Mapping Electric Vehicle Impacts: Greenhouse Gas Emissions, Fuel Costs, and Energy Justice in the United States

by

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Preface

Electric vehicles will become increasingly prevalent over the next few decades to accelerate decarbonization of the transportation sector. This thesis uses a spatial lens to explore the intersection of transportation, decarbonization, and energy justice to deepen our understanding of the potentially uneven impacts of the electric vehicle transition in the United States. This work will be submitted to a journal under the same title for publication.

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Abstract

The impact of the electric vehicle (EV) transition on household transportation energy burdens (i.e., percentage of income spent on vehicle fuels) in the U.S. is not well known. This study addresses this gap by comparing EVs to internal combustion engine vehicles (ICEVs) in terms of greenhouse gas emissions (GHGs), fuel costs, and transportation energy burden. The results indicate that over 90% of U.S. households (measured by census tract) would see some savings in both GHGs and energy burden by adopting an EV and for 60% of U.S. households these savings would be moderate to high. Savings are especially pronounced in the American West (e.g., California, Washington) and parts of the Northeast (e.g., New York) primarily due to a varying combination of cleaner electricity grids, lower electricity prices (relative to gas prices), and smaller drive-cycle and temperature-related impacts on fuel efficiency. Moreover, adopting an EV would more than double the percentage of households that have low transportation energy burdens (less than 2% of income spent on fuel annually) which equates to 80% of all U.S. households. Despite significant reductions of energy burdens in most cases, over half of the lowest income households would have high EV energy burdens (greater than 4% income spent on fuel annually), and over three quarters would have high EV energy burdens if at-home charging is unavailable. Addressing this requires targeted policies to promote energy justice in lower-income communities, including subsidizing charging infrastructure, strategies to reduce electricity costs, and increasing availability to low-carbon transport modes (e.g., public transit, biking, and car sharing).

Keywords
electric vehicles, decarbonization, life cycle greenhouse gas emissions, fuel costs, levelized cost of charging, area median income, transportation energy burden, energy justice, spatial analysis and mapping

1 Introduction

Transportation accounts for the largest portion of greenhouse gases (GHG) emitted in the U.S., with direct emissions from passenger vehicles and light-duty trucks comprising roughly 16% of total GHGs alone [1]. Electrification is the primary pathway to reduce these emissions and reaching zero carbon intensity in the transportation sector by 2050 will require complete electrification and decarbonization of the grid [2].

To better understand the potential benefits and tradeoffs of electric vehicles (EVs), extensive research has been conducted. Studies have shown that EV adoption can significantly reduce GHG emissions and other air pollutants depending on the type of EV and geographically variable circumstances such as the source of electricity, driving and charging patterns, charging infrastructure, policies, and climate [3–11]. Numerous studies have explored the regional variability of EV-related GHG emissions in the U.S. [4,5,12–25,21]. The total cost of ownership of EVs versus conventional internal combustion engine vehicles (ICEVs) is also well-studied and debated [26–30], with a few studies assessing the variability of EV costs in U.S. cities [29,30] or at the state level [21,31]. There is agreement that EV operating costs (e.g., fuel and maintenance) tend to be lower than those of ICEVs [26,27,31–33] and are a key factor in making EVs cost-competitive, in addition to federal tax incentives [27,28,30].

Sovacool et al. (2019) argue that EV research has been largely “descriptive or positive” and not “normative or critical” (p. 205) and proposed an energy justice framework for electric mobility that considered four elements of justice (and potential EV-related injustices): distributive (e.g., lack of access due to high cost), procedural (e.g., exclusion from planning process), cosmopolitan (e.g., exacerbation of other vehicle-related and environmental externalities), and recognition (e.g., economic losses in the conventional vehicle market) [34].

Energy justice research in the U.S. has primarily focused on household energy burden, or the portion of income spent on home energy services [35]. Consideration of transportation dynamics in energy burden research is particularly lacking in the U.S. [35,36], but is more prevalent in Europe (e.g., [37–39]), where domestic and transport energy poverty has been coined ‘double energy vulnerability’ [38]. Transport energy poverty, or transportation energy burden in the U.S. [40–43], is analogous to household energy burden and falls under the larger umbrella of transport poverty [37,38], or "the inability to attain a socially- and materially-necessitated level of transport services" [37 p2].

A few studies of transportation energy burden in the U.S. have found that low income households [40–43], particularly Black, Latinx, and Native American households [41] face disproportionate burdens. Additionally, suburban and rural households tend to experience higher transportation energy burdens than do urban households [37,40–43], primarily due to lack of public transit and greater distances to essential services and employment locations [37]. A recent justice-focused analysis found that adopting EVs in the state of Illinois can reduce regional differences in transportation energy vulnerability [43].

However, potential patterns of EV energy burdens, which fall under distributional justice, have not been investigated for the entire U.S., nor have any studies assessed how and where EV energy burdens relate to GHG emissions. This study addresses this research gap by using a spatial model to evaluate three essential factors associated with the EV transition: transportation energy burden, fuel costs, and GHG emissions. We focus on the following questions:

1. Where and to what extent do new battery electric vehicles (BEVs) and ICEVs reduce current transportation energy burdens and how do these outcomes vary across income groups?
2. Relative to new ICEVs, where and to what extent do BEVs reduce GHG emissions in addition to energy burdens?

To answer these questions, we calculated census tract-level transportation energy burdens and GHG emissions of new BEV and ICEV models using a spatially explicit life cycle assessment approach. We compared new BEV and ICEV energy burdens to transportation energy burdens of the current on-road vehicle stock [40]. Then we compared the spatial variation and extent of energy burdens and GHG emissions for BEVs and ICEVs.

2 Methods

This study drew on data and methods from previous EV and transportation energy burden research, including vehicle parameters and GHG emissions [4,5], travel behavior and transportation energy burden [40], and vehicle fuel costs [31]. For GHG emission and fuel cost comparisons, we used 2020 vehicle models for two powertrains (ICEV and BEV) and three vehicle classes (i.e., sedan, sport utility vehicle [SUV], and pickup truck) and assumed that households would switch to the same vehicle class (e.g., sedan ICEV to sedan BEV). To ensure comparability, we applied vehicle and travel behavior parameters consistently across the calculations. The geographic scope of the study is the United States, excluding territories (e.g., Puerto Rico). See Appendix I for additional details.

2.1 Fuel Costs

For fuel cost calculations, we modified data and methods from Borlaug et al. [31] by including different vehicle parameters, county instead of state level fuel prices, and more recent data. For each combination of powertrain, vehicle class, and county, we calculated the fuel cost factor (FCF) in terms of U.S. dollars per mile (USD mile^{-1}), which reflects lifetime vehicle fuel costs divided by the lifetime vehicle miles traveled (VMT) of the vehicle (VMT_{life}):

$$FCF = \frac{\sum_{y=2022}^{y+L} \frac{VMT_y * FC * C_{fuel} * P_{fuel,y} * \frac{1}{\eta}}{(1+dr)^{y-2022}}}{VMT_{life}} \quad (1)$$

where L is the lifespan of the vehicle (years) [4,5], VMT_y is annual vehicle VMT for year y [4,5,44] (see S1.2), FC is fuel consumption (gallon or kilowatt-hour [kWh] mile^{-1}) [4,5,45–47] (see S1.4), C_{fuel} is the cost of fuel (U.S. dollars [USD] gallon^{-1} or kWh^{-1}) [31,40,48,49] (see S1.7), $P_{fuel,y}$ is the fuel price projection for year y [50] (see S1.7.2), η is the charging efficiency (only applicable to BEVs) [4,5], and dr is the discount rate [31,51]. Since the cost of charging an EV is influenced by factors such as charging location, time of day, and power level [31], we calculated the levelized cost of charging (LCOC; in USD kWh^{-1}) instead of simply electricity prices (see S1.7.1).

2.2 GHG Emissions

For GHG emissions, we modified data and methods from Woody et al. [4,5] by adding Alaska and Hawaii and using one different decarbonization scenario. For each combination of powertrain, vehicle class, and county, we calculated the life cycle emissions factor (LEF) in terms of grams of carbon dioxide equivalents per mile (gCO_2e mile^{-1}), which reflects cradle-to-grave lifecycle GHG emissions of the vehicle divided by the lifetime vehicle VMT:

$$LEF = \frac{VCE + \sum_{y=2022}^{y+L} VMT_y * FC * EF_{fuel,y} * \frac{1}{\eta}}{VMT_{life}} \tag{2}$$

where VCE is vehicle cycle emissions (gCO_2e) [4,5] and EF_{fuel} is the fuel emissions factor (gCO_2e gallon^{-1} or kWh^{-1}), which varies by year y for electricity only [4,5,52,53] (see S1.8). The remaining variables are the same as those in equation (1).

2.3 Household and Tract-Level Results

Figure 1 displays the variables used to calculate household transportation energy burdens and GHG emissions at the census tract level. Zhou et al. [40] estimated travel behavior (i.e., annual household VMT) at the census tract level for 220 different household classifications (defined by income, workers, and vehicles) (see S1.3). We filtered out zero vehicle households (approximately 9% of U.S. households) from the dataset and multiplied the county-level FCF and LEF values by corresponding annual household VMT to calculate annual household fuel costs and GHG emissions at the tract-household classification level.

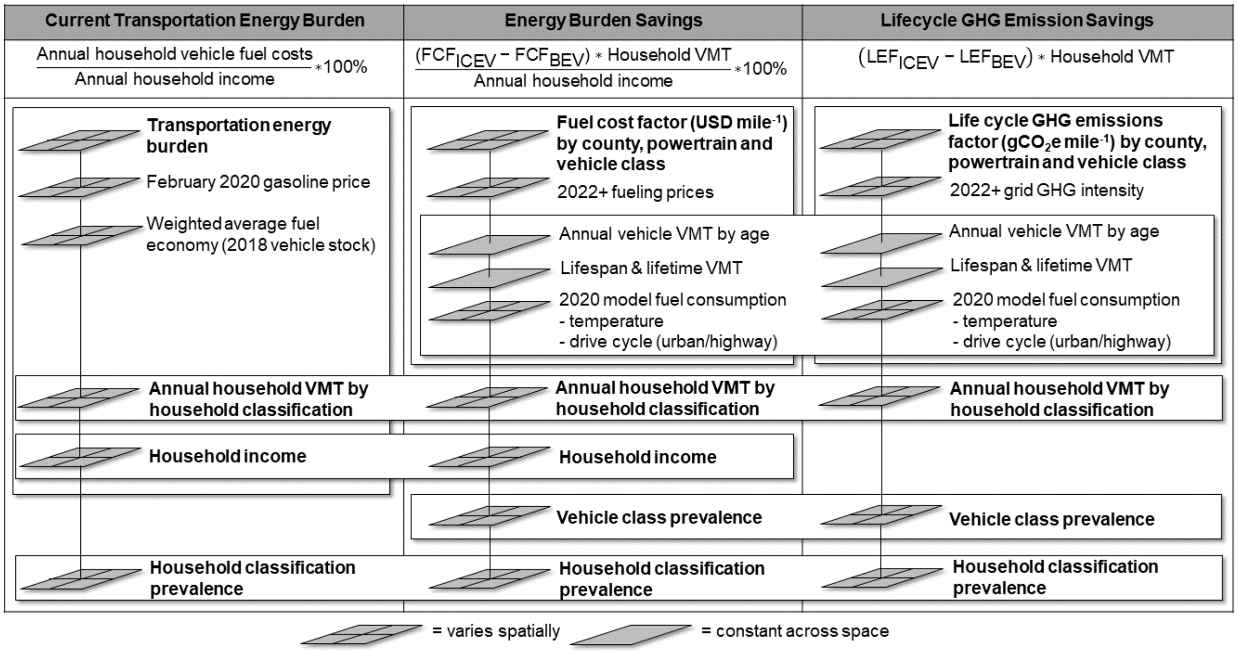

Figure 1. *Graphic representation of variables included in this study. BEV = battery electric vehicle; FCF = fuel cost factor; GHG = greenhouse gas emissions; ICEV = internal combustion engine vehicle; LCOC = levelized cost of charging; LEF = life cycle emissions factor; USD = U.S. dollars; VMT = vehicle miles traveled.*

