UNIVERSITY OF CALIFORNIA

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Planning for sustainable transportation through the integration of technology, public policy, and behavioral change: A data-driven approach

A dissertation submitted in partial satisfaction of

the requirements for the degree of

Doctor of Philosophy in Urban Planning

by

Bo Liu

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ABSTRACT OF THE DISSERTATION

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through the integration of technology, public policy, and behavioral change:

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Doctor of Philosophy in Urban Planning

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Professor George M. De Shazo, Co-Chair

Professor Deepak Rajagopal, Co-Chair

Transportation contributes importantly to the economy and society, but at substantial environmental cost. While much progress has been made to increase the energy efficiency of transportation systems, their continued expansion is a major threat to global climate change and urban air quality. Additional mitigation strategies are needed to reduce the negative environmental and public health impacts of transportation. In this dissertation, I tackle the complexity of achieving sustainable transportation by addressing questions arise at various stages of technology development and deployment.

The first essay assesses the life cycle environmental impacts of technology pathways that convert waste resources into alternative transportation fuels and identifies the most efficient

pathways for all US counties with respect to both energy production and climate benefits. I find that utilizing these resources in the contiguous US can generate 3.1 to 3.8 exajoules (EJ) of renewable energy annually, which would be a net energy gain of 2.4 to 3.2 EJ, and would displace GHG emissions of 103 to 178 million metric tons of CO_2 equivalent every year.

The second essay uses machine learning techniques to identify the most powerful socioeconomic, demographic, and geospatial predictors for plug-in electric vehicle (PEV) adoption across California census tracts. I find that the market penetration of PEVs is generally higher in more affluent neighborhoods with many homeowners and highly-educated residents. The lack of pro-environment intention and behaviors as well as the proportions of low-income households and low-value and high-density housing units negatively associate with PEV adoption. I also find that the deployment of workplace charging may be more effective than the deployment of public DC fast charging.

The third essay analyzes the energy and environmental impacts of transit bus electrification and identifies strategies for charging infrastructure deployment at public transit agencies in Los Angeles County. I find that the transition to battery electric buses would increase particulate matter emissions from brake and tire wear in the near term and immediately reduce NOx, CO, and GHG emissions. Smart charging would be a critical element in the planning of transit bus electrification, as it reduces costs associated with charging infrastructure and electric demand by lowering charger needs and shaving peak load.

In concert, the three essays in this dissertation expand the current literature in multiple fields and the findings presented in each of the three essays have important implications for research and practices in the area of sustainable transportation at various geographical scales.

The dissertation of Bo Liu is approved.

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2020

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Finally, I would like to extend my sincere thanks to my parents for their unconditional love and support thoughout my life. Their dedication to education has inspired me since I was young and has taught me to stay positive amidst challenging circumstances.

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Planning for sustainable transportation through the integration of technology, public policy, and behavioral change: A data-driven approach

Chapter 1: Introduction

Motivation

Due to high levels of vehicle ownership and use in Organization for Economic Co-operation and Development (OECD) countries and a rapid growth in both private vehicle ownership and freight movement in developing countries, the transportation sector saw a faster increase in greenhouse gas (GHG) emissions than any other energy end-use sector globally since the early 2000s (IEA, 2015; IPCC, 2015). In both the United States and the State of California, transportation is the largest source of GHG emissions – accounting for 28 percent and 40 percent of total GHG emissions in 2018, respectively (CARB, 2020; US EPA, 2020). Besides its contribution to climate change, transportation also negatively affects air quality in urban areas. According to American Lung Association (2018), California has eight of the ten most polluted US cities in terms of ozone pollution and seven of the ten most polluted US cities in terms of particulate matter. In California, transportation is the major source for a number of air pollutants, including ROG[1], CO, and NOx (CARB, 2017). Under certain conditions (i.e., sunlight, temperature, humidity, etc.), these pollutants chemically react with one another and with particulate matter to produce smog, which consists of ozone, particle pollution, and peroxyacetyl nitrate. Ozone and particle pollution can cause respiratory diseases and increase the risk of other

[1] Reactive Organic Gases (ROG), refer to photochemically reactive chemical gases, composed of non-methane hydrocarbons. Retrieved from: https://www.arb.ca.gov/html/gloss.htm#R

health threats such as premature death and cardiopulmonary harm (American Lung Association, 2018).

Mitigation strategies have addressed the negative environmental and public health impacts of transportation, but more are needed. In recent years, researchers have tested alternative biomass sources such as agricultural waste and algae as an alternative to food-crop based and cellulosic biofuels as transportation fuels. The use of alternative biomass resources avoids competition with food production and reduces both deforestation and the amount of land devoted to agriculture. In addition, the global levelized cost[2] of electricity generation from solar and wind has declined significantly since 2010 and all commercially-used renewables – such as solar photovoltaic, concentrated solar power, and onshore and offshore wind – are projected to be cheaper than fossil fuels by 2020 (IRENA, 2018). While renewable sources of energy are generally less reliable than conventionally generated power, advancements in energy storage technologies (such as high-capacity batteries) have the potential to greatly relieve the intermittency issue of renewables (Braff et al., 2016). Since 2010, the State of California has adopted a variety of policies and programs to spur the market growth of electric vehicles. As a result, light-duty plug-in electric vehicle (PEV) sales in California reached over 637,000 vehicles as of October 2019, which accounts for approximately half of the US market (Alliance of Automobile Manufacturers, 2020). In addition, 110 battery electric buses (BEB) were in operation and 626 more were on order, awarded, or planned across California public transit agencies in 2018 (CARB, 2018). These positive changes in alternative transportation fuels, renewable electricity, and transport electrification together lay the foundation for a path to more sustainable transportation.

[2] Levelized cost is a measure of lifetime costs per unit energy production.

In transportation research, emissions are often estimated using the "ASIF" framework (IPCC, 2015; Schipper et al., 2000). This framework breaks down transport emissions reduction efforts into four categories: (1) *Activity*: total vehicle, passenger, or freight distance traveled; (2) *System infrastructure and mode choice*: urban form, transport infrastructure, and the resulting choice between travel modes; (3) *Energy intensity*: efficiency variations between vehicle or engine designs and driver or operator usage patterns; (4) *Fuel emission factor*: the amount of emissions per unit of fuel consumption. The ASIF framework serves as a foundation for this dissertation, which aims to address specific planning, policy and implementation issues associated with alternative fuel production and transport electrification.

The overarching goals of this dissertation are to investigate the impacts of technology (i.e., advanced biofuel and propulsion technologies) and public policy on the planning, design, and implementation of sustainable transportation, and further to explore how to effectively address the barriers to the adoption of clean transportation technologies. Depending on technology maturity, policymakers, planners, and the general public may respond differently to various types of clean transportation technologies. In addition, stakeholders and implementation-related issues vary by specific type of clean transportation technologies. In this dissertation, I tackle the complexity of achieving sustainable transportation by developing data-driven analytical frameworks, which I use to address questions arose at various stages of technology development and deployment.

An Overview of the Three Essays

The three pieces of research in this dissertation address practical planning, policy, and implementation issues associated with alternative fuels and transportation electrification under a multi-modal and multi-scale framework for the transition to sustainable urban transportation. The first essay assesses the life cycle environmental impacts of technology pathways that convert waste resources into alternative transportation fuels and identifies the most efficient pathways for all US counties with respect to both energy production and climate benefits (Liu & Rajagopal, 2019). The second essay uses machine learning techniques to identify the most powerful socioeconomic, demographic, and geospatial predictors for plug-in electric vehicle adoption across California census tracts. The third essay identifies barriers to the adoption of battery electric buses and outlines potential pathways for a 100 percent electrified transit network in Los Angeles County taking into account social, economic and technological constraints. In concert, the three essays in this dissertation expand the current literature in multiple fields and provide insights for infrastructure and environmental planning at various geographical scales. Table 1-1 summarizes the main topics, geographical scales, data sources and main methods for each of the three essays.

Table 1-1. An overview of the three essays

	Essay One (Chapter 2)	Essay Two (Chapter 3)	Essay Three (Chapter 4)
Main topic area	Waste-based biofuels	Plug-in electric vehicles	Battery electric buses
Geographical scale	US county level and national level	California census tract level	Los Angeles County
Major data sources	• The US Billion-ton Study • The Emissions & Generation Resource Integrated Database • The Life Cycle Assessment Harmonization Project • Literature review	• The American Community Survey • IHS Markit electric vehicle sales data • Alternative Fuel Data Center • California Department of Transportation	• OpenMobilityData • National Transit Database • American Public Transportation Association • Original equipment manufacturers • Transit agencies
Main methods	• Life cycle assessment • Spatial analysis • Scenario analysis	• LASSO regression • Monte Carlo sampling	• Network analysis • Scenario analysis

In Chapters 2-4, I discuss each of the three essays in details. The three essays are organized in the chronological order of technology development and deployment. Chapter 2 focuses on technology development and evaluates the environmental impacts of certain technologies before entering large-scale deployment. Chapter 3 focuses on the early stage of technology deployment and offers insights for how to achieve larger-scale deployment. Chapter 4 focuses on large-scale technology deployment and analyzes the infrastructure needs and costs in order to support the transition. In Chapter 5, I conclude the dissertation with the most important findings from the three essays and the broader implications for urban planning, public policy, and environmental studies.

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Chapter 2: Life cycle energy and climate benefits of energy recovery from wastes and biomass residues in the US

Material from: Liu, B., Rajagopal, D. Life-cycle energy and climate benefits of energy recovery from wastes and biomass residues in the United States. *Nat Energy* **4**, 700–708 (2019). https://doi.org/10.1038/s41560-019-0430-2

Abstract

Agricultural and forestry residues, animal manure, and municipal solid waste (MSW) are replenishable and widely available. But effectively harnessing these heterogeneous and diffuse resources for energy and environmental benefits requires a holistic assessment of alternative conversion pathways that account for spatial factors. We analyze the potential renewable energy production, net energy gain, and greenhouse gas (GHG) emissions reduction for each distinct type of waste feedstocks under different conversion technology pathways from a life cycle assessment (LCA) perspective. We find that utilizing all available wastes and residues in the contiguous US can generate 3.1 to 3.8 exajoules (EJ) of renewable energy, which would be a net energy gain of 2.4 to 3.2 EJ, and would displace GHG emissions of 103 to 178 million metric tons of CO_2 equivalent. For any given waste feedstock in US counties where it is available, no single conversion pathway simultaneously maximizes renewable energy production, net energy gain, and GHG mitigation, except in rare instances. Maximizing the benefits of waste conversion requires attention to: first, the life cycle implications of different technology pathways; second, the spatial distribution of waste feedstocks; and third, the local conditions under which waste feedstocks will be processed.

Introduction

In the new millennium, energy insecurity, global climate change, and stagnant rural economies have led to policies supporting domestic biofuels as a renewable alternative fuel in more than 60 countries worldwide (FAO, 2008). As a consequence, global production of ethanol and biodiesel combined almost quadrupled (from about 35 billion to 135 billion liters) in the short span from 2005 to 2016 (REN21, 2017). But these policies had two major flaws. Firstly, appropriation of edible crops for biofuel (mainly, corn and sugarcane for ethanol, and soybean, canola and palm for biodiesel) was an important factor responsible for food price inflation alongside other factors such as rising income that drove to rapid growth in food demand (especially meat demand), rising energy prices, adverse weather shocks, currency fluctuations, and trade policies (de Gorter et al., 2013; FAO, 2008; Hochman et al., 2014; Tadasse et al., 2016; To & Grafton, 2015). The consequences of food price inflation were particularly severe for poorer households in developing countries (Runge & Senauer, 2007). Secondly, these crops required intensive use of land, water, nitrogen, and other farm chemicals, which meant low, and in the worst case, uncertain net environmental benefits (Crutzen et al., 2016; Farrell et al., 2006; Lambin & Meyfroidt, 2011; Melillo et al., 2009; Rajagopal & Zilberman, 2008).

Being widely available and replenishable, wastes and biomass residues from agricultural, dairy, forestry and household activities seem to contain the basic attributes of a sustainable energy resource in stark contrast to bioenergy from food crops (Campbell & Block, 2010; Tonini et al., 2016; Whalen et al., 2017). The US Department of Energy 2016 Billion Ton Study estimates an annual availability of 233 million metric tons (MMT) of dry waste in the contiguous US (US Department of Energy, 2016). To put this in perspective, the approximately 60 billion liters of corn ethanol produced in the US in 2017 required about 150 MMT of corn (assuming a yield of 402 liters of ethanol per MT). Furthermore, wastes and biomass residues can be used to derive a number of alternative energy products including electricity, heat, biomethane (or renewable natural gas), ethanol, renewable diesel, or bio jet fuel, each through various conversion pathways that are at different stages of technical and economic maturity (Campbell & Block, 2010; Carreras-Sospedra et al., 2016; de Jong et al., 2015, 2017; Staples et al., 2017; Tonini et al., 2016; W.-C. Wang & Tao, 2016). Beyond energy production and mitigating climate change, efficient use of wastes and residues is integral to the achievement of sustainable development (United Nations, 2018), and to redesigning our economies to minimize material and energy throughput, i.e., towards becoming a circular economy (Geissdoerfer et al., 2017; Stahel, 2016). But at the same time, the sustainable use of these resources hinges on overcoming some challenges. The collection, transport and storage of biomass feedstocks are costly and could account for over 50% of total cost in the supply chain of bioenergy products (Liu et al., 2017). The composition of wastes also varies from one location to another, and their processing requires substantial energy inputs. In addition, national-scale policies tend to ignore local trade-offs leading to suboptimal use of scarce resources (Laurent & Espinosa, 2015). Effectively harnessing the full energetic and environmental potential of this resource, therefore, requires a holistic assessment of alternative competing pathways to their utilization taking into account the spatial distribution of each specific type of wastes and the local conditions under which they will be processed. The majority of previous LCA studies have either focused on a smaller number of waste types (Aguirre-Villegas et al., 2014; Aguirre-Villegas & Larson, 2017; Banks et al., 2011; Broun & Sattler, 2016; Campbell & Block, 2010; Macias-Corral et al., 2008; Morris, 2017; Nuss et al., 2013; Pressley et al., 2014; H. Wang et al., 2015), certain types of bioenergy products (Anex et al., 2010; Baral & Malins, 2014; de Jong et al., 2015, 2017; Iribarren et al., 2012;

Tonini et al., 2016), or certain conversion technologies (Astrup et al., 2009; Banks et al., 2011; Fruergaard & Astrup, 2011; Gabra et al., 2001b, 2001a; Iribarren et al., 2012; Macias-Corral et al., 2008; Møller et al., 2009; Swanson et al., 2010; Tews et al., 2014). Comparing the effectiveness and environmental impacts of all feasible conversion pathways for all types of wastes from a systems perspective is necessary for policies that address the best use of wastes and biomass residues.

Given this context, the questions motivating this study are the following: first, what factors determine the net energy gain and the global warming potential (GWP) of energy recovery from waste? Second, which pathways simultaneously maximize renewable energy production, net energy gain, and climate benefits for each type of wastes and how does this vary given the spatial distribution of their availability (specifically, in the contiguous US[3])? Third, what are the aggregate energy and climate benefits when all available wastes and biomass residues across the contiguous US are dedicated for a specific policy objective such as maximizing renewable energy production, maximizing net energy gain, or maximizing climate benefits? These questions are aimed at deriving general insights on the optimal use of wastes and biomass residues, and also illustrating their overall climate change mitigation potential in the context of a large country, specifically the US. To this end, we quantify life cycle GHG emissions and net energy gain for fifteen conversion pathways (Table 2-1) and twenty-nine waste feedstocks with spatially explicit estimates of waste potential for the US. We find that the source of electricity consumed during processing and the environmental footprint of the displaced products are key in determining the best use of wastes and biomass residues. The utilization of all available wastes

[3] Biomass availability in Alaska and Hawaii were not estimated in the 2016 Billion-Ton Report, thus the two states were not included in this analysis.

and residues in the contiguous US can generate 3.1-3.8 EJ of renewable energy but deliver only 2.4-3.2 EJ of net energy gain, and displace 103-178 million metric ton CO_2e of GHG emissions. For any given waste feedstock in all US counties where it is available, no single conversion pathway simultaneously maximizes renewable energy production, net energy gain and GHG mitigation, except in rare instances.

Table 2-1. Description and attributes of conversion pathways

Conversion pathway	Abb. name	Description	Feedstock feasibility	Energy input	Energy output (main)	Energy output (co-products)	Displaced products	References
Combined heat and power (CHP)	E1	Thermal combustion through biomass CHP plants	All	Electricity, heat, diesel	Electricity	Heat	State power grids, natural gas-based heat	(Astrup et al., 2009; Fruergaard & Astrup, 2011; Tonini et al., 2016)
Gasification + CHP	E2	Syngas is produced via gasification and is then combusted in gas engines to produce electricity and heat	All	Electricity, heat	Electricity	Heat	State power grids, natural gas-based heat	(Nuss et al., 2013; Sikarwar et al., 2016; Tonini et al., 2016)
Integrated gasification combined cycle (IGCC)	E3	Electricity generation through combined gas and steam turbines with no heat recovery	All	Electricity, heat	Electricity	N/A	State power grids	(Argonne National Laboratory, 2016; Nuss et al., 2013; Tonini et al., 2016)
Anaerobic digestion + CHP	E4	Biogas is produced via anaerobic digestion and is then combusted in gas engines to produce electricity and heat	Animal manure, municipal solid waste (MSW)	Natural gas, diesel	Electricity	Heat	State power grids, natural gas-based heat	(Aguirre-Villegas et al., 2014; Banks et al., 2011; Energy research Centre of the Netherlands, 2017; Fruergaard & Astrup, 2011; Møller et al., 2009)
Gasification	M1	Syngas is produced via gasification and is then upgraded and purified to produce methane.	All	Electricity, heat	Methane	N/A	Natural gas	(Sikarwar et al., 2016; Tonini et al., 2016)
Anaerobic digestion	M2	Biogas is produced via anaerobic digestion and is then upgraded and compressed for pipeline transmission	Animal manure, MSW	Electricity, heat, diesel	Methane	N/A	Natural gas	(Aguirre-Villegas et al., 2014; Argonne National Laboratory, 2016; Fruergaard & Astrup, 2011; Møller et al., 2009)
Enzymatic hydrolysis + fermentation	Eth1	Ethanol production via pretreatment, enzymatic hydrolysis, and fermentation	Ag and forest residues, construction and demolition (CD) waste, MSW wood, paper, yard trimmings	Natural gas, diesel	Ethanol	Electricity	Petroleum based gasoline, state power grids	(Anex et al., 2010; Argonne National Laboratory, 2016; Mu et al., 2010)
Gasification + Fischer-Tropsch (FT) synthesis	Rd1	Gasification to decompose biomass into syngas, and FT synthesis to convert syngas into liquid fuels with the	Ag and forest residues, CD waste, MSW wood, paper,	Electricity	Renewable diesel	Renewable gasoline, bio jet fuel, methane, electricity	Petroleum based diesel, gasoline and jet fuel,	(Argonne National Laboratory, 2016; de Jong et al., 2017;

Conversion pathway	Abb. name	Description	Feedstock feasibility	Energy input	Energy output (main)	Energy output (co-products)	Displaced products	References
		presence of catalysts; excess steam is used for electricity generation	plastics, yard trimmings				natural gas, state power grids	Pressley et al., 2014; Swanson et al., 2010)
Pyrolysis + hydroprocessing	Rd2	Thermochemical conversion of a feedstock into bio-oil, bio-char, and pyrolysis gas; and integrated with hydrocracking and hydrotreatment processes for liquid fuel production	Ag and forest residues, CD waste, food waste, MSW wood, paper, plastics, yard trimmings	Electricity, natural gas	Renewable diesel	Renewable gasoline	Petroleum based diesel and gasoline	(Iribarren et al., 2012; H. Wang et al., 2015)
Alcohol-to-Jet (ethanol)	Bj1	Bio jet production with ethanol as the intermediate product	Ag and forest residues, CD waste, MSW wood, paper, yard trimmings	Hydrogen, electricity	Bio jet fuel	Renewable diesel, renewable gasoline	Petroleum based diesel, gasoline and jet fuel	(Argonne National Laboratory, 2016)
Sugar-to-Jet (fermentation)	Bj2	Sugar is separated from waste feedstock and is then converted into hydrocarbon or hydrocarbon intermediates through fermentation	Ag and forest residues, CD waste, MSW wood, paper, yard trimmings	Hydrogen	Bio jet fuel	N/A	Petroleum based jet fuel	(Argonne National Laboratory, 2016)
Pyrolysis-in situ	Bj3	Feedstock is dried, ground, and then converted to a mixture of bio-oil, gas, and char with high temperature (above 500 ℃). The conversion is continued by hydro-deoxygenating the bio-oil with hydrogen, which is produced through SMR of process off-gases	Forest residues, CD waste, MSW wood, paper, yard trimmings	Electricity	Bio jet fuel	Renewable diesel, renewable gasoline	Petroleum based diesel, gasoline and jet fuel	(de Jong et al., 2015, 2017; Tews et al., 2014)
Pyrolysis-ex situ	Bj4	Same process as Bj5 except that hydrogen is produced from SMR of natural gas	Forest residues, CD waste, MSW wood, paper, yard trimmings	Hydrogen	Bio jet fuel	Renewable diesel, renewable gasoline	Petroleum based diesel, gasoline and jet fuel	(de Jong et al., 2015, 2017; Tews et al., 2014)
Hydrothermal liquefaction (HTL)-in situ	Bj5	Wet feedstock is converted into biocrude under temperature of 250-550 ℃ (with water as a medium), and is then hydro-deoxygenated with	Forest residues, CD waste, MSW wood paper, yard trimmings	Electricity	Bio jet fuel	Renewable diesel, renewable gasoline	Petroleum based diesel, gasoline and jet fuel	(de Jong et al., 2015, 2017; Tews et al., 2014)

Conversion pathway	Abb. name	Description	Feedstock feasibility	Energy input	Energy output (main)	Energy output (co-products)	Displaced products	References
		hydrogen, which is produced through steam methane reforming (SMR) of process off-gases and also anaerobic digestion of wastewater						
HTL-ex situ	Bj6	Same process as Bj3 except that hydrogen is produced from SMR of natural gas	Forest residues, CD waste, MSW wood paper, yard trimmings	Electricity, hydrogen	Bio jet fuel	Renewable diesel, renewable gasoline	Petroleum based diesel, gasoline and jet fuel	(de Jong et al., 2015, 2017; Tews et al., 2014)

Methods

An overview of conversion technology pathways

The fifteen conversion technology pathways included in this study can be categorized into five groups: electricity pathways (E1-E4), methane pathways(M1-M2), ethanol pathway (Eth1), renewable diesel pathways (Rd1-Rd2), and bio jet fuel pathways (Bj1-Bj6). Details about the conversion pathways including process description, feedstock feasibility, energy inputs and outputs, the co-products, the displaced products, and the references are presented in Table 2-1.

Approach to energy and emissions accounting

We conducted a life cycle analysis (LCA) to estimate the energy balances and GHG emissions associated with the conversion of a given feedstock to the final energy product(s) in each county. The different phases of the life cycle that are accounted for include collection of waste, transport to the conversion facility, processing (including pre-treatment), transmission and distribution, and end use (Figure 2-1). Thornley et al. (2015) showed that different functional units would result in varying outcomes when comparing alternative uses of biomass and the function unit should correspond with "the actual nature of the research questions" (Thornley et al., 2015). Since this study mainly focuses on the optimal use of wastes, the functional unit of this LCA is thus one megagram (Mg) of wet waste.

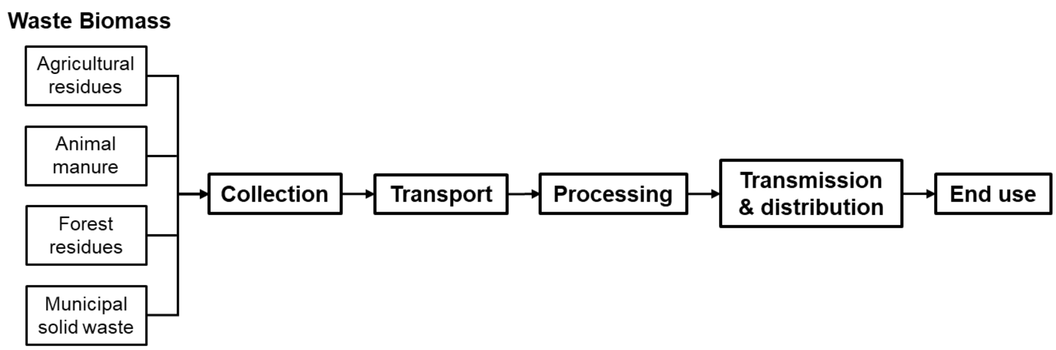


Figure 2-1. System boundary for the life cycle analysis of energy and GHG emissions

Energy and emissions from collection and transport of feedstock are estimated based on this activity requiring heavy-duty diesel trucks. Feedstock-specific technology data (including lower heating values, moisture content, non-biogenic carbon content, energy inputs and outputs by conversion pathway) were collected from the literature to calculate energy and emissions flows in each phase as well as the overall net energy gains (Argonne National Laboratory, 2016; Astrup et al., 2009; Energy research Centre of the Netherlands, 2017; Gabra et al., 2001b; Tonini et al., 2016; US EPA, 2016; Williams et al., 2015). Table 2-1 shows additional data sources. Losses during transmission and distribution were taken into account (Argonne National Laboratory, 2016). Emissions associated with the provision of energy inputs were based on life cycle emissions intensities of electricity generation and other fossil-based fuel production (heat, natural gas, diesel, hydrogen) (Cooney et al., 2016; Ecoinvent Centre, 2015; Lee et al., 2018). Emissions intensities of the production of electricity and fossil-based fuels vary geographically, and variation across states in such emissions intensities were taken into account (Supplementary Table 2-1). Life cycle GHG emissions intensities of state power grids were estimated by multiplying a state's generation mix from the Emissions & Generation Resource Integrated Database (eGRID2016) with life cycle GHG emissions intensities of respective electricity generation technologies from the LCA Harmonization project (NREL, n.d.; US EPA, 2018a). Life cycle GHG emissions intensities of petroleum-based fuels (i.e., diesel, gasoline and jet fuels) by region were obtained from Cooney et al. (2016). Life cycle GHG emissions intensities of natural gas-based heat, hydrogen and natural gas were obtained from Ecoinvent Centre (2015), Lee et al. (2018), and NREL (n.d.) respectively. The GWP for non-CO_2 GHG is based on IPCC AR5 100-year conversion factors (Edenhofer et al., 2011). Supplementary Table 2-1 shows the emissions intensities used to calculate both emissions related to energy use in all conversion pathways and emissions offset from displacing current electricity generation and petroleum-based fuel production.

Comparing the burdens associated with converting a given feedstock to different end products does not, however, paint a complete picture of the benefits of choosing one conversion pathway over another. The ultimate environmental benefit of any given pathway is also a function of the process(es) or product(s) that it displaces. For instance, if conversion of manure to renewable natural gas for pipeline injection entails more GHG emissions relative to conversion to biogas for onsite power generation, it is plausible that the former is more beneficial if electricity from biogas displaces were to clean electricity while renewable natural gas displaces diesel used in trucks or displaces fossil natural gas. Figure 2-2 illustrates a simple schematic representation of this concept. It shows the conversion of a primary resource into a final energy product. Z denotes the life cycle emissions of a given type (say, GHG) from the extraction (or harvesting) of the primary resource through conversion to the finished energy product. Given this set up, production of bioelectricity will displace a certain amount of (Z_{NG-E} - Z_{B-E}) of GHG emissions while production of bio-gasoline will displace a certain amount of (Z_{O-G} – Z_{B-G}) of GHG emissions. The greater of these two displacements would represent the better use of biomass from a GHG emissions perspective. Posen et al. (2014) illustrate this idea in the context of converting cellulosic biomass to ethanol and displacing gasoline vis-à-vis producing bioethylene and displacing fossil-fuel derived ethylene.

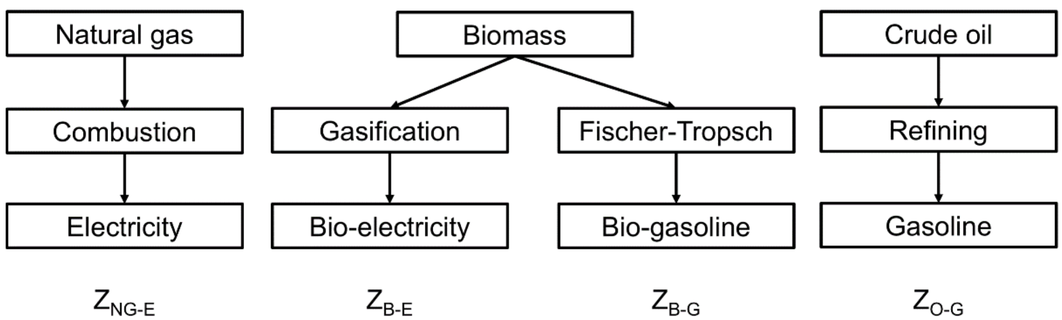


Figure 2-2. A schematic illustration of the displacement approach

For the handling of co-products, we chose the displacement method over allocation methods based on energy or economics for the following reasons: First, the International Standards Organization (ISO) advocates the use of the displacement method (International Organization for Standardization, 2006) and it has been adopted as the default method in many LCA models and biofuel regulation development in the US. Second, many pathways yield a number of different types of energy products – electricity, heat, methane, and/or liquid fuels. The conventional products to be displaced can easily be defined. Third, distinguishing the main-product and co-products in this study is mainly for categorizing the pathways into five groups. We intended to examine the conversion pathways from a systems perspective, that is, for all types of energy products via each conversion pathway instead of the main products only. The displacement method represents the idea of system expansion and is more suitable for our analysis. Fourth, the characteristics (utility, energy form, etc.) of electricity are different from those of other types of energy products; so is each other type of energy product. Allocation simply based on energy content may result in distorted results because various types of energy products may have different utilities. In addition, the price ratios for an economic allocation may be challenging as some of the energy products from waste conversion may be non-commoditized and the prices may fluctuate and vary greatly by geographic location. Net GHG emissions were calculated by subtracting displaced emissions from the life cycle emissions of each conversion pathway.

Biogenic CO_2 emissions are included throughout life cycles. The GWP of biogenic CO_2 emissions was estimated by multiplying GWP_{bio} indices from the full impulse response functions (FIRF) method in a 100-year time horizon and biogenic CO_2 emissions based on initial organic carbon content in waste feedstock. Agricultural residues and animal feed were assumed to come from annual crops, the GWP_{bio} of which is equal to 0. Thus, the GWP of biogenic CO_2 emissions from agricultural residues and animal manure is 0. Supplementary Table 2-2 shows the method and data sources for estimating GWP of biogenic CO_2 emissions from forest residues and MSW. To be consistent with assumptions made by US EPA (US EPA, 2016), the carbon in three MSW feedstocks – plastics, rubber and leather, and textile – was treated as 100 percent fossil carbon. The fossil CO_2 emissions from the three MSW feedstocks were included in the processing phase or the end use phase depending on each specific conversion pathway. Thus, net GWP of a given feedstock converted through a given pathway is equivalent to the sum of net GHG emissions and the GWP of biogenic emissions. Emissions and energy related to material use (such as enzymes and catalysts) are not included in the analysis.

The basic county-level calculations we performed in order to assess the potentials of energy production and life cycle GWP are the following:

$$EP_{i,j,c} = WW_{i,c} \times \sum_k (EO_{i,j,k} \times (1 - TD_k)) \quad \ldots (1)$$

$$NE_{i,j,c} = EP_{i,j,c} - WW_{i,c} \times (\sum_l EI_{i,j,l} + E_{collection,i} + E_{transport} \times D1) \quad \ldots (2)$$

$$GWP_{i,j,c} = WW_{i,e} \times (E_{collection,i} + E_{transport} \times D1) \times EmissI_{diesel,c} + \sum_l (EI_{i,j,l} \times EmissI_{l,c})) + Emiss_{process} + W_{i,j,k} \times EmissI_{diesel,c} \times D2 + Emiss_{enduse} + GWP_i^{bioCO2} - EP_{i,j,k} \times EmissI_{m,c} \quad \ldots (3)$$

$$GWP_i^{bioCO2} = GWP_{bio,i} \times Emiss_{bioCO2,i} \quad \ldots (4)$$

where,

$EP_{i,j,c}$ - Renewable energy production (MJ) of feedstock *i* via conversion pathway *j* in county *c*;

$WW_{i,c}$ - wet weight (kg) of feedstock *i* in county *c*;

$EO_{i,j,k}$ - energy output *k* (MJ/kg) of feedstock *i* via conversion pathway *j*;

TD_k - transmission and distribution loss of energy output k, 6.5% assumed for electricity, 20% for heat, and 2% for methane;

$NE_{i,j,c}$ - net energy (MJ) of feedstock *i* via conversion pathway *j* in county *c*;

$EI_{i,j,l}$ - energy input *l* (MJ/kg) of feedstock *i* via conversion pathway *j*;

$GWP_{i,j,c}$ - net GWP (gCO_2e) of feedstock *i* via conversion pathway *j* in county *c*;

$E_{collection,i}$ - Energy consumption rate (MJ/kg) of collecting feedstock *i*;

$E_{transport}$ - Energy consumption rate (MJ/kg-km) of transporting feedstock *i* to conversion facility;

D1 - Transport distance (km) from temporary storage or collection site to conversion facility, 150 km assumed;

$EmissI_{diesel,c}$ - life cycle GHG emissions intensity (gCO_2e/MJ) of petroleum-based diesel in county *c*;

$EmissI_{l,c}$ - life cycle GHG emissions intensity (gCO_2e/MJ) of energy input *l* in county *c*;

$Emiss_{process}$ – direct GHG emissions (excluding biogenic CO_2) during processing;

$W_{i,j,k}$ - physical weight (kg) of energy output *k* of feedstock *i* via conversion pathway *j*;

D2 - Transport distance (km) for distribution, 150 km assumed;

$Emiss_{enduse}$ – direct GHG emissions (excluding biogenic CO_2) during end use;

GWP_i^{bioCO2} – GWP (gCO_2e) of biogenic carbon in feedstock *i*

$EP_{i,j,k}$ - energy production (MJ) of output k of feedstock i via conversion pathway j;

$EmissI_{m,c}$ - life cycle GHG emissions intensity (gCO_2e/MJ) of energy product m (which output k can substitute) in county c;

$GWP_{bio,i}$ - biogenic CO_2 global warming index with full impulse response functions for feedstock i;

$Emiss_{bioco2,i}$ - biogenic CO2 emissions of feedstock i.

For the comparison of conversion pathways, county-level results were first aggregated to the national level and by feedstock. Weighted average (by weight) of results by feedstock in each of the four broader categories of waste resources were calculated for the comparison by waste type. For the current management practices for wastes and residues, we used the same emissions accounting method and life cycle framework to estimate the GWP (Supplementary Table 2-3).

Sensitivity analysis

We conducted a sensitivity analysis of net GHG emissions to explore the impacts of emissions intensity of current state power grids and transportation distance. For the sensitivity analysis on electricity, two additional electricity generation scenarios were constructed: “cleaner power” - assuming a 50% reduction in emissions intensity of power grids in all states; and “fossil rollback” - assuming a 50% increase in emissions intensity of power grids in all states. In addition, a range of 25 - 150 km was examined to test the sensitivity of transportation distance.

Technical availability of waste resources

County-level waste availability data were obtained from the base-year estimates under the reference scenario in the US DOE’s BT16. BT16 estimates the biophysical potential, the spatial distribution, economic constraints, as well as environmental impacts associated with existing and potential biomass resources (US Department of Energy, 2016). Waste resources included in this study comprise of four types of wastes: agricultural residues (14 feedstocks, including both primary and secondary agricultural residues as defined in BT16), animal manure (2 feedstocks), forest residues (4 feedstocks), and municipal solid waste (9 feedstocks). Technical availability was defined as the maximum potential of waste resources without taking into account feedstock costs. BT16 reports dry weight of waste feedstocks, and wet weight was calculated with moisture content to account for collection and transport emissions.

Scenario analysis

To explore the optimal utilization of waste biomass resources, we developed three alternative scenarios: maximum renewable energy production (MEP), maximum net energy (MNE), and maximum GHG emissions reduction (MER). For all scenarios, the optimal conversion pathway for each feedstock was selected based on the maximum value of energy or emissions reduction. Under each scenario, the county-level results were then added up to get the potentials of total renewable energy production, net energy, and emissions reduction at the national level.

Results and Discussion

Technical comparison of conversion pathways

We first estimate renewable energy production, net energy gain, and GHG footprint of different conversion pathways on a per unit wet weight basis for various types of wastes. Feedstock-level results are depicted in Supplementary Figures 2-1 to 2-3. The methods section explains how we first calculate these for each distinct waste biomass source at the US county-level, and subsequently, compute a mass weighted-average for each of the four broad categories of wastes at the national level. The renewable energy yield across conversion pathways ranges from 0.2 to 13.1 gigajoules (GJ) per megagram (Mg) of waste, while the net energy gain ranges from -2.4 to 11.6 GJ per Mg (Figure 1a and Figure 1b). It is clear that the energy value of co-products is critical to achieving positive net energy for a number of conversion pathways and waste feedstocks. Except for animal manure-related pathways, all conversion pathways result in positive net energy gains and considerable energy return on investment (EROI). For animal manure, only anaerobic digestion (M2) yields positive net energy and its EROI is only slightly greater than 1. Other available technology pathways for the processing of animal manure require a substantial amount of thermal energy inputs to either combust or gasify the feedstock. The net GWP across the pathways ranges from -0.9 to 0.7 metric ton (Mt) CO_2e per Mg (Figure 1d). As with the importance of co-products in net energy gain, emissions avoided by the resulting co-product(s) displacing a substitute accounts for a substantial portion of the climate benefits for most pathways.

Looking into each broad waste category, for agricultural and forest residues, combined heat and power generation (CHP) offers both the greatest net energy gain and climate benefits. For MSW, CHP offers the highest net energy gain while anaerobic digestion returns more climate benefits than other pathways. When compared with current management practices, all conversion pathways result in climate benefits for agricultural residues. As for animal manure, only anaerobic digestion producing either methane (M2) or electricity and heat (E4) yields climate benefits. This corresponds with previous studies, indicate that anaerobic digestion is the optimal conversion pathway for animal manure (Aguirre-Villegas et al., 2014; Aguirre-Villegas & Larson, 2017; Tonini et al., 2016). Although some pathways appear not to contribute to climate change mitigation (i.e., result in positive net GWP), all conversion pathways for forest residues yield smaller net GWP relative to burning them on-site. When compared to landfilling without any methane flaring or capturing, all conversion pathways for MSW result in smaller negative effects on the climate. However, landfilling with methane capture and onsite CHP would greatly reduce the GHG emissions of landfilling and become more attractive than renewable diesel related conversion pathways (Figure 2-3).

Break-down of GHG emission sources

Disaggregating the contribution to total GHG emissions from the different stages in the production chain shows that emissions during the processing stage, which requires electricity and heat input, and credits for avoided emissions attributable to displaced products are key determinants of GHG emissions for most conversion pathways (Figure 2-3). This is generally in line with results from a number of recent studies, such as de Jong et al. (2017), Pressley et al. (2014), and Tonini et al. (2016). For agricultural residues, current management practice (i.e., left and decayed on field) entail no GWP due to the fact that the GWP_{bio} index for annual crops is zero. Although emissions from growing the crops (with a GWP_{bio} of 0) used as animal feed can be neglected, emissions from direct land application of manure mainly consist of methane and N_2O emissions from animal farm operations. For MSW, the major sources of non-biogenic carbon are contained in plastics, rubber and leather, and textiles. For non-electricity pathways, non-biogenic carbon in MSW feedstocks is transferred into energy products and eventually emitted into the atmosphere as CO_2 during end use. This explains a large amount of emissions during the end-use stage for these pathways. For electricity-related pathways (E1-E4), non-biogenic carbon is emitted as CO_2 during the processing phase. For other types of MSW feedstocks, biogenic carbon is emitted as biogenic CO_2 at various phases. Thus, we treated biogenic CO_2 as a separate source of GHG emissions.

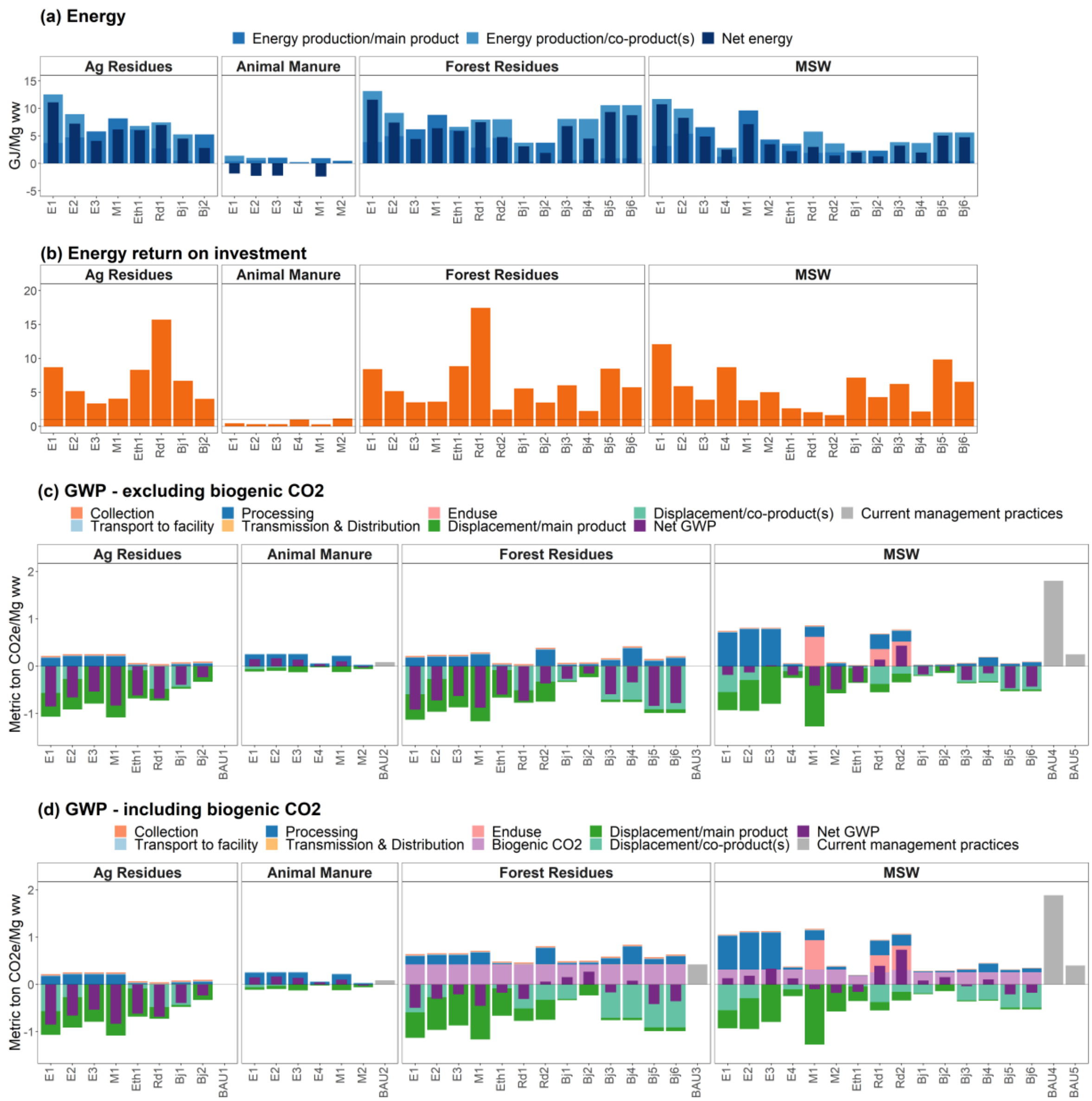


Figure 2-3. Energy, net energy and emissions from waste biomass utilization in the US

(a) Energy production and net energy by waste type and conversion pathway; (b) Energy return on investment by waste type and conversion pathway (the horizontal line refers to an EROI of 1); (c) Life cycle emissions when biogenic CO_2 is excluded; and (d) Life cycle emissions when biogenic CO_2 is included. Electricity pathways: E1 – CHP, E2 - Gasification + CHP, E3 - IGCC, E4 - anaerobic digestion + CHP; Methane pathways: M1 – gasification, M2 - anaerobic digestion; Ethanol pathway: Eth1 - enzymatic hydrolysis + fermentation; Renewable diesel pathways: Rd1 - gasification + FT synthesis, Rd2 - pyrolysis + hydroprocessing; Bio jet fuel pathways: Bj1 - ATJ (ethanol), Bj2 - STJ (fermentation), Bj3 - pyrolysis (in situ), Bj4 - pyrolysis (ex situ), Bj5 - HTL (in situ), Bj6 - HTL (ex situ). Business-as-usual practices: BAU1 - left on field (agricultural residues), BAU2 - direct land application (animal manure), BAU3 – burning on-site (forest residues), BAU4 – landfilling without methane flaring or capture (MSW), BAU5 - landfilling with 75% of methane capture and use for on-site CHP (MSW). See Table 2-1 for additional details on conversion pathways.

