trip distance in Scenario B.

All travel indicators are correlated with annual travel distance: the higher the annual travel distance, the lower the fuel consumption per distance of ICEVs, the higher the fuel consumption per distance of BEVs, the higher average speed, and the higher the fraction of electrifiable trip distance. Most of the indicators scale approximately linearly with the annual travel distance quintile number. The correlation between annual travel distance and the fraction of electrifiable trip distance is particularly strong, and implies that vehicles with a high annual travel distance, for which BEVs might yield high annual emission benefits, also tend to be vehicles whose daily trip patterns are the most difficult to electrificy.

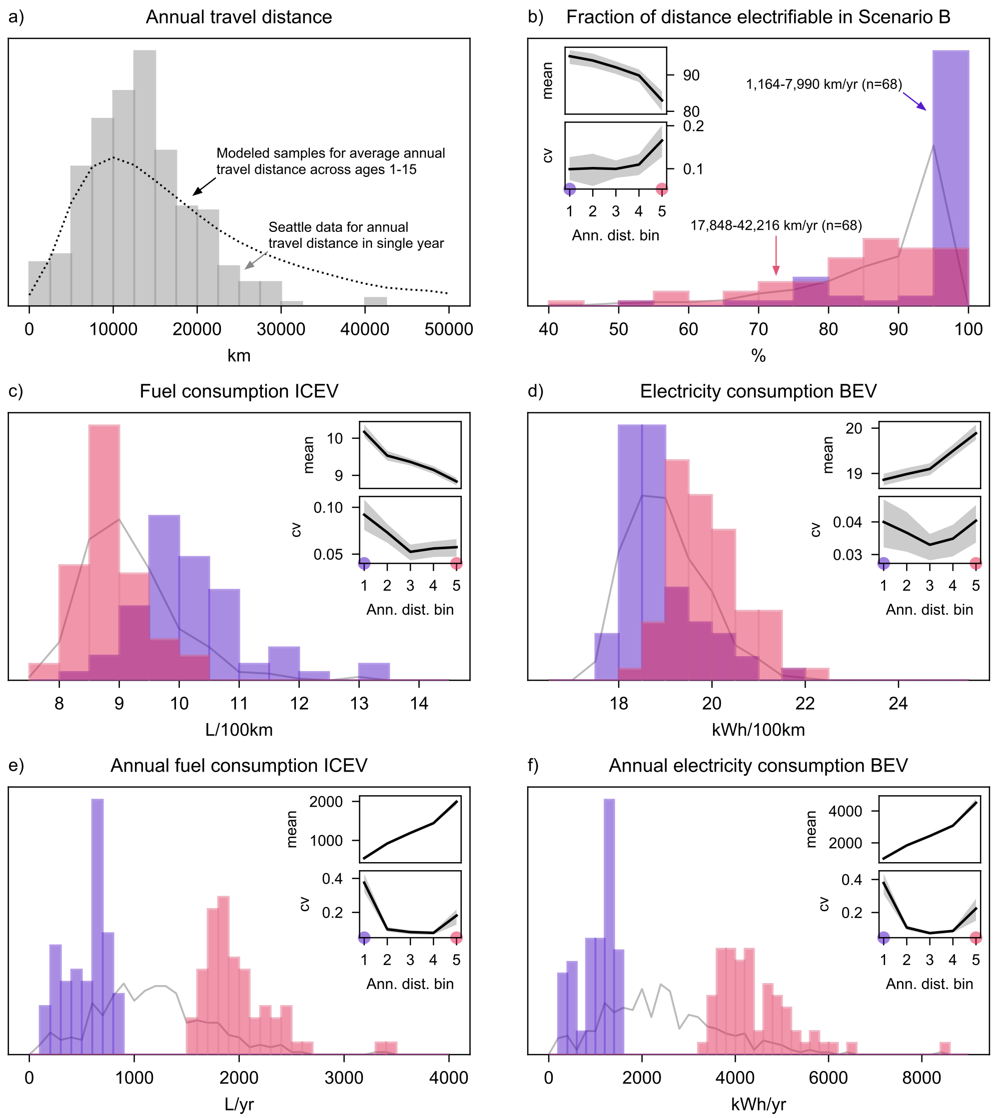

Figure 4-8: Heterogeneity of indicators across the 337 individual vehicles in the Seattle longitudinal dataset that made more than 50 trips in 2005 and whose household is located in suburban areas of Seattle with a population density of between 2,500 and 8,000 people/mi^2. For indicators 2-6 (b-f), separate distributions are shown for people whose annual travel distance in that year was in the lowest quintile (1,164–7,990 km/year) and for people whose annual travel distance in that year was in the highest quintile (17,848–42,216 km/year). The mean and coefficient of variance (cv) of those distributions as a function of the annual travel distance quintile is shown in the small inset figures. Shaded areas in the insets represent the 95% confidence interval of the corresponding mean, evaluating using the boostrap. The overall distribution (across all 337 vehicles) is shown as a grey line in the background. For each vehicle in the Seattle database, results are calculated 10 times, once for each class-type combination shown in Table 4.4), and then averaged across all ICEVs and BEVs. Additional indicators are shown in Figure B-9 in Appendix B.

Fuel consumption per distance and annual travel distance are less strongly correlated across individual vehicles than they were correlated across regions, however. In addition, annual travel distance is more heterogeneous across individual vehicles than across regions (see Figure 4-5). As a consequence, the annual fuel consumption across individual vehicles is highly heterogeneous for both ICEVs and BEVs. There is a large number of vehicles in the fleet whose annual fuel consumption is far below the average, and there is a large number of vehicles in the fleet whose annual fuel consumption is far above the average.

4.3.3 Impact of local climate on fuel efficiency and share of electrifiable trips

As shown in Figure 4-4, the fuel efficiency of gasoline ICEVs as a function of local climate is more sensitive to warm temperatures than to cold temperatures, while the opposite is true for BEVs (Figure 4-9). This sensitivity mostly results from electrical load from heating, ventilation, and air conditioning (HVAC) system components, but includes other aspects such as powertrain efficiency. In both cases, sensitivity to temperature is higher for urban driving, where average driving speeds are lower, than for rural driving. The fraction of trips not electrifiable also increases with increasing auxiliary load, and can almost double in areas with very cold winters and hot summers.

The average difference between the ambient index temperature, as defined in Figure 4-1, and the reference temperature of 20 °C is larger for negative deviations (cold weather) and positive deviations (warm weather). The coldest state is Alaska, with an average negative deviation of -16 °C, weighted by where vehicles are located and by the time of day people typically drive. The state with the highest year-round average warm temperature effect is Florida, with an average positive deviation of 7 °C. The effects of positive and negative deviations from 20 °C are cumulative. Nonetheless, Florida remains the state with the highest average fuel consumption per distance of ICEVs due to climate, and Alaska the state with the highest average electricity consumption of BEVs due to climate among all 50 states.

4.3.4 Validation of trip pattern adjustment algorithm for BEVs in Scenario B

We find that the current travel patterns of Nissan Leaf BEVs, as measured in NHTS, closely resembles those of Scenario B, where long trips are removed from the trip distance distribution (Figure 4-10). In NHTS, the Leaf has a 25% lower annual travel distance than the Civic, and makes almost 3 times fewer travel days with a cumulative daily travel distance of more than 100 km. Both of these metrics closely resemble the output of our model in Scenario B.

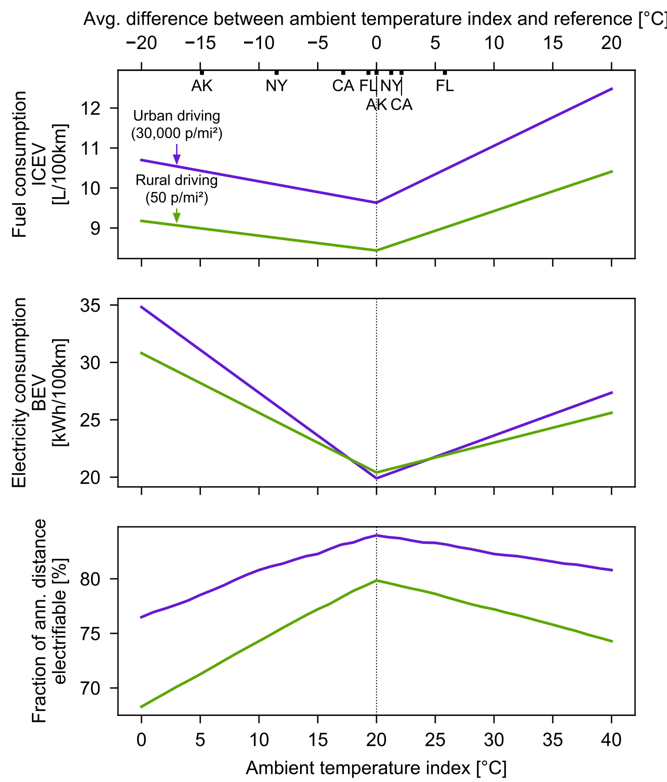

Figure 4-9: Impact of local climate on fuel consumption per distance for ICEVs (top), BEVs (middle), and of the fraction of electrifiable trip distance, β (bottom), depending on the average difference between the ambient temperature index (see Figure 4-1) and the reference temperature of 20 °C (hour-degrees per hour of heating or cooling load; see Equation 4.9). Results are weighted across the five classes shown in Table 4.4). Indicated at the top is the average difference in 4 States: Alaska (AK), New York (NY), California (CA), and Florida (FL), weighted both by at what time of day people drive, and where in the state vehicle are located. Note that the effects of negative deviation from 20 °C (cold temperature effect) and positive deviation (warm temperature effect) are cumulative: to obtain the final average fuel consumption per distance in a given state due to temperature, the two differences to the lowest point on the curve must be added. Effects differ for urban and for rural driving due to the different average driving speed.

For the Tesla Model S and X, we observe a smaller drop in annual travel distance compared to comparable ICEVs, and no change in the frequency of long trips (Figure 4-10). Our model reflects both of these observations, although the corresponding metrics observed in NHTS data are subject to high uncertainties due to the limited number of samples. The smaller differences between the trip patterns of these vehicles and corresponding ICEVs compared to what we observed for the Nissan Leaf may be a result of the combination of a higher battery capacity (at least 75 kWh for the Teslas, compared to 24-40 kWh for the Leafs) and the availability of a network of fast chargers in many locations. Our model takes into account battery capacity in adjusting average annual travel

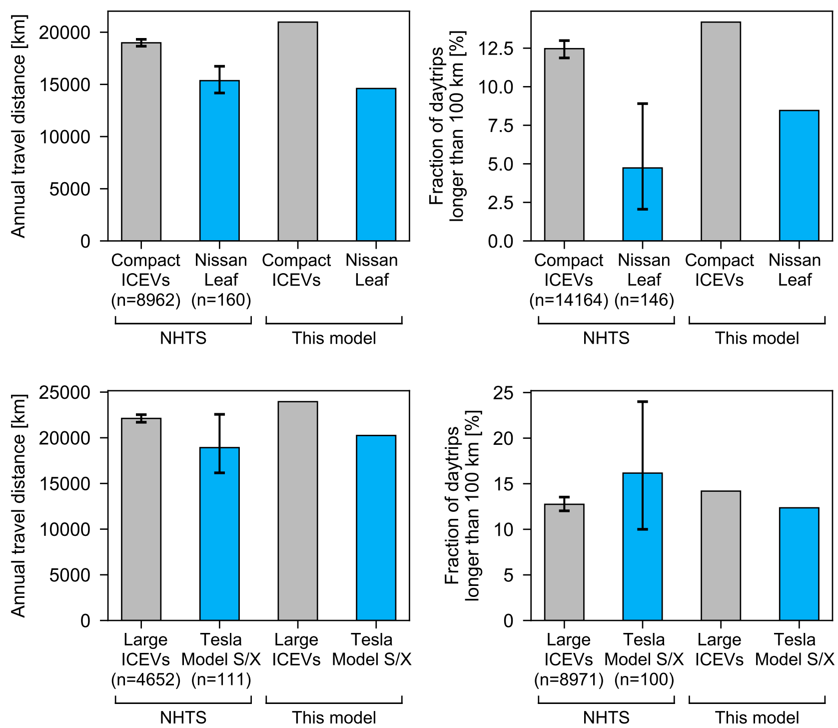

Figure 4-10: The difference in annual travel distance (left) and the frequency of long trips (right) between ICEVs and BEVs, as measured in the data and calculated by our model. The error bars reflect the 95% confidence interval of the corresponding population-average mean, evaluated using the bootstrap. Note that the BEVs in NHTS have different battery capacities, depending on their model year and trim levels, while the BEVs we model in this chapter have a fixed battery capacity for a given model, indicated in Table 4.4.

distance and the frequency of long trips, but does not consider differences in charging station availability between different models.

4.4 Discussion

In this chapter, we investigate the determinants of energy consumption and emissions resulting from personal vehicle travel with gasoline internal combustion engine and battery electric vehicles. Based on the heterogeneity in these determinants across regions and across individual vehicles within those regions, we quantify the variation in fuel consumption per distance, annual travel distance, and the share of trips that would be electrifiable with a BEV. We show that both ICEV and BEV fuel efficiency vary considerably across regions—ICEV efficiency mostly due to local driving patterns, BEV efficiency mostly due to local climate—and that ICEV fuel efficiency is more sensitive to individual driving patterns. We also show that there is a certain amount of variation of annual travel distance and the fraction of trip distance that is electrifiable across location and vehicle models, but there substantially more variation in these two indicators across individual vehicles.

To calculate emissions and costs of ownership of different vehicles, the product of annual travel distance and fuel consumption per distance, annual fuel consumption, is often used. We find that average annual travel distance is correlated positively with average trip length, and for ICEVs, negatively with average fuel consumption per distance. Because of this correlation, annual fuel consumption varies less across locations than either annual travel distance or fuel consumption per distance. The observation that annual fuel consumption is relatively constant across different locations is analogous to the notion of a constant travel time budget [102, 140].

The observed variation in indicators across regions is largely guided by population density. Within a given population density bracket, however, there are outliers. One of the most notable outliers is New York City, where average annual fuel consumption per vehicle is 20%-40% lower than for other locations in the same population density bracket. At the same time, the number of vehicles per capita is lower by almost a factor of four compared to the rest of the country, including other urban areas (see Table B.3 in Appendix B). This supports the notion that properties of the built environment, including access to other modes of transport, can strongly affect travel demand for personal vehicle travel and therefore emissions—even if under a fixed total travel time budget. At the same time, replacing a single, average ICE vehicle with a BEV may yield lower emissions benefits in New York City than other urban areas, since average annual travel distance and fuel consumption per distance are lower.

In any region, annual travel distance, fuel consumption per distance, and annual fuel consumption vary considerably across individual vehicles. Therefore, in any region, there are numerous vehicles for which a replacement with a BEV would lead to substantially higher energy and emission savings than for the average vehicle in that region. This variation is caused not only by differences across different vehicle classes, but also indiviudal driving patterns. Annual travel distance is also correlated with fuel consumption per distance and the frequency of long trips among individual vehicles. However, there is enough variance in each of those factors there are numerous vehicles that make frequent short and/or slow trips but still have a high total travel distance. Fundamentally, this considerable heterogeneity suggests that while population-aggregate behavior adheres to certain constants even across dense urban and rural areas, individual human behavior always exhibits a substantial amount of variation.

The framework and results presented here can inform the spatial evaluation of emissions and costs of different light-duty vehicle technologies. This potential is explored in Chapter 5. Our results can also improve our fundamental understanding of the determinants of energy use and emissions resulting from personal vehicle travel activity, and how these determinants might change as we electrify our light-duty vehicle fleet. Furthermore, our results can assist the development of tools that inform consumers directly about expected fuel efficiency, emissions, and costs of different cars, based on location and on estimated annual travel distance. Existing platforms that make personalized vehicle recommendations based on individual driving patterns, such as MyGreenCar [144], require users to collect actual driving data first, and are limited in their ability to consider the randomness of driving patterns over time. This framework can serve as a baseline for combining instantly available predictions for vehicle-specific fuel efficiency and related indicators with updates for those predictions based on personally collected travel data.

Chapter 5

Heterogeneity in emissions savings and costs of battery electric vehicles

Abstract

Battery electric vehicles (BEVs) promise to lower GHG emissions, but their effective emission reductions are subject to scientific and public debate. Most studies that compare the lifecycle GHG emissions of battery electric vehicles (BEVs) with combustion engine vehicles (ICEVs) consider vehicles operated under average conditions with average drive patterns. Building on the results from Chapter 4, we evaluate how the difference in lifecycle emissions and costs of ownership between BEVs and gasoline ICEVs varies across locations in the United States, and across individual vehicles within those locations. We consider the impact of annual travel distance, typical speed profiles, the frequency of long trips, local climate, the local electricity mix, and local taxes and fees. We find that the emissions savings of a typical BEV range from 900 kgCO_2eq/year to 3600 kgCO_2eq/year, depending on location. The electricity mix is the most important contributor to this variation, followed by local climate. The difference in costs of ownership between BEVs and ICEVs also varies with location, driven by local fuel prices and taxes. The typical BEV is more affordable than a comparable ICEV across the country, without subsidies. Different vehicle classes and individual driving patterns within a given region each lead to as much variability in emission and costs of BEVs compared to ICEVs as all regional factors together. Combined, these effects mean that a share of 10% BEVs in the fleet can reduce fleet-wide emissions by anywhere between 1% and 10% compared to if those BEVs had been new ICEVs. We also estimate that BEVs sold in 2018 have achieved almost double the emissions reductions that one would estimate based on compact cars operated under average conditions. These results can inform the evaluation of regional efforts to decarbonize transport and can be used to create platforms that provide personalized information on the emissions and costs of different cars to consumers.[1]

[1]A version of this chapter is in preparation for submission with co-author Jessika E. Trancik. [139]

5.1 Introduction

Existing studies have found that battery electric vehicles (BEVs) reduce greenhouse gas (GHG) emissions by about 25-40% with an average U.S. or European electricity mix compared to gasoline internal combustion engine vehicles (ICEVs) of similar size and class [96, 154, 23, 138] (see also Chapter 2). The reductions tend to be higher when fuel economy ratings have been adjusted for real-world driving patterns and the consumption of auxiliary electrical equipment such as lights and air conditioning, as is the case in Chapter 2. The BEV emissions savings in percent have been found to be relatively consistent across different vehicle sizes and classes. Most emissions originate from the operating phase [96, 138].

However, the above studies do not capture the variability in emissions savings resulting from replacing a specific vehicle with a BEV. For instance, studies found that within the US, regional differences in the electricity mix [90, 184] and local climate [208] can impact emission intensity of the Nissan Leaf considerably. This heterogeneity implies that the difference in emission between the Nissan Leaf a comparable ICEV depends on the specific location within the U.S. where the Leaf is operated. At the same time, the sales of electric vehicles are spread unevenly across space. More than 50% of electric vehicles sales in the U.S. have occurred in California [71], where the combined market share of BEVs and plug-in hybrids has reached almost 10% [71]. This interaction between spatially heterogeneous emissions savings and BEV adoption patterns implies that the emissions reductions achieved by BEVs on the ground are likely different from what is suggested by studies that consider country-wide average emissions reductions. In addition, location-specific information on the emissions of driving different types of vehicles can be used to provide personalized information to consumers, and to design efficient policies that aim to maximize emission reductions achieved by electrifying road vehicle powertrains.

The electricity mix and local climate are not the only factors affecting emissions of electric vehicles. Driving patterns and traffic conditions affect average fuel efficiency (fuel economy) [128, 206] and annual miles traveled. Variations in driving patterns can also have implications for the potential to electrify longer trips [151, 128] (see also Chapter 4). Notably, driving patterns don't just affect operating emissions of BEVs, but also those of ICEVs. The effects of driving patterns on BEV and ICEV operating emissions can result in a net larger difference in emissions between BEVs and ICEVs. The same is also true for local climate, where ambient temperature and weather conditions affect the fuel efficiency of ICEVs and BEVs in different ways, as shown in Chapter 4.

In addition to systematically varying across regions, driving patterns may also vary across individual vehicles within a region—and with driving patterns, average annual travel distance and fuel efficiency. Research has shown that each person's daily and annual travel routines are different, even among people living in a similar location [88, 15, 188]. As a result, emission reductions resulting from a new BEV being added to the fleet instead of a new ICEV may vary substantially across individual vehicles in a given location and of a given vehicle class.

As discussed in Chapter 2, it is important to consider the costs of BEVs relative to similarly sized ICEVs to evaluate their potential to reduce GHG emissions. High upfront costs are suspected to be one of the main inhibitors to electric vehicle adoption [32, 174, 14, 118]. As is the case with emissions, the difference in costs between BEVs and ICEVs is likely to vary substantially across space as well [207]. Gasoline and electricity prices, for instance, may influence operating costs of both vehicle types, and have been found to have a substantial impact on the willingness to adopt BEVs [109]. Driving patterns, both their systematic variation between locations as well as individual heterogeneity between vehicles, can also be expected to contribute to the heterogeneity in costs.

In this Chapter, we aim to evaluate the heterogeneity in emission savings and cost increases of BEVs compared to gasoline ICEVs. We address four key elements that are missing in current literature on the heterogeneous emissions reduction potential of BEVs. First, we model how driving patterns affect the emissions reduction potential, making use of the results from Chapter 4. Second, we not only evaluate GHG emissions, but also costs of ownership to consumers. This allows us to gauge whether electric vehicles are more affordable than comparable ICEVs in some parts of the country even without subsidies, and whether lower costs correlate with higher emissions savings. To do so, we rely on the framework from Chapter 2. Third, we model both BEVs and ICEVs, and calculate the spatial heterogeneity of the difference in emissions and costs between the two. And fourth, we combine an evaluation the heterogeneity in emission reductions of BEVs compared to ICEVs across space with an evaluation of this heterogeneity across individual vehicles within a region. This aspect is also based on the results from Chapter 4, and helps us identify the importance of personalized information on emissions and costs of different types of vehicles.

The central goal of this chapter is to establish a framework that can be used to provide personalized information to consumers about the emissions and costs of different types of vehicles and to quantify the effects of regional light-duty vehicle policies. As such, this work may be of interest to current and future car owners, cars manufacturers, and policymakers alike. The analysis also

Table 5.1: List of factors that vary across space, individual vehicles (in a given location), and time (for an individual vehicle). For each factor, the table indicates whether it affects GHG emissions and/or costs, and whether it applies to internal combustion engine vehicles (ICEVs) and/or battery electric vehicles (BEVs).

		Varies across			Affects...				...of...	
		Locations	Vehicles (in given location)	Time (for given vehicle)	Annual travel distance	Fuel efficiency	Emissions intensity of fuel / veh.	Cost intensity of fuel / veh.	ICEV	BEV
1	Electricity mix	X		X			X			X
2	Annual travel distance	X	X	X	X				X	X
3	Typical speed profiles[a]	X	X		X				X	X
4	Frequency of long trips	X	X		X	X				X
5	Local climate[b]	X		X		X			X	X
6	Household electricity price	X						X		X
7	Gasoline price	X						X	X	
8	Taxes, titles, and fees	X						X	X	X
9	Vehicle model / class	X	X		X	X	X	X	X	X

[a] Drive cycles refer to typical profiles of speed over time, which affect average fuel economy achieved with different vehicles. [b] Local climate affects the use of heating and air conditioning systems in vehicles. They also have a small effect on powertrain efficiency and drag.

lets us test and provide quantitative answers to popular questions asked by prospective BEV owners, such as: Do BEVs reduce more emissions in cities or in rural areas? Does cold weather affect the emission reductions of BEVs? Do places where the gasoline price is low much better when comparing BEV costs to ICEV? And do emission reductions vary substantially from one vehicle to another?

This chapter is organized as follows. In the next section, we describe the methods used for our analysis. Then, we evaluate the spatial heterogeneity of the difference in emissions and costs between BEVs and ICEVs, before extending the analysis to individual driving patterns and different vehicle classes. Finally, we discuss the significance of our results for key decision-makers.

5.2 Methods

We model the difference in GHG emissions and costs of ownership for five different pairs of vehicles, each of which consists of a BEV and an ICEV. The pairs are identical to those used in Chapter 4. Lifecycle emissions and costs are calculated using an extended version of a parametrized emissions and cost model from Chapter 2 [138]. We combine this model with the driving pattern analysis and vehicle energy model introduced in Chapter 4 and several additional data sources to calculate differences in annual emissions and costs between BEVs and ICEVs across regions within the U.S., and across individual vehicles within those regions. We then derive implications of the combined

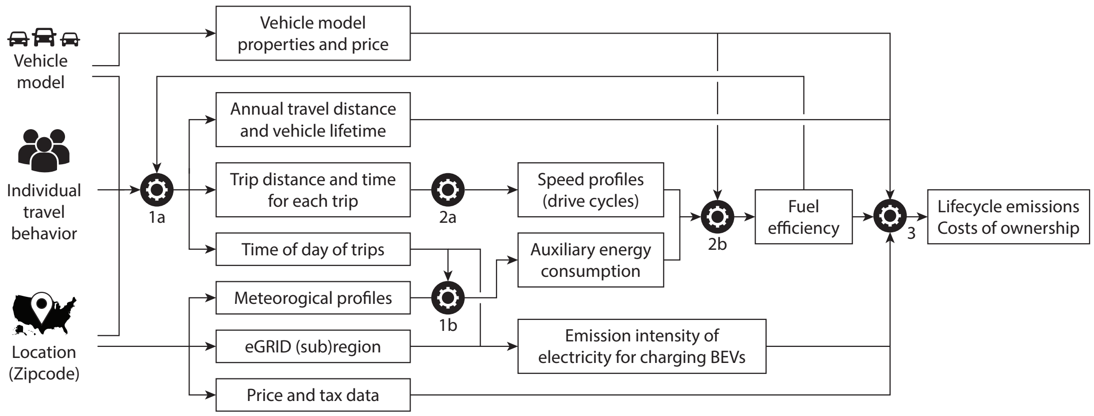

Figure 5-1: Flow of information showing how variability in lifecycle emissions and costs of ownership of personal vehicles is linked to vehicle model characteristics, individual travel behaviors, and location. A list of all factors that are taken into consideration is shown in Table 5.1. The cogwheels with numbers below them represent individual model components: (1a) a model that produces distributions for annual travel distance and trip distance and time for ICEVs and BEVs; (1b) a model that estimates the consumption of air conditioning and heating systems based on meteorological conditions; (2a) a model that probabilistically matches GPS-based speed profiles to trips based on their distance and time (TripEnergy, [128]); (2b) a model that converts speed profiles and auxiliary load into fuel economy; and (3) a parametrized emissions and cost model. 1a, 1b, 2a, and 2b are explained in Chapter 4. 3 is based on Chapter 2 (see Appendix A, section A.3), and modified as explained in Appendix C, section B.1.

heterogeneity for meeting greenhouse gas reduction targets.

5.2.1 Model overview

We calculate the difference in GHG emissions and costs between BEVs and ICEVs, using five different BEV-ICEV pairs that represent five vehicle classes. Together, the five comparisons reflect a wide range of vehicle sizes, classes, and performance levels. We then calculate the average across these five pairs, weighted by the share of each vehicle class in a given region. Characteristics of these vehicles are shown in Table 5.2. Pick-up trucks, vans, and two-seater sports cars are not considered as there currently are no BEV alternatives for these vehicles on the market.

For each of the five comparisons, we evaluate how the difference in emissions and costs varies across locations within the United States and across individual vehicles within those locations. For regional differences, we consider driving patterns, local climate, electricity mix, fuel costs, taxes and fees, as well as the local vehicle class mix (Figure 5-1, Table 5.1). For differences across individual vehicles, we consider driving patterns and the vehicle class. A list of all factors is provided in Table 5.1.

Table 5.2: Vehicle models used in this Chapter. The models are identical to those assessed in Chapter 4 (see Table 4.4). To calculate the difference in emissions between BEVs and ICEVs, the five comparisons are weighted by the class shares indicated in the last row, normalized to 100%. Unless annotated otherwise, properties are obtained from publicly available certification data [67] and manufacturer websites.

	Comparison 1 (compact car)		Comparison 2 (mid-size or compact executive car)		Comparison 3 (large car)		Comparison 4 (compact crossover sport-utility vehicle)		Comparison 5 (mid-size sport-utility vehicle)	
	Honda Civic	Nissan Leaf	BMW 3-series	Tesla Model 3	Mercedes S-Class	Tesla Model S	Chevrolet Equinox	Hyundai Kona	Audi Q7 55 SE Prem.	Jaguar i-Pace
Trim	5-door 1.5L Manual	Base	330i	Standard plus	S450 4matic	75D	2.0L FWD		3.0L Auto AWD	
Technology	ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV	ICEV	BEV
Model year	2019	2019	2019	2019	2019	2019	2019	2019	2019	2019
U.S. sales in 2018[a]	325,760	14,715	44,578	140,317	14,978	25,745	332,618	0[b]	37,417	393[b]
Curb weight (kg)	1332	1557	1625	1645	2125	2163	1564	1685	2145	2170
Rated power (hp)	158	214	255	282	362	398	252	201	333	400
Rated fuel econ.[c]	34	112	28	131	22	111	25	120	21	76
—L or kWh/100 km	7.1	18.8	8.3	16.0	10.8	18.9	9.2	17.5	11.2	27.6
Battery cap. (kWh)		40		50		75		65		75
Price excl. tax (USD)	23,050	29,900	40,250	38,990	94,250	76,000	29,700	36,950	62,250	68,700
Avg. share of class[d]	10%		18%		8%		21%		9%	

[a] Listed sales are new cars sold across all available trims and model years between January 1st 2018 and December 31st 2018; [37] [b] The Hyundai Kona was introduced into the market in 2019, the Jaguar i-Pace in late 2018; [c] U.S. fuel economy ratings are adjusted for aggressive driving, cold starts, air conditioning use, and electric vehicle charging losses, and may differ from fuel efficiency rating for the same vehicle models in other countries; [d] Average share of vehicle class, as per 2017 NHTS. Shares have been obtained by matching make and model codes in NHTS to EPA vehicle class definitions. Classes not covered in this analysis, because there are no corresponding BEVs, include pickup trucks (27% of vehicles), vans (6%), and 2-seater sports cars (1%).

As was the case in Chapter 4, the fundamental geographical unit of analysis is the zipcode. To model driving patterns, each zipcode is matched with travel survey data based on the zipcode's average population density and state. To model climate-related auxiliary loads of vehicles, each zipcode is matched with the three closest meteorological stations based on the longitude and latitude of the zipcode's center (see Table 4.3 in Chapter 4). To collect price and tax information as well as region-specific emission factors for electricity, each zipcode gets matched with corresponding data based on which electricity grid, state, or metropolitan area the zipcode falls into (see Tables C.1–C.3 in the Appendix). Results that consider multiple zipcodes at once, such as a distribution of emission reductions of BEVs across the entire U.S., are weighted using each zipcode's estimated number of vehicles (see also Table 4.3).

5.2.2 Modeling lifecycle emissions and cost of ownership

Lifecycle GHG emissions and costs of ownership are calculated using an existing, parametrized model that estimates emissions and costs as a function of key vehicle characteristics [138]. As was the case in Chapter 4, we calculate emissions and costs on a per-vehicle-year basis, rather than the per-vehicle-km unit used in Chapter 2. We argue that the former more closely reflects the total emissions savings achievable by replacing one internal combustion engine vehicle with one electric vehicle.

The GHG emission parameters are based on the lifecycle inventories of Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET), developed at the Argonne National Laboratory (ANL) [12]. It takes into account emissions from the fuel cycle, including fuel production and distribution, and the vehicle cycle. For this study, we update the previous model from Chapter 2 [138] to reflect the 2018 inventories of GREET as described in Appendix B of Chapter 4.

The original cost of ownership model takes into account vehicle purchasing price, fuel costs, and maintenance costs [138]. Here, we extend the model to estimate vehicle depreciation (rather than just modeling the purchasing price) and to include state-specific taxes, title, tags, and fees due upon acquisition of a new vehicle. The revised cost model is described in Appendix C, section B.1.

While regular maintenance costs are included, we do not consider repair costs. These costs are less predictable, and model-specific data is scarce. We also exclude insurance costs, as these tend to depend as much on characteristics of the vehicle owner as they depend on properties of the vehicle itself.

We also note that our cost model does not consider federal and state subsidies currently available electric vehicles. The federal subsides are ending soon, or have already ended, for some manufacturers [52]. Others, such as the state subsidies in California, are only applicable to households below a certain income. In the Appendix, we show an example of how results are affected if Federal subsidies were taken into account (Figure C-12).

5.2.3 Heterogeneity in annual travel distance and fuel efficiency

We rely on the modeling framework and results from Chapter 4 to model the heterogeneity in annual travel distance and fuel efficiency of different vehicles. The modeling procedures described in this subsection are explained in detail in Chapter 4. To model the heterogeneity across regions due to driving patterns, the National Household Travel Survey (NHTS, [78]) data is split into 49 subsections. Each subsection represents one of eight population density brackets from 50 to 30,000 people/mi^2 and one of 6 states for which we have the most data (New York, California, Texas, Georgia, Wisconsin, and North Carolina) or all others. The 49 combinations are listed in Table 4.2 in Chapter 4. Population-average annual travel distance is then calculated for each subset.

To calculate the population-average annual travel distance for a given NHTS subset, we average the population-average annual travel distance for each vehicle age up to the vehicle's lifetime. In this study, we use a lifetime of 15 years [48] to calculate lifecycle GHG emissions, and an average duration of first ownership of 7 years [197] to calculate costs of ownership during those 7 years.

To calculate the population-average fuel efficiency for a given NHTS subset, we use TripEnergy [151, 128], the vehicle model introduced in Chapter 3 and expanded in Chapter 4. This model probabilistically matches information on trip distance and duration for each individual trip in a travel survey (here, NHTS) with detailed speed profiles from a GPS-based drive cycle database, and combines these matched profiles with a parametrized vehicle energy model to calculate fuel efficiency. The combined trip matching and vehicle energy model has been found to yield average errors of 7% compared to detailed vehicle simulators given full drive cycle data [151]. We expanded in Chapter 4 to account for engine cold start and to include a more detailed evaluation of the impact of meteorological conditions on fuel efficiency.

To model the heterogeneity in fuel efficiency across regions due to local climate, we calculate a temperature index for each of the 1020 meteorological stations in the TMY3 dataset [200, 147]. This temperature index is then used in the extended TripEnergy vehicle model to account for impacts of climate on fuel efficiency. We weigh this index by the time of day that people drive in each of the NHTS regions. Information on spatial heterogeneity of driving patterns and on local climate are then combined by matching both types of information to each of the 32,989 zipcodes.

We match the aggregate distribution in annual travel distance and fuel efficiency across regions with a distribution of the same indicators across individual vehicles within Seattle using an additional, longitudinal travel survey dataset [162]. To calculate the average annual travel distance and the lifetime of an individual vehicle, we combine an autocorrelation-model to sample annual travel distance in each year with a survival-rate model to sample at what age the vehicle is removed from the fleet. This procedure is explained in Section 5.2.4 in Chapter 4.

One concern of BEVs is their limited battery capacity. Because the range of BEVs is limited; their recharging time is longer than the refueling time of ICEVs; and the density of charging stations is smaller than the density of gasoline stations, BEV owners may chose to use a different vehicle to undertake particularly long trips [151]. In Chapter 4, we introduced two scenarios: Scenario A and Scenario B. In Scenario A, BEVs have the same travel patterns as ICEVs of the same class. In Scenario B, we assume that only those daytrips (the cumulative sum of individual trips made during a given travel day) whose energy consumption exceeds 80% of the BEV's energy consumption are removed from the trip distance distribution. This removal of long trips affects the annual travel distance as well as the average fuel efficiency, because the average fuel efficiency of the removed trips may be different from the average fuel efficiency across all trips.

We showed that travel patterns of the Nissan Leaf observed in NHTS closely match those of Scenario B (Figure 4-10). In this Chapter, we therefore work with Scenario B as a baseline. Specifically, only those trips included in Scenario B are considered to calculate the emission reductions and costs of BEVs compared to ICEVs. This reflects the assumption that the long trips removed from the trip distance distribution are made with a different vehicle or mode whose emissions and costs per distance are similar to the emissions and costs of the ICEV that the BEV is compared to. The trips that cannot be electrified in Scenario B are made with an ICEV that corresponds to the baseline ICEV of the comparison shown in Table 5.2. Therefore, the non-electrified trips do not contribute to the difference in annual emissions or costs between ICEVs and BEVs.