To calculate the transportation energy burden of a new ICEV or BEV, we divided the annual household fuel costs by household income:

$$Transportation\ energy\ burden = \frac{Annual\ household\ vehicle\ fuel\ costs}{Annual\ household\ income} * 100\% \qquad (3)$$

'Energy burden savings' refers to the difference between ICEV and BEV burdens, while 'GHG savings' refers to GHG emission reductions. 'Current transportation energy burden' refers to household vehicle fuel burdens calculated by Zhou et al. [40] using February 2020 gas prices and weighted fuel economies of the current on-road vehicle stock (as of 2018), which consists primarily of ICEVs.

Since the results include multiple vehicle classes and household classifications for each census tract, we aggregated them to facilitate analysis and reporting. We weighted results for the three vehicle classes by prevalence in the tract, based on the 2017 National Household Travel Survey (NHTS) [40,44] (see S1.5). Likewise, we weighted results for the 220 household classifications by prevalence and aggregated to tract-level. We used a population-weighted average for reporting national-level results. Energy burden for households with varying income levels is somewhat obscured at the aggregated tract level, so our main unit of analysis for transportation energy burden is at the tract-income bin level, aligning with the U.S. Department of Energy's Low-Income Energy Affordability Data Tool [54]. For each tract, we aggregated the results to seven income bins based on area median income (AMI) [55,56]: 0-30% AMI, 30-60% AMI, 60-80% AMI, 80-100% AMI, 100-150% AMI, 150-200% AMI, and 200%+ AMI.

2.4 Categorizing Results

To compare across GHG and energy burden savings, we categorized the tract-level results based on their percentile ranking: "low" (≤25th percentile), "moderate" (>25th percentile and ≤75th percentile), or "high" (>75th percentile). Since no standard threshold for high transportation energy burden exists in the literature, we used this method to determine the delineations between low, moderate, and high current transportation energy burden. Tract-income bin level analysis revealed that burdens above 3.9% are high, and below 1.8% are low. We rounded these values up to 4 and 2%, respectively.

2.5 Scenario and Sensitivity Analyses

We conducted scenario and sensitivity analyses to assess the models and their parameters. We ran four scenarios (Table 1): one baseline representing primarily residential charging ("baseline-residential charging"), another baseline representing public without at-home charging ("baseline-public charging"), one worst-case for BEVs, and one best-case for BEVs.

We included the baseline-public charging scenario because research has shown that interrelated factors such as housing type, housing tenure, and household income impact access to EV charging, with renters, households living in multi-family dwellings, and lower income households less likely to have access to residential EV charging [57,58]. The calculated LCOC may not always reflect real-world public charging costs, which are affected by electric vehicle supply equipment (EVSE) costs, profit margins, and built-in incentives (e.g., free charging); rather, LCOC is intended to reflect the true cost of charging [31].

We conducted a parametric sensitivity analysis for 12 parameters, adjusting each ±10% while keeping the others unchanged. We then calculated the percent change in the results; a change greater than 10% indicates the model is relatively sensitive to the parameter.

Table 1. *Parameter assumptions for four scenarios.*

Parameter	**Variable**	**Baseline - Residential**	**Baseline - Public**	**Best Case for BEV**	**Worst Case for BEV**	**Source**
Lifetime VMT	VMT_{life}	Baseline	Baseline	BEV lifetime +20%	BEV lifetime - 20%	[4,5]
Annual vehicle VMT by age	VMT_y	Baseline	Baseline	Baseline	Baseline	[4,5,44]
Fuel consumption	FC	Baseline	Baseline	Baseline	Baseline	[4,5,45–47]
BEV charging efficiency	η	85%	85%	+10%	-10%	[4,5]
Gasoline price	C_{fuel}	Baseline	Baseline	Baseline	Baseline	[40]
LCOC	C_{fuel}	Moderate	Moderate	Low	High	[31,48,49]
Charge Mix		81% res, 14% pub, 5% DCFC	40% pub, 60% DCFC	100% res L1	100% DCFC	[31,59]
EVSE costs		Moderate	Moderate	None	High + grid upgrade	[a]
O&M costs		8%	8%	1%	12%	[a]
EIA Fuel Price Projection	$P_{fuel,y}$	Reference	Reference	High oil price	Low oil price	[50] [b]
Discount rate	dr	3.5%	3.5%	3.0%	7.0%	[31,51]
Vehicle cycle emissions	VCE	Baseline	Baseline	Baseline	Baseline	[4,5]
Gasoline emissions factor	EF_{fuel}	Baseline	Baseline	+10%	-10%	[4,5]
Electric grid emissions factor (NREL Cambium Standard Scenarios)	$EF_{fuel,y}$	Mid Case - No New Policy	Mid Case - No New Policy	Mid Case - 95% Decarbonization by 2035	High Renewable Energy Costs	[52,53]

[a] Source: Based on email correspondence with Borlaug (NREL) on May 24 and 25, 2022

[b] U.S. EIA fuel price projections are for motor gasoline and residential electricity (baseline-residential and best case) or commercial electricity (baseline-public and worst case)

BEV = battery electric vehicle; DCFC = direct current fast charging; EIA = Energy Information Administration; EVSE = electric vehicle supply equipment; L1 = level 1 (charging); LCOC = levelized cost of charging; NREL = National Renewable Energy Laboratory; O&M = operations and maintenance; pub = public; res = residential; VMT = vehicle miles traveled

3 Results

Over 90% of households see some level of savings for both GHG and energy burden, confirming the potential for widespread co-benefits from EV adoption. BEVs generally reduce transportation energy burden significantly more than ICEVs; however, over half of the lowest income households continue to experience high BEV energy burdens. The scenario analysis indicates that future grid decarbonization, current and future fuel prices, and charging accessibility will impact the extent to which EV benefits can be realized.

3.1 Changes in Transportation Energy Burden

The national average energy burden of the current vehicle stock is 3.6%. As expected, in the baseline-residential charging scenario, adopting new BEVs or new ICEVs would result in lower national average energy burdens. Furthermore, national average burdens of a new BEV (1.4 to 2% depending on vehicle class) are lower than those of a new ICEV (2.3 to 3.4% depending on vehicle class).

3.1.1 Tract-Level Results

Current vehicle stock and new ICEV burdens are moderate for most census tracts (Figure 2a,d), while BEV burdens for most tracts are low (Figure 2b). New BEV adoption results in average fuel cost reductions of 55%, with 71% of households seeing over a 50% reduction in fuel costs (Figure 2c). By comparison, new ICEV adoption results in average fuel cost reductions of 27%, with only 2% of households seeing over a 50% reduction (Figure 2e).

The greatest fuel cost reductions (50 to 81%) from adopting a BEV occur in the American South and West, while increases in energy burden (as much as 219%) occur for a very small percentage of U.S. households (0.1%) living in Alaska, Michigan, Maine, Rhode Island, and Massachusetts (Figure 2c). Areas with high BEV energy burden reductions have either lower LCOC relative to gasoline prices, relatively smaller temperature and drive cycle-related impacts on fuel consumption, or both (Figure S9, Figure S11-S14).

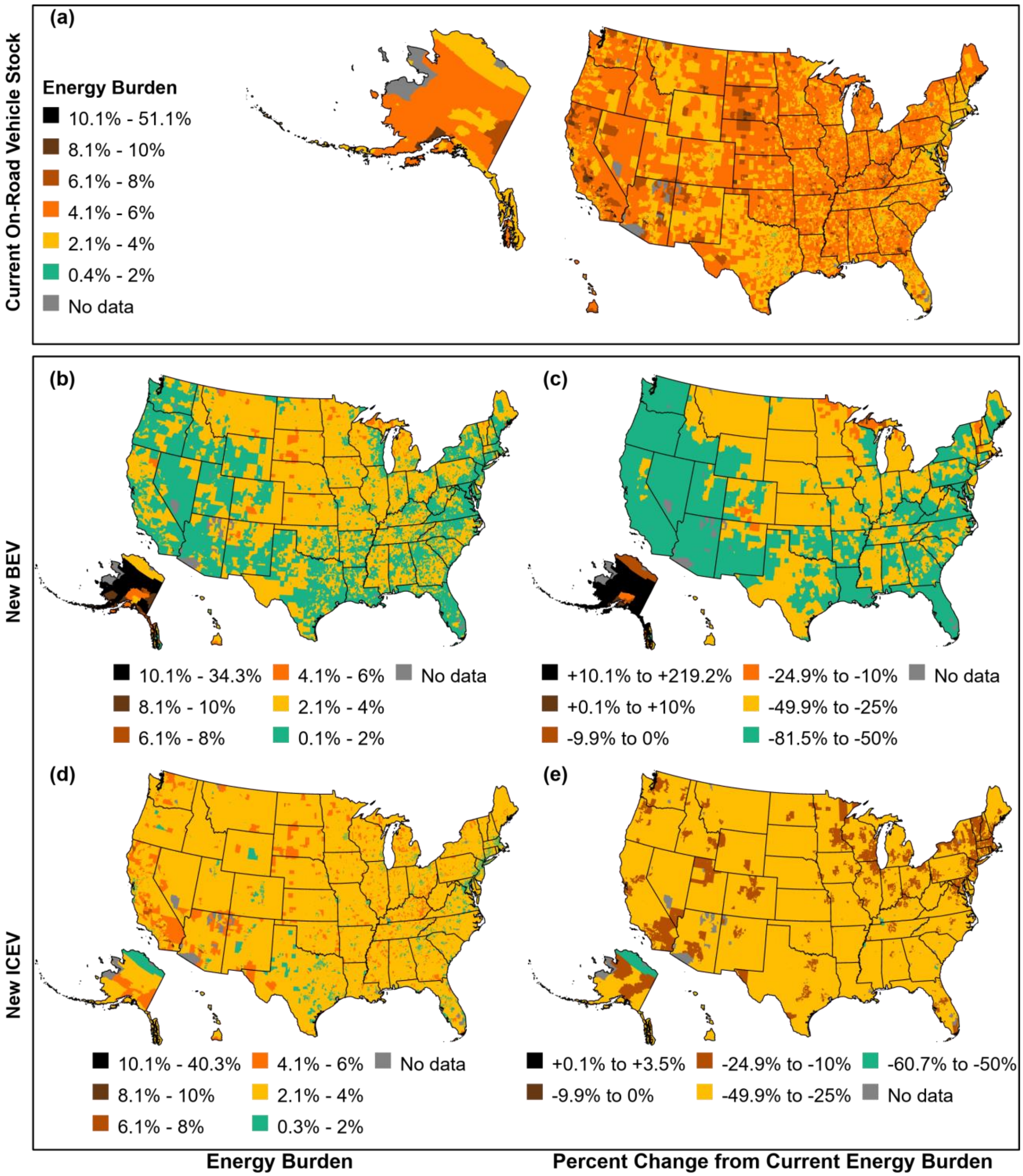

Figure 2. *Geographic distribution of average transportation energy burdens, census tract level.* ***(a)*** *Energy burden for the current on-road vehicle stock from [40].* ***(b-e)*** *Energy burdens and percent changes from current energy burden for a new ICEV and new BEV. BEV = battery electric vehicle; ICEV = internal combustion engine vehicle.*