Sensitivity analysis of emission estimates

Given that electricity consumption during biomass processing is the major source of energy inputs and emissions across most conversion pathways, we conducted a sensitivity analysis on the emissions intensities of state power grids. Note that even though biomass processing requires significant heat energy, it is typically derived from natural gas, whose emissions intensity is much less variable across regions relative to the emissions intensity of electricity. Results show that cleaner power grids in general would yield less climate benefits for electricity pathways and more climate benefits for non-electricity pathways (Figure 2-4). For cleaner power grids, electricity-related pathways would on one hand result in fewer emissions during the processing stage, but would on the other hand lead to less climate benefits from the displacement of grid electricity. For the majority of non-electricity pathways, electricity is only an input so that cleaner power grids would result in less emissions during the processing stage and the overall life cycle. For instance, whereas converting agricultural and forest residues into electricity through CHP (E1) and biomethane through gasification (M1) appear equally beneficial under current conditions, M1 becomes more beneficial when power grids are cleaner. We also conducted another sensitivity analysis on transportation distance (Figure 2-5). However, distances ranging from 25 to 150 km negligibly affect our GHG emissions results. Thus, we assumed 150 km as the transportation distance in order to provide conservative estimates for net energy gain and GHG emissions.

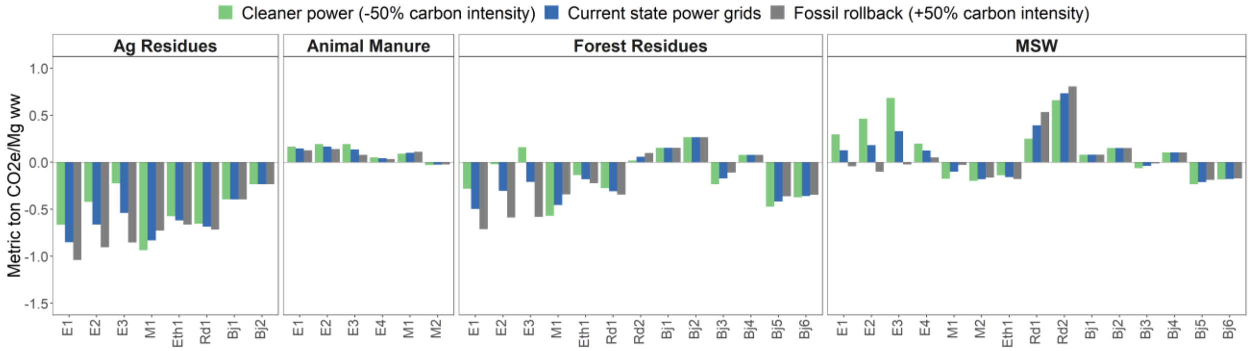


Figure 2-4. Sensitivity analysis of emission estimates
Electricity pathways: E1 – CHP, E2 - Gasification + CHP, E3 - IGCC, E4 - anaerobic digestion + CHP; Methane pathways: M1 – gasification, M2 - anaerobic digestion; Ethanol pathway: Eth1 - enzymatic hydrolysis + fermentation; Renewable diesel pathways: Rd1 - gasification + FT synthesis, Rd2 - pyrolysis + hydroprocessing; Bio jet fuel pathways: Bj1 - ATJ (ethanol), Bj2 - STJ (fermentation), Bj3 - pyrolysis (in situ), Bj4 - pyrolysis (ex situ), Bj5 - HTL (in situ), Bj6 - HTL (ex situ).

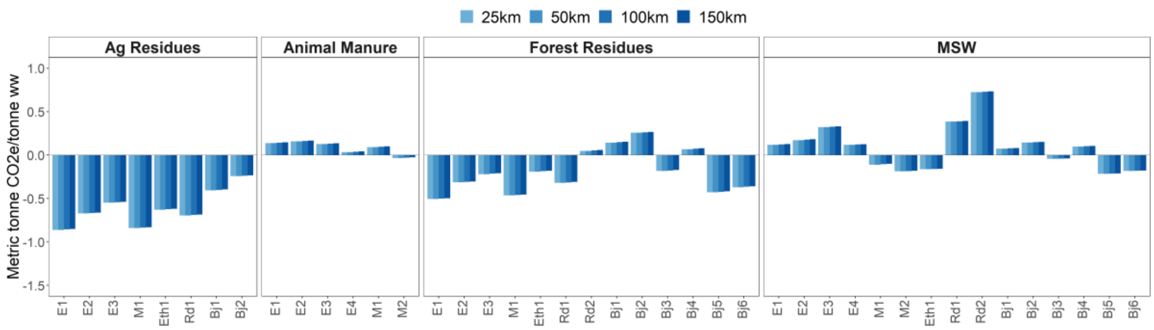


Figure 2-5. Sensitivity analysis of GWP on transportation distance
Electricity pathways: E1 - CHP; E2 - gasification + CHP; E3 - IGCC; E4 - anaerobic digestion + CHP; M1 - gasification; M2 - anaerobic digestion; Eth1 - enzymatic hydrolysis + fermentation; Rd1 - gasification + FT synthesis; Rd2 - pyrolysis + hydroprocessing; Bj1 - ATJ (ethanol); Bj2 - STJ (fermentation); Bj3 - pyrolysis (in situ); Bj4 - pyrolysis (ex situ); Bj5 - HTL (in situ); Bj6 - HTL (ex situ).

Maximizing aggregate energy and climate benefits

We next describe the maximum energy and climate benefits achievable at a national scale through optimal utilization of waste biomass generated in each county within the US taking into account spatial variation in the electricity mix. As noted earlier, about 233 MMT of dry waste resources are available annually in the contiguous US. The spatial distribution of this total resource base is depicted in Figures 2-6 and 2-7. Approximately 25% of this total is concentrated in 115 counties, 50% are in 374 counties, and 75% are in 884 counties. The availability of all waste resources combined varies by county and it reaches as high as over 2 million dry Mg in Los Angeles County, California (Figure 2-6). Agricultural states in the Pacific West, the Midwest and the South in general stand out with more agricultural residues than other regions. Counties in the Mountain West and the South are endowed with substantial forest residues. In the Mountain West, these forest residues mainly consist of fuel reduction thinning from wildfire mitigation, whereas forest residues in the South are mostly mill residues. The availability of animal manure corresponds with livestock and poultry production, which is concentrated in California and the Midwest. The availability of MSW is concentrated in densely-populated regions such as Southern California, Florida, and parts of the Northeast. Overall, however, some of the largest metropolitan areas stand out in terms of the availability of total waste resources.

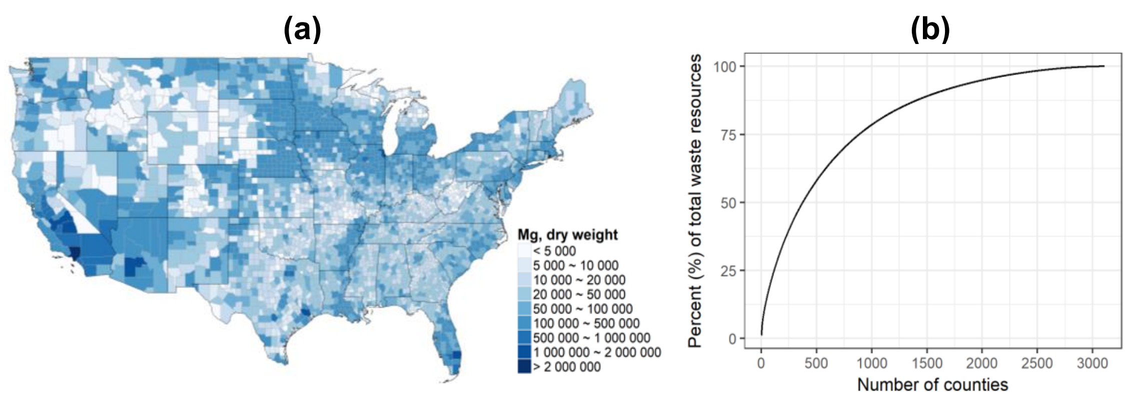


Figure 2-6. Distribution of waste resources in the US
(a) County-level waste production (Mg) in 2015; (b) Distribution of total waste production by the number of counties.

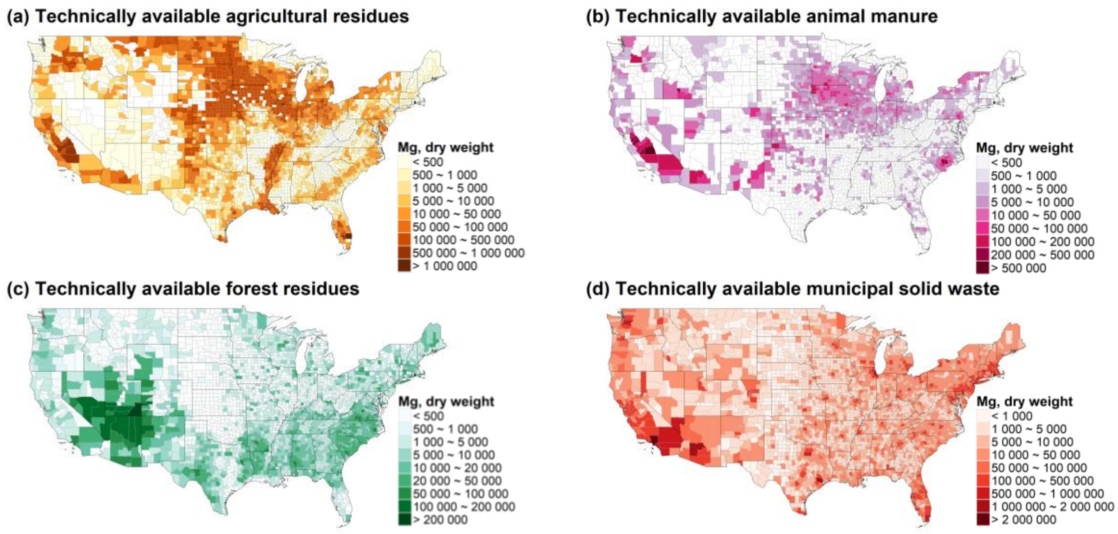


Figure 2-7. Spatial distribution of technically available biomass potential from waste resources
(a) Agricultural residues; (b) Animal manure; (c) Forest residues; and (d) Municipal solid waste.

Searching for the optimal conversion pathway with respect to all three criteria - renewable energy, net energy and GWP, we find that no single pathway exists for any given type of waste across all US counties and states, except in rare instances (Table 2-2). Across different types of agricultural residues, combined heat and power generation (E1) consistently stands out with respect to all three criteria for a substantial fraction of counties and states. As for animal manure, no single pathway satisfies all three criteria. For forest residues and municipal wastes, optimal conversion pathways that satisfy all three criteria vary by specific waste feedstocks. The percentage of locations where there is a single optimal pathway varies substantially.

Table 2-2. Synergies between renewable energy, net energy, and GWP at the county and state levels

Waste type	Feedstock	Total number of counties with feedstock available	All three criteria aligned		Total number of states with feedstock available	All three criteria aligned		Optimal pathway
			Number of counties	Percent (%)		Number of states	Percent (%)	
Ag. Residues	Barley straw	136	52	38	14	5	36	E1
	Citrus residues	118	53	45	9	3	33	E1
	Corn stover	1276	793	62	36	22	61	E1
	Cotton gin trash	815	329	40	17	6	35	E1
	Cotton residues	796	305	38	17	6	35	E1
	Noncitrus residues	1686	795	47	48	20	42	E1
	Oats straw	12	4	33	2	1	50	E1
	Rice hulls	144	77	53	6	3	50	E1
	Rice straw	148	80	54	6	3	50	E1
	Sorghum stubble	191	161	84	9	6	67	E1
	Sugarcane bagasse	29	11	38	3	2	67	E1
	Sugarcane trash	29	11	38	3	2	67	E1
	Tree nut residues	620	234	38	40	14	35	E1
	Wheat straw	696	207	30	32	11	34	E1
Animal Manure	Hogs, 1000+ head	934	0	0	37	0	0	-
	Milk cows, 500+ head	639	0	0	44	0	0	-
Forest Residues	Primary mill residues	488	178	36	44	12	27	E1
	Secondary mill residues	2418	590	24	49	11	22	E1
	Other forest residues	1256	588	47	35	15	43	-
	Other forest thinnings	304	96	32	11	5	45	E1
MSW	CD waste	3109	0	0	49	0	0	-
	Food waste	2792	0	0	48	0	0	-
	MSW wood	3109	2487	80	49	39	80	Bj5
	Paper and paperboard	3109	0	0	49	0	0	-
	Plastics	3109	0	0	49	0	0	-
	Rubber and leather	3109	0	0	49	0	0	-
	Textiles	3109	0	0	49	0	0	-
	Yard trimmings	3066	0	0	49	0	0	-
	Other MSW	3109	0	0	49	0	0	-

Since there lacks a single pathway that aligns all three criteria for any given waste feedstock across locations, there is a need to consider three distinct scenarios of optimal use of biomass wastes – maximum energy production (MEP), maximum net energy (MNE), and maximum emissions reduction (MER). For each county in the US, we first select the conversion pathway for each type of waste under each of the three scenarios. The national results are the aggregation of county-level results. Scenario results suggest that there is substantial benefit from utilizing wastes and biomass residues to either displace energy production or reduce GHG emissions or both (Table 2-3). As one would expect, MEP results in the highest potential of renewable energy production, which totals 3.8 exajoules (EJ), or 3.7% of total US energy demand in 2016 (EIA, 2017), and MER results in the highest potential of emissions reduction that is 178 MMT CO_2e – 2.7% of total US GHG emissions in 2016 (US EPA, 2018b). The MNE scenario has the highest potential of net energy as well as a moderate amount of emissions reduction (75% of MER). A break-down of scenario results by waste feedstock reveals the preferred conversion pathways under each of the three scenarios (Supplementary Table 2-4). CHP (E1) is the preferred option for agricultural resides under both the MEP and MNE scenarios, while either CHP(E1) or gasification (M1) may maximize GHG emissions reduction depending on specific feedstock. For dairy manure, CHP (E1) is the preferred option that maximizes renewable energy production, but anaerobic digestion to biomethane (M2) maximizes both net energy gains and climate benefits. For forest residues, CHP (E1) results in the largest amount of renewable energy and net energy gain, while either HTL with in-situ hydrogen production (Bj5) or gasification (M1) maximizes GHG emissions reduction. Different from other categories of wastes, optimal use of MSW feedstocks would require a greater number of conversion technology pathways depending on the specific feedstock. Non-biogenic carbon in

MSW is concentrated in three feedstocks - plastics, rubber and leather, and textiles. Thus, the non-biogenic carbon is immediately emitted into the atmosphere when processing those feedstocks instead of being stored in landfills. While the inclusion of biogenic CO_2 reduces net GWP for forest residues and MSW (Figure 2-3), it does not change the ranking of conversion pathways under the three scenarios.

Table 2-3. Total renewable energy production, net energy gain, and GWP across scenarios

Policy scenarios	Renewable energy production		Net energy gain		GWP	
	EJ	Index	EJ	Index	MMT CO_2e	Index
MEP[1]	3.8	100%	2.9	89%	-103	58%
MNE[2]	3.7	96%	3.2	100%	-133	75%
MER[3]	3.1	81%	2.4	76%	-178	100%

Note: [1]MEP: Maximum renewable energy production scenario.
[2]MNE: Maximum net energy gain scenario.
[3]MER: Maximum GHG emissions reduction scenario.

The county-level distribution of renewable energy production, net energy gain, and its associated climate benefits also indicates that most counties would lose a relatively small amount of energy production potential when switching from the MEP scenario to the MER scenario while most counties would see a greater increase in terms of emissions reduction (Figure 2-8). Maximizing energy production would result in negative net energy in 125 counties and emissions increase in 532 counties (Figure 2-8). Therefore, maximizing either net energy or emissions reduction would lead to better utilization of wastes and residues relative to maximizing renewable energy. Given that the terms “renewable energy” and “clean energy” tend to often be used interchangeably by policy makers, this analysis shows that there exist potential tradeoffs between different criteria relevant to sustainable development.

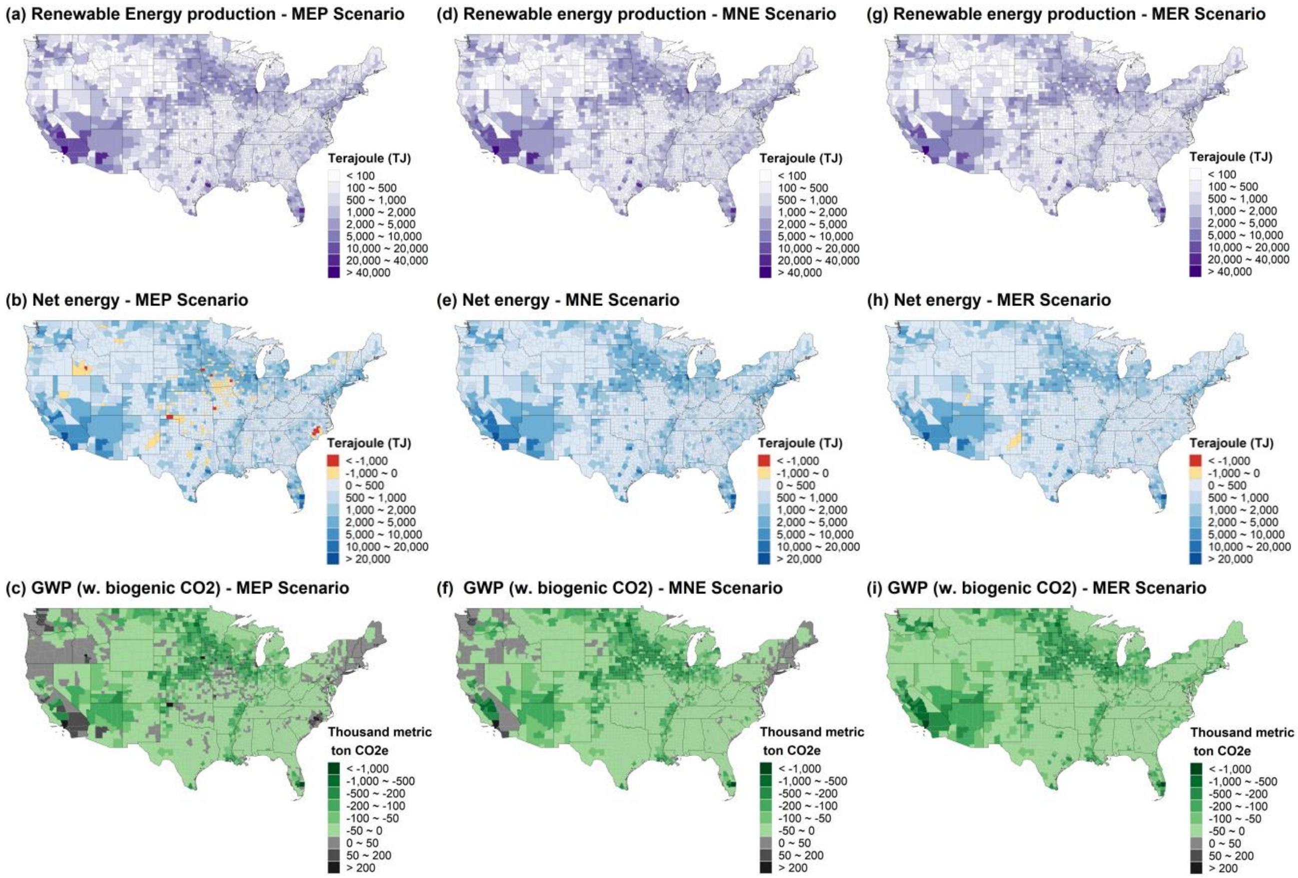


Figure 2-8. County-level renewable energy production, net energy and emissions
a, b, c - The maximum renewable energy production (MEP) scenario; d, e, f - The maximum net energy (MNE) scenario; g, h, i - The maximum GHG emissions reduction (MER) scenario.

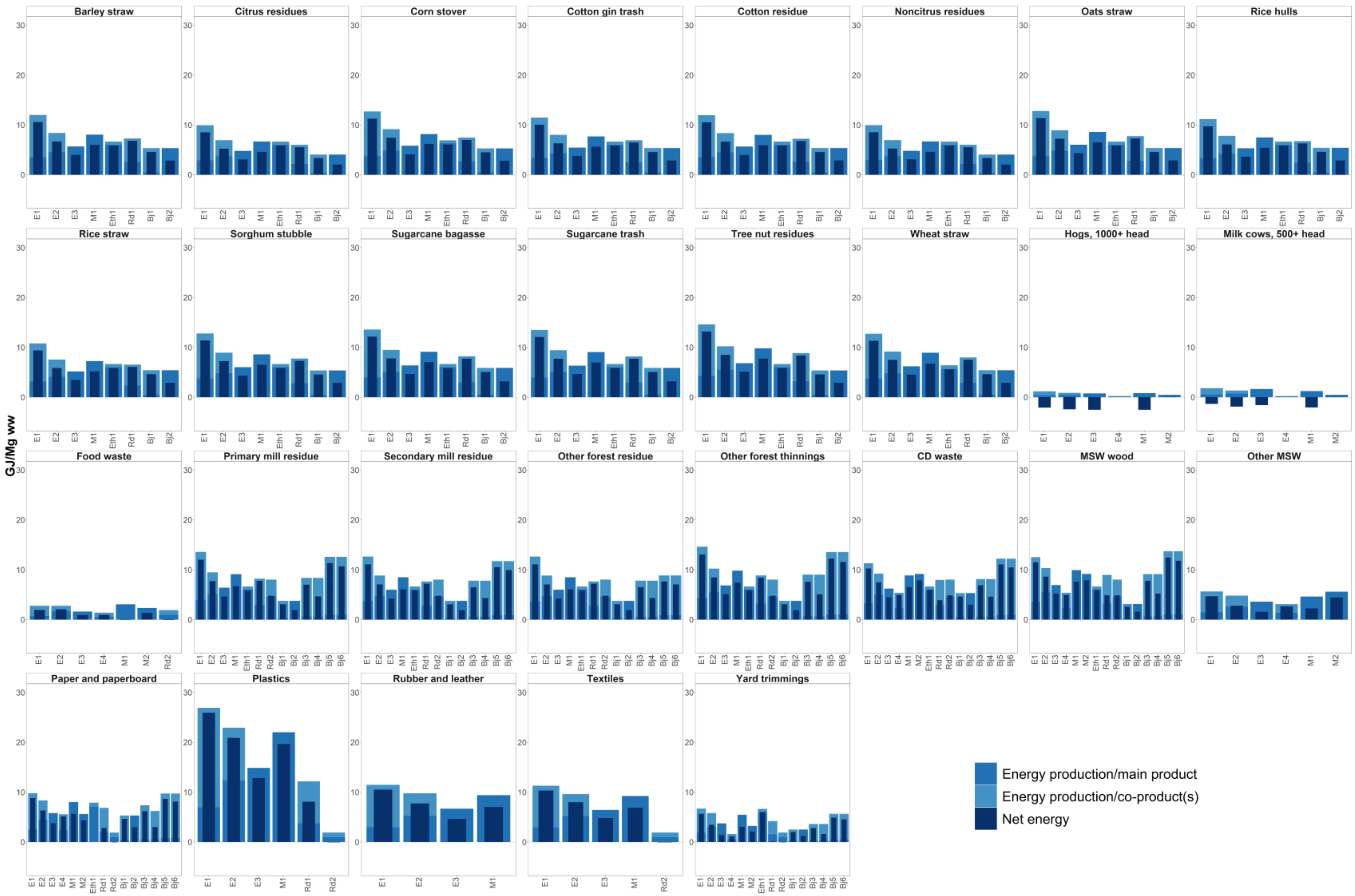
Conclusions

Maximizing the benefits of waste conversion requires attention to: first, the life cycle implications of different technology pathways; second, the spatial distribution of waste feedstocks; and third, the local conditions under which waste feedstocks will be processed. The policy insight that emerges from this analysis is that national mandates such as the US Renewable Fuel Standard (RFS) likely do not maximize even renewable energy production, let alone environmental benefits. Likewise, renewable portfolio standards, a widely employed policy in the electricity sector, could lead to sub-optimal use of waste biomass. In the literature, bioenergy and biofuel policies have been analyzed mainly from the perspective of climate change mitigation, food security, or cost, but this analysis shows they also do not optimize energy production. From a methodological perspective, this analysis illustrates the value of combining LCA with spatial analytical techniques for multi-criteria assessment of alternative conversion pathways and the identification of hot spots for the refinement of existing energy policies. Indexing volumetric targets and mandates as well as financial subsidies for renewable energy to life cycle emissions-based performance measures will lead to more sustainable use of wastes and biomass residues.

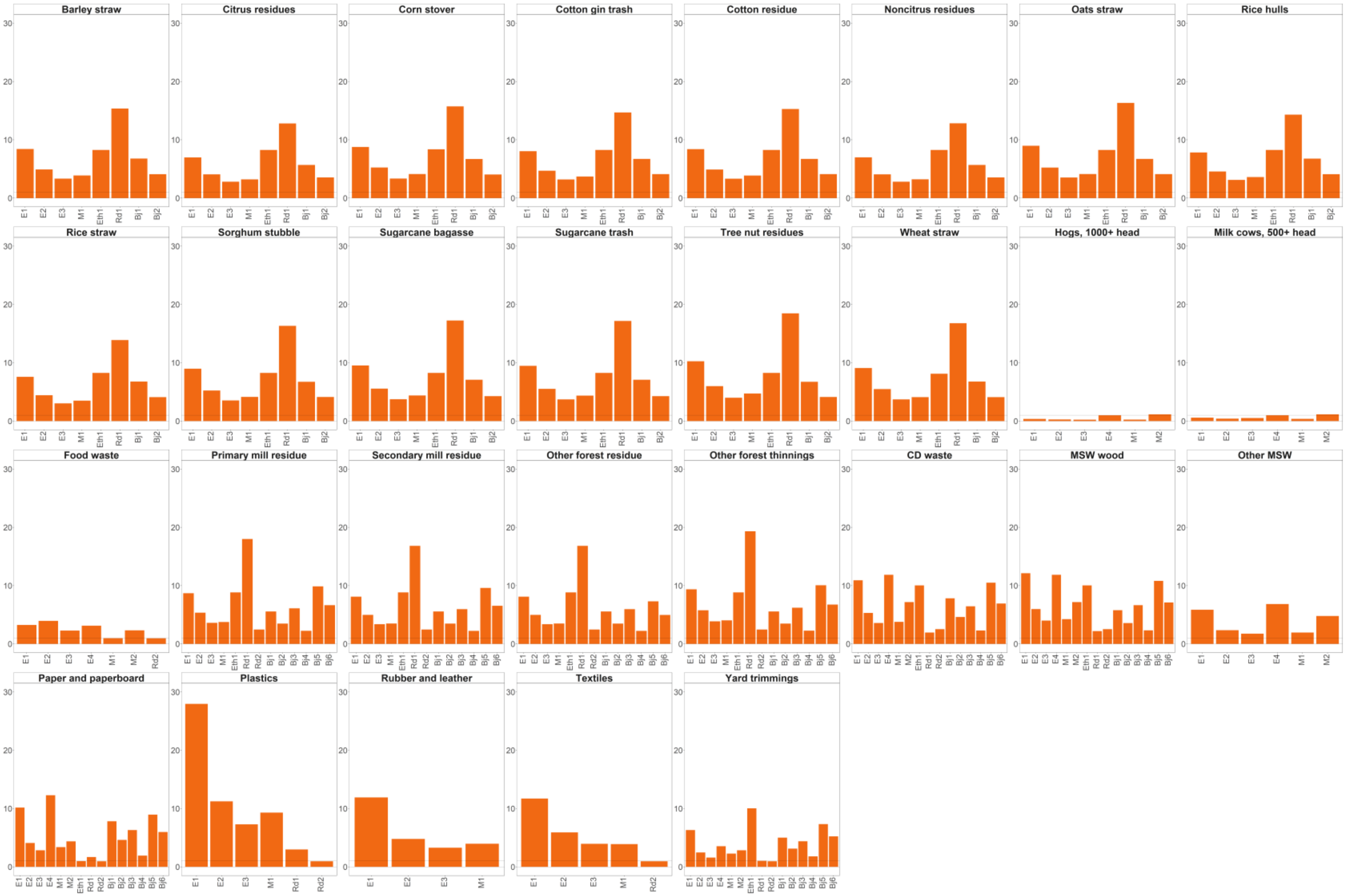
This study is a first step towards using a common system boundary for a consistent comparison of a large variety of waste conversion technologies from the twin perspectives of net energy gain and climate benefits. Incorporating non-GHG environmental considerations including air quality impacts and fresh water use and water quality impacts, as well as an assessment of the levelized life cycle cost of energy for the different pathways are two important directions for future research.

Appendix: Supplementary Information

Supplementary Figures

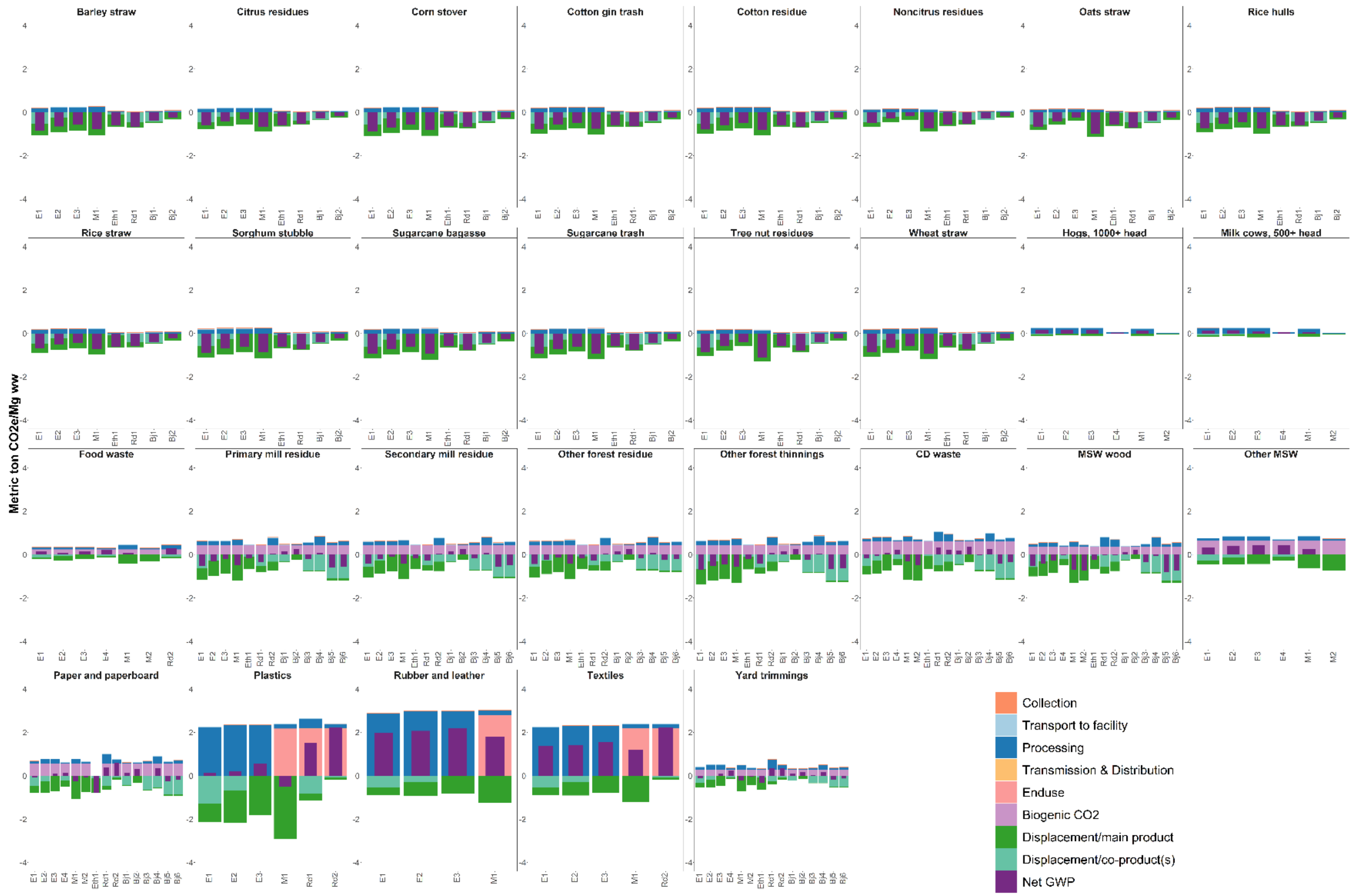


Supplementary Figure 2-1. Renewable energy production and net energy gain by feedstock and conversion pathway
E1 - CHP; E2 - gasification + CHP; E3 - IGCC; E4 - anaerobic digestion + CHP; M1 - gasification; M2 - anaerobic digestion; Eth1 - enzymatic hydrolysis + fermentation; Rd1 - gasification + FT synthesis; Rd2 - pyrolysis + hydroprocessing; Bj1 - ATJ (ethanol); Bj2 - STJ (fermentation); Bj3 - pyrolysis (in situ); Bj4 - pyrolysis (ex situ); Bj5 - HTL (in situ); Bj6 - HTL (ex situ).



Supplementary Figure 2-2. EROI by feedstock and conversion pathway

E1 - CHP; E2 - gasification + CHP; E3 - IGCC; E4 - anaerobic digestion + CHP; M1 - gasification; M2 - anaerobic digestion; Eth1 - enzymatic hydrolysis + fermentation; Rd1 - gasification + FT synthesis; Rd2 - pyrolysis + hydroprocessing; Bj1 - ATJ (ethanol); Bj2 - STJ (fermentation); Bj3 - pyrolysis (in situ); Bj4 - pyrolysis (ex situ); Bj5 - HTL (in situ); Bj6 - HTL (ex situ).



Supplementary Figure 2-3. GWP by feedstock and conversion pathway

E1 - CHP; E2 - gasification + CHP; E3 - IGCC; E4 - anaerobic digestion + CHP; M1 - gasification; M2 - anaerobic digestion; Eth1 - enzymatic hydrolysis + fermentation; Rd1 - gasification + FT synthesis; Rd2 - pyrolysis + hydroprocessing; Bj1 - ATJ (ethanol); Bj2 - STJ (fermentation); Bj3 - pyrolysis (in situ); Bj4 - pyrolysis (ex situ); Bj5 - HTL (in situ); Bj6 - HTL (ex situ).

Supplementary Tables

Supplementary Table 2-1. Life cycle GHG emission intensities (gCO2/MJ) of electricity and fossil-based fuels

State	Electricity mix	Natural gas-based Heat	Hydrogen	Natural gas-based electricity	Gasoline	Jet fuels	Diesel
Alaska	120.4	64.0	119.0	132.4	99.0	89.0	96.2
Alabama	120.6	64.0	119.0	132.4	95.2	87.2	90.8
Arkansas	148.7	64.0	119.0	132.4	95.2	87.2	90.8
Arizona	119.7	64.0	119.0	132.4	99.0	89.0	96.2
California	70.4	64.0	119.0	132.4	99.0	89.0	96.2
Colorado	182.0	64.0	119.0	132.4	96.0	87.9	90.8
Connecticut	69.2	64.0	119.0	132.4	94.9	88.3	90.1
District of Columbia	50.0	64.0	119.0	132.4	94.9	88.3	90.1
Delaware	141.7	64.0	119.0	132.4	94.9	88.3	90.1
Florida	137.5	64.0	119.0	132.4	94.9	88.3	90.1
Georgia	132.5	64.0	119.0	132.4	94.9	88.3	90.1
Hawaii	200.4	64.0	119.0	132.4	99.0	89.0	96.2
Iowa	136.5	64.0	119.0	132.4	97.2	88.9	92.8
Idaho	31.0	64.0	119.0	132.4	96.0	87.9	90.8
Illinois	101.5	64.0	119.0	132.4	97.2	88.9	92.8
Indiana	227.4	64.0	119.0	132.4	97.2	88.9	92.8
Kansas	139.9	64.0	119.0	132.4	97.2	88.9	92.8
Kentucky	244.8	64.0	119.0	132.4	97.2	88.9	92.8
Louisiana	128.8	64.0	119.0	132.4	95.2	87.2	90.8
Massachusetts	108.3	64.0	119.0	132.4	94.9	88.3	90.1
Maryland	123.8	64.0	119.0	132.4	94.9	88.3	90.1
Maine	51.4	64.0	119.0	132.4	94.9	88.3	90.1
Michigan	139.8	64.0	119.0	132.4	97.2	88.9	92.8
Minnesota	127.4	64.0	119.0	132.4	97.2	88.9	92.8
Missouri	220.5	64.0	119.0	132.4	97.2	88.9	92.8
Mississippi	129.4	64.0	119.0	132.4	95.2	87.2	90.8
Montana	148.4	64.0	119.0	132.4	96.0	87.9	90.8
North Carolina	120.9	64.0	119.0	132.4	94.9	88.3	90.1
North Dakota	196.8	64.0	119.0	132.4	97.2	88.9	92.8
Nebraska	164.0	64.0	119.0	132.4	97.2	88.9	92.8
New Hampshire	42.2	64.0	119.0	132.4	94.9	88.3	90.1
New Jersey	82.0	64.0	119.0	132.4	94.9	88.3	90.1
New Mexico	193.4	64.0	119.0	132.4	95.2	87.2	90.8
Nevada	114.6	64.0	119.0	132.4	99.0	89.0	96.2
New York	62.4	64.0	119.0	132.4	94.9	88.3	90.1
Ohio	194.4	64.0	119.0	132.4	97.2	88.9	92.8
Oklahoma	129.1	64.0	119.0	132.4	97.2	88.9	92.8
Oregon	44.0	64.0	119.0	132.4	99.0	89.0	96.2
Pennsylvania	113.9	64.0	119.0	132.4	94.9	88.3	90.1
Rhode Island	128.2	64.0	119.0	132.4	94.9	88.3	90.1
South Carolina	84.3	64.0	119.0	132.4	94.9	88.3	90.1
South Dakota	68.9	64.0	119.0	132.4	97.2	88.9	92.8
Tennessee	128.3	64.0	119.0	132.4	97.2	88.9	92.8
Texas	141.1	64.0	119.0	132.4	95.2	87.2	90.8
Utah	217.5	64.0	119.0	132.4	96.0	87.9	90.8
Virginia	110.3	64.0	119.0	132.4	94.9	88.3	90.1
Vermont	5.2	64.0	119.0	132.4	94.9	88.3	90.1
Washington	26.5	64.0	119.0	132.4	99.0	89.0	96.2
Wisconsin	173.4	64.0	119.0	132.4	97.2	88.9	92.8
West Virginia	259.9	64.0	119.0	132.4	94.9	88.3	90.1
Wyoming	238.9	64.0	119.0	132.4	96.0	87.9	90.8

Supplementary Table 2-2. The method and data sources for estimating GWP of biogenic CO_2 emissions per Mg of wet forest residues and MSW

		A	B	C	D	E	F
	Formula			1*(1-A/100)*B/100*(44/12)			C*D
	References	(US Department of Energy, 2016; Williams et al., 2015)	(Barlaz, 1998; US EPA, 2016; X. Wang et al., 2011)			(Cherubini et al., 2011)	
Waste type	**Feedstock**	**Moisture content (%)**	**Initial organic carbon content in dry weight (%)**[1]	**Biogenic CO_2 emissions** (metric ton CO_2e/Mg)	**Fossil CO_2 emissions** (metric ton CO_2e/Mg)	**GWP_{bio}**	**GWP of biogenic CO_2 emissions** (metric ton CO_2e/Mg)
Forest Residues	Primary mill residues	40	45	0.98	0	0.43	0.42
	Secondary mill residues	40	45	0.98	0	0.43	0.42
	Other forest residues	40	45	0.98	0	0.43	0.42
	Other forest thinnings	40	45	0.98	0	0.43	0.42
MSW	CD waste	15	45	1.39	0	0.43	0.60
	Food waste	70	51	0.56	0	0.43	0.24
	MSW wood	50	45	0.82	0	0.43	0.35
	Paper and paperboard	15	41	1.29	0	0.43	0.56
	Plastics[2]	10	66	0	2.18	0.43	0
	Rubber and leather[2]	10	85	0	2.81	0.43	0
	Textiles[2]	15	70	0	2.18	0.43	0
	Yard trimmings	60	46	0.67	0	0.43	0.29
	Other MSW	4	42	1.48	0	0.43	0.64

Note: [1] median value in a range of estimates from the references

[2] We assumed that the organic carbon is 100% fossil carbon, which corresponds with EPA (2016). The fossil CO_2 emissions of these three feedstocks are included either in the processing phase for electricity-related pathways or in the end use phase for other conversion pathways.