In Figure 5-7 and C-12, we relax this assumption to consider Scenario A. Scenario A reflects a case where charging infrastructure is abundantly available, charging speed is not perceived as a deterrent to make long trips with BEVs, and people are willing to adjust their travel behavior to charge BEVs on long trips. In either scenario, we do not consider rebound effects, such as a more frequent use of the BEV due to lower operating costs. The results shown in Figure 4-10 in Chapter 4 suggest that such rebound effects, if they exist, are either small, or cancel themselves out with other aspects affecting the travel behavior of BEV owners.

5.2.4 Heterogeneity in the electricity mix

The electricity generation mix is based the average generation mix in each of the 26 eGRID subregions [66]. Emission intensities in 2016 range from 140 (NYUP) to 797 (HIOA) gCO_2eq/kWh, including losses from the transmission and distribution of electricity. Charging losses are included in the fuel economy calculations.

We adjust the eGRID subregion electricity emission factors depending on what the time of day charging occurs, based on when each trip ends. The adjustment factors, relative to the average emission factor for the corresponding region, are derived from previous work [90], using consumption-based marginal emission factors of the corresponding eGRID major region (not subregion, as those are not available). For instance, the 2016 eGRID emission factor for the SERC Mississippi Valley subregion is 398 gCO_2eq/kWh [66]. The marginal emission factor in the corresponding eGRID region, SERC, at 8 AM was estimated to be 395 gCO_2eq/kWh, 30.3% lower than the average (attributional) emission factor at the time of 566 gCO_2eq/kWh [90]. Therefore, the emission factor in the SERC Mississippi Valley subregion at 8 AM is calculated to be $398\,(1-0.303) = 277$ gCO_2eq/kWh. All final emission factors as a function of time of day are shown in Table C.3 in the Appendix.

We acknowledge the limited spatial resolution and temporal accuracy of hourly marginal emission factors that we use. In addition, the calculation of marginal emissions is subject to a wide range of assumptions, including whether a generation- or consumption-based electricity mix is used, whether and how transmission capacity constraints are taken into account, and whether short-term marginal emissions (the response of the supply mix to instantaneous changes in demand given current infrastructure) or long-term marginal emissions (the response of supply infrastructure to sustained changes in demand patterns) are considered. While different calculation approaches for emission factors could change the emission reductions of BEVs compared to ICEVs for a specifically selected location, the results presented in this work are robust to such uncertainties. In Appendix C, we show results for a case where fixed attributional emission factors are used instead of hourly, marginal ones (Figure C-12).

5.2.5 Heterogeneity in prices and taxes

All price parameters are based on publicly available data. The electricity prices are calculated by state, as the inflation-adjusted 10-year average between 2008 and 2017 [60]. The fuel prices are obtained by metropolitan area, state, or U.S. subregion, depending on the most specific data available that matches the zipcode in question [61]. Fuel prices are also determined using a inflation-adjusted 10-year average from 2008 to 2017. Separate prices are obtained for regular and premium gasoline. Vehicle tax, tag, title, and fees are estimated for each state and each vehicle model, based on the vehicle's manufacturer's suggested retail price (MSRP), using CarMax [36]. Tables containing all price data used can be found in the Appendix (Tables C.1 and C.2).

5.2.6 Modeling the implications of this heterogeneity for meeting emission targets

To asssess the implications of the variability in emissions savings of BEVs compared to ICEVs for meeting transporation climate targets, we compare fleet-wide emission reductions among all cars and SUVs as a function of the percentage of vehicles in the fleet that are new BEVs instead of new ICEVs. We then compare these emission reductions across different scenarios for BEV adoption patterns across locations and individual vehicles within those locations. We also estimate the share of BEVs required in the fleet to meet a 27% emissions reduction target compared to 2005 emissions. This target is based on the U.S. Nationally Determined Contribution (NDC), aiming to reduce country-wide GHG emissions across all sectors by 26-28% relative to the 2005 baseline [193].

To determine the fleet-wide lifecycle GHG emissions in 2005, we first estimate fleet-wide lifecycle emissions in 2019. We multiply average annual emissions per ICEV across the five vehicle classes shown in Table 5.2 by 194 million non-truck light-duty vehicles in 2019. We then adjust these emissions by -8% due to the smaller number of vehicle in the fleet in 2005 [53]. Average annual miles traveled per vehicle are not adjusted between 2005 and 2019, as they have remained steady since 2005 [79].

Next, we account for the difference in fuel efficiency between the average new 2019 ICEV and the average ICEV on the road in 2005. The average new car in 2017 had a 28% higher fuel efficiency than the average new car in 2005, and about a 22% higher fuel efficiency than the average car on the road in 2005 [70]. We lower this increase by 1% to 21% because some vehicles sold in 2017 were hybrids and electric vehicles. Given these trends, we extrapolate that the average new ICEV in 2019 (rather than 2017) has about a 24% higher fuel efficiency than the average car on the road in 2005. Since 11% of average ICEV lifecycle emissions come from vehicle production (see Figure 4-4 and 2-2), we estimate that the average lifecycle emissions of 2019 model ICEVs are $100 - 100/((89 * 1.24 + 11)/100) = 18\%$ lower than average lifecycle emissions of the average ICEV on the road in 2005. This implies an assumption that vehicle production emissions (per vehicle) and fuel supply chain emissions (per amount of fuel produced) have remained constant since 2005.

Based on these calculations, we estimate that the fleetwide emissions of 2019 model cars and SUVs are $100 - 100 \times 1.08 \times 0.82 = 11\%$ lower than average lifecycle emissions of ICEVs on the road in 2005. This decrease is compatible with an observed 7% decrease in overall transportation tailpipe emissions between the average vehicle on the road in 2017 and the average vehicle on the road in 2005 [69].

5.3 Results

5.3.1 Heterogeneity across locations within the United States

We find that the difference in GHG emissions and costs of ownership between BEVs and ICEVs range from -900 kgCO_2eq/year (BEVs emit 900 kgCO_2eq/year less than ICEVs) to -3600 kgCO_2eq/year (Figure 5-3a) across locations. There are no locations in the country where emissions of BEVs are higher than those of ICEVs. The electricity mix is the dominant factor contributing to regional differences, followed by local driving patterns and local climate (Figure 5-2a). Driving patterns alone, when all other factors are held constant, can lead to variations in the emissions reductions of BEVs by a factor of 1.5. A negative correlation between the impact of fuel efficiency and the impact of annual travel distance, however, means that BEVs reduce almost as much emissions per year on average in rural areas as in urban areas. Vehicles achieve the highest emission reductions in specific urban environments where average annual travel distance is higher than usual. Local climate alone also leads to variations in emissions reductions by a factor of 1.4. Only very cold climates, however, such as parts Alaska, result in substantial decreases in emissions savings of BEVs (see also the map in Figure 5-3).

Cost differences between BEVs and ICEVs are dominated by the level of prices, taxes, and fees in each state (Figure 5-3b, 5-2b). Driving patterns have a smaller, but still notable impact. In all locations, BEVs cost less than ICEVs, without taking into account subsidies for BEVs. Notably, the findings for costs are sensitive to the specific models used for the comparison (see models in Table

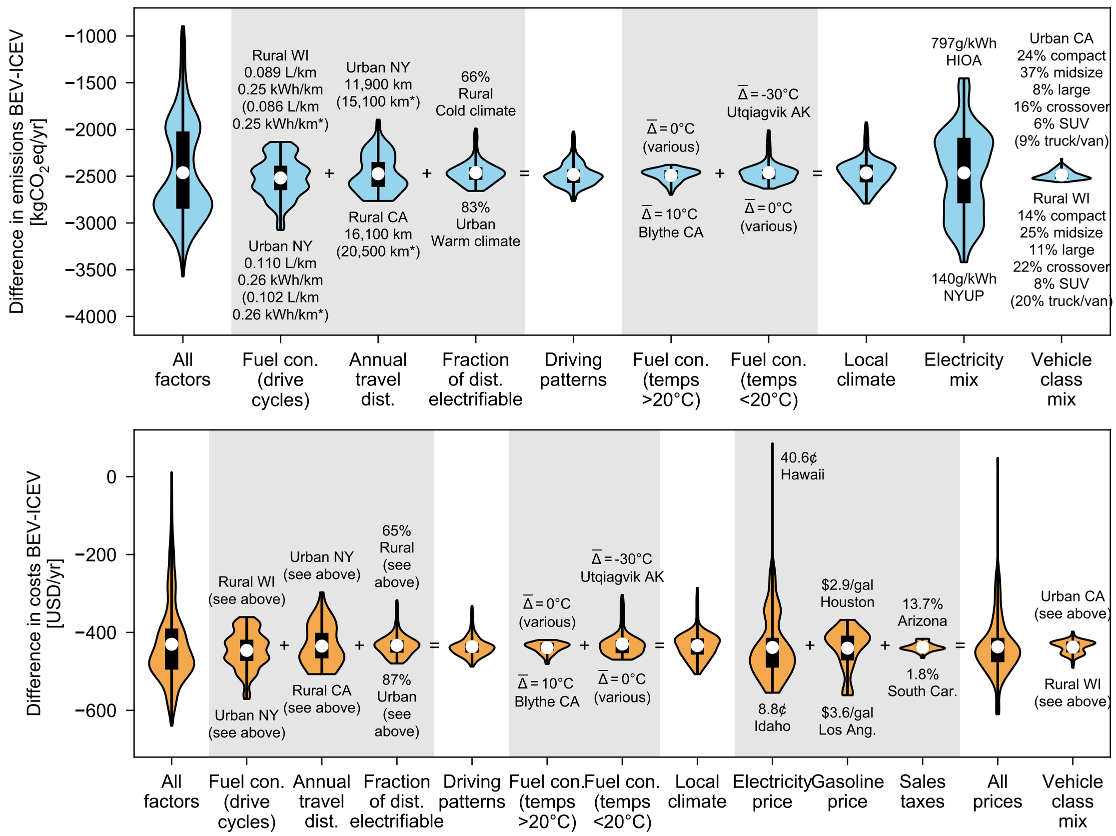

Figure 5-2: Probability density functions of the differences in lifecycle GHG emissions (top, blue) and costs of ownership (bottom, orange; without subsidies) between BEVs and ICEVs 5.1. The numbers reflect the weighted average of the five comparison pairs listed in Table 5.2, weighted by the share of each comparisons class in each location. Shown are all factors listed in table 5.1 individually, combined to groups (driving patterns, local climate, and prices), and combined into a single distribution. The values above and below each column indicate the underlying parameters corresponding to the extreme ends of the column. The values for temperatures above and below 20 °C indicate the average cooling and heating-degree hours per hour (average temperature difference), respectively, weighted by the time of day that people drive. For each individual factor, all other factors are set to their average. Fuel efficiency and annual travel distance values represent the average across the five vehicle classes in Table 5.2. Average ICEV emissions across the five classes are 5458 $kgCO_2eq$/year, average ICEV costs are $4727/year (including vehicle depreciation). Distributions of ICEV baseline emissions across regions are shown in Appendix C, Figures C-4 and C-5. A version showing metrics per km instead of per year is available in Appendix C (Figure C-1). *The values in brackets are the values obtained when including all trips, not just those trips that are electrifiable (see column 4 in above plot and the list of scenarios in Table 4.1).

5.2).

There are factors that have a considerable impact on the annual emissions and costs of both vehicles, but because the impact has a similar sign and magnitude for both vehicle types, the difference in emission and costs between the two vehicles is affected less. This is particularly true for the impact of warm temperatures on fuel efficiency: the consumption of air conditioning systems leads to a similar decrease in fuel efficiency in both cars (see Figure 4-4 in Chapter 4). Therefore, the difference in emissions and costs between the two cars is hardly affected, even though fuel efficiency decreases due to air conditioning usage in both cases.

5.3.2 Heterogeneity across individual vehicles in a given location

The difference in emissions and costs between BEVs and ICEVs varies substantially across individual vehicles in a given region (Figure 5-4). This variation can in part be attributed to different vehicle classes, with SUVs showing higher emission reductions can compact cars. We find that absolute emission reductions of the BEVs compared to ICEVs of the same class are higher for larger vehicles, especially SUVs, than for compact cars. These effects can be amplified in areas where BEVs achieve high emission reductions in general. Compared to the Audi Q7, the Jaguar i-Pace reduces emissions by 4100 kgCO_2eq/year under average conditions in urban California, which is almost 10 times the amount of the average reduction that the Nissan Leaf achieves compared to the Honda Civic in rural Wisconsin.

Individual driving patterns contribute substantially to the heterogeneity across individual vehicles as well (Figure 5-4). The heterogeneity in average annual travel distance leads to a variation in emissions of BEVs compared to ICEVs that can be larger than the variation across regions or vehicle classes. The impact of average annual travel distance is particularly large when baseline emission savings are high, for instance for SUVs in urban California. The relative importance of annual travel distance is substantially lower when emissions are evaluated per km instead of per year. We show results per km in Appendix C, Figures C-1 to C-3. We also observe that the time of day of charging, interacting with hourly emission factors of the electricity grid (see Table C.3, leads to a small variation in emissions of BEVs compared to ICEVs. The amount of this variation depends on the magnitude of variation of the electricity emission factors over time.)

Notably, the combined contribution to the variation in emissions savings of BEVs of the four aspects related to individual travel patterns shown in Figure 5-4 is smaller than the contribution of average annual travel distance alone (Figure 5-4). This is because annual travel distance is

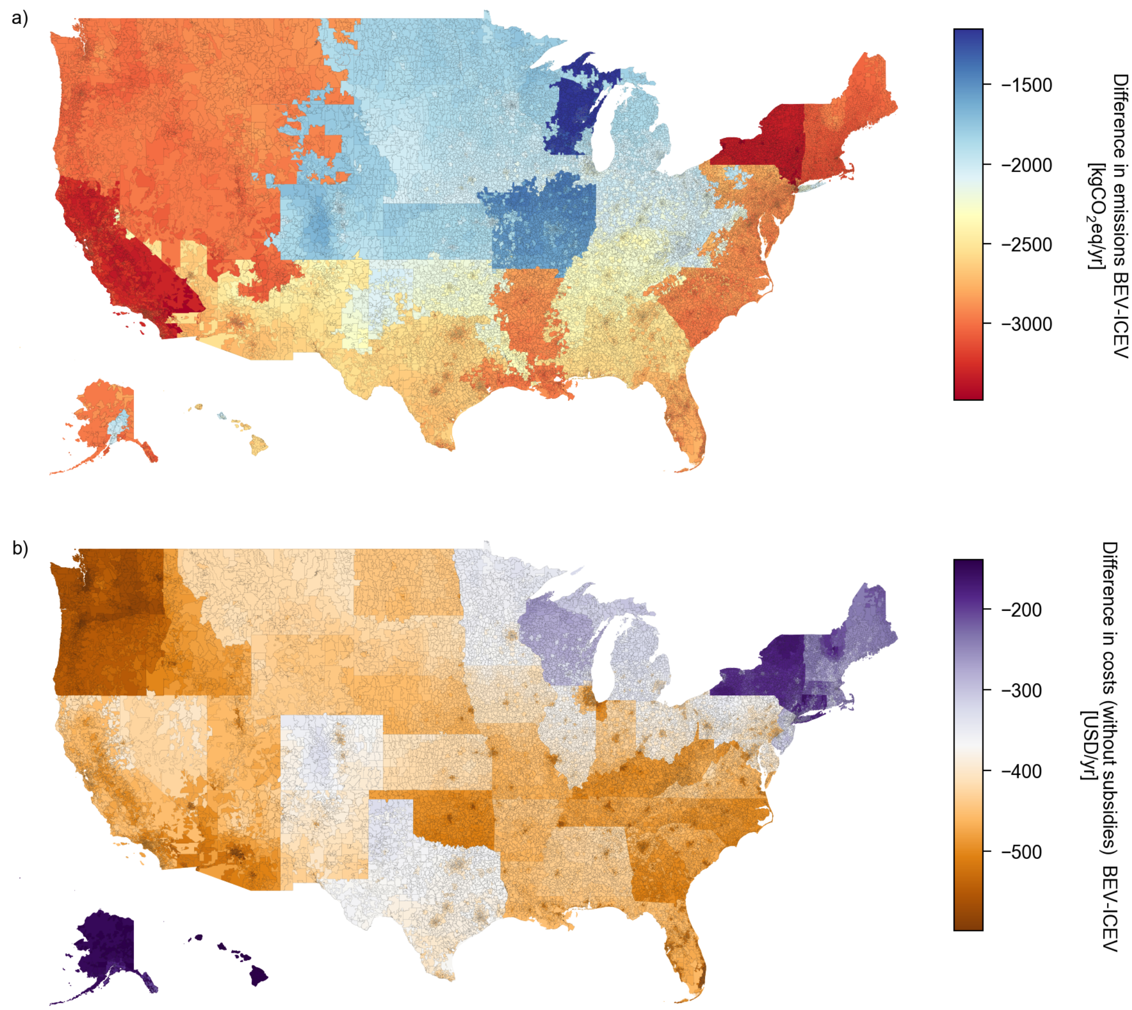

Figure 5-3: Difference in GHG emissions (top) and costs of ownership (bottom, without subsidies) between BEVs and ICEVs by zipcode area. A negative number means that BEVs have lower emissions or costs. The numbers reflect the weighted average of the five comparison pairs listed in Table 5.2, weighted by the share of each comparisons class in each location. Average ICEV emissions across the five classes are 5458 $kgCO_2eq$/year, average ICEV costs are $4727/year (including vehicle depreciation). Distributions of ICEV baseline emissions across regions are shown in Appendix C, Figures C-4 and C-5. Maps for each individual class, comparing two specific models, are available in Appendix C (Figures C-7–C-11). Note that small areas on these maps may contain a large number of vehicles; for probability density functions of the emission and cost differences, see Figure 5-2. The patches in the bottom-left corners show Alaska (left, shrunk by a factor of 15) and Hawaii (right, same scale as the U.S. mainland). A version showing metrics per km instead of per year is available in Appendix C (Figure C-2). The projection used is WGS 84/Pseudo-Mercator.

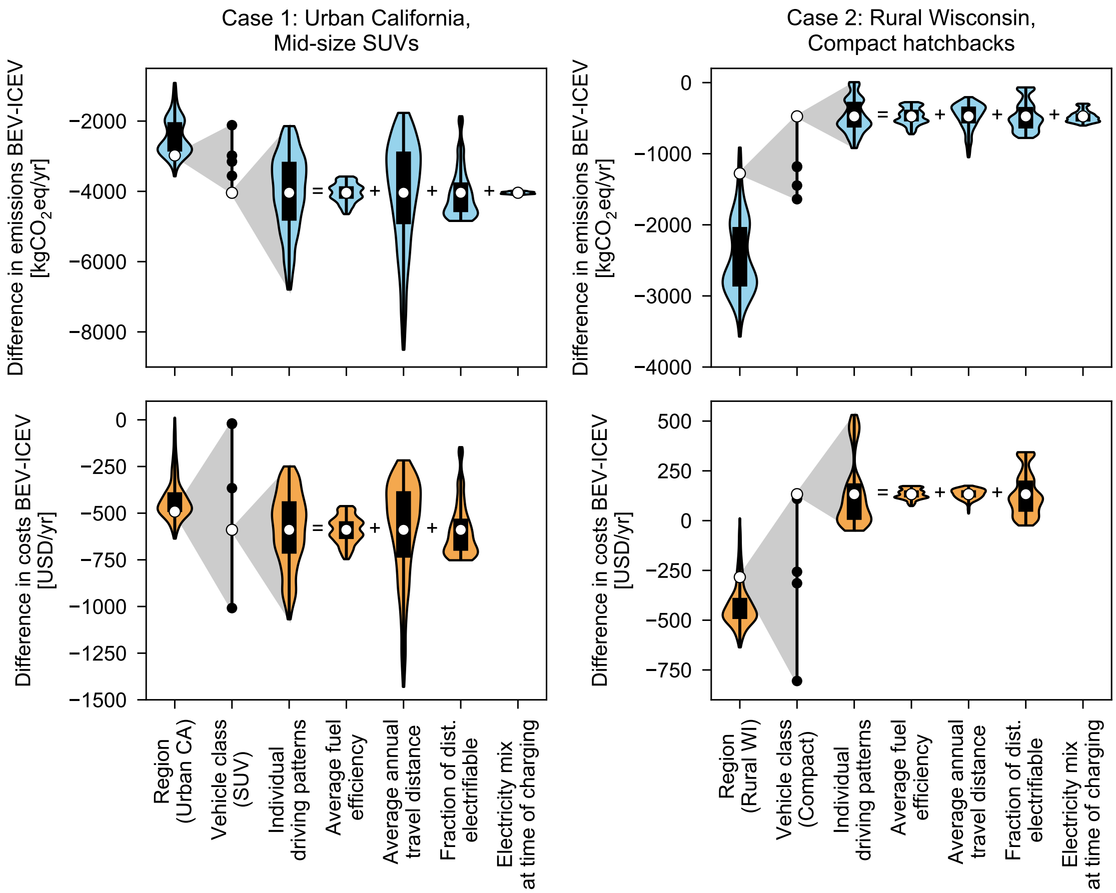

Figure 5-4: Impact of vehicle class and driving patterns of individual vehicles on the difference in lifecycle GHG emissions (top) and costs of ownership (bottom) between BEVs and ICEVs in two cases: (1) vehicles in urban California whose household is located in areas with a population density of 5,000 people/mi^2 or more; and (2) vehicles in rural Wisconsin whose household is located in areas with a population density of 100 people/mi^2 or less. The distributions across regions on the left of each subplot are the same for both cases, and are equivalent to the distributions across all spatially heterogeneous factors in Figure 5-2. Distributions across individual travel patterns are cut off at the 5th and 95th percentile values. White circles indicated the corresponding regional averages across vehicle classes and individual driving patterns (first column) and region-class averages across individual driving patterns (second to last column). A version showing metrics per km instead of per year is available in Appendix C (Figure C-3). Details on how average fuel efficiency, annual travel distance, the fraction of electrifiable trip distance, and the time of day of charging vary across individual vehicles can be found in Figures 4-8, 4-3, and 4-2.

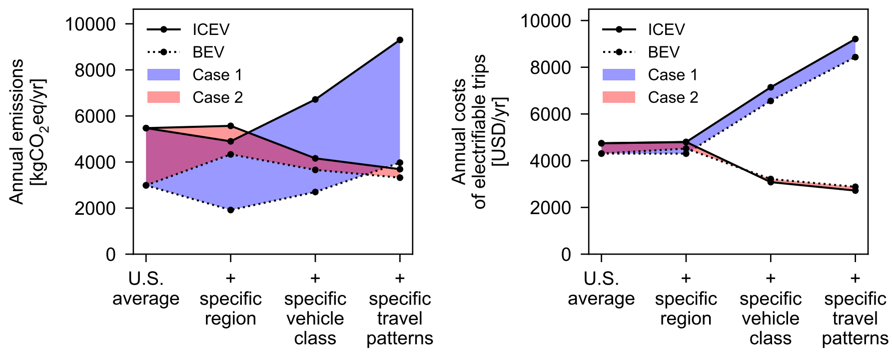

Figure 5-5: Absolute emissions and costs per year, and the difference in emissions and costs, for an ICEV and a BEV in two specific cases. Case 1 is an SUV in urban California (same as case 1 in Figure 5-4) whose annual travel distance is larger than the median in that region and for that class. Case 2 is a compact hatchback in rural Wisconsin (same as case 2 in Figure 5-4) whose annual travel distance is smaller than the median in that region and for that class. The effects from left to right are applied cumulatively: first, regional effects on emissions and costs of the different vehicles are added, modeling the average across the 5 classes modeled (as in Figure 5-2). Second, effects of the specific vehicle class are added, and finally, average annual travel distance is adjusted. BEV emissions and costs include operating emissions and costs from ICEVs for trips that are not electrifiable in Scenario B of Chapter 4 (see Table 4.1 and Figure 4-6).

positively correlated with average trip distance, which, in turn, is positively correlated with ICEV fuel efficiency and negatively correlated with the fraction of distance that is electrifiable (see Figure 4-8 in Chapter 4).

The variation in the difference in costs between ICEVs and BEVs due to individual travel patterns is mainly driven by the average annual travel distance, and the fraction of that distance that is electrifiable. Depending on baseline emissions, either annual travel distance or the fraction of electrifiable trips dominates the variability in cost savings. Overall, individual travel patterns contribute about equally to the variability in cost savings of BEVs as they contribute to the variability in emissions savings. Finally, vehicle class has a substantial impact on the cost difference as well. This impact is sensitive to the specific vehicle models chosen.

Combined, the heterogeneity shown in Figure 5-4 means that some vehicles achieve emissions savings of more than 7,000 kgCO_2eq/year when that vehicle is a BEV instead of a comparable new ICEV. And even in rural MT, where average conditions mean that emissions savings of BEVs are lower on average than for most of the country, there are individual vehicles for which electrification would lead to substantial emissions savings at little to no costs to the consumer.

While replacing larger vehicles that drive frequently with BEVs leads to more emissions savings than replacing small vehicles that drive less, it should be noted that absolute annual emissions

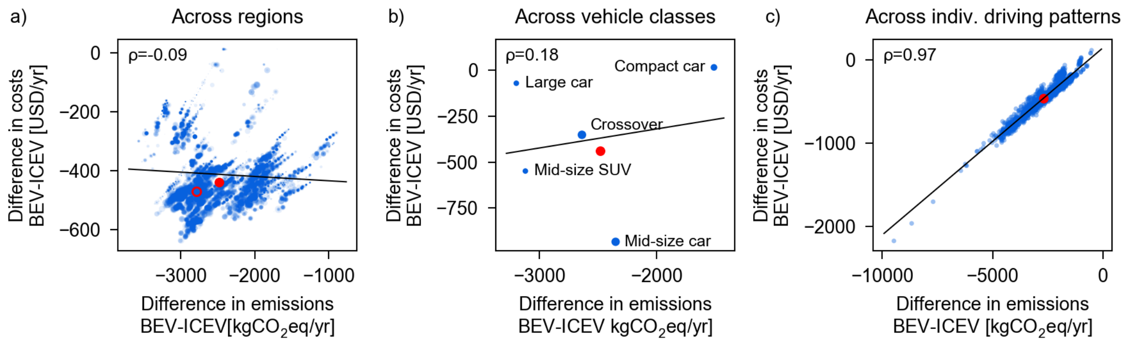

Figure 5-6: Correlation between the difference in costs and the difference in emissions between ICEVs and BEVs, across a) regions, b) the five vehicle classes listed in Table 5.2, and c) across individual driving patterns. In each subplot, the other two aspects are averaged. The full red circles indicates averages across all aspects, and therefore share the same values in all subplots. The empty red circle in subplot a) indicates the estimated average weighted by where BEVs have been sold so far. The diameters of the blue circles in subplots a) and b) are proportional to the number of vehicles in each zipcode (for a) and the share of the corresponding class in the fleet (for b). The numbers next to ρ indicate the Pearson correlation coefficient between the difference in emissions and costs across all data points. The black lines show a linear least squares fit across the data points.

increase with increasing vehicle size and use across all technologies (Figure 5-5). Therefore, the average compact ICEV in rural MT that has a lower annual travel distance than the median in that region produces lower annual emissions than the average mid-size SUV BEV in urban CA that has a higher annual travel distance than the median in that region (Figure 5-4). This emphasizes that individual preferences and travel behavior not only affect the emissions and costs of BEVs relative to ICEVs, but also the absolute amount of emissions generated through individual travel activity each year.

5.3.3 Implications for the emission reductions potential of BEVs

The heterogeneity in emission reductions and costs of BEVs explored in Figures 5-2 to 5-4 implies that the effective emission reductions achieved by and costs to consumers incurred by BEVs will depend on where they are being sold, what vehicles (in terms of class) they are replacing, and who (in terms of individual driving patterns) is driving them. These three factors largely determine the emission reductions achieved by a given number of BEVs, and have a substantial impact on the change in travel costs to consumers resulting from BEV adoption. We estimate that typical 2019 model BEVs achieve almost double the emission reductions (2820 kgCO_2eq/year) compared compact BEVs operated under average conditions (1510 $kgCO_2eq$/year) when considering the class mix of vehicles in the fleet and where BEVs have been sold so far (Figure 5-6). Some specific vehicles are likely to have achieved emission reductions of three to four times the U.S. average for compact cars. Simultaneously, the high sales numbers of the Tesla Model 3 in 2018 (see Table 5.2) correlates with high cost savings compared to the BMW 330i, assumed here to be a comparable ICEV (Figure 5-6).

Emission savings and costs savings of BEVs compared to ICEVs are largely uncorrelated across regions and across vehicle classes (for the specific models assessed here). Within a given region and for a given class, however, high emission savings run alongside high cost savings (Figure 5-6). A key reason for this observation is that the annual travel distance and the fraction of that distance that is electrifiable are the major determinants of BEV costs compared to ICEVs across individual driving patterns, and are also positively correlated with BEV emission reductions (see Figure 5-4).

If ICEVs that are to be replaced by BEVs are selected randomly across the country, 33% of the fleet needs to consist of BEVs to achieve a 27% reduction in GHG emissions compared to 2005 emissions of the U.S. car and SUV fleet (Figure 5-7). If vehicles for which a switch to BEVs achieve the highest emission reductions are prioritized first, 18% BEVs are sufficient. This number drops to 12% if we assume that all trips can be electrified by those BEVs (Scenario A in Table 4.1). Similarly, a share of 10% BEVs in the fleet can lead to between 1% and 10% emission reductions compared to new 2019 ICEVs. Even just taking into account regional conditions, but not vehicle class and individual driving patterns (within a given region), the required share of BEVs to reduce emissions by 27% below the baseline varies between 26% and 40%.

Additional measures that apply to all types of vehicles can help reduce fleet-wide emissions further. Such measures include changes to driving style (as discussed in Chapter 3) and downsizing of vehicles (as discussed in Chapter 2). If all vehicles were compact cars similar to the characteristics of the Honda Civic, fleet-wide emissions would drop by 25%. This scenario could also correspond to a hybridization of all ICEVs to HEVs (without downsizing), since we've shown in Chapter 2 that HEVs reduce emissions by about 25% compared to comparably sized ICEVs. Together, electrification, improving driving style, and downsizing can act together to reduce emissions by over 50% compared to 2005 levels, with today's electricity mix and a 50% share of BEVs.

Replacing vehicles that achieve high emission reductions first can also have substantial implications for costs to consumers. Across regions in the U.S., differences in emission reductions of BEVs compared to ICEVs are negatively negatively correlated with the difference in costs between

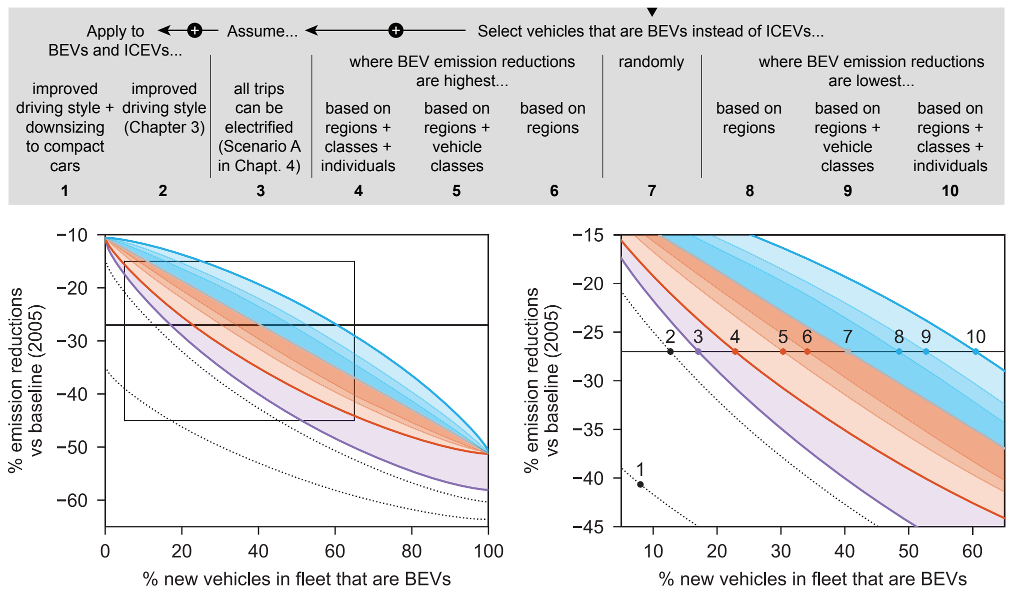

Figure 5-7: Annual greenhouse gas emission reductions in % as a function of the share of 2019 model year battery electric vehicles (BEVs) in the fleet, compared to a baseline case where those vehicles are new (2019 model year) ICEVs instead. The horizontal line at -27% reflects the U.S. Nationally Determined Contribution (NDC) for reducing GHG emissions compared to a 2005 baseline [193]. The gray line (case 7) shows the baseline case, where BEVs replaced with ICEVs are randomly selected across locations, vehicle classes, and individuals. Cases 4-6 and 8-10 represent cases where the vehicles in the fleet that are BEVs instead of ICEVs are selected using specific criteria. Case 3 assumes that all trips can be electrified (Scenario A in Table 4.1), otherwise following the selection rules of case 4. Cases 1 and 2 reflect changes applied to both ICEVs and BEVs (that is, all vehicles in the fleet) on top of case 3. Only cars and SUVs are considered; pickups are excluded from the analysis since BEV alternatives for pickups currently don't exist. The method used to calculate 2005 baseline emissions is outlined in section 5.2.6.

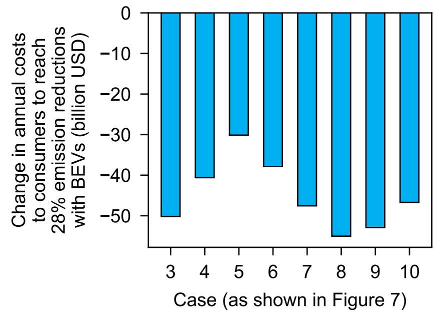

Figure 5-8: Changes in costs to consumers resulting from meeting the 27% reduction target compared to 2005 emissions by adopting BEVs, for cases 3–10 in Figure 5-7.

the two vehicles, meaning that replacing ICEVs with BEVs in the best regions first (in terms of emission reductions) leads to only a small increase in costs to consumers (Figure 5-8). Prioritizing vehicles whose driving patterns correlate with high emission reductions can decrease costs to consumers at current price levels, and emission reductions and cost savings of BEVs are correlated positively across individual vehicles.

5.4 Discussion

This chapter presents a comprehensive framework to quantify the heterogeneity in emissions and costs of battery electric vehicles (BEVs) compared to internal combustion engine vehicles (ICEVs) across locations and individual vehicles in those locations. Our analysis identifies the relative impact of ten different factors on the variation in emissions and costs. We then identify implications for consumers and policy makers in their effort to decarbonize personal transport.

We find that location, vehicle class, and individual driving patterns contribute about equally to the variation in emissions and costs of BEVs compared to similarly sized ICEVs. BEVs reduce emissions the most in areas with a clean electricity mix, dense traffic and correspondingly slow trips, high annual travel distance, and a mild to warm climate, in decreasing order of importance. Notably, these locations are areas that may particularly profit from reductions in urban air pollutions promised by BEVs as well. Among individual vehicles within a region, they reduce emissions the most for drivers that have a high annual travel distance, operate large vehicles, and frequently make short trips, again in decreasing order of importance. Across regions, the cost difference between the two vehicle types strongly depends on prices of the selected models, and is largely uncorrelated with emissions savings. In all parts the country, the average BEV is more affordable than comparable ICEVs. Across vehicle classes, cost savings largely depend on the ICEV models selected as a baseline for comparison. For a given region and vehicle class, however, lower costs of BEVs compared to ICEVs run alongside higher emission savings.

Our results illustrate the complex interaction between different individual factors that affect emissions and costs of the two vehicle types. For example, intuition may suggest that higher annual miles traveled leads to higher emission reductions. While this is true when all other factors are being held constant, higher annual miles traveled are correlated with longer trips and less congested driving. Therefore, BEVs are only marginally more effective in reducing emissions in urban areas than in rural areas.