3.1.2 Results by Income (Tract-Level)

While around 33% of households currently have low transportation energy burdens, fuel cost reductions from BEV adoption are significant enough that more than double the American households (i.e., over 80%) would have low BEV energy burdens (Figure 3). Moreover, the percentage of high burden households drops by almost two-thirds to 7%.

However, as expected, the lowest income households continue to experience the highest burdens (Figure 3). While households with incomes 30-80% of AMI would have low to moderate BEV energy burdens, with very few still experiencing high burdens, the opposite is true for households with incomes less than 30% of AMI: essentially all would experience moderate (42%) or high (54%) BEV burdens; very few (4%) would experience low BEV burdens.

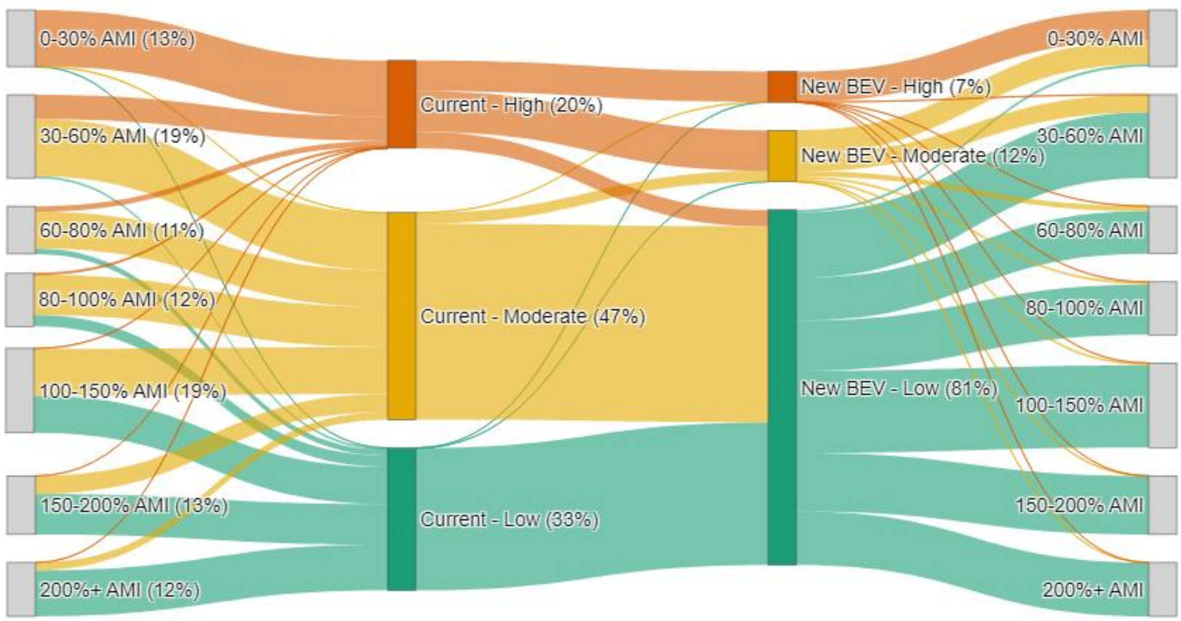

Figure 3. *Change in high, moderate, and low energy burden households from the current vehicle stock to a new BEV. The seven income bins are shown on the far left and far right to show the change in distribution for each income level. AMI = area median income; BEV = battery electric vehicle.*

In most tracts, 0-30% AMI households experience current transportation energy burdens above 10% that range as high as 95% (Figure 4a). BEV adoption would significantly reduce burdens overall. Most households with high BEV energy burden have burdens below 6%; very high BEV burdens ranging from 10 to 64% are concentrated in the Midwest, Alaska, and Hawaii (Figure 4c). Around 22% of high BEV burden tracts are urban (24% of households), while the remaining 78% of high BEV burden tracts are suburban or rural (76% of households).

Overall, transportation energy burdens are reduced as incomes increase; most 30-60% AMI households have low or moderate BEV energy burdens, with the lowest burdens concentrated in the West and Southeast regions (Figure 4d, e). Alaska is a notable outlier for

BEV energy burden, with a median of 13.3% for 0-30% AMI households and 4.2% for 30-60% AMI households (Figure 4e). For 0-30% AMI households in all other states, median BEV energy burden stays below 10% and drops below the high burden threshold of 4% starting with Washington (Figure 4e).

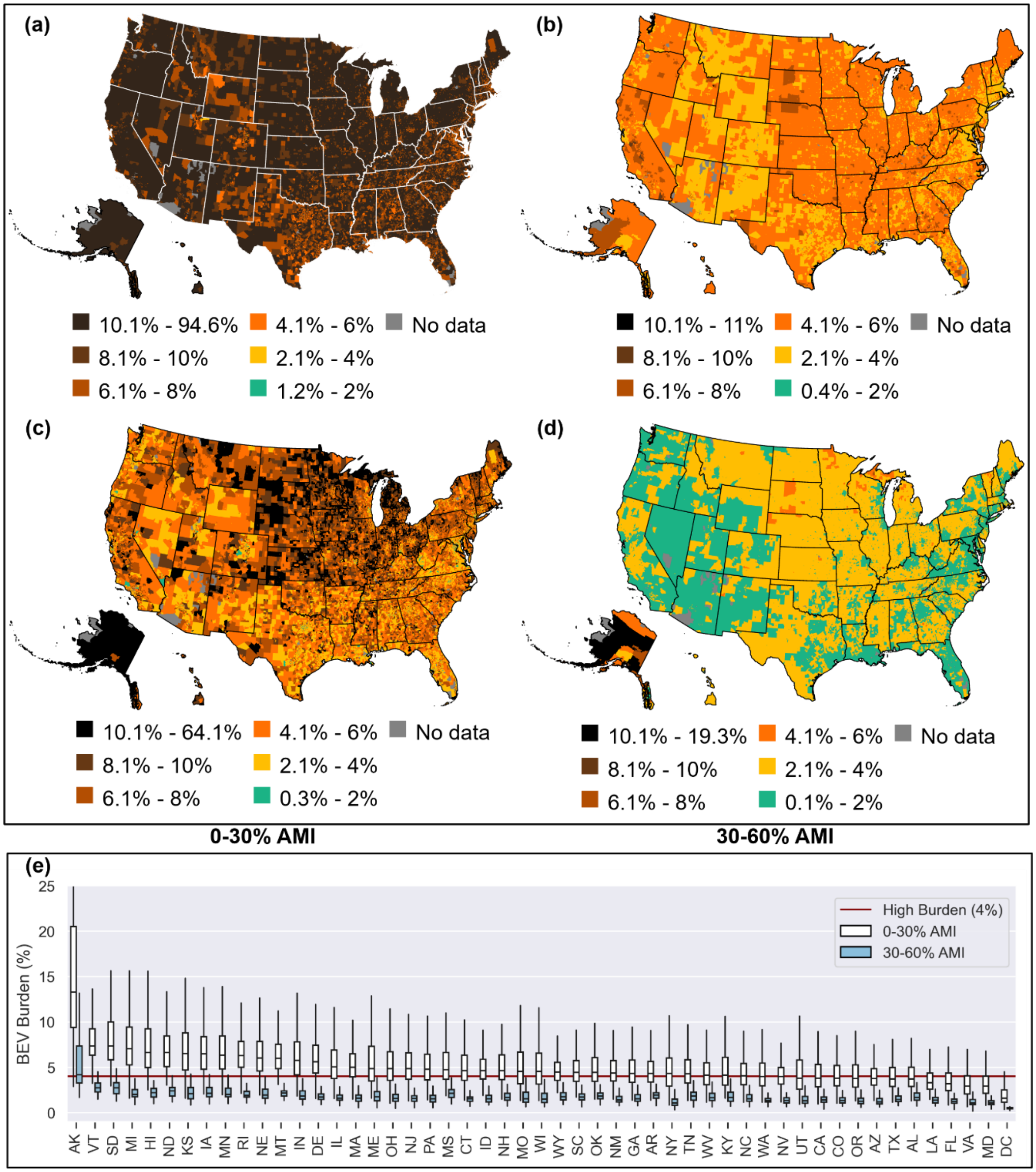

Figure 4. *Transportation energy burdens of low-income households.* ***(a-d)*** *Geographic distribution of current and BEV energy burdens for low-income households (<60% AMI).* ***(e)*** *Boxplots of BEV energy burden by state for households with 0-30% and 30-60% AMI. States are sorted by median 0-30% AMI burden. Whisker represents 1.5 times the interquartile range (note: extent of top whisker for Alaska is cut off for readability). Outliers are not shown. AMI = area median income; BEV = battery electric vehicle.*

3.1.3 Charging Access

Aligning with findings from Borlaug et al. [31], the true levelized cost of public charging (i.e., Level 2 and direct current fast charging [DCFC]) is higher than residential charging, largely because of the higher EVSE costs. Median baseline-public LCOC is 0.22 USD kWh^{-1}, while the baseline-residential LCOC is 0.16 USD kWh^{-1} (Figure 5a; also see S1.9). Therefore, in the baseline-public charging scenario, BEV energy burdens are higher and follow the same low income-high burden pattern (Figure 5b), with over three quarters (77%) of the lowest income households experiencing high BEV energy burdens. Notably, BEV energy burdens in the baseline-public charging scenario are generally still lower than new ICEV energy burdens (Figure 5b).