Supplementary Table 2-3. Key assumptions and data sources for estimating GWP of current management practices

Waste category	Current management practice	Phases considered in life cycles	GWP_{bio}	References
Agricultural residues	Left on field	Biogenic CO_2 emissions	0	(Cherubini et al., 2011)
Animal manure	Direct land application	Collection, sand recovery, storage, land application, biogenic CO_2 emissions	0	(Aguirre-Villegas et al., 2014; Aguirre-Villegas & Larson, 2017; Cherubini et al., 2011)
Forest residues	Burning on-site	Biogenic CO_2 emissions	0.43	(Cherubini et al., 2011; Miner et al., 2014)
MSW	landfilling without methane capture	Collection, methane leakage, biogenic CO_2 emissions	0.43	(Cherubini et al., 2011; US EPA, 2016)
	landfilling with 75% of methane captured and subsequently used for on-site CHP	Collection, methane leakage, biogenic CO_2 emissions, processing (i.e., electricity and heat generation), displacement benefits	0.43	(Cherubini et al., 2011; Morris, 2017; Tonini et al., 2016; US EPA, 2016)

Supplementary Table 2-4. Optimal conversion pathways for each type of feedstock under each scenario

Type of waste resources	Feedstock	Technically feasible conversion pathways	MEP Scenario		MNE Scenario		MER Scenario	
			Technology choice	Energy production (PJ)	Technology choice	Net energy (PJ)	Technology choice	Net GWP (MMT CO_2e)
Agricultural residues	Barley straw	E1-E3, M1, Eth1, Rd1, Bj1-Bj2	E1	5.9	E1	5.2	M1	-0.5
	Citrus residues	E1-E3, M1, Eth1, Rd1, Bj1-Bj2	E1	20.7	E1	17.7	M1	-1.4
	Corn stover	E1-E3, M1, Eth1, Rd1, Bj1-Bj2	E1	1214.3	E1	1075.8	M1	-88.0
	Cotton gin trash	E1-E3, M1, Eth1, Rd1, Bj1-Bj2	E1	20.7	E1	18.2	M1	-1.4
	Cotton residues	E1-E3, M1, Eth1, Rd1, Bj1-Bj2	E1	45.9	E1	40.4	M1	-3.2
	Noncitrus residues	E1-E3, M1, Eth1, Rd1, Bj1-Bj2	E1	34.8	E1	29.8	M1	-2.6
	Oats straw	E1-E3, M1, Eth1, Rd1, Bj1-Bj2	E1	0.09	E1	0.08	E1	-0.007
	Rice hulls	E1-E3, M1, Eth1, Rd1, Bj1-Bj2	E1	15.8	E1	13.8	E1	-1.1
	Rice straw	E1-E3, M1, Eth1, Rd1, Bj1-Bj2	E1	54.8	E1	47.6	E1	-3.8
	Sorghum stubble	E1-E3, M1, Eth1, Rd1, Bj1-Bj2	E1	11.6	E1	10.3	E1	-0.8
	Sugarcane bagasse	E1-E3, M1, Eth1, Rd1, Bj1-Bj2	E1	51.6	E1	46.2	E1	-3.6
	Sugarcane trash	E1-E3, M1, Eth1, Rd1, Bj1-Bj2	E1	13.7	E1	12.3	E1	-1.0
	Tree nut residues	E1-E3, M1, Eth1, Rd1, Bj1-Bj2	E1	23.1	E1	20.8	M1	-1.8
	Wheat straw	E1-E3, M1, Eth1, Rd1, Bj1-Bj2	E1	173.4	E1	154.3	E1	-13.5
Animal manure	Hogs, 1000+ head	E1-E4, M1-M2	E1	129.9	M2	6.3	M2	-2.8
	Milk cows, 500+ head	E1-E4, M1-M2	E1	99.1	M2	3.1	M2	-1.7
Forest residues	Primary mill residues	E1-E3, M1, Eth1, Rd1-Rd2, Bj1-Bj6	E1	10.0	E1	8.8	Bj5	-0.5
	Secondary mill residues	E1-E3, M1, Eth1, Rd1-Rd2, Bj1-Bj6	E1	79.1	E1	69.4	Bj5	-3.6
	Other forest residues	E1-E3, M1, Eth1, Rd1-Rd2, Bj1-Bj6	E1	234.1	E1	205.3	M1	-8.9
	Other forest thinnings	E1-E3, M1, Eth1, Rd1-Rd2, Bj1-Bj6	E1	116.1	E1	103.7	Bj5	-6.2
MSW	CD waste	All	Bj5	298.1	Bj5	269.8	M2	-12.2
	Food waste	E1-E4, M1-M2, Rd2	M1	70.3	E2	47.5	M2	0.2
	MSW wood	All	Bj5	163.2	Bj5	148.1	Bj5	-9.7
	Paper and paperboard	All	E1	167.8	E1	151.3	Eth1	-13.3
	Plastics	E1-E4, M1-M2, Rd1-Rd2	E1	540.6	E1	521.2	M1	-11.4
	Rubber and leather	E1-E4, M1-M2	E1	50.8	E1	46.5	M1	7.8
	Textiles	E1-E4, M1-M2, Rd2	E1	98.6	E1	90.2	M1	10.1
	Yard trimmings	All	E1	61.3	Eth1	54.7	Eth1	-2.9
	Other MSW	E1-E4, M1-M2	E1	14.0	E1	11.6	M2	0.01
			Total:	3819.7		3230.2		-177.8

Note: E1 - CHP; E2 - gasification + CHP; E3 - IGCC; E4 - anaerobic digestion + CHP; M1 - gasification; M2 - anaerobic digestion; Eth1 - enzymatic hydrolysis + fermentation; Rd1 - gasification + FT synthesis; Rd2 - pyrolysis + hydroprocessing; Bj1 - ATJ (ethanol); Bj2 - STJ (fermentation); Bj3 - pyrolysis (in situ); Bj4 - pyrolysis (ex situ); Bj5 - HTL (in situ); Bj6 - HTL (ex situ).

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Chapter 3: What neighborhood-level characteristics predict plug-in electric vehicle adoption in California? Insights from lasso regression with Monte Carlo sampling

Abstract

Given California's relatively clean power grid and high population density, the adoption of plug-in electric vehicles (PEVs) yields positive net environmental benefits and contributes to a number of environmental and political goals. With the increasing availability of market data, a better understanding of PEV adoption behaviors at the neighborhood level will benefit research, planning, and policy making in the area of transportation electrification. This study aims at quantifying the PEV market growth across California, identifying the most important factors for the prediction of neighborhood-level PEV adoption, and estimating the effects of away-from-home charging infrastructure and high-occupancy vehicle (HOV) lane access. Using a PEV market dataset for 2010 to 2018, I find that cumulative new PEV sales in California reached over 507,000 vehicles by the end of 2018. Although PEV adoption has taken place in 98% of census tracts, the growth has been uneven across the California market. Using regularization along with Monte Carlo sampling, I am able to select the most powerful predictors and estimate their associations with the adoption of PEVs by technology type and price range. I find that homeownership and the number of households are strong predictors of PEV adoption, while higher-density housing and population density are negatively associated with PEV adoption. Other important factors include pro-environment intention and behaviors, education, age, income, wealth, employment, and commute patterns. In addition, motivations for adoption and preferences for specific PEV technologies vary by neighborhood. I also find that the deployment of workplace charging is more effective than the deployment of direct current (DC) fast chargers,

and the positive effect of away-from-home charging infrastructure is likely to be stronger as the PEV market continues to mature.

Introduction

Compared to internal combustion engine vehicles (ICEVs), plug-in electric vehicles (PEVs) are superior from many public policy and public health perspectives, including locally or regionally produced electricity as fuel supply that enhances energy security, higher energy efficiency that reduces energy consumption, no tailpipe emissions, and less noise pollution. However, from a life cycle perspective, both vehicle manufacturing and electricity generation produce substantial emissions (Hawkins et al., 2013; Holland et al., 2016, 2019; IEA, 2019; Michalek et al., 2011). Although PEVs have the potential to mitigate climate change, the net environmental benefits of PEVs displacing ICEVs vary by location (Holland et al., 2016, 2019). Holland et al. (2016) attribute this high geographic variation to the discrepancy in regional electricity mix and population density, which affect the environmental impacts of PEVs and ICEVs, respectively. For regions with a relatively clean power grid and high population density, which describes much of the State of California, promoting PEV adoption contributes to a number of environmental and political goals.

Previous studies have indicated that PEV adoption can be affected by a number of factors, including consumer characteristics, regulatory and financial incentives, and the availability of charging infrastructure. Using the stated preference approach, researchers found that socioeconomic background (for example, education and income levels), attitudes towards PEVs, particularly perceived functional barriers (for example, electric range and charging time), environmental awareness, and technology-oriented lifestyles are likely to influence the intention to purchase or use PEVs (Hidrue et al., 2011; Egbue & Long, 2012; Carley et al., 2013; Hackbarth & Madlener, 2013; Jensen et al., 2013; Plötz et al., 2014; Jansson, Nordlund, et al., 2017; White & Sintov, 2017; Haustein & Jensen, 2018; Westin et al., 2018; Axsen et al., 2018; Carley et al., 2019). However, these studies sometimes yield contradictory results given that stated preferences and actual actions do not always align (Coffman et al., 2017) and that perceptions and preferences may change over time (Carley et al., 2019). There is a growing body of literature exploring the impacts of various policy incentives, including financial incentives such as tax credits and rebates (Tal & Nicholas, 2016; DeShazo et al., 2017; Hardman et al., 2017), non-financial incentives such as charging infrastructure deployment and high-occupancy vehicle (HOV) lane access (Hardman, 2019; Mersky et al., 2016; Sheldon & DeShazo, 2017), or both types (Bjerkan et al., 2016; Jenn et al., 2018; Münzel et al., 2019; Narassimhan & Johnson, 2018; Wee et al., 2018). Although the magnitude of estimated effects of policy incentives varies, there is a general consensus that financial incentives increase PEV uptake and the effects of non-financial incentives would depend on local conditions. The varying results are mainly due to the differences in analytical techniques, geographic areas, and time spans of data. A third body of literature has focused on the assessment of charging infrastructure deployment. Using market data, a number of studies have found significant contribution of public charging infrastructure to PEV adoption in the US (Narassimhan & Johnson, 2018; Li et al., 2017; Vergis & Chen, 2015), Europe (Mersky et al., 2016), China (Ou et al., 2020), and across the globe (Sierzchula et al., 2014). The majority of these studies did not distinguish among various power levels of chargers, although consumers may well respond differently to various power levels (Greene et al., 2020).

Across the three bodies of literature, there are two major limitations - the availability of market data and the choice of geographical scale. Studies focusing on the individual customer level have not captured the neighborhood effects where social learning takes place (Westin et al., 2018; Carley et al., 2019; Jansson, Pettersson, et al., 2017), whereas focusing on a large geographical scale (for example, the country level) risks losing power in predicting sales by certain critical factors at the local and regional levels, especially when the market penetration of PEVs is low (Sierzchula et al., 2014). Recent studies have also indicated the need for differentiating between the two types of PEVs (Carley et al., 2019; DeShazo et al., 2017; Narassimhan & Johnson, 2018; Vergis & Chen, 2015; Westin et al., 2018) - battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). These two vehicle technologies have intrinsic differences in design. PHEVs are equipped with both an internal combustion engine (ICE) and an electric motor, which enable operations in an ICE mode, a full electric mode, or a combination of the two. In contrast, BEVs solely rely on an electric powertrain that is supported by on-board battery storage and an external electricity supply via battery charging. These differences result in varying emissions reduction potentials and charging needs. Consumers may also respond differently to the two technologies in terms of motivation to purchase and usage patterns. To maximize the environmental and public health benefits of transportation electrification and the cost-effectiveness of charging infrastructure deployment, future efforts on promoting PEVs would require respective attention to each of these.

Given the increasing availability of market data in California, a better understanding of PEV adoption at the neighborhood level will benefit research, planning, and policy making in a number of ways. First, since the net benefits of PEV adoption depend on local conditions (Holland et al., 2016, 2019), assessing neighborhood-level PEV adoption behaviors is fundamental to strategizing and prioritizing California's efforts on GHG emissions reduction especially in the light-duty transportation sector. Such analyses can also provide more realistic and spatially explicit representations of the zero-emission vehicle transition for air quality modeling and health impact assessments, such as those by Wang et al. (2020) and Zhao et al. (2019). Second, understanding the PEV market growth across communities and the gaps in PEV adoption can help to advance environmental justice because disadvantaged and low-income communities are disproportionately affected by the negative externalities of transportation. Evaluating the effectiveness and distributional effects of existing PEV policies can inform the design and targeting of future policy incentives and investment decisions. Third, understanding the geographic concentrations of PEVs will benefit charging infrastructure planning, as it prepares electric utilities for potential load increases and grid upgrades in certain areas. It also serves as a starting point for travel demand modeling of PEV associated trips or activities, which can inform investment decisions on charging infrastructure deployment, especially workplace charging and direct current (DC) fast charging. In addition, smaller and more homogeneous geographic units, such as census tracts, are often regarded as less biased proxies for individual characteristics, such as socioeconomics and living conditions. Given the availability of census tract level information from existing surveys, for example, the American Community Survey, it is possible to analyze aggregate PEV adoption behaviors in a more cost-effective way.

The main goals of this study are to quantify the PEV market growth in California, to identify the most important factors that are associated with the neighborhood-level PEV adoption, and to estimate the effects of away-from-home charging infrastructure and HOV lane access. In this study, I define neighborhoods as census tracts within California. I first compile a large set of candidate predictor variables that have been reported in the literature, and then use regularization along with Monte Carlo sampling to select the most powerful predictors and estimate their effects. This approach is used to evaluate the adoption of PEVs by technology type and price range. Results and policy implications are discussed for each vehicle type and across vehicle types. This study also explores PEV adoption through the lens of social and environmental equity by quantifying growth across various types of communities (by the designation of disadvantaged communities and household income quartile). Here, I show that homeownership and housing occupancies are strong predictors of PEV adoption, and higher-density housing and population density negatively associate with PEV adoption. Other important factors for predicting PEV adoption include pro-environment intention and behaviors, education, age, income, wealth, employment, and commute patterns. In addition, motivations for adoption and preferences for specific PEV technology vary by neighborhood. I also find that the deployment of workplace charging is more effective than the deployment of DC fast chargers, and the positive effects of HOV lane access and the availability of away-from-home charging infrastructure are likely to grow substantially as the PEV market continues to mature.

Methods

Monthly new electric vehicle registrations between January 2010 and December 2018 in California were obtained from IHS Markit. Their vehicle registration dataset includes vehicle make, model, type, the manufacturer's suggested retail price (MSRP), and the census tract where each vehicle was registered. Cumulative new PEV, BEV, and PHEV registrations between 2010 and 2018 were estimated. I used a MSRP of $40,000 to distinguish between a luxury vehicle and an economy vehicle. In this analysis, I hypothesize that income and wealth drive the adoption of luxury vehicles, while fuel cost savings and the opportunity to reduce commute time via free access to high-occupancy vehicle (HOV) lanes motivate the adoption of economy vehicles. Vehicle quantity and share of the fleet were treated as response variables that describe the absolute and relative adoption levels, respectively. In this study, I define vehicle share as the ratio of cumulative new PEV/BEV/PHEV registrations as of December 2018 to total light-duty vehicle registrations in 2018. This ratio, to a large extent, represents the relative adoption that takes into account the overall vehicle ownership within a neighborhood. Modeling vehicle quantity simulates the addition of PEVs in neighborhoods or the addition of people whose PEV ownership may be higher or lower, whereas modeling vehicle share simulates the overall new vehicle purchase rate and the substitution between an ICEV and a PEV. Total light-duty vehicle registrations by the end of 2018 at the ZIP code level were obtained from the California Department of Motor Vehicles. I used the US Department of Housing and Urban Development's ZIP code-to-tract crosswalk file (the 4th Quarter 2018 version) to estimate total light-duty vehicles at the census tract level. To address the positive skewness, I applied a fourth root transformation to all response variables. Given the use of the fourth-root transformation on the response variables, the estimated effects of the predictor variables should be interpreted as $4\beta_i *$

$\hat{Y}^3$, which means that the effects of predictor variables would vary depending on current PEV adoption.

In addition, I compiled a large dataset with 338 potential predictor variables representing demographic and socioeconomic characteristics, regional road and charging infrastructure, and neighborhood "greenness" at the California census tract level (Table 3-1). Census tract level demographic and socioeconomic information was extracted from the 2018 American Community Survey 5-year Estimates (2013-2018). The ACS estimates describe residential and household-level characteristics. Besides households, companies, government agencies, or any organizations that own vehicle fleets also contribute to PEV adoption. To account for these non-household adopters within a neighborhood, the workplace area characteristics from the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES, Version 7) were used to estimate densities of various job types. The average job densities between 2010 and 2017 are included as potential drivers for adoption decisions at companies, government agencies, and other organizations with vehicle fleets. I estimated population densities, household densities, and job densities using the total unprotected land area at the census tract level, which was obtained from the US EPA's Smart Location Database (Ramsey & Bell, 2014). Access to HOV lanes and the availability of charging infrastructure are also considered as drivers of PEV adoption. I obtained the spatial distribution of HOV lanes from the California Department of Transportation (Caltrans). I estimated the aggregate length of HOV lanes within 10-km, 25-km, and 50-km radii of the population weighted centroids of each census tract. The availability of charging infrastructure was obtained from the US Department of Energy's Alternative Fuels Data Center (AFDC). For each census tract, I estimated the amounts of electric vehicle supply equipment (EVSE) by both charger power level (Level 1, Level 2, and DC fast) and access type (public and private) within 10 km, 25 km, and 50 km radiuses of the population weighted centroids. California's Proposition 23 was an unsuccessful 2010 ballot measure to suspend the Global Warming Solutions Act of 2006 (also known as the Assembly Bill 32). Sheldon & DeShazo (2017) used the vote on Proposition 23 to represent the "greenness" or "brownness" of voter attitudes by neighborhood, where a higher share of "no" votes was assumed to represent higher level of pro-environment intention.

Table 3-1. Variable description and data sources

Variable group	Description		Data source
PEV adoption	• Cumulative PEV, BEV, PHEV registrations by price range • The shares of cumulative PEV, BEV, PHEV registrations in total light-duty vehicle registrations		• IHS Markit • California DMV
Demographic & socioeconomic characteristics	• Age • Sex • Race • Place of birth • Education	• Household • Housing • Occupation, industry, & worker class • Commute • House heating fuel	• ACS 5-year Estimates (2013-2018)
	• Average job density by type, 2012-2017		• LODES (Version 7)
Infrastructure	• HOV lane length (10 km, 25 km, 50 km radiuses)		• Caltrans
	• Number of EVSE by power level and access type (10-km, 25-km, and 50-km radii)		• AFDC
Neighborhood "greenness"	• The proportion of "no" votes on Proposition 23		• Office of the California Secretary of State

The least absolute shrinkage and selection operator (lasso) is a popular technique for simultaneous model selection and parameter estimation in linear regression (Homrighausen & McDonald, 2013; Severson et al., 2015; Tibshirani, 1996). The lasso assigns weights to variables for the best possible prediction and imposes a penalty for adding additional variables. When a variable does not add enough predictive power, the lasso will set its weight to be 0. Thus, the lasso procedure returns models with smaller dimensions and high predictive power. The tuning parameter λ is critical to controlling the strength of the penalty. As λ increases, more coefficients are shrunk to zero. The selection of the optimal λ is commonly performed via K-fold cross validation (Friedman et al., 2010; Homrighausen & McDonald, 2013; Roberts & Nowak, 2014; Tibshirani, 1996), in which the dataset is randomly partitioned into K groups. For each iteration in a loop, one group of the dataset is treated as the validation set and the rest as the calibration set. Mean cross-validated error is then estimated and used as the criterion for the selection of optimal λ. However, due to the randomness in the dataset partitioning, cross validation may result in algorithmic instability (Roberts & Nowak, 2014; Xu et al., 2011). Thus, I integrated cross validation with Monte Carlo sampling (Severson et al., 2015) for the partitioning to enhance stability in both model selection and parameter estimation. The lasso regression was performed using the glmnet package (Version 3.0-2) in R (Version 3.6.2). I first randomly split the whole dataset into a training dataset (80% of all observations) and a testing dataset (20% of all observations). I ran a 10-fold cross validation for 1000 iterations. For each iteration, two λ values were retrieved: lambda.min, which gives the minimum mean cross-validated error; and lambda.1se, the largest λ that gives the error that is within one standard error of the minimum cross-validated error. I then trained the lasso models using the two λ values and the whole training dataset, which returns two candidate models for each iteration. I estimated root mean squared errors of predictions, R^2, and adjusted R^2 as evaluation criteria for both the training and testing datasets. I estimated model selection frequencies for both λ types. For each of the two groups (lambda.min and lambda.1se), selection criteria include a model dimension of no greater than 50 and the highest selection frequency. Between the two candidate models, I considered the model with the higher out-of-sample adjusted R^2 to be the final model. Variables selected by the final model were further examined using all 1000 candidate models selected by the specific λ type. I analyzed the distributions and variability of coefficient estimates for these variables to enhance confidence in interpreting the effects of these variables.

To better understand the varying effects of the most important variables across vehicle categories, I extracted a subset of variables for cross-model comparison. This subset of variables includes the ones that were consistently selected by all final models, the more powerful predictors (with median coefficient estimates greater than 0.0005) selected by any of the final models, and all infrastructure-related variables (such as the quantity of various types of chargers and the length of HOV lanes) selected by the final models. I also used this subset of variables to draw implications for accelerating PEV adoption especially in disadvantaged and low-income communities.

Results and Discussion

Electric vehicle market growth in California: 2010-2018

Since 2010, the California electric vehicle market has been growing rapidly (Figure 3-1). Although hybrid electric vehicles (HEVs) have dominated overall electric vehicle sales, their market share of new electric vehicle sales has been decreasing since 2015. In contrast, PEVs have gained more popularity and their monthly sales have surpassed HEV sales since 2017. Starting in mid-2018, the sales of BEVs alone has exceeded HEV sales and the PHEV sales has also begun a toe-to-toe competition with HEV sales. As of December 2018, cumulative new PEV sales in California reached over 507,000 vehicles, which accounts for approximately 40.2% of all new light-duty electric vehicles sold in the California market. The average annual growth rate of PEVs between 2015 and 2018 was 40%, which is 2.7 times as that of HEVs (15%). During the same time period, BEVs grew 44% every year on average and PHEVs grew 36% annually.

Between 2010 and 2018, at least one PEV was sold in 98% of the census tracts in California. The highest cumulative PEV sales at the neighborhood level reached 1,538 vehicles by the end of 2018, while the same cumulative figure for BEVs was 1,497 and PHEVs was 524 (Figure 3-2). The California PEV market has been growing unevenly across neighborhoods. Although two census tracts consistently have higher sales across all three vehicle categories, the majority of the ten census tracts with the highest BEV sales are not aligned with the ones in PHEV sales. This suggests consumers respond differently across neighborhoods with respect to the two types of PEV technologies. For instance, Santa Clara County Tract 5117.05 in "Silicon Valley" is where the Tesla is headquartered, which may explain the vigorously growing BEV sales and the stagnant PHEV sales within the neighborhood.

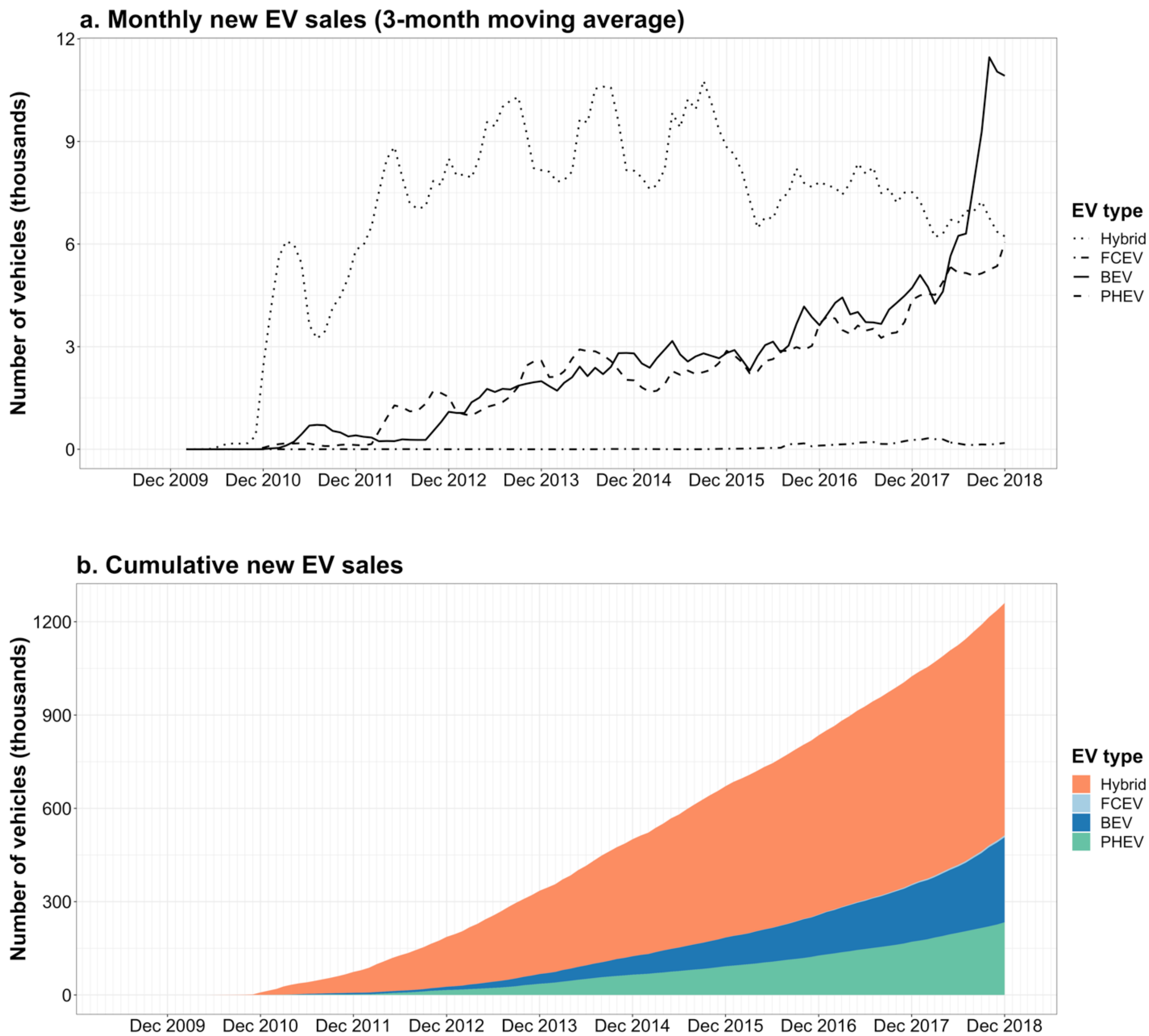


Figure 3-1. New EV sales by vehicle type in California, 2010-2018

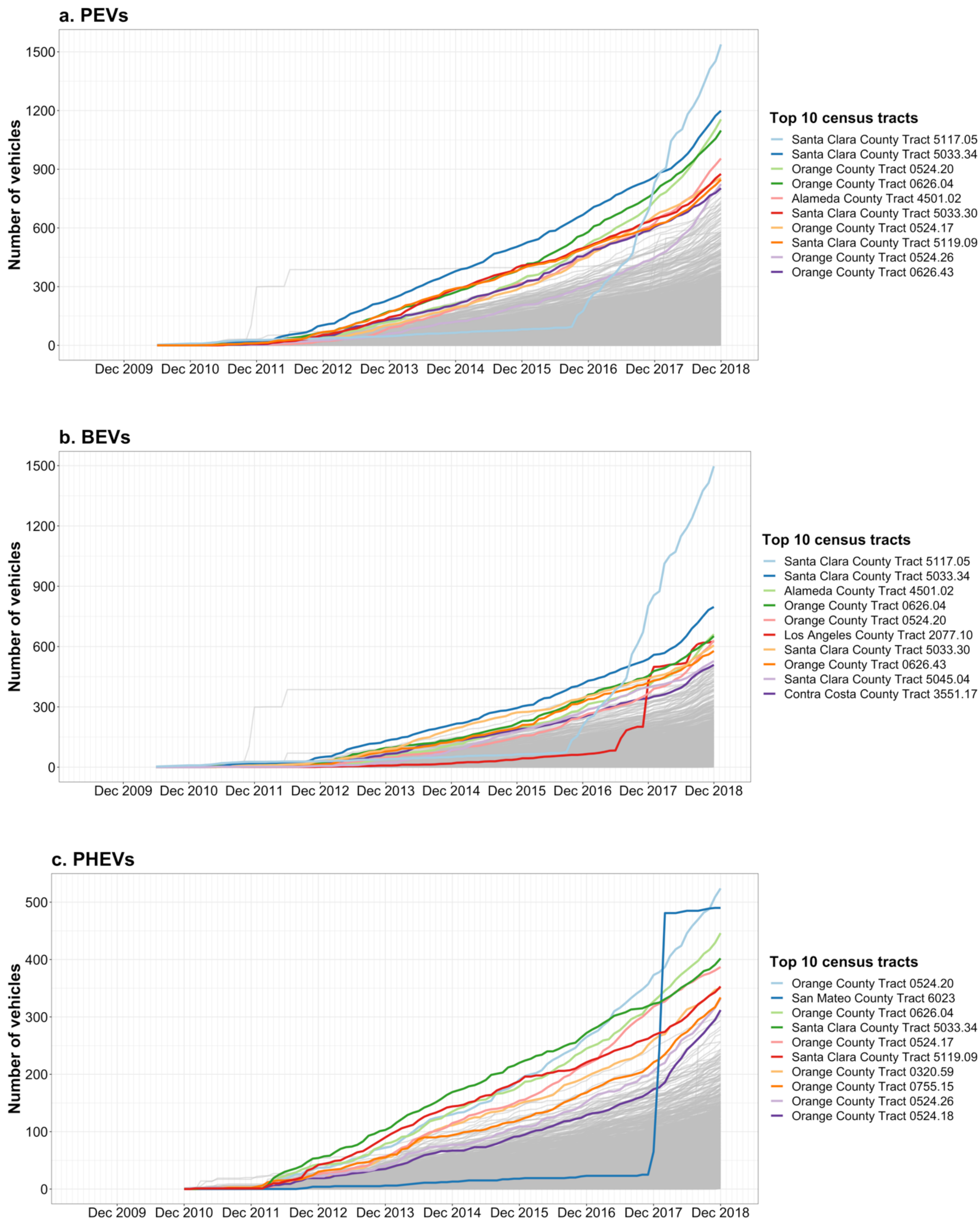


Figure 3-2. Cumulative new PEV sales across California census tracts, 2010-2018

Predictive models for PEV adoption

To understand the variation in neighborhood-level PEV adoption, 18 response variables were used to represent all three vehicle categories - PEVs, BEVs, and PHEVs. These response variables include the quantity of cumulative sales, its share in total light duty vehicles, and the breakdown of the two PEV technologies by price range - luxury vehicles and economy vehicles. After the fourth-root transformation, the majority of response variables follow an approximately symmetric and normal distribution (Figure 3-3).

With Monte Carlo sampling and cross validation, the frequency of each unique model selected by each specific lambda type was estimated. For example, among PEV models with $\sqrt[4]{Y1}$ as the response variable, the selected model using lambda.1se has a dimension of 19 and an out-of-sample adjusted R^2 of 0.79, while the selected model by lambda.min has a dimension of 19 and an out-of-sample adjusted R^2 of 0.80 (Figure 4). Thus, I considered the latter to be the final model given its slightly improved prediction performance. All the 18 final predictive models have low out-of-sample RMSE and the out-of-sample adjusted R^2 ranges from 0.62 to 0.82 (Table 2). Using lasso, the model dimensions were greatly reduced from 338 potential predictor variables to as low as 18 predictor variables. Models for vehicle quantity have consistently smaller dimensions than respective models for vehicle share, as the total variation in vehicle share is smaller than in vehicle quantity. Coefficient estimates from the final models and their estimated ranges as indicated by all 1000 candidate models are discussed in the following sections.

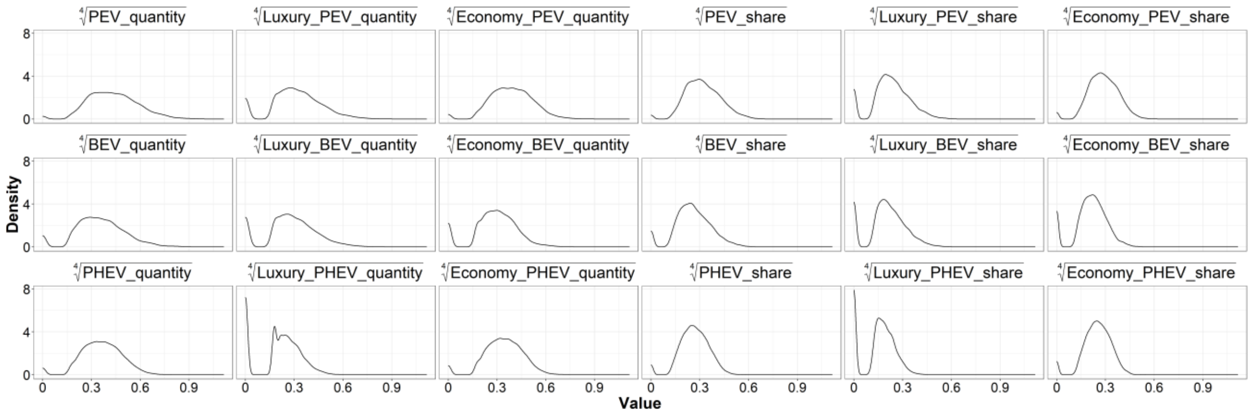
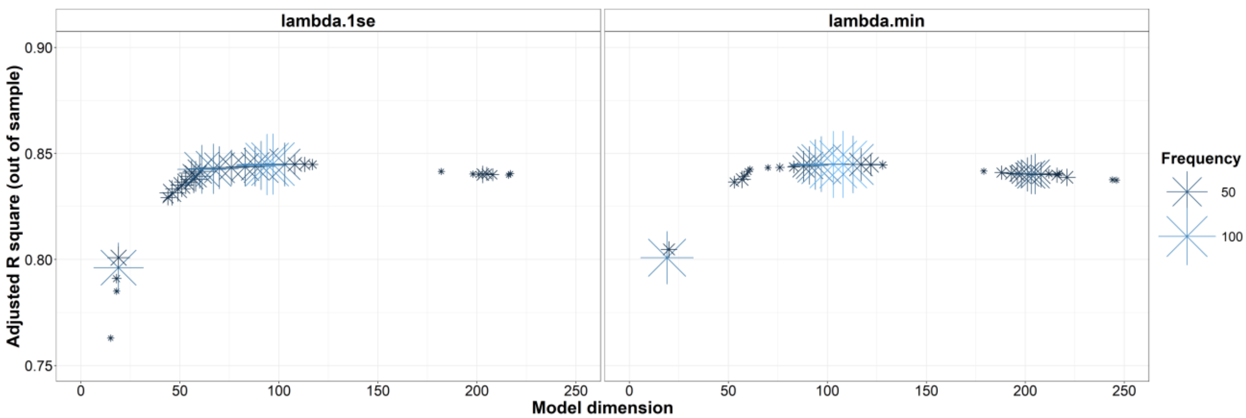


Figure 3-3. Distributions of response variables



Note: Y1 is the number of cumulative new luxury and economy vehicles in thousands.

Figure 3-4. Model selection for predicting the number of cumulative new PEV luxury and economy vehicles in a tract (000s)

Table 3-2. Performance of selected predictive models

Vehicle type	Response variable[a]	Obs.	Model dimension	RMSE (training)	R^2 (training)	Adjusted R^2 (training)	RMSE (testing)	R^2 (testing)	Adjusted R^2 (testing)
PEV	$\sqrt[4]{Y1}$	7826	19	0.07	0.80	0.80	0.07	0.80	0.80
	$\sqrt[4]{Y2}$	7826	19	0.08	0.76	0.76	0.08	0.74	0.74
	$\sqrt[4]{Y3}$	7826	25	0.07	0.76	0.76	0.06	0.76	0.76
	$\sqrt[4]{Y4}$	7825[b]	48	0.05	0.82	0.82	0.04	0.83	0.82
	$\sqrt[4]{Y5}$	7825[b]	49	0.05	0.78	0.77	0.05	0.76	0.76
	$\sqrt[4]{Y6}$	7826	49	0.05	0.76	0.75	0.04	0.78	0.77
BEV	$\sqrt[4]{Y1}$	7826	20	0.07	0.77	0.76	0.07	0.75	0.75
	$\sqrt[4]{Y2}$	7826	18	0.08	0.74	0.74	0.08	0.72	0.72
	$\sqrt[4]{Y3}$	7826	29	0.08	0.68	0.67	0.08	0.67	0.66
	$\sqrt[4]{Y4}$	7825[b]	36	0.05	0.77	0.77	0.05	0.76	0.76
	$\sqrt[4]{Y5}$	7825[b]	49	0.06	0.76	0.76	0.06	0.75	0.74
	$\sqrt[4]{Y6}$	7826	47	0.06	0.66	0.66	0.06	0.66	0.65
PHEV	$\sqrt[4]{Y1}$	7826	33	0.06	0.74	0.74	0.06	0.74	0.73
	$\sqrt[4]{Y2}$	7826	27	0.08	0.65	0.64	0.08	0.63	0.62
	$\sqrt[4]{Y3}$	7826	34	0.06	0.71	0.70	0.06	0.71	0.70
	$\sqrt[4]{Y4}$	7826	46	0.05	0.73	0.73	0.04	0.74	0.74
	$\sqrt[4]{Y5}$	7826	48	0.06	0.64	0.64	0.06	0.63	0.62
	$\sqrt[4]{Y6}$	7826	50	0.05	0.69	0.69	0.04	0.71	0.70

Note: [a] Y1 – the number of cumulative new luxury and economy vehicles in thousands;
Y2 – the number of cumulative new luxury vehicles in thousands;
Y3 – the number of cumulative new economy vehicles in thousands;
Y4 – the share of cumulative new luxury and economy vehicles in total light-duty vehicles (%);
Y5 – the share of cumulative new luxury vehicles in total light-duty vehicles (%);
Y6 – the share of cumulative new economy vehicles in total light-duty vehicles (%);
[b] After using the ZIP code-to-tract crosswalk for the estimation of total light-duty vehicle count at the census tract level I removed Santa Clara County Tract 5117.05 due to its unrealistically high vehicle share using the estimated total light-duty vehicle count.

PEV adoption

When predicting neighborhood-level PEV quantity, the final model indicates that housing characteristics, employment, income and wealth, education, race, and infrastructure have the largest effects (Figure 3-5). The number of households and the number of homeowners within a neighborhood have the strongest positive associations with cumulative PEV sales, which indicates that the growth of the California PEV market mainly takes place in neighborhoods with fewer housing vacancies. The non-existence of variables describing employer characteristics shows that employers have not played a role that is as important as households in driving neighborhood-level PEV quantity. Civilian workforce size of a neighborhood is also positively associated with the PEV quantity.

Income and wealth have consistently important roles in predicting the overall PEV quantity. Neighborhoods with higher shares of households earning more than $200k annually and two vehicles available, those with higher shares of housing units valued between $500k and $1 million, those with higher shares of residents occupied in management, business, science and arts, and those with greater median housing values would generally see a great number of PEVs. For neighborhoods with higher shares of low-value owner-occupied housing units ($150k-$300k) and greater proportions of residents occupied in natural resources, construction, and maintenance, the total number of PEVs is generally smaller. The final model also suggests a positive association between median household income and the PEV quantity. However, this may not always hold true when compared to the coefficient estimates across all 1000 candidate models. The uncertain effect of median household income and the consistent effects of the relative numbers of highest-income and wealthy residents indicate that the PEV growth has been mainly driven by the most affluent households within a neighborhood.

In addition, the number of residents who are at least 25 years old the share of well-educated residents (especially those with bachelor's or higher degrees) and the relative size of foreign-born Asian populations are positively associated with PEV quantity. The PEV models also suggest a joint effect from education and gender. The shares of well-educated male residents with high-school and above education or college and above education are positively associated with the PEV quantity.

Although there are a greater number of selected predictor variables that represent demographic and socioeconomic characteristics, the PEV models also suggest positive effects from both the length of HOV lanes within a 10 km radius ($\beta \in [0.00004, 0.0001]$) and the number of public DC fast chargers within a 50 km radius ($\beta \in [0.00002, 0.00006]$). Thus, an increase of 10 km in HOV lane length is positively associated with an increase of 0.2-0.5 PEVs for a neighborhood with cumulative PEV sales of 500 vehicles and an increase of 1.6-4 PEVs for a neighborhood with 1000 vehicles. Similarly, an increase of 100 DC fast chargers is positively associated with 1-3 more PEVs for a neighborhood with cumulative PEV sales of 500 vehicles and 8-24 more PEVs for a neighborhood with cumulative PEV sales of 1000 vehicles. Our results show that these associations are likely to be stronger when the PEV market continues to mature.

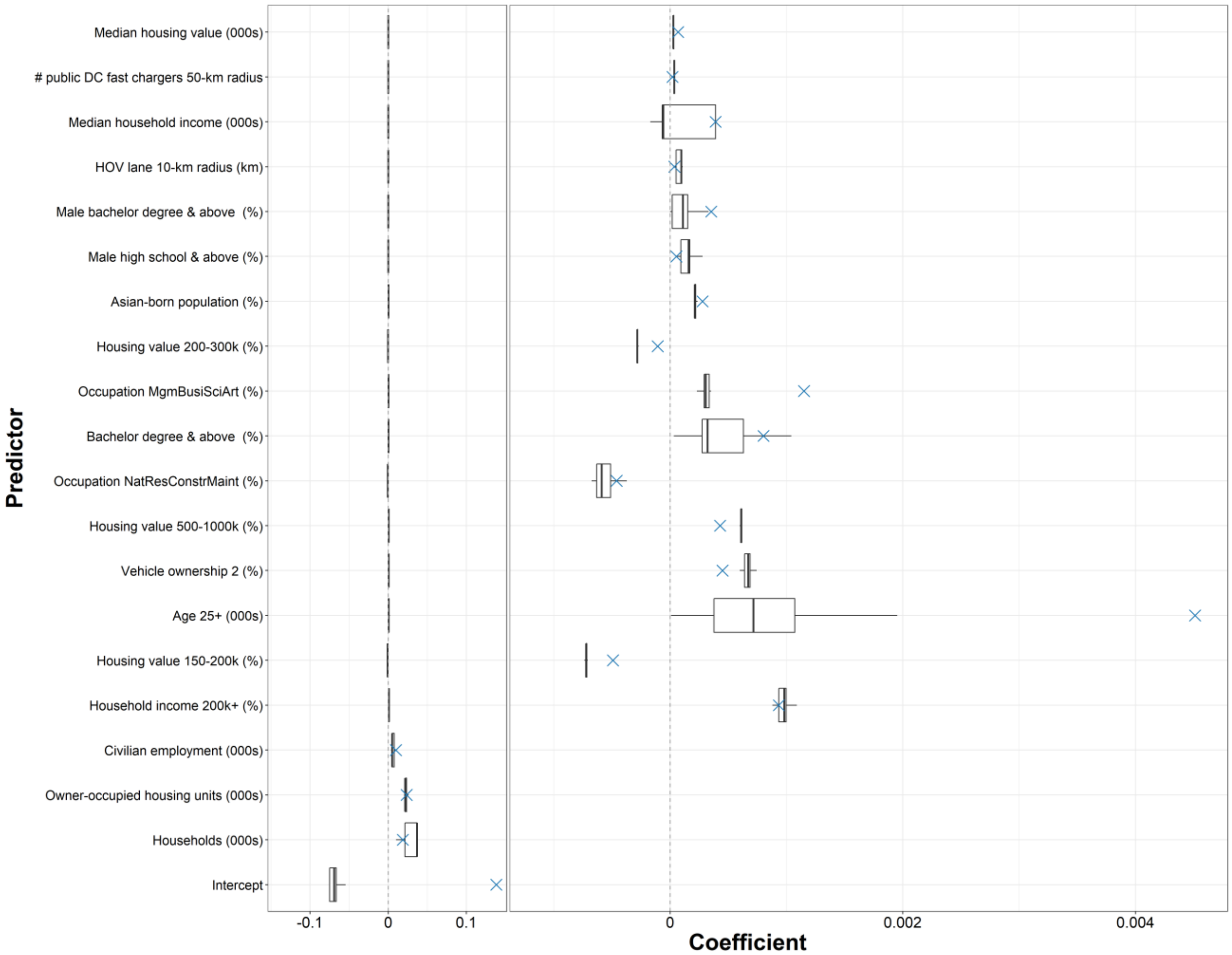


Figure 3-5. Results of models predicting the number of cumulative new luxury and economy PEVs (000s) in a tract

“X” represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.

By modeling luxury and economy vehicles separately, I find that different predictor variables tend to predict luxury and economy PEV sales (Figure 3-6 and Figure 3-7). The final luxury PEV model demonstrates a positive effect from mean household income instead of median household income and a negative effect from the relative number of households with low housing values ($100k-150k), which suggest that the market growth of luxury PEVs has a stronger association with the most affluent households within a neighborhood, as expected. The final luxury PEV model also shows a positive effect from another variable representing the interaction between gender and education - the relative number of college-educated female residents.

In addition to the variables selected by the final PEV model, the quantity of economy PEVs is also positively associated with the relative number of residents employed in the manufacturing sector, neighborhood-level housing occupancy rate, the size of education-completed female population, and the share of households with an annual income between $150k and $200k. The quantity of economy PEVs is negatively associated with the relative number of residents employed in agriculture, forestry, fishing and hunting, and mining sectors and neighborhood-level housing vacancy rate. Although the final economy PEV model demonstrates a positive association between the quantity of economy PEVs and median household income, the majority of the 1000 candidate models suggest that the association is negative. Thus, median household income is not a good predictor for neighborhood-level PEV quantity.