Another example is that intuition may suggest that cold winters severely reduce the emission reductions of BEVs. While cold winters have a larger relative impact (in percent) on BEV fuel economy than on ICEV fuel economy, the absolute impact on fuel efficiency (in energy per distance) is more similar, meaning that only the most extreme climates have a substantial impact on the emission reductions achieved by BEVs. It's also important to note that the fuel economy of BEVs may be reduced by 50% or more on a particularly cold day at night, but such conditions don't exist during the day and throughout the year in any location.

We note that our modeling framework does not taking into account that certain conditions can change over time, both across an individual vehicle's lifetime when purchased today, as well as across longer time horizons as the share of BEVs in the light-duty vehicle fleet increases. For instance, the electricity mix can change. If the emission intensity of electricity continues to decrease, as it has over the past decade [69], effective emission reduction will be higher than shown here. Similarly, costs of BEVs compared to ICEVs may decrease further with increasing adoption. These effects imply that promoting BEVs in areas with higher emission reductions and low costs can in turn lead to higher emission reductions and lower costs in areas where emission reductions currently are more moderate, and costs are higher.

The heterogeneity of emission reductions has implications for decarbonizing personal transport in the U.S. We show that BEVs sold in urban areas in California, the state where more than 50% of all U.S. BEV sales took place [71], achieved 1.3–2.7 times the emission reductions, depending on vehicle class, than one would estimate based on conducting the analysis using only compact vehicles operated under average conditions. If only 'ideal' vehicles were replaced with BEVs, emission reductions could be even higher, with a share of 10% BEVs in the fleet achieving up to 10% emission reductions compared to new ICEVs. Our region-specific results add to the number of factors policy makers may want to consider in designing and evaluating light-duty vehicle policies, and can assist the quantification of benefits and costs of regional policies.

Despite their competitive costs and existing subsidies, however, BEV adoption rates are still low. In part, this may be because consumers are not fully aware of the difference in costs of ownership between BEVs and ICEVs, and may be skeptical about emission reductions of BEVs. Therefore, an effective measure to increase adoption may be to strengthen consumer awareness. Since higher emission reductions of BEVs occur alongside lower costs relative to ICEVs within a region and for a given vehicle class, providing personalized information to consumers may increase emission reductions achieved per BEV sold while increasing the overall adoption rate. The results presented in this work can serve as a framework to design personalized information for consumers on the emissions and costs of any vehicle model on the market that takes into account their location and their driving habits. An example for such a platform, carboncounter.com, is discussed in the final chapter of this thesis.

Chapter 6

Carboncounter: Informing consumer perceptions of EVs through interactive data

Abstract

U.S. marked shares of battery and plug-in hybrid electric vehicles have settled around 2% in 2018 and the first half of 2019, despite the potential environmental and economic benefits of these vehicles. One possible reason is that consumers are not sufficiently informed about the economic and environmental efficacy of electric vehicles in comparison to combustion engine vehicles. Based on the results in Chapter 2, we developed Carboncounter.com, a website that lets consumers interactively explore emissions and costs of most vehicle models currently offered on the U.S. market, and compare them against emission targets. Through a survey launched on that website, we evaluate the potential impact of Carboncounter on consumer perception of the economic and environmental benefits of electric vehicles. Results suggest that interacting with Carboncounter has made consumers perceive the emission and cost benefits of electric vehicles more favorably. At the same time, we observe that range and charging time considerations may be of higher concern to typical visitors of Carboncounter than costs. We conclude that informational platforms such as Carboncounter can make a valuable contribution to meeting transportation climate targets in the U.S. and worldwide by providing information to consumers. The case of Carboncounter also illustrates how scientific results can translated into an interactive and customizable experience that informs a wide range of audiences.

6.1 Introduction

Plug-in hybrid vehicles (PHEVs) and battery electric vehicles (BEVs), shortened here to electric vehicles (EVs), can reduce greenhouse gas emissions substantially compared to gasoline internal combustion engine vehicles (see Chapters 2 and 5). At the same time, they don't cost more for consumers than comparable internal combustion engine vehicles. Nonetheless, the market share EVs in the U.S. has not exceeded 2% [123].

The low market share of EVs may be an example of the so-called energy-efficiency gap, referring to the difference between the cost-minimizing level of energy efficiency and the level of energy efficiency actually realized [93, 87, 86, 8]. Many causes have been proposed as explanations for this gap, including range anxiety, myopia, bounded rationality, disincentives of manufacturers and car dealers to sell electric cars, and risk aversion [93, 81, 166, 164]. Most of these possible explanation assume, however, that consumers have perfect information about the different model options available to them in terms of energy efficiency and costs.

Information on cars, including their efficiency and cost properties, is both a large business and as well as subject to federal regulation. Numerous car information portals allow consumers to browse and compare models, look up fuel consumption information, and obtain cost of ownership estimates. In the U.S., fuel consumption is reported as fuel economy, in miles per gallon (MPG). This information on rated fuel economy is then included in the so-called window sticker [63] and placed on car information portals. The EPA has undertaken several revisions to add more information such as fuel costs (rather than just fuel economy) and CO_2 emissions [92], although the most recent design improvement proposals [43] have not been implemented. Researchers have found that the specific type of information that is presented on these window stickers, and the way in which this information is presented, can change consumer perceptions of different types of cars. [55, 114].

Existing platforms that display information on environmental or economic aspects of cars are limited in their ability to let consumers compare models across different powertrain technologies. The environmental information displayed focuses on the officially rated fuel economy, not addressing common questions about the emissions of battery production and electricity generation for PHEVs and BEVs. Furthermore, most existing platforms only offer limited personalization options that allow user to tailor the assessment to their driving habits and region-specific factors. Researchers have also found that fuel economy, which scales inversely with fuel consumption and emissions per distance, can be a misleading metric for fuel efficiency or environmental performance [7]. Finally, current platforms do not offer a reference point that informs consumers about what level of fuel economy or emissions is sufficient to meet climate policy targets.

To contribute to addressing this gap in consumer information, we developed Carboncounter.com

[136], based on the emissions and cost model presented in Chapter 2. Carboncounter lets consumers explore the lifecycle emissions and costs of ownership of over 1,000 vehicle models and trims offered on the U.S. market, and compare emissions against climate targets. Launched in fall 2016, the platform has received widespread media coverage, and has had over 100,000 unique visitors. We ask whether this platform has the potential to change consumer's perceptions of the environmental and economic performance of EVs, and whether it can influence consumer's purchasing decisions. To do so, we launched a survey on Carboncounter, asking first-time and returning visitors about their perceptions of the environmental and economic performance, range issues, and other characteristics of EVs in comparison to ICEVs.

This work is intended to serve as a basis for further research on the impact of consumer information on their purchasing decisions, and therefore on the potential of information platforms to contribute to a decarbonization of the transportation sector. It also illustrates a pratical application of the models and results from Chapters 2-5 in this thesis. More broadly, Carboncounter demonstrates how scientific results can be translated into interactive information with the potential to reach a broad audience.

6.2 Method

6.2.1 Website development

Carboncounter is a conventional website accessible on any device that has an Internet connection and a modern web browser. It was developed using two open-source libraries: AngularJS, a framework enabling the efficient integration of user interface, data sources, and calculation algorithms [89]; and D3, a data visualization library [29]. All vehicle data, parameters, and calculation routines are loaded into Javascript (and therefore the browser cache) upon initialization of the tool, ensuring that the view (visualization of results) is updated in less than 100 ms after a user makes a change to parameters or the vehicle selection.

Carboncounter is based on the lifecycle emissions and cost of ownership model introduced in Chapter 2 and expanded in Chapter 5. This model estimates emissions and costs of any car model, given a number of publicly available vehicle properties and location-specific parameters. Vehicle properties include its powertrain technology, class, curb weight, battery power (for HEVs and FCVs), battery capacity (for PHEVs and BEVs), fuel cell power (for FCVs), whether or not carbon fiber is used to lightweight the vehicle. The main view on Carboncounter is based on Figure 2-1,

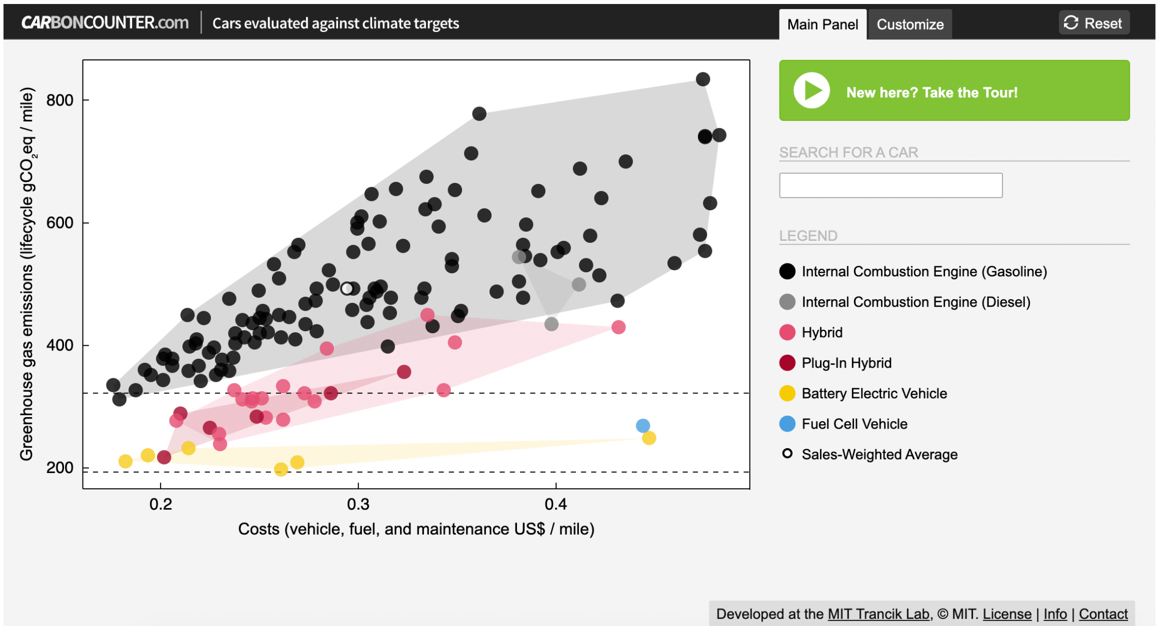

Figure 6-1: Screenshot of Carboncounter.com in August 2017 with the main panel being active.

showing emissions and costs of about 100 of the most popular vehicle models on a scatterplot (Figure 6-1). Additional models can be added manually, and individual models of interest can be highlighted, using the search function.

The main panel to the right of the cost-carbon scatter plot shows the color legend, lets users search for individual car models, and offers a tutorial called 'tour.' The tutorial walks users through the functions of the tool and presents key findings. Key findings included in the tutorial are (1) consumers don't have to pay more for a low-carbon-emitting vehicle; (2) while the average greenhouse gas emissions of all cars are more than 50% higher than the 2030 target, most hybrid and electric vehicles meet that target today, with today's electricity mix; (3) costs are sensitive to fuel and electricity prices as well as the federal tax refund; and (4) emissions of EVs are sensitive to the electricity mix. A full transcript of the tutorial is available in Appendix D, section D.2.

The customize panel, accessible though a link in the top-right corner of the website, lets users adjust 25 parameters and other settings. These include annual travel distance, emission intensity of the electricity mix, and whether or not the federal tax refund on electric vehicles is applied to cost calculations. Once a user changes one of these settings, the results in the plot area on the left are updated in real-time, with an animation smoothing the transition between previous and current results.

6.2.2 Survey

Two years after the launch of Carboncounter, we set up a survey that asked users to answer a series of questions before starting to use the tool. The goals of the survey were to: (1) evaluate the demographic characteristics of Carboncounter users; (2) assess the perceived quality of Carboncounter and collect suggestions for improvements; (3) examine user's perceptions of environmental, cost, range, charging, and driving experience issues associated with EVs; and (4) conduct a first estimation of whether Carboncounter has the potential to affect those perceptions and therefore the likelihood of users to purchase a BEV in the future.

The survey was open between August 11th 2017 and September 4th 2017. During this window, we received 309 completed responses. All visitors were offered the opportunity to take part in the survey. The pool of respondents therefore represents a convenience sample of people who visited Carboncounter and were willing to fill out the survey. About 1,300 users visited the website during this time, indicating a 24% response rate. 41 of the 309 respondents were returning visitors to the site, meaning that they had used Carboncounter previously before answering the survey. 268 respondents were first-time visitors. A full transcript of the survey questions and aggregated answers is available in Appendix D, section D.3.

Each visitor of Carboncounter was presented with an option to opt into the survey (see Figure D-1 in the Appendix). The rest of the tool was not accessible until the user either accepted to declined the survey, or closed the invitation window. This implies that respondents who indicated in the survey that they are first-time visitors did not interact with the information presented on Carboncounter before filling out the survey.

Based the survey answers, we construct a linear regression model to estimate the relationship between visitor characteristics, including whether they had visited Carboncounter previously, and their perception of the environmental and economic efficacy of EVs. As independent variables, we select characteristics reflecting the demographic characteristics, attitudes, and preferences indicated by respondents that are unlikely to be affected by visiting information platforms such as Carboncounter. Further details on how survey responses are transformed into model variables are available in Appendix D, section D.4. Using the same set of independent variables, we construct a second model to estimate the relationship between the same characteristics and the visitors' self-reported probability that their next vehicle is going to be an EV. In both models, all independent variables are normalized to a mean of 0 and a standard deviation of 1. We report tests for the

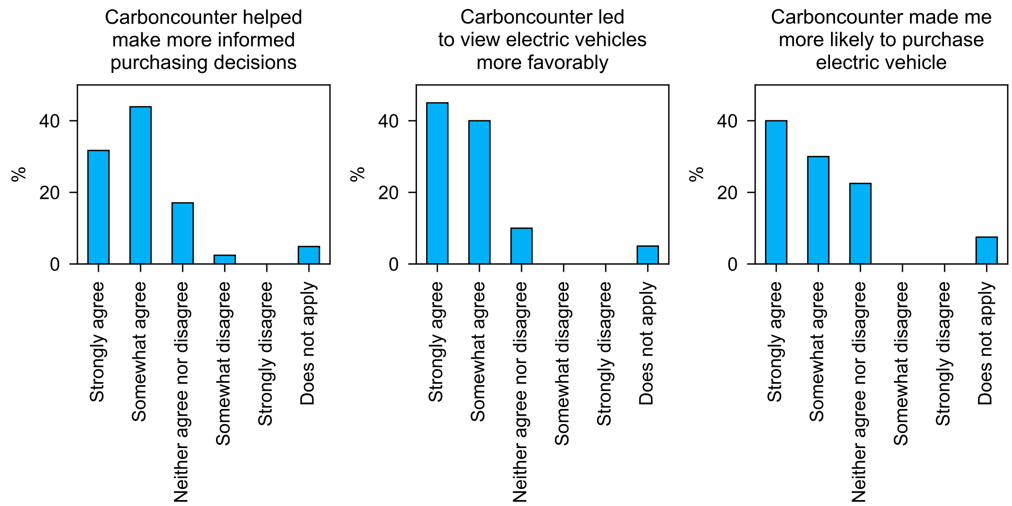

Figure 6-2: Self-reported impact of Carboncounter on perception of BEVs and on the likelihood to purchase a BEV as the next vehicle.

normality of the distribution and the independence of residuals for the two models in Appendix D (Figure D-2).

6.3 Results

Almost 50% of respondents that were returning visitors stated that Carboncounter has made them view EVs more favorably, and made them more likely to purchase an EV in the future (Figure 6-2). No respondent indicated that the website made them view EVs less favorably or made them less likely to purchase one. Consequently, most people stated that Carboncounter has helped them make more informed purchasing decisions.

Visitors who had used Carboncounter before filling out the survey indicated an average likelihood of purchasing a plug-in electric vehicle (BEV or PHEV) as their next vehicle of 72% (Figure 6-3). First-time visitors indicated 60% on average. The perception of EV emissions and costs relative to ICEVs, measured using a Likert scale index combining the score of three individual questions, is also higher for returning visitors (11.5) and first-time visitors (9.8).

The perception of EV range and charging issues, measured using a Likert scale index combining the score of four individual questions, is lower than the index on emissions and costs. This suggests that respondents are more concerned with the range, recharging times, and the availability of charging options of BEVs than they are concerned with the costs and negative environmental impacts of BEVs. In addition, we measured no significant difference in the perception of BEV

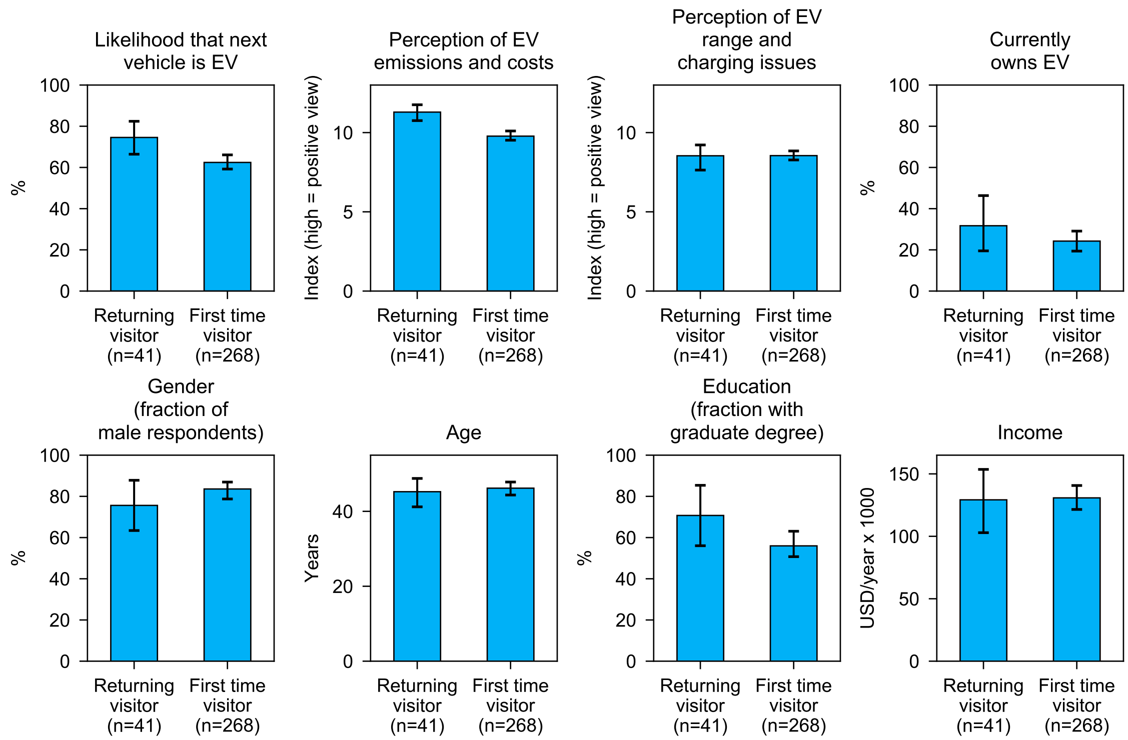

Figure 6-3: Average values of indicators and demographic characteristics for returning visitors (who had used Carboncounter at least once before filling out the survey) and first-time visitors (who did not have the chance to use Carboncounter before filling out the survey). Error bars represent the 95% confidence interval, ranging from the 2.5th to the 97.5th percentile as calculated using the bootstrap.

range and charging issues between returning and first-time visitors.

Survey respondents were predominantly male, highly educated, and wealthy (Figure 6-3). There were no significant differences in those respondent characteristics between first-time and returning visitors, although returning visitors may have slightly higher average education levels than first-time visitors.

We also find that frequent drivers (those who drive more than 10,000 miles per year) are more likely to own an EV, but have the same perception of EV emissions and costs as well as range and charging issues as less frequent drivers. Furthermore, we find that having driven an EV, and in particular owning an EV already makes people more likely to purchase an EV again as their next vehicle (Figure 6-5). On average, survey respondents showed a high likelihood of purchasing an EV as their next vehicle (62%), and high EV ownership (30%).

To test whether visiting Carboncounter has had a significant impact on the perception of EV emissions and costs and the likelihood to purchase an EV when taking into account other, possibly

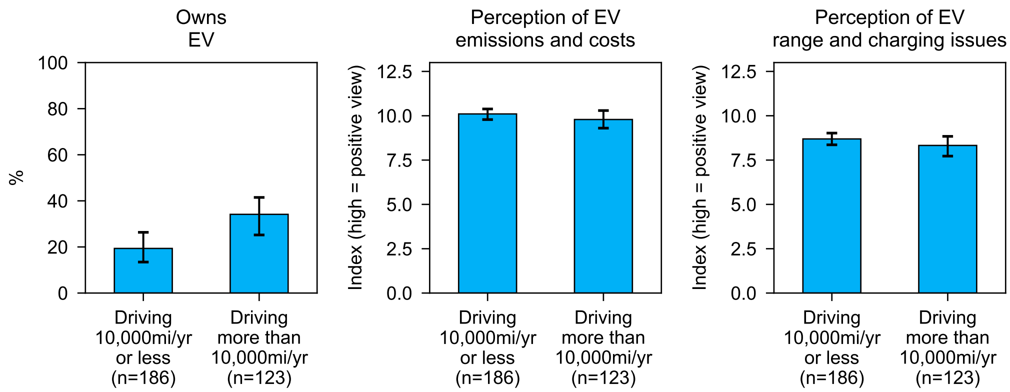

Figure 6-4: Difference in EV ownership and perception of EV emissions/costs and range/charging issues between people who report that they drive 10,000 miles per year or less and people who report that they drive more.

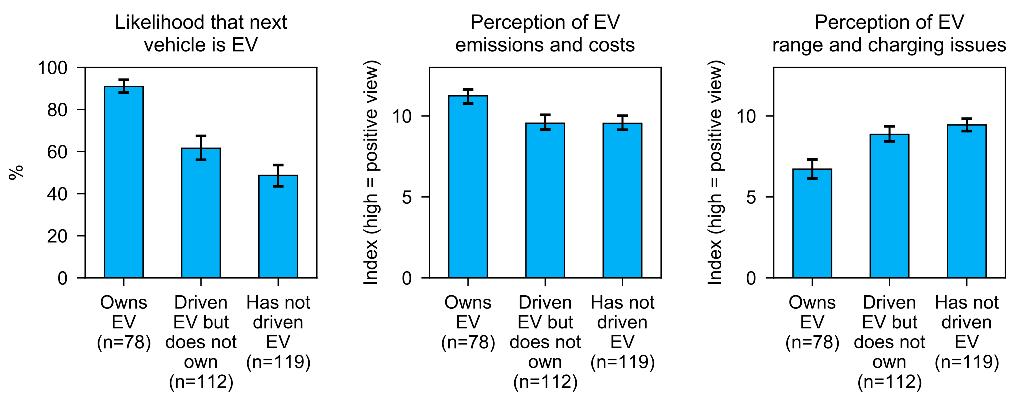

Figure 6-5: Difference in likelihood that next vehicle purchase is going to be an EV and perception of emissions/costs and range/charging issues of EVs between EV owners, people who don't own an EV but have driven one before, and people who have never driven one.

confounding variables, we conduct two multivariate linear regression models. For the first model, we use the Likert scale index of the perception of EV emissions and costs as the dependent variable (Table 6.1, left side). For the second model, we use the percentage likelihood to purchase an EV as the next vehicle as the dependent variable (Table 6.1, right side).

While having visited Carboncounter has a positive effect on the likelihood to purchase an EV as the next vehicle, this effect is not significant once other explanatory variables are considered (Table 6.1, model 1). The strongest predictors for the likelihood to purchase an EV as the next car are whether the person currently owns an EV already, whether they're generally interested in car technology and keep up with the newest models, and whether they like the sound and feel of a combustion engine. Concerns about range and recharging times of EVs did not significantly

Table 6.1: Results of linear regressions on the likelihood to purchase an EV as the next vehicle (in % from 0 to 100; model 1) and on the perception of EV emissions and costs (from 1 to 13; model 2). All predictors have been normalized to a mean of 0 and a standard deviation of 1. Descriptions of how each variable was obtained from survey data and an analysis of the model residuals are available in Appendix D, Figure D-2 and section D.4. 7 responses were removed from the set of completed responses (309) because they did not contain answer to all questions used in the model. ** indicates a significance at the 1% level, *** indicates a significance at the 0.1% level.

	Model 1 Likelihood to purchase EV					Model 2 Perception of EV emissions and costs				
	Coef		p-value	Lower	Upper	Coef		p-value	Lower	Upper
Constant	64.664	***	0.000	61.717	67.611	11.968	***	0.000	11.73	12.205
Currently owns electric vehicle	12.120	***	0.000	8.825	15.416	0.378	**	0.006	0.112	0.643
Has visited Carboncounter before	1.356		0.380	-1.681	4.393	0.327	**	0.009	0.082	0.572
Annual driving distance	0.587		0.711	-2.528	3.702	-0.032		0.802	-0.283	0.219
Environmental attitude	4.787	**	0.002	1.748	7.825	0.650	***	0.000	0.405	0.895
Interest in car technology	5.983	***	0.000	2.964	9.001	0.467	***	0.000	0.223	0.71
Range and charging concerns	-2.528		0.132	-5.819	0.763	-0.381	**	0.005	-0.647	-0.116
Sound of combustion engine	-8.767	***	0.000	-5.548	-11.985	-0.448	***	0.001	-0.188	-0.708
Income	1.570		0.314	-1.493	4.632	-0.052		0.680	-0.299	0.195
Age	-2.170		0.188	-5.405	1.065	-0.016		0.906	-0.277	0.245
	$n = 302; R^2_{adj} = 0.360$					$n = 302; R^2_{adj} = 0.268$				

affect the self-reported likelihood to purchase one, even though many visitors stated that they are concerned about these issues.

The regression model confirms the observation made based on Figure 6-3 that returning visitors had a significantly better perception of BEV emissions and costs than those who did not (Table 6.1, model 2). Visitors who are more worried about the range and recharging times also showed a significantly worse perception of the emissions and costs of EVs. Other predictors showed a similar effect, and with similar significance, in model 2 (measuring the effect on the perception of EV emissions and costs) as in model 1 (measuring the effect on the self-reported likelihood that the next vehicle is going to be an EV).

6.4 Discussion

Carboncounter aims to address the gap in consumer information on the environmental and economic performance of electric vehicles. The popularity of the platform, achieved without any advertisement spending, suggests that consumers are looking for such information. Results from our survey also suggest that this type of information has the potential to shift the perception of the environmental and economic performance of EVs by consumers, and potentially make consumers more likely to purchase an EV as their next vehicle.

The survey design used here is subject to shortcomings. In particular, respondents were not allocated randomly to a group of people that had the opportunity to use Carboncounter before answering the survey, and to a group that did not. Instead, the group that had used Carboncounter before answering the survey decided to return to the platform. This group may exhibit difference in opinions from first-time visitors that were not caused by Carboncounter. The fact that perceptions of BEV range and charging issues were almost identical between the two groups, however, indicates that at least some of the measured difference in the perception of environmental and economic efficacy of BEVs between first-time visitors and returning visitors may have been caused by Carboncounter. Nonetheless, further research will be needed to quantify this effect more accurately.

The magnitude of the impact of Carboncounter on consumer perception and purchasing behavior may also depend on the design, layout, and features of Carboncounter. Based on respondent feedback, for instance, we will include an alternative barchart view in future versions of the website, displaying more information on the individual contributors to total emissions and costs. Such additional information may not only lead to a better overall user experience, but may also increase the learning effect experienced by users of Carboncounter.

The demographic characteristics of the survey sample diverged strongly from the national average. Respondents were highly educated, predominantly male, and had a high average annual income. These characteristics are similar to those that have been suggested to be typical for EV buyers [39, 179]. For widespread adoption of EVs, all demographic sections of the market need to be addressed. Tools like Carboncounter could make a contribution towards this goal. Carboncounter highlights that EVs can have economic benefits, particularly for frequent drivers. In addition, tools that are primarily of interest to people that are already interested in EVs, but do increase the adoption rate among those people, may lead to improved access to EVs for the rest of the population as well, because increased adoption rates among early adoptions may lead to lower technology costs, better charging infrastructure, and higher societal awareness of EVs as a consequence.

Consumers are among the key individual decision makers in the transition process towards an electrified, low-carbon vehicle fleet. Because of their potential impact on EV adoption rates, informational platforms such as Carboncounter can make a valuable contribution to meeting transportation climate targets in the U.S. and worldwide. This chapter illustrates how the results from Chapters 2–5 can be used to inform the development of such platforms. In addition, the case of

Carboncounter illustrates how scientific results can be transformed into tools that address decision markers directly, providing an interactive and customizable experience that can reach a wide range of audiences and that can sustainably inform the understanding of the research topics covered in this thesis.

Appendix A

Supporting Information for Chapter 2

A.1 Discussion of uncertainties in greenhouse gas emission targets

The greenhouse gas (GHG) emission targets shown in Figures 1, 3 and 4 in the main article are subject to uncertainties, and sensitive to climate change policy choices. This chapter briefly discusses the major uncertainties and choices.

First, climate change mitigation targets (in terms of maximum average global warming compared to pre-industrial temperature levels) as well as the corresponding maximum globally allowed GHG emissions are subject to both scientific uncertainties and political debate. Less stringent climate change targets would lead to higher (less stringent) GHG emission targets for light-duty vehicles (LDVs).

Second, the allocation of globally permitted GHG emissions to specific countries is subject to debate as well. If fewer emissions are allocated to industrialized or Annex I countries, targets for LDVs in the U.S. would need to be lower.

Third, our derivation assumed that all GHGs associated with the materials supply chain for vehicle and fuel production are emitted within the U.S. In reality, this is not the case. For instance, a fraction of the emissions due to the production and distribution of each vehicle occur outside of the U.S., even if the final manufacturing process takes places within the U.S. Our U.S. emission targets are therefore somewhat conservative; that is, they are more stringent than they might in reality need to be. However, in terms of global climate change mitigation, this simplification in our method does not lessen the challenge of decarbonization; ultimately, it is the global carbon budget that counts, and production- and consumer-based emission schemes are only accounting devices. If domestic decarbonization efforts are measured in such a way as to neglect emissions embodied in trade, one must be careful not to overestimate apparent progress and underestimate the need for more stringent emissions reductions. Embodied carbon leakage has been estimated to constitute more than 25% of global emissions [161, 20].

Fourth, the vehicle miles travelled (VMT) were assumed to follow the U.S. Energy Information Administration (EIA)-projected 0.9% increase per year [103]. If VMT are higher, the targets would need to be lower by the reciprocal of the same factor, and vice-versa. The trajectory of VMT by light-duty vehicles is linked to the development of VMT in other transportation sectors (see next point).

Finally, our targets assume that the shares of emissions allocated to each end-use sector do not change with time. If, as one example, VMT by passenger air travel increase significantly, and the carbon intensity per mile of air traffic cannot be mitigated considerably, other sectors may have to compensate by further reducing their GHG emissions so as to reach overall emissions targets. A modal shift from cars to air travel may decrease the VMT for cars as well, but not necessarily enough to compensate for the increase in air travel.

Combined, these factors can have a substantial impact on the GHG emission intensities of LDVs that will be required to meet climate change policy goals. The allocations of emissions across time, regions, and sectors are policy choices that have to be made. The future growth in VMT, on the other hand, cannot be controlled directly by GHG emission policies. Therefore, we conducted a sensitivity analysis for the targets with respect to the annual growth of VMT, assuming that the sectoral allocations stay constant. The results are depicted in Figures A-1 and A-2.

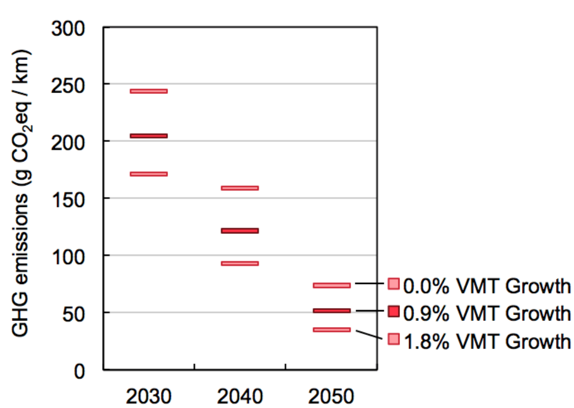

Figure A-1: Sensitivity analysis for the GHG emission targets for personal LDVs with respect to the annual growth rate of vehicle miles traveled (VMT) between 2012 and the year of the target. 0.9% is the baseline case used in the main article.

A.2 Cost-carbon space of current light-duty vehicles under varying conditions

In Section S2.1, we map out the cost-carbon space under a low-carbon electricity scenario for different electricity prices. In Section S2.2, we map out the cost-carbon space considering uncertainties in five parameters: the lifetime of lithium-ion batteries; the discount rate; the drive cycles (driving patterns); the vehicle life in years; and the vehicle lifetime driving distance.

Costs and emissions under a low-carbon electricity scenario

Figure A-2 shows the same information as Figure 1a in the main article, but under a scenario where electricity is produced from low-carbon sources only, resulting in a GHG emission intensity of electricity production and distribution of 24.3 gCO_2eq/kWh (as opposed to the baseline case of 623 gCO_2eq/kWh).

We observe that with a fully decarbonized electricity mix, BEVs are able to meet the 2050 target, while PHEVs are located in between the 2040 and the 2050 target (assuming that the fraction of the distance in which PHEVs are driven in charge depleting and charge sustaining modes remains constant at 57% and 43%, respectively).

The costs to the consumer of BEVs and PHEVs are fairly insensitive to electricity costs. We find that even a doubling of the electricity price does not change the cost comparison between BEVs and ICEVs substantially. This is because the cost of electricity for charging BEVs and PHEVs represents a relatively small fraction of total costs (see Figure 2 in the main article).

Finally, Figure A-2 shows the GHG target ranges resulting from the uncertainty in future annual vehicle miles traveled by light-duty vehicles (see Figure A-1). We note that our conclusions as to which technologies are able to meet what targets, and under what conditions, are robust to these uncertainties.

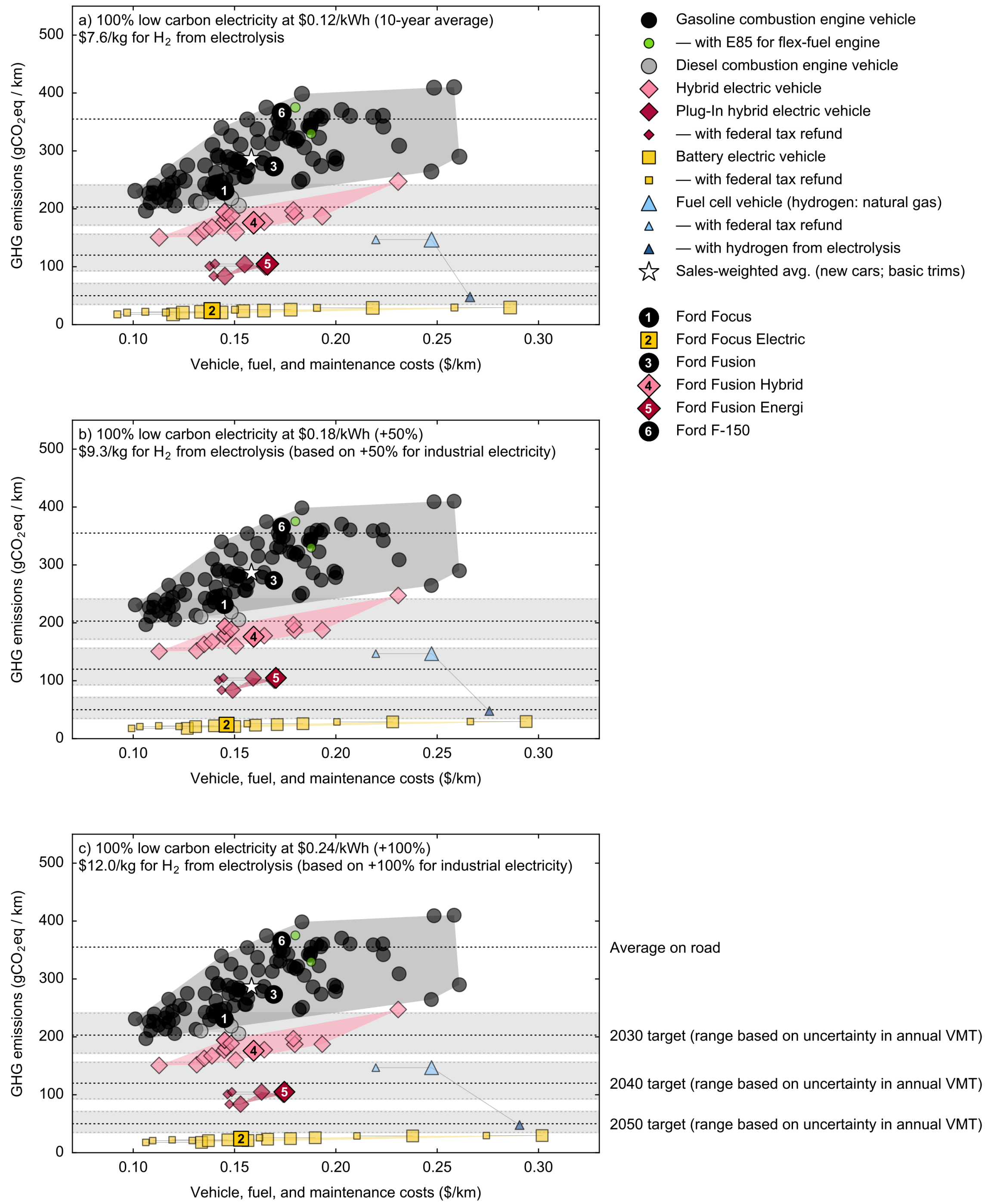

Figure A-2: Same cost-carbon plot as Figure 1a in the main article, but with a low-carbon electricity mix (24 gCO_2eq/kWh instead of 623 gCO_2eq/kWh). Plots (a) - (c) represent different scenarios for the increase in electricity price for this electricity mix: (a) 0% (no increase); (b) 50% increase; and (c) 100% increase. The electricity price increases are also applied to industrial electricity prices that are used to calculate the costs of hydrogen (H_2) produced with electrolysis. The uncertainty bands (shaded areas) for the targets reflect the uncertainties in future growth in annual vehicle miles traveled (VMT) shown in Figure A-1.