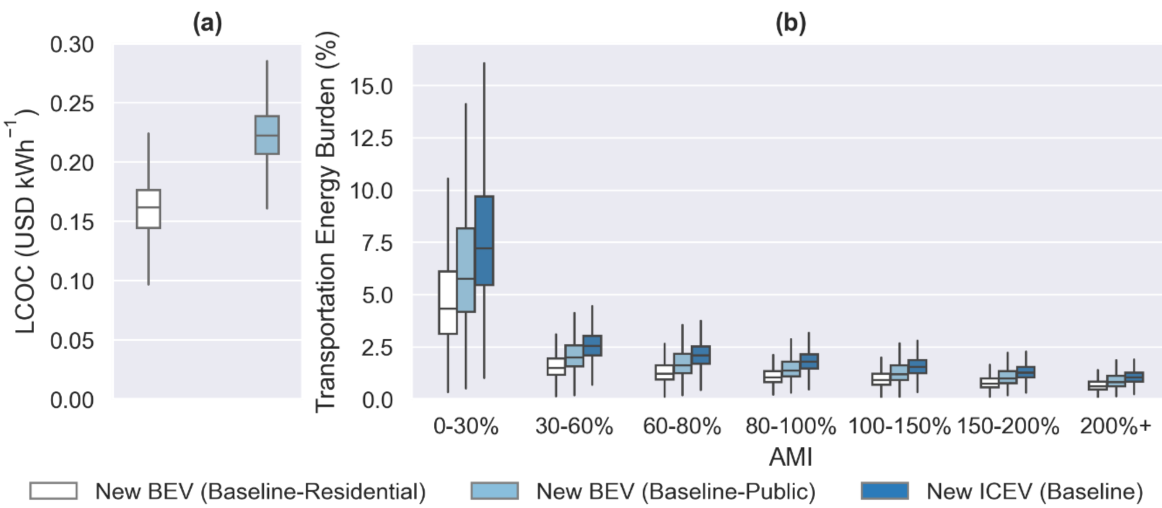

Figure 5. *LCOC and energy burden results for a new BEV and ICEV in the two baseline scenarios.* ***(a)*** *Boxplots of LCOC (U.S. dollars per kilowatt-hour [USD kWh^{-1}]).* ***(b)*** *Boxplots of energy burden by income bin. Whisker represents 1.5 times the interquartile range. Outliers are not shown. Note: ICEV assumptions are the same across baseline scenarios. AMI = area median income; BEV = battery electric vehicle; ICEV = internal combustion engine vehicle; LCOC = levelized cost of charging.*

3.2 Geographic Distribution of Household GHG and Energy Burden Savings

By purchasing a new BEV instead of an ICEV, households in tracts with high annual savings potential would see GHG savings of more than 4.1 metric tons CO_2e (tCO_2e) household-year^{-1} (Figure 6b) and energy burden savings of more than 1.3% (Figure 6c; $595 or more). On the other hand, we delineate low GHG savings potential by 2.3 tCO_2e household-year^{-1} or less (Figure 6b) and low energy burden savings potential by 0.6% or less (Figure 6c; $273 or less). The remaining tracts fall in between these thresholds in the moderate category.

Overall, 60% of households live in census tracts with both moderate to high GHG and energy burden savings potential and approximately 91% of households would see some level of

GHG and energy burden savings. The category with the most households (27%) is both moderate GHG savings and energy burden savings (Figure 6a, d). Eight percent of U.S. households have both high energy burden and GHG reduction potential and are concentrated in the Pacific West, Arizona, and New York ("Both High," Figure 6a, d). "Both High" tracts have a combination of one or more of the following factors: smaller impacts on BEV fuel efficiency due to milder temperatures (Figure S9a-b, Figure S11), lower electricity prices relative to gas prices (Figure S9c-d, Figure S12, Figure S13), current and future electric grids with low carbon intensity (Figure S9e-f, Figure S14), higher relative VMT (Figure S10a), and lower incomes (Figure S10b). Variations due to VMT and income are mostly observed at regional and local levels (e.g., urban versus suburban and rural).

The remaining portions of the U.S. exhibit low savings potential for either or both factors. Around 8% of households live in "Both Low" tracts, which are scattered throughout the U.S., with roughly half in the Midwest (Figure 6a, d). Additionally, for one or both factors, there are areas where BEVs and ICEVs perform similarly (i.e., savings are close to zero)[1] and where BEVs definitively perform worse; however, less than 1.3% of households fall into each of these categories. The tracts with low GHG and energy burden savings potential have a combination of one or more of the following factors: greater impacts on fuel efficiency due to extreme cold temperatures (Figure S9a-b, Figure S11), higher electricity prices relative to gas prices (Figure S9c-d, Figure S12, Figure S13), current and future electric grids with moderate to high carbon intensity (Figure S9e-f, Figure S14), lower relative VMT (Figure S10a), and higher incomes (Figure S10b).

[1] We consider BEVs and ICEVs to perform similarly when GHG emissions and energy burdens are less than 5% different between the two powertrains.

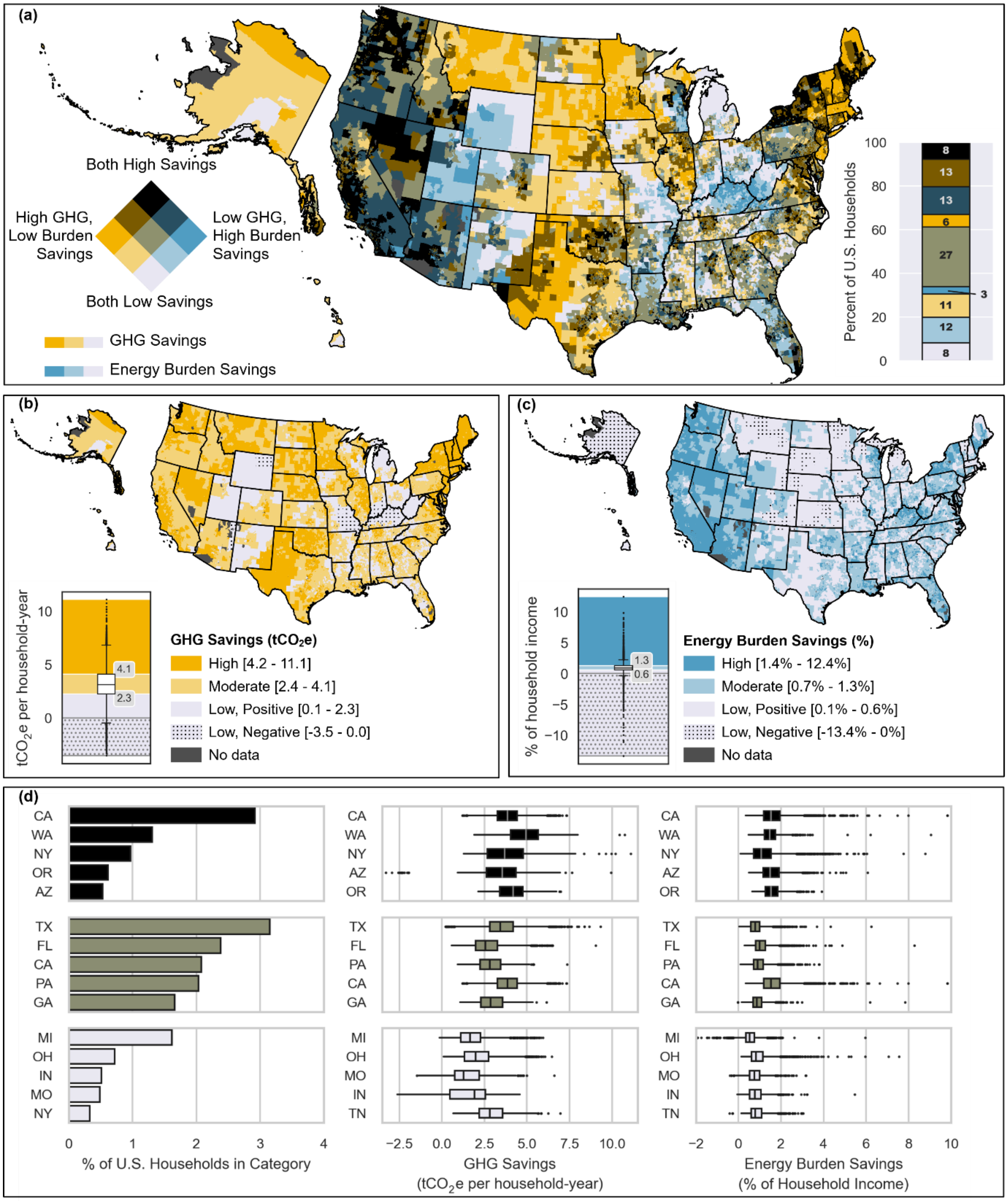

Figure 6. *Geographic distribution of GHG and energy burden savings, census tract level.* ***(a)*** *Bivariate map of GHG and energy burden savings, with the percentage of U.S. households in each bivariate category.* ***(b)*** *Geographic distribution and boxplot of potential GHG savings.* ***(c)*** *Geographic distribution and boxplot of potential energy burden savings.* ***(d)*** *Top five states by households in "Both High," "Both Moderate," and "Both Low" categories, with boxplots showing the range of GHG and energy burden savings for each state. GHG = greenhouse gas emissions; tCO$_2$e = metric tons of carbon dioxide equivalents.*

3.3 Sensitivity Analysis

Based on the sensitivity analyses (see S1.11), the GHG model is most sensitive to the gasoline combustion emissions factor and ICEV fuel consumption parameter (±17.2%; Figure S15a). The other parameters result in less than a 10% change. The fuel cost model is much more sensitive (Figure S15b). Most of the parameters result in over 10% changes (±13.7 to 29.6%), with ICEV fuel consumption and initial and future gas prices showing the most sensitivity.

3.4 Worst and Best-Case for BEV Scenarios

National average savings for the worst- and best-case scenarios range from -1.1 to 3% for energy burden and 2.1 to 4.9 tCO_2e household-year^{-1} for GHGs (Figure S16). Overall, in the worst-case scenario, BEV energy burdens are greater than ICEV burdens for 98% of households due to high-cost DCFC-only charging (Figure S17); however, BEV GHG emissions are greater for only 8% of households that are concentrated primarily in Midwest and South-Central states, where the electric grid remains dominated by fossil fuels due to high renewable energy costs (Figure S18). Research on charging patterns indicates that 100% DCFC charging is unlikely in the real world, while the baseline-public charging scenario is closer to reality for EV owners that do not have reliable at-home charging access [59].

Conversely, in the best-case scenario, BEV fuel costs would be greater than ICEV costs for only 0.07% of households concentrated in Alaska and Maine where high electricity prices and low BEV fuel efficiency persist (Figure S17). All households would see GHG savings due to 95% decarbonization by 2035 (Figure S18).