The effects of infrastructure-related variables also vary between luxury and economy PEVs. None of these variables was selected by the final luxury PEV model. However, the economy PEV quantity is positively associated with the two previously identified variables: the length of HOV lanes within a 10 km radius ($\beta \in [0.00005, 0.0001]$) and the number of public

DC fast chargers within a 50 km radius ($\beta \in [0.00003, 0.0001]$). These coefficient estimates from the economy PEV models are slightly greater than those in the PEV models. Luxury PEV drivers may live in closer proximity to work and household activities and are more likely to have access to home charging, so their needs for using HOV lanes and public DC fast chargers are much lower than economy PEV drivers. Thus, the access to HOV lanes and the availability of public DC fast chargers have stronger associations with the uptake of economy PEVs than luxury PEVs.

Overall, there is a larger number of predictor variables selected by the final economy PEV model as compared to the final PEV model and the final luxury PEV model. Our results indicate that there is a greater diversity in the motivations to purchase economy PEVs and factors predicting PEV adoption vary between luxury and economy vehicles.

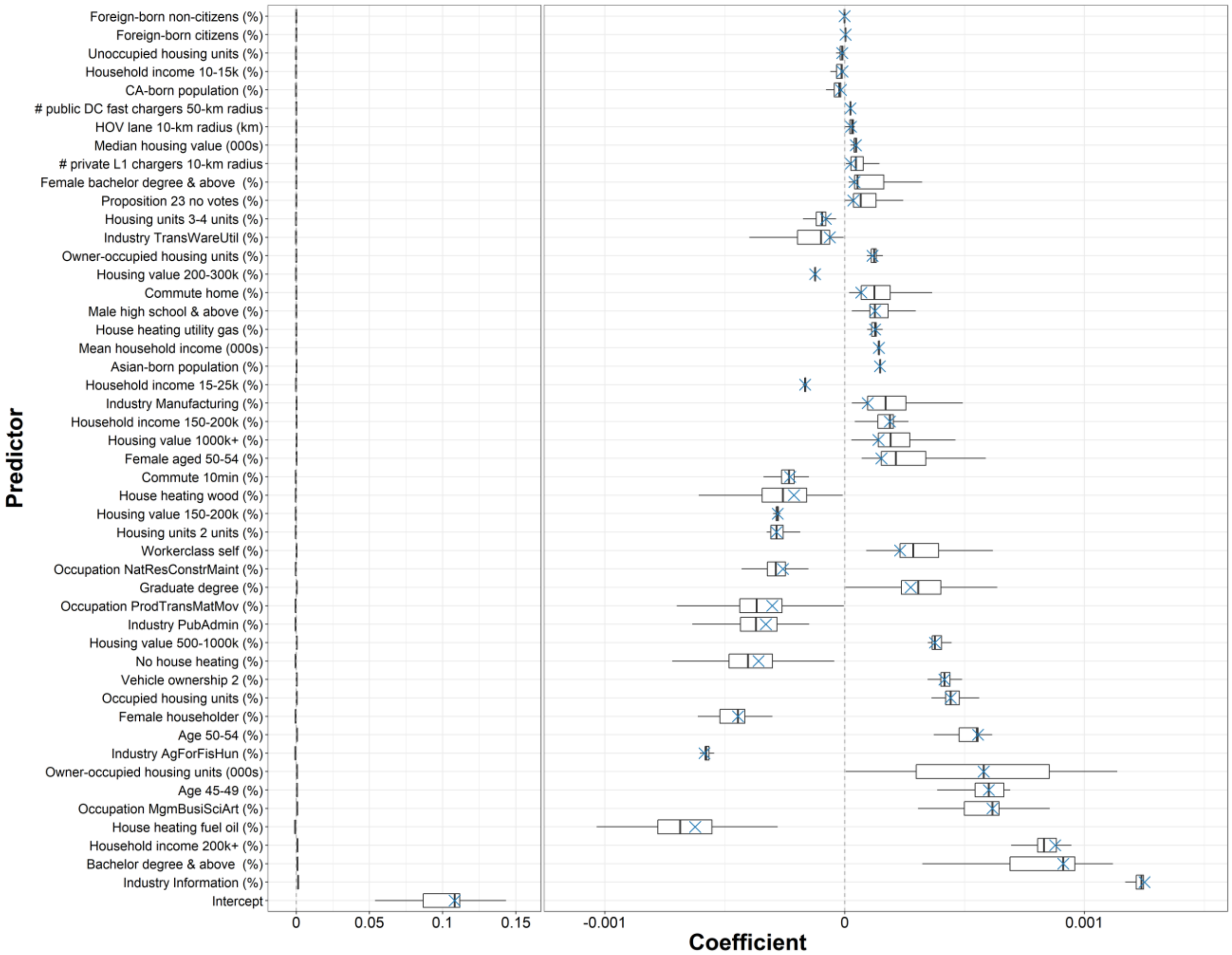


Figure 3-6. Results of models predicting the number of cumulative new luxury PEVs (000s) in a tract

"X" represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.

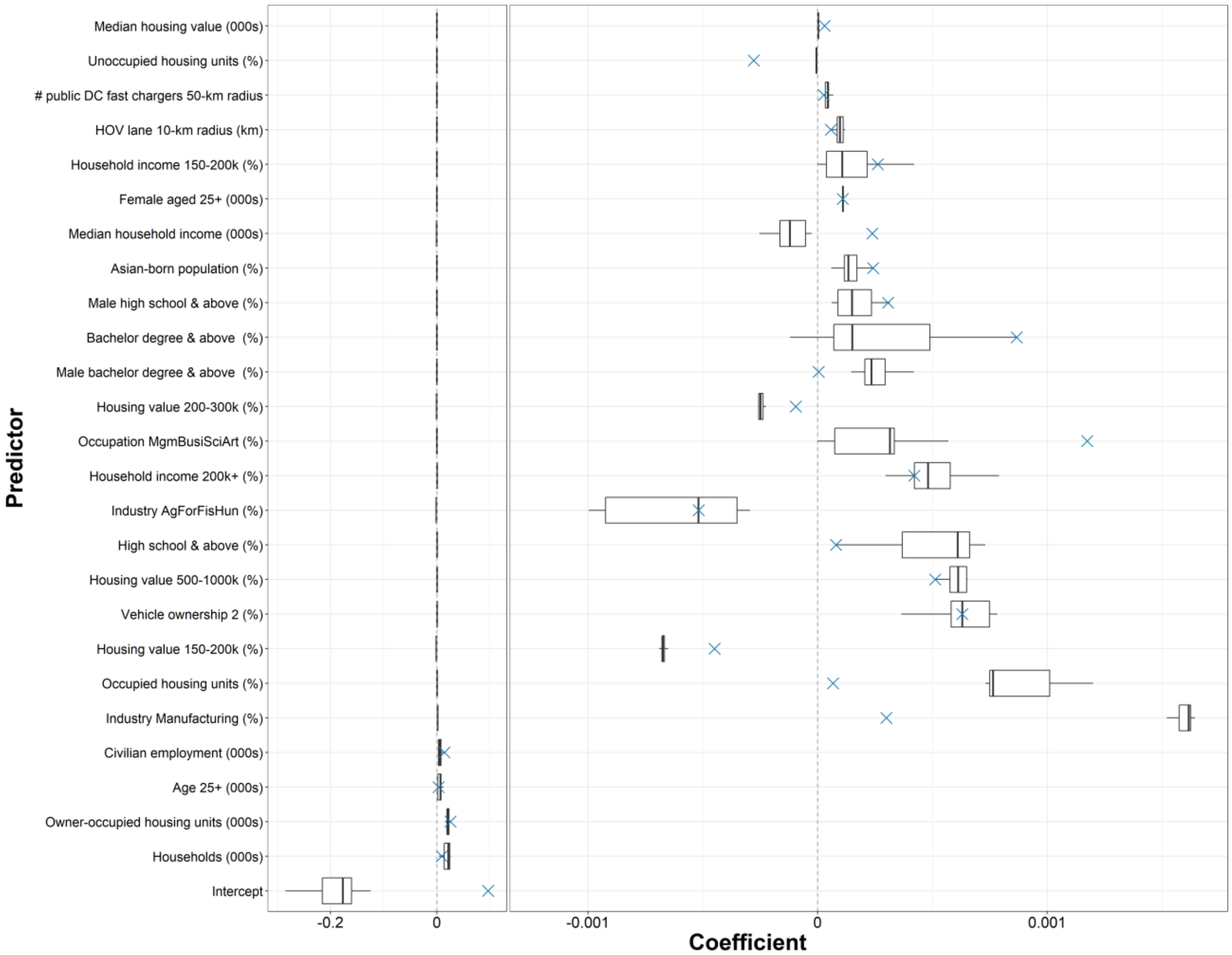


Figure 3-7. Results of models predicting the number of cumulative new economy PEVs (000s) in a tract

"X" represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.

When predicting neighborhood-level PEV share in total light-duty vehicle stock, coefficient estimates from the final model are all within the inter-quartile ranges of respective coefficients across all candidate models (Figure 3-8). The final model indicates that variables that predict neighborhood-level PEV share include pro-environment intention and behaviors, employment, income, wealth, education, housing and commuting patterns, and infrastructure.

Among the 48 predictor variables selected by the final model, the proportion of residents employed in the information sector has the largest positive effect on PEV share whereas the largest negative effect comes from the proportion of residents using fuel oil and kerosene for house heating. The proportion of residents who voted “no” on Proposition 23 has a positive effect on PEV share. Both predictors represent the levels of pro-environment intention and behaviors. Thus, neighborhoods with higher levels of pro-environment intention would see relatively higher PEV shares and neighborhoods lacking pro-environment behaviors would see relatively lower PEV shares. The final model for predicting the PEV share also captured a negative effect from the proportion of residents using wood for heating and a positive effect from the proportion of residents using utility gas for heating, which indicates that neighborhoods in a rural setting would see relatively lower PEV shares in the total light-duty vehicle stock.

Similar to the prediction of PEV quantity, employment, income and wealth have also played important roles in predicting PEV shares. Neighborhoods with greater proportions of residents who are employed in the information technology and manufacturing sectors, occupied in management, business, science and arts, or self-employed, neighborhoods with higher shares of households earning more than $150k annually or owning two vehicles, neighborhoods with higher shares of owner-occupied housing units with values greater than $500k, and neighborhoods with greater mean household income and greater median housing values would generally have a larger size of PEV stock relative to the total light-duty vehicle stock. In contrast, the proportions of residents working in relatively lower-paid industrial sectors (especially agriculture, forestry, fishing and hunting, mining, the public sector, transportation and warehousing, and utilities) and occupations (especially production, transportation, material moving, natural resources, construction, and maintenance), the share of lower-income households (especially those earning between $10k and $25k or with no heating available), and the share of lower-value owner-occupied housing units (especially those valued between $150k and $300k) negatively associate with the PEV share in total light-duty vehicle stock. The models also show a negative association between the PEV share and the share of female-householder households, which can be explained by the fact that households with female householders on average earn less than other types of family households (US Census Bureau, 2019). To a large extent, this negative association is aligned with the negative effects of lower incomes.

Educational attainment rates in higher education and the relative sizes of middle-aged populations (age groups between 45 and 54 as well as females between 50 and 54) are positively associated with the share of PEVs in total light-duty vehicle stock. The education-related variables include the proportions of well-educated and highly-educated residents (with at least college-level education), highly-educated residents (with graduate education), educated male residents (with at least high-school completion), and well-educated and highly-educated female residents. Besides the positive effect of the relative size of foreign-born Asian population, the models also indicate relatively smaller effects from three additional variables related to place of birth: the relative number of California-born residents (negative), the relative number of foreign-born US citizens (positive), and the relative number of foreign-born non-US citizens (negative). Several housing characteristics also have relatively greater effects in predicting the PEV share.

Homeownership in both absolute and relative terms is positively associated with the PEV share. The proportions of duplexes, triplexes and quadraplexes in total housing units negatively associate with the PEV share. In terms of commuting patterns, the proportion of residents commuting for less than 10 minutes is negatively associated with the PEV share while the proportion of residents working from home positively associates with the PEV share. For residents commuting for less than 10 minutes, they are less likely to drive a PEV due to the lower fuel cost savings associated with short commute distances. For residents working from home, they are less likely to own a vehicle in general. The PEV share is determined by both the PEV adoption and the total vehicle stock in a neighborhood.

In addition to these attitudinal, socioeconomic and demographic characteristics, the models predicting the PEV share have suggested positive effects from three infrastructure-related variables, including the number of private Level 1 chargers within a 10 km radius ($\beta \in [0.000005, 0.0002]$), the length of HOV lanes within a 10 km radius ($\beta \in [0.000002, 0.00004]$), and the number of public DC fast chargers within a 50 km radius ($\beta \in [0.00002, 0.00004]$). These coefficient estimates indicate that an increase of 100 private Level 1 chargers within in a 10 km radius is associated with a percentage point increase of up to 0.008 in PEV share for a neighborhood with a cumulative PEV share of 10% and a percentage point increase of up to 0.06 for a neighborhood with a cumulative PEV share of 20%. Similarly, an increase of 10 km in HOV lane length within a 10 km radius is associated with a percentage point increase of up to 0.0002 for a neighborhood with a cumulative PEV share of 10% and a percentage point increase of up to 0.001 for a neighborhood with a cumulative PEV share of 20%. In addition, an increase of 100 public DC fast chargers within a 50 km radius is associated with a percentage point increase of up to 0.002 for a neighborhood with a cumulative PEV share of 10% and a percentage point increase of up to 0.01 for a neighborhood with a cumulative PEV share of 20%. The positive effect of private Level 1 chargers suggests that the availability of Level 1 chargers in workplace remains important for promoting PEV adoption. Both the prediction of PEV quantity and the prediction of PEV share demonstrate that HOV lane access and the availability of DC fast chargers are essential in promoting PEV adoption in both absolute and relative terms.

When predicting luxury PEV share and economy PEV share separately (Figure 9 and Figure 10), I also observed some effects from additional predictor variables that are specific for each of the two response variables. Similar to the findings in the modeling of PEV quantity, more homeowners, higher attainment rates in higher education, higher levels of income and wealth, employment in certain high-paid industries or occupations, and larger middle-aged populations are all aligned with higher shares of both luxury PEVs and economy PEVs in total light-duty vehicle stock. When predicting luxury PEV share, the final model suggests that certain types of organizations also play a role in predicting neighborhood-level luxury PEV adoption. The average job density in the manufacturing sector or the wholesale sector between 2010 and 2017 is positively associated with luxury PEV adoption. When predicting economy PEV share, the final model suggests that there are a greater number of variables that represent commuting patterns. Neighborhood-level average commute time and the proportion of residents commuting for over 60 minutes are positively associated with economy PEV share, whereas the proportions of residents commuting for less than 10 minutes, residents driving for less than 10 minutes to work, and public transit riders negatively associate with economy PEV share. In contrast, the share of public transit riders is the only commute-related variable selected by the final model for luxury PEV share. The proportion of residents who voted “no” on Proposition 23 is a predictor of economy PEV share but not luxury PEV share. Although homeownership, education, income, wealth, and age have larger effects in predicting the adoption of both luxury PEVs and economy PEVs, the level of pro-environment intention only predicts the economy PEV share.

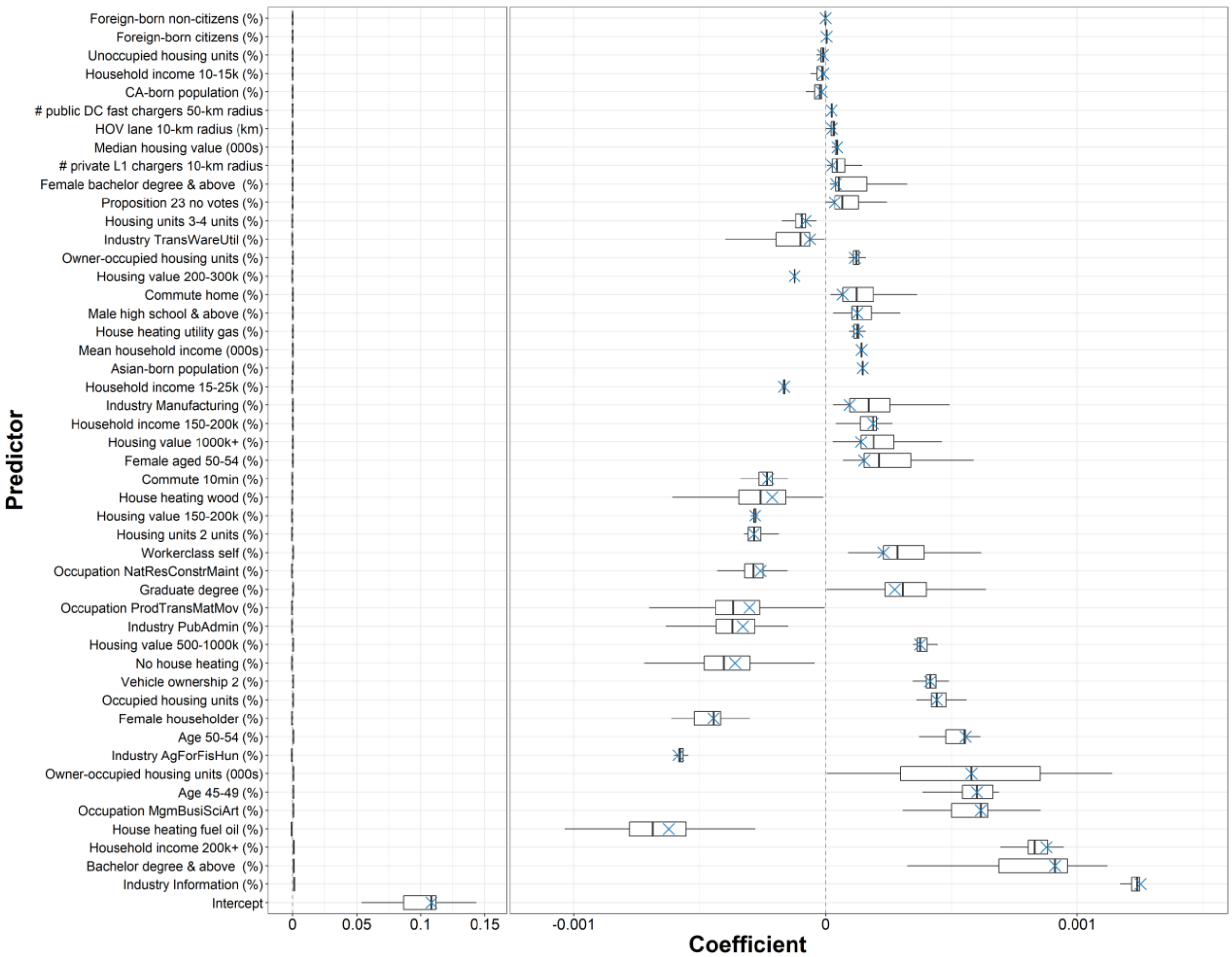


Figure 3-8. Results of models predicting the share of cumulative new luxury and economy PEVs (%) in the total vehicle stock of a tract

"X" represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.

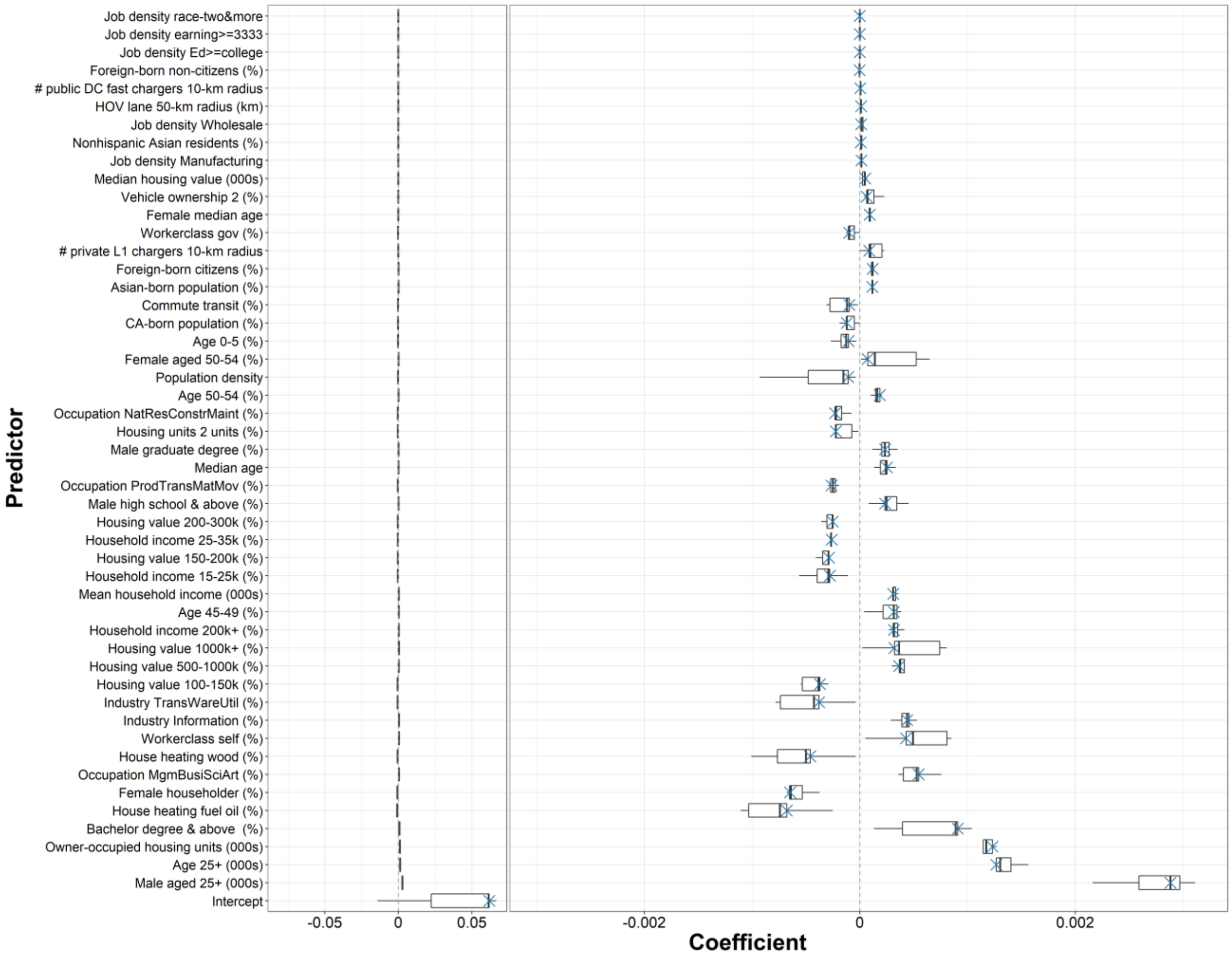


Figure 3-9. Results of models predicting the share of cumulative new luxury PEVs (%) in the total vehicle stock of a tract

"X" represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.

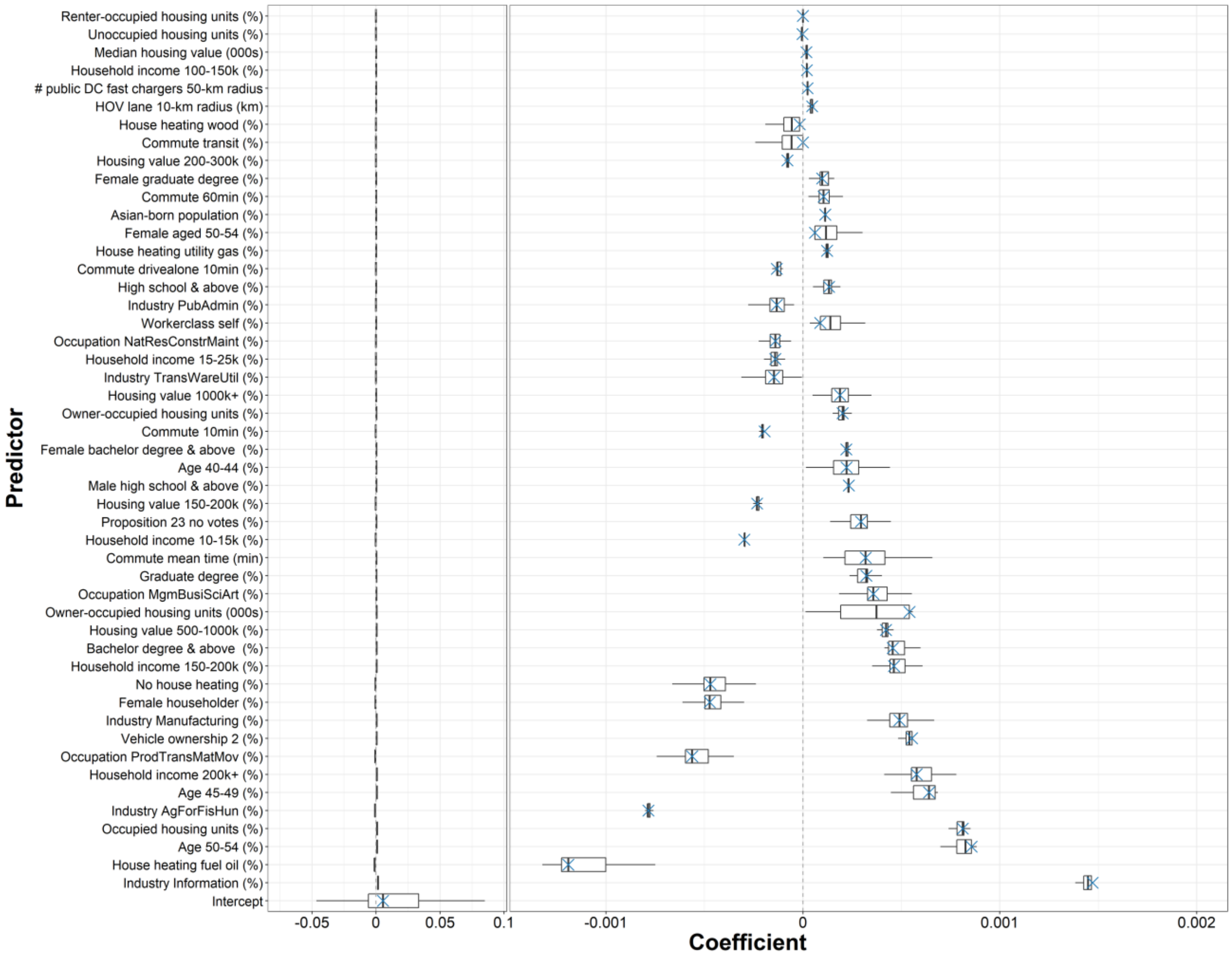


Figure 3-10. Results of models predicting the share of cumulative new economy PEVs (%) in the total vehicle stock of a tract

"X" represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.

BEV adoption

As neighborhood-level preferences for BEVs and PHEVs vary (Figure 3-2), modeling the two types of PEVs separately could provide additional insights on PEV adoption in California. All three final models for predicting BEV quantity indicate that BEVs have a stronger presence in neighborhoods with less housing vacancies, more homeowners, more employed residents, and more adults who are at least 25 years old (Supplementary Figures 3-1, 3-2, & 3-3). Previously discussed variables including income, wealth, education, age, and residents' employment status in certain occupations or industries remain important in predicting the quantity of BEVs, luxury BEVs, and economy BEVs. Although the final models for BEVs and economy BEVs suggest that median household income is positively associated with the vehicle quantity, the majority of models under both vehicle categories demonstrate a negative association. In contrast, median household income and mean household income have consistently positive effects in predicting luxury BEVs and the effect of mean household income is 2-3 times greater than that of median household income. The median household income of a neighborhood indicates the income level of the average household, whereas mean household income of a neighborhood is collectively determined by all households across different income levels. A neighborhood with higher mean than median income generally indicates there are more affluent households within the neighborhood. These differing results on median and mean household income in my models indicate that the most affluent households within the more affluent neighborhoods are more likely to adopt luxury BEVs, so the neighborhood-level average income level may not be a good predictor for the adoption of economy BEVs. In addition, the proportion of Asian residents has a relatively large positive effect in predicting the quantity of BEVs and economy BEVs, and the proportion of foreign-born Asian residents has a positive yet smaller effect that is consistent across all three BEV categories. Our results show that the relative size of Asian populations has a stronger association with the neighborhood-level quantity of BEVs, and especially economy BEVs, than any other racial/ethnic groups.

In terms of infrastructure, the availability of public DC fast chargers has a consistently positive effect in predicting the quantity of economy BEVs ($\beta = 0.0001$). That is, holding everything else constant, an increase of 100 public DC fast chargers within a 10km radius is associated with 0.04 more economy BEVs for a neighborhood with cumulative economy BEV sales of 100 vehicles and 0.32 more economy BEVs for a neighborhood with cumulative economy BEV sales of 200 vehicles. The effects are aligned with the role of public DC fast chargers within a 50 km radius in predicting the quantity of economy PEVs ($\beta \in [0.00003, 0.0001]$). These findings indicate that the availability of public DC fast chargers on a regional scale supports the overall adoption of economy PEVs and the availability of public DC fast chargers on a local scale particularly supports the adoption of economy BEVs.

When predicting the shares of BEVs in total light-duty vehicle stock, there are also a greater number of variables selected by the final models as compared to the final models predicting the quantity. The levels of pro-environment intention and behaviors are important in predicting BEV shares. The proportion of households using fuel oil and kerosene for heating consistently has the largest negative effect across all three vehicle categories, and the relative number of residents who voted “no” on Proposition 23 has a relatively large and positive association with economy BEV share (Supplementary Figures 3-4, 3-5, & 3-6). Similar to what I have observed in the modeling of BEV quantity, income, wealth, education, age, employment, and Asian populations also explain the neighborhood-level variations in BEV shares. The roles of mean and median household incomes in predicting the shares of luxury BEVs and economy

BEVs resemble those in predicting BEV quantity. These findings indicate that the highest-earning households and the more affluent neighborhoods in general are more likely to adopt luxury BEVs than economy BEVs, although economy BEVs are more popular in less affluent neighborhoods. Although over half of the models suggest that the number of homeowners has a positive association with BEV share and economy BEV share, the ranges of coefficient estimates show that homeownership may also negatively associate with the shares of BEVs and economy BEVs. Thus, homeownership alone may not predict BEV adoption. However, homeownership consistently has a positive association with luxury BEV share, which is also negatively associated with the proportion of duplexes and population density. These findings further indicate that homeownership and housing type jointly predict BEV adoption and homeowners with single-family housing are more likely to substitute an ICEV with a BEV.

Modeling luxury BEV share and economy BEV share separately have also demonstrated the varying motivations for BEV adoption. With respect to infrastructure, the effect of the number of public DC fast chargers within a 10 km radius in the prediction of economy PEV share is 10 times as its effect in predicting luxury BEV share. Models for predicting economy BEV share also demonstrate positive effects from the number of public DC fast chargers on broader geographical scales (within both the 25km and 50km radiuses). In addition, models for predicting luxury BEV share suggest that the availability of private Level 1 chargers and HOV lane access positively associate with luxury BEV share. These results indicate that workplace charging, public DC fast charging, and HOV lane access are positively associated with the uptake of BEVs. The second major difference between the two sets of models lies in the effects of commute time, which predicts economy BEV share but not luxury BEV share. The proportions of residents driving alone to work for less than 10 minutes or generally commuting for less than 10 minutes are negatively associated with economy BEV share, whereas the relative number of residents commuting for 20-24 minutes in a single-occupancy vehicle positively associates with economy BEV share. Our results are consistent with the current state of economy BEVs, that is, their limited range does not seamlessly support frequent long-distance travels and the savings on fuel costs do not offset their high upfront costs when vehicle usage is low. Previous studies showed that these disadvantages of economy BEV technologies affect an individual's attitude towards PEV adoption (Carley et al., 2013, 2019; Jensen et al., 2013). Thus, the perceived functional barriers and the revealed preferences are aligned in the adoption of economy BEVs. Another major difference between the two vehicle categories is the role of organizations in driving the adoption of luxury BEVs. The models for luxury BEV share captured three variables that represent employer adoption behaviors (Supplementary Figure 3-5). Although households have a much greater contribution to luxury BEV adoption, the average job densities in the wholesale and manufacturing sectors positively associate with luxury BEV share and the average job density in the health and social assistance sector is negatively associated with luxury BEV share.

PHEV adoption

All three sets of models predicting PHEV quantity indicate that greater cumulative PHEV sales generally take place in neighborhoods with fewer housing vacancies, more homeowners, more employed residents, and more adults. Consistent with previous results, the quantity of PHEVs also positively associates with income, wealth, education, middle-aged populations, and employment in certain occupations or industries. The proportion of residents employed in the information technology sector consistently has a large and positive effect in predicting the quantity of PHEVs, luxury PHEVs and economy PHEVs.

Different from predicting the quantity of PEVs and BEVs, commute-related variables have showed importance in predicting the quantity of PHEVs and especially economy PHEVs (Figure 17 & Figure 19). The proportions of residents driving alone to work and especially those commuting for over 45 minutes positively associates with the adoption of economy PHEVs. HOV lane access has consistently positive effects in predicting PHEV adoption across all three vehicle categories. These results indicate that a longer commute and the opportunity to reduce commute time by accessing HOV lanes motivate the adoption of PHEVs. In terms of charging infrastructure, the number of public DC fast chargers in the region has a positive yet small effect in predicting the number of PHEVs and economy PHEVs, while the number of private chargers especially Level 2 chargers positively associates with the number of luxury PHEVs. These results are aligned with our previous findings on BEV adoption.

When predicting PHEV shares in total light-duty vehicle stock, homeownership and employment in the information technology sector have consistently strong associations with neighborhood-level PHEV adoption in both absolute and relative terms (Supplementary Figures 3-7 & 3-10). While neighborhood-level average commute time has a large positive effect on economy PHEV share, the neighborhood-level average household size has the largest negative effect on luxury PHEV share. Similar to predicting the quantity of PHEVs, a longer commute (as represented by the proportions of residents with longer commute time) positively associates with economy PHEV share. Both median household income and mean household income have consistently positive effects in predicting the share of luxury PHEVs, whereas none of these two variables plays a role in predicting the share of economy PHEVs. Our results show that highest-earning households and the more affluent neighborhoods in general are more likely to adopt luxury PHEVs than economy PHEVs, which is aligned with what I observed on BEV adoption.

In terms of charging infrastructure, the regional deployment of public DC fast chargers has a positive association with economy PHEV share. Private chargers (especially Level 1 chargers within a 10 km radius, all private chargers with in a 50 km radius, Level 2 chargers within a 50 km radius) are positively associated with luxury PHEV share. However, the number of public Level 1 chargers on a regional scale has a negative effect in the prediction of luxury PHEV share. In addition, the availability of HOV lanes has a consistently positive effect on PHEV share, luxury PHEV share, and economy PHEV share. The length of HOV lanes within a 10 km radius demonstrates a greater positive association with economy PHEV share, while the length of HOV lanes within a 50 km radius has a greater positive association with luxury PHEV share.

Insights from cross-model comparison

In this study, I define PEV adoption as in both absolute and relative terms. Taking into account both, a cross-model comparison explores the varying effects of the most frequently selected and most powerful independent variables in order to offer additional insights on the adoption motivations and technology preferences of potential PEV buyers. In summary, the most consistent and powerful variables in predicting neighborhood-level PEV adoption include homeownership, occupied housing units, pro-environment intention and behaviors, age, education, race, income, wealth, employment, and commute patterns (Table 3-3).

Housing characteristics are the most powerful predictors of PEV adoption. Homeownership is generally a strong predictor of PEV adoption, but it is not associated with the uptake of economy BEVs. While the number of households within a neighborhood is powerful predictor of the quantity of PEVs of all types, housing occupancy rate predicts the adoption economy PEVs especially economy BEVs. The effects of the proportion of residents using wood for heating suggest that neighborhoods in a rural setting are less likely to have high shares of luxury PEVs and economy PHEVs. As demonstrated by the proportion of housing units using fuel oil and kerosene for heating and the relative number of residents voted "no" on Proposition 23, the levels of pro-environment intention and behaviors associate with economy PEV shares. The varying effects indicate that the levels of pro-environment intention and behaviors play a more significant role in motivating economy BEV adoption than economy PHEV adoption.

Besides the large household effects, there are also large population effects on the adoption of PEVs. The number of adults who are at least 25 years old positively associates with the adoption of luxury PEVs and economy PHEV quantity, whereas the number of female adults who are at least 25 years old positively associates with the quantity of economy PEVs and luxury

PHEVs. Middle-aged populations have also demonstrated certain preferences that vary by age group. The proportion of residents aged between 50 and 54 positively associates with PEV shares and the quantity of PHEVs, whereas the relative size of the age group between 45 and 49 is a predictor of economy PHEV share and economy BEV quantity. In addition, education and race have relatively large effects on PEV adoption. Attainment rates in various levels of education have varying effects on PEV adoption. The proportion of well-educated and highly-educated residents positively associates with the adoption of PEVs especially luxury PEVs and economy PHEVs. The proportion of educated residents generally explains the adoption of economy PEVs especially economy BEVs, whereas the proportion of highly-educated residents is a predictor of economy BEV adoption. The relative number of well-educated and highly-educated male residents have relatively larger association with the adoption of luxury BEVs and economy PHEVs. The relative size of Asian populations positively associates with the adoption of economy BEVs and the share of luxury BEVs.

The proportion of highest-earning households positively associates with the adoption of PEVs of all types except luxury PHEVs, and the varying effect sizes indicate that highest-earning households have relatively stronger preferences for luxury BEVs and economy PHEVs. Neighborhoods with a greater share of low-income households are less likely to adopt PEVs. Neighborhoods with larger proportions of 2-vehicle households would generally have more PEVs and greater shares of PEVs, and these neighborhoods have a greater preference for economy PEVs. Wealth as represented by housing values also shows consistency in predicting PEV adoption. Our results show that neighborhoods with greater proportions of households with housing values between $500k and $1 million and greater median housing values drive the adoption of PEVs of all types, and households with housing values above $1 million have greater preferences for BEVs and luxury PHEVs. On the other hand, neighborhoods with greater proportions of low-value housing units (especially valued between $200k and $300k) or housings units with no heating available usually have lower adoption. Thus, it becomes obvious that the more affluent neighborhoods are more likely to adopt PEVs as compared to the less affluent neighborhoods and the highest-earning households are more likely to adopt BEVs and luxury PHEVs.

The employment status of residents is another set of variables that have demonstrated importance in predicting PEV adoption. Neighborhoods with more employed residents are more likely to have a larger number of PEVs, especially luxury PHEVs and economy BEVs. Although occupational status in management, business, science and arts has a consistently positive effect on PEV adoption, employment in other occupations or industrial sectors generally has greater power in predicting the adoption of specific types of PEVs. Occupations in production, transportation and material moving have a stronger negative effect in the prediction of economy BEVs and luxury PHEVs. Employment in the information technology sector has demonstrated a strong positive effect in predicting PHEV adoption, whereas employment in the manufacturing sector and the professional, scientific, management, and the administrative and waste management service sectors have relatively large roles in predicting the adoption of economy BEVs. Employment in the transportation, warehousing and utilities sectors has a stronger negative effect in predicting the adoption of economy BEVs, although it also negatively associates with the shares of luxury PEVs. Employment in the agriculture, forestry, fishing, hunting and mining sectors has shown negative effects in predicting the adoption of economy PEVs especially economy PHEVs. Long commute time also motivates the adoption of economy PHEVs, as the proportion of residents commuting for over 60 minutes has relatively large effects in predicting both the quantity and the share of economy PHEVs. The employment status and commute patterns of residents reflect various income levels and travel needs, and the varying effects of the selected variables in this group are aligned with the discussions on income and wealth as well as the perceived functional barriers and advantages of specific PEV technologies.

In general, the availability of charging infrastructure and HOV lane access positively associate with PEV adoption. The effects also vary by technology. Our results show that workplace charging is important in predicting the adoption of luxury PEVs particularly luxury PHEVs, and public DC fast chargers have a positive association with the adoption of economy BEVs. In addition, the availability of public DC fast chargers on a local scale benefits luxury BEVs and the availability of public DC fast chargers on a regional scale supports the adoption of economy PHEVs. I also find a negative effect of the regional deployment of public Level 1 chargers in the prediction of luxury PHEVs, which indicates that the deployment of public slow chargers is not an effective strategy in promoting PEV adoption. In terms of HOV lane access, I find that this incentive positively associates with the adoption of PHEVs and luxury BEVs. More specifically, the availability of HOV lanes on a local scale positively associates with the adoption of economy PHEVs and the share of luxury BEVs. In contrast, the availability of HOV lanes on a regional scale has a more significant role in predicting the adoption of luxury PHEVs comparing to its roles in predicting the shares of luxury BEVs and economy PHEVs.

Table 3-3. Coefficient estimates (median values) of selected predictor variables

Variable group	Variable	Vehicle quantity (000s)				Vehicle share in total light-duty vehicle stock (%)			
		Luxury		Economy		Luxury		Economy	
		BEV	PHEV	BEV	PHEV	BEV	PHEV	BEV	PHEV
Housing	Owner-occupied housing units (000s)	0.02	0.02	0.01	0.02	0.001	0.004	-0.0002	0.004
	Households (000s)	0.02	0.01	0.01	0.01	-	0.0001	-	-
	Occupied housing units (%)	-	-	0.0009	0.0005	-	-	0.001	0.0006
Pro-environment intention & behaviors	House heating wood (%)	-	-	-	-	-0.0003	-0.0005	-	-0.00008
	House heating fuel oil (%)	-	-	-	-	-0.0009	-	-0.002	-0.0003
	Proposition 23 no votes (%)	-	-	-	-	-	-	0.0008	0.00009
Age	Age 25+ (000s)	0.007	0.005	-	0.003	0.003	0.003	-	-
	Female aged 25+ (000s)	-	0.0004	0.003	0.002	-	-	-	-
	Male aged 45-49 (%)	-	-	-	-	-	0.0004	0.001	-
	Age 45-49 (%)	-	-	0.00008	-	-	-	-	0.0006
	Age 50-54 (%)	-	0.0006	-	0.0005	0.0002	0.0004	0.0005	0.0005
Education	Bachelor degree & above (%)	0.0008	0.0004	0.00005	0.0003	0.0008	0.001	0.00003	0.0005
	High school & above (%)	-	-	0.001	0.0004	-	-	0.001	0.00005
	Graduate degree (%)	-	-	0.0007	-	-	-	0.0006	-
	Male bachelor degree & above (%)	0.0007	0.00008	-	0.0002	0.00003	-	-	0.0001
Race	Nonhispanic Asian residents (%)	-	-	0.0005	-	0.0002	-	0.0002	-
Income & wealth	Household income 200k+ (%)	0.0009	-	0.0002	0.0004	0.0005	-	0.0001	0.0005
	Female householder (%)	-0.0007	-	-	-	-0.0007	-0.0002	-0.0003	-0.0005
	Vehicle ownership 2 (%)	-	0.0003	0.0005	0.0006	0.00008	0.00008	0.0003	0.0004
	Housing value 500-1000k (%)	0.0006	0.0005	0.0006	0.0005	0.0004	0.0003	0.0004	0.0003
	Housing value 1000k+ (%)	-	-	-	-	0.0004	0.0001	0.0005	-
	Median housing value (000s)	0.00004	0.00002	0.00001	0.000002	0.00005	0.00004	0.000002	0.00002
	Housing value 200-300k (%)	-0.0005	-0.0006	-0.0003	-0.0005	-0.0002	-0.0003	-0.0001	-0.0003
	Housing value 150-200k (%)	-0.0007	-0.0006	-	-0.0007	-0.0003	-0.0002	-	-0.0003
	Housing value 100-150k (%)	-0.0007	-	-	-0.0005	-0.0003	-0.00004	-	-0.0003
	No house heating (%)	-	-	-0.001	-	-	-	-0.0009	-0.0003
Employment	Civilian employment (000s)	0.003	0.01	0.01	0.004	-	0.002	-	-
	Occupation MgmBusiSciArt (%)	0.0003	0.0005	0.0001	0.00006	0.0005	0.0003	0.0001	0.0002
	Occupation ProdTransMatMov (%)	-	-0.0004	-0.001	-	-0.00007	-0.0005	-0.0009	-0.0004

Variable group	Variable	Vehicle quantity (000s)				Vehicle share in total light-duty vehicle stock (%)			
		Luxury		Economy		Luxury		Economy	
		BEV	PHEV	BEV	PHEV	BEV	PHEV	BEV	PHEV
	Industry Information (%)	-	0.0006	-	0.002	-	0.0009	0.0009	0.002
	Industry Manufacturing (%)	-	-	0.001	-	-	-	0.0007	-
	Industry ProfSciMgmAdmWas (%)	-	-	0.0005	-	-	-	0.0003	-
	Industry TransWareUtil (%)	-	-	-0.001	-	-0.0005	-0.0003	-0.001	-
	Industry AgForFisHun (%)	-	-	-0.0002	-0.0009	-0.0003	-	-0.0001	-0.0009
	Workerclass self (%)	-	-	-	-	0.0003	0.0007	-	0.0001
Commute	Commute 60min (%)	-	-	-	0.001	-	-	-	0.0005
Charging infrastructure	# private L1 chargers 10-km radius	-	-	-	-	0.0001	0.0002	-	-
	# private chargers 50-km radius	-	0.000008	-	-	-	0.000007	-	-
	# private L2 chargers 50-km radius	-	0.0000008	-	-	-	0.0000003	-	-
	# public DC fast chargers 10-km radius	-	-	0.0001	-	0.00002	-	0.00006	-
	# public DC fast chargers 25-km radius	-	-	-	-	-	-	0.00002	-
	# public DC fast chargers 50-km radius	-	-	-	0.00003	-	-	0.00006	0.00002
	# public L1 chargers 50-km radius	-	-	-	-	-	-0.00008	-	-
HOV lane access	HOV lane 10-km radius (km)	-	-	-	0.00008	0.00004	-	-	0.00004
	HOV lane 50-km radius (km)	-	0.00003	-	-	0.000006	0.00001	-	0.000005

PEV adoption through the lens of social and environmental equity

Although California policymakers have prioritized disadvantaged[4] and low-income[5] communities and households for the state-wide climate investments (SB 535[6] and AB 1550[7]), there is a wide disparity in the adoption of PEVs between these "priority populations" and other communities (Figure 3-11). Disadvantaged communities account for 25% of all census tracts in California. However, only 8% of cumulative new PEV sales, 6% of cumulative new BEV sales, and 9% of cumulative new PHEV sales in California have taken place within disadvantaged communities by the end of 2018. Within disadvantaged communities, the most popular vehicle category is economy PHEVs (44%), followed by economy BEVs (25%), luxury BEVs (20%), and luxury PHEVs (11%). The average MSRP of these four types of vehicles in disadvantaged communities are $32,535, $31,534, $62,377, and $58,225, respectively. Within all other tracts, economy PHEVs also have the highest market share (35%), which is followed by luxury BEVs (30%), economy BEVs (25%), and luxury PHEVs (10%). The average MSRP of these four types of vehicles are $33,043, $63,554, $31,667, and $57,711, respectively.