Sensitivities of costs and emissions subject to various parameter uncertainties

Here we show the results of sensitivity analyses with respect to the multiple parameters shown in Table A.1. The results are shown in Figure A-3.

Our sensitivity analysis shows that a full replacement of the lithium-ion batteries in BEVs and PHEVs does not have a major effect on the lifecycle GHG emissions of BEVs and PHEVs (Figure A-3b). In terms of costs, the impact is larger (assuming a battery price corresponding to $200/kWh): on average, the total vehicle, fuel, and maintenance costs to the consumer of BEVs increase by about 7.5% when considering the battery replacement at the beginning of year 8. This implies that if a full battery replacement is necessary, and it has to be paid by the consumer, PHEVs, and especially BEVs, become, in some cases, less financially attractive.

We also show that a low discount rate benefits alternative-fuel vehicles, especially BEVs and PHEVs (Figure A-3c and d). This is because the upfront costs (vehicle prices) are particularly large compared to the operating costs (fuel and maintenance) for these vehicle types. If consumers act myopically — that is, perceive future costs as relatively unimportant when making their purchasing decisions — ICEVs can be considerably more attractive than HEVs, PHEVs, and BEVs compared to a case where consumers evaluate costs with greater long-term financial focus. Of course, this is not always an option due to limited budget flexibility.

The drive cycle has a larger impact on the GHG emissions of ICEVs than on those of other powertrain technologies. This is because ICEV technology is the only technology that does not recuperate braking energy. Therefore, ICEV fuel economies are substantially worse in the city drive cycle than in the highway drive cycle. HEVs, PHEVs, and FCVs, on the other hand, have similar fuel economies in both drive cycles. Most BEVs even perform slightly better in the city cycle. For these reasons, the powertrain technologies are much closer together in terms of emissions when only highway driving is considered (Figure A-3f) than when only city driving is considered (Figure A-3e).

We also find that a shorter lifetime (with the same total lifetime distance driven) results in lower relative costs of alternative-fuel vehicles such as PHEVs and BEVs, because the high operating costs of ICEVs are discounted less strongly (Figure A-3g and h). This may be relevant for fleet managers (as opposed to private vehicle owners) whose cars may have a shorter lifetime, at a higher annual driving distance, than privately owned cars.

While the costs of PHEVs and BEVs profit from a shorter lifetime for a given total lifetime distance driven, they profit from a longer lifetime distance (Figure A-3i and j). This, again, may be relevant for fleet managers of taxi or car sharing services, as those vehicles tend to be driven for distances significantly above average. It should be noted, however, that reliability concerns for PHEVs, BEVs, and FCVs (in particular the batteries and the fuel cells) are particularly relevant for very long lifetime driving distances such as those shown in Figure A-3j.

Table A.1: Parameter values for sensitivity analyses described in section S2.2 and shown in Figure A-3. The sensitivity analysis investigates the effect of varying each parameter between three different values (Default, Case 1, and Case 2) while holding all other parameters constant at their Default values. For each parameter, Case 1 is shown in the left plot of Figure A-3 and Case 2 is shown in the right plot.

Parameter	Default	Case 1 (left)	Case 2 (right)	Notes
Lithium-Ion battery replacement	No replacement	No replacement	1 replacement	We assume replacement costs of $200/kWh. The replacement costs for the Nissan Leaf are currently $230/kWh ($5,500 for a 24 kWh battery [44]), those for the 60 kWh Tesla Model S are $167/kWh ($10,000 for a 60 kWh battery [28]). The costs are discounted, assuming that the replacement takes place after half the car's lifetime (beginning of year 8). Emissions for the production of the additional battery are calculated the same way as for the first battery.
Discount rate	8%	0%	16%	Some studies have found that consumers behave myopically when it comes to considering future fuel prices in their purchasing decisions for cars [92]. This can be described with a high discount rate.
Driving pattern	Combined (55% city and 45% highway)	City only	Highway only	We analyze two extreme cases of driving patterns: 100% city cycle (FTP-75) driving, and 100% highway cycle (HWFET) driving. We use the official reported adjusted fuel economy ratings to determine the fuel economies of the different models under these cycles.
Lifetime in years	14 years	7 years	21 years	The lifetime distance driven (see parameter below) is assumed to be constant at 272,000 km. Therefore, the annual distance driven changes.
Lifetime distance driven	272,600 km (169,400 miles)	136,000 km (84,500 miles)	408,800 km (254,000 miles)	The assumed lifetime (see row above) is 14 years in each case, however the annual driving distance changes.

A.3 Calculation of emissions and costs

Emissions and costs were calculated using parametrized formulas. For GHG emissions, these formulas consist of a set of vehicle parameters (such as curb weight and fuel economy), and a set of intensity coefficients X_i that we derived from GREET, the lifecycle assessment (LCA) model we used [11]. These coefficients can represent emission intensities (amount of emission per amount of material), energy intensities (amount of electricity per amount of material), or mass intensities (amount of component mass per functional unit of that component).

Cost calculations are simpler, as they only consist of the vehicle purchasing price, the fuel costs (which is a product of fuel price and fuel consumption), and some annual maintenance cost rate. Future costs are discounted. The following section discusses these calculations in more detail.

Emissions and costs of the fuel cycle

Generally, it was assumed that vehicles are fueled with regular gasoline; premium gasoline was only used if the manufacturer explicitly recommends or requires the use of premium gasoline for even the most basic trim. For PHEVs, we further assume that 57% of the distance is driven in charge depleting mode (using mostly electricity as a fuel), and 43% is driven in charge sustaining mode (using gasoline as a fuel, and electricity only from recuperation of braking energy). These values are consistent with GREET's default settings. For PHEVs with a serial-parallel powertrain configuration, 14% of the energy used during charge depleting mode comes from gasoline, and 86% from electricity in the battery. For PHEVs with a strictly serial configuration (only the Chevrolet Volt), we assume that all energy comes from the battery during charge depleting mode. We also note that the charging efficiency of PHEVs and BEVs is already included in the EPA fuel economy estimates for these vehicle types.

For gasoline, diesel, and electricity prices, we used a constant fuel price, based on a 10-year average of the inflation-adjusted monthly price in the U.S. between 2004 and 2013. This resulted in a regular gasoline price of $3.14/gallon (averaged over all formulations), a premium gasoline price of $3.41/gallon, a diesel price of $3.39/gallon, and a residential electricity price of $0.121/kWh or $4.10/gallon-equivalent [104]. The E85 (corn ethanol) price was set to 20% below the regular gasoline price, resulting in $2.51/gallon. We note that this is an estimated difference [56], which in reality varies considerably with time and region. The price of hydrogen was derived from a cost study by the National Renewable Energy Laboratory (NREL) [163]. Using linear interpolation of

NREL's sensitivity analysis, we first adjusted hydrogen prices so that they were based on a 10-year average of industrial natural gas and electricity prices. We then added 0.40 cents per MJ_{eq} of taxes, or 48 cents per kg, to the hydrogen prices. This is the same as the current average tax on gasoline with respect to its lower heating value (48.5 cents per gallon, or 0.40 cents per MJ_{eq}). The resulting hydrogen prices are $4.11/kg ($4.17/gallon-equivalent) for hydrogen from steam methane reforming (SMR), and $7.59/kg ($7.70/gallon-equivalent) for hydrogen from electrolysis, including pressurization and storage.

The carbon emissions of the fuel cycle per mile (not km) driven, $E_{fuelcycle}$ (in gCO_2eq/mile), are calculated as a function of the fuel consumption in miles per gallon (or miles per gallon-equivalent of gasoline), and the carbon intensity of electricity generation, as follows:

$$E_{fuelcycle} = C_1 + C_2 \cdot \frac{1}{FE} + C_3 \cdot \frac{1}{FE} \cdot E_{electricity} + C_4 + C_5 \cdot \frac{1}{FE} + C_6 \cdot \frac{1}{FE} \cdot E_{electricity} \tag{A.1}$$

where FE is the fuel economy in miles per gallon of gasoline-equivalent, and $E_{electricity}$ is the carbon intensity of electricity generation and distribution in gCO_2eq/kWh. The intensity coefficients $C1$ to $C6$ are extracted empirically from GREET and shown in Table A.2. The fuel economies (FE) of all vehicles analyzed are shown in Table A.4.

For PHEVs, the calculation is more complicated. There are two fuel economy values, and thus two emission intensities $E_{fuelcycle}$: One for the charge sustaining cycle (CS), when the car is driven in its 'combustion-mode', and one for the charge depleting cycle (CD), when the car is (mainly) driven in electric mode. Following GREET's split, we calculate the GHG emissions of PHEVs assuming that 57% of the distance is driven in CD, and 43% in CS. In addition, there are two types of PHEV drivetrain configurations: Serial (also called extended range), and serial-parallel. While serial hybrids use only electricity as a power source in CD mode, serial-parallel hybrids typically use a certain amount of gasoline as well. This implies that the fuel economy rating for their CD mode does not exclusively refer to electricity consumption. For serial-parallel hybrids, we therefore assumed that 14% of the energy per mile used during CD comes from gasoline, and 86% from electricity, following GREET's default values. The classification of each PHEV as either series or serial-parallel can be found in Table A.4.

The costs of the different fuels are shown in Table A.2 as well. The costs (average, minimum, and maximum) refer to the mean, minimum, and maximum monthly average of the respective fuel price, when adjusted for inflation, in 2013 dollars, observed between 2004 and 2013. The hydrogen prices are derived from the respective (industrial) natural gas and electricity prices.

Emissions and costs of the vehicle cycle

The carbon emissions of the vehicle cycle, $E_{vehiclecycle}$ (in gCO_2eq), are calculated as follows:

$$\begin{aligned} E_{vehiclecycle} = X_2 + X_3 \cdot E_{electricity} + m_{scaling} \cdot (X_4 + X_5 \cdot E_{electricity}) + P_{batt} \cdot (X_7 + X_8 \cdot E_{electricity}) + \\ C_{batt} \cdot (X_{10} + X_{11} \cdot E_{electricity}) + P_{fc} \cdot (X_{13} + X_{14} \cdot E_{electricity}) \end{aligned} \quad \text{(A.2)}$$

where $E_{electricity}$ is the carbon intensity of electricity generation and distribution in gCO_2eq/kWh, P_{batt} is the power in kW of the power battery (for HEVs and FCVs), C_{batt} is the capacity in kWh of the energy battery (for PHEVs and BEVs), and P_{fc} is the nominal power of the fuel cell system (for FCVs). The corresponding values for all vehicles are shown in Table A.4. $m_{scaling}$ is the remaining mass after subtracting from the curb weight the mass of the fixed components (tires, fluids, etc.), the battery, and the fuel cell system:

$$m_{scaling} = m_{curbweight} - X_1 - X_6 \cdot P_{batt} - X_9 \cdot C_{batt} - X_{12} \cdot P_{fc} \quad \text{(A.3)}$$

The curb weights for all vehicles analyzed are shown in Table A.4. All the coefficients (X_1 to X_{14}) are extracted from GREET, as shown in Table A.3. For all vehicles but FCVs, this approach reproduces the exact results of GREET with the corresponding inputs. For FCVs, our results are only an approximation of GREET's results. This is because in GREET, the power of the fuel cell (P_{fc}) has interdependencies with some of the coefficients X_i due to how the materials mix is calculated. The X_i would therefore, in theory, be a function of P_{fc}. However, this only has a minor effect on the final GHG emissions (error in $E_{vehiclecycle} \ll 1\%$), and can be neglected.

The vehicle costs are determined by the purchasing price and the costs for tires and regular maintenance. The purchasing price was assumed to be the manufacturer's suggested retail prices (MSRPs, Table A.4), while the annual tire and maintenance costs can be found in Table A.3.

Total emissions and costs per mile driven

The lifecycle costs per mile (not km) driven, C (in US$/mile), are calculated as follows:

$$C = \frac{C_{MSRP}}{L \cdot D} + \sum_{y=1}^{L} \frac{C_{fuel} \cdot FE^{-1} + C_{maintenance} \cdot D^{-1}}{(1+r)^{y-1}} \tag{A.4}$$

where C_{MSRP} is the purchasing price of the vehicle, L is the lifetime in years, D is the annual distance driven with each car, r is the discount rate, C_{fuel} is the fuel price in US$ per gallon-equivalent of fuel, FE is the fuel consumption in gallon-equivalents per mile, and $C_{maintenance}$ are the costs for tires and regular maintenance in US$ per year.

Total greenhouse gas emissions per mile driven, E, are calculated as:

$$E = \frac{E_{vehiclecycle}}{L \cdot D} + E_{fuelcycle} \tag{A.5}$$

Parameters of each vehicle model

Table A.4 displays the inputs used in Equations A.1-A.3 for each individual vehicle analyzed, as well as the number of units sold in 2014, which was used to calculate sales-weighted averages. The vehicle data was obtained from Cars.com [38], and the sales data from goodcarbadcar.net for model-level sales data [33] and hybridcars.com for sales data specific to HEV, PHEV, and BEV trims [42]. For those models for which several trims and engine sizes are available, the basic (most affordable) trim is analyzed. An exception is made for models that are offered with different powertrain technologies (such as the Toyota Camry ICEV and the Toyota Camry HEV). In these cases, the trim of the technology with the smaller feature set is upgraded to match the basic trim of the technology with the more extensive feature set, allowing for a direct comparison of these models. An overview of these cases can be found in table A.5.

The data for all vehicle models and their trims was gathered using an automated process. However, it was necessary to approximate the weight of each chosen trim, as only a range of lowest and highest curb weights was available, but not the weight of each specific trim. The curb weight was therefore calculated using a linear interpolation with respect to the MSRP: The lowest curb weight (lower end of range) was assigned to the trim with the lowest MSRP, the highest curb weight to the trim with the highest MSRP. The resulting curb weight was then assumed to scale linearly with the increase in MSRP. For vehicles where the trim with the lowest MSRP corresponds to the trim with the best fuel economy (about 80% of all vehicles), the chosen curb weight was therefore simply the lower end of the range. The error in curb weight due to this approximation is smaller than 50 kg (< 5%) for almost all vehicles.

The fuel economy ratings represent the official combined ratings assigned by the EPA (55% city and 45% highway driving). These are adjusted ratings that take into account the use of auxiliaries, driving in cold and hot conditions, aggressive driving patterns, and charging losses of PHEVs and BEVs.[64]

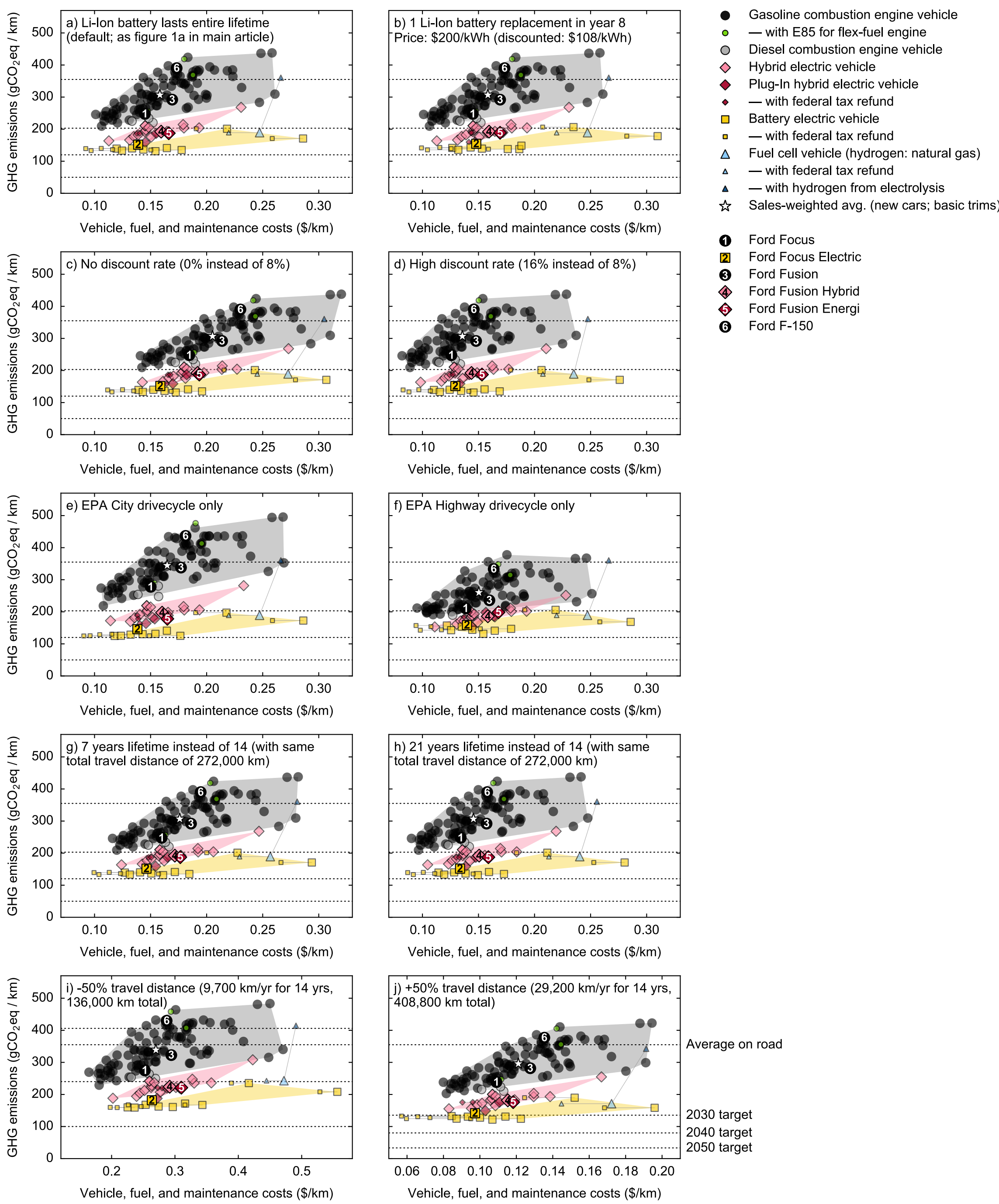

Figure A-3: Results of the sensitivity analyses described in section S2.2. The parameters that are changed in each subfigure are shown in Table A.1. The changes in lifetime travel distances (plots i and j) change the emission targets: the lower the lifetime driving distance, the higher (less stringent) the emission targets per mile driven. Therefore, the 2030 target is located above the current average emissions of cars on the road in plot i).

Table A.2: Greenhouse gas emission and cost factors of the fuel cycle. gGHG in the units of factors C_1, C_2, C_4, and C_5 refers to greenhouse gas emissions in gCO_2eq *without* emissions from electricity use, since the impact of electricity is accounted for separately by factors C_3 and C_6 in Eq. A.1. $\$/gal_{eq}$ refers to the price per one gallon-equivalent of gasoline; that is, the price per 121.9 MJ of lower heating value.

	Carbon Intensity Coefficients						Costs		
	Feedstock			Combustion					
Fuel	C_1 gGHG/mile	C_2 gGHG/gal	C_3 kWh/gal	C_4 gGHG/mile	C_5 gGHG/gal	C_6 kWh/gal	Average $\$/gal_{eq}$	Monthly min. $\$/gal_{eq}$	Monthly max. $\$/gal_{eq}$
Biodiesel (Forest-Based Residue Biooil)	0.00	-6157	1.52	0.00	0	8596			
Bioethanol (E85 Corn Ethanol)	0.00	-755	1.14	2.18	8456	0	2.51	1.49	3.56
Biogasoline (Forest-Based Residue Biooil)	0.00	-5869	1.64	0.00	2	8432			
Diesel	0.00	1709	0.49	0.20	8871	0	3.39	1.94	5.17
Electricity for charging BEV and PHEV	0.00	0	32.88	0.00	0	0	4.10	3.48	4.50
Gasoline Premium	0.00	1857	0.59	2.18	8607	0	3.41	2.14	4.73
Gasoline Regular	0.00	1857	0.59	2.18	8607	0	3.14	1.86	4.47
H2 from Electrolysis	0.00	0	52.29	0.00	0	0	7.47	7.11	7.77
H2 from Natural Gas	0.00	11478	4.30	3.27	0	0	4.05	3.62	6.03

Table A.3: Greenhouse gas emission and cost factors of the vehicle cycle. kgGHG in the units of factors X2, X4, X7, X10, and X13 refer to greenhouse gas emissions in $kgCO_2eq$ *without* emissions from electricity use, since the impact of electricity is accounted for separately by factors X3, X5, X8, X11, and X14.

	Carbon Intensity Coefficients														Costs
	Fixed parts (Tires, Fluids, etc)			Scaling Parts		Power Battery			Energy Battery			Fuel Cell System			Tires/Main.
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	
Class	kg	gGHG	kWh	kgGHG/kg	kWh/kg	kg/kW	kgGHG/kW	kWh/kW	kg/kWh	kgGHG/kWh	kWh/kWh	kg/kW	kgGHG/kW	kWh/kW	$/yr
Car (ICEV)	58.76	1,716	1,120	2.40	2.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	895.50
SUV (ICEV)	80.51	2,301	1,244	2.36	2.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1,012.50
PickUp (ICEV)	80.51	2,301	1,244	2.38	2.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1,012.50
Car (HEV)	42.39	1,640	1,106	2.40	2.37	1.25	5.01	6.22	0.00	0.00	0.00	0.00	0.00	0.00	895.50
SUV (HEV)	59.38	2,203	1,226	2.39	2.36	1.25	5.01	6.22	0.00	0.00	0.00	0.00	0.00	0.00	1,012.50
PickUp (HEV)	59.38	2,203	1,226	2.39	2.37	1.25	5.01	6.22	0.00	0.00	0.00	0.00	0.00	0.00	1,012.50
Car (PHEV)	42.39	1,656	1,174	2.41	2.38	0.00	0.00	0.00	9.43	33.62	24.69	0.00	0.00	0.00	771.25
SUV (PHEV)	59.38	2,219	1,294	2.40	2.37	0.00	0.00	0.00	9.43	33.62	24.69	0.00	0.00	0.00	873.75
PickUp (PHEV)	59.38	2,219	1,294	2.40	2.39	0.00	0.00	0.00	9.43	33.62	24.69	0.00	0.00	0.00	873.75
Car (BEV)	35.25	1,140	1,141	2.40	2.41	0.00	0.00	0.00	7.52	24.50	14.77	0.00	0.00	0.00	647.00
SUV (BEV)	50.30	1,471	1,246	2.38	2.39	0.00	0.00	0.00	7.52	24.50	14.77	0.00	0.00	0.00	735.00
PickUp (BEV)	50.30	1,471	1,246	2.37	2.40	0.00	0.00	0.00	7.52	24.50	14.77	0.00	0.00	0.00	735.00
Car (FCV)	35.25	1,124	1,074	2.41	2.43	1.25	5.01	6.22	0.00	0.00	0.00	5.00	56.48	40.89	647.00
SUV (FCV)	50.30	1,455	1,179	2.39	2.42	1.25	5.01	6.22	0.00	0.00	0.00	5.00	56.48	40.89	735.00
PickUp (FCV)	50.30	1,455	1,179	2.38	2.43	1.25	5.01	6.22	0.00	0.00	0.00	5.00	56.48	40.89	735.00

Table A.4: Input data for basic trims of all vehicles analyzed [38, 33, 42]. For each model, the most basic (affordable) trim is chosen, except for the models shown in Table A.5. Cweight = curb weight; FE = Fuel Economy; FE/2 = Fuel Economy in charge depleting (CD) mode for PHEVs; MPG = miles per gallon; MRSP = Manufacturer Recommended Selling Price; Ftax = federal tax refund; PBatt = power battery (HEV and FCV); Ebatt = energy battery (PHEVs and BEVs); FC = fuel cell power; PCon = Plug-in Hybrid (PHEV) drivetrain configuration (ser = serial, s-p = serial-parallel); Grs = number of gears; Pwr = nominal engine/motor power in hp (horsepower). Within 'fuel' column: Prem. Gas. = premium gasoline; SMR = steam methane reforming; Elysis = electrolysis; AS manual = auto-shift manual.

Description		Input													Trim Information		
Model	Trim	# Sold	Class	Type	Fuel	Cweight	FE	FE/2	MSRP	Ftax	Pbatt	Ebatt	FC	PCon	Transmission	Grs	Pwr
						kg	MPG	MPG	US$	US$	kW	kWh	kW				hp
Acura MDX	3.5L	65,603	Mid-size SUV	ICEV	Prem. Gas.	1826	23		$42,290						6-spd automatic	6	290
BMW 3-Series & 4-Series	i	142,232	Compact Car	ICEV	Prem. Gas.	1495	28		$32,750						8-spd automatic	4	180
BMW 5-Series	i	52,704	Mid-size Car	ICEV	Prem. Gas.	1730	27		$49,500						8-spd automatic	4	240
BMW i3	Base	6,092	Subcompact Car	BEV	Electricity	1270	124		$41,350	$7,500		22			1-spd automatic	0	170
Buick Enclave	Convenience	62,300	Full-size SUV	ICEV	Gasoline	2143	20		$38,890						6-spd automatic	6	288
Buick LaCrosse	Base	51,468	Mid-size Car	ICEV	Gasoline	1704	29		$33,535						6-spd automatic	4	182
Cadillac SRX	Base	53,578	Mid-size SUV	ICEV	Gasoline	1940	20		$37,605						6-spd automatic	6	308
Chevrolet Bolt***	0	0	Subcompact Car	BEV	Electricity	1624	115		$37,500			60			1-spd automatic	0	201
Chevrolet Camaro	LS w/1LS	86,297	Sports Car	ICEV	Gasoline	1679	21		$23,555						6-spd manual	6	323
Chevrolet Cruze	2LT Auto	273,060	Compact Car	ICEV	Gasoline	1533	30		$22,580						6-spd automatic	4	138
Chevrolet Cruze Diesel	Diesel	0	Compact Car	ICEV	Diesel	1574	33		$24,985						6-spd automatic	4	151
Chevrolet Equinox	LS	242,242	Mid-size SUV	ICEV	Gasoline	1705	26		$24,440						6-spd automatic	4	182
Chevrolet Impala	LS w/1LS	140,280	Full-size Car	ICEV	Gasoline	1669	25		$26,860						6-spd automatic	4	195
Chevrolet Malibu	LS w/1LS	188,519	Mid-size Car	ICEV	Gasoline	1539	29		$22,340						6-spd automatic	4	196
Chevrolet Silverado	w/1WT	529,755	Pickup	ICEV	Gasoline	2072	20		$25,575						6-spd automatic	6	285
Chevrolet Sonic	LS Manual	93,518	Subcompact Car	ICEV	Gasoline	1220	29		$14,170						5-spd manual	4	138

Table A.4 Continued: Input data for all vehicles analyzed

Description		Input													Trim Information		
Model	Trim	# Sold	Class	Type	Fuel	Cweight	FE	FE/2	MSRP	Ftax	Pbatt	Ebatt	FC	PCon	Transmission	Grs	Pwr
Chevrolet Spark	1LT Auto	38,014	Subcompact Car	ICEV	Gasoline	1059	33		$14,995						2-spd CVT	4	84
Chevrolet Spark EV	1LT	1,145	Subcompact Car	BEV	Electricity	1356	119		$26,685	$7,500		19			1-spd automatic	0	130
Chevrolet Suburban	LS	55,009	Full-size SUV	ICEV	Gasoline	2574	17		$46,300						6-spd automatic	8	320
Chevrolet Tahoe	LS	97,726	Full-size SUV	ICEV	Gasoline	2480	17		$43,600						6-spd automatic	8	320
Chevrolet Traverse	LS	103,943	Full-size SUV	ICEV	Gasoline	2108	20		$30,795						6-spd automatic	6	281
Chevrolet Volt	Base	18,805	Compact Car	PHEV	El./Prem.Gas.	1717	37	97	$34,185	$7,500		17		ser	1-spd automatic	0	149
Chrysler 200	LX	117,363	Mid-size Car	ICEV	Gasoline	1543	24		$21,795						4-spd automatic	4	173
Chrysler 300	Base	53,382	Full-size Car	ICEV	Gasoline	1797	23		$31,395						8-spd automatic	6	292
Chrysler Town & Country	Touring	138,040	Car	ICEV	Gasoline	2110	20		$30,765						6-spd automatic	6	283
Dodge Avenger	SE	51,705	Mid-size Car	ICEV	Gasoline	1542	24		$20,595						4-spd automatic	4	173
Dodge Challenger	SXT	51,611	Sports Car	ICEV	Gasoline	1739	21		$26,495						5-spd automatic	6	305
Dodge Charger	SE	94,099	Sports Car	ICEV	Gasoline	1797	21		$26,995						5-spd automatic	6	292
Dodge Dart	SE	83,858	Compact Car	ICEV	Gasoline	1445	29		$16,495						6-spd manual	4	160
Dodge Durango	SXT	64,398	Full-size SUV	ICEV	Gasoline	2157	21		$29,995						8-spd automatic	6	290
Dodge Grand Caravan	AVP/SE	134,152	Car	ICEV	Gasoline	1960	20		$20,895						6-spd automatic	6	283
Dodge Journey	SE	93,572	Mid-size SUV	ICEV	Gasoline	1732	22		$19,995						4-spd automatic	4	173
Fiat 500	Lounge	32,205	Subcompact Car	ICEV	Gasoline	1096	34		$18,500		40				5-spd manual	4	101
Fiat 500E	Base	1,503	Subcompact Car	BEV	Electricity	1352	115		$31,800	$7,500		24			1-spd automatic	0	111
Ford C-Max Energi	SEL	8,433	Compact Car	PHEV	Electr./Gas.	1750	38	88	$31,635	$4,007		8		s-p	2-spd CVT	4	141
Ford C-Max Hybrid	SEL	19,162	Compact Car	HEV	Gasoline	1636	39		$27,170		40				2-spd CVT	4	141
Ford Edge	SE	108,864	Mid-size SUV	ICEV	Gasoline	1840	22		$28,100						6-spd automatic	6	285
Ford Escape	S	306,212	Compact SUV	ICEV	Gasoline	1588	25		$23,100						6-spd automatic	4	168
Ford Explorer	Base	189,339	Mid-size SUV	ICEV	Gasoline	2057	20		$30,015						6-spd automatic	6	290
Ford F-Series	XL	753,851	Pickup	ICEV	Gas/E85	2125	19		$25,025						6-spd automatic	6	302
Ford Fiesta	S	63,192	Subcompact Car	ICEV	Gasoline	1151	31		$14,100						5-spd manual	4	120

Table A.4 Continued: Input data for all vehicles analyzed

Description		Input													Trim Information		
Model	Trim	# Sold	Class	Type	Fuel	Cweight	FE	FE/2	MSRP	Ftax	Pbatt	Ebatt	FC	PCon	Transmission	Grs	Pwr
Ford Focus	Titanium	217,670	Compact Car	ICEV	Gas/E85	1386	31		$24,065						6-spd AS manual	4	160
Ford Focus Electric	Base**	1,964	Compact Car	BEV	Electricity	1651	105		$30,165	$7,500		23			1-spd automatic	0	143
Ford Fusion	Titanium**	259,905	Mid-size Car	ICEV	Gasoline	1577	26		$23,935						6-spd automatic	4	175
Ford Fusion Energi	SE Luxury	11,550	Mid-size Car	PHEV	Electr./Gas.	1775	38	88	$32,590	$4,007		8		s-p	2-spd CVT	4	141
Ford Fusion Hybrid	Titanium**	35,405	Mid-size Car	HEV	Gasoline	1640	42		$27,280		40				2-spd CVT	4	141
Ford Mustang	V6	82,635	Sports Car	ICEV	Gasoline	1588	22		$22,510						6-spd manual	6	305
Ford Taurus	SE	52,395	Full-size Car	ICEV	Gasoline	1830	22		$26,780						6-spd automatic	6	288
GMC Acadia	SLE-1	83,972	Full-size SUV	ICEV	Gasoline	2112	20		$34,485						6-spd automatic	6	288
GMC Sierra	Base	211,833	Pickup	ICEV	Gasoline	2072	20		$26,075						6-spd automatic	6	285
GMC Terrain	SLE-1	105,016	Mid-size SUV	ICEV	Gasoline	1748	26		$26,465						6-spd automatic	4	182
Honda Accord	EX**	374,397	Mid-size Car	ICEV	Gasoline	1500	28		$25,680						2-spd CVT	4	185
Honda Accord Hybrid	Base	13,977	Mid-size Car	HEV	Gasoline	1610	47		$29,155		40				1-spd CVT	4	141
Honda Civic	EX	320,911	Mid-size Car	ICEV	Gasoline	1288	33		$21,090						2-spd CVT	4	143
Honda Civic Hybrid	Base	5,070	Mid-size Car	HEV	Gasoline	1306	45		$24,635		40				2-spd CVT	4	90
Honda CR-V	LX	335,019	Compact SUV	ICEV	Gasoline	1499	26		$23,120						5-spd automatic	4	185
Honda Fit [2015]	LX	59,340	Subcompact Car	ICEV	Gasoline	1140	32		$15,650						6-spd manual	4	130
Honda Odyssey	LX	122,738	Car	ICEV	Gasoline	1994	22		$28,825						6-spd automatic	6	248
Honda Pilot	LX	108,857	Mid-size SUV	ICEV	Gasoline	1950	21		$29,670						5-spd automatic	6	250
Hyundai Accent	GLS	63,309	Subcompact Car	ICEV	Gasoline	1125	31		$14,645						6-spd manual	4	138
Hyundai Elantra	SE	222,023	Compact Car	ICEV	Gasoline	1258	31		$17,200						6-spd manual	4	145
Hyundai Santa Fe	GLS	107,906	Mid-size SUV	ICEV	Gasoline	1771	21		$29,900						6-spd automatic	6	290
Hyundai Sonata	SE	195,884	Mid-size Car	ICEV	Gasoline	1523	28		$24,300						6-spd automatic	4	192
Hyundai Sonata Hybrid	Base	21,052	Mid-size Car	HEV	Gasoline	1568	38		$26,000		40				6-spd automatic	4	159
Jeep Cherokee	Sport	178,508	Mid-size SUV	ICEV	Gasoline	1669	25		$22,995						9-spd automatic	4	184
Jeep Compass	Sport	61,264	Compact SUV	ICEV	Gasoline	1405	26		$18,795						5-spd manual	4	158