4 Discussion

Our analysis indicates the potential for widespread co-benefits from EV adoption; however, the significant spatial and income-level variation emphasizes the need for regional and localized approaches to address high BEV burdens and slow grid decarbonization. Additionally, we consider the impact of fuel price and travel behavior uncertainty on our results.

Figure 7 provides insights into where cross-sectoral policies are necessary to improve EV benefits. Regions with moderate- to high-energy burden savings but low GHG savings potential (Figure 7a) should pursue grid decarbonization policies, while the focus should be more on electricity prices for regions with the opposite trend (Figure 7b). “Both Low” areas (Figure 7c) require both types of policies to increase EV benefits.

Because high BEV energy burdens are distributed across the U.S. and largely impact lower income households, with the highest burdens in the Midwest, Alaska, and Hawaii (Figure 7d), localities across the U.S. should consider additional policies to reduce BEV energy burdens alongside EV adoption policies. Since BEVs are more fuel efficient than ICEVs, we must consider the other three factors contributing to transportation energy burden, namely, income, VMT, and fuel prices. Addressing income inequality is a broader discussion point in distributional justice conversations (e.g., [60,61]); however, this is beyond our scope.

Regarding VMT, approximately 22% of high BEV burden tracts are urban, suggesting an opportunity for reducing energy burden via investment in other transportation modes such as transit, biking, and walking [41,60]. This same notion can be found in decarbonization literature, which finds that vehicle electrification is unlikely to meet passenger transport mitigation targets alone, and therefore demand-side solutions (e.g., densification, mode switching, behavioral changes) are essential [2,62–64] and have the potential to reduce emissions by 20 to 50% between 2010 and 2050 [64].

The remaining 78% of high BEV burden tracts are suburban or rural and may lack access to alternate transportation modes. Increasing access to alternatives, such as transit and car sharing, can alleviate car dependence, but may not be feasible, particularly in rural communities.

Reducing high electricity prices is another option, such as through time-of-use and EV-specific electricity rates [31,65]. For Alaska and Hawaii, which have the highest electricity prices in the U.S., decreasing dependence on oil-fired power is key to reducing costs [66,67]. Also, a pilot study of pairing rooftop solar and EV incentives indicates promising gains in reducing carbon intensity and electricity prices for low and moderate income households [68]. In addition to reducing electricity prices, ensuring the relative stability of electricity prices, which are generally not subject to the same volatility as gasoline prices, is key to reducing energy price vulnerability for low-income households.

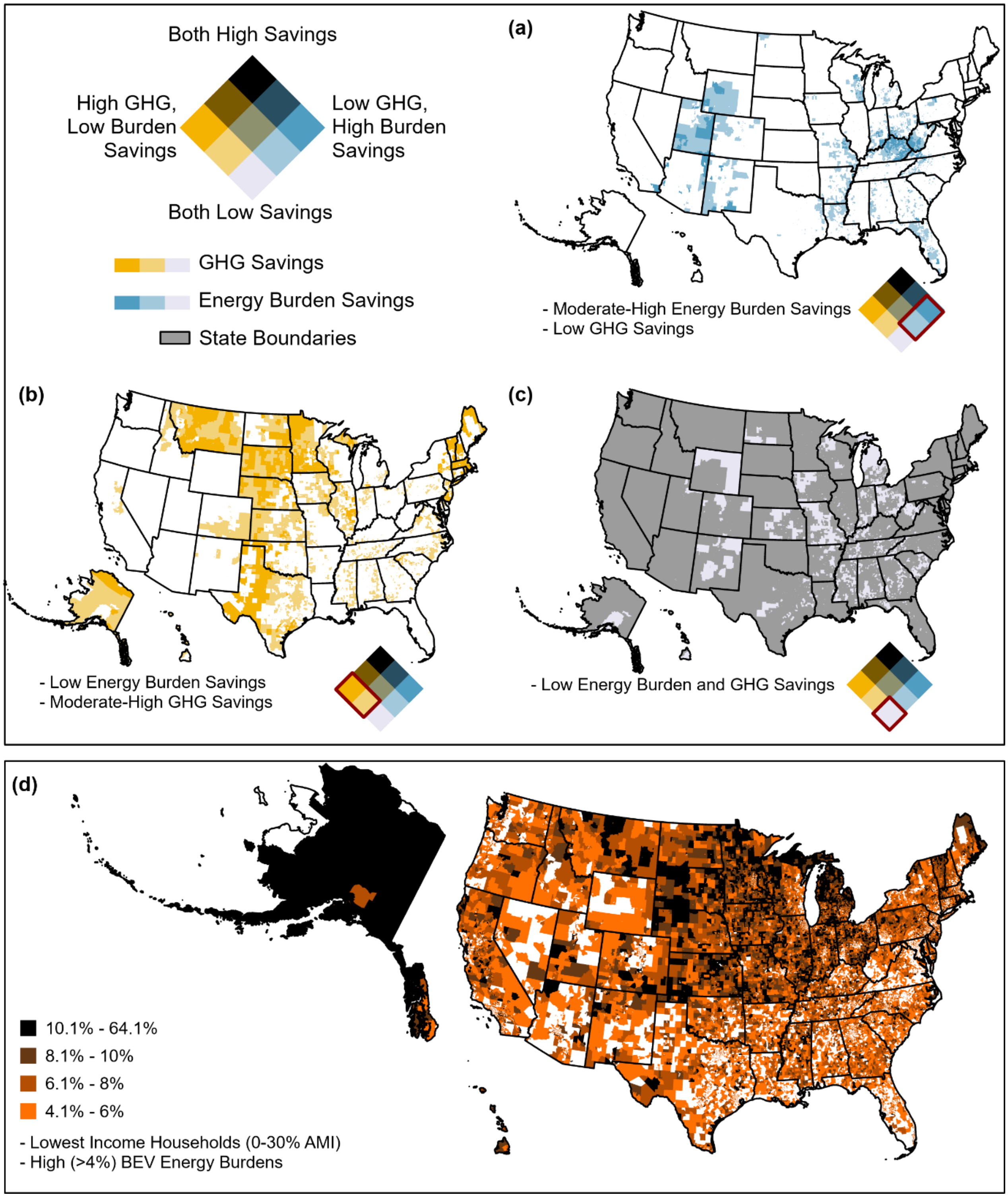

Figure 7. *Examples of identifying regions for specific policy interventions.* ***(a)*** *Regions where energy burden savings are moderate to high, but GHG savings are low.* ***(b)*** *Regions where energy burden savings are low, but GHG savings are moderate to high.* ***(c)*** *Regions where both energy burden and GHG savings are low.* ***(d)*** *Regions where the lowest income households have high BEV energy burdens. AMI = area median income; BEV = battery electric vehicle; GHG = greenhouse gas.*

Important considerations for our transportation energy burden analysis are the metric's sensitivity to energy prices [39,69], which was confirmed by our sensitivity analysis, and to travel behavior. While we consider "high" transportation energy burdens to be above 4%, we cannot make any definitive assertions as to whether burdens above this threshold are unaffordable (or vice versa), particularly since we use a modeled approach. Furthermore, our high and low thresholds are derived from "current" transportation energy burden based on pre-COVID-19 pandemic gasoline prices (February 2020). Our brief analysis indicates that August 2022 transportation energy burdens average almost 70% higher than 2020 burdens (S1.13), so our "current" burden appears to represent a conservative case. Also, the U.S. Energy Information Administration (EIA)'s fuel price projections used for new BEV and ICEV cost estimates are generally conservative. Our modeled vehicle lifespans range from 17 to over 18 years and therefore spikes in prices may not significantly impact our results, though sustained increases (or decreases) would, as indicated by the sensitivity analysis. Finally, Zhou et al. [40] note that the tract-level annual household VMT is modeled and therefore does not necessarily reflect travel behavior for every household. In fact, the model was found to underestimate VMT for lower income households and overestimate VMT for higher income households and therefore our results may underestimate transportation energy burdens for lower income households. Overall, these limitations represent areas for further refinement and study.

In addition to outstanding transportation energy burden hurdles, the upfront cost of BEVs is a major barrier. Although recent studies have indicated that the total cost of ownership of BEVs can be comparable or less than that of ICEVs, most savings are from lower operating costs and federal incentives [26–28]. We can hypothesize that areas with similar BEV and ICEV fuel costs identified in our study would have higher overall total cost of ownership for BEVs, but this represents an area for future study. Nonetheless, EV ownership in the U.S. has been dominated by households with higher incomes and levels of education [70–72], representing an additional distributional justice concern [34]. However, this aligns with typical trends for most new technologies and while adoption tends to become more equitable over time [61,73], policy interventions are necessary to increase EV accessibility for low and moderate income households.

Such policies include incentives for new and used vehicles, particularly those that are not exclusively tied to taxes [74], programs that specifically target low income households (e.g., California’s Enhanced Fleet Modernization Program) [71,74,75], raising awareness about BEVs (e.g., Drive Electric Vermont) [34,71,76], and increasing access to residential or cheaper public charging, particularly for renters, households living in multi-family dwellings, and lower income households [34,57,58].

The 2022 Inflation Reduction Act (IRA) improves the existing federal tax credit program by lifting the cap on manufacturer credits, which allows future adopters the same opportunities as early adopters, and eliminates some barriers for lower and moderate income households, such as limiting eligibility by income and vehicle cost, adding a credit for used vehicles, and allowing credit transfers at point-of-sale [77]. Additionally, the Neighborhood Access and Equity Grants in the IRA provide funding for affordable transportation and other programs in disadvantaged and underserved communities [78] and could be used to pursue alternative low-carbon transport modes, as discussed above.

5 Conclusion

Our study is the first to jointly consider the spatial variation of EV-related energy burdens and GHG emissions in the U.S. Our results indicate that EVs can significantly reduce energy burdens, particularly more so than new ICEVs, which confirms conjectures in the literature about the energy burden reduction potential of EVs. We have also identified where and how EV energy burdens and GHG emissions vary together spatially, which can better inform location-specific and cross-sectoral electricity and transportation policymaking.

Sovacool et al. proposed an energy justice framework for assessing EVs [34], and this study only addresses a small portion of this framework. As EV adoption accelerates in the U.S., further justice-focused research is needed. Energy justice scholars highlight that household and transportation energy burdens should be jointly studied, particularly as low-carbon technology diffusion and electrification progresses [37]. Future spatially explicit analyses could use our framework to consider both transportation- and household-related factors (e.g., GHG emissions and air pollution, the total cost of ownership, EV charging infrastructure, urban form, access to vehicles and other transport modes, housing type, race and ethnicity, household energy burdens) to deepen our understanding of how EVs fit into broader transportation and energy justice concerns.

Appendices

Appendix I – Supplementary Methods

The following sections provide additional detail regarding the methods used in this analysis. Additionally, supporting data is available at https://css.umich.edu/research/data-downloads.

S1.1 Overview of Data Sources

Table S1 below provides a summary of the main parameters used in the analysis, including a general description, the variable, the spatial scale, and the source.