As of December 2018, 60% of new PEV adoption in California comes from census tracts in the top income quartile, which is followed by the third income quartile (24% of all new PEVs), the second income quartile (11% of all new PEVs), and the lowest income quartile (5% of all

[4] In California, disadvantaged communities are defined as census tracts with the top 25 percent scores in California Environmental Protection Agency's CalEnvironScreen 3.0 tool.
[5] In California, low-income communities are defined as census tracts with a median household income that is no greater than 80 percent of the statewide median income or the threshold designated as low-income in the California Department of Housing and Community Development's 2016 State Income Limits.
[6] SB 535 (De León, Chapter 830, Statutes of 2012) directed the identification of disadvantaged communities and required a minimum of 25% of state-wide climate investments to be allocated for benefiting disadvantaged communities and a minimum of 10% of investments to be within these communities.
[7] AB 1550 (Gomez, Chapter 369, Statutes of 2016) increased the minimum share of state-wide climate investments within disadvantaged communities from 10% in SB 535 to 25% and required at least 5% of investments to be within and benefiting low-income communities and households as well as at least 5% of investments for low-income communities and households that are within half a mile of disadvantaged communities.

new PEVs). A breakdown of PEV adoption by vehicle type and price range indicates that the adoption of luxury PHEVs has been much slower than other three vehicle categories across all income quartiles. Economy PHEVs are the most popular vehicle category in all three lower income quartiles, whereas the quantity of luxury BEVs surpasses that of economy PHEVs within tracts in the top income quartile. Within each income quartile, economy BEVs consistently account for 25% of all PEVs and luxury PHEVs consistently account for 10% of all PEVs. However, the share of luxury BEVs increases as income increases - ranging from 19% in the lowest quartile to 34% in the top quartile, and the share of economy PHEVs decreases as income increases - ranging from 46% in the lowest quartile to 32% in the top quartile. The preference for economy PHEVs in low-income communities are higher than the preference for luxury BEVs.

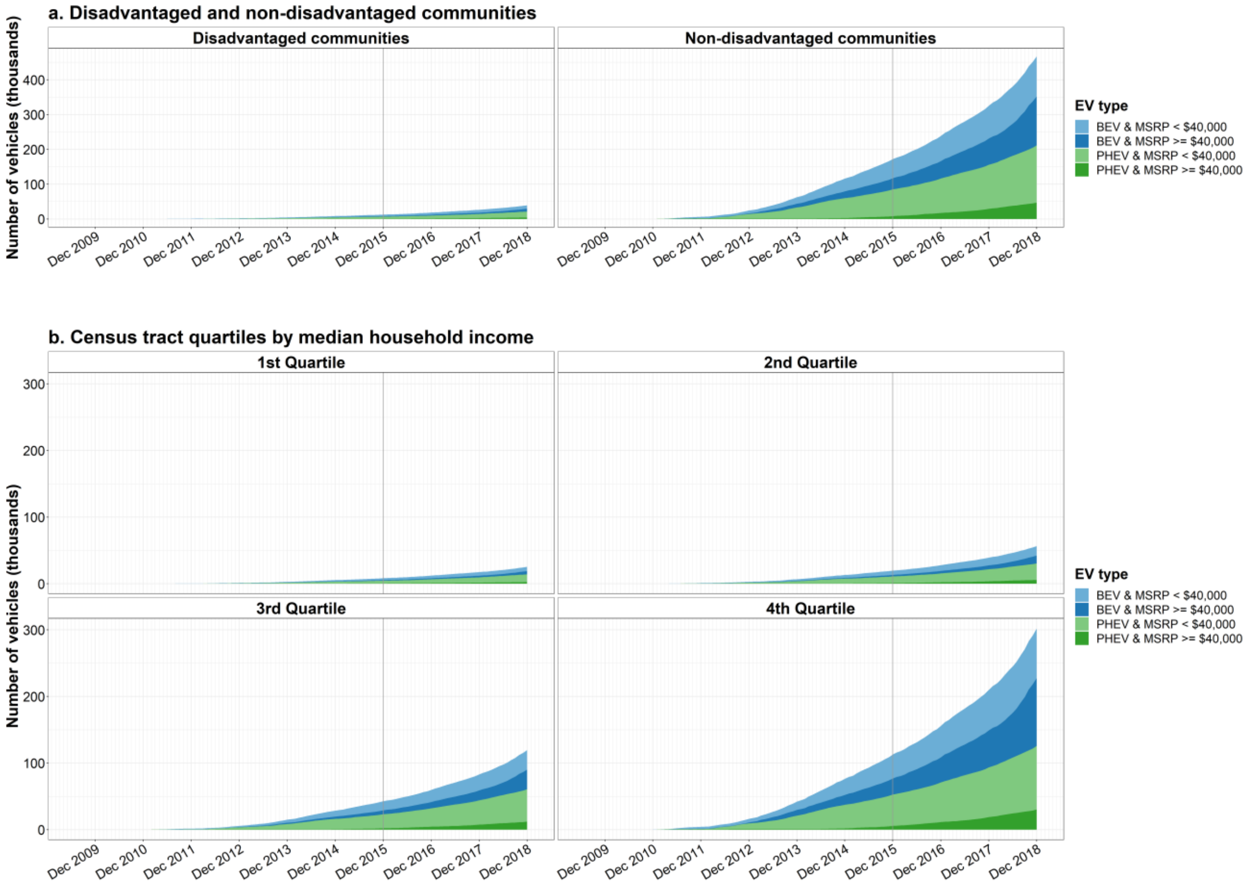


Figure 3-11. Cumulative new PEV sales by socioeconomic status

Since 2010, the state of California has implemented the Clean Vehicle Rebate Project as a key effort to incentive PEV adoption. In 2016, the state added additional rebates totaling $2000 for residents with incomes below 300% of the federal poverty level (Center for Sustainable Energy, 2020). Given that the designated assistance for residents of disadvantaged, low-income, and moderate-income communities started in 2016, a comparison of growth in PEV adoption between December 2015 and December 2018 across census tract groups could offer some insights about the effectiveness of the additional financial incentives designated for these "priority populations". During this time period, cumulative PEV adoption increased by 46%

annually on average in disadvantaged communities and 40% annually on average in non-disadvantaged communities (Table 3-4). The average annual growth rate of cumulative BEV adoption is similar in both disadvantage communities (44%) and non-disadvantaged communities (43%). PHEV adoption in disadvantaged communities has an average annual growth rate of 47%, which is 12 percentage points higher than in non-disadvantaged communities. A further breakdown by price range indicates that disadvantaged communities have seen higher growth rates among all four vehicle categories than non-disadvantaged communities. Within disadvantaged communities, the cumulative adoption of luxury PHEVs increased by 85% on average each year, which is followed by luxury BEVs (an average annual increase of 73%), economy PHEVs (an average annual increase of 42%), and economy BEVs (an average annual increase of 31%). Whereas in non-disadvantaged communities, luxury PHEVs grew by 78% annually on average, luxury BEVs grew by 64% annually on average, and both economy PHEVs and economy BEVs have an average annual growth rate of 28%. Although disadvantaged communities have a lower level of cumulative PEV adoption than non-disadvantaged communities, their consistently higher growth rates across all four vehicle categories between 2015 and 2018 indicate that the designated assistance for disadvantaged communities has made a difference. Thus, additional and continuous assistance is essential in further accelerating PEV adoption in disadvantaged communities.

Across the income quartiles, the average annual growth rate of cumulative PEV sales between 2015 and 2018 ranges from 39% in the top quartile to 45% in the lowest quartile. Except for luxury BEVs, average annual growth rates are generally higher in tracts from the lowest income quartile and second income quartile than other two income quartiles. These results indicate that the additional rebates for low-income and moderate-income communities may have played a role in promoting PEV adoption within these communities. In addition, the average annual growth of luxury BEVs is higher in moderate-income communities than low-income communities, which is consistent with modeling results in the previous sections showing the shares of low-income and low-wealth households limit the growth of luxury BEVs (Supplementary Figures 3-3 & 3-6). Given the disparity in the growth rates between low-income and moderate-income communities, additional assistance for low-income communities is necessary.

Table 3-4. Average annual growth rates of cumulative PEV adoption in 2015-2018

Vehicle type	**Disadvantaged communities**	**Non-disadvantaged communities**	**Census tracts by income quartile**			
			1st (lowest)	2nd	3rd	4th (highest)
PEV	46%	40%	45%	42%	41%	39%
Luxury PEV	77%	67%	75%	76%	74%	64%
Economy PEV	37%	29%	38%	33%	31%	27%
BEV	44%	43%	43%	44%	44%	43%
Luxury BEV	73%	64%	69%	73%	71%	62%
Economy BEV	31%	28%	31%	30%	29%	27%
PHEV	47%	35%	47%	41%	38%	34%
Luxury PHEV	86%	78%	87%	82%	82%	75%
Economy PHEV	42%	29%	42%	35%	32%	27%

Previous studies have demonstrated that the large-scale adoption of PEVs benefits California overall from a GHG mitigation perspective, and it also provides greater net environmental benefits (when taking into account health co-benefits) for dense urban areas and disadvantaged communities (Holland et al., 2016, 2019; Wang et al., 2020). By comparing the most important indicators as suggested by the cross-model comparison, I can identify additional strategies for accelerating large-scale adoption of PEVs particularly within disadvantaged and low-income communities. As shown in Table 3-5, disadvantaged and low-income communities on average lag behind in a number of areas, including homeownership, attainment rates in higher levels of education, income and wealth, and employment status in higher-paid occupations or industrial sectors. The average number of homeowners in disadvantaged communities is only three-fifths of that in non-disadvantaged communities. The average number of homeowners in neighborhoods from the lowest income quartile is less than half of that in neighborhoods from the highest income quartile. Another major difference lies in educational attainment rates. The average attainment rates in higher levels of education within disadvantaged communities resemble those in the lowest-income communities, whereas the average attainment rates in non-disadvantaged communities are similar to the average attainment rates in communities from the third income quartile. On average, less than 15% of residents have at least a bachelor's degree in both disadvantage communities and lowest-income communities, whereas the proportion of such residents in the highest-income communities is about 2.8 times greater. Among these six groups of communities, the distributions of household income and property values also vary a lot. In addition, the more affluent communities generally have higher proportions of residents with higher-paid jobs and lower proportions of residents with lower-paid jobs.

Although the availability of workplace charging surrounding disadvantaged communities is greater than other tracts, it does not necessarily mean residents in the disadvantaged communities have access to these workplace chargers. These private chargers are more likely to be accessible for workers with higher-paid jobs instead of the majority of residents living in the disadvantaged communities. Although there are more public DC fast chargers near disadvantaged communities as compared to other tracts, Hardman (2018) found that public charging is perceived as less preferred than home and workplace charging.

Table 3-5. Summary statistics (mean values) for selected predictor variables

Variable	Disadvantaged communities	Non-disadvantaged communities	Census tracts by income quartile			
			1st (lowest)	2nd	3rd	4th (highest)
Owner-occupied housing units (000s)	0.6	1.0	0.5	0.8	1.0	1.2
Households (000s)	1.4	1.7	1.5	1.6	1.7	1.8
Occupied housing units (%)	94.1	92.3	91.3	92.0	93.3	94.3
House heating wood (%)	0.5	2.2	2.3	2.5	1.5	0.7
House heating fuel oil (%)	0.1	0.3	0.5	0.3	0.2	0.1
Proposition 23 no votes (%)	63.8	61.7	61.7	61.2	61.6	64.4
Age 25+ (000s)	3.0	3.4	2.9	3.2	3.5	3.6
Female aged 25+ (000s)	1.6	1.7	1.5	1.7	1.8	1.8
Male aged 45-49 (%)	6.3	6.7	5.8	6.3	6.8	7.5
Age 45-49 (%)	6.3	6.7	5.8	6.3	6.7	7.5
Age 50-54 (%)	6.1	6.9	5.8	6.3	6.8	7.7
Bachelor degree & above (%)	14.7	38.5	14.8	23.9	36.0	55.9
High school & above (%)	66.3	87.5	67.9	79.1	87.9	94.3
Graduate degree (%)	4.1	15.0	4.4	7.8	12.9	24.1
Male bachelor degree & above (%)	14.0	38.9	14.5	23.4	35.7	57.5
Nonhispanic Asian residents (%)	9.0	15.1	8.0	10.7	14.6	20.9
Household income 200k+ (%)	2.7	13.0	1.8	4.4	9.6	25.9
Female householder (%)	20.3	11.6	19.7	15.2	11.9	8.3
Vehicle ownership 2 (%)	32.7	38.5	31.4	36.1	38.6	42.1
Housing value 500-1000k (%)	19.2	35.8	15.1	24.6	39.2	47.8
Housing value 1000k+ (%)	2.1	15.3	2.4	3.9	9.0	32.8
Median housing value (000s)	354.0	612.8	310.8	409.3	550.3	925.6
Housing value 200-300k (%)	17.5	10.8	19.6	17.9	10.0	2.2
Housing value 150-200k (%)	8.2	4.0	11.1	6.2	2.2	0.5
Housing value 100-150k (%)	6.2	2.7	8.8	3.6	1.3	0.5
No house heating (%)	7.8	2.5	6.8	4.4	2.5	1.4
Civilian employment (000s)	2.1	2.4	1.9	2.3	2.5	2.6
Occupation MgmBusiSciArt (%)	21.5	43.1	21.2	30.7	41.7	57.4
Occupation ProdTransMatMov (%)	20.2	9.8	18.3	14.7	10.5	6.1
Industry Information (%)	1.9	3.1	1.6	2.3	3.0	4.4
Industry Manufacturing (%)	10.7	8.6	9.0	8.8	8.7	10.0
Industry ProfSciMgmAdmWas (%)	10.4	14.0	10.3	11.2	12.8	18.1
Industry TransWareUtil (%)	7.2	4.6	6.2	5.9	5.1	3.7
Industry AgForFisHun (%)	4.2	2.0	5.4	2.8	1.4	0.7
Workerclass self (%)	7.5	8.8	8.1	8.2	8.5	9.0
Commute 60min (%)	12.5	12.0	11.4	11.5	12.5	13.2
# private L1 chargers 10-km radius	4.3	3.1	2.7	3.9	3.4	3.7
# private chargers 50-km radius	871.2	522.6	608.3	613.5	604.2	608.1
# private L2 chargers 50-km radius	804.7	484.6	563.3	569.0	560.3	561.5
# public DC fast chargers 10-km radius	38.7	33.4	30.7	34.1	33.1	41.1
# public DC fast chargers 25-km radius	200.3	137.5	153.2	142.8	144.0	171.8
# public DC fast chargers 50-km radius	456.3	358.5	332.9	357.9	384.2	455.5
# public L1 chargers 50-km radius	21.7	30.5	19.9	23.0	28.8	41.5
HOV lane 10-km radius (km)	56.7	38.7	36.5	47.4	45.0	43.7
HOV lane 50-km radius (km)	735.6	484.7	510.8	555.8	560.8	558.9

Conclusions

Between 2010 and 2018, cumulative new PEV sales in California reached over 507,000 vehicles, which accounts for two-fifths of all new electric vehicles sold in the California light-duty vehicle market. Although PEV adoption has taken place in 98% of census tracts, the growth has been uneven across the California market. Although disadvantaged communities account for a quarter of all census tracts in California, only 8% of cumulative new PEV sales, 6% of cumulative new BEV sales, and 9% of cumulative new PHEV sales have occurred in disadvantaged communities. When categorizing California census tracts by median household income quartiles, 60% of state-wide PEV adoption has concentrated in the top income quartile and only 5% has occurred in the lowest income quartile. By comparing growth rates across various types of communities, I find higher growth rates of PEV adoption in disadvantaged and low-income communities after the implementation of designated assistance for these communities.

By modeling the absolute and relative PEV adoption levels by the technology type and price range, this study identifies the most powerful predictor variables for each of the 18 response variables. A large volume of cumulative sales is not always aligned with a large proportion in the total light-duty vehicle stock. Thus, modeling both the quantity and the share offers complementary insights on PEV adoption. The final models have varying dimensions and selected variables, which indicates that motivations for adoption and preferences for a specific PEV technology vary by community. Although neighborhood-level PEV adoption depends on both household and employer decisions, the vast majority of selected predictor variables are constructs representing residential characteristics. Thus, households have a much greater contribution to the growth of the California PEV market than organizations. In general, the most powerful predictor variables for neighborhood-level PEV adoption can be categorized into five groups, including housing characteristics, pro-environment intention and behaviors, demographic characteristics, socioeconomic characteristics, and infrastructure.

The market penetration of PEVs is generally higher in more affluent neighborhoods with many homeowners and highly-educated residents. These neighborhoods typically have larger proportions of residents employed in the information technology sector or occupied in management, business, science and arts, residents with bachelor's or higher degrees, middle-aged residents, and households with annual incomes greater than $200K and two vehicles available. On the other hand, the lack of pro-environment behaviors and the proportions of low-income households and low-value and high-density housing units negatively associate with PEV adoption. In addition, neighborhood-level preferences for the adoption of BEVs and PHEVs vary. For instance, the proportions of Asian populations and foreign-born Asian populations have positive associations with BEV adoption, whereas employment in the information technology sector have shown a greater positive effect in predicting PHEV adoption.

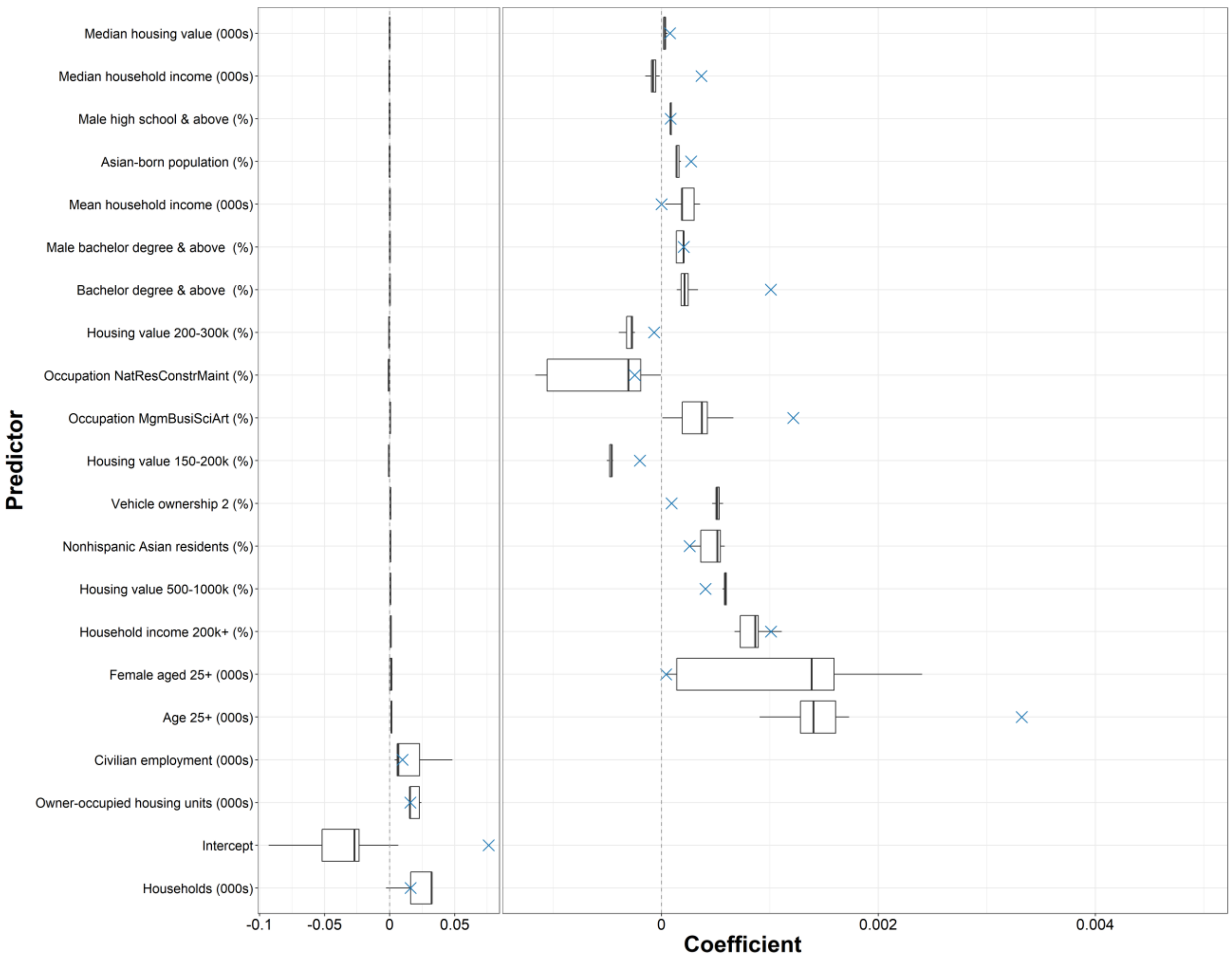
When taking into account both technology type and price range, there are additional insights on adoption motivations and technology preferences across the four vehicle groups: luxury BEVs, economy BEVs, luxury PHEVs, and economy PHEVs. The levels of pro-environment intention and behaviors play a more significant role in motivating economy BEV adoption than economy PHEV adoption. The proportion of residents who are at least 25 years old has relatively larger effects in predicting the adoption of luxury BEVs, luxury PHEVs, and economy PHEVs. The proportion of residents with at least high school completion positively associates with the adoption of economy BEVs and economy PHEVs, whereas the proportion of highly-educated residents is a predictor of economy BEV adoption. Highest-earning households have relatively stronger preferences for luxury BEVs and economy PHEVs than economy BEVs. Two-vehicle households have demonstrated greater preferences for economy PHEVs and economy BEVs. Earnings, travel behaviors and subsequent charging needs vary by occupation, industry, and worker class, resulting in varying preferences for specific PEV technology across different types of employment status and commute patterns. In addition, long commute time and the opportunity to reduce commute time by accessing HOV lanes are associated with the adoption of economy PHEVs.

In this study, I am particularly interested in exploring the roles of away-from-home charging infrastructure and HOV lane access in predicting PEV adoption. Holding everything else constant, an increase of 10 km in the length of HOV lanes within a 10 km radius is associated with an increase of 0.2-0.5 PEVs for a neighborhood with cumulative PEV sales of 500 vehicles and a percentage point increase of up to 0.0002 for a neighborhood with a cumulative PEV share of 10%. Similarly, an increase of 100 public DC fast chargers within a 50 km radius is associated with 1-3 more PEVs for a neighborhood with cumulative PEV sales of 500 vehicles and a percentage point increase of up to 0.002 for a neighborhood with a cumulative PEV share of 10%. In addition, an increase of 100 private Level 1 chargers within in a 10 km radius is associated with a percentage point increase of up to 0.008 in PEV share for a neighborhood with a cumulative PEV share of 10%. Thus, the deployment of workplace charging may be more effective than the deployment of public DC fast charging, which is consistent with previous studies (Hardman et al., 2018). When taking into account both technology type and price range, I find that (1) workplace charging is important for the adoption of luxury PEVs particularly luxury PHEVs; (2) the availability of public DC fast chargers positively associates with the adoption of economy BEVs; (3) public DC fast chargers on a local scale supports luxury BEVs, and public DC fast chargers on a regional scale also supports economy PHEVs; (4) the deployment of public slow chargers negatively associates with PEV adoption, and thus may not be an effective strategy to incentivize PEV adoption; (5) HOV lane access positively associates with the adoption of PHEVs and luxury BEVs. Although this study shows a positive effect of HOV lane access in predicting PEV adoption, as Sheldon & DeShazo (2017) discussed, the overall impact of allowing PEVs free access to HOV lanes would depend on the net environmental benefits as a result of increased PEV adoption and the increased congestion costs due to the reduced time savings and reliability.

From a methodological perspective, this study demonstrates the advantages of integrating lasso regression with Monte Carlo sampling in the prediction of neighborhood-level PEV adoption. First, model dimension has greatly reduced from 338 potential predictor variables to 18-50 predictor variables. All the best predictive models have low out-of-sample RMSE and relatively high values of out-of-sample adjusted R^2 (0.62 - 0.82). This approach maintains a reasonable balance between statistical bias and variance. Second, the coupling of Monte Carlo sampling reduces the uncertainty that is rooted in the process of cross-validation for parameter tuning, which enhances the confidence in interpreting the effects of selected predictor variables. Third, this study takes full advantage of census tract level information that is publicly available and offers an analytical framework for understanding neighborhood-level PEV adoption in a more cost-effective way. Analyzing neighborhood-level aggregate PEV adoption also captures the effect of the observability of PEV use, which a number of recent studies have found a relatively large positive effect on an individual's adoption decision (Carley et al., 2019; Jansson, Pettersson, et al., 2017; Westin et al., 2018). This study also has a number of limitations. First, the modeling framework focuses on predictive power instead of explanatory power, which limits the ability to test causal relationships. However, testing the causal aspects of PEV adoption is not the focus of this study. Exploring the causal effects of the most important variables identified in this study is one direction of future research. Second, vehicle share in this study is defined as the ratio of cumulative new PEV sales to total light-duty vehicle stock due to the lack of data on new light-duty vehicle sales, which include both ICEV and EV sales. In addition, the study only focuses on the new vehicle market. The accounting for PEV sales in the used vehicle market is another direction of future research to assess PEV adoption, especially in disadvantaged and low-income communities. Lastly, future research may benefit from using a multi-level modeling approach that accounts for demographic and socioeconomic characteristics at both neighborhood and regional levels, as census tracts are based on geographical boundaries for data collection instead of where household activities and social interactions actually take place.

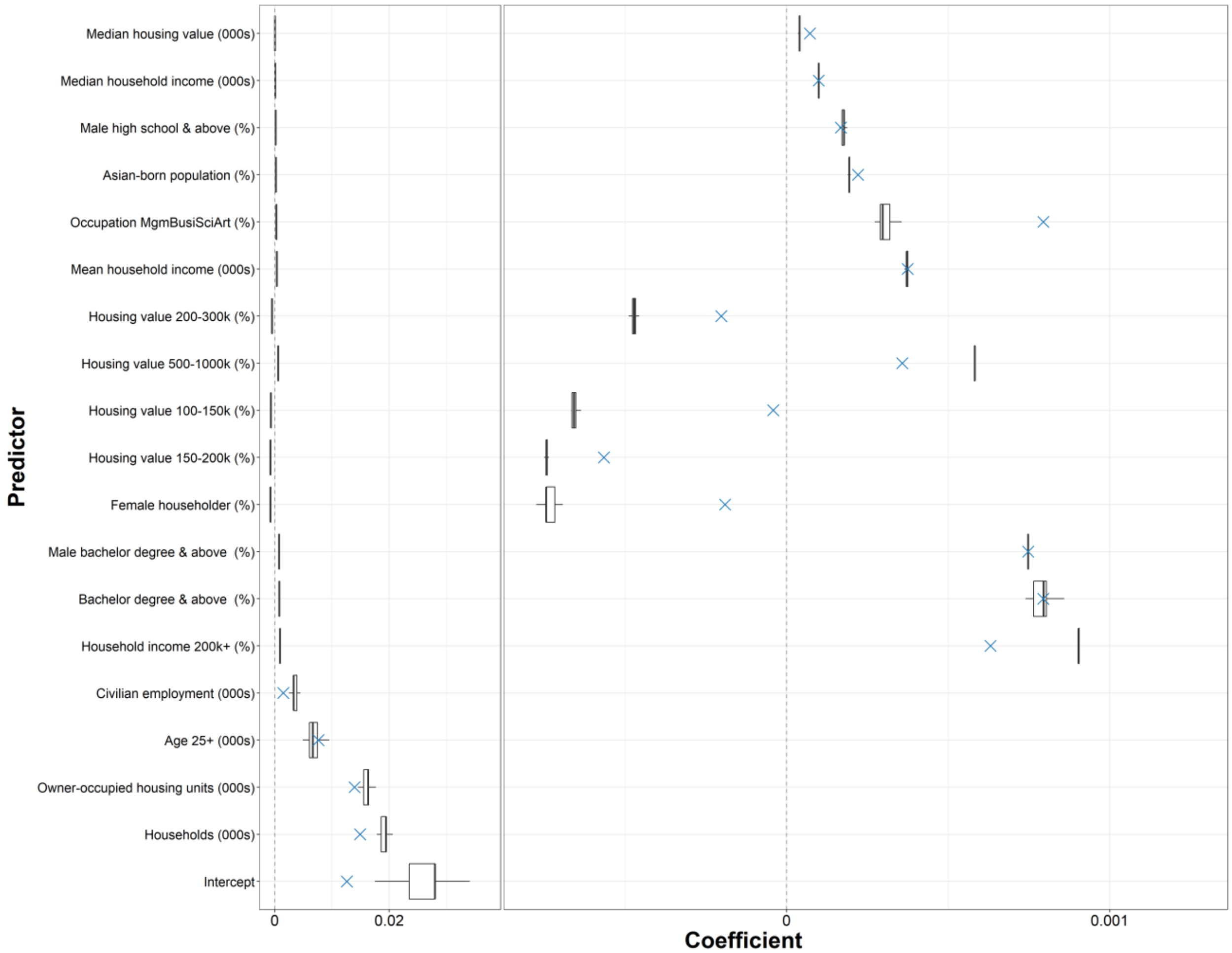
Appendix: Supplementary Information

Supplementary Figures



Supplementary Figure 3-1. Results of models predicting the number of cumulative new luxury and economy BEVs (000s) in a tract

"X" represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.



Supplementary Figure 3-2. Results of models predicting the number of cumulative new luxury BEVs (000s) in a tract

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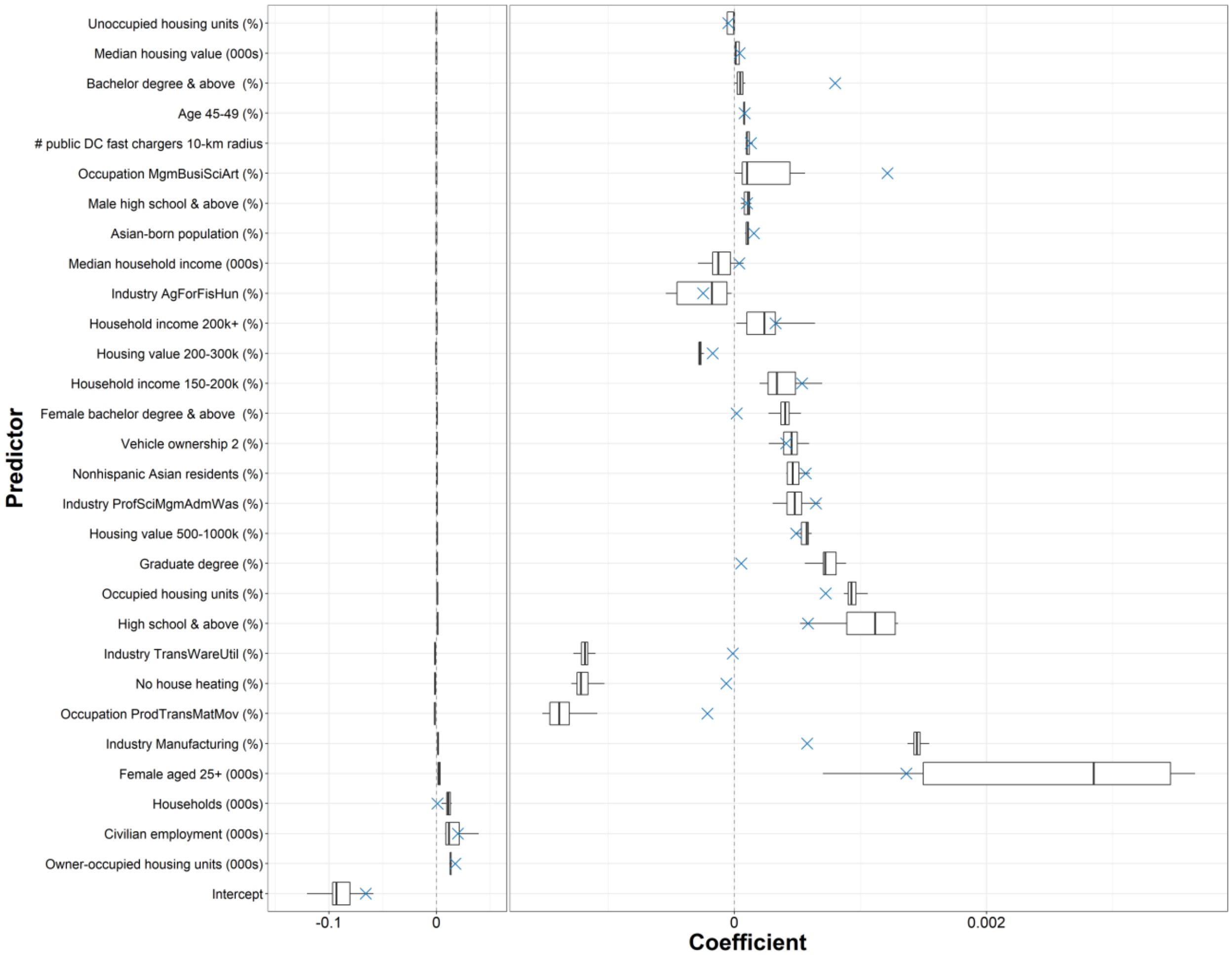

Supplementary Figure 3-3. Results of models predicting the number of cumulative new economy BEVs (000s) in a tract

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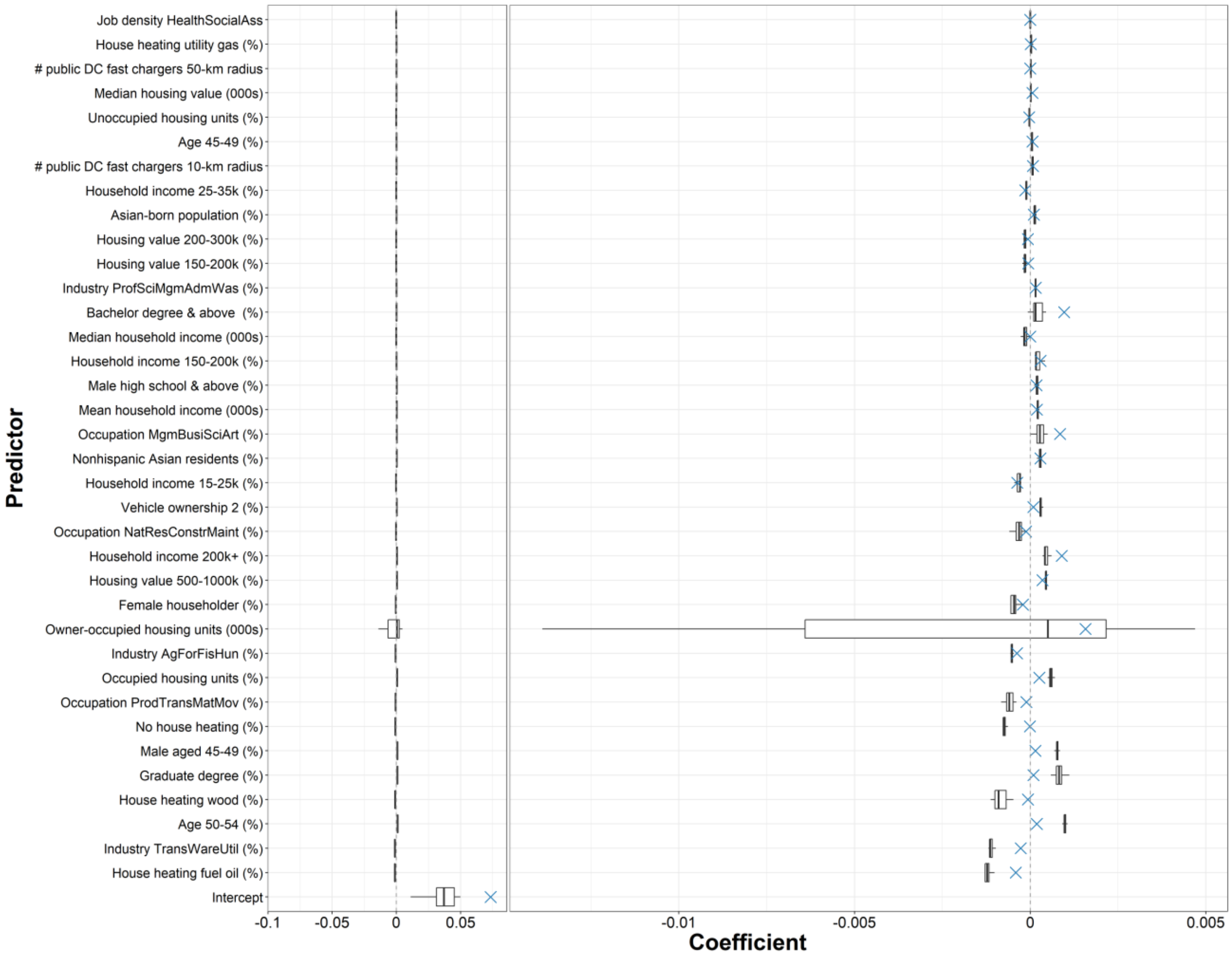
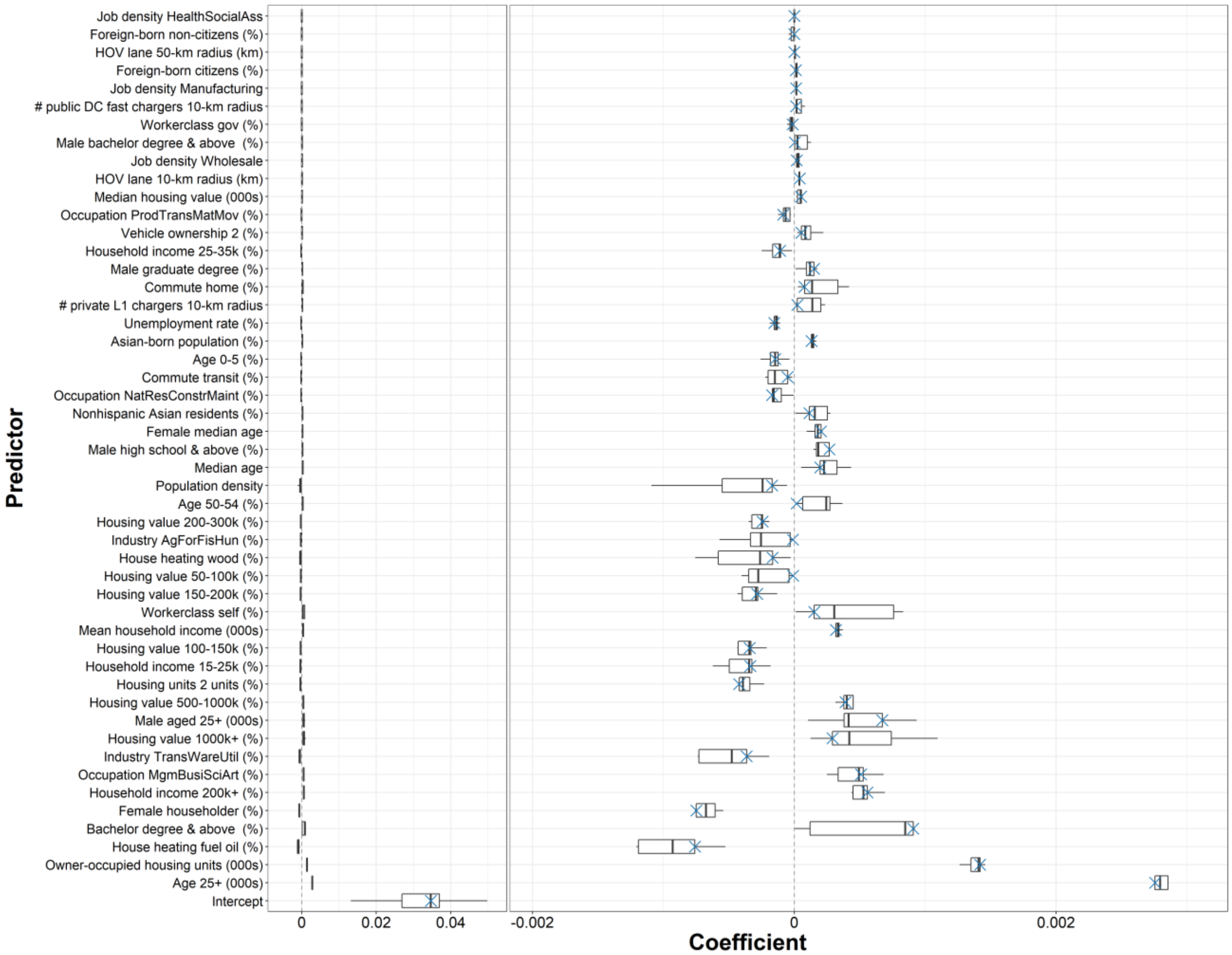


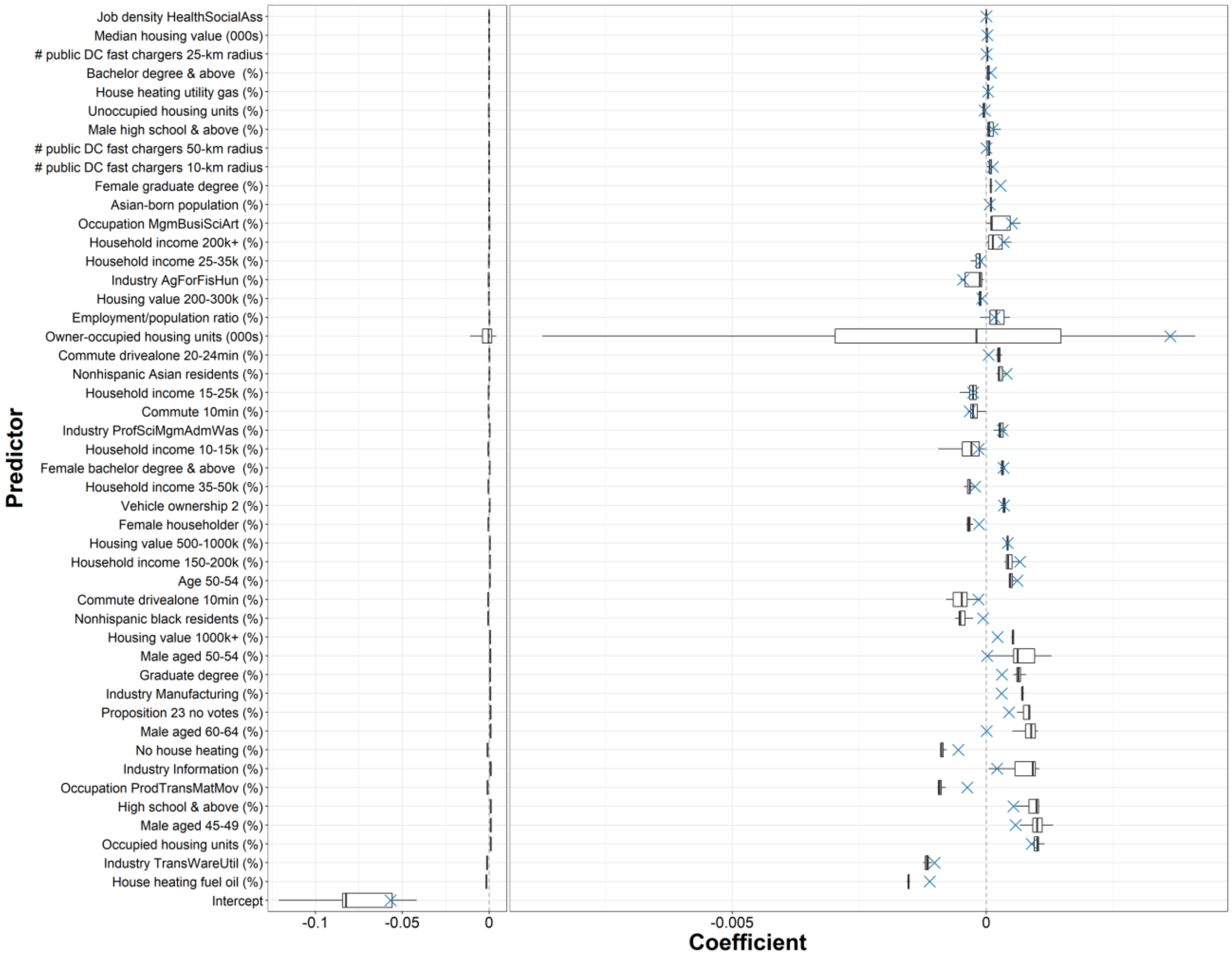
Supplementary Figure 3-4. Results of models predicting the share of cumulative new luxury and economy BEVs (%) in the total vehicle stock of a tract

"X" represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.