Table A.4 Continued: Input data for all vehicles analyzed

Description		Input													Trim Information		
Model	Trim	# Sold	Class	Type	Fuel	Cweight	FE	FE/2	MSRP	Ftax	Pbatt	Ebatt	FC	PCon	Transmission	Grs	Pwr
Jeep Grand Cherokee	Laredo	183,786	Mid-size SUV	ICEV	Gas/E85	2062	20		$29,495						8-spd automatic	6	290
Jeep Patriot	Sport	93,462	Compact SUV	ICEV	Gasoline	1422	26		$16,395						5-spd manual	4	158
Jeep Wrangler	Sport	175,328	Compact SUV	ICEV	Gasoline	1760	19		$22,395						6-spd manual	6	285
Kia Forte	LX	69,336	Compact Car	ICEV	Gasoline	1241	29		$15,900						6-spd manual	4	148
Kia Optima	LX	145,244	Mid-size Car	ICEV	Gasoline	1468	27		$21,500						6-spd automatic	4	192
Kia Optima Hybrid	LX	13,776	Mid-size Car	HEV	Gasoline	1586	38		$25,995		40				6-spd automatic	4	159
Kia Sorento	LX	102,520	Mid-size SUV	ICEV	Gasoline	1630	22		$24,100						6-spd automatic	4	191
Kia Soul	Base	145,316	Compact Car	ICEV	Gasoline	1231	26		$14,900						6-spd manual	4	130
Lexus CT 200h	Premium	17,673	Compact Car	HEV	Gasoline	1420	41		$32,050		40				2-spd CVT	4	98
Lexus ES 300h	Base	14,837	Full-size Car	HEV	Gasoline	1660	39		$39,500		40				2-spd CVT	4	156
Lexus ES 350	Base	57,671	Full-size Car	ICEV	Gasoline	1610	25		$36,620						6-spd automatic	6	268
Lexus IS	Base	51,358	Compact Car	ICEV	Gasoline	1570	24		$36,100						6-spd automatic	6	204
Lexus RX 350	Base	98,139	Mid-size SUV	ICEV	Gasoline	1895	21		$39,760						6-spd automatic	6	270
Lexus RX 450h	Base	9,351	Mid-size SUV	HEV	Gasoline	2050	30		$46,410		60				2-spd CVT	6	245
Lincoln MKZ	Base	23,976	Compact Car	ICEV	Gasoline	1687	26		$35,190						6-spd automatic	4	240
Lincoln MKZ Hybrid	Base	10,033	Compact Car	HEV	Gasoline	1736	37		$35,190		40				2-spd CVT	4	141
Mazda 3	i SV	104,985	Compact Car	ICEV	Gasoline	1261	33		$16,945						6-spd manual	4	155
Mazda 6	i Sport	53,224	Mid-size Car	ICEV	Gasoline	1444	29		$20,990						6-spd manual	4	184
Mazda CX-5	Sport	99,122	Compact SUV	ICEV	Gasoline	1449	29		$21,395						6-spd manual	4	155
Mercedes-Benz C-Class	Sport	75,065	Compact Car	ICEV	Prem. Gas.	1555	25		$35,800						7-spd automatic	4	201
Mercedes-Benz E-Class	Base	66,400	Mid-size Car	ICEV	Prem. Gas.	1642	24		$51,900						7-spd automatic	6	302
Nissan Altima	2.5	335,644	Mid-size Car	ICEV	Gasoline	1410	31		$22,170						2-spd CVT	4	182
Nissan Frontier	S	74,323	Pickup	ICEV	Gasoline	1682	21		$17,990						5-spd manual	4	152
Nissan Leaf	S	30,200	Compact Car	BEV	Electricity	1477	113		$28,980	$7,500		24			1-spd automatic	0	107
Nissan Maxima	3.5 S	50,401	Full-size Car	ICEV	Prem. Gas.	1613	22		$31,290						2-spd CVT	6	290

Table A.4 Continued: Input data for all vehicles analyzed

Description		Input													Trim Information		
Model	Trim	# Sold	Class	Type	Fuel	Cweight	FE	FE/2	MSRP	Ftax	Pbatt	Ebatt	FC	PCon	Transmission	Grs	Pwr
Nissan Pathfinder	S	79,111	Mid-size SUV	ICEV	Gasoline	1891	22		$29,210						2-spd CVT	6	260
Nissan Rogue	S	199,199	Mid-size SUV	ICEV	Gasoline	1539	29		$22,790						2-spd CVT	4	170
Nissan Sentra	S	183,268	Mid-size Car	ICEV	Gasoline	1285	30		$15,990						6-spd manual	4	130
Nissan Versa	1.6 S	139,781	Subcompact Car	ICEV	Gasoline	1105	30		$11,990						5-spd manual	4	109
Ram P/U	Tradesman	439,789	Pickup	ICEV	Gasoline	2048	20		$25,060						8-spd automatic	6	305
Smart Fortwo	passion	7,859	Subcompact Car	ICEV	Gasoline	827	36		$14,930						5-spd AS manual	3	70
Smart Fortwo electric drive	passion	2,594	Subcompact Car	BEV	Electricity	970	107		$25,000	$7,500		18			1-spd automatic	0	74
Subaru Forester	2.5i	159,953	Compact SUV	ICEV	Gasoline	1490	25		$21,995						6-spd manual	4	170
Subaru Impreza	2.0i	57,996	Compact Car	ICEV	Gasoline	1335	28		$17,895						5-spd manual	4	148
Subaru Legacy	2.5i	52,270	Mid-size Car	ICEV	Gasoline	1504	24		$20,295						6-spd manual	4	173
Subaru Outback	2.5i	138,790	Mid-size SUV	ICEV	Gasoline	1553	25		$23,495						6-spd manual	4	173
Subaru XV Crosstrek	2.0i Premium	70,956	Compact SUV	ICEV	Gasoline	1405	26		$21,995						5-spd manual	4	148
Tesla Model 3***	0	0	Compact Car	BEV	Electricity	1565	125		$35,000			55			1-spd automatic	0	201
Tesla Model S	Base (60kWh)	16,550	Full-size Car	BEV	Electricity	2108	95		$69,900	$7,500		60			1-spd automatic	0	302
Toyota 4Runner	SR5	76,906	Mid-size SUV	ICEV	Gasoline	1996	19		$32,820						5-spd automatic	6	270
Toyota Avalon	XLE Premium	50,135	Full-size Car	ICEV	Gasoline	1578	25		$33,445						6-spd automatic	6	268
Toyota Avalon Hybrid	XLE Premium	17,048	Full-size Car	HEV	Gasoline	1630	39		$35,805		40				2-spd CVT	4	156
Toyota Camry	LE	389,091	Mid-size Car	ICEV	Gasoline	1453	29		$22,870						6-spd automatic	4	178
Toyota Camry Hybrid	LE	39,515	Mid-size Car	HEV	Gasoline	1551	41		$26,790		40				2-spd CVT	4	156
Toyota Corolla/Matrix	L	339,498	Compact Car	ICEV	Gasoline	1270	31		$16,800						6-spd manual	4	132
Toyota Highlander	LE	146,127	Mid-size SUV	ICEV	Gasoline	1875	22		$29,215						6-spd automatic	4	185
Toyota Mirai	0	1	Mid-size Car	FCV	Hydrogen	1850	66		$57,500	$7,500	40		90		1-spd direct	0	151
Toyota Prius	Two	122,776	Mid-size Car	HEV	Gasoline	1380	49		$24,200		40				2-spd CVT	4	98
Toyota Prius C	One	40,570	Subcompact Car	HEV	Gasoline	1134	49		$19,080		40				2-spd CVT	4	73
Toyota Prius Plug-In	Base	13,264	Mid-size Car	PHEV	Electr./Gas.	1436	50	95	$29,990	$1,500		4		s-p	2-spd CVT	4	98

Table A.4 Continued: Input data for all vehicles analyzed

Description		Input													Trim Information		
Model	Trim	# Sold	Class	Type	Fuel	Cweight	FE	FE/2	MSRP	Ftax	Pbatt	Ebatt	FC	PCon	Transmission	Grs	Pwr
Toyota Prius V	Two	30,762	Full-size Car	HEV	Gasoline	1485	42		$26,750		40				2-spd CVT	4	98
Toyota RAV4	XLE	266,514	Compact SUV	ICEV	Gasoline	1577	27		$25,000						6-spd automatic	4	176
Toyota RAV4 EV	Base	1,184	Compact SUV	BEV	Electricity	1829	76		$49,800	$7,500		42			1-spd automatic	0	154
Toyota Sienna	L V6	124,502	Car	ICEV	Gasoline	1955	21		$26,920						6-spd automatic	6	266
Toyota Tacoma	Base	155,041	Pickup	ICEV	Gasoline	1508	23		$18,125						5-spd manual	4	159
Toyota Tundra	SR V6	118,493	Pickup	ICEV	Gasoline	2159	18		$26,200						5-spd automatic	6	270
Volkswagen Jetta Hybrid	Base	1,939	Compact Car	HEV	Gasoline	1502	45		$25,560		40				7-spd AS manual	4	150
Volkswagen Jetta Sedan	2.0L S	122,192	Compact Car	ICEV	Gasoline	1288	28		$16,895						5-spd manual	4	115
Volkswagen Jetta TDI	2.0L TDI Value	0	Compact Car	ICEV	Diesel	1470	34		$21,295						6-spd manual	4	140
Volkswagen Passat	1.8T SE	96,649	Mid-size Car	ICEV	Gasoline	1482	28		$25,875						6-spd automatic	4	170
Volkswagen Passat TDI	2.0L TDI SE	0	Mid-size Car	ICEV	Diesel	1539	35		$26,675						6-spd manual	4	140

* The BMW i3 was modeled with a lightweight material mix to account for the heavy use of carbon fiber within its chassis. Only 50% of the emission penalty (as modeled by GREET) was awarded, since BMW claims to use renewable electricity for the final production stages of the carbon fiber parts.

** These trims were modified further to correspond more closely to the respective HEV, PHEV, or BEV trims. See footnotes below Table A.5 for details.

*** The curb weight, fuel economy, and (for the Tesla Model 3) battery size were estimated based on early projections and properties of models of similar size and shape.

Table A.5: List of vehicle models for which a trim other than the most basic (most affordable) trim was chosen in order to match the feature set of the most basic HEV, PHEV, or BEV version of the same model.

Model	Basic trim			Chosen trim			Matched with
	Name	MSRP	Fuel economy	Name	MSRP	Fuel economy	
Chevrolet Cruze	LS Manual	$17,520	29	2LT Auto	$22,580	30	Cruze Diesel (Diesel ICEV)
Chevrolet Spark	LS Manual	$12,170	34	1LT Auto	$14,995	33	Spark EV 1LT (BEV)
FIAT 500	Pop	$16,445	34	Lounge	$18,500	34	500e Battery Electric (BEV)
Ford C-Max Hybrid	SE	$24,170	39	SEL	$27,170	39	C-Max Energi SEL (PHEV)
Ford Focus	S	$16,810	30	Titanium	$24,065	31	Focus Electric Base (BEV)
Ford Focus Electric	Base	$29,170	104	Base*	$30,165	104	Focus Titanium (ICEV)
Ford Fusion	S	$21,970	26	Titanium**	$28,800	26	Fusion Energi SE Luxury (PHEV)
Ford Fusion Hybrid	S	$26,270	42	Titanium**	$30,800	42	Fusion Energi SE Luxury (PHEV)
Honda Accord	LX	$21,955	28	EX***	$25,680	28	Accord Hybrid Base (HEV)
Honda Civic	LX	$18,190	31	EX	$21,090	33	Civic Hybrid Base (HEV)
Hyundai Sonata	GLS	$21,450	28	SE	$24,300	28	Sonata Hybrid Base (HEV)
smart fortwo	pure	$13,270	36	passion	$14,930	36	fortwo electric passion (BEV)
Toyota Avalon	XLE	$31,590	25	XLE Premium	$33,445	25	Avalon Hybrid XLE Premium (HEV)
Toyota Camry	L	$22,425	29	LE	$22,870	29	Camry Hybrid LE (HEV)
Toyota RAV4	LE	$23,550	27	XLE	$25,000	27	RAV4 EV Base (BEV)
Volkswagen Jetta	2.0L Base	$15,695	28	2.0L S	$16,895	28	Jetta Hybrid Base (HEV)
Volkswagen Passat	1.8T S	$22,095	28	1.8T SE	$25,875	28	Passat 2.0L TDI SE

* The leather seat option ($995) was added to this trim to match the seats of the Ford Focus Titanium.

** The price of this trim was decreased by $1800 to match the ‘SE Luxury’ (rather than the ‘Titanium’) feature set of the Ford Fusion Energi.

*** The CVT transmission option ($800) was added manually to this trim to match the transmission system of the Honda Accord Hybrid.

Appendix B

Supporting Information for Chapter 4

B.1 Updated emissions model

To calculate lifecycle emissions, we rely on model from Chapter 2 (see Appendix B), with updated coefficients for vehicle production emissions to reflect the 2018 version of GREET [12]. Equations A.2 and A.3 remain the same, but coefficients from Table B.1 are used instead of those shown in Table A.3.

Table B.1: Updated emission factors for vehicle production emissions, based on the 2018 version of GREET [12], corresponding to equations A.2 and A.3. These factors replace those in Table A.3 for the analysis in chapters 4 and 5.

			Fixed parts (tires, fluids,...)			Scaling Parts		Power Battery			Energy Battery			Fuel Cell System		
			kg X1	$kgCO_2eq$ X2	kWh X3	$kgCO_2eq$ / kg X4	kWh / kg X5	kg/kW X6	$kgCO_2eq$ / kW X7	kWh / kW X8	kg/kWh X9	$kgCO_2eq$ / kWh X10	kWh / kWh X11	kg/kW X12	$kgCO_2eq$ / kW X13	kWh / kW X14
ICEV	Conv.	Car	0	1492	1125	1.86	3.92	0	0	0	0	0	0	0	0	0
		SUV/Truck	0	2202	1335	1.84	3.92	0	0	0	0	0	0	0	0	0
	Lightw.	Car	0	1482	1114	4.43	6.57	0	0	0	0	0	0	0	0	0
		SUV/Truck	0	2187	1320	4.44	6.54	0	0	0	0	0	0	0	0	0
HEV	Conv.	Car	0	1418	1109	1.85	4.04	0.44	4.30	2.50	0	0	0	0	0	0
		SUV/Truck	0	2106	1316	1.83	4.03	0.44	4.30	2.50	0	0	0	0	0	0
	Lightw.	Car	0	1412	1103	4.27	6.53	0.44	4.30	2.50	0	0	0	0	0	0
		SUV/Truck	0	2096	1306	4.27	6.43	0.44	4.30	2.50	0	0	0	0	0	0
PHEV	Conv.	Car	0	1418	1109	1.85	4.03	0	0	0	10.53	39.77	34.84	0	0	0
		SUV/Truck	0	2106	1316	1.81	4.04	0	0	0	10.53	39.22	34.58	0	0	0
	Lightw.	Car	0	1412	1103	4.14	6.42	0	0	0	10.53	39.77	34.84	0	0	0
		SUV/Truck	0	2096	1306	3.56	5.42	0	0	0	10.53	39.40	34.67	0	0	0
BEV	Conv.	Car	0	914	1077	1.91	4.19	0	0	0	6.71	47.35	21.36	0	0	0
		SUV/Truck	0	1376	1268	1.88	4.16	0	0	0	6.71	46.80	21.10	0	0	0
	Lightw.	Car	0	908	1071	4.76	6.94	0	0	0	6.71	47.35	21.36	0	0	0
		SUV/Truck	0	1367	1259	4.77	6.84	0	0	0	6.71	46.97	21.18	0	0	0
FCV	Conv.	Car	0	2975	3423	1.86	4.20	0.44	4.30	2.50	0	0	0	6.19	6.01	2.61
		SUV/Truck	0	3969	4221	1.85	4.17	0.44	4.30	2.50	0	0	0	6.19	5.99	2.61
	Lightw.	Car	0	1725	2259	5.66	8.25	0.44	4.30	2.50	0	0	0	6.19	3.26	1.65
		SUV/Truck	0	2362	2704	5.33	7.72	0.44	4.30	2.50	0	0	0	12.38	2.73	1.39

B.2 Additional results

Figures B-1 and B-2 show additional details on modeling annual travel distance and lifetime across individual vehicles. Model outputs using three different correlation coefficients (see also Figure 4-3) are compared against the data (Figure B-1), and the heterogeneity in annual travel distance, vehicle lifetime, and lifetime travel distance is shown (Figure B-2).

Figures B-3 to B-8 show the full results from analyzing National Household Travel Survey (NHTS) data, depicting all indicators for all vehicle classes and all 49 population density-state combinations.

Finally, Figure B-9 expands Figure 4-8 by showing two additional metrics not shown in the main plot.

Additional details on annual travel distance and vehicle lifetime across individual vehicles

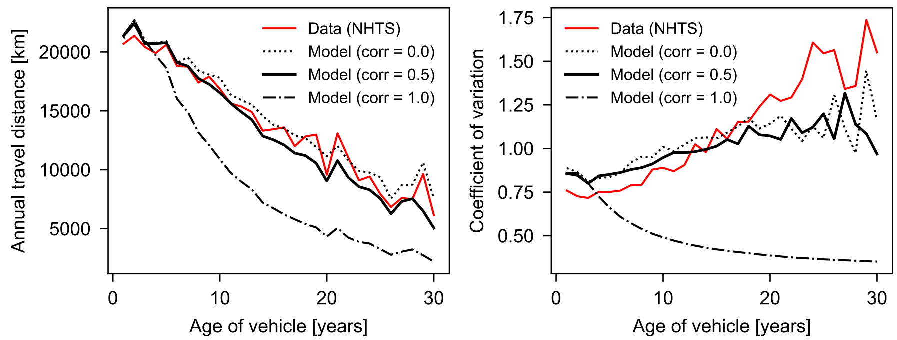

Figure B-1: Output of the annual travel distance and vehicle lifetime model compared against the input data from the 2017 National Household Travel Survey (NHTS). Shown are model outputs for the three different correlation coefficients also shown in Figure 4-3: 0.0, 0.5, and 1.0.

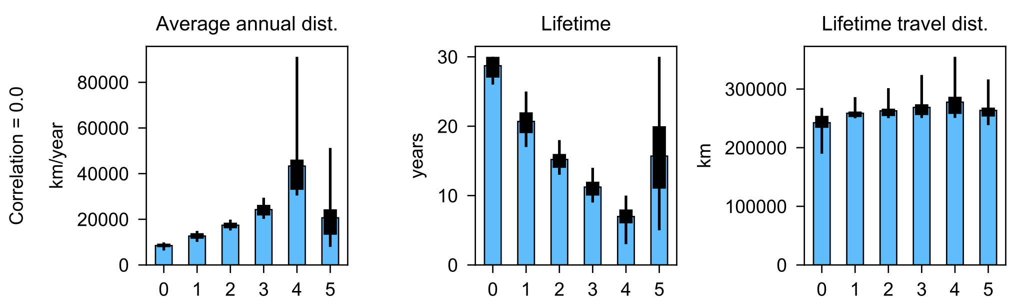

Figure B-2: Mean values and distributions in average annual travel distance, vehicle lifetime, and lifetime travel distance using the model described in Chapter 4. Shown are model outputs for correlation coefficient 0.5 (see Figure 4-3).

Additional indicators and full results for heterogeneity across regions

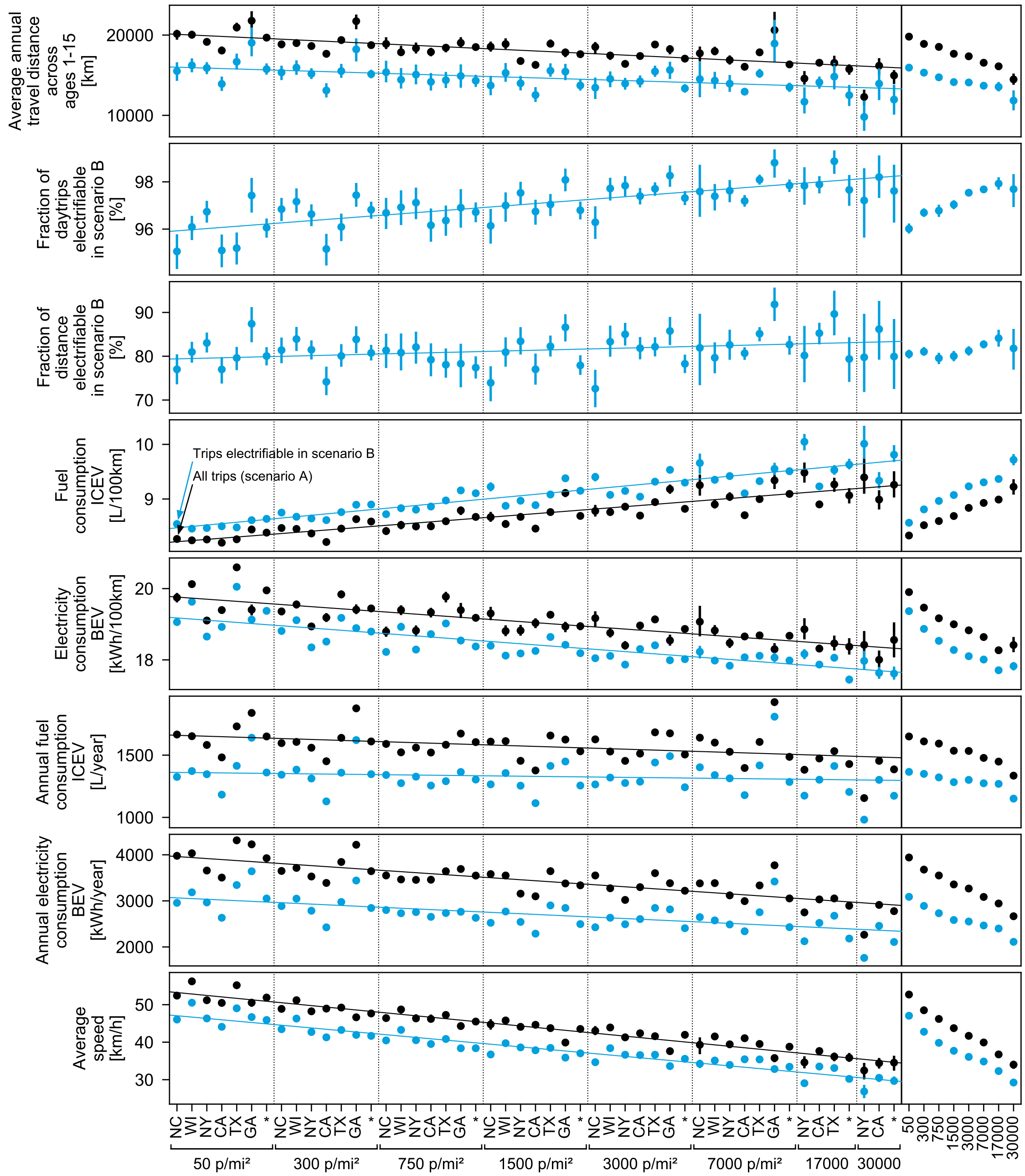

Figure B-3: Spatial variation of indicators for all 49 population density-state combinations shown in Table 4.2 as a result of varying population density, and heterogeneity across selected states within a given population density bracket for 50 and 30000 people/mi². Black items refer to Scenario A in Table 4.1, blue items to Scenario B, only including the vehicle travel days (daytrips) that are electrifiable. Results are weighted across the five classes shown in Table 4.4). The lines between 50 and 30000 people/mi² show a least mean squares fit to the corresponding points. Indicator results. Note that this figure only shows indicators as measured or derived from NHTS data. The impact of climate on fuel efficiency is not considered.

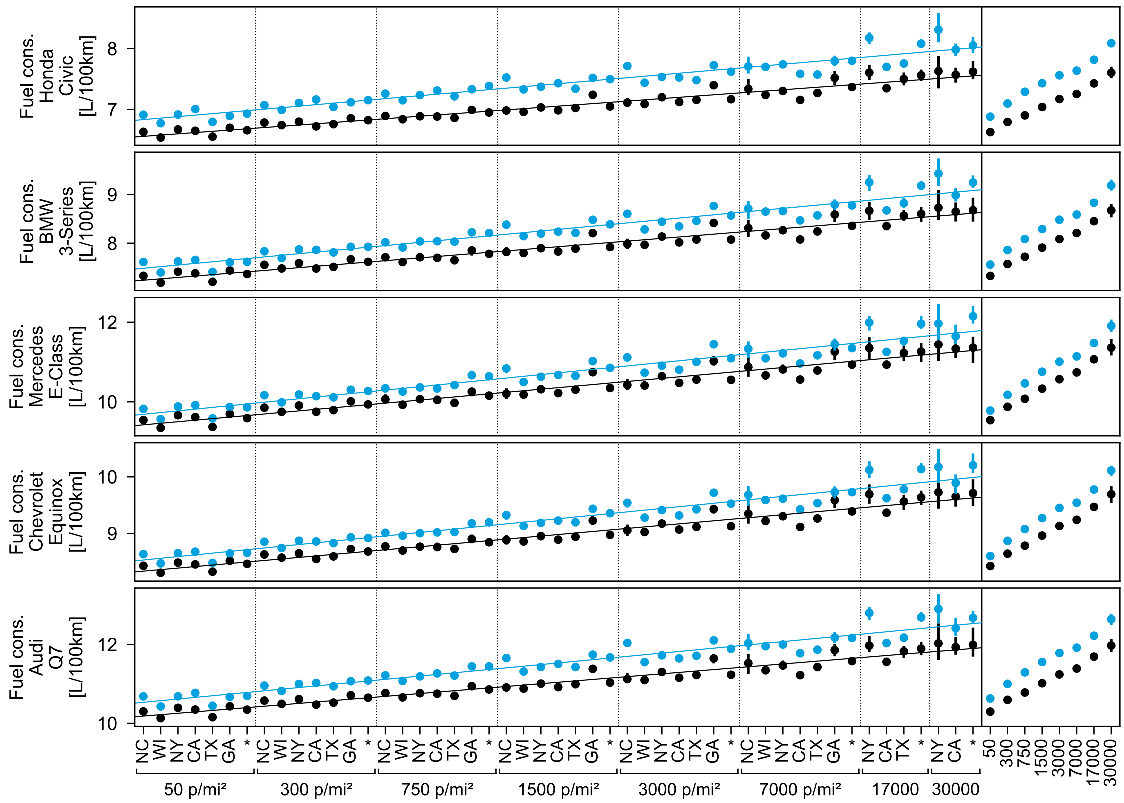

Figure B-4: Fuel efficiency for each specific ICEV model across regions. Note that this figure only shows indicators as measured or derived from NHTS data. The impact of climate on fuel efficiency is not considered.

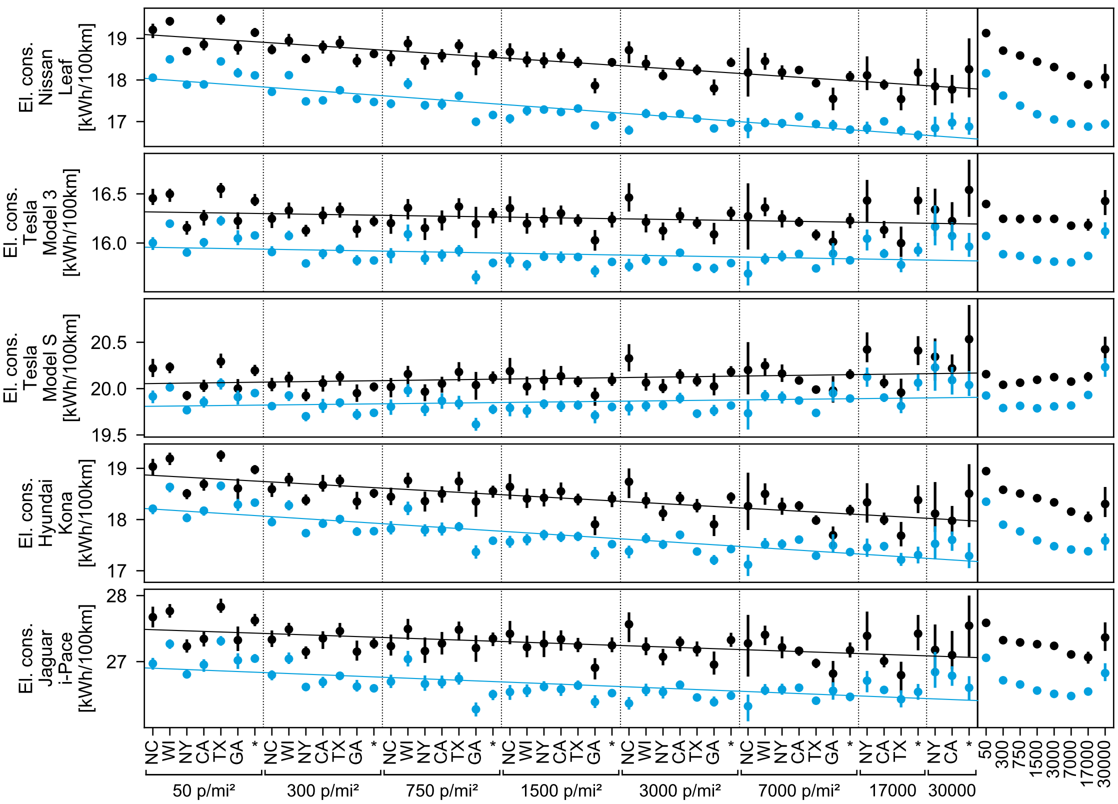

Figure B-5: Fuel efficiency for each specific BEV model across regions. Note that this figure only shows indicators as measured or derived from NHTS data. The impact of climate on fuel efficiency is not considered.

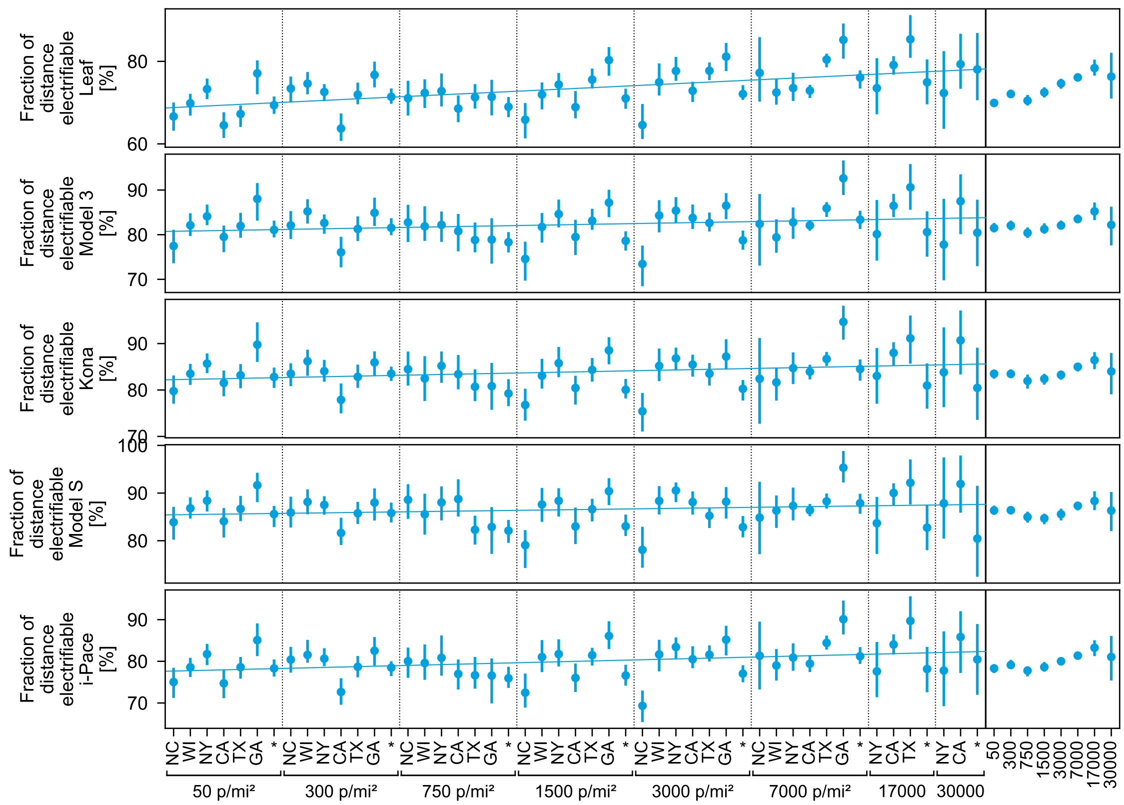

Figure B-6: Fraction of trip distance that is electrifiable in Scenario B for each specific BEV model. The fraction depends both on the battery capacity of the model as well as on fuel consumption. Note that this figure only shows indicators as measured or derived from NHTS data. The impact of climate on fuel efficiency is not considered.

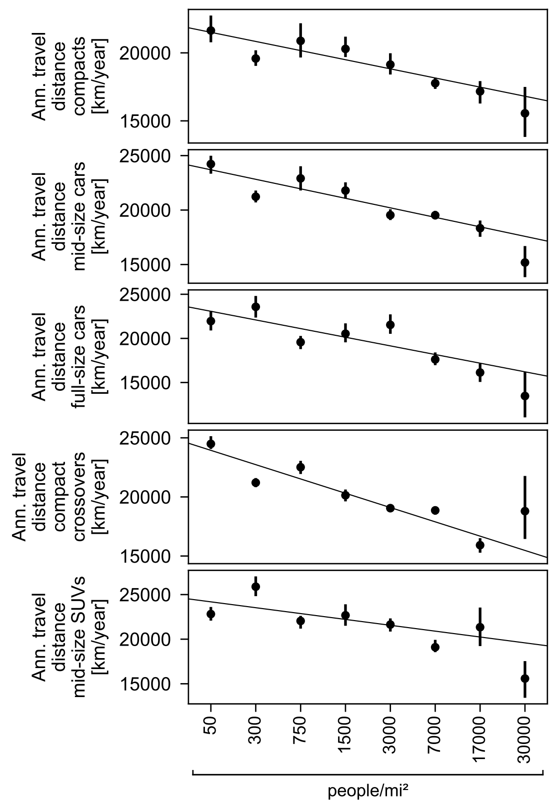

Figure B-7: Annual travel distance for each vehicle class.

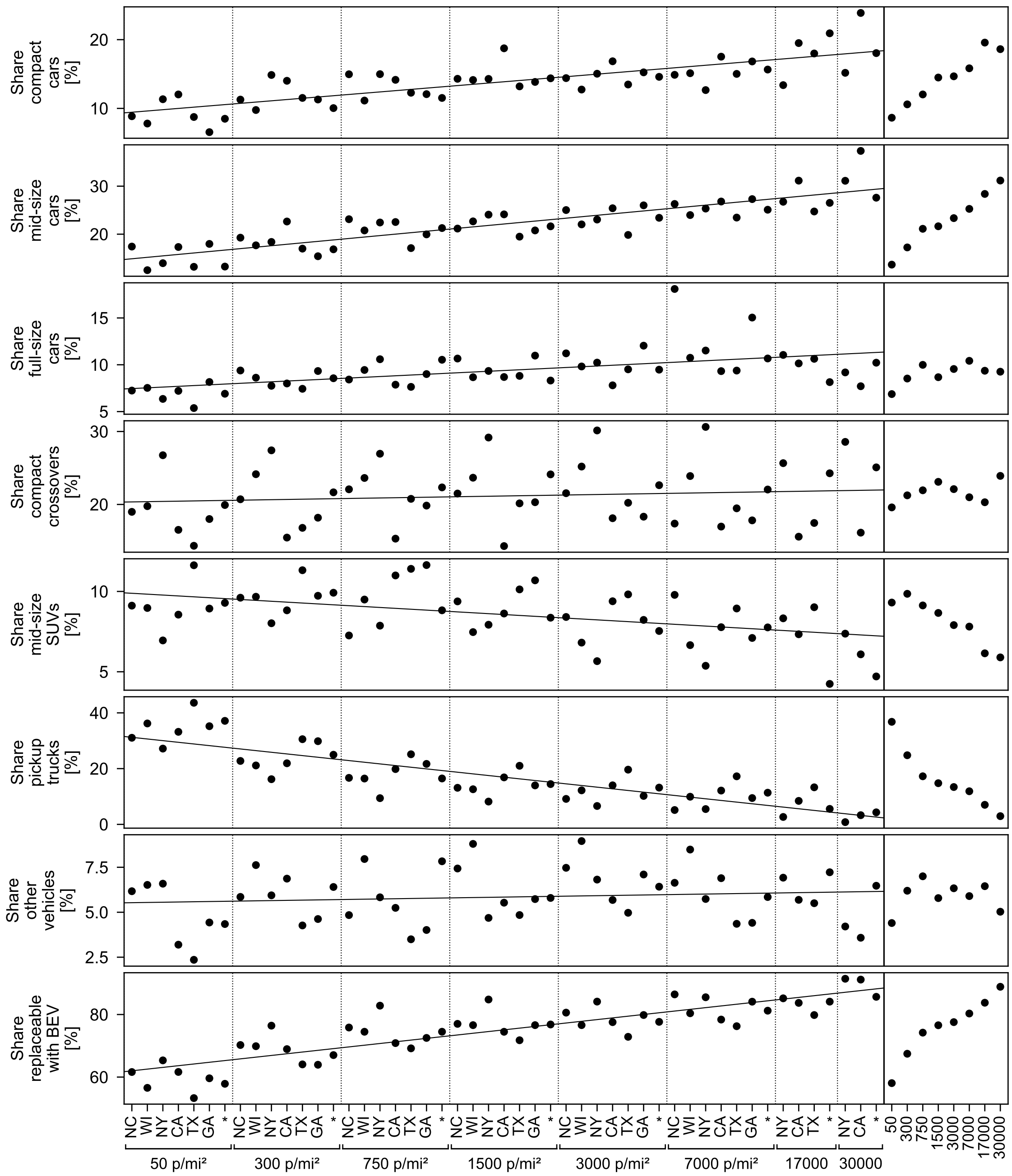

Figure B-8: Share of each vehicle class in each region. The first five classes are used for the analysis; pickup trucks and other vehicles, which include vans and 2-seater sports cars, are not included. The last row shows the fraction of vehicles that belong to classes 1-5.