Table S1. *Summary of variables and data sources.*

Parameter	Description	Variable	Spatial Scale	Source
Vehicle and Demographic Parameters				
Lifetime VMT	Vehicle miles traveled over the lifetime of the vehicle for each vehicle class (see S1.2)	VMT_{life}	Constant	[4,5]
Annual vehicle VMT by age	Standardized U.S. VMT profile of average annual per-vehicle VMT by vehicle age and vehicle class derived from the 2017 NHTS [44] (see S1.2)	VMT_y	Constant	[4,5,44]
Fuel consumption (gallons or kWh per mile)	Fuel consumption for each powertrain and vehicle class adjusted for county-level drive cycle and temperature conditions (see S1.4)	FC	County	[4,5,45–47]
BEV charging efficiency (%)	Ratio of energy added to battery to total energy consumed	η	Constant	[4,5]
Annual household VMT weighted by household type	Tract-level estimated annual household VMT for 220 different household classifications (defined by income, workers, and vehicles) with zero vehicle households filtered out (see S1.3)		Tract	[40] [a]
Vehicle class prevalence (%)	Prevalence of vehicle classes in 18 geographic groups derived from the 2017 NHTS [44] (see S1.5)		Tract	[40,44]
Area median income	Median income defined for a given area (i.e., a metropolitan area or non-metropolitan county) by the U.S. Department of Housing and Urban Development (see S1.6)		County or county subdivision	[55]
Population	Estimated population from the 2018 5-Year ACS (Table B01003)		County or tract	[79]
Households	Estimated households from the 2018 5-Year ACS (Table B25003)		County or tract	[79]
Lifetime Fuel Cost Factor (USD per mile)	Lifetime fuel cost factors for each powertrain and vehicle class	FCF	County	This study
Gasoline price (USD per gallon)	Temporal snapshot of gas prices on February 26, 2020, from GasBuddy.com, aggregated from ZIP5 to ZIP3 to county	C_{fuel}	County	[40]

Parameter	Description	Variable	Spatial Scale	Source
LCOC (USD per kWh)	Levelized cost of charging a BEV (see S1.7.1), including:	C_{fuel}	County	This study, [31]
	• Charge mix		Constant	[31,59]
	• Cost of EVSE and installation		Constant	[b]
	• Annual O&M costs		Constant	
	• Electricity prices		County	[48,49]
Fuel price projections	Motor gasoline and residential and commercial electricity price projections for 2021-2050 from the EIA's 2021 Annual Energy Outlook, indexed to 2020	$P_{fuel,y}$	Constant	[50]
Discount rate	Rate used to calculate the present value of future spending using the social rate of time preference of 3.5% from [51]	dr	Constant	[31,51]
Life Cycle GHG Emissions Factor (gCO_2e per mile)	Life cycle GHG emissions factors for each powertrain and vehicle class (see S1.8)	LEF	County	[4,5], this study
Vehicle cycle GHG emissions (gCO_2e)	GHG emissions associated with the vehicle materials, manufacturing, assembly, and disposal for each powertrain and vehicle class (see S1.8)	VCE	Constant	[4,5]
Gasoline carbon intensity (gCO_2e/gallon gasoline)	Well-to-wheel GHG emissions associated with the upstream production and combustion of gasoline (see S1.8)	EF_{fuel}	Constant	[4,5]
Electricity carbon intensity (gCO_2e/kWh)	GHG emissions associated with electricity production from NREL's Cambium Standard Scenarios (see S1.8.1)	$EF_{fuel,y}$	Balancing area (contiguous U.S.); eGRID subregion (AK and HI)	[52,53]
Transportation energy burden (%)	Portion of income spent on annual fuel costs (2020 prices)		Tract	[40]

[a] Disaggregated data provided by authors.
[b] Source: Based on email correspondence with Borlaug (NREL) on May 24 and 25, 2022

ACS = American Community Survey; BEV = battery electric vehicle; EIA = Energy Information Administration; EVSE = electric vehicle supply equipment; GHG = greenhouse gas; kWh = kilowatt-hours; LCOC = levelized cost of charging; NHTS = National Household Travel Survey; NREL = National Renewable Energy Laboratory; O&M = operations and maintenance; USD = U.S. dollars; VMT = vehicle miles traveled

S1.2 Standard U.S VMT Profile by Vehicle Age and Vehicle Class

A typical U.S. profile of annual vehicle miles traveled by vehicle age and vehicle class was derived from the 2017 NHTS, following the methods from [4,5]. We used the vehicle file and filter for only relevant vehicle classes (01=Automobile/Car/Station Wagon, 03=SUV [Santa Fe, Tahoe, Jeep, etc.], and 04=Pickup Truck). We also filtered out values from the 'ANNMILES' and 'VEHAGE' fields designated as 'Not ascertained' (-9) or equal to 0. We then calculated the average VMT by age for each vehicle class using the 'BESTMILE' field.

We used assumptions from [4,5] for lifetime VMT for each vehicle class, which are summarized in Table S2. We then used the average VMT by age for each vehicle class and the lifetime VMT assumptions to determine the average annual VMT profile for each vehicle class, with the annual VMT in the final year of the vehicle's life determined such that cumulative lifetime VMT is exactly the value in Table S2.

Table S2. *Baseline lifetime vehicle miles traveled values from Woody et al. [4,5] for three vehicle classes: sedan, sport utility vehicle (SUV), and truck.*

Vehicle Class	Baseline Lifetime VMT
Sedan	184,250
SUV	205,263
Truck	206,207

S1.3 Spatially Variable Annual Household VMT

Zhou et al. [40] estimated annual household VMT using the 2017 NHTS and gradient boosting machine regression analysis for 220 different household classifications (defined by income, number of workers, and number of vehicles) in each census tract. We used this data (i.e., annual household VMT at the census tract-household classification level) to calculate annual household emissions, costs, and burdens. To aggregate up to a certain grouping (e.g., census tract), the results were weighted by the prevalence of each household classification in each group.

We note that approximately 1000 tracts comprising 0.35% of the U.S. population do not have household VMT data; this appears to be due to small or no household population living there or lack of other data to produce model results. Also, approximately 8.7% of households do not own any vehicles and were included in the dataset. We filtered out zero-vehicle households to get estimated VMT and transportation energy burden for only vehicle-owning households. Additionally, when the results were aggregated to the census tract-income bin level (based on AMI, see S1.6), we removed one census tract-income group (0-30% AMI) with greater than 100% current energy burden.

S1.4 Fuel Economy and Consumption

To calculate adjusted county-level fuel economy, we used data and methods from [4,5], which were based on methods originally developed by the U.S. Environmental Protection Agency [80] for drive cycle and Wu et al. [14] for temperature. We started with fuel economies of base models for the two different drive cycles represented by the Urban Dynamometer Driving Schedule (UDDS) and the Highway Fuel Economy Test (HWFET), which are reproduced below in Table S3. See the Supplementary Information of [5] for the full drive cycle and temperature adjustment procedure.

Table S3. *Baseline fuel economy values from Woody et al. [4,5] for two different drive cycles by vehicle class and powertrain.*

Vehicle Class	Powertrain	UDDS	HWFET	Unit
Midsize Sedan	ICEV	37.1	49.6	MPG
	BEV	145.2	180.7	Wh/mile
Midsize SUV	ICEV	32.7	39.9	MPG
	BEV	188.9	248.1	Wh/mile
Pickup Truck	ICEV	25.4	31.3	MPG
	BEV	225.8	306.9	Wh/mile

BEV = battery electric vehicle; HWFET = Highway Fuel Economy Test; ICEV = internal combustion engine vehicle; MPG = miles per gallon; SUV = sport utility vehicle; UDDS = Urban Dynamometer Driving Schedule; Wh = watt-hour

S1.5 Vehicle Class Prevalence

To obtain one value for each census tract, the vehicle class results were weighted using vehicle class prevalence. Spatially variable vehicle class prevalence (i.e., percentage of sedans, SUVs, and trucks) was derived from the 2017 NHTS [44] for 18 groups used in [40] that are distinguished by geographic region (Northeast, Midwest, Pacific, South Central, South Atlantic, Mountain) and housing unit density (urban, suburban, rural) (Figure S1a). For each group, the proportion of sedans, SUVs, and trucks was determined from NHTS data (Figure S1b).

Each census tract was assigned one of the 18 groups based on its geographic location and housing unit density. The geographic regions are based on U.S. Census Divisions (Figure S1a) [81]. We calculated census tract-level housing unit density using housing unit data from the 2018 Five-Year American Community Survey (Table B25001) [79] and land area data from the 2019 cartographic boundary file [82]. To assign a density group, we followed methods from [40], which used groupings close to the U.S. Department of Housing and Urban Development (HUD)'s neighborhood descriptions [83] —tracts with housing unit density less than 100 units per square mile are considered rural, between 100 and 2000 housing units per square mile are considered suburban, and greater than or equal to 2000 housing units per square mile are considered urban.