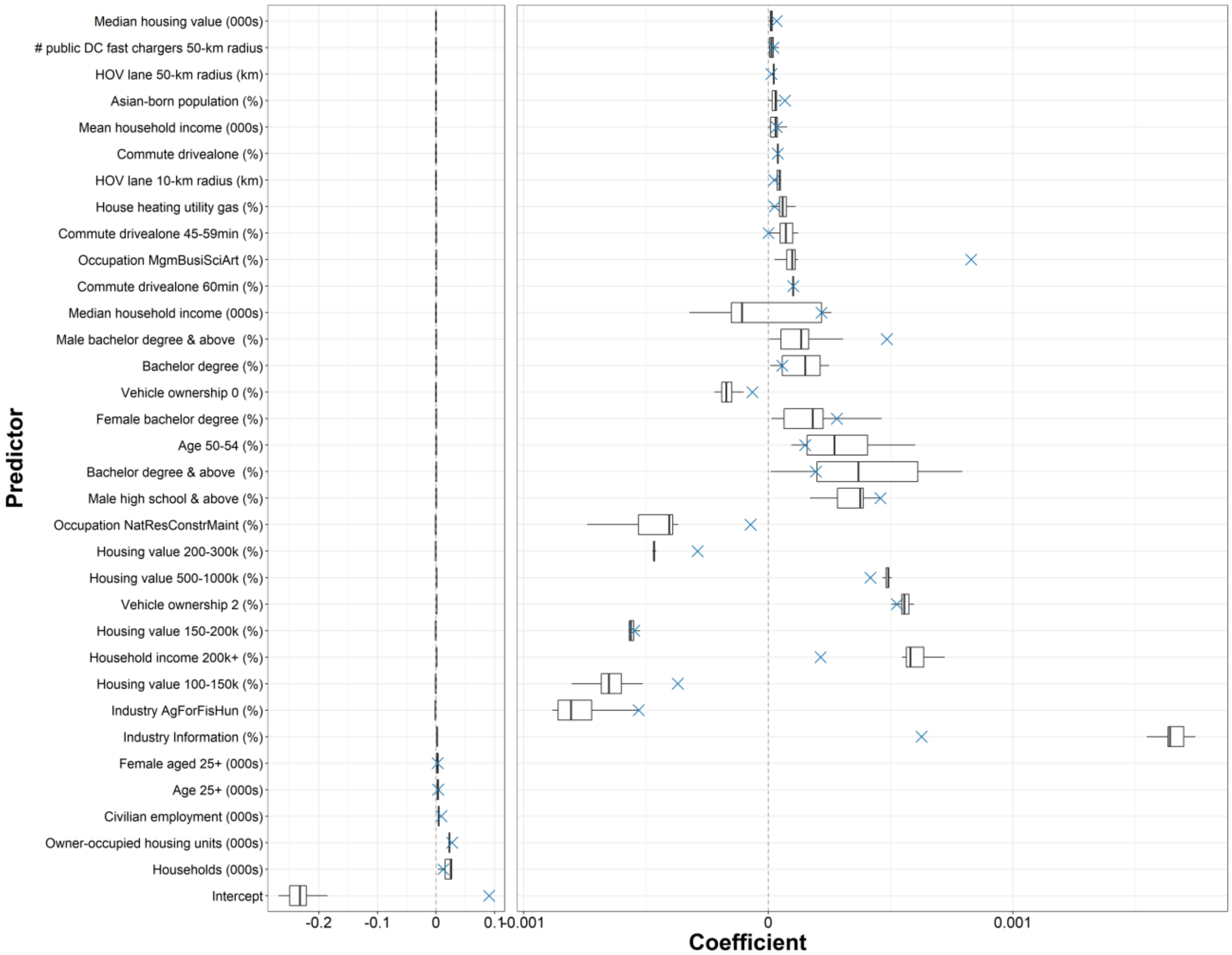
Supplementary Figure 3-5. Results of models predicting the share of cumulative new luxury BEVs (%) in the total vehicle stock of a tract

"X" represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.



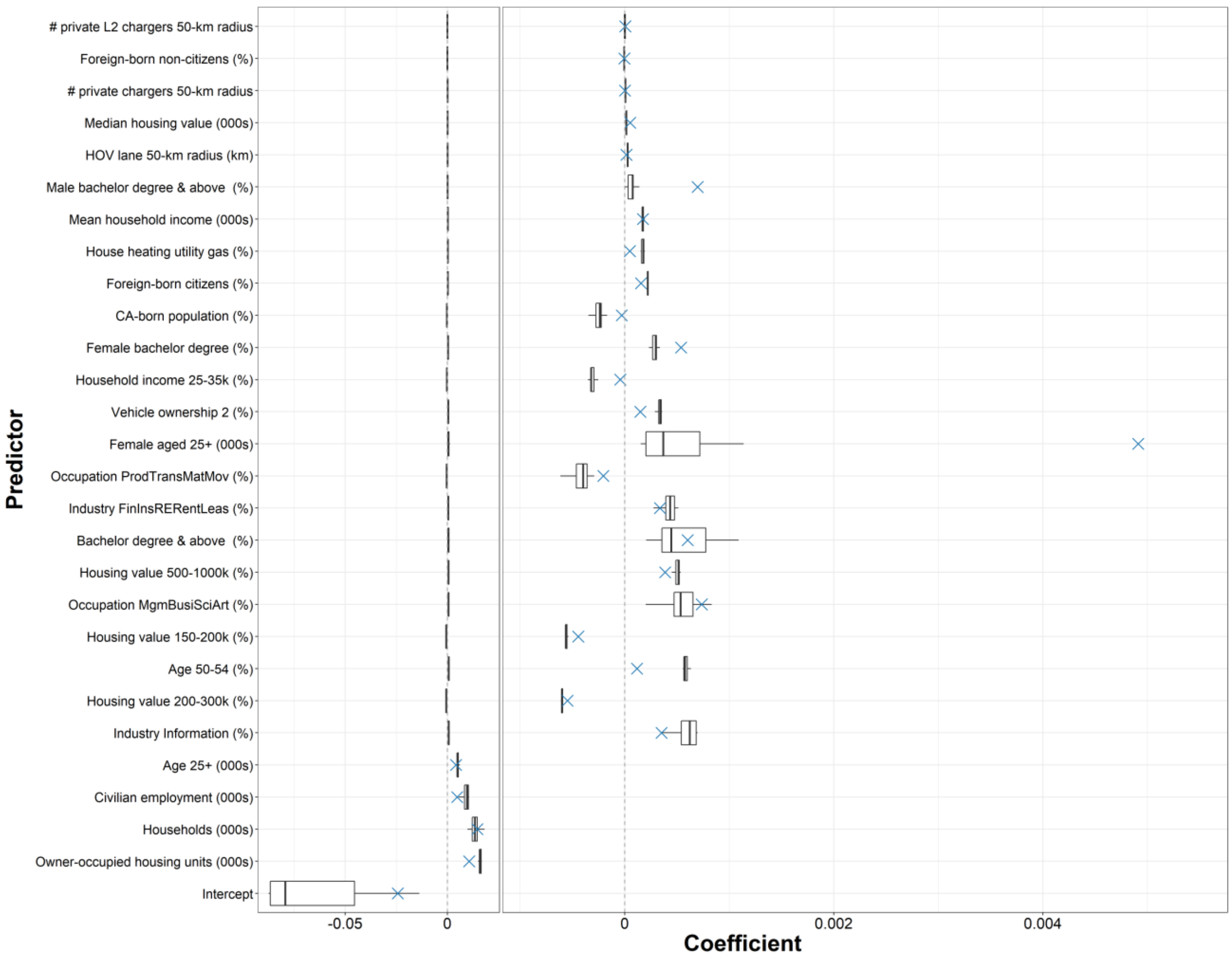
Supplementary Figure 3-6. Results of models predicting the share of cumulative new economy BEVs (%) in the total vehicle stock of a tract

“X” represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.



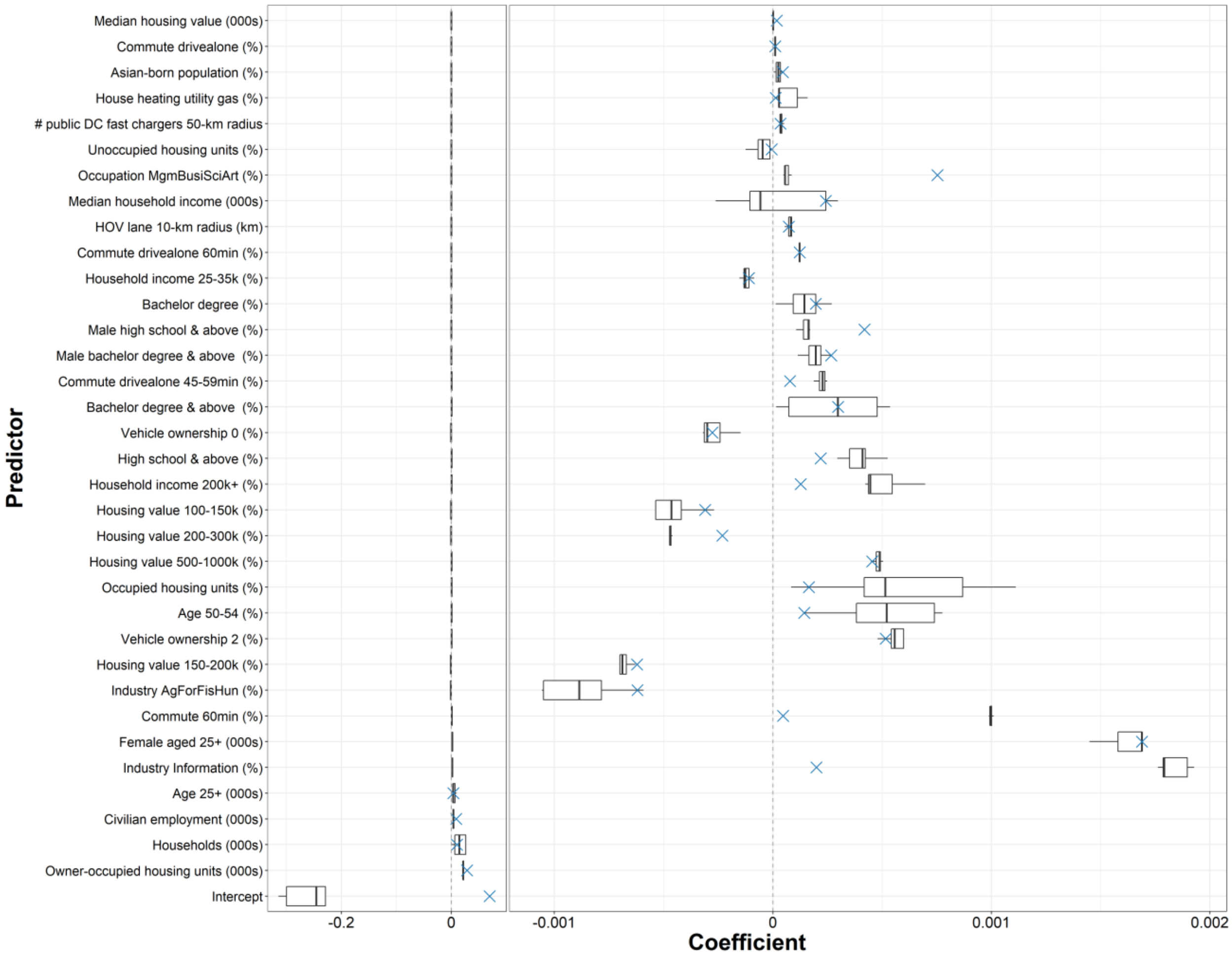
Supplementary Figure 3-7. Results of models predicting the number of cumulative new luxury and economy PHEVs (000s) in a tract

"X" represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.



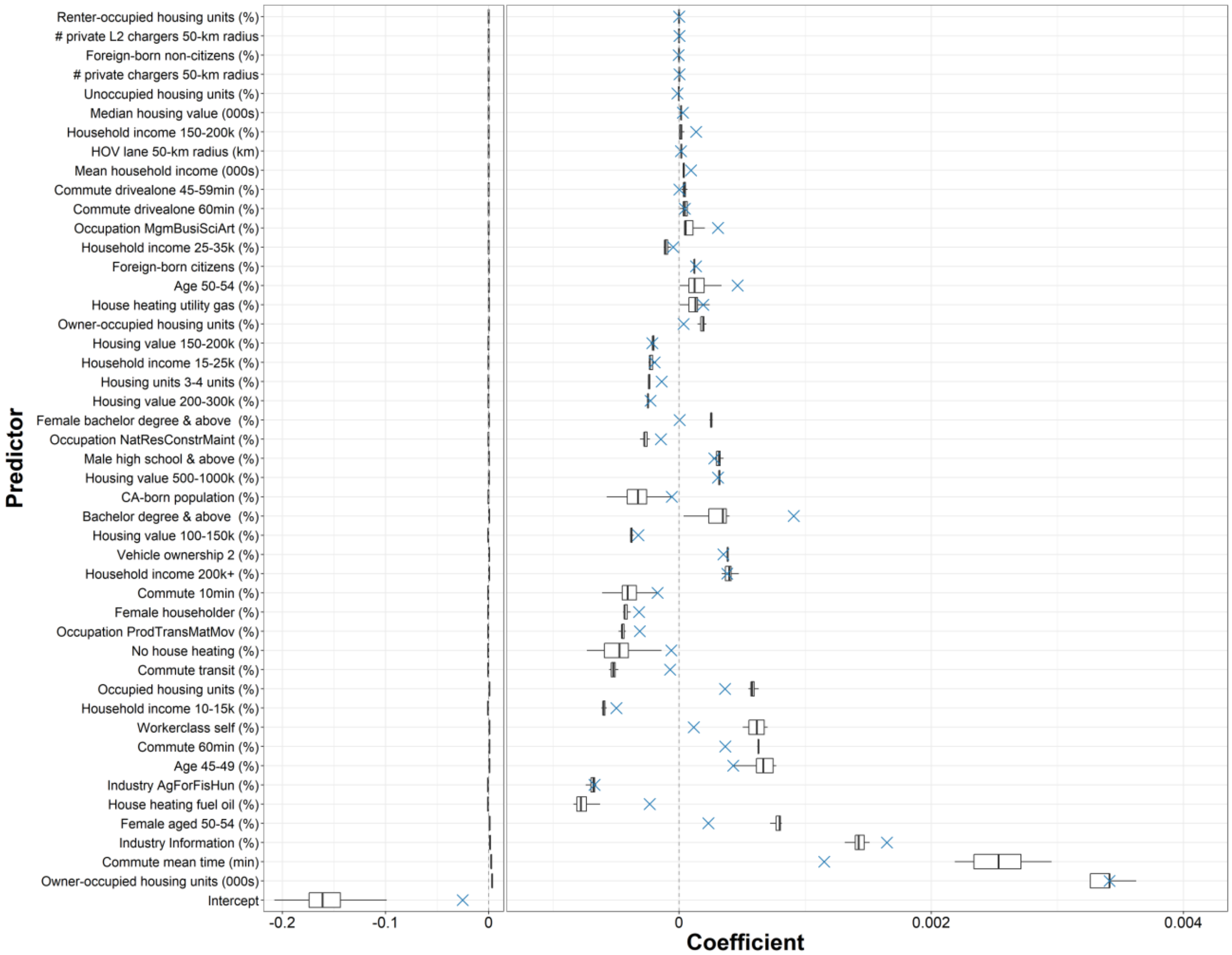
Supplementary Figure 3-8. Results of models predicting the number of cumulative new luxury PHEVs (000s) in a tract

"X" represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.



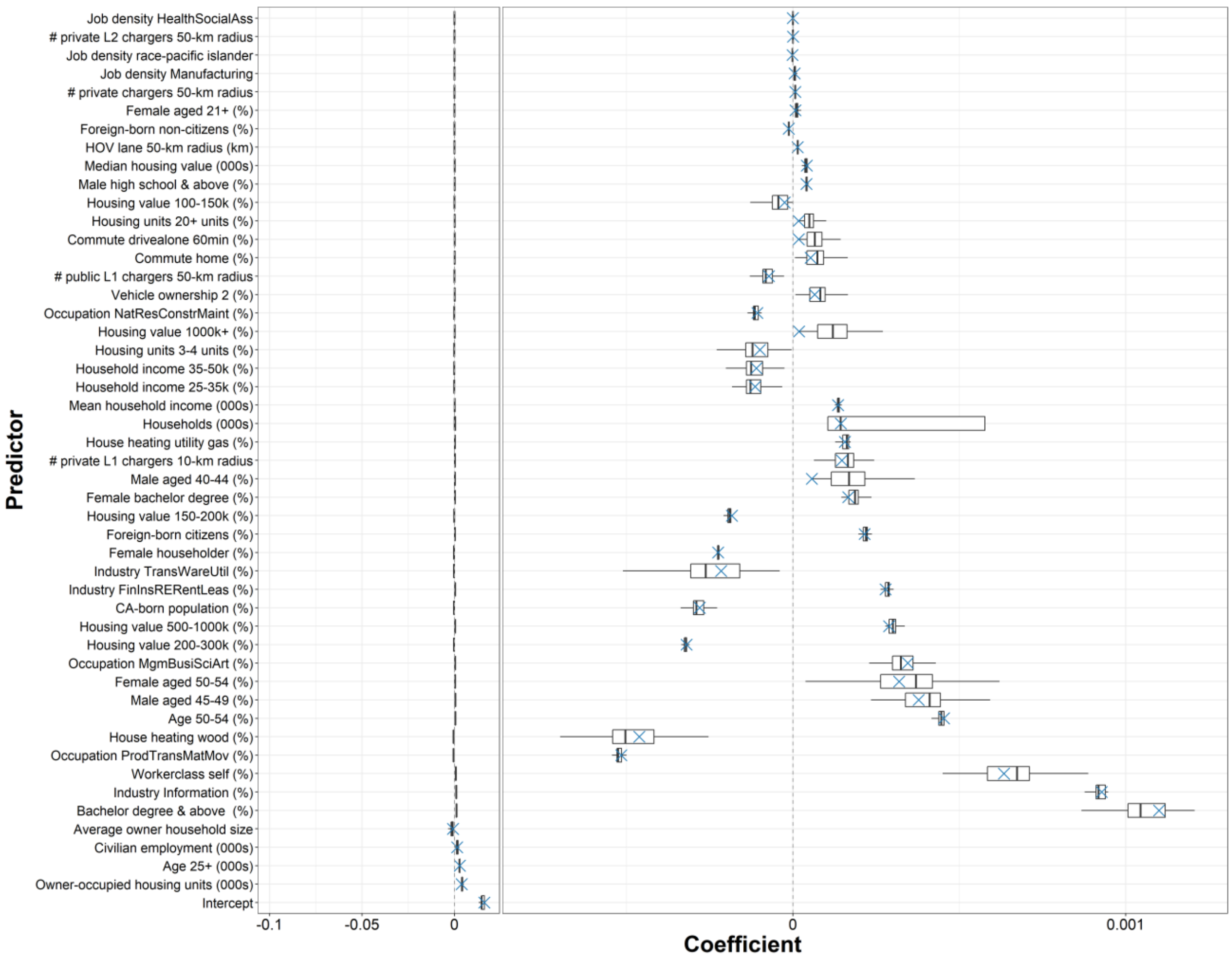
Supplementary Figure 3-9. Results of models predicting the number of cumulative new economy PHEVs (000s) in a tract

“X” represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.



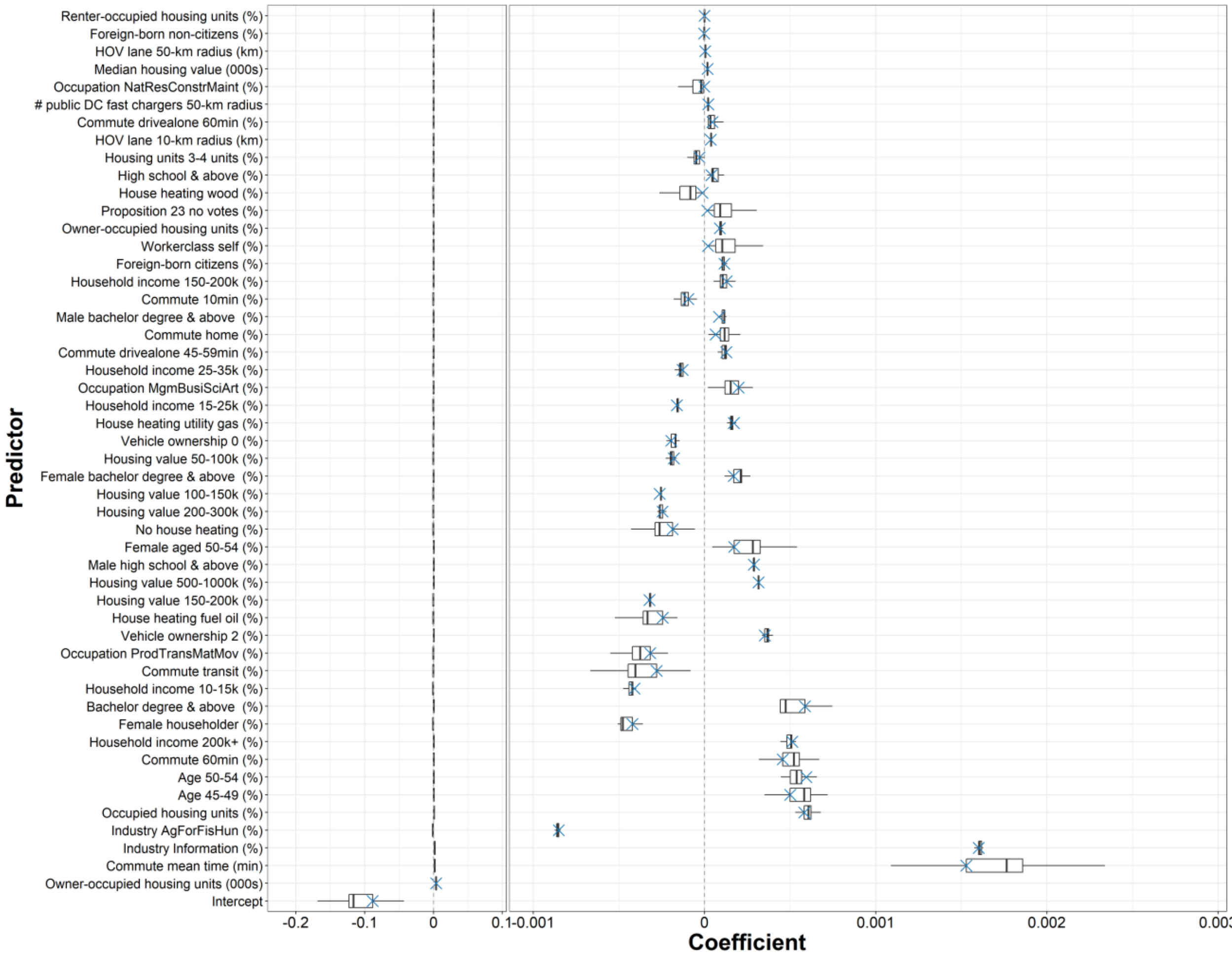
Supplementary Figure 3-10. Results of models predicting the share of cumulative new luxury and economy PHEVs (%) in the total vehicle stock of a tract

"X" represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.



Supplementary Figure 3-11. Results of models predicting the share of cumulative new luxury PHEVs (%) in the total vehicle stock of a tract

"X" represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.



Supplementary Figure 3-12. Results of models predicting the share of cumulative new economy PHEVs (%) in the total vehicle stock of a tract

“X” represents coefficient estimates from the final model, and boxes and whiskers show the range of coefficient estimates from all 1000 candidate models.

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Chapter 4: The use of General Transit Feed Specification data for the regional planning of transit bus electrification: A case study of Los Angeles County

Abstract

Transit bus electrification offers an important opportunity to improve air quality in urban communities and contribute to greenhouse gas (GHG) emissions reduction. Besides the high upfront costs of battery electric buses (BEBs), the deployment of charging infrastructure remains another significant challenge for the wider adoption of BEBs. Through the development of the Infrastructure Planning for Electric Buses (IPEB) tool, I designed a data-driven framework to model bus fleet turnover, analyze the energy and environmental impacts of transit bus electrification, and estimate charging infrastructure needs and costs in Los Angeles County from 2020 to 2040. I find that California's Innovative Clean Transit (ICT) regulation and local BEB transition commitments would result in a significant increase in electricity demand at transit agencies over the next five to ten years. The transition to BEBs would increase particulate matter emissions from brake and tire wear in the near term and immediately reduce NOx, CO, and GHG emissions. By replacing CNG buses with BEBs at the ten transit agencies I analyzed, Los Angeles County could reduce its weekday GHG emissions by 411-473 metric tons in 2025 and up to 888 metric tons by 2040. In addition, I find that 100-kW and 200-kW plug-in chargers along with the deployment of smart charging could support the full pre-pandemic services for the majority of buses across the ten transit agencies, with the exception of six LA Metro buses. Smart charging would be a critical element in the planning of transit bus electrification, as it reduces costs associated with charging infrastructure and electric demand by lowering charger needs and shaving peak load. With certain objectives, such as minimizing total costs and

minimizing interference with the provision of transit services, the optimal scheme of charging infrastructure deployment can be identified for the cost-effective planning of transit bus electrification.

Introduction

Transit bus electrification offers an important opportunity to improve air quality in urban communities and contribute to greenhouse gas (GHG) emissions reduction. Air pollution disproportionally affects disadvantaged and low-income communities, where many people live close to busy roads with bus routes and freight activity (Chandler et al., 2016). Zero-emission buses (ZEB) have no tailpipe emissions and research has shown that life-cycle GHG emissions are at least 50 to 70 percent lower than those of diesel or compressed natural gas (CNG) buses (Chandler et al., 2016).

California has adopted a variety of policies and incentive programs, such as the Zero-Emission Truck and Bus Pilot Commercial Deployment Projects and the Hybrid and Zero-Emission Truck and Bus Voucher Incentive Project, to spur the growth of the electric vehicle market in the medium-duty and heavy-duty vehicle sectors. These incentive programs aim to incentivize the adoption of zero-emission vehicles by offsetting the high upfront costs. Vehicle purchase costs have decreased over time and ZEB technologies are moving towards lifecycle cost parity with conventional bus technologies (Ambrose et al., 2017; CARB, 2018a; Deliali et al., 2020; Johnson et al., 2020). As of May 2018, 132 zero-emission buses (110 battery electric buses and 22 fuel cell electric buses) are in operation across California and additional 655 zero-emission buses are on order, awarded, or planned (CARB, 2018b). In December 2018, the California Air Resources Board adopted the Innovative Clean Transit (ICT) regulation. The ICT regulation requires a gradual transition to ZEBs by 2040 for all transit agencies in California. Table 1 shows the timeline of ZEB purchasing requirements under the ICT regulation (CARB, 2019). Starting in 2023, transit agencies are required to have increasing fractions of ZEBs in new bus purchases, which culminates in a requirement that all new buses be zero-emission in 2029. In Los Angeles County, four transit agencies, including the Los Angeles County Metropolitan Transportation Authority (LA Metro), Foothill Transit, the Los Angeles Department of Transportation (LADOT), and the Santa Monica Big Blue Bus, have committed to a 100 percent electric fleet in operation by 2030. Given these state regulations and local commitments, public transit buses will be on the leading edge of vehicle electrification in the medium-duty and heavy-duty vehicle sectors.

Table 4-1. ZEB purchasing requirements under California's ICT regulation

Starting date[a]	Minimum share of ZEBs in new bus purchases[a]	Applicable bus type[a]	Type of transit agencies[a]
January 1, 2023	25%	Buses	Large transit agencies[c]
January 1, 2026	25%	All buses[b]	Small transit agencies[d]
	50%	All buses	Large transit agencies
January 1, 2029	100%	All buses	All transit agencies

Notes: [a] Data source: CARB (2019).
[b] All buses include buses, articulated buses (i.e., 54-foot to 60-foot buses with two connected passenger compartments), double-deckers, and coaches or motor coaches;
[c] Large transit agencies in the South Coast refer to agencies with more than 65 buses in annual maximum service;
[d] Small transit agencies in the South Coast refer to agencies with 65 or fewer buses in annual maximum service.

Although both battery electric buses (BEB) and fuel cell electric buses (FCEB) are both considered as ZEBs, BEBs are expected to be the primary technology to be widely adopted in California given the high costs and limited availability of FCEBs (Ambrose, Pappas, & Kendall, 2017). Besides the high initial purchase price relative to conventional buses, adding BEBs to a transit operator's fleet requires substantial charging infrastructure investments as well. In concert, high vehicle and infrastructure costs pose a significant challenge to the wider adoption of BEBs. In this chapter, my goals are to: (1) review the most recent technology development in BEBs and charging infrastructure; (2) analyze charging needs, charging infrastructure costs, and grid impact of transit bus electrification in Los Angeles County, taking into account actual fleet turnover behaviors and transit bus operations; and (3) provide insights on the regional planning of BEB charging infrastructure in the context of a large metropolitan area, like Los Angeles. In order to achieve these goals, I developed the Infrastructure Planning for Electric Buses (IPEB) tool, which is discussed in details in the methods section.

Depending on battery capacities and transit vehicle operations, some routes may be served by buses operating on a single, slow charge obtained off-duty at a bus depot. Others operating on longer or more demanding routes may require on-route fast charging to augment an initial bus depot slow charge. The costs associated with charging will vary by the type of charging being deployed, the location of charging and its connection to electric utilities, and the daily service profile of the BEB fleet. Thus, effective charging infrastructure planning is critical to operating transit services with BEBs.

First, effective charging infrastructure planning helps transit agencies minimize costs associated with charging infrastructure and electric demand, and eventually reduce the lifecycle costs of BEBs. In addition, charging at bus depots may significantly affect local electric grid infrastructure when a large number of buses are charged simultaneously. On-route fast charging will demand very high power for short intervals, which can stress the grid and limit where such charging can occur. Understanding the growth and patterns of BEB charging, as well as vehicle route and service schedules will prepare the electric utilities for expected load increases and the grid upgrades needed to accommodate them.

In this study, I developed a data-driven analytical framework to support research and practice in the area of BEB charging infrastructure planning. I start with the projections of bus fleet turnover over time and a review of current technology development in BEB and charging technologies, and then estimate the electricity consumption, emissions change, charger needs, and charging infrastructure costs based on the projected number of BEBs and transit bus operations from 2020 to 2040. In the following section, I describe the methods and data sources used for the analysis and the key findings. Finally, I conclude with implications for the energy and environmental impacts of transit bus electrification and charging infrastructure planning.

Methods

I developed the IPEB based on actual bus fleet turnover behaviors and operations at ten public transit agencies operating in Los Angeles County (Table 4-2 and Figure 4-1). These transit agencies in general are among the largest by fleet size in the County and all publish their General Transit Feed Specification (GTFS)static datasets. As demonstrated in Figure 4-2, the IPEB consists of three modules: (1) a fleet turnover module, which takes into account historical bus retirement schedules and requirements for ZEB purchase under the ICT regulation; (2) a transit bus operations module that optimizes vehicle-level operations and estimates daily distance traveled at the vehicle level; and (3) an infrastructure planning module that optimizes the deployment of charging infrastructure. Details on each of the three modules are further described below.

Table 4-2. Transit agency profiles

Transit agency	Service area (km^2)[a]	Bus fleet size in 2020[b]	Number of bus depots[c]	Number of bus routes[d]	Target year for 100% electric fleet[e]
LA Metro	3675	2,346	11	143	2030
Foothill Transit	847	376	2	39	2030
LADOT	1204	321	4	46	2030
Long Beach Transit	254	224	1	40	2040
Big Blue Bus	153	195	1	20	2030
Torrance Transit System	267	63	1	11	2040
GTrans	104	54	1	5	2040
Culver CityBus	85	54	1	8	2040
Glendale Beelines	101	38	1	1	2040
Norwalk Transit System	96	33	1	6	2040

Note: [a] Data source: the National Transit Database agency profiles
[b] Data source: the National Transit Database and the American Public Transportation Association's Public Transportation Vehicle Database
[c] Data source: transit agency websites
[d] Data source: General Transit Feed Specification static datasets
[e] The 2030 target year is based on agency announcements and the 2040 target year is based on the requirement in the ICT regulation.

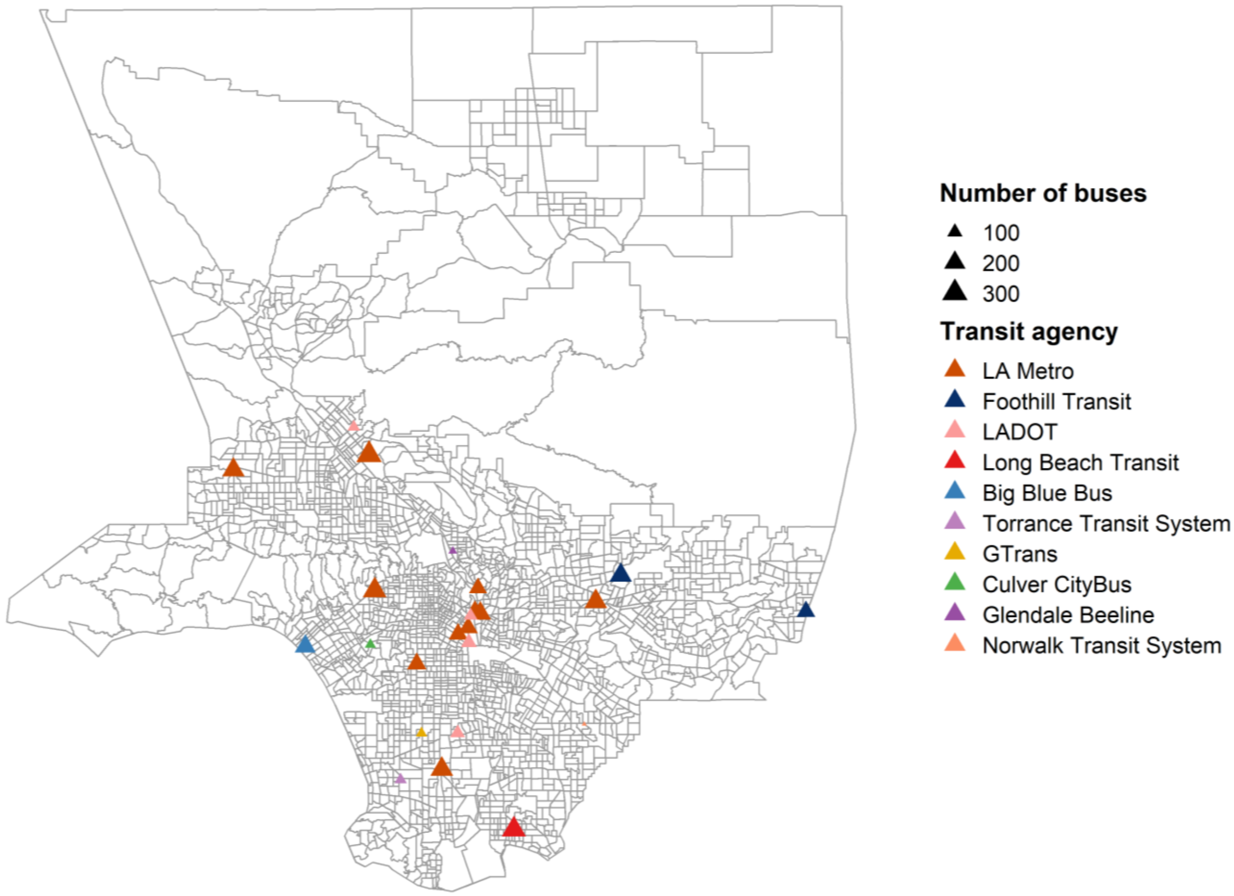


Figure 4-1. Bus depots maintained by the ten Los Angeles County transit agencies

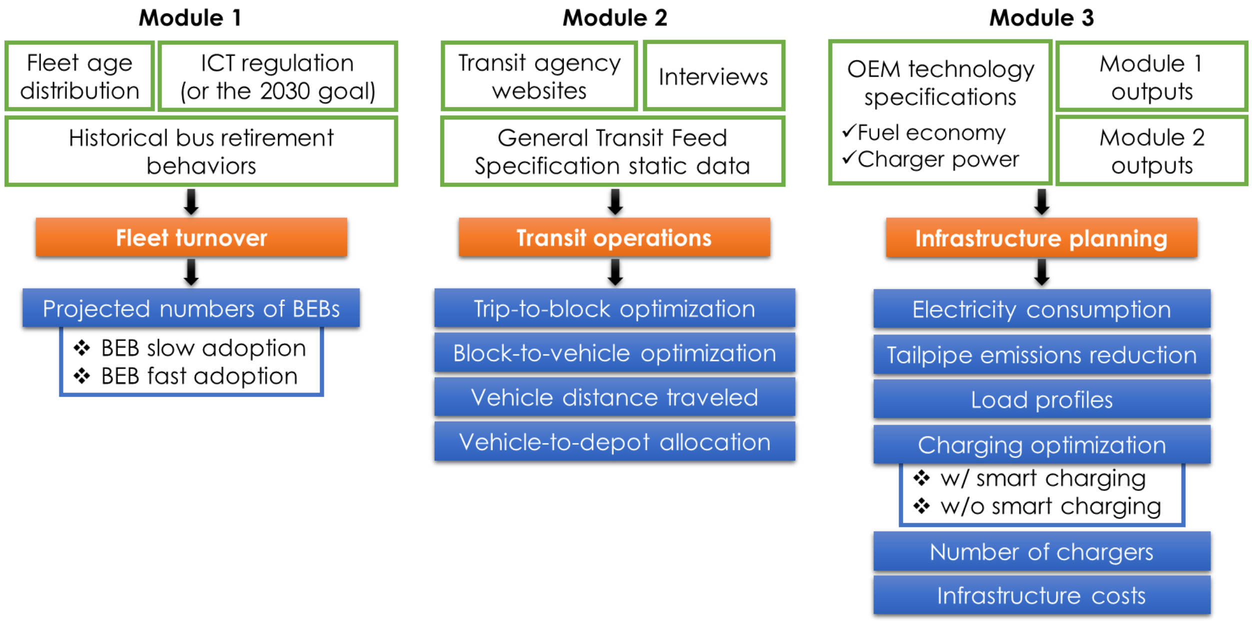


Figure 4-2. An overview of the IPEB tool

The fleet turnover module. Major data sources include the National Transit Database (NTD) and the Public Transportation Vehicle Database (PTVD). Since 1974, the NTD has served as the primary source of information on the financial, operating, and asset conditions of the US public transit systems. The annual vehicles datasets contain the age distribution of revenue fleets by vehicle type for each transit agency. I extrapolated historical bus life-cycle years at each transit agency using vehicle age distributions between 2015 and 2019. The American Public Transit Association (APTA) maintains the PTVD, which gets updated annually. The PTVD complements the NTD vehicles datasets by adding additional vehicle-level details such as fuel type, manufacturer, model, and capital costs for each member organization. The APTA also maintains a list of transit agencies and service providers by city, county, and state. I used this list for the initial screening of transit agencies that provide transit services in Los

Angeles County. According to the APTA, there are over 100 regional and local transit operators in Los Angeles County.

I used both data sources to compile the fleet composition for each transit agency in 2020 (Supplementary Table 4-1), which serves as the baseline for the fleet turnover module. I developed three scenarios of fleet turnover: the reference scenario and two BEB adoption scenarios. In the reference scenario, vehicle retirement takes place at the end of assumed bus life cycles, which are based on historical bus retirement behaviors. The two BEB adoption scenarios are based on the fleet turnover schedules in the reference scenario. For agencies that do not have a target of a 100 percent electric bus fleet by 2030, I assumed that agencies would meet the minimum requirements (25-100% in new purchases) during early years and eventually catch up later in order to have a 100 percent electric fleet by 2040. This represents a slow BEB adoption in earlier years, which I note as the BEB-slow scenario. Whereas in the BEB-fast scenario, I assumed that agencies would either implement a shorter bus life cycle than the reference scenario or immediately switch to BEBs whenever vehicle retirement takes place. A shorter life cycle results in faster retirement of conventional buses and thus leads to a quicker turnover and BEB adoption. For agencies with the target of becoming 100 percent electric by 2030 (i.e., LA Metro, Foothill Transit, LADOT, and Big Blue Bus), simply meeting the minimum requirements under the ICT regulation will not be enough; they will need to act early as possible. For LA Metro and Foothill Transit, given their recent purchases of CNG buses, some buses may have to be retired before the typical 12-year minimum service life. Specific assumptions on bus life cycle years for each transit agency are listed in Supplementary Table 4-2.