Additional indicators for heterogeneity across individual vehicles

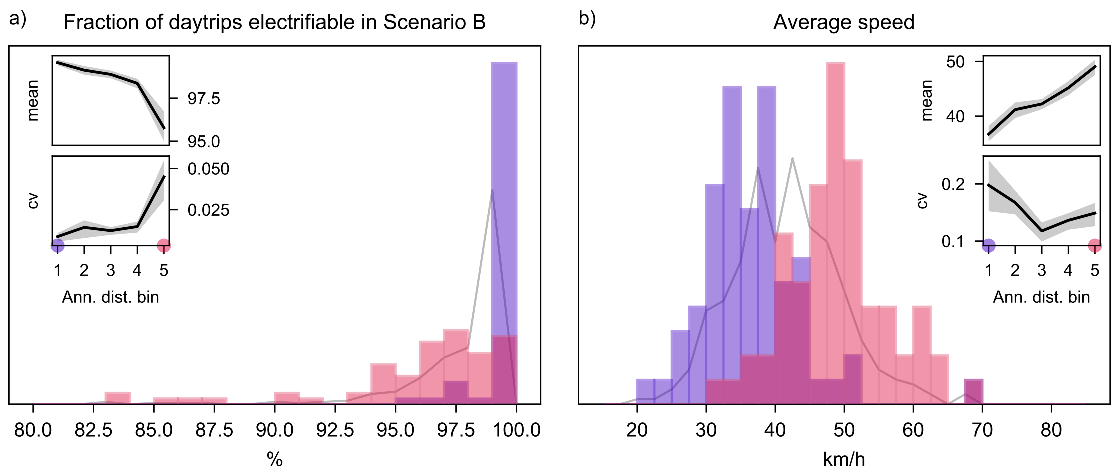

Figure B-9: Expansion of Figure 4-8, showing results for two additional indicators: the fraction of daytrips not electrificable in Scenario B, and the average trip speed.

B.3 Tables

Table B.3 shows summary statistics for each of the 49 population density-state combinations used to asses the heterogeneity of travel patterns across regions in the U.S., based on data from the 2017 National Household Travel Survey (NHTS). Table B.3 shows the average heating and cooling degrees per hour for each of the 50 U.S. states.

Table B.2: Summary of statistics of the National Household Travel Survey (NHTS) subsets used for the analysis in this chapter. An asterisk (*) for state indicates all states not listed explicitly for the corresponding population density bracket. Pden = Population density; Veh/cap = average number of vehicles per person; Annual dist. 1-15 = population-average annual travel distance of vehicles aged 1-15.

		Number of rows in data			Veh/cap	Vehicle class shares				Trip time		Annual dist. 1-15		Individual trip averages			Travel hours per day	
Pop. den. p/mi^2	State	Trips	Daytrips	Vehicles		Cars %	Vans %	SUVs %	Pickups %	8AM %	4PM %	Per veh. km	Per cap. km	Distance km	Duration min	Speed m/s	Vehicle h/day/veh	Person h/day/cap
50	NC	6782	1804	3213	1.07	41%	7%	23%	29%	7%	10%	20147	21581	20.2	23.2	51.8	1.07	1.14
50	WI	11263	3066	5463	1.21	36%	8%	23%	32%	7%	10%	20042	24159	19.4	20.7	56.0	0.98	1.18
50	NY	13185	3500	5974	0.91	41%	8%	26%	24%	7%	10%	19151	17486	17.6	20.6	51.1	1.03	0.94
50	CA	8601	2219	4594	1.09	41%	6%	21%	31%	8%	8%	18073	19701	18.6	22.1	50.0	0.99	1.08
50	TX	9110	2385	4346	1.04	32%	4%	23%	41%	7%	9%	20949	21824	20.7	22.5	54.8	1.05	1.09
50	GA	3827	1041	1853	1.06	38%	6%	23%	33%	7%	9%	21785	23076	18.6	22.0	49.9	1.20	1.27
50	*	19556	5208	9762	1.13	36%	6%	23%	34%	7%	9%	19682	22171	18.9	21.8	51.4	1.05	1.18
300	NC	12061	3065	5175	1.01	47%	6%	24%	22%	7%	8%	18853	19109	16.3	20.0	48.6	1.06	1.08
300	WI	10356	2678	4056	1.04	44%	9%	28%	19%	7%	11%	19004	19696	15.5	18.1	50.8	1.03	1.06
300	NY	16488	4224	6671	0.89	50%	6%	29%	15%	8%	9%	18635	16593	15.7	19.5	48.3	1.06	0.94
300	CA	9659	2541	4673	1.01	52%	6%	21%	20%	7%	8%	17667	17932	17.2	21.1	49.0	0.99	1.00
300	TX	11206	2849	4615	0.90	42%	4%	25%	29%	8%	9%	19377	17491	17.4	21.2	48.9	1.08	0.98
300	GA	8321	2218	3633	0.96	42%	6%	24%	28%	7%	9%	21732	20940	16.5	21.2	46.3	1.29	1.24
300	*	26139	6772	11228	1.01	44%	7%	27%	23%	6%	9%	18748	18993	15.7	19.8	47.3	1.08	1.10
750	NC	6396	1567	2359	0.96	53%	6%	24%	16%	8%	9%	18899	18122	14.7	19.0	46.1	1.12	1.08
750	WI	5638	1461	2036	0.94	49%	9%	27%	15%	7%	10%	17864	16824	14.2	17.5	48.2	1.01	0.96
750	NY	5963	1507	2283	0.86	54%	7%	30%	8%	8%	9%	18363	15779	14.4	18.6	46.0	1.09	0.94
750	CA	6711	1716	2876	0.94	52%	6%	24%	18%	9%	9%	17894	16747	14.9	19.3	45.8	1.07	1.00
750	TX	8192	2065	3135	0.85	43%	4%	29%	24%	8%	10%	18427	15699	15.6	19.9	46.9	1.08	0.92
750	GA	5287	1357	2143	0.90	47%	5%	29%	20%	7%	7%	19034	17219	14.9	20.2	43.9	1.19	1.07
750	*	17543	4489	6815	0.92	51%	8%	25%	16%	7%	10%	18505	16974	14.1	18.6	45.3	1.12	1.03
1500	NC	6988	1726	2585	0.90	54%	7%	26%	13%	7%	9%	18555	16612	13.9	18.6	44.7	1.14	1.02
1500	WI	7233	1809	2519	0.90	53%	9%	26%	11%	7%	10%	18880	17075	13.2	17.2	46.2	1.12	1.01
1500	NY	9715	2458	3581	0.78	56%	5%	31%	8%	8%	10%	16770	13131	13.3	18.1	43.9	1.05	0.82
1500	CA	9998	2555	4230	0.90	56%	5%	22%	16%	8%	10%	16283	14596	13.6	18.2	44.2	1.01	0.90
1500	TX	14505	3645	5383	0.84	46%	5%	29%	20%	8%	9%	18920	15811	14.5	19.8	43.3	1.20	1.00
1500	GA	8398	2146	3199	0.86	53%	6%	28%	12%	8%	9%	17840	15334	12.5	18.8	39.4	1.24	1.07
1500	*	22356	5608	8468	0.91	52%	6%	28%	13%	8%	9%	17618	16074	13.3	18.3	43.6	1.11	1.01
3000	NC	7166	1708	2424	0.83	58%	7%	26%	9%	8%	9%	18527	15312	12.9	18.0	42.8	1.18	0.98
3000	WI	9770	2434	3355	0.86	53%	10%	27%	11%	8%	10%	17454	15014	11.7	15.9	43.2	1.11	0.95
3000	NY	12339	3026	4292	0.78	55%	7%	31%	7%	8%	10%	16413	12881	11.6	16.9	41.2	1.09	0.86
3000	CA	17725	4526	7168	0.88	57%	6%	24%	13%	8%	9%	17392	15292	12.8	18.1	42.1	1.13	1.00
3000	TX	28514	7118	10280	0.84	49%	5%	27%	18%	8%	10%	18822	15752	13.2	19.0	41.3	1.25	1.04
3000	GA	9316	2326	3402	0.82	60%	6%	23%	10%	9%	10%	18247	14888	11.9	19.0	37.6	1.33	1.09
3000	*	30651	7649	11380	0.88	55%	7%	26%	12%	8%	9%	17065	14970	12.2	17.5	41.8	1.12	0.98
7000	NC	1713	438	640	0.79	67%	3%	24%	6%	7%	10%	17727	13971	12.1	18.5	40.7	1.19	0.94
7000	WI	9825	2409	3278	0.81	57%	9%	25%	9%	8%	11%	17985	14645	11.2	16.1	41.0	1.20	0.98
7000	NY	10205	2471	3508	0.69	57%	7%	31%	5%	7%	8%	16888	11606	11.3	17.2	39.4	1.17	0.81
7000	CA	41539	10620	16436	0.83	60%	6%	22%	12%	9%	9%	16051	13271	12.9	18.9	40.9	1.07	0.89
7000	TX	40788	10219	14451	0.81	53%	4%	26%	16%	8%	9%	17849	14400	12.5	18.9	39.3	1.24	1.00
7000	GA	3154	806	1146	0.82	67%	4%	22%	8%	9%	11%	20616	16972	11.4	19.1	35.7	1.58	1.30
7000	*	27525	6811	9922	0.82	59%	6%	25%	10%	8%	10%	16346	13437	11.0	17.1	38.6	1.16	0.95
17000	NY	3363	850	1260	0.53	57%	7%	33%	3%	8%	6%	14582	7706	11.2	19.5	35.1	1.14	0.60
17000	CA	14820	3827	5785	0.77	66%	6%	20%	8%	8%	9%	16553	12705	12.8	20.5	37.3	1.22	0.93
17000	TX	4323	1113	1590	0.77	58%	5%	24%	13%	9%	8%	16536	12697	11.3	18.8	35.3	1.29	0.99
17000	*	4984	1306	1881	0.62	64%	8%	23%	5%	9%	8%	15758	9707	11.3	18.8	36.4	1.19	0.73
30000	NY	1007	295	595	0.26	63%	7%	30%	1%	8%	8%	12296	3194	14.1	26.1	32.2	1.04	0.27
30000	CA	1998	566	877	0.59	73%	3%	18%	5%	9%	7%	16178	9531	13.0	22.7	34.0	1.30	0.77
30000	*	1463	395	625	0.51	64%	6%	27%	3%	9%	9%	14966	7598	12.3	21.4	34.9	1.17	0.60
ALL	ALL	583665	148592	231163	0.86	52%	6%	25%	16%	8%	9%	17692	15243	14.4	19.3	44.5	1.09	0.94

Table B.3: Average deviations from the reference temperature, 20 °C, per state, weighted by the time of day people are driving and where in each state vehicles are located. These values correspond to average heating or cooling-degree hours per hour. They can be multiplied by $P_{H,+}$ and $P_{H,-}$ in Table 4.4, respectively, and summed, to obtained the total auxiliary load on a given vehicle due to local climatic conditions. Country-wide averages are shown in the last row. Default weights are used to calculate each index.

State	Heating (H_+) °C	Cooling (H_-) °C
AK	0.0	15.6
AL	4.3	3.9
AR	4.1	5.3
AZ	7.2	2.5
CA	2.6	3.2
CO	2.0	9.2
CT	1.5	9.0
DC	3.0	7.0
DE	2.2	7.3
FL	6.2	1.1
GA	3.7	4.4
HI	6.8	0.0
IA	2.1	10.1
ID	2.0	9.6
IL	2.2	9.2
IN	2.2	8.7
KS	3.2	7.2
KY	2.8	6.9
LA	5.0	2.8
MA	1.4	9.3
MD	2.9	7.0
ME	1.0	11.5
MI	1.8	10.2
MN	1.7	12.4
MO	3.1	7.1
MS	4.7	3.8
MT	1.4	11.5
NC	3.4	5.1
ND	1.4	13.5
NE	2.7	9.5
NH	1.6	10.6
NJ	2.1	7.7
NM	3.3	6.1
NV	5.5	4.7
NY	1.6	9.0
OH	2.0	9.0
OK	4.1	5.8
OR	1.3	7.2
PA	1.9	8.4
RI	1.7	9.1
SC	3.8	4.2
SD	1.9	11.6
TN	3.5	5.7
TX	5.6	3.0
UT	3.0	8.5
VA	2.9	6.4
VT	1.0	11.3
WA	1.2	7.9
WI	1.4	11.5
WV	2.1	7.7
WY	1.6	11.0

Appendix C

Supporting Information for Chapter 5

C.1 Updated cost model

Expanding on the model from Chapter 2 and Appendix A, we calculate GHG emissions and costs of ownership of the 10 different light-duty vehicle models shown in Table 5.2. GHG emissions are calculated using an existing model that estimates lifecycle greenhouse gas emissions as a function of vehicle fuel economy, powertrain type, class, curb weight, and battery capacity. This model is based on GREET [78] and described in Appendix A. Contrary to the default settings in GREET, we include emissions from petroleum well infrastructure and powerplant construction (although both contributions as small). We used the updated equations and inventories described in Appendix B.

To model costs of ownership, we also refer to the model described in Appendix A. This model takes into account vehicle purchasing price, fuel costs, and maintenance costs. Here, we extend the model to estimate vehicle depreciation (rather than just modeling the purchasing price), purchasing taxes, title, tags, and fees. Ownership costs are defined by:

$$C = P\left(1 - \frac{1}{(1+q_0)(1+d+q)^T}\right) + M_{p,0} + PM_p + F_{i,0} + PF_i + \sum_{t=1}^{T} \frac{d_t\ P_{fuel}\ F + d_t\ M_d + F_d}{(1+d)^t} \tag{C.1}$$

where P is the vehicle's recommended purchasing price before taxes and fees (MSRP), T is the duration of ownership, d is the discount rate, q is the annual depreciation rate, q_0 is the additional annual depreciation in the first year, M_p is the part of maintenance costs that doesn't depend on annual miles driven, and is assumed to scale with price P, F_i represents initial taxes, title, tags, and fees and scales with price P as well, d_t is the annual driving distance in year t, P_{fuel} is the fuel price,

F is the fuel consumption, and M_d is the part of maintenance costs that depends on annual miles driven.

The first term in equation C.1 represents the assumption that the owner purchases the vehicle for its price, and then sells the vehicle for the value remaining after T years. This results in similar cost calculations as if the vehicle was leased.

Here, we assume that the duration of ownership T is equivalent to the vehicle lifetime (15 years on average in all regions; varies across individual vehicles). The average duration of ownership of a newly purchased vehicle in the United States is only 6.5 years [197]. However, selecting a duration of ownership T to calculate costs that is different from the vehicle lifetime used to calculate emissions would result in unintended discrepancies between cost and emission calculations for individual vehicles, for which annual travel distance is sampled in each given year.

For the depreciation rate q, we assume 15%, and an additional 10% in the first year (q_0). In reality, the depreciation rates depend on vehicle make, model, and factors such as annual driving distance. Our approach provides a reasonable general estimate, given the limited availability for corresponding model-specific data. For the discount rate d, we use 4%. We use a lower discount rate than in Chapter 2 because we model vehicle depreciation explicitly.

To determine $M_{p,0}$, M_p, and M_d, we use the typical annual maintenance costs shown in Table A.3. Here, we allocate these annual maintenance costs by one third each to $M_{p,0}$, M_p, and M_d for an average vehicle ($33,000 and 18,500 km per year), and scale maintenance costs for a corresponding vehicle depending on that vehicle's price P and annual driving distance d_t.

As noted in the main article, fuel prices and electricity prices are obtained from the Energy Information Agency [60, 61]. We use inflation-adjusted 10-year averages from 2008 to 2017. Vehicle tax, tag, title, and fees are estimated using an online calculator on CarMax [36]. Prices and fees are shown in Tables C.1 and C.2.

Finally, we note that we do not include repair costs and insurance costs. Public information specific to certain vehicle models, classes, or technologies on these items is rare, and both can depend more on properties of the vehicle owner, their driving habits, and their specific location than on properties of the vehicle itself.

C.2 Additional results

Difference in emissions and costs per km instead of per year

Figure C-2 shows the difference in emissions and costs between BEVs and ICEVs per km rather than per year. Indicating emissions per km is commonly done in many lifecycle assessment studies. In this case, the average annual travel distance, which is lower in urban areas than in rural areas, affects the number of km across which vehicle production emissions and vehicle acquisition costs are allocated, rather than being multiplied with operating emissions and costs. Because operating emission account for approximately 80% of all emissions, but only approximately 20% of all costs (see Figure 2-2), this results in a larger difference between urban and rural areas for emission reductions than for the annual metrics, but a smaller difference in costs.

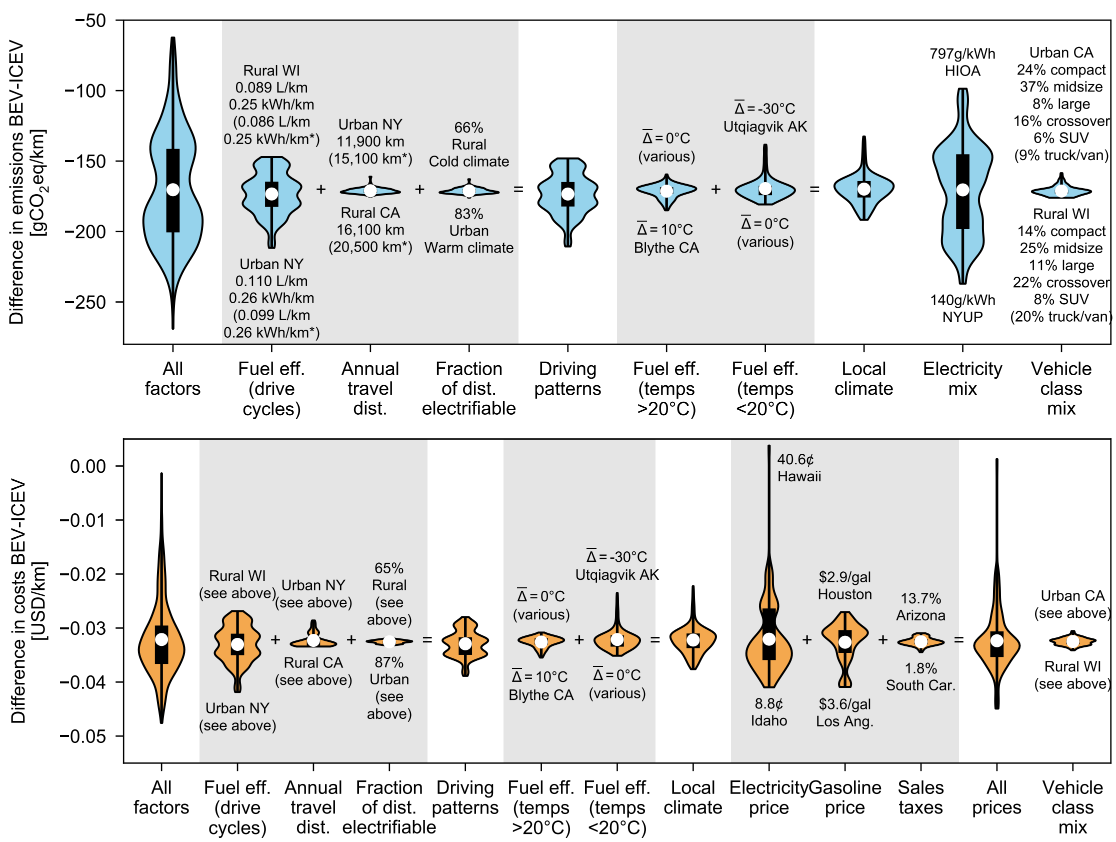

Figure C-1: Probability density functions of the differences in lifecycle greenhouse gas emissions (top, blue) and costs of ownership (bottom, orange; without subsidies) between BEVs and ICEVs. This is the same as Figure 5-2, but with emissions and costs per km instead of per year.

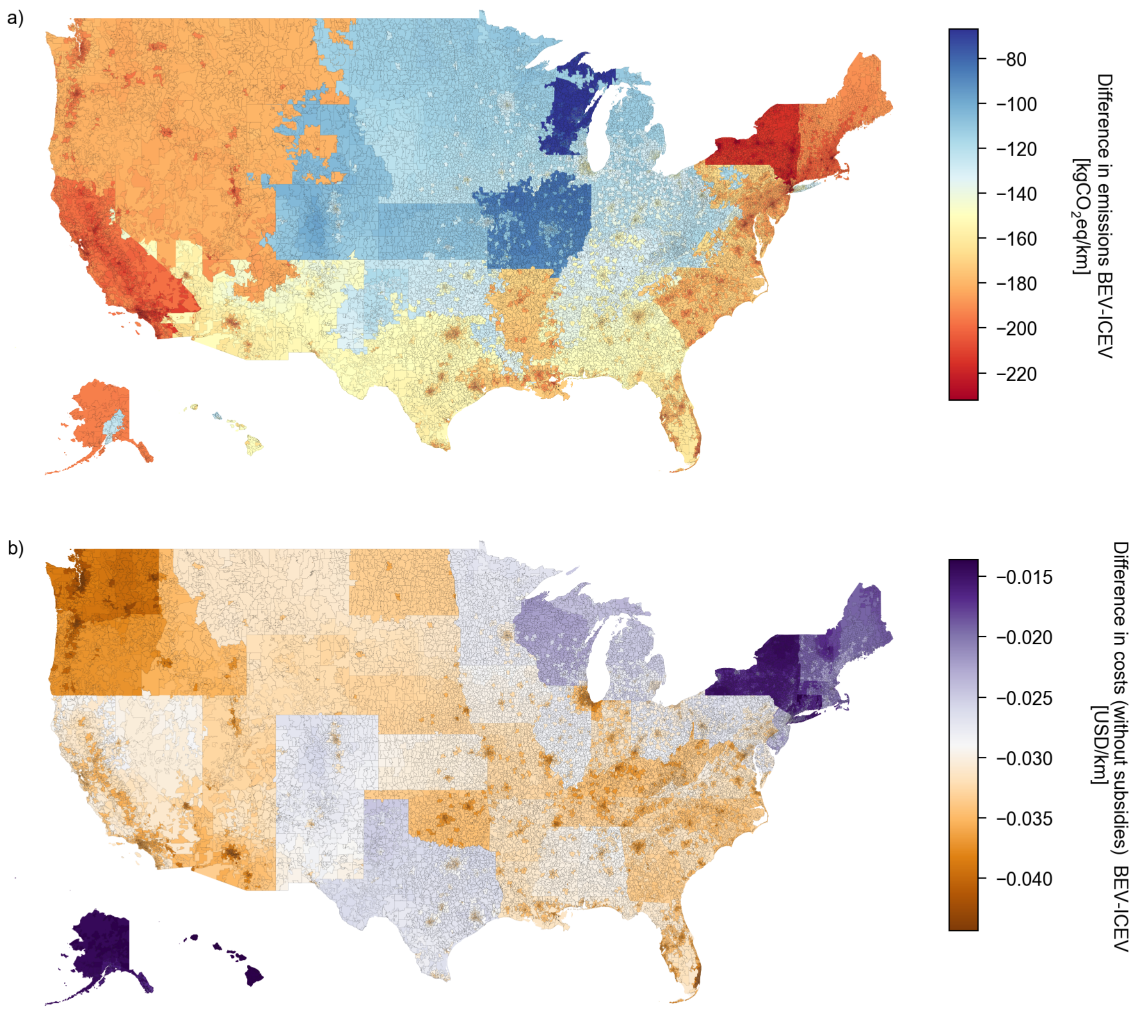

Figure C-2: Difference in greenhouse gas emissions (top) and costs of ownership (bottom, without subsidies) per km between the 2019 Nissan Leaf battery electric vehicle and the 2019 Ford Focus combustion engine vehicle by zipcode area. A negative number means that the Nissan Leaf is better. The patches in the bottom-left corners show Alaska (left, shrunk by a factor of 15) and Hawaii (right, same scale as the U.S. mainland). The projection used is WGS 84/Pseudo-Mercator.

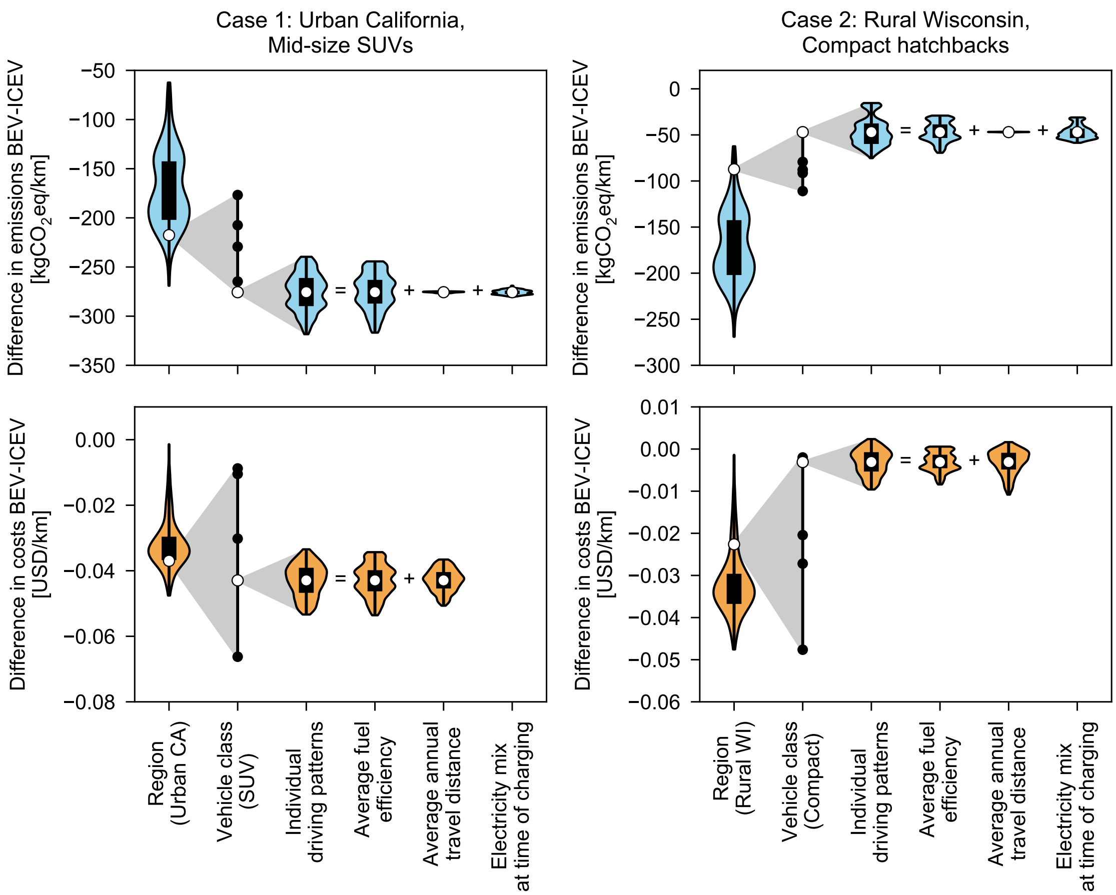

Figure C-3: Impact of vehicle class and driving patterns of individual vehicles on the difference in lifecycle greenhouse gas emissions (top) and costs of ownership (bottom) between BEVs and ICEVs in two cases: (1) vehicles in urban California whose household is located in areas with a population density of 5,000 people/mi^2 or more; and (2) vehicles in rural Wisconsin whose household is located in areas with a population density of 100 people/mi^2 or less. This is the same as Figure 5-4, but with emissions and costs per km instead of per year.

Baseline emissions of ICEVs

Figures C-4 and C-5 show baseline emissions of 2019 ICEVs across regions, averaged across the 5 vehicle classes in Table 5.2 and weighted by each class' average share in each location (see Figure B-8). Costs are heavily driven by fuel prices and taxes, which we consider at the state level. Effects of urban-rural differences in driving patterns, namely the impact of travel patterns on average fuel efficiency and average annual travel distance, almost cancel each other out to some extent. Nonetheless, baseline emissions and costs are slightly lower in urban areas than in rural areas.

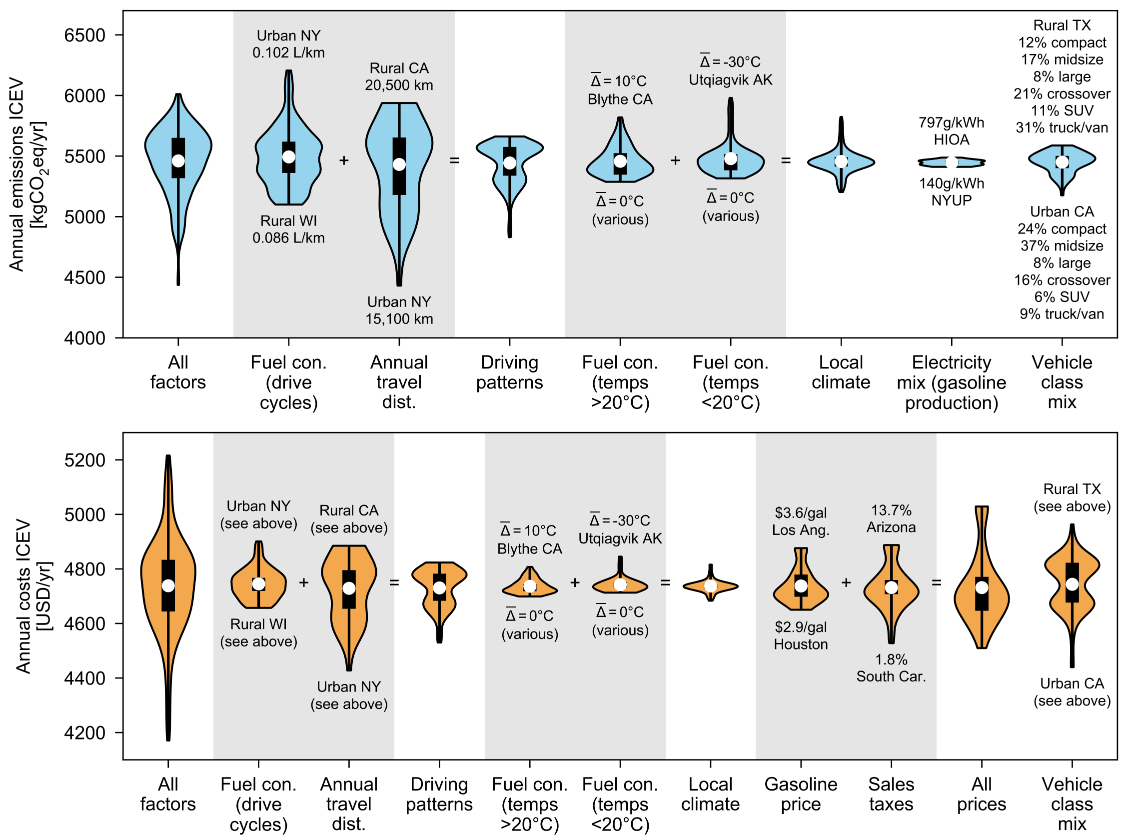

Figure C-4: Probability density functions of the baseline emissions (top, blue) and costs of ownership (bottom, orange) of 2019 ICEVs across the country, weighted by each of the five vehicle classes' share in each given region. The local electricity mix affects emissions because local emission factors are used to estimate supply chain emissions from fuel and electricity production, including gasoline production.

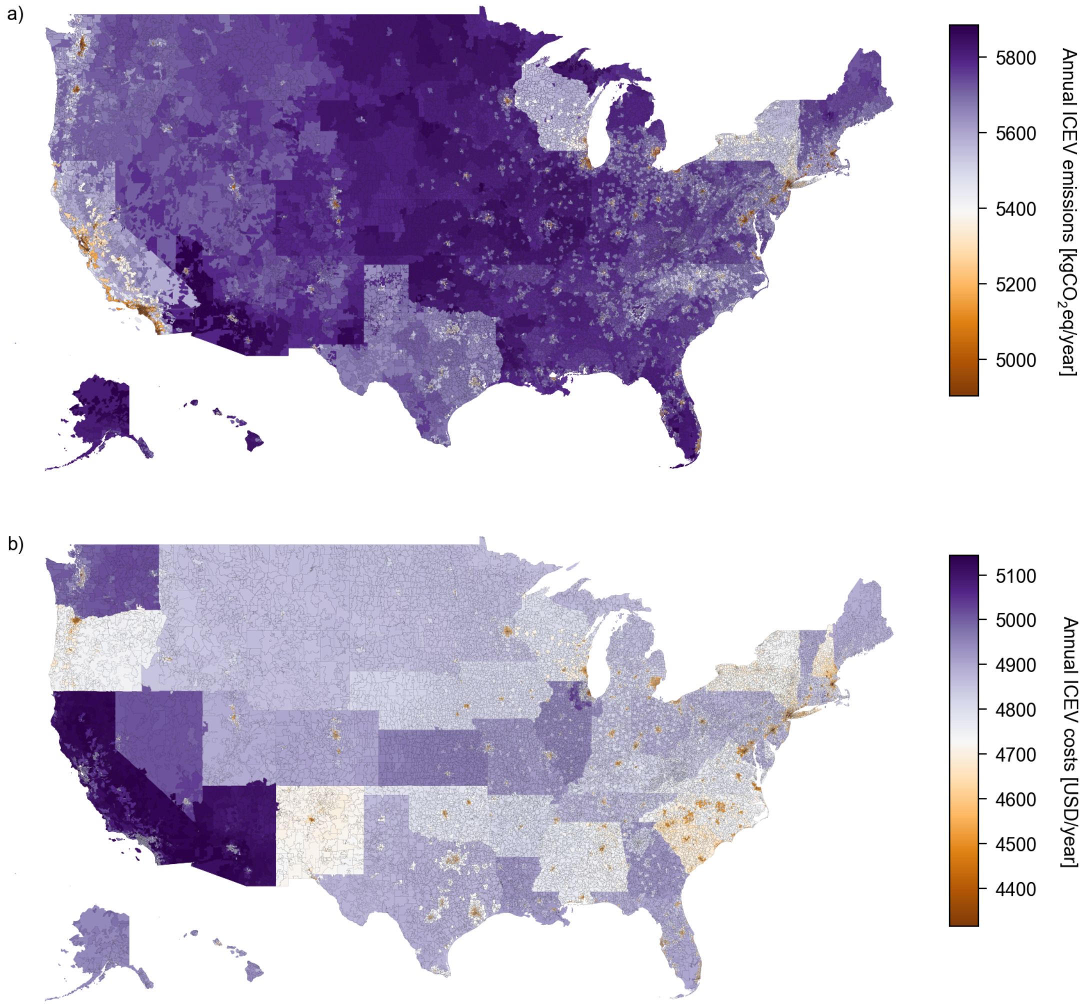

Figure C-5: Map of baseline annual emissions and costs of 2019 model ICEVs across the country, weighted by each of the five vehicle classes' share in each given region. The patches in the bottom-left corners show Alaska (left, shrunk by a factor of 15) and Hawaii (right, same scale as the U.S. mainland). The projection used is WGS 84/Pseudo-Mercator.