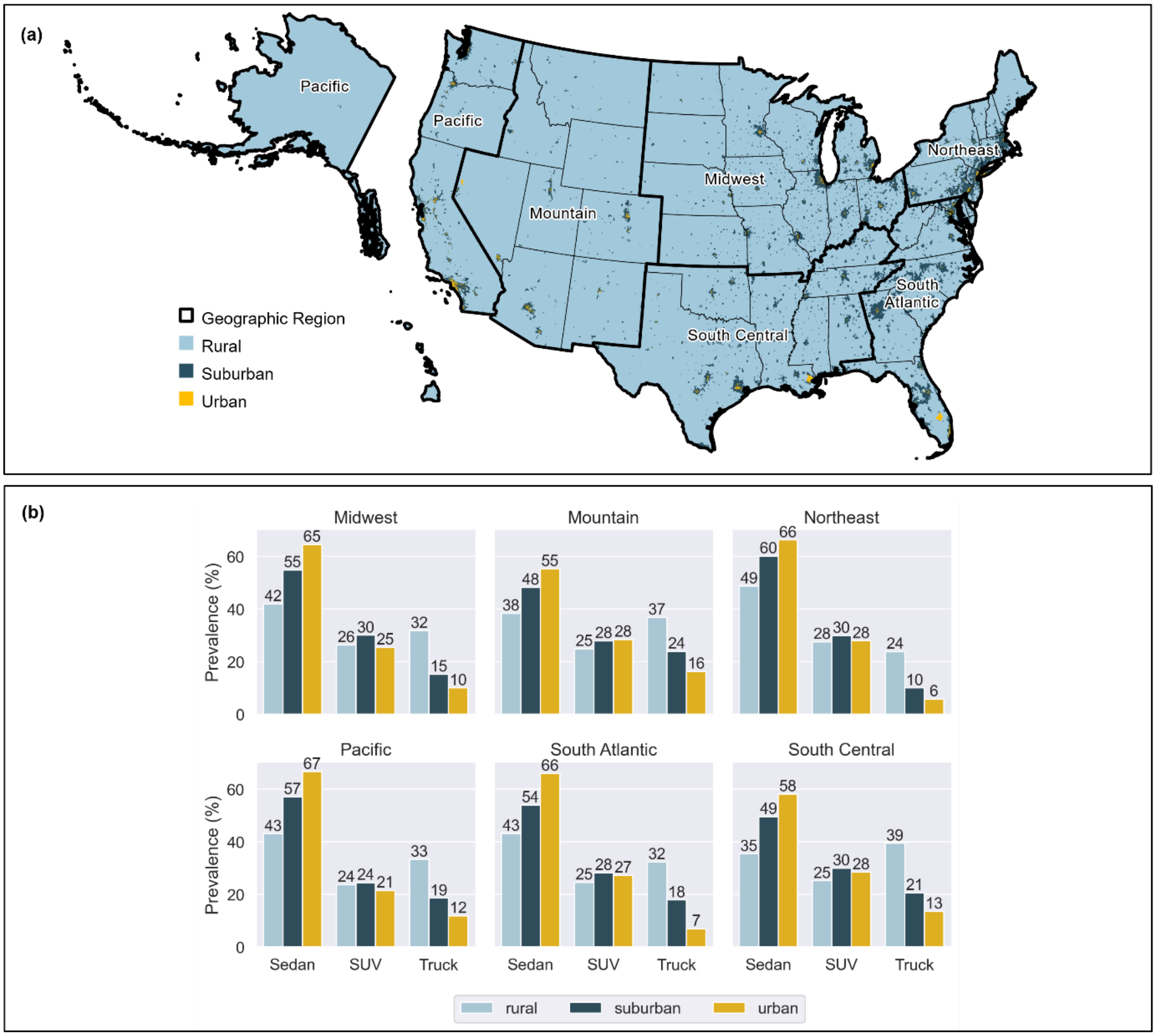

Figure S1. (a) *Six geographic regions and geographic distribution of rural, suburban, and urban designations.* ***(b)*** *Vehicle class prevalence in six geographic regions and three housing unit density groups. SUV = sport utility vehicle.*

S1.6 Area Median Income Bins

For each census tract, the results were aggregated to seven income bins based on AMI, which is defined for a given area (i.e., a metropolitan area or non-metropolitan county) by HUD [55]. We used data from the IPUMS National Historical Geographic Information System [56] to map AMI to census tracts. We then assigned an AMI bin to each census tract-household classification group based on the midpoint household income.

S1.7 Lifetime Fuel Costs

We calculated county-level lifetime fuel costs of an ICEV and BEV for three vehicle classes. We used gasoline prices from [40] and calculated the mean price at the county-level. As noted in the main text, we calculated the LCOC instead of simply using electricity prices for the BEV fuel price (see S1.7.1).

S1.7.1 Levelized Cost of Charging

Our LCOC calculations used modified methods and code from [31] and we summarize the procedure in this section and subsections. The major modifications were to calculate county-level LCOC instead of state level and utilize updated data for some parameters. The assumptions used in the calculations are summarized in Table S4.

LCOC ($LCOC_{county}$) is generally expressed as the capital cost (including installation, $C_{capital}$) and operations and maintenance (O&M) costs ($C_{O\&M}$) of EVSE spread across the lifetime energy of the EVSE (E_{life}) plus the county-level retail electricity price ($C_{elec,county}$). We assumed the annual O&M costs were a certain percentage of capital costs ($P_{O\&M}$), which were discounted (dr) and summed over the lifespan of the EVSE (L_{EVSE}).

$$LCOC_{county} = \frac{C_{capital} + \sum_{i=1}^{L_{EVSE}} \frac{C_{capital} * P_{O\&M}}{(1 + dr)^i}}{E_{life}} + C_{elec,county}$$

LCOC was calculated for three different types of charging sites: residential (R) Level 1 (L1) and Level 2 (L2), public/workplace L2 (P), and direct current fast charging (DCFC or D). L1 charging refers to using 120-volt power from a standard U.S. outlet, while L2 refers to 240-volt power that is common for large home appliances. The county-level LCOC values for each type of charging site were combined based on a charge mix (CM) to calculate the combined LCOC:

$$LCOC_{county,comb} = CM_R * LCOC_{county,R} + CM_P * LCOC_{county,P} + CM_D * LCOC_{county,D}$$

Table S4. *Assumptions for LCOC calculations for all four scenarios.*

Parameter	Variable	Baseline-Residential	Baseline-Public	Best Case for BEV	Worst Case for BEV	Source
Residential	CM_R	**81%**	**0%**	**100%**	**0%**	[31] [a]
Time-of-use rates		Opportunistic	N/A	Opportunistic	N/A	[31] [b]
Level 1	$CM_{R,L1}$	16%	N/A	100%	N/A	[31] [a]
Equipment ($/plug)	$C_{capital,L1}$	$ -	N/A	$ -	N/A	[c]
Installation ($/plug)		$500	N/A	$ -	N/A	[c]
O&M (% of capital)	$P_{O\&M,L1}$	2%	N/A	-	N/A	[c, d]
Lifespan (years)	L_{EVSE}	10	10	10	10	[84]
Level 2	$CM_{R,L1}$	84%	0%	0%	0%	[31] [a]
Equipment ($/plug)	$C_{capital,L2\ res}$	$800	N/A	N/A	N/A	[c]
Installation ($/plug)		$1,100	N/A	N/A	N/A	[c]
O&M (% of capital)	$P_{O\&M,L2\ res}$	2%	N/A	N/A	N/A	[c, d]
Lifespan (years)	L_{EVSE}	10	10	10	10	[84]
Public/Workplace	CM_P	**14%**	**40%**	**0%**	**0%**	[31] [a, e]
Level 2						[31]
Utilization (kWh/day)	$U_{L2\ pub}$	30	30	N/A	N/A	[31], derived from [85]
Equipment ($/plug)	$C_{capital,L2\ pub}$	$3,800	$3,800	N/A	N/A	[c]
Installation ($/plug)		$4,800	$4,800	N/A	N/A	[c]
O&M (% of capital)	$P_{O\&M,L2\ pub}$	8%	8%	N/A	N/A	[c]
Lifespan (years)	L_{EVSE}	10	10	N/A	N/A	[84]
DCFC	CM_D	**5%**	**60%**	**0%**	**100%**	[31] [a, e]
Profile 1						
Capacity per plug (kW)	N/A	50	50	N/A	50	[86] via [31]
Number of plugs	N/A	1	1	N/A	1	[86] via [31]
Total station capacity (kW)	N/A	50	50	N/A	50	[86] via [31]
Utilization	N/A	1.14%	1.14%	N/A	1.14%	[86] via [31]
Equipment ($/plug)	N/A	$29,400	$29,400	N/A	$36,600	[c]
Installation ($/plug)	N/A	$34,800	$34,800	N/A	$48,600	[c]
Grid Upgrade	N/A	N/A	N/A	N/A	N/A	[31]
O&M (% of capital)	N/A	8%	8%	N/A	12%	[c]
Profile 2						
Capacity per plug (kW)	N/A	50	50	N/A	50	[86] via [31]
Number of plugs	N/A	1	1	N/A	1	[86] via [31]
Total station capacity (kW)	N/A	50	50	N/A	50	[86] via [31]
Utilization	N/A	11.71%	11.71%	N/A	11.71%	[86] via [31]
Equipment ($/plug)	N/A	$29,400	$29,400	N/A	$36,600	[c]
Installation ($/plug)	N/A	$34,800	$34,800	N/A	$48,600	[c]
Grid Upgrade	N/A	N/A	N/A	N/A	N/A	[31]
O&M (% of capital)	N/A	8%	8%	N/A	12%	[c]

Parameter	Variable	Baseline-Residential	Baseline-Public	Best Case for BEV	Worst Case for BEV	Source
Profile 3						
Capacity per plug (kW)	N/A	150	150	N/A	150	[86] via [31]
Number of plugs	N/A	4	4	N/A	4	[86] via [31]
Total station capacity (kW)	N/A	600	600	N/A	600	[86] via [31]
Utilization	N/A	13.67%	13.67%	N/A	13.67%	[86] via [31]
Equipment ($/plug)	N/A	$84,400	$84,400	N/A	$102,900	[c]
Installation ($/plug)	N/A	$86,400	$86,400	N/A	$136,400	[c]
Grid Upgrade	N/A	N/A	N/A	N/A	$125,000	[31]
O&M (% of capital)	N/A	8%	8%	N/A	12%	[c]
Profile 4						
Capacity per plug (kW)	N/A	150	150	N/A	150	[86] via [31]
Number of plugs	N/A	20	20	N/A	20	[86] via [31]
Total station capacity (kW)	N/A	3000	3000	N/A	3000	[86] via [31]
Utilization	N/A	20.70%	20.70%	N/A	20.70%	[86] via [31]
Equipment ($/plug)	N/A	$84,400	$84,400	N/A	$102,900	[c]
Installation ($/plug)	N/A	$86,400	$86,400	N/A	$136,400	[c]
Grid Upgrade	N/A	N/A	N/A	N/A	$125,000	[31]
O&M (% of capital)	N/A	8%	8%	N/A	12%	[c]

[a] Charge mix for baseline-residential charging scenario derived by [31] from [87]
[b] For the best case for BEV scenario, we deviate from Borlaug et al. by assuming opportunistic instead of 100% TOU prices
[c] Source: Based on email correspondence with Borlaug (NREL) on May 24 and 25, 2022
[d] Baseline assumption based on low end of O&M costs for public/workplace L2 and DCFC
[e] Baseline-public charge mix derived from [59], assuming 1.3 days of public L1/L2 charging and 2 days of public DCFC charging per week (Figure 3a-b)

BEV = battery electric vehicle; CM = charge mix; DCFC = direct current fast charging; kW = kilowatt; L1 = Level 1; L2 = Level 2; NREL = National Renewable Energy Laboratory; O&M = operations and maintenance; TOU = time-of-use

S1.7.1.1 EIA Electricity Prices

Retail electricity prices were obtained from the EIA’s 2019 and 2020 average annual residential and commercial electricity prices (form EIA-861) [88]. The year 2019 was a census year for form EIA-861, meaning that data was collected from all covered utilities [89]. A census year only occurs every 8 years, and as such 2020 data is from a sample that excludes smaller utilities [89]. Therefore, we updated the 2019 census data with 2020 data for applicable utilities.

Retail electricity prices were available for each utility and mapped to each U.S. county based on the utility’s service territory (see Service Territory file from [49]). For counties that are served by multiple utilities, the median utility price was assigned and for counties with no utility listed, the median state retail price was assigned.