The transit bus operations module. The major data source for this module is the General Transit Feed Specification (GTFS) static datasets obtained from OpenMobilityData, which hosts historical transit data in both GTFS static and GTFS-realtime formats. The GTFS is a standardized format that many transit agencies and service providers use to publish their service schedules and associated geographic information such as bus stops, routes, and vehicle trips. Application developers can use the GTFS datasets to visualize the information across transit operators. Given that the majority of transit agencies have reduced service provision during the COVID-19 pandemic, I retrieved GTFS datasets that were published between April 2019 and November 2019 to represent full pre-pandemic operation.

In the GTFS format, vehicle movement is organized around a number of key concepts, including shapes, trips, stop times, stops, routes, and blocks. A trip is made of one or many shapes that define the path of vehicle movement during a trip. Thus, the distance of a trip can be estimated by the total length of all shapes within a trip (Eq. 1). The start time of a trip is the arrival time of a bus at the first stop of a trip, and the departure time at the last stop gives the end time of a trip. Thus, the time difference between the end time of a trip and the start time of its subsequent trip within the same block represents the dwell time of a bus at a stop in between two consecutive trips. The potential for the deployment of on-route charging is based on these bus dwell times. A trip may be as long as an entire route or a portion of a route, depending on where the first stop of the trip is along the route. A block consists of a sequence of trips assigned to a single bus (Eq. 2).

According to the GTFS datasets for the ten Los Angeles County transit agencies, the total number of blocks does not always match the total number of vehicles in service. In other words, a block as specified in the GTFS datasets may not always be interpreted as a vehicle. This is because transit agencies may specify blocks for GTFS in four possible ways: (1) a vehicle runs one block (for instance, GTrans and Culver CityBus); (2) a vehicle runs multiple blocks, and a vehicle ID can be retrieved from a block ID (for instance, LA Metro, Torrance Transit System, Culver CityBus, and Glendale Beeline); (3) a vehicle runs multiple blocks, but there is no direct link between a block and a vehicle (for instance, Foothill Transit, LADOT, and Long Beach Transit); and (4) there is no block information (for instance, Big Blue Bus and Norwalk Transit System). To address these varying ways of assigning blocks and vehicles, I developed an algorithm to optimize block-to-vehicle matching. This algorithm first chains blocks by matching the end stop of a block and the start stop of another block while ensuring the shortest time interval between the start time of the next block and the end time of a block. This step accounts for the fact that a vehicle may continue moving onto the next block right after completing the first block without returning to the bus depot. After the first-round of chaining, there are remaining blocks that are not perfectly aligned with one another. In other words, no end stop matches any of the start stops. This could be because a vehicle runs a block and then returns to the depot before starting the next block. To account for this situation, the algorithm continues with another round of chaining by only matching blocks by the chronological order. After the two rounds of chaining, the block-to-vehicle assignments are optimized. The optimization results were verified against the number of vehicles operated in maximum service (VOMS) at each agency. When no block information was available, I ran a trip-to-block optimization, the algorithm for which is the same as the first-round of block-to-vehicle optimization (i.e., matching both stops and times) as trips within a block are connected by the same nodes (i.e., the last stop of a trip or the first stop of a trip). I assumed the maximum vehicle dwell times between two trips are 20 minutes. When the dwell time is greater than 20 minutes, the trip-to-block matching stops and then the algorithm moves on to the chaining of the next set of trips. After both the trip-to-block optimization (when needed) and the block-to-vehicle optimization, revenue distance traveled of a bus can be estimated by aggregating the length of all trips that are assigned to the bus (Eq. 3). To account for non-revenue "deadhead miles", which are the distances traveled with no passengers on board between a depot and a bus stop or when changing routes, I estimated the daily average deadhead-distance-to-revenue-distance ratios for each agency using the NTD 2019 service dataset. These agency-level ratios were then used to estimate the total distance traveled for each vehicle (Eq. 4). The equations for estimating the vehicle-level total distance traveled are the following:

$$Trip_{j,i} = \sum_{1}^{m} Shape_{i,m} \qquad \text{…Eq. (1)}$$

$$Block_{k,j} = \sum_{1}^{i} Trip_{j,i} \qquad \text{...Eq. (2)}$$

$$Vehicle_{l,k} = \sum_{1}^{j} Block_{k,j} \qquad \text{...Eq. (3)}$$

$$TOT\_Vehicle_{l,k} = Vehicle_{l,k} * (1 + R_l) \qquad \text{...Eq. (4)}$$

where,

$TOT\_Vehicle_{l,k}$ - total distance traveled by Vehicle *k* at Agency *l*;

$Vehicle_{l,k}$ - revenue distance traveled by Vehicle *k* at Agency *l*;

R_l - the average deadhead-distance-to-revenue-distance ratio at Agency *l*;

$Block_{k,j}$ - distance traveled by Vehicle *k* in Block *j*;

$Trip_{j,i}$ - the length of Trip *i* within Block *j*;

$Shape_{i,m}$ - the length of Shape *m* within Trip *i*.

For transit agencies with multiple depots, the transit operations module also optimizes the vehicle-to-depot allocation. I developed an algorithm to calculate the driving distances between each depot and the first stop of a vehicle using the openrouteservice API. The process of vehicle-to-depot allocation then assigns each vehicle to a depot according to the minimum distance. When a depot reaches its parking capacity, it is removed from the allocation process and other vehicles continue to be assigned to other depots according to the new minimum distance. The location and parking capacity of each bus depot was either obtained from transit agency websites and reports or manually verified using the satellite imagery on Google Maps. In Los Angeles County, there are three multi-depot transit agencies: LA Metro (11 bus depots), Foothill Transit (2 bus depots), and LADOT (4 bus depots). The vehicle-to-depot allocation process was applied to LA Metro and LADOT. Foothill Transit's GTFS data include bus depot information in the service identification numbers, which can be directly used to identify vehicle-to-depot allocation without the need to run the allocation process.

The infrastructure planning module. The module relies on outputs from the first two modules and a review of the most recent development in both BEB vehicle and charging technologies. The technology review provides additional inputs to the infrastructure planning module, including: (1) the original equipment manufacturer (OEM) claimed range and battery size for each available BEB model, which are used to estimate average BEB fuel economy (km/kWh) by bus type and length; and (2) the charger power levels and efficiencies of each type of charging infrastructure. According to an interview with the operations team at the Foothill Transit (R. Cordero, personal communication, November 29, 2018), OEMs tend to claim the highest possible electric range in optimal, rather than typical, operating conditions . To account for this, I applied a coefficient of 0.7 to all OEM-claimed ranges to reflect the actual operating conditions. The coefficient is based on actual testing results from Foothill Transit.

With estimates of both fuel economy and required total vehicle distance (revenue plus non-revenue service distance) traveled, I could then estimate daily electricity consumption at the vehicle level. In addition, with emission rates of criteria air pollutants and GHGs obtained from the EMission FACtor (EMFAC) model, I could also estimate the avoided tailpipe emissions. The California Air Resources Board maintains the EMFAC model, which estimates on-road mobile vehicle emissions of major criterial pollutants and GHGs at various geographical scales in California. I obtained emission rates of PM2.5, PM10, NOx, CO, CO_2, CH_4, and N_2O from the latest version of the model, i.e., EMFAC2017 (v1.0.3). The avoided tailpipe emissions in a given year are estimated via multiplying projected electric vehicle kilometers traveled (eVKT) by the differences in projected emission rates (g/km) between a BEB and a CNG bus of that year in Los Angeles County. Details on specific emission rates over time can be found in Supplementary Table 4-3. Depot-level and/or agency-level estimates are aggregated from vehicle-level estimates.

The main focus of the infrastructure planning module is to estimate charger needs, costs, and grid impact (i.e., load profiles of BEB charging events) when deploying the three types of charging infrastructure: at-depot plug-in charging, on-route conductive charging, and on-route wireless charging. The analysis on charging needs and grid impact is based on the BEB quantities in future years (i.e., Module 1 outputs), daily vehicle distance traveled (i.e., Module 2 outputs), average BEB fuel economy under actual operating conditions, and charger power levels and efficiencies. Given that transit services peak during weekdays, I estimated daily charging needs and load profiles for weekdays to show the highest electrical loads over the course of a week. Specific assumptions on the deployment of each type of chargers are listed in Table 4-3.

For agencies with multiple bus depots, I assume electrification takes place depot by depot. This assumption is based on LA Metro’s strategy to fully electrify their Division 8 and 9 depots as a first step of the transition to a 100 percent electric fleet. At each depot, when only a portion of buses are projected to be electric at a certain year, electrification was assumed to start with buses traveling the longest distances for the estimation of the greatest charging needs. To estimate the potential load profiles, I designed two charging scenarios: (1) the unmanaged charging scenario, in which I assume that charging for all BEBs starts simultaneously with at-depot plug-in chargers; and (2) the managed charging scenario, where I assume charging is managed by a smart charging management system that queues the charging of BEBs in order to minimize the number of chargers needed and to reduce the peak load. For the managed charging scenario, I use a bin-packing[8] algorithm to estimate the maximum number of chargers needed within a fixed charging time period (i.e., between 9pm and 6am the next day). In Los Angeles County, the two electric utilities implement time-of-use (TOU) electric rates for their commercial customers. The lowest evening rates start at 8pm within the Los Angeles Department of Water and Power (LADWP) territory, while the Southern California Edison (SCE) starts charging the lowest evening rates at 9pm. Among the ten transit agencies included in the study, there are 15 bus depots located within the SCE territory and 9 bus depots located within the LADWP territory. To be consistent, I assume charging at all 24 bus depots starts at 9pm. To avoid interfering with service provision during the morning peak hours, I assume at-depot charging would have to be completed by 6am the next day under the managed charging scenario. When charging cannot be completed with a standard slow charger (at 100-kW power level) within the available time period, fast chargers (at 200-kW power level) would be deployed. I assume the charging efficiency of plug-in chargers to be 91.4 percent based on actual testing results from the National Renewable Energy Laboratory(L. Eudy & Jeffers, 2018a, 2017; Johnson et al., 2020). Under the managed charging scenario, when charging for certain buses

[8] Fitting objects of different sizes into bins of the same size.

(i.e., the ones with the longest daily distances traveled) cannot be completed before 6am next day, I assume that on-route overhead charging will be deployed to complement at-depot plug-in charging. Thus, the charging needs under the unmanaged charging scenario will be solely based on the use of 100-kW plug-in chargers at the depot, whereas charging under the managed charging scenario may be completed by a number of slow plug-in chargers, a number of faster plug-in chargers, and a number of on-route overhead chargers. Total charging infrastructure costs are based on the unit costs of each type of chargers and the number of chargers needed under each of the two charging scenarios. For each bus depot, hourly load profiles are estimated under each charging scenario and each BEB turnover scenario.

Table 4-3. BEB charging infrastructure assumptions

Category	At-depot plug-in charging	On-route overhead charging	References
Charger power (kW)	100/200	325	(ICF, 2019; Johnson et al., 2020)
Charging efficiency	91.4%	91.4%	(L. Eudy & Jeffers, 2018a, 2017; Johnson et al., 2020)
Charger capital costs ($ per charger)	40,000/50,000	495,636	(ICF, 2019; Johnson et al., 2020)
Charger installation costs ($ per charger)	17,050	202,811	(Johnson et al., 2020)
Charger maintenance costs ($ per charger)	48,000/66,000	216,000	(ICF, 2019; Johnson et al., 2020)
Charger total costs ($ per charger)	105,050/133,050	914,447	Based on the above three categories
Charging period	9pm-6am	Whenever needed	

Results and Discussion

The current state of BEB and charging technologies

Although a growing number of conventional bus manufacturers have announced plans for new BEB production lines, there are currently four manufacturers that dominate the BEB market in the US: Build Your Dream (BYD), Proterra, GreenPower, and New Flyer (Supplementary Table 4-4). With a continuous monitoring and evaluation of Proterra buses purchased and operated by Foothill Transit, researchers at the National Renewable Energy Laboratory (NREL) found that the fuel economy of 11-meter BEBs ranges from 0.69 to 0.84 km per kWh and the fuel economy of 12-meter BEBs ranges from 0.72 to 0.80 km per kWh during the evaluation period from 2014 to 2019 (L. Eudy et al., 2016; L. Eudy & Jeffers, 2017, 2018b, 2018c, 2019a, 2019b, 2020). Based on BEB testing results across six transit agencies in the US, Deliali et al. (2020) estimated the average fuel economy of 0.61 km per kWh, which did not account for bus types and length.

Based on the specifications I obtained directly from these manufacturers (Supplementary Table 4-4), I estimated the range and average energy consumption rate under typical operating conditions by bus type and length (Table 4-4). Taking into account the typical operating conditions, BEBs can be operated for up to 371 km after one full charge and average fuel economy ranges from 0.32 to 0.90 km per kWh. Larger buses such as double-deckers and articulated buses have greater gross vehicle weight and more passenger capacities, thus they consume more energy when in operation. This study only distinguishes between articulated and other transit buses. As shown in Table 4-4, the average fuel economy of buses in the first five categories range from 0.32 to 0.90 kWh per mile with a medium value of 0.54. In addition, 12-meter buses are the most common ones that transit agencies operate in the County. Thus, I assume a fuel economy of 0.32 km per kWh for articulated buses and 0.54 km per kWh for all other buses in the estimation of daily electricity consumption. NREL's fuel economy estimates were based on two Proterra models, while the estimates in Table 4-4 were based on all available models and manufacturers.

Table 4-4. Range and average fuel economy of BEBs under typical operating conditions

Bus type	Length (m)	Number of available models	Electric range (km)	Average fuel economy* (km/kWh)
Bus	9	2	154-197	0.90 (0.04)
	11	8	84-270	0.59 (0.02)
	12	13	84-371	0.54 (0.02)
Double-decker	14	2	197-259	0.50 (0.08)
Articulated bus	18	5	62-259	0.32 (0.02)
Conversion	-	2	169-225	0.56 (0.14)

Note: * Numbers in parenthesis are standard errors.

Currently, there are three types of charging available for BEBs: plug-in charging, overhead charging (including roof-mounted and inverted pantographs), and inductive charging (Figure 3). The power of currently available plug-in chargers ranges from 50 to 200 kW, and an overhead conductive charger has a power level between 175 and 600 kW. The most advanced wireless charger to date may charge a bus with the highest power of 250 kW (NASEM, 2020). Plug-in charging is by far the most common and the cheapest option for BEB charging. For plug-in charging, BEBs are usually charged at night while they are parked at the depots. This reduces fuel costs when time-of-use electricity rates are in place. However, this type of charging may require BEBs to be equipped with large batteries in order to operate on longer routes, which increases the initial vehicle costs for long-range BEBs. On-route charging such as pantographs and inductive charging offers the benefit of opportunity charging, which reduces the need for large battery packs and allows for extended range throughout the day. These two types of charging are significantly costlier than standard plug-in charging and often require additional effort and expenses for permitting and right-of-way leases or purchases. Given the high costs of wireless chargers, the lack of interoperability among wireless charger providers, and limited availability of wireless charging models, I consider only overhead conductive charging as the option for on-route charging when needed.

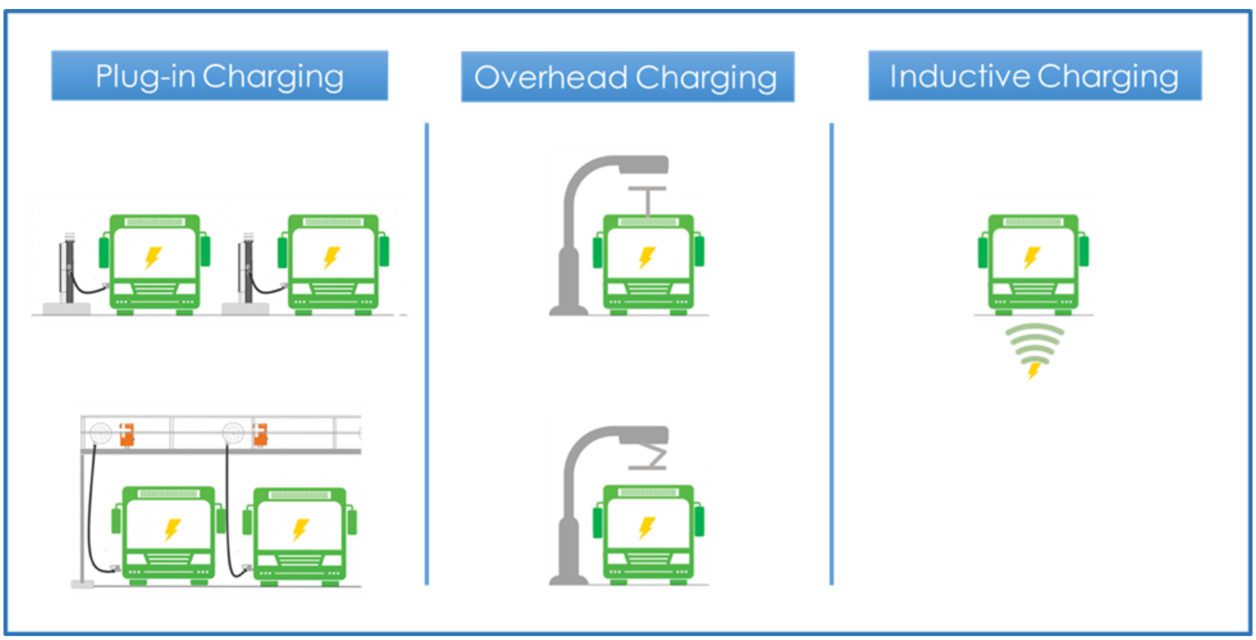


Figure 4-3. Currently available BEB charging infrastructure

Projected eVKT, energy consumption and tailpipe emissions reduction

According to the definitions in the ICT regulation, there are six large transit agencies (a fleet size of 65 or more buses) and four small transit agencies (a fleet size of less than 65 buses) in the County. The fleet size of transit bus services at these agencies ranges from 33 to 2,446 buses, and the total number of buses with all ten agencies combined is 3,804.

Across the ten transit agencies, 53 BEBs are currently in operation (Table 4-5). When agencies meet the minimum requirements in the ICT regulation (i.e., the BEB-slow scenario), there would be 1,346 BEBs in 2025 and 3,600 BEBs in 2030. When agencies seek to accelerate this BEB transition (i.e., the BEB-fast scenario), there would be 1,588 BEBs by 2025 and 3,663 BEBs by 2030. Among the ten agencies, a bus may be assigned with the same schedules and trips every weekday and the vehicle assignment may also vary by day. Depending on each agency's operation schedules, a bus may be assigned to run multiple trips on the same route every day, and a bus could also be assigned for trips on different routes. At the vehicle level, a bus may be operated for as long as 633 km on a typical weekday.

As a result of public transit bus electrification, total weekday daily eVKT in the County would increase to 290-333 thousand km by 2025 and continue to grow to 627 thousand km by 2040 (Figure 4-4a). With the potential growth of BEBs under both adoption scenarios, the regional electricity demand for transit bus operations on a weekday would increase to 639-719 MWh in 2025 and 1280 MWh in 2030 (Figure 4-4b). Among the transit agencies, LA Metro has the highest electricity consumption with 438-497 MWh in 2025 and 881 MWh starting in 2030, which is followed by Foothill Transit with a daily electricity demand of 61-70 MWh in 2025 and 107 MWh in 2030.

Currently the vast majority of buses operated in Los Angeles County are CNG buses. Along with the transition to BEBs, there are emission changes in both the near term and longer term (Figure 4-5). Given the added vehicle weight due to the battery packs, BEBs are projected to have greater particulate matter emissions from break wear and tire wear as compared to CNG buses in the near term. Although there are no tailpipe emissions of particulate matter during the operation of BEBs, the significant portion of emissions from break wear and tire wear would result in an increase in both PM10 and PM2.5 emissions in the region. In the longer term, when BEB vehicle technology improves with similar weights to CNG buses, there will be net benefits in the reduction of particulate matter emissions. For the other two criteria pollutants (NOx and CO) and GHGs, the transition to BEBs would immediately yield positive net environmental benefits. The daily reduction of NOx emissions ranges from 87-100 kg in 2025 to 188 kg in 2040, and CO emissions would reduce by 9-10 metric tons daily in 2025 and the amount doubles in 2040. By replacing CNG buses with BEBs at the ten transit agencies, the county could reduce its weekday GHG emissions by 411-473 metric tons in 2025 and up to 888 metric tons by 2040.

Table 4-5. Projected numbers of BEBs in operation and BEB shares by agency

Transit agency	Bus type	2020		BEB-slow scenario						BEB-fast scenario					
				2025		2030		2040		2025		2030		2040	
		Num.	%	Num.	%	Num.	%	Num.	%	Num.	%	Num.	%	Num.	%
LA Metro*	Bus	0	0	549	35	2076	100	2076	100	731	42	2076	100	2076	100
	Articulated bus	0		305		370		370		305		370		370	
Foothill Transit	Bus	33	9	114	38	346	100	346	100	128	42	346	100	346	100
	Articulated bus	0		30		30		30		30		30		30	
LADOT*	Bus	4	1	159	50	321	100	321	100	186	58	321	100	321	100
Long Beach Transit	Bus	10	4	115	51	163	79	211	100	115	51	171	82	211	100
	Articulated bus	0		0		13		13		0		13		13	
Big Blue Bus	Bus	0	0	43	33	167	100	167	100	43	33	167	100	167	100
	Articulated bus	0		21		28		28		21		28		28	
Torrance Transit System	Bus	0	0	0	0	32	51	63	100	0	0	53	84	63	100
GTrans	Bus	6	11	6	11	6	11	54	100	16	30	16	30	54	100
Culver CityBus	Bus	0	0	4	7	15	28	54	100	10	19	26	48	54	100
Glendale Beeline	Bus	0	0	0	0	16	42	38	100	0	0	20	53	38	100
Norwalk Transit System	Bus	0	0	0	0	17	52	33	100	3	9	26	79	33	100
	Total	53		1346		3600		3804		1588		3663		3804	

Note: *LA Metro and LADOT currently have BEBs on order or being delivered. Additional BEBs were assumed to be in operation starting in 2021.

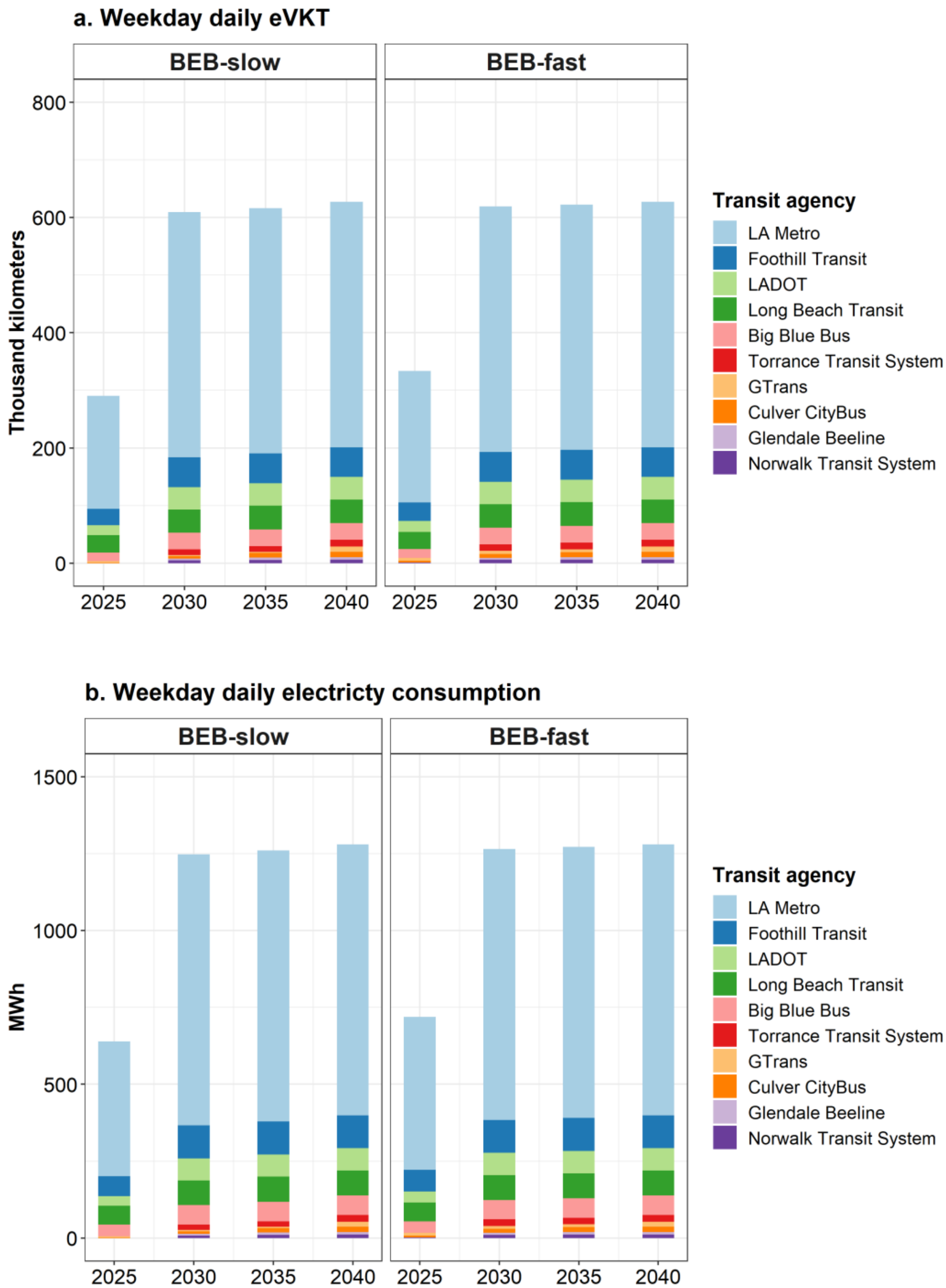


Figure 4-4. Projected weekday daily eVKT (a) and electricity consumption (b) in 2025-2040

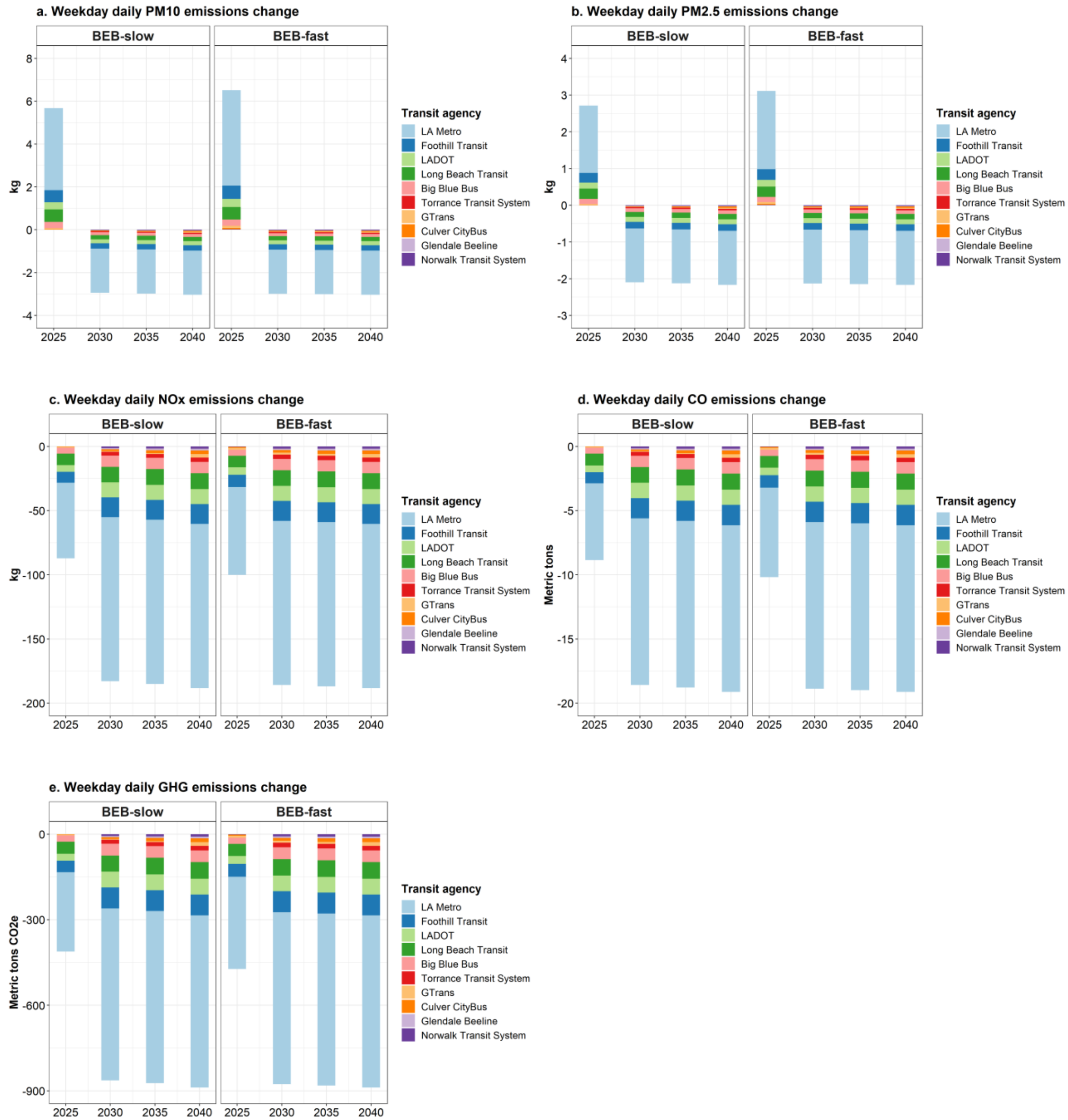


Figure 4-5. Projected weekday daily emissions change in 2025-2040
(a) PM10, (b) PM2.5, (c) NOx, (d) CO, (e) GHGs.

Charging infrastructure needs and grid impact

Given that the ten transit agencies have varying timelines for the transition to BEBs, load profiles are estimated for the first year that the bus fleet becomes 100 percent electric (i.e., 2030 or 2040). These facility-level load profiles are estimated to offer insights for the longer-term grid impact fully electrified bus fleets.

Among all ten transit agencies, there are six LA Metro buses that have a long daily VKT requirements that cannot be fully charged by a 100-kW or 200-kW plug-in charger at the depot within the time period between 9pm and 6am the next day. Thus, on-route charging is required to provide additional energy so that service is not compromised. The charging needs for the six buses were analyzed separately as on-route charging needs (Table 4-6) that are in concurrent with the deployment of smart charging and 200-kW plug-in chargers under the managed charging scenario. For the six buses, information on trip-level stop time and location was compiled for the screening of potential siting of on-route chargers and the estimation of energy provision through these chargers. I estimated the dwell time of each vehicle on each trip end, and the siting of on-route chargers was based on the trip end (i.e., a stop) that a vehicle has the greatest total dwell time within a day. The analysis takes into account the time of the moving parts of a pantograph reaching the bus or the time of moving parts of a bus reaching the pantograph, which I assumed to be 2 minutes each time when an on-route charging event takes place. Thus, the actual possible on-route charging time would be less than the total vehicle dwell time. Results in Table 5 indicate that these six buses would be supported by both a plug-in charger at the depot and an overhead charger at the identified bus stop. There are three unique stop IDs identified through the process, which indicates that LA Metro would require at least three additional on-route chargers (Figure 4-6) to support these six buses besides the deployment of smart charging and 200-kW chargers.

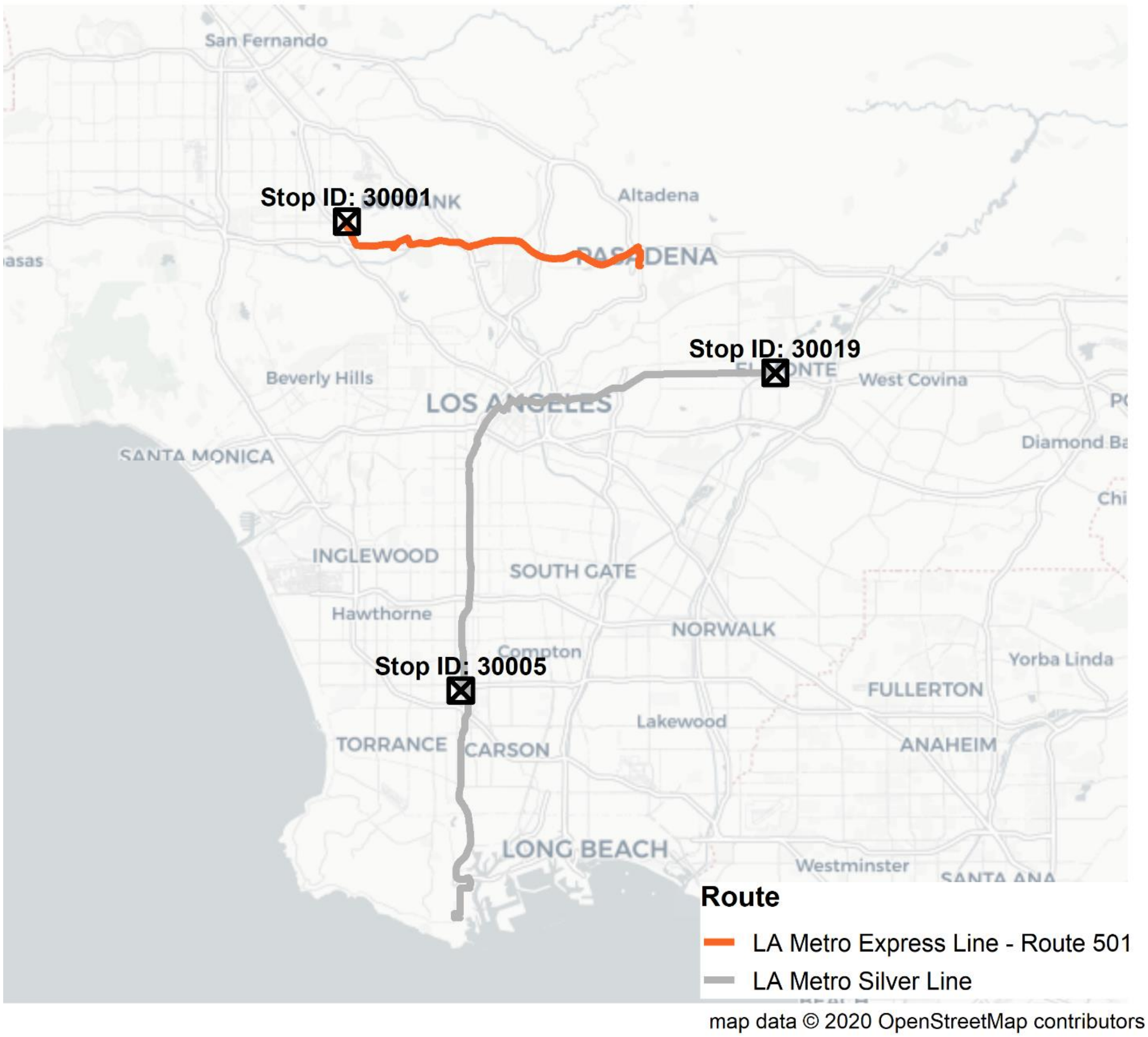


Figure 4-6. Recommended locations for the installation of on-route overhead chargers

Table 4-6. On-route charging needs for six LA Metro buses

Vehicle ID	Division	Stop ID	Total weekday dwell time at the stop (min)	Num. of trips arriving at/leaving this stop	Total actual possible charging time at the stop (min)	Total daily electricity required for service (kWh)	Obtainable electricity via on-route chargers (kWh)	Electricity to be obtained via plug-in chargers at the depot	Required charge time between 9 pm and 6 am (min)
501010	15	30001	145	9	127	1707	629	1078	708
910010	9	30019	80	5	70	1836	347	1490	978
910020	9	30019	87	4	79	1681	391	1290	847
910050	9	30005	89	4	81	1693	401	1292	848
910080	9	30019	86	5	76	1979	376	1603	1052
910510	18	30019	85	4	77	1742	381	1361	893

Load profiles and charging infrastructure costs are discussed in the contexts of a large transit agency (LA Metro), a medium-sized transit agency (Foothill Transit), and a small transit agency (Culver CityBus). Results for other transit agencies are shown in Supplementary Figures 4-1 to 4-7.

The peak loads would occur at the beginning of the assumed charging time period, given that the largest number of buses are charged simultaneously at the assumed 9pm start. After certain buses get fully charged, the electric load would gradually decrease until 0 when all buses are fully charged. The overall charging time at a depot depends on when the last bus completes a full charge. When charging is unmanaged, the electrical load at LA Metro bus depots would peak at 14.8 - 24.5 MW in 2030 (Figure 4-7). Under the unmanaged charging scenario, only charging at Division 3 and Division 7 can be completed before 6am of the next day. Buses assigned for the longer distances would require longer charging times. At these two depots, the longest daily distances are shorter than those at other depots, thus the overall charging needs would be lower and the overall charging time would be shorter. At all other bus depots, a full charge for certain buses may continue until noon or as long as 3pm in the afternoon because some buses at these depots run very long distances, which result in higher energy demand and longer overall charging time. Thus, the sole deployment of slow plug-in chargers would probably not be able to fully support the bus operations at the majority of LA Metro facilities in the unmanaged charging scenario. In contrast, the peak loads under the managed charging scenario can be reduced by up to 63%. Under this scenario, the peak load at the depot level ranges from 6.6 to 19.2 MW. Foothill Transit maintains two bus depots in Arcadia and Pomona. By 2030, I estimate that the electrical load under the unmanaged charging scenario would peak at 16.9 MW and 11.6 MW at each of the two facilities, respectively. Under this charging scenario, the provision of services may be affected given that a full charge for certain buses would not be completed until 1pm the next day. When smart charging and fast plug-in chargers are deployed, the peak loads would be reduced to 10.8 MW (i.e., a 36% decrease) at the Acadia facility and 5.1 MW (i.e., a 56 % decrease) at the Pomona facility. Culver CityBus is a small transit agency that manages one bus depot. By 2040, the daily charging electric load at Culver CityBus would range from 2.2 MW under the managed charging scenario to 5.4 MW under the unmanaged charging scenario. Although all buses can be fully charged by 4am under the unmanaged charging scenario, the peak load would be 1.5 times higher than that under the managed charging scenario.

A major difference between the two charging management scenarios is whether to deploy smart charging, which could potentially reduce costs in two ways. First, it reduces the maximum number of chargers needed by queuing the charging of all buses instead of having them charged at the same time. Some buses are operated for shorter distances and do not require 9 hours to be fully charged. The sharing of chargers through an energy management system has the potential to reduce capital investments on charging equipments. In addition, the use of smart charging reduces peak load and thus reduces electricity costs when peak demand charges are in place. With unmanaged charging, LA Metro would need 2,135 100-kW chargers when 100 percent electrification takes place and charging for some buses may last until noon, which may interfere with service provision. With smart charging, LA Metro would require 859 100-kW chargers, 181 200-kW chargers, and three 325-kW on-route overhead chargers in total, compared with 2,135 100-kW chargers for weekday services in the unmanaged scenario. The total charging infrastructure costs under the unmanaged charging scenario is estimated to be $224.3 million over a 12-year charger life cycle, while the total charging infrastructure costs under the managed charging scenario is $117.1 million, which is 48% less than the unmanaged charging scenario.

Although the software and hardware costs of smart charging are not included, it is very likely that the total infrastructure costs under the managed charging scenario could remain significantly lower than those under the unmanaged charging scenario.

In 2030, Foothill Transit would require 285 100-kW chargers under the unmanaged charging scenario, resulting in estimated charging infrastructure costs of $30.0 million. With managed charging, 103 100-kW chargers and 28 200-kW chargers would be required and total charging infrastructure costs would reduce to $14.5 million. I find that all Foothill Transit buses could be fully supported by plug-in chargers at the depots with no need for additional deployment of on-route chargers. However, Foothill Transit installed two on-route overhead chargers in 2015 (Hanlin et al., 2018). The future charging infrastructure costs on the deployment of plug-in chargers would be lower than my estimates, given that one on-route overhead chargers can serve multiple buses.

For a small transit agency like Culver CityBus, the deployment of smart charging would be critical in reducing costs for the transition to BEBs. In 2040, smart charging could cut down charger needs by 59%, from 54 100-kW chargers under the unmanaged charging scenario to 22 100-kW chargers under the managed charging scenario. The reduced charger needs would lead to estimated cost savings of $3.4 million on charging infrastructure deployment. I estimate that there would be no need for 200-kW plug-in chargers or on-route overhead chargers at Culver CityBus.