Implications of our modeling approach for U.S. average emissions and costs

While the modeling framework presented in Chapter 4 and 5 allows us to model the heterogeneity in the difference in emissions and costs between BEVs and ICEVs across locations, our modeling approach also has implications for the U.S. average difference in emissions and costs compared to a simpler approach. Relative to a 'naive' approach, using a single number for the U.S. average electricity mix, official EPA adjusted fuel economy ratings for combined city and highway driving, and no removal of long trips from the trip distance distribution, our method results in a 20% lower estimate for annual emission reductions of BEVs (Figure C-6). This difference is largely due to the poorer average fuel consumption of the BEV as estimated by our vehicle energy model compared to the EPA rating (see Figure 4-4), and due to the removal of long trips from the trip distance distribution (see Scenario B in Figures 4-6 and B-6). It is partially outweighed by the observation that the average electricity mix used to charge BEVs when weighted by the estimated number of vehicles in each zipcode is slightly cleaner than the U.S. average mix across all electricity users (Figure C-6, yellow bar), and by the observation that those trips that are being removed from the trip-distance distribution would have achieved lower emission reductions per distance than the average trip (Figure C-6, purple bar to the right).

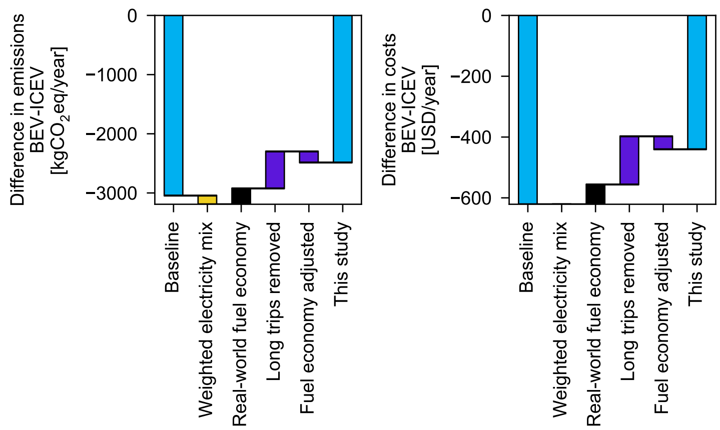

Figure C-6: The left-most bars show emissions calculated using a single number for the emissions intensity of charging BEVs (475 gCO_2eq/kWh at the household plug), constant EPA rated fuel economies for both vehicles, and no driving pattern adjustment for BEVs. The right-most bars show U.S. average results produced by this model. 'Weighted electricity mix' accounts for the fact that the average U.S. electricity mix doesn't exactly represent the average electricity mix used for charging a random light-duty vehicle, based on how many vehicles are located in each eGRID subregion. 'Real-world fuel economy' uses the fuel economy model described in chapter S1.2 rather than EPA-rated fuel economies (see also Figure 4-4). 'Long trips removed' enables the removal of trips whose daytrips exceed 80% of BEV battery capacity from the modeled set of trips, and adjusts annual travel distance accordingly (see also Figures 4-6). 'Fuel economy adjusted' accounts for the fact that removing trips from the trip time/distance distribution changes the average fuel economy of both vehicles (see also Figure 4-4).

Comparisons between specific models

Figures C-7 to C-11 show the variation in the difference in annual emissions and costs between ICEVs and BEVs for specific model comparisons, rather than aggregated across all models as is the case in Figure 5-3. While results for the different vehicle classes yield similar patterns overall, we observe that urban-rural differences are sensitive to the fuel efficiency characteristics for the corresponding models. If BEV highway fuel economy is relatively good, and ICEV city fuel economy is relatively good, as is the case for the Tesla Model 3 and the BMW 3-Series (Figure C-8), BEVs have similar annual emission reductions in urban areas as in rural areas, and cost slightly more. If BEV highway fuel economy is poor, and ICEV city fuel economy worse (relative to highway fuel economy), as is the case for the Nissan Leaf and the Honda Civic (Figure C-7), both emissions and costs are substantially lower for BEVs in urban areas compared to rural areas. Interestingly, large vehicles with a high battery capacity tend to perform better in suburban areas than in either urban or rural areas (Figures C-8 and C-11), because the electrifiable annual travel distance (the product of annual travel distance and the share of electrifiable trips) is highest in low-density suburban areas for those vehicles.

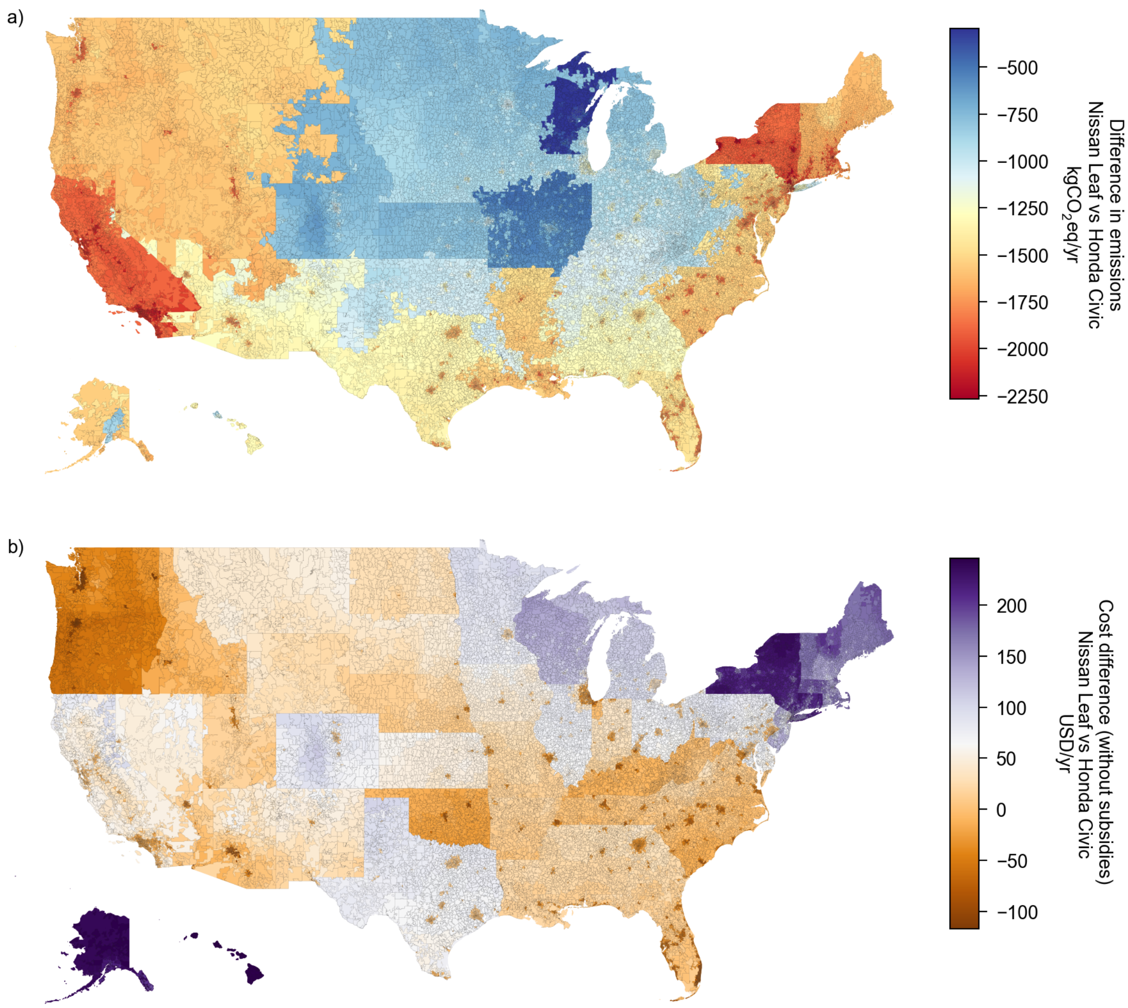

Figure C-7: Relative (percentage) difference in annual greenhouse gas emissions (top) and costs of ownership (bottom, without subsidies) between the 2019 Nissan Leaf battery electric vehicle and the 2019 Honda Civic combustion engine vehicle by zipcode area. A negative number means that the Nissan Leaf is better.

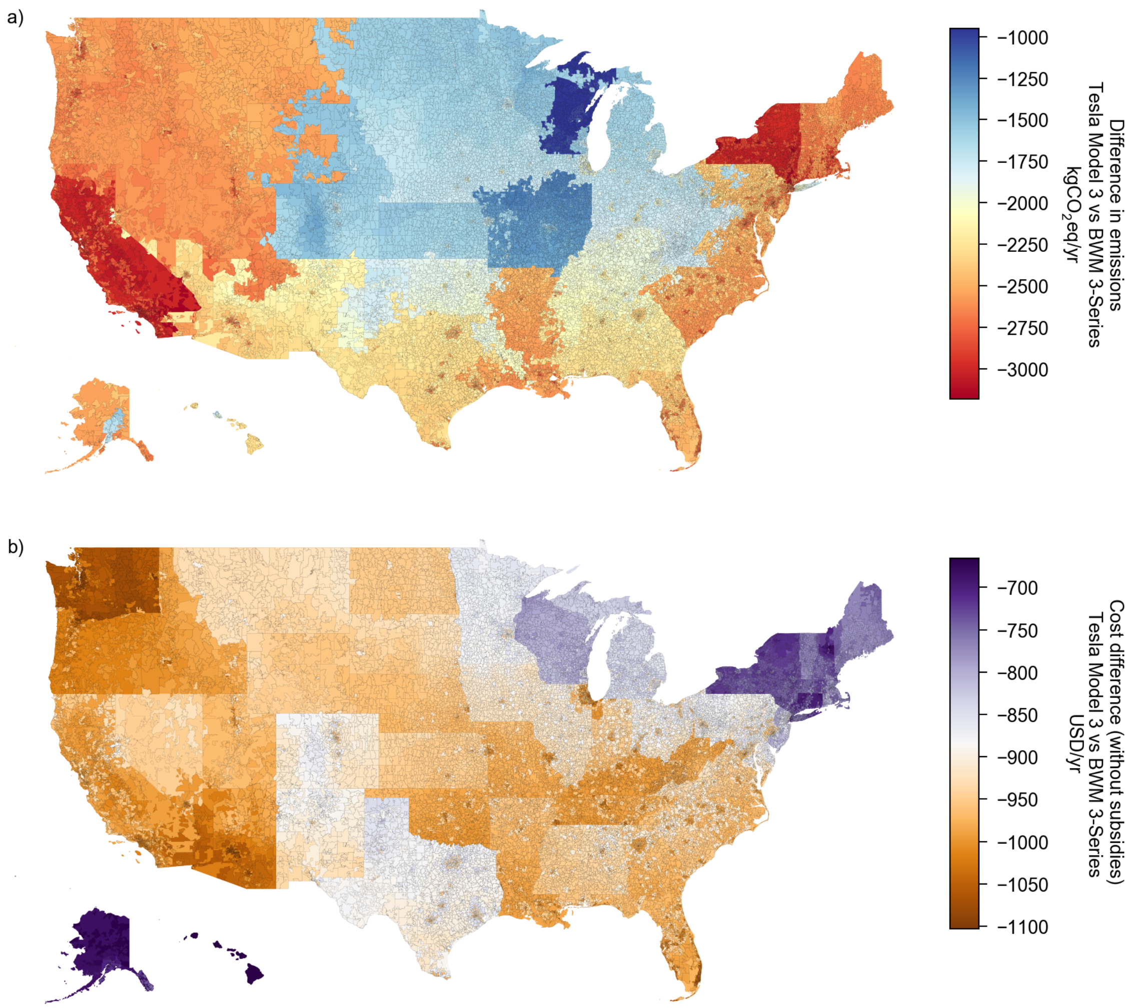

Figure C-8: Relative (percentage) difference in annual greenhouse gas emissions (top) and costs of ownership (bottom, without subsidies) between the 2019 Tesla Model 3 battery electric vehicle and the 2019 BMW 3-Series combustion engine vehicle by zipcode area. A negative number means that the Model 3 is better.

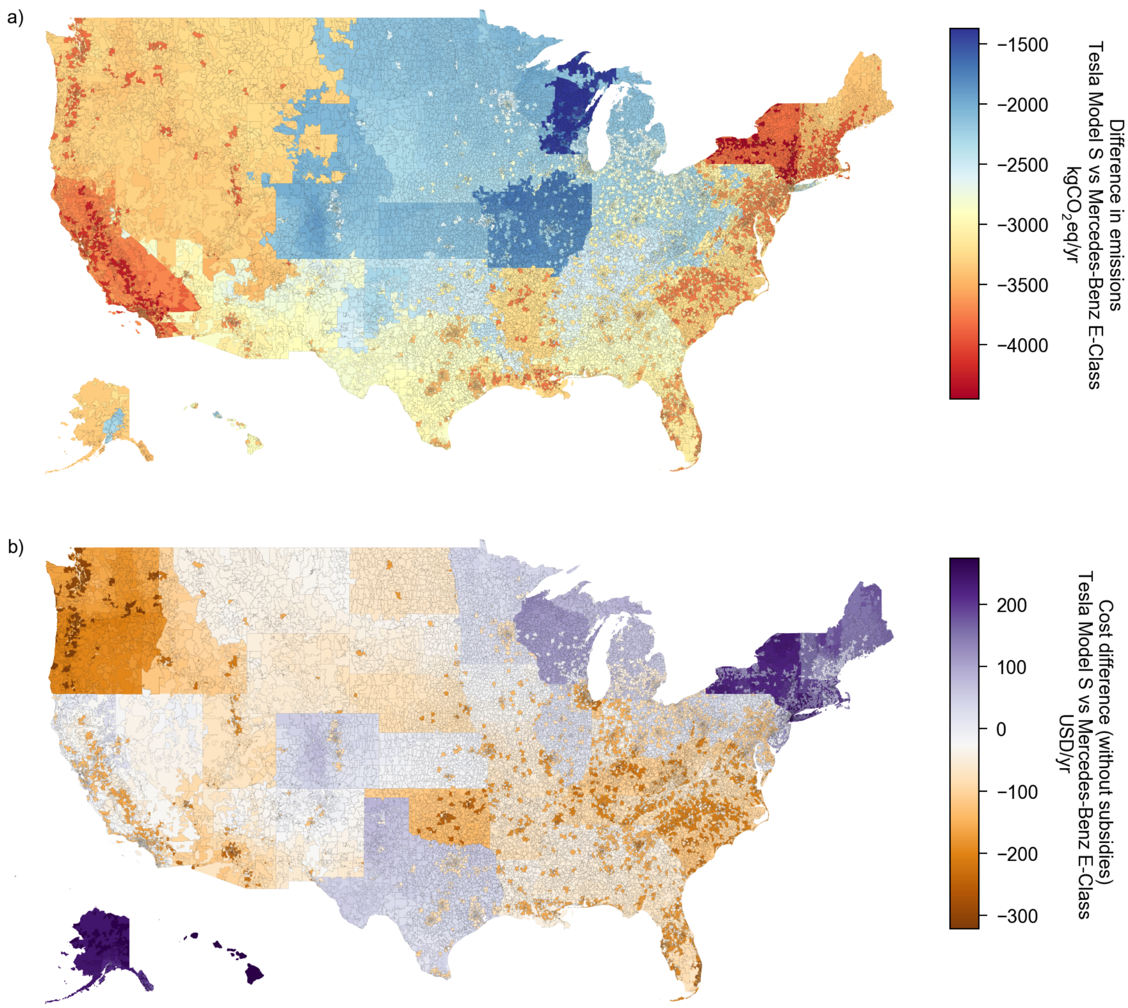

Figure C-9: Relative (percentage) difference in annual greenhouse gas emissions (top) and costs of ownership (bottom, without subsidies) between the 2019 Tesla Model S battery electric vehicle and the 2019 Mercedes-Benz E Class combustion engine vehicle by zipcode area. A negative number means that the Model S is better.

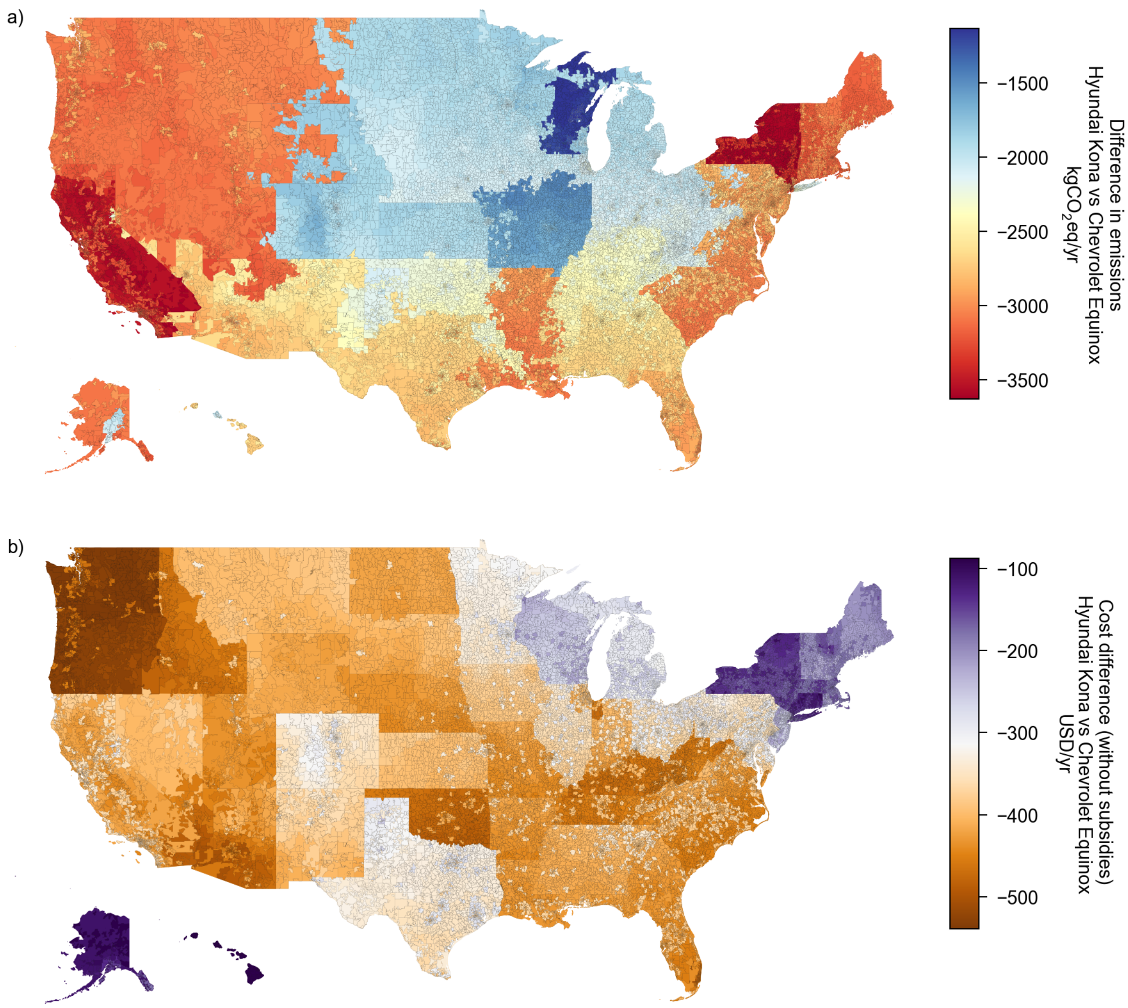

Figure C-10: Relative (percentage) difference in annual greenhouse gas emissions (top) and costs of ownership (bottom, without subsidies) between the 2019 Hyundai Kona battery electric vehicle and the 2019 Chevrolet Equinox combustion engine vehicle by zipcode area. A negative number means that the Kona is better.

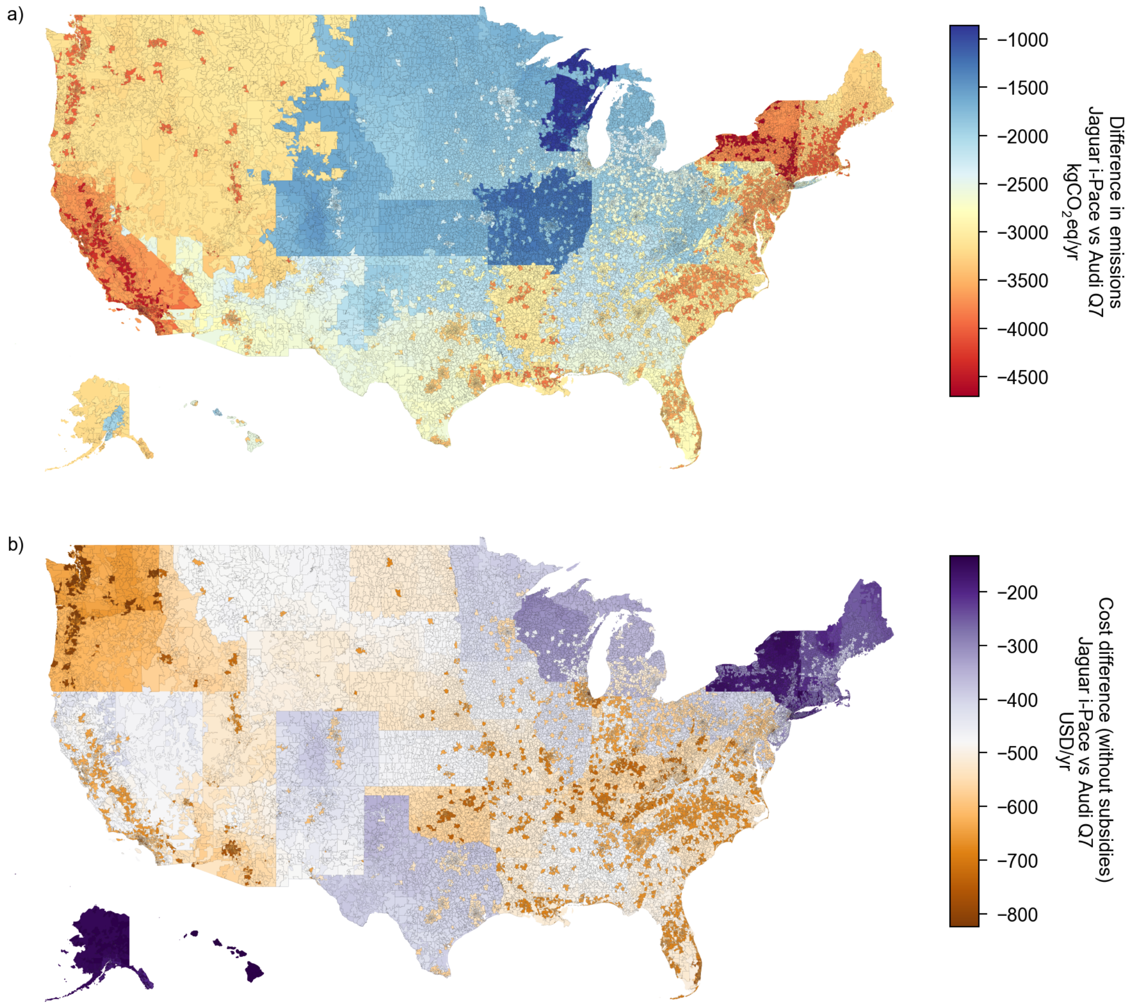

Figure C-11: Relative (percentage) difference in annual greenhouse gas emissions (top) and costs of ownership (bottom, without subsidies) between the 2019 Jaguar i-Pace battery electric vehicle and the 2019 Audi Q7 combustion engine vehicle by zipcode area. A negative number means that the i-Pace is better.

Additional modeling scenarios

As indicated in Figure C-6, reductions in annual emissions of the BEVs compared to ICEVs increase when no trips are being removed from the trip-distance distribution (Figure C-12; see also Figure 4-6 in Chapter 4). Figure C-12 shows that the heterogeneity increases as well. This is because BEV emissions in areas with a clean electricity mix particularly profit from electrifying all trips, while BEV emissions in areas with a high-carbon mix hardly profit at all: emissions of BEVs and ICEVs are almost identical for the non-electrified trips on those areas.

Attributional emission factors represent the average production-based electricity mix in a given subgrid, dividing the total amount of emissions caused by electricity generation and distribution in a year by the total amount of electricity produced in that year. Attributional emission factors do not take into account where electricity consumers are being located (consumption-based vs production-based), and they do not take into account what time of day electricity is being used, and how an additional marginal unit of demand might affect supply during that time of day (marginal emission factors). While results for a given, specific subgrid region may change by switching from the default, marginal emission factors to attributional emission factors, the country-wide heterogeneity in annual emission reduction BEVs compard to ICEVs remain almost identical (C-12, also see Table C.3 for a comparison between the grid-specific attributional and marginal emission factors used in this study).

While scheduled to be phased out over time, customers in the U.S. are still eligible for federal subsidies of up to $7,500 for purchasing a Nissan Leaf BEV [52]. When these current federal subsidies are taken into account, costs of ownership of BEVs compared to ICEVs decrease substantially (Figure C-12). Another prominent item of discussion regarding the costs of BEVs is that because they do not use gasoline, and therefore do not contribute to highway funding through fuel taxes [110]. Therefore, some states have introduced additional annual fees for BEVs of $50–$200/year [47]. Such fees increase costs of ownership of BEVs relative to ICEVs, but their impact is smaller than other factors causing differences in the costs of ownership of BEVs relative to ICEVs. Even with such fees, BEVs are more affordable than comparable ICEVs in many parts of the country (Figure C-12).

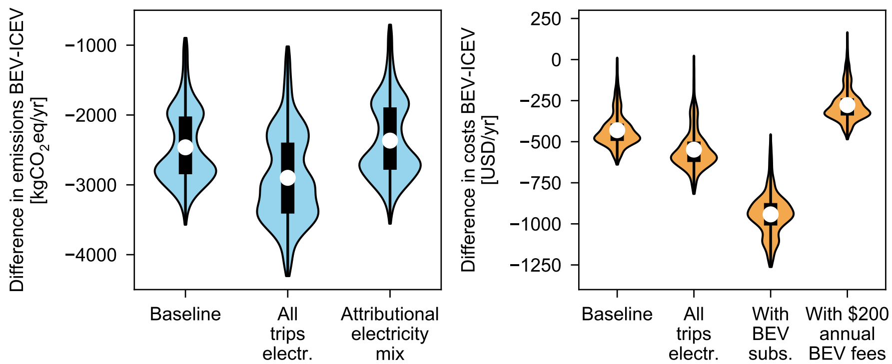

Figure C-12: Probability density functions of the differences in lifecycle greenhouse gas emissions (left, blue) and costs of ownership (right, orange) between the 2019 Nissan Leaf battery electric vehicle and the 2019 Ford Focus combustion engine vehicle 5.1. 'All trips electr.' shows results for a case where all trips are being electrified by the BEV (Scenario A in Table 4.1). 'Attributional electricity mix' shows results with a constant emissions factor used in each grid, without the consideration of time of day of emissions or the marginal suppliers. 'With BEV subsidies' shows results with federal state subsidies in place. Federal subsidies are $7500, state subsidies are up to $2500. 'With $200 annual BEV fees' shows results with a $200 annual fee added to BEV costs—a fee that some states have introduced in order to compensate for the loss in gasoline tax income from BEVs [47]. Effective costs are slightly lower than $200/year due to the net-present valule approach used, discounting costs occurring in the future by 4% per year.

C.3 Data

Table C.1 shows electricity prices and taxes, Table C.2 shows gasoline prices, and Table C.3 show hourly grid-specific emission factors used.

Table C.1: Electricity prices and tax, title, and fee costs by state. Tax, title, and fee costs upon vehicle acquisition are calculated as the sum of the fixed portion (left column) and the portion that scales with the vehicle price (right column). The vehicle price is set to the vehicle MSRP (Manufacturer Suggested Retail Price), as shown in Table 5.2.

		Taxes, title, fees	
State	Electricity price (US¢$_{2018}$/kWh)	Fixed (USD$_{2018}$)	Additional (USD$_{2018}$ per $1000 vehicle MSRP)
AK	18.86	364.0	61
AL	11.64	370.0	40
AR	10.19	364.0	61
AZ	11.98	412.5	125
CA	16.69	810.0	120
CO	11.92	120.0	90
CT	20.6	405.0	60
DC	13.68	364.0	61
DE	14.52	332.5	37
FL	12.77	855.0	60
GA	11.54	85.0	70
HI	33.21	364.0	61
IA	11.53	250.0	50
ID	8.82	255.0	60
IL	12.07	510.0	92
IN	10.79	60.0	70
KS	11.21	435.0	98
KY	9.58	105.0	60
LA	10.25	375.0	100
MA	18.12	295.0	62
MD	14.21	364.0	61
ME	16.98	364.0	61
MI	13.55	555.0	60
MN	11.63	457.5	65
MO	10.14	332.5	87
MS	11.39	250.0	50
MT	10.52	364.0	61
NC	11.31	440.0	30
ND	9.15	364.0	61
NE	9.94	77.5	55
NH	17.94	50.0	0
NJ	16.93	210.0	70
NM	11.84	265.0	30
NV	13.37	760.0	81
NY	20.11	342.5	85
OH	12.16	412.5	75
OK	10.23	427.5	33
OR	10.07	275.0	0
PA	13.46	330.0	60
RI	17.46	410.0	70
SC	11.92	495.0	1
SD	10.21	364.0	61
TN	10.21	247.5	73
TX	13.29	320.0	62
UT	10.09	655.0	66
VA	11.28	455.0	32
VT	17.3	364.0	61
WA	8.85	150.0	89
WI	13.66	322.5	56
WV	9.22	364.0	61
WY	10.05	364.0	61

Table C.2: Gasoline prices by region. For each zipcode, the smallest applicable region is used. For instance if a New England zipcode is located in the Boston core-based statistical area (CBSA), the price for Boston is used. If the zipcode is located in Massachusetts (MA), but not the Boston CBSA, the price for MA is used. If it is located in New England, but not Massachusetts, the price for New England is used.

Region	List of states in region	Gasoline price (USD_{2018}/gallon)
Boston		3.11
CA		3.56
CO		3.05
Central Atlantic	DC, DE, MD, NJ, NY, PA	3.18
Chicago		3.31
Cleveland		3.08
Denver		3.04
FL		3.1
Gulf Coast	AL, AR, LA, MS, NM, TX	2.96
Houston		2.92
Los Angeles		3.59
Lower Atlantic	FL, GA, NC, SC, VA, WV	3.06
MA		3.11
MN		3.05
Miami		3.26
Midwest	IA, IL, IN, KS, KY, MI, MN, MO, ND, NE, OH, OK, SD, TN, WI	3.08
NY		3.32
New England	CT, MA, ME, NH, RI, VT	3.18
New York City		3.18
OH		3.07
Rocky Mountains	CO, ID, MT, UT, WY	3.1
San Francisco		3.58
Seattle		3.38
TX		2.96
WA		3.37
West Coast Except CA	AK, AZ, HI, NV, OR, WA	3.28

Table C.3: Electricity emission factors used for each EPA subgrid. Each zipcode is allocated to a specific subgrid by matching the zipcode shapefile's centroid position to the corresponding subgrid shapefile. Marginal emission factors by time of day are derived for each grid[184], scaled up or down so to each subgrid (for details, see the main article). Average marginal emission factors are obtained by multiplying hourly emission factors with the charging load. Vehicles are assumed to be charged instantaneously in the hour during which the last trip of a given travel day ends (see Figure 4-2)

		Attributional	Marginal, by time of day ($gCO2_2eq/kWh$)																								
Subgrid	Grid	$gCO2_2eq/kWh$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Avg
AKGD		469	534	529	485	474	482	502	573	589	605	697	721	657	529	446	386	355	355	370	414	458	490	510	537	581	446
AKMS		344	392	389	357	348	354	369	421	433	444	512	529	482	389	328	284	261	261	272	304	337	360	375	395	427	328
AZNM	WECC	443	391	386	391	391	372	358	330	307	316	358	396	409	409	400	386	382	372	367	367	372	376	372	376	382	376
CAMX	WECC	288	253	250	253	253	241	232	214	199	205	232	257	265	265	259	250	247	241	238	238	241	244	241	244	247	244
ERCT	TRE	579	499	529	543	553	548	523	490	465	460	460	450	450	446	450	450	450	450	446	440	440	436	436	446	465	448
FRCC	FRCC	545	620	615	564	551	560	584	666	685	703	810	838	763	615	518	449	412	412	431	482	533	569	593	624	675	518
HIMS		478	544	539	495	483	491	512	584	600	616	710	734	669	539	454	394	361	361	377	422	467	499	520	547	592	454
HIOA		751	855	848	778	760	772	805	919	944	969	1117	1155	1052	848	715	619	568	568	594	664	734	785	817	861	931	715
MROE	MRO	845	1349	994	1474	1468	1463	1463	1390	1458	1224	1119	1234	1296	1265	1240	1187	1129	1135	1036	926	880	854	942	1057	1182	1068
MROW	MRO	693	1107	816	1209	1204	1201	1201	1140	1196	1004	918	1012	1063	1038	1017	974	927	931	850	760	722	701	773	867	970	876
NEWE	NPCC	291	471	324	587	627	648	599	524	604	551	538	631	666	675	645	627	645	622	591	582	515	493	569	466	471	583
NWPP	WECC	460	406	400	406	406	387	372	343	318	328	372	411	425	425	415	400	396	387	381	381	387	391	387	391	396	390
NYCW	NPCC	336	545	375	679	725	750	693	606	699	637	622	729	770	780	745	725	745	719	683	673	596	570	658	539	545	674
NYLI	NPCC	607	984	677	1225	1309	1354	1252	1094	1262	1150	1123	1317	1391	1409	1346	1309	1346	1299	1233	1215	1076	1029	1188	974	984	1216
NYUP	NPCC	185	300	207	374	400	413	382	334	385	351	343	402	425	430	411	400	411	396	377	371	328	314	363	297	300	371
RFCE	RFC	421	464	532	430	421	424	452	486	434	448	448	384	332	304	304	310	310	316	335	350	375	390	372	415	440	352
RFCM	RFC	777	858	983	795	778	784	835	898	801	829	829	710	614	562	562	574	574	585	619	647	693	721	688	766	813	651
RFCW	RFC	701	773	886	717	701	707	753	810	723	747	747	640	553	507	507	517	517	527	558	584	624	650	620	691	733	587
RMPA	WECC	882	777	767	777	777	740	712	657	610	628	712	787	814	814	795	767	759	740	730	730	740	749	740	749	759	747
SPNO	SERC	800	789	821	923	930	917	834	673	558	488	506	635	769	847	847	814	776	756	743	711	686	667	686	673	718	732
SPSO	SERC	748	738	769	864	870	859	780	630	523	456	474	594	720	792	792	762	726	708	696	665	642	624	642	630	672	685
SRMV	SERC	518	511	532	598	602	594	540	436	361	316	328	411	498	548	548	527	502	490	481	460	444	432	444	436	465	474
SRMW	SERC	900	888	924	1039	1047	1033	939	757	628	549	570	714	866	953	953	916	873	851	837	800	772	751	772	757	808	824
SRSO	SERC	580	572	596	669	675	665	605	488	405	354	367	460	558	614	614	591	563	548	539	516	497	484	497	488	521	531
SRTV	SERC	678	669	696	783	789	778	707	571	473	414	429	538	652	718	718	690	658	641	631	603	581	566	581	571	609	621
SRVC	SERC	435	429	447	502	506	499	454	366	304	265	275	345	418	460	460	443	422	411	404	387	373	363	373	366	390	398

Appendix D

Supporting Information for Chapter 6

D.1 Additional figures

Figure D-1 shows the survey launch window presented to users upon visiting Carboncounter. Figure D-2 shows an analysis of the residuals from the linear regression models in Table 6.1. Residuals are almost normally distributed, and their variance is consistent across the range of fitted values. However, residuals show a bias towards the upper and lower end of the range of possible response values (0-100% for model 1, 1-13 for model 2). Therefore, coefficients shown in Table 6.1 may be biased.