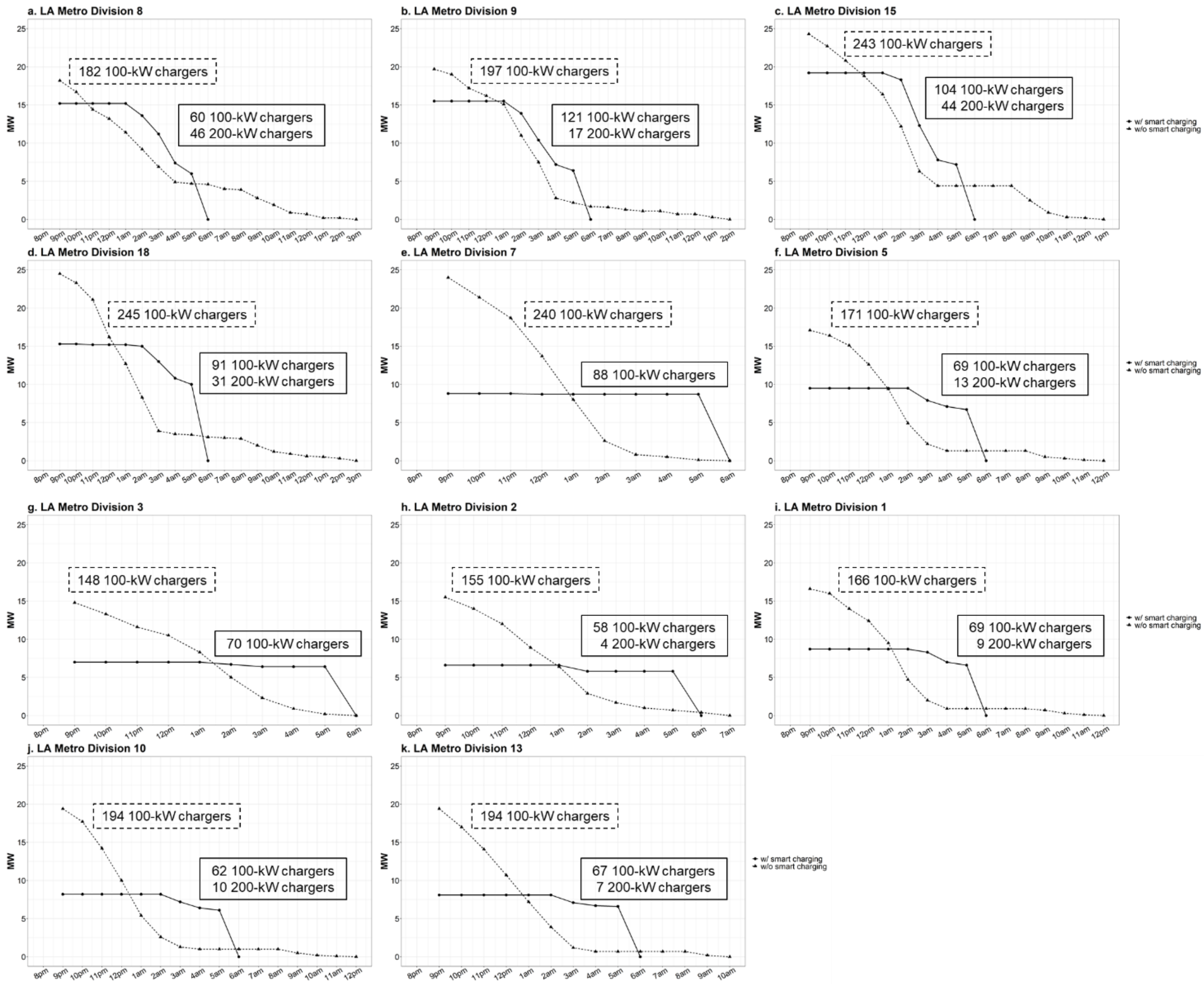


Figure 4-7. Projected charging load profiles at LA Metro facilities in 2030

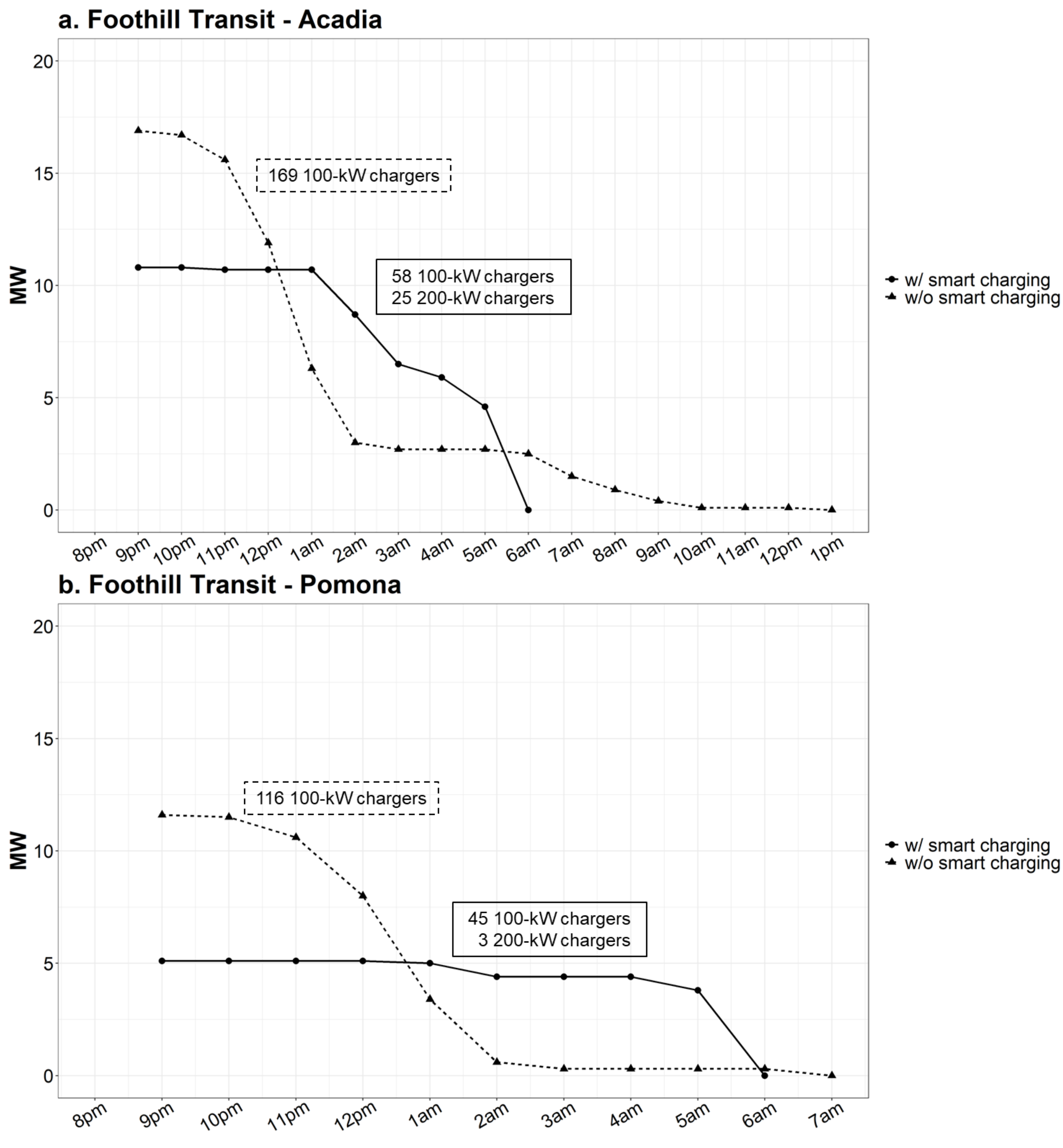


Figure 4-8. Projected charging load profiles at Foothill Transit facilities in 2030

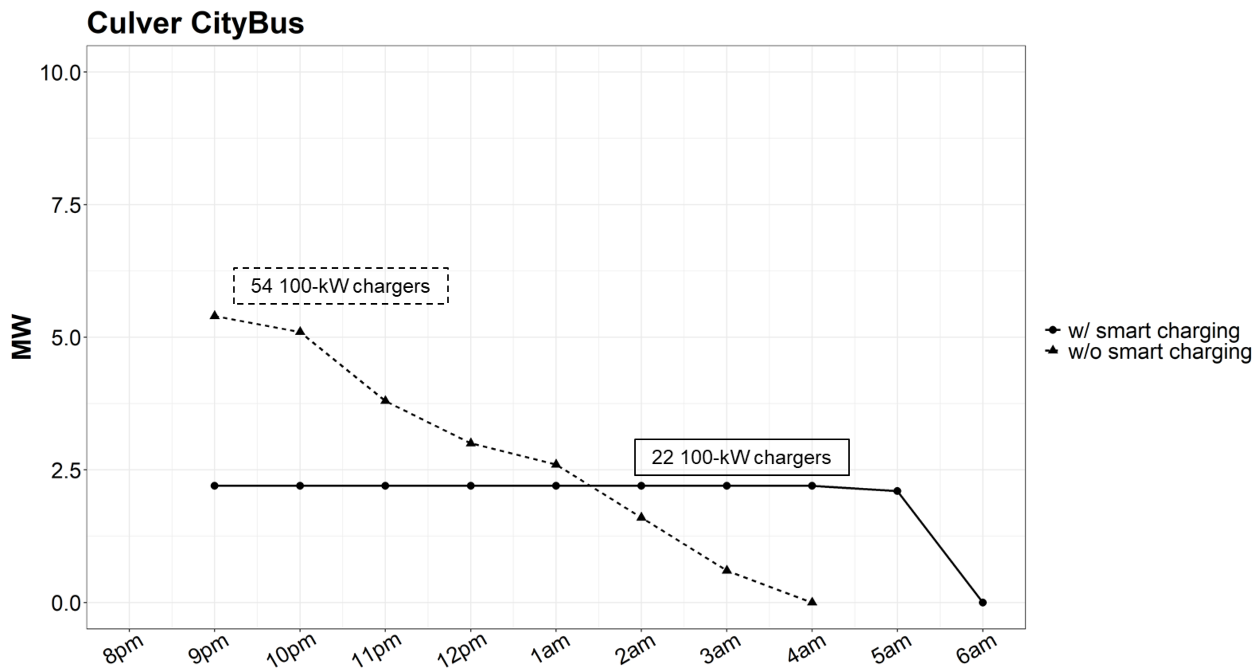


Figure 4-9. Projected charging load profiles at Culver CityBus in 2040

Conclusions

California policymakers have implemented the ICT regulation to require transit agencies to gradually transition to ZEBs by 2040. Besides the high upfront costs of BEB purchases, the deployment of charging infrastructure remains another significant challenge for the wider adoption of BEBs. This study differs from previous studies that used fixed assumptions about vehicle distances traveled and/or fixed charger-to-vehicle ratios in order to estimate charger needs and the environmental impacts of BEB adoption. Through the development of the Infrastructure Planning for Electric Buses (IPEB) tool, this study takes a more realistic approach by examining actual fleet turnover and transit service operating characteristics.

In this chapter, I explored a number of existing datasets, including the National Transit Database, the APTA's Public Transportation Vehicle Database, GTFS static datasets from ten transit agencies that provide service in Los Angeles County. With this agency and vehicle-level information as well as the ICT regulation, I was able to model fleet turnover and analyze bus fleet operations with an evidence-based, data-driven approach. Results from these data analytics activities serve as a foundation to the IPEB tool and the analysis of energy and environmental impacts of BEB adoption, and more importantly, charging infrastructure planning particularly with respect to charger needs and costs.

In Los Angeles County there are 53 BEBs currently in operation at four transit agencies. Given the ICT regulation and other local vehicle transition commitments, the potential growth of BEBs in the transit bus fleets at the ten transit agencies examined here would result in a significant increase in electricity demand over the next five to ten years. Although there are no tailpipe emissions, the increased vehicle weight of BEBs due to the carrying of heavy battery packs would result in greater particulate matter emissions from brake and tire wear in the near term. As for NOx, CO, and GHG emissions, the transition to BEBs brings about positive environmental changes right away. By replacing CNG buses with BEBs at the ten transit agencies I analyzed, Los Angeles County could reduce its weekday GHG emissions by 411-473 metric tons in 2025 and up to 888 metric tons by 2040.

This study has demonstrated the technical feasibility of transit electrification at major transit agencies in Los Angeles County, taking into account transit bus service schedules and the current state of BEB vehicle and infrastructure technologies. I find that 100-kW and 200-kW plug-in chargers along with the deployment of smart charging could support the full pre-pandemic services for the majority of buses across the ten transit agencies, with the exception of six LA Metro buses. When the physical space at a bus depot limits the large-scale deployment of plug-in chargers, on-route charging may remain important in supporting fleet operation. In addition, on-route charging can serve multiple buses and may increase resilience when power outages occur (Linscott & Posner, 2020). Another potential advantage of deploying on-route charging is that it allows for the sharing of charging infrastructure among transit agencies and may reduce charging infrastructure costs on a regional scale. The impacts of charging infrastructure sharing among transit agencies is a direction for future research.

This study also showed the highly variable electric grid impacts of deploying standard plug-in charging at bus depots with and without smart charging – due to a flattened load versus a maximum load. As demonstrated in the estimated load profiles and charging infrastructure costs, smart charging would be a critical element in the planning of transit bus electrification at the facility level. First, it reduces charger needs by queuing the charging of all buses instead of having them charged at the same time. Thus, it reduces capital investments on charging equipments. In addition, the use of smart charging significantly reduces peak load and thus reduces electricity costs when additional demand charges are in place.

From a methodological perspective, I developed an analytical framework for optimizing trip-to-block assignment, block-to-vehicle assignments, and vehicle-to-depot allocation in order to minimize deadheading. I also proposed the use of trip-level vehicle dwell time for the siting and analysis of on-route charging deployment. The ultimate grid impact of transit bus electrification is determined by a number of factors: the actual siting of charging equipment (at-depot versus on-route), the connectivity of charging (conductive versus inductive), the speed of charging (standard versus fast charging), the type of BEB technologies (long-range versus short-range), and connection to the utility grid. With certain objectives, such as minimizing total costs and minimizing interference with transit services, the optimal scheme of charging infrastructure deployment can be identified for the cost-effective planning of transit bus electrification.

Appendix: Supplementary Information

Supplementary Tables

Supplementary Table 4-1. Transit bus fleet age distribution in Los Angeles County, 2020

Transit agency	Bus type	Years old																		
		0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17+**	**Subtotal**
LA Metro	Bus	0	295	0	0	0	350	550	0	150	0	91	91	258	0	0	0	18	273	2076
	Articulated bus	0	0	0	0	0	0	0	0	0	0	0	0	0	96	95	158	0	0	370
Foothill Transit	Bus	0	44	32	30	106	0	0	14	14	30	0	0	10	0	63	0	0	0	346
	Articulated bus	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30	0	0	0	30
LADOT	Bus	0	5	0	20	29	54	0	31	129	5	0	24	0	5	19	0	0	0	321
Long Beach Transit	Bus	0	0	40	10	0	8	0	31	33	0	0	25	0	15	0	36	0	13	211
	Articulated bus	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	13
Big Blue Bus	Bus	0	0	26	20	5	15	13	45	0	0	24	0	0	0	10	0	9	0	167
	Articulated bus	0	0	0	0	0	7	0	0	0	0	21	0	0	0	0	0	0	0	28
Torrance Transit System	Bus	0	0	0	0	0	24	0	0	9	20	10	0	0	0	0	0	0	0	63
GTrans	Bus	0	0	0	5	0	1	0	0	0	0	18	17	0	0	0	13	0	0	54
Culver CityBus	Bus	0	0	0	0	18	0	6	0	16	4	0	6	0	0	0	0	0	4	54
Glendale Beeline	Bus	2	0	0	0	11	0	0	10	4	0	0	10	0	0	0	1	0	0	38
Norwalk Transit System	Bus	0	0	1	2	4	0	0	12	2	0	3	6	0	0	0	1	0	2	33
																			Total	**3804**

Supplementary Table 4-2. Bus life cycle assumptions across scenarios

Transit agency	Bus type	Historical bus life cycle (years)	Reference scenario bus life cycle (years)	BEB-slow scenario bus life cycle (years)	BEB-fast scenario bus life cycle (years)
LA Metro	Bus	16-18+	16	10-16[a]	10-14[a]
	Articulated bus	14+	16	10-16[a]	10-14[a]
Foothill Transit	Bus	15+	14	10-14[a]	10-14[a]
	Articulated bus	-	14	14	14
LADOT	Bus	16	14	14	14
Long Beach Transit	Bus	13-16+	16	14-16[b]	12-14[b]
	Articulated bus	-	14	14	12
Big Blue Bus	Bus	14-16+	14	14	12
	Articulated bus	-	14	14	12
Torrance Transit System	Bus	-	14	14	14
GTrans	Bus	15+	14	14	14
Culver CityBus	Bus	15-18+	14	14	14
Glendale Beeline	Bus	14-16	16	16	14
Norwalk Transit System	Bus	16+	16	16	14

Note: [a] In order to achieve the goal of 100% electric fleet by 2030, some buses have to be retired before the end of the 12-year minimum service life.
[b] In the APTA's PTVD, Long Beach Transit has laid out plans for BEB purchases in 2021-2025, which determines the near-term bus retirement schedules.

Supplementary Table 4-3. Emission rates for Los Angeles County in EMFAC2017 (v1.0.3)

Year	BEB[a]		CNG bus							
	PM 2.5 (g/km)	PM10 (g/km)	PM2.5 (g/km)	PM10 (g/km)	NOx (g/km)	CO (g/km)	CO_2 (g/km)	CH_4 (g/km)	N_2O (g/km)	GHGs[b] (g/km)
2020	0.035	0.085	0.026	0.066	0.79	28.76	1234.37	4.18	0.25	1418.09
2021	0.035	0.085	0.026	0.066	0.51	29.75	1237.60	4.04	0.25	1417.68
2022	0.035	0.085	0.025	0.066	0.30	30.51	1240.04	3.93	0.25	1417.00
2023	0.035	0.085	0.025	0.066	0.30	30.51	1240.02	3.93	0.25	1416.98
2024	0.035	0.085	0.025	0.066	0.30	30.52	1240.49	3.93	0.25	1417.53
2025	0.035	0.085	0.025	0.066	0.30	30.52	1240.53	3.93	0.25	1417.58
2026	0.035	0.085	0.025	0.066	0.30	30.52	1240.53	3.93	0.25	1417.58
2027	0.035	0.085	0.025	0.066	0.30	30.53	1240.86	3.93	0.25	1417.97
2028	0.022	0.061	0.025	0.066	0.30	30.50	1239.92	3.93	0.25	1416.87
2029	0.022	0.061	0.025	0.066	0.30	30.50	1239.93	3.93	0.25	1416.89
2030	0.022	0.061	0.025	0.066	0.30	30.50	1239.78	3.93	0.25	1416.72
2031	0.022	0.061	0.025	0.066	0.30	30.50	1240.07	3.93	0.25	1417.07
2032	0.022	0.061	0.025	0.066	0.30	30.50	1240.06	3.93	0.25	1417.05
2033	0.022	0.061	0.025	0.066	0.30	30.50	1240.01	3.93	0.25	1417.00
2034	0.022	0.061	0.025	0.066	0.30	30.50	1240.00	3.93	0.25	1416.99
2035	0.022	0.061	0.025	0.066	0.30	30.50	1240.00	3.93	0.25	1416.99
2036	0.022	0.061	0.025	0.066	0.30	30.50	1240.00	3.93	0.25	1416.99
2037	0.022	0.061	0.025	0.066	0.30	30.50	1240.00	3.93	0.25	1416.99
2038	0.022	0.061	0.025	0.066	0.30	30.50	1240.00	3.93	0.25	1416.99
2039	0.022	0.061	0.025	0.066	0.30	30.50	1240.00	3.93	0.25	1416.99
2040	0.022	0.061	0.025	0.066	0.30	30.50	1240.00	3.93	0.25	1416.99

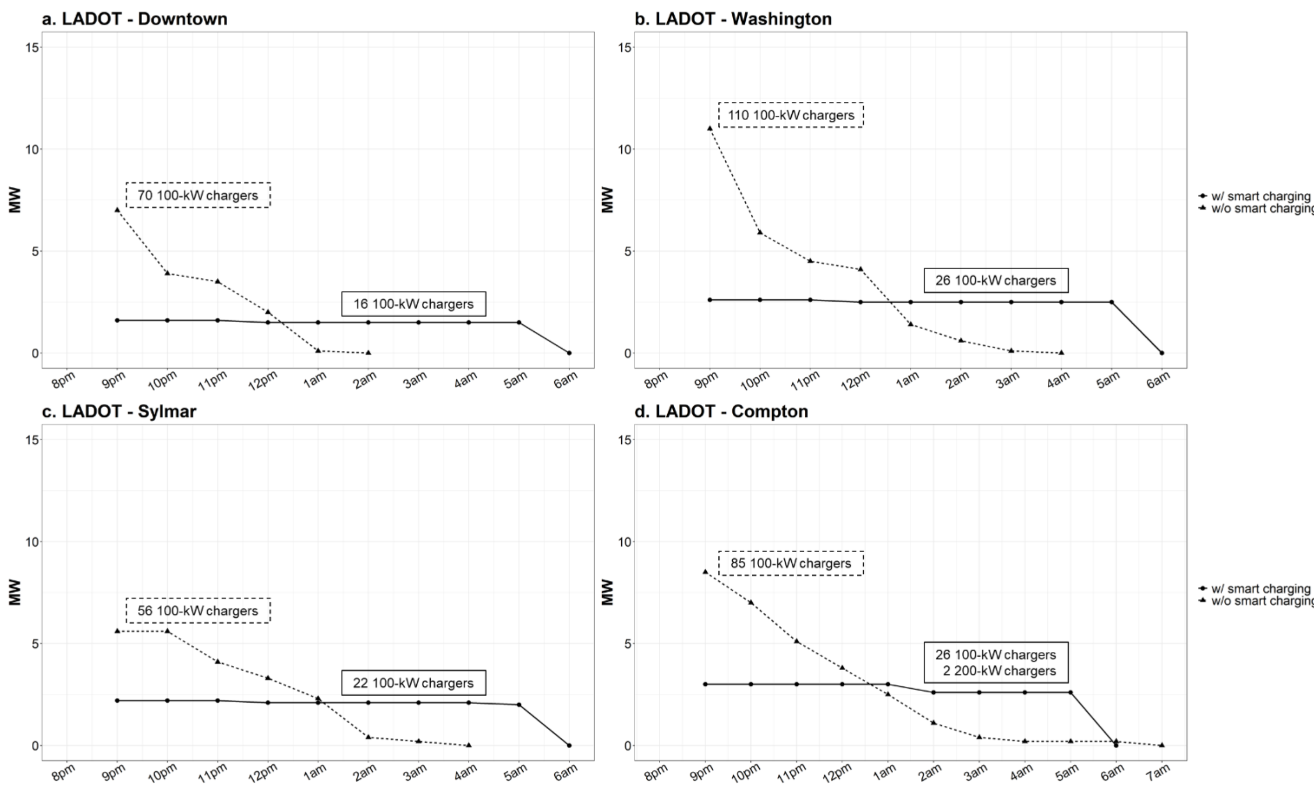
Note: [a] Emission rates of NOx, CO, CO_2, CH_4, N_2O for BEBs are 0. EMFAC2017(v1.0.3) have BEB particulate matter emission rates until 2028. The emission rates in 2029-2040 are assumed to be the same as those in 2028. PM emissions are from tire wear and break wear.

[b] GHG emissions rates are the weighted sum of CO_2, CH_4, and N_2O emission rates using the 100-year global warming potentials from the Intergovernmental Panel on Climate Change's Fifth Assessment Report (AR5).

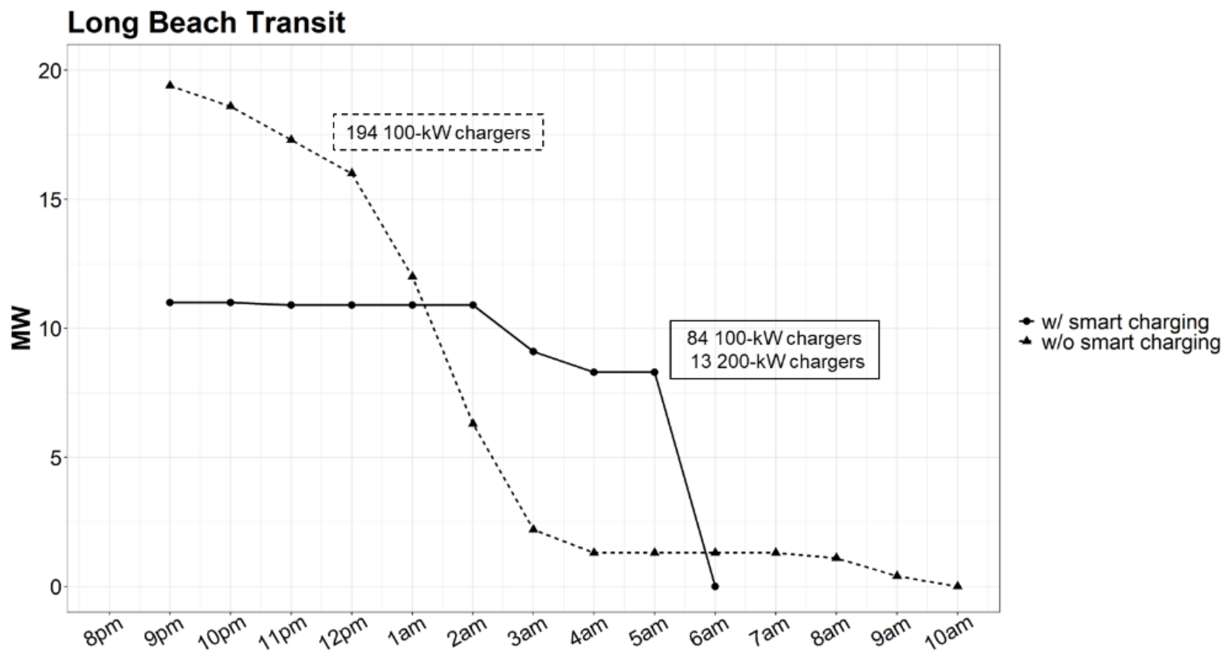
Supplementary Table 4-4. Bus specifications from major BEB manufacturers in the US (as of November 2020)

OEM	Model	Bus type	Length (m)	Max. range (km)	Battery size (kWh)	Charging Power level (kW)
BYD	k7m	bus	9	220	180	80/ 200
	k9s	bus	11	346	352	
	k9mc	bus	12	285	352	
	k11	articulated	18	370	652	
	C10MS	double-decker	14	370	446	
Proterra	ZX5	bus	11	386	440	75/ 150/ 250/ 500
	ZX5	bus	12	529	660	
	XR	bus	11	195	220	
	E2	bus	11	377	440	
	XR	bus	12	190	220	
	E2	bus	12	370	440	
	E2 max	bus	12	528	660	
GreenPower	EV250	bus	9	282	210	50/ 100/ 200
	EV350	bus	12	322	430	
	EV550	double-decker	14	282	478	
New Flyer	Xcelsior CHARGE	bus	11	121	160	50/ 90/ 100/ 125/ 150/ 175/ 300/ 450/ 600
		bus	11	161	213	
		bus	11	257	311	
		bus	11	314	388	
		bus	12	121	160	
		bus	12	161	213	
		bus	12	185	267	
		bus	12	257	311	
		bus	12	314	388	
		bus	12	362	466	
		articulated	18	89	213	
		articulated	18	113	267	
		articulated	18	137	320	
		articulated	18	217	466	
Gillig		bus	12	241	444	-
Lightening eMotors		conversion	-	322	322	-
Complete Coach Works	ZEPS	conversion	-	241	403	-

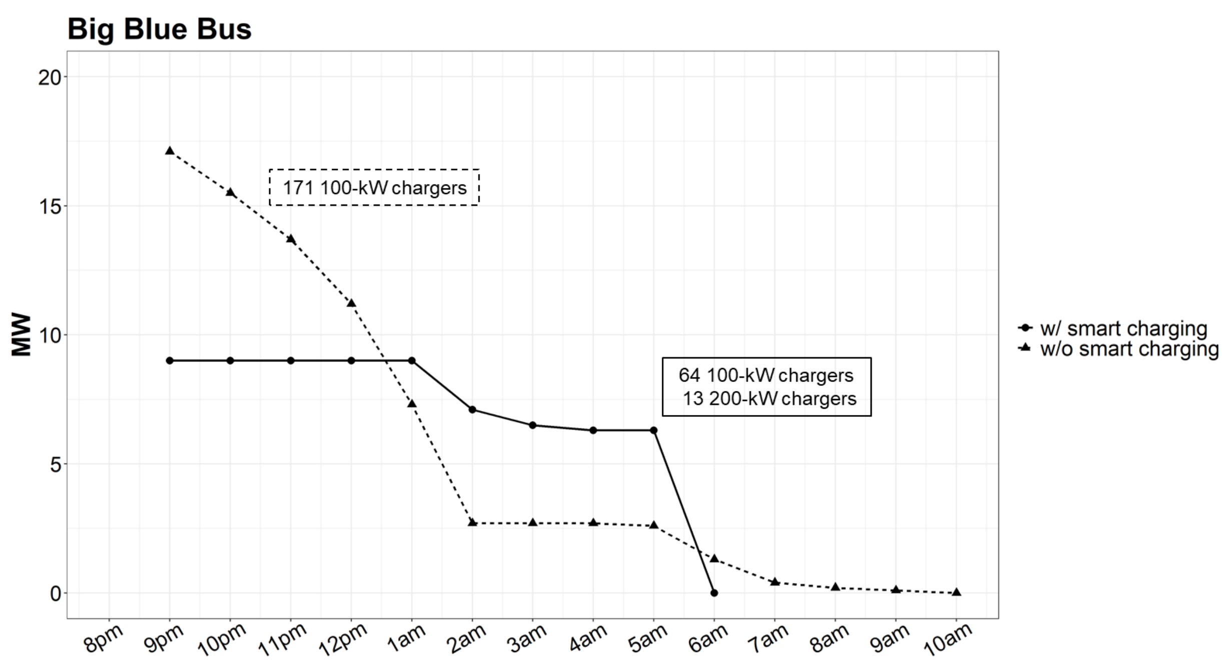
Supplementary Figures



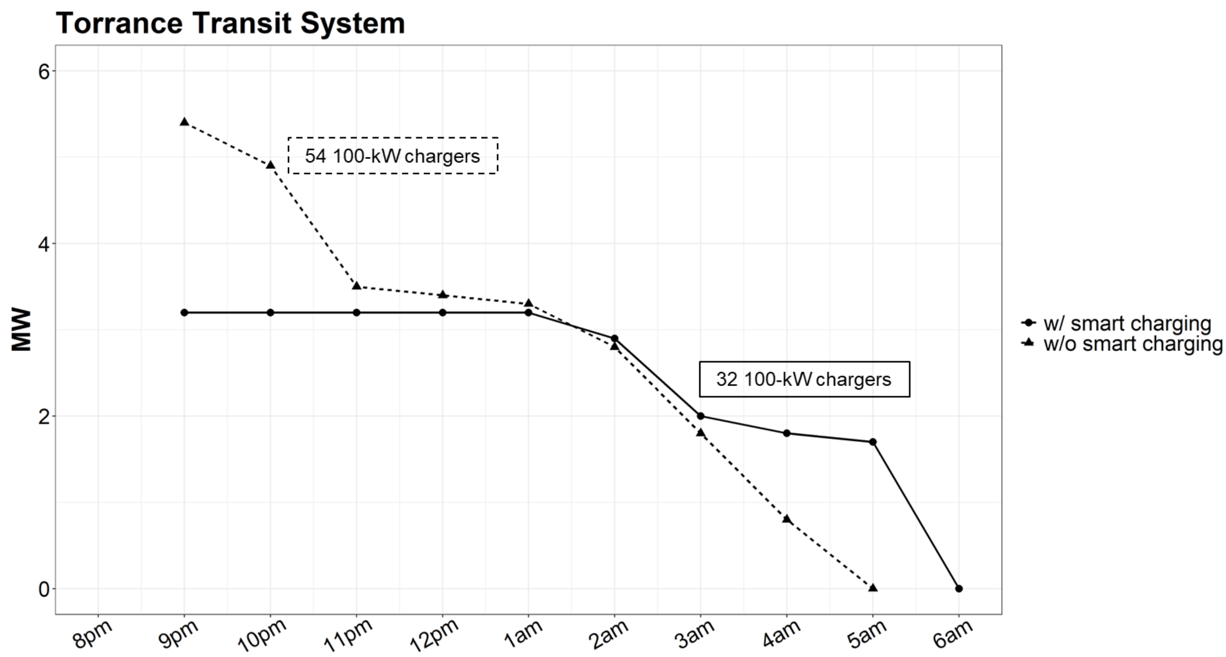
Supplementary Figure 4-1. Projected charging load profiles at LADOT facilities in 2030



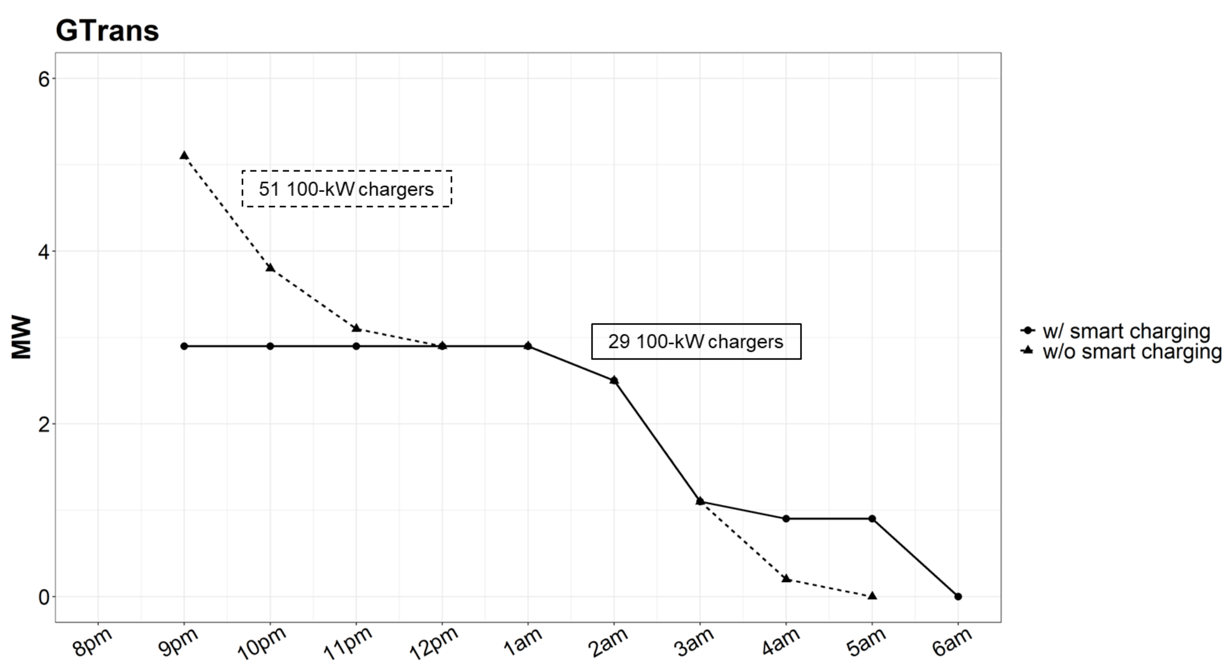
Supplementary Figure 4-2. Projected charging load profiles at Long Beach Transit in 2040



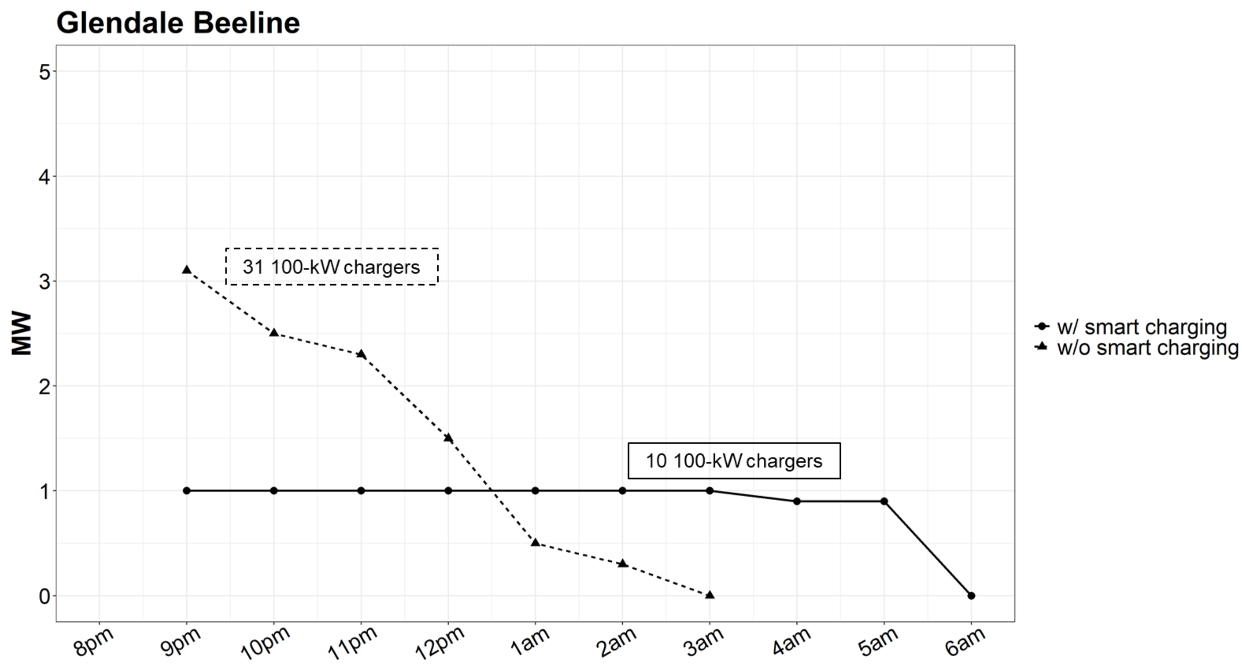
Supplementary Figure 4-3. Projected charging load profiles at Big Blue Bus in 2030



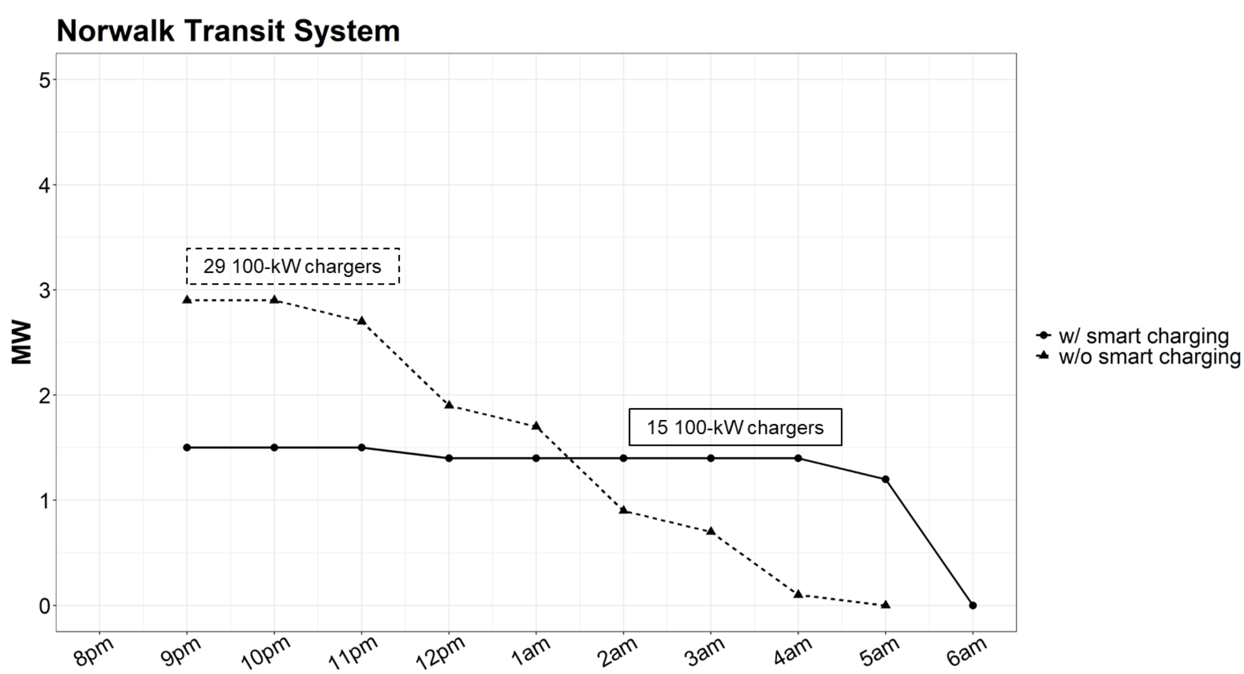
Supplementary Figure 4-4. Projected charging load profiles at Torrance Transit System in 2040



Supplementary Figure 4-5. Projected charging load profiles at GTrans in 2040



Supplementary Figure 4-6. Projected charging load profiles at Glendale Beeline in 2040



Supplementary Figure 4-7. Projected charging load profiles at Norwalk Transit System in 2040

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Chapter 5: Conclusions

Transportation contributes importantly to the economy and society, but at substantial environmental cost. While much progress has been made to increase the energy efficiency of transportation systems, their continued expansion is a major threat to global climate change and urban air quality. Additional mitigation strategies are needed to reduce the negative environmental and public health impacts of transportation. Depending on technology maturity, policymakers, planners, and the general public may respond differently to various types of clean transportation technologies. Stakeholders and implementation-related issues also vary by specific type of clean transportation technologies. In this dissertation, I tackle the complexity of achieving sustainable transportation by developing data-driven analytical frameworks. I use these frameworks to address questions arise at various stages of technology development and deployment for the transition to sustainable transportation. More specifically, I investigate: (1) the life cycle energy and environmental impacts of fifteen advanced biofuel production pathways across the US (Chapter 2); (2) the most powerful socioeconomic, demographic, and geospatial predictors for plug-in electric vehicle adoption across California neighborhoods (Chapter 3); and (3) the energy and environmental impacts of transit bus electrification and strategies for charging infrastructure deployment at public transit agencies in the context of a large metropolitan area (Chapter 4). In concert, the three essays in this dissertation expand the current literature in multiple fields and the findings presented in each of the three essays have important implications for the planning, design, and implementation of sustainable transportation at various geographical scales.

First, the production of advanced biofuels remains important in the transition to sustainable transportation, especially before we overcome major barriers to large-scale transportation electrification. With a particular focus on wastes and biomass residues, I find that utilizing these resources in the contiguous US can generate 3.1 to 3.8 exajoules (EJ) of renewable energy annually, which would be a net energy gain of 2.4 to 3.2 EJ, and would displace GHG emissions of 103 to 178 million metric tons of CO_2 equivalent every year. Maximizing the benefits of energy recovery from waste requires attention to the life cycle implications of various technology pathways, the spatial distribution of waste feedstocks, and the local conditions under which waste feedstocks will be processed.

Second, national mandates such as the US Renewable Fuel Standard (RFS) likely do not maximize even renewable energy production, let alone environmental benefits. Likewise, renewable portfolio standards, a widely employed policy in the electricity sector, could lead to sub-optimal use of waste biomass. In the literature, bioenergy and biofuel policies have been analyzed mainly from the perspective of climate change mitigation, food security, or cost, but my analysis shows they also do not optimize energy production. It is important to combine life cycle assessment with spatial analytical techniques for multi-criteria assessment of technology pathways and the identification of hot spots for the refinement of existing energy policies. Indexing volumetric targets and mandates as well as financial subsidies for renewable energy to life cycle emissions-based performance measures will lead to more sustainable production of advanced biofuels.

Third, a revealed preference approach using vehicle registration data and neighborhood-level characteristics from existing data sources can help policymakers and planners better understand the adoption of plug-in electric vehicles (PEV) in a cost-effective way. Although PEV adoption has taken place in 98% of census tracts in California between 2010 and 2018, the growth has been uneven across the California market. Using lasso regression and Monte Carlo sampling, I find that the market penetration of PEVs is generally higher in more affluent neighborhoods with many homeowners and highly-educated residents. These neighborhoods typically have larger proportions of residents employed in the information technology sector or occupied in management, business, science and arts, residents with bachelor's or higher degrees, middle-aged residents, and households with annual incomes greater than $200K and two vehicles available. The lack of pro-environment intention and behaviors as well as the proportions of low-income households and low-value and high-density housing units negatively associate with PEV adoption. The deployment of workplace charging may be more effective than the deployment of public DC fast charging. The deployment of public slow chargers negatively associates with PEV adoption, and thus may not be an effective strategy to incentivize PEV adoption. Although high occupancy vehicle (HOV) lane access positively associates with PEV adoption, the overall impact of allowing PEVs free access to HOV lanes would depend on the net environmental benefits as a result of increased PEV adoption on one hand, and the possible degradation of HOV lane operations due to increased HOV lane traffic that reduces time savings and reliability on the other.

Fourth, neighborhood-level PEV adoption behaviors in California vary by vehicle technology and price range. For instance, pro-environment intention and behaviors play a more significant role in predicting the adoption of economy battery electric vehicles (BEVs) than economy plug-in hybrid electric vehicles (PHEVs). The proportion of residents with at least high school completion positively associates with the adoption of economy BEVs and economy PHEVs, whereas the proportion of highly-educated residents is a predictor of economy BEV adoption. Highest-earning households have relatively stronger preferences for luxury BEVs and economy PHEVs than economy BEVs. Two-vehicle households have demonstrated greater preferences for economy PHEVs and economy BEVs. Earnings, travel behaviors and subsequent charging needs vary by occupation, industry, and worker class, resulting in varying preferences for specific PEV technology across different types of employment status and commute patterns. Long neighborhood average commute times and the opportunity to reduce commute time by accessing HOV lanes appears to motivate the adoption of economy PHEVs.

In addition, effective planning of charging infrastructure deployment is critical to the successful transition to battery electric buses (BEBs) at public transit agencies. Using the Infrastructure Planning for Electric Buses (IPEB) tool that I developed, I find that California's Innovative Clean Transit regulation and local BEB transition commitments would result in a significant increase in electricity demand at transit agencies over the next five to ten years. The transition to BEBs would increase particulate matter emissions from brake and tire wear in the near term and immediately reduce NOx, CO, and GHG emissions. With projected electrification efforts at ten public transit agencies that I analyzed, Los Angeles County could reduce its weekday GHG emissions by 411-473 metric tons in 2025 and up to 888 metric tons by 2040. Plug-in chargers along with the deployment of smart charging could support the full pre-pandemic services for the majority of buses across the ten transit agencies, with the exception of six LA Metro buses. Smart charging would be a critical element in the planning of transit bus electrification, as it reduces costs associated with charging infrastructure and electric demand by lowering charger needs and shaving peak load. With certain objectives, such as minimizing total costs and minimizing interference with the provision of transit services, the optimal scheme of charging infrastructure deployment can be identified for the cost-effective planning of transit bus electrification.

Overall, I take a data-driven approach in this dissertation and apply systems thinking to the interdisciplinary and applied research. This dissertation not only benefits future research in the area of sustainable transportation, but also exemplifies potential strategies for improving planning practices and policy making across multiple geographical scales.