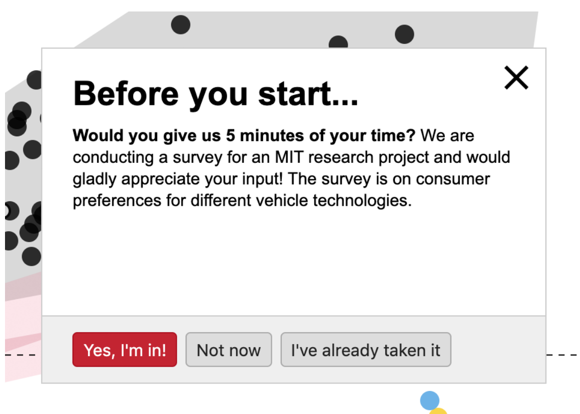

Figure D-1: Screenshot of invitation to answer the survey. The rest of the tool was not accessible until the user either accepted to declined the survey, or closed the invitation window.

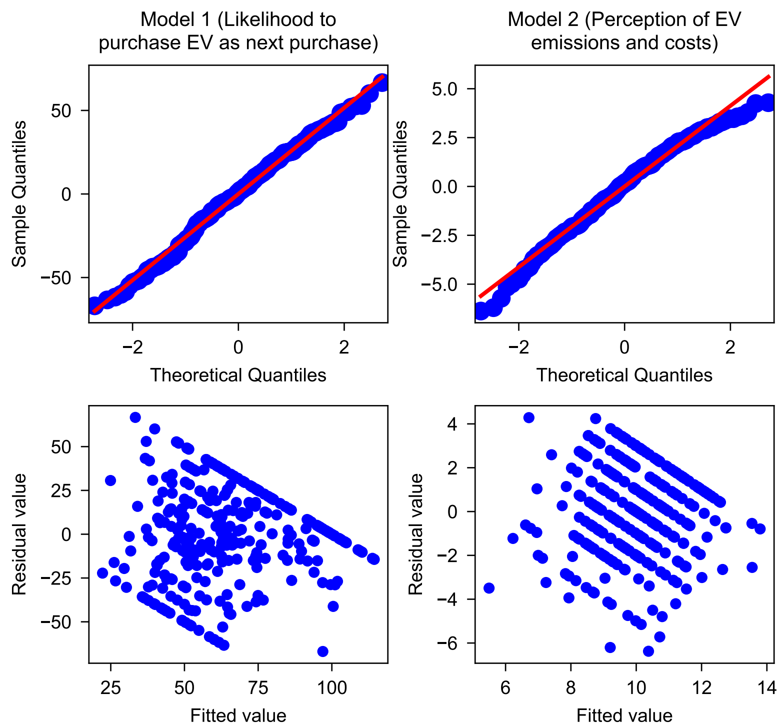

Figure D-2: The top row shows QQ-plots of the residuals of the two linear regression models shown in Table 6.1. The bottom row shows a comparison between the fitted values (x-axis) and residuals (y-axis) for the same two models.

D.2 Tutorial transcript

This section shows the transcript of the 12 tutorial steps that were shown to the user if they took the tour through the tool.

New here? Take the Tour! This tour will take your through the basics of the Carboncounter app. To start, click 'Next' in the bottom right corner of this box.

The plot area The plot area shows more than 100 popular new car models in the U.S. Move over each data point to get more information. You'll find some data points connected by grey lines; these indicate multiple versions (trims) of the same model. Colors represent different powertrain technologies, as indicated by the legend below.

Make a list You can also click on a data point* to add a car to your list of highlighted cars. The same can be achieved using the search for a car field below. *On a touch device, tap the data point a second time (after tapping it a first time to highlight it).

The axes The x axis shows the lifetime cost of each vehicle per mile driven. This combines the vehicle purchasing price, fuel/charging costs, and regular maintenance costs. We subtract federal tax refunds where applicable. The y axis shows the greenhouse gas emissions of each vehicle per mile driven. This combines emissions from the production and distribution of both the car and its fuel, meaning that we include emissions from electricity generation and battery production.

The targets Near the bottom of the chart, you will notice horizontal lines. These indicate estimated greenhouse gas emission targets that the average car on the road (not just new ones sold) should meet in the coming decades to be consistent with limiting global warming to 2 °C. Moving over a target line will tell you which year it corresponds to.

Average conditions The graph you see now on the left corresponds to the default parameter values in our model. The default parameters values are set to represent the average U.S. driving behavior, the average U.S. electricity mix, and 10-year average fuel and electricity prices for the U.S.

What does this tell us? Our results show that you don't have to pay more for a low-carbon-emitting vehicle. Many electric vehicles are the same price, or cheaper, than similar gasoline cars. The average greenhouse gas emissions of all cars shown here are more than 50% higher than the 2030 climate target, with no internal combustion vehicles meeting the target. Most hybrid and electric vehicles, on the other hand, already meet the 2030 goal today, with today's electricity mix.

Current fuel prices With the current (May 2016) low gasoline and diesel prices, the cost of gasoline powered cars goes down slightly compared to hybrid and electric ones. But not that much, as you can see by switching between current fuel prices (shown now) and the long-term average prices (shown previously) by using the 'Previous' and 'Next' buttons below.

Cleaner electricity Greenhouse gas emissions from electricity production in California are less than half the U.S. average, and it shows. If we apply a relatively clean electricity mix, such as California's, the emission reduction advantage of electric vehicles becomes larger. Emissions from electric vehicles drop below the 2040 climate target.

Best prices for electric vehicles In addition to the federal tax refunds for plug-in hybrids and electric vehicles, we can simulate a best-case scenario for electric vehicles by adding state tax refunds, which are available in some states. Here, we add those of California. This scenario is based on the 10-year avarege fuel price again. Here, electric vehicles are cheaper than their combustion engine counterparts.

Worst prices for electric vehicles Once we turn off the federal tax refunds that are available today for electric vehicles, they become more expensive. Nevertheless, some specific electric vehicles, such as the Nissan Leaf, are still comparable in cost to combustion engine vehicles of the same class. This is because electric vehicles have very low operational (fuel and maintenance) costs.

Filter by vehicle class To check this, let's filter cars so that only compact cars (not including compact SUVs or pickups) are highlighted. Within this vehicle class, we observe that some electric vehicles indeed have similar costs to combustion vehicles even without any of today's tax refunds.

Done – but there's much more This concludes the introductory tour, but there's much more to explore. Click on the 'Custom Parameters' tab to see what the future of transportation could look like, and how different cars stack up against climate targets and each other.

We have set all parameters back to default for now. You can reset them yourself at any point with the reset button on the toolbar above.

D.3 Survey questions and answers

(Welcome page) We appreciate your taking the time to answer these questions!

This survey consists of 20 questions and will take between 6 and 8 minutes.

This survey is part of a scientific research project at MIT. Your decision to complete this survey is voluntary. There is no way for us to identify you. The only information we will have, in addition to your responses, is the time at which you completed the survey. The results of the research may be presented at scientific meetings or published in scientific journals.

Clicking on the '»' button on the bottom of this page indicates that you are at least 18 years of age and agree to complete this survey voluntarily.

(page break) Before we start, please read this description of the different vehicle technologies:

A conventional vehicle is a car, SUV, or truck with an internal combustion engine that runs on gasoline or diesel. A conventional vehicle can be refueled at any gas station.

A (regular) hybrid is a vehicle that has both a combustion engine and an electric motor. The battery that powers the electric motor is charged using energy generated from braking. These cars are not designed to be plugged into an outlet. Example: Toyota Prius.

A plug-in hybrid is a hybrid whose battery can be charged directly from a power plug. Plug-in hybrids can often operate on electricity alone and use gasoline as a backup fuel. Examples: Chevrolet Volt, Toyota Prius Prime.

A battery electric vehicle is a car that does not have a combustion engine. It requires electricity from a power plug. Examples: Tesla Model S, Nissan Leaf, Chevrolet Bolt.

Q1. Please complete the following sentence by selecting ONE of the following responses that BEST describes why you are interested in using the Carbon Counter:

1. To learn how conventional and electric cars differ in purchasing price

2. To learn how conventional and electric cars differ in total costs of ownership

3. To learn how conventional and electric cars differ in performance

4. To learn how conventional cars and electric cars differ in emissions

5. To learn how conventional cars compare to electric cars in general

6. I am simply curious. I have read (or heard) about it and want to know more

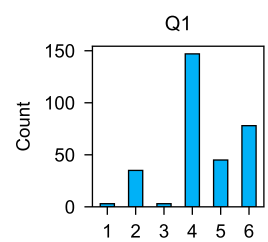

Figure D-3: Responses to survey question 1.

Q2. Please indicate how strongly you agree or disagree with the following statements. Check one box for each. Only count where you are driving yourself.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
1. I drive more than most people I know					
2. I often have to drive in heavy traffic					

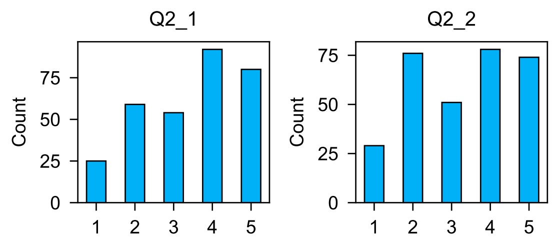

Figure D-4: Responses to survey question 2. 1 = Strongly agree; 5 = Strongly disagree.

Q3. Approximately how many miles do you drive per year? (your best guess - only count miles where you are driving yourself)

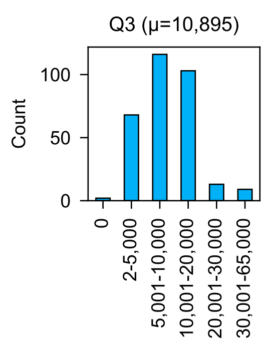

Figure D-5: Responses to survey question 3.

Q4. Please indicate how strongly you agree or disagree with the following statements. Check one box for each.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
1. I think of a car simply as a tool for getting me from A to B					
2. I like the sound of a combustion engine					
3. I enjoy driving					
4. Driving would be more enjoyable if I owned a more luxurious and/or faster car					
5. I keep up with the latest car-related technology					
6. I keep up with newly launched car models					
7. I want the car I drive to be at the cutting edge of new vehicle technology					

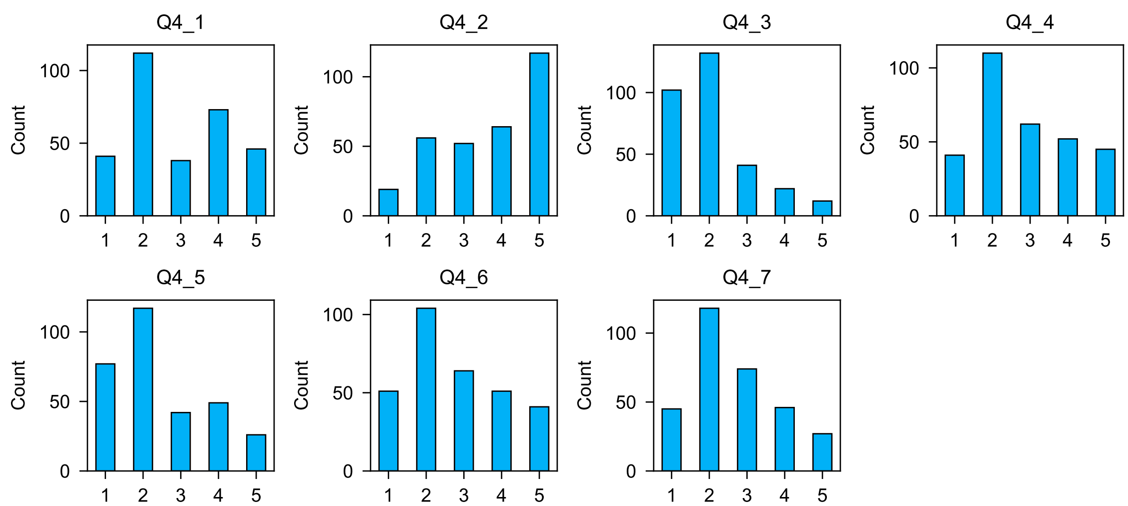

Figure D-6: Responses to survey question 4. 1 = Strongly agree; 5 = Strongly disagree.

Q5. Approximately how many miles do you drive per year? (your best guess - only count miles where you are driving yourself)

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
1. We must urgently find ways to reduce our energy use					
2. Driving contributes to excessive energy use					
3. High use of oil is a serious national security concern					
4. Car emissions contribute significantly to health and environmental problems					
5. Adoption of electric vehicles will help to solve oil-related national security problems					
6. Adoption of electric vehicles will improve air quality					
7. Adoption of electric vehicles will help mitigate climate change					
8. I do not consider the environment when purchasing a car					

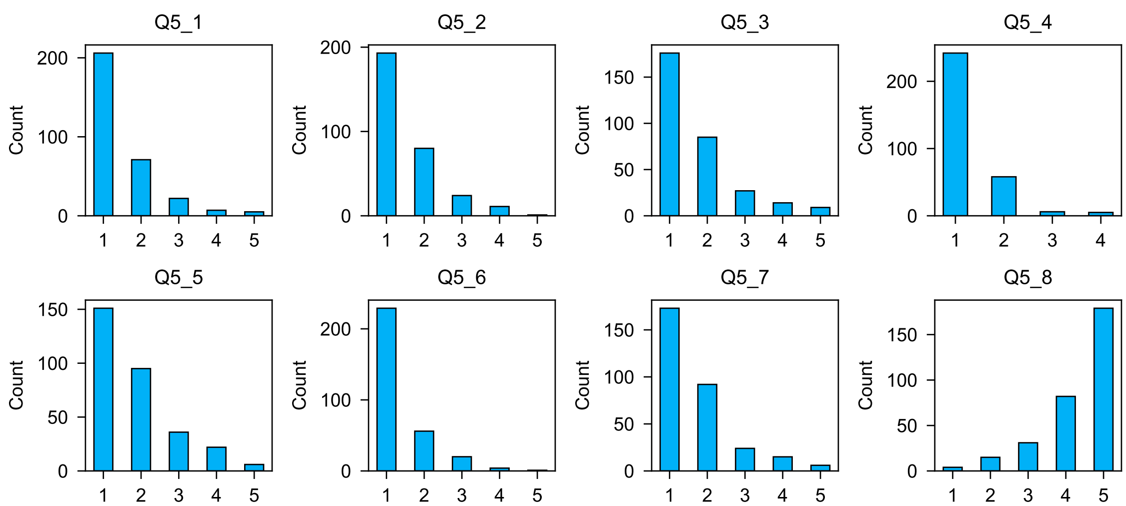

Figure D-7: Responses to survey question 5. 1 = Strongly agree; 5 = Strongly disagree.

Q6. When considering a vehicle to lease or purchase, how important to you are each of the following? Check one box for each.

	Extremely important	Very important	Moderately important	Slightly important	Not at all important
1. Purchasing or leasing price					
2. Fuel economy					
3. Regular maintenance costs					
4. Repair costs					
5. Leg and headroom					
6. Trunk and storage space					
7. Four-wheel-drive (4WD) capability					
8. Safety rating					
9. Performance and power					
10. Reliability					
11. Comfort and style					
12. Manufacturer name and brand					
13. Vehicle is a hybrid					
14. Vehicle is fully electric					

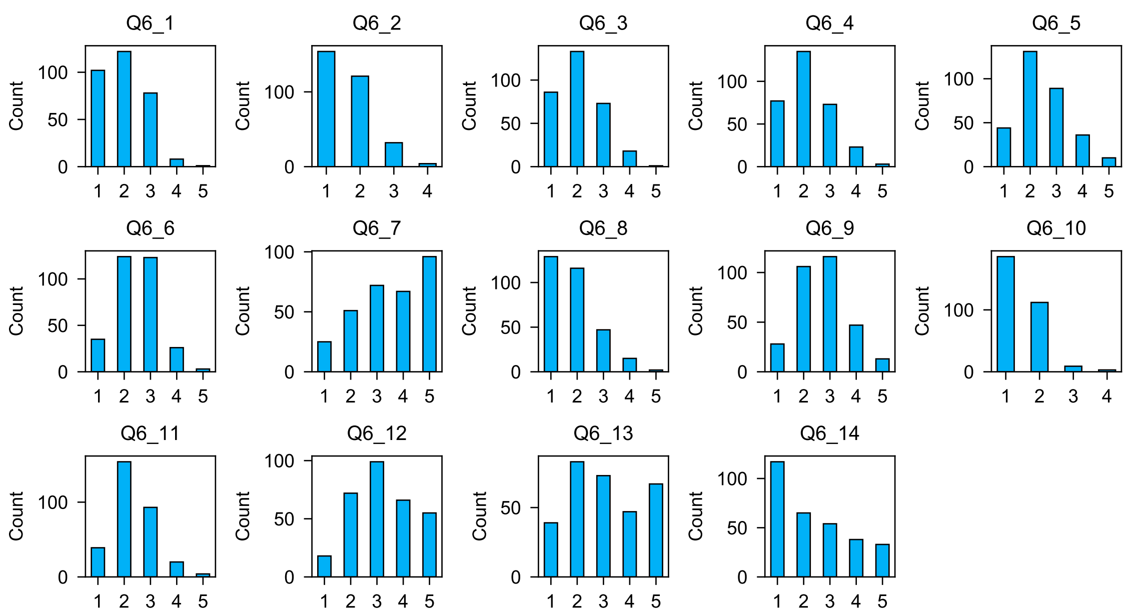

Figure D-8: Responses to survey question 6. 1 = Extremely important; 5 = Not at all important.

Q7. Which of the following to do you currently own? Check all that apply. If you currently do not own a vehicle, but have owned one before, please mark what your last purchase was.

1. Conventional combustion engine vehicle (gasoline or diesel)
2. Hybrid
3. Plug-in hybrid
4. Battery electric vehicle
5. Another type of vehicle
6. I have never owned a vehicle.

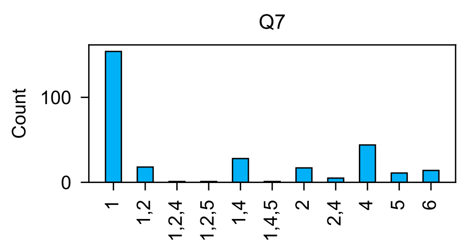

Figure D-9: Responses to survey question 7.

Q8. Do you have a friend, relative or acquaintance that owns an electric vehicle (plug-in hybrid or battery electric vehicle)?

1. Yes
2. No
3. I don't know

Q9. Have you ever driven any friend's, relative's or acquaintance's electric vehicle (plug-in hybrid or battery electric vehicle)?

1. Yes
2. No
3. I don't know

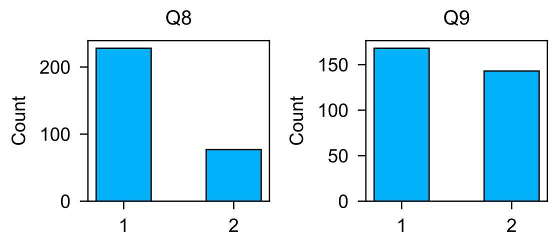

Figure D-10: Responses to survey questions 8 and 9.

Q10. How likely is it that the next vehicle you buy or lease will be one of the following? Please choose the appropriate probability in %.

- Conventional (slider from 0-100% in 10% steps)
- Hybrid (slider from 0-100% in 10% steps)
- Plug-in hybrid (slider from 0-100% in 10% steps)
- Battery electric vehicle (slider from 0-100% in 10% steps)

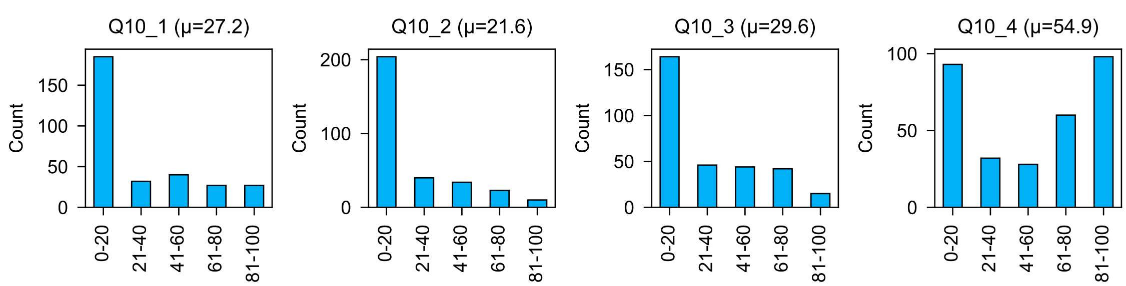

Figure D-11: Responses to survey question 10.

Q11. Please indicate how strongly you agree or disagree with the following statements. Check one box for each.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
1. The cost of owning an electric vehicle is lower than a similarly sized conventional vehicle					
2. Electric vehicles pollute more than conventional vehicles					
3. Electric vehicle owners are saving money and the environment					
4. I am not concerned about gasoline prices					
5. The driving range of most electric vehicles would not meet my driving needs					
6. Current electric vehicle technology is not reliable enough					
7. Limited availability of charging stations has hindered the adoption of electric vehicles					
8. Long charging times have hindered the adoption of electric vehicles					
9. I don't know enough about electric vehicles to make an informed purchasing decision					
10. The government should do more to incentivize the adoption of electric vehicles					

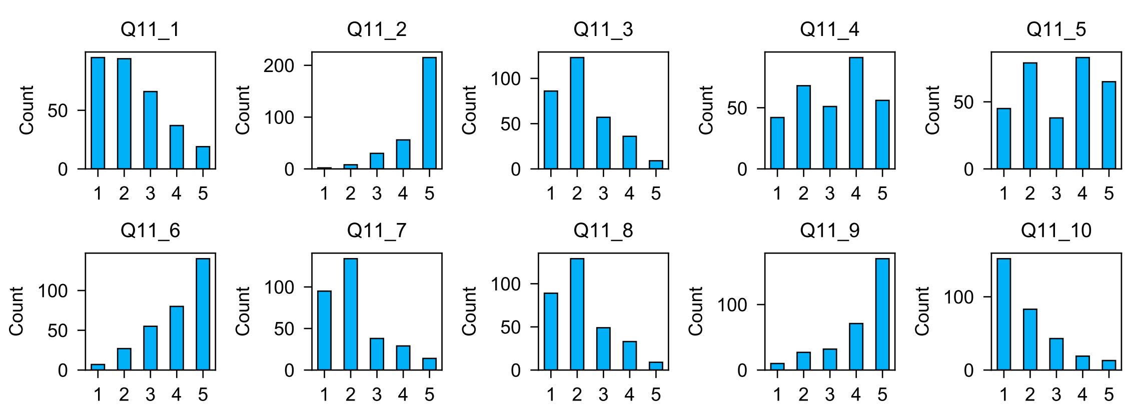

Figure D-12: Responses to survey question 11. 1 = Strongly agree; 5 = Strongly disagree.

Q12. Is this your first time visiting carboncounter.com?

- Yes
- No

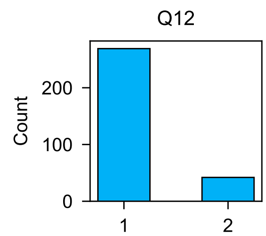

Figure D-13: Responses to survey question 12a.

Q12b. Approximately how many times have you visited carboncounter.com before?

- Just once.
- Two or three times.
- Between three and five times.
- Between six and ten times.
- More than ten times.

Q12c. When was the last time you used carboncounter.com?

- Earlier today
- Several days to a week ago
- Several weeks to a month ago
- Several months to a year ago
- I don't know

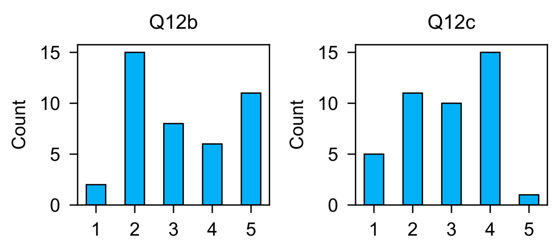

Figure D-14: Responses to survey question 12b and 12c.

Q12d. Indicate how strongly you agree or disagree with the following statements. Check one box for each.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree	Does not apply
Carboncounter.com was easy to understand and use						
Carboncounter.com has helped me to make a more informed vehicle purchasing decision						
Carboncounter.com has led me to view electric vehicles more favorably						
Carboncounter.com has made me more likely to purchase an electric vehicle						

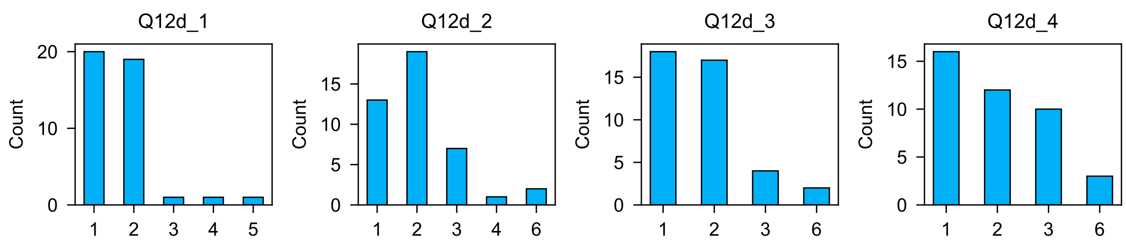

Figure D-15: Responses to survey question 12d. 1 = Strongly agree; 5 = Strongly disagree; 6 = Does not apply.

Q12e. Any other feedback on carboncounter.com you would like to leave? (This question is optional) (open textbox)

1. I would like to click on a car model and read the CO2eq numbers. 2. I can choose international units, but parameters like gallon does not change to litres and miles does not change into kilometers. Please make this more useable for other parts of the world. 3. Reading the report from IVL (link below) it looks like the CO2eq emission from production of the battery is higher than from your analysis. Who is right? http://www.ivl.se/download/18.5922281715bdaebede9559/1496046218976/C243+The+life+cycle+energy+consumption+and+CO2+emissions+from+lithium+ion+batteries+.pdf

I'd like to see vehicle manufacture CO2 load separated. Also, I'd like to have SI units all over the place; right now it's a bit of a mish-and-mash. For example the fuel price is in $/gallon - I'd like to see $/litre. If possible, currency conversion would also help ;-)

Where is the Bolt??! I think it used to be on Carboncounter but it has disappeared! And it's the car I'm about to purchase.

It would be helpful to update carboncounter.com with new models as soon as data is available. There is at least one PHEV that is available now, but it is not represented in the tool.

Great visualization and instant feedback when customizing parameters! Please keep it up to date with the new EV models coming.

Would be great if the emissions in number were indicated on mouseover event on the graph plot.

This is a terrific resource, please keep working on it!

Would be awesome to be updated with additional vehicles and models currently available on the market (eg. Subaru crosstrek, chevy bolt, etc.)

I would love to have the option to share a link to a specific customization. Also, many of the questions in this survey assumed that I didn't already owned a fully electric vehicle, so some of my answers may be a bit misleading in this regard.

This is a terrific resource that I think could help people evaluate choices and see the current situation in terms of vehicle choices and global greenhouse goals in sharp perspective. A key point is the ability to show that making good choices for the environment is not more expensive. Thank you for your *outstanding work.*

Please incorporate all (weighted) lifecycle impacts.

I just came back hoping to customise the graph axes as I had before, but was very disappointed to find that the site appears to have been 'dumbed down' and I now find it much less useful than it was. Is the old version (or its axis-changing capability) still available? Specifically, I would like to plot embodied CO2e against various parameters to use the relationship as a predictive tool for unlisted models. Last time I found the best fit to kerb weight, this time I wanted to check whether this relationship had been updated and try plotting it against purchase price. I also tried to find my car (Nissan e-NV200) and was disappointed to see that there are still only five BEVs listed, which must be an order of magnitude fewer than the models that are now available.

Please add the Tesla Model 3 and Chevy Bolt and more EVS to the website

It would be interesting to see how the carbon footprint divides up between production and operation of each vehicle.

Make it easier to use

Helpful resource to teach others about the market in general not just for informing individual purchasing decisions. Which is an impact multiplier.

Would like to be able to view in table form.

earlier version I think had more information on each car than current version does. Maybe I've not found how to get it on the new one. Glad to see it was updated as it went some years with original data.

Reanault Zoe, the top-seller in Europe is missing.

I would like to be able to filter by All wheel drive vs 2 wheel drive.

Please try to update your data more often with latest cars. For example: I don't see Subaru Crosstrek in the list but that car is in the market for more than 2 years. Also try to add all trims for a Make and Model. In general you should keep your site up-to-date with more data and latest vehicles. Good job btw!

Really cool website! It would be useful to show which kind of emissions of electricity generation you were using for the calculations of the picture. Like a small summary below the picture were the emissions and the mix is shown directly noticable. Thanks!

Initial purchase cost of most EVs is to high. They remain a luxury item for the average consumer.

Q13. What is your gender?

- Male
- Female
- Other

Q14. What is your age? (in years)

- Below 20
- 20-29
- 30-39
- 40-49
- 50-59
- 60 or older

Q15. Which of the following best describes your highest level of education you completed?

- Less than high school degree
- High school/GED
- Some college
- 2-year college/Associate degree
- 4-year college/University degree
- Graduate or professional degree (MS, PhD, MD, JD, etc.)

Q16. How many people are there in your household? (textfield)

Q17. How many of the people in your household do NOT have a driver's license? (textfield)

Q18. What is your annual household income?

- Less than $10,000
- $10,000 - $19,999
- $20,000 - $39,999
- $40,000 - $59,999
- $60,000 - $79,999
- $80,000 - $99,999
- $100,000 - $199,999
- $200,000 or more
- I prefer not to answer this question

Q19. What kind of device have you predominantly been using (or, if it's your first time, are you using right now) to visit carboncounter.com?

- Laptop/desktop computer
- Tablet
- Mobile phone
- Other

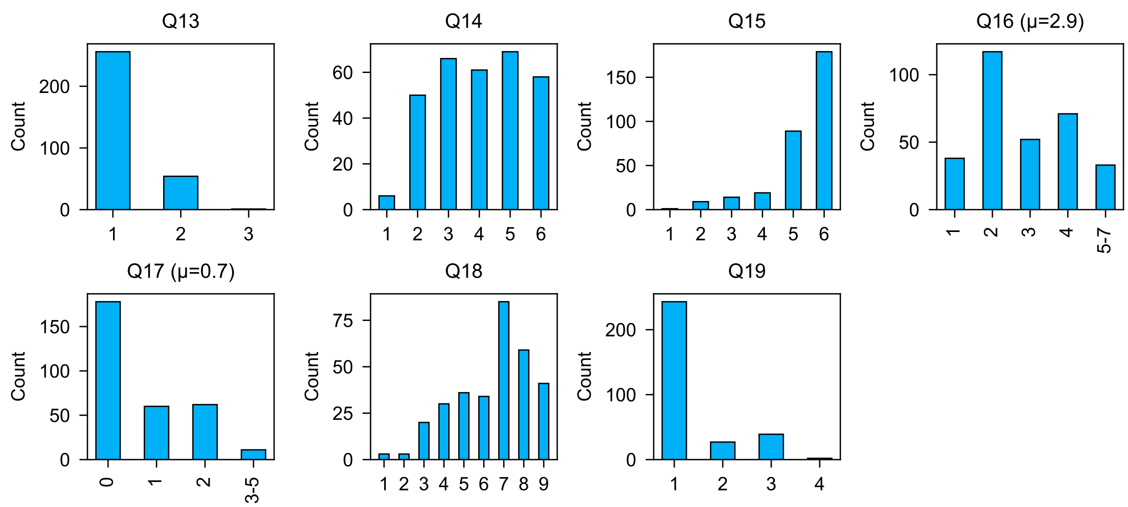

Figure D-16: Responses to survey questions 13 to 19.

Q20. Final question! Indicate how strongly you agree or disagree with the following statements. Check one box for each.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The survey provided me with enough information on the different vehicle types to answer all questions					
The survey felt fair and balanced					
The questions in this survey were easy to understand					
I feel confident about my answers					
This survey was far too long					
Participating in this survey was fun					

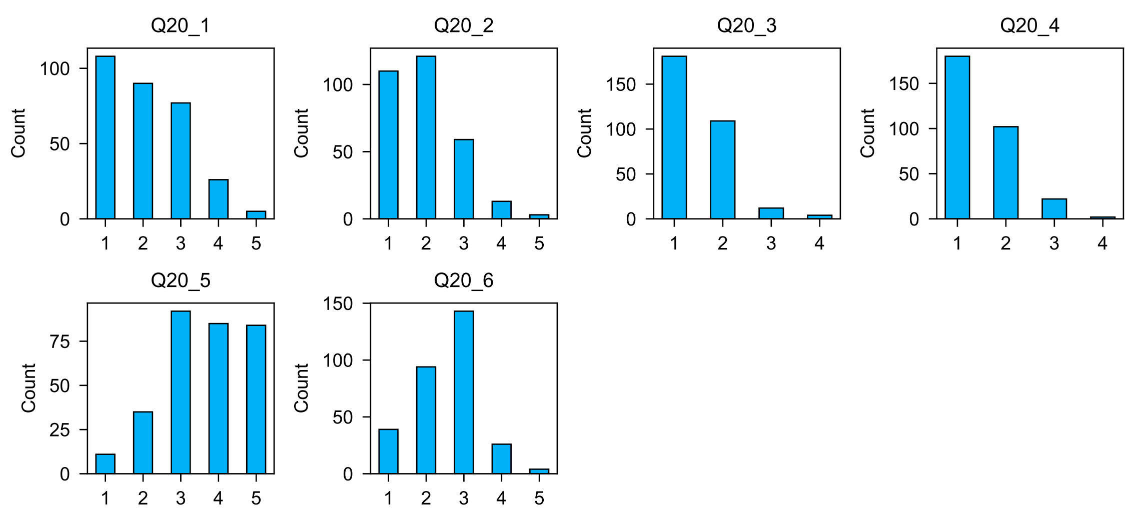

Figure D-17: Responses to survey question 20. 1 = Strongly agree; 5 = Strongly disagree.

D.4 Transformed response variables

Likelihood to purchase EV In the regression models (Table 6.1) and Figures 6-3 and 6-5, this variable is defined as the sum of the percentage that the next vehicle is going to be a plug-in hybrid and the percentage that the next vehicle is going to be a battery electric vehicle (Q10, see D-11. Possible values range from 0 to 100. For responses for which the sum across the four technologies is greater than 100, responses are normalized to sum to 100.

Perception of EV emissions and costs In the regression models (Table 6.1) and Figures 6-3–6-5, this variable is defined as 10 minus the sum of answers to questions Q11.1 and Q11.3 plus the answer to question Q11.2 (see Figure D-12). The resulting values range from 1 to 13, with 13 being the most positive perception of EV emissions and costs.

Perception of EV range and charging issues In the regression models (Table 6.1) and Figures 6-3–6-5, this variable is defined as 16 minus the sum of answers to questions Q11.5, Q11.7, and Q11.8 (see Figure D-12). The resulting values range from 1 to 13, with 13 reflecting the highest amount of concerns regarding EV range and charging issues.

Has visited Carboncounter before In the regression models (Table 6.1), this variable is 0 if the user had never visited Carboncounter before, and 1 if they had.

Annual driving distance In the regression models (Table 6.1), this variable is defined as the natural logarithm of the indicated annual driving distance in miles plus 1. For instance, if the reported annual driving distance is 1000 miles, the value is set to $log(1000 + 1) = 6.91$.

Environmental attitude In the regression models (Table 6.1), this variable is defined as 21 minus the sum of answers to questions Q5.1 to Q5.4 (see Figure D-7). The resulting values range from 1 to 17, with 17 being the most positive attitude.

Interest in car technology In the regression models (Table 6.1), this variable is defined as 11 minus the sum of answers to questions Q4.6 and Q4.7 (see Figure D-6). The resulting values range from 1 to 9, with 9 being the highest amount of interest.

Sound of combustion engine In the regression models (Table 6.1), this variable is defined as the answer to question Q7.2 (see Figure D-9). The resulting values range from 1 to 5, with 5 reflecting the highest affinity for the sound of a combustion engine.

Income In the regression models (Table 6.1) and in Figure 6-3, this variable is defined as the answer to question Q18 (see Figure D-16). For each income bracket, the middle value is applied. For 'Less than $10,000', $5,000 is applied; for '$200,000 or more', $250,000 is applied.

Age In the regression models (Table 6.1) and in Figure 6-3, this variable is defined as the answer to question Q14 (see Figure D-16). For each age bracket, the middle value is applied. For 'Below 20', 18 years is applied; for '60 or older', 70 years is applied.

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