Retail electricity prices for Competitive Retail Areas in Texas are provided on Form EIA-861 by Retail Energy Providers (REPs) or Retail Power Marketers (RPMs), which sell electricity to customers but do not own any of the transmission and distribution infrastructure. The transmission and distribution infrastructure are owned by transmission and distribution utilities (TDUs), which have known service territories like utilities across the rest of the U.S. (see Delivery Companies file from [49]). However, there is no direct mapping of RPMs to TDUs since RPMs could sell electricity for any number of TDUs. In other words, a customer in a given county has a choice to purchase electricity from several RPMs, which offer different retail prices, but a known TDU will deliver electricity to that customer regardless of the RPM they choose. Therefore, no single retail price can be mapped to Texas counties where this is applicable. As such, we simply calculated a customer-weighted average RPM price (12.6 cents per kWh) and assigned this price to all TDUs and therefore all counties within the service territory of these TDUs. This was not applicable to all Texas customers since there are also cooperatives or publicly owned utilities that operate separately from the TDUs (see [90]).

S1.7.1.2 URDB Electricity Prices

Residential, industrial, and commercial prices were also pulled from the Utility Rate Database (URDB) [48] for residential and DCFC charging. We used modified code from [31] to download and process the URDB data. Processing included filtering out expired rates, classifying rates by type (e.g., tiered, seasonal, time-of-use, or EV-specific), filtering out inapplicable rates based on key phrases, filtering out null rates, and combining the base rate and adjustments into a total rate.

S1.7.1.3 Residential LCOC

Residential LCOC is summarized by the following equation:

$$LCOC_{county,R} = \frac{CM_{R,L1} * \left(C_{capital,L1} + \sum_{i=1}^{L_{EVSE}} \frac{C_{capital,L1} * P_{O\&M,L1}}{(1+dr)^i}\right) +}{E_{life}}$$

$$+ \frac{CM_{R,L2} * \left(C_{capital,L2\ res} + \sum_{i=1}^{L_{EVSE}} \frac{C_{capital,L2\ res} * P_{O\&M,L2\ res}}{(1+dr)^i}\right)}{E_{life}} + C_{res\ elec,county}$$

We allocated L1 and L2 capital costs based on the assumed amount of L1 and L2 charging ($CM_{R,L1}$ and $CM_{R,L2}$). E_{life} is specified as the amount of electricity used to charge the vehicle over the lifespan of the EVSE (i.e., the total VMT over the lifespan of the EVSE

[$VMT_{cumulative,L_{EVSE}}$] multiplied by fuel consumption per mile [FC_{county}] and the inverse of the charging efficiency [$\frac{1}{\eta}$]) multiplied by the portion of charging occurring at home (CM_R):

$$E_{life} = VMT_{cumulative,L_{EVSE}} * FC_{county} * \frac{1}{\eta} * CM_R$$

We added the average county-level residential price of electricity ($C_{res\ elec,county}$) to capital and O&M costs. The residential price of electricity for each county was either from the EIA data, or the TOU residential price from the URDB if applicable and less than the EIA price. In other words, we assumed the vehicle owner is "opportunistic" and optimizes their charging habits to minimize costs.

For the TOU residential rates from the URDB, we do not have detailed time series charging profiles to which we can directly apply the rates. Instead, we assumed that charging occurs during the time of day when rates are lowest and occurs consistently across all tiers, days, months, and customers. Mathematically, this translates to calculating the mean tiered rate for each hour, choosing the minimum rate for the day, averaging across days (i.e., weekday versus weekend), and then averaging again across all months.

S1.7.1.4 Public/Workplace Level 2

For the LCOC of public/workplace charging ($LCOC_{county,P}$), the capital and O&M costs were calculated similar to residential charging, but only include Level 2 charging. E_{life} is calculated assuming a certain amount of energy usage per day ($U_{L2\ pub}$), 365 days per year, for the lifespan of the EVSE. The cost of electricity is based on average county-level commercial prices from the EIA. No URDB rates are used for the public/workplace Level 2 charging site.

$$LCOC_{county,P} = \frac{C_{capital,L2\ pub} + \sum_{i=1}^{L_{EVSE}} \frac{C_{capital,L2\ pub} * P_{O\&M,L2\ pub}}{(1+dr)^i}}{U_{L2\ pub} * \frac{365\ day}{year} * L_{EVSE}} + C_{com\ elec,county}$$

S1.7.1.5 DCFC

As the basis for calculating the average electricity price for DCFC, we used the same four DCFC station types as [31] that have varying size and usage profiles:

Profile 1. Low-usage single 50-kW charger with 1.14% utilization,
Profile 2. High-usage single 50-kW charger with 11.7% utilization,
Profile 3. Medium-sized station with four 150-kW plugs and 13.7% utilization, and
Profile 4. High-usage and large station with 20 150-kW plugs and 20.7% utilization.

The following procedure was used to calculate the DCFC LCOC:

1. For each profile:
    a. Calculated average annual cost of electricity for each applicable rate in the URDB. More details included in the next section.
    b. Aggregated the URDB rates to utility level, such that the minimum rate is chosen for utilities with multiple applicable rates.
    c. Mapped utilities to counties base on their service territory, assigned the median cost if there is more than one utility in a county and assigned the state median cost if no utilities are listed for a county
    d. Fed the county-level electricity prices and other assumptions (Table S7) into the National Renewable Energy Laboratory's Electric Vehicle Infrastructure – Financial Analysis Scenario Tool (EVI-FAST) [91] to calculate LCOC.
2. Combined the profiles to calculate one weighted LCOC per county. Weighting was based on total annual load of each profile and the prevalence of each station size in the U.S. based on charging station information from the Alternative Fuels Data Center [92].

Step 1a – Calculating the Average Annual Cost of Electricity

The URDB was filtered for industrial and commercial rates and then processed as described in S1.7.1.2. For the key phrase filtering, we used the same criteria as [31] originally developed by Muratori et al. [93], with some minor modifications (Table S5). We also manually checked 830 industrial and commercial rates using filters on the description field (i.e., "between," "kW," and "kilowatt") or due to observed outliers (i.e., rates of hundreds of dollars per kWh). We updated 551 of these rates to include additional information on peak capacity, peak usage, and minimum voltage requirements.

Table S5. *Modifications to Muratori et al. [93] criteria for filtering applicable electricity rates for the direct current fast charging (DCFC) station type.*

Modification	Filter				
Added	Distribution generation Electric hot water heat	Electric pump Heat pump	Manufacture Net meter	Pipeline Railroad	Space heat Well pump
Removed	Watt Well				

The station profiles have power output for each 15-minute increment of the year from which the peak power and total energy usage for each month was calculated. If a rate's peak capacity (i.e., demand) or energy usage requirements did not apply to the profile (e.g., the rate's maximum peak capacity was less than the charging profile's maximum peak power output), the rate was filtered out. We note that for Profile 1, the maximum usage exceeded 50 kW by a small amount, so we adjusted this to 50 to ensure that rates applicable to maximum power usage of 50 kW or less were not filtered out.

The rates were applied to the year-long profiles to account for variations in season, TOU, and levels of demand and energy use. Both demand and energy charges may have tiered pricing, in which the rate changes if a certain level of demand or energy use is exceeded. Table S6 summarizes the approach to calculate the average annual price of electricity for each profile and rate combination.

Table S6. *Summary of calculations of annual electricity price components.*

Component	Description & Equation
Average annual price of electricity	There are three main parts of the total cost of electricity: fixed charges, demand charges, and energy charges. Total annual charges are summed over the year and then divided by the total annual energy usage to get an average annual price ($ per kWh) for each profile and rate combination: $C_{DCFC\ elec,p,r} = \frac{C_{r,annual\ fixed} + C_{p,r,annual\ demand} + C_{p,r,annual\ energy}}{E_{p,annual}}$
Fixed	The fixed charges are monthly charges that are simply summed over the full year: $C_{r,annual\ fixed} = C_{r,monthly\ fixed} * 12$
Demand - Seasonal/ monthly	The annual cost of demand for seasonal/monthly rates is the cost of demand for each month and tier multiplied by the maximum monthly demand for each month and tier: $C_{p,r,annual\ demand\ s/m} = \sum_{m=1}^{12}\sum_{t=1}^{T} C_{r,demand,m,t} * D_{p,month\ max,m,t}$
Demand - TOU	The annual cost of demand for TOU rates is the same as seasonal/monthly rates, with the addition of day and hour to designate the time of peak demand for the month: $C_{p,r,annual\ demand\ TOU} = \sum_{m=1}^{12}\sum_{t=1}^{T} C_{r,demand,m,d,h,t} * D_{p,month\ max,m,d,h,t}$
Energy	The energy charges are tiered and may include seasonal and TOU rates and can be summarized as the cost of energy for each month, day, hour, and tier, multiplied by the energy usage for each month, day, hour, and tier: $C_{p,r,annual\ energy} = \sum_{m=1}^{12}\sum_{d=1}^{7}\sum_{h=1}^{24}\sum_{t=1}^{T} C_{r,energy,m,d,h,t} * E_{p,m,d,h,t}$

C = cost; d = day; E = energy use; h = hour; kWh = kilowatt-hour; m = month; p = profile; r = rate; s/m = seasonal/monthly; t = tier; T = total tiers; TOU = time-of-use

Step 1d – Calculation of LCOC using EVI-FAST

We developed an Excel macro program to feed assumptions into EVI-FAST [91], including the county-level electricity price and parameters in Table S7. We included 12 different DCFC LCOC calculations that cover the 4 profiles and baseline, minimum, and maximum assumptions for each profile. Not all 12 LCOC versions are included in the scenario analysis but were calculated for completeness.

Table S7. *EVI-FAST assumptions.*

EVI-FAST Field [a]	**Assumption**	**Source**
Rent of parking space ($/year)	0	[31] [b]
Grid efficiency	87%	[c]
Project operational life (years)	20	[c]
Installation time (months)	6	[91]
Demand ramp-up (years)	0	[c]
Demand charges ($/year)	0	[d]
Internet ($/year)	$600	[94] via [31]
Total tax rate (state, federal, local)	21%	[94] via [31]
Capital gains tax	15%	[94] via [31]
Leveraged after-tax nominal discount rate	5.4%	[51] via [31]
Debt interest rate (compounded monthly)	2.25%	[c]

[a] Default values are used for the remaining assumptions in EVI-FAST.
[b] Land costs are not included in the analysis.
[c] Source: Based on email correspondence with Borlaug (NREL) on May 24 and 25, 2022
[d] Demand charges already accounted for in URDB rates.

EVI-FAST = Electric Vehicle Infrastructure – Financial Analysis Scenario Tool; NREL = National Renewable Energy Laboratory; URDB = Utility Rate Database

S1.7.2 Fuel Price Projections

As discussed in the main text, we obtained price projections indexed to 2020 from the EIA's 2021 Annual Energy Outlook [50]. Specifically, we used the data browser to plot energy prices from Table 3 for motor gasoline, commercial electricity, and residential electricity for the Reference, High Oil Price, and Low Oil Price scenarios and use the "Index to Start as Percent" setting. The projections (Figure S2) were used to calculate prices from 2022 to 2050, with the LCOC and February 2020 gas prices from GasBuddy via [40] used as the initial electricity and gas prices, respectively, for 2020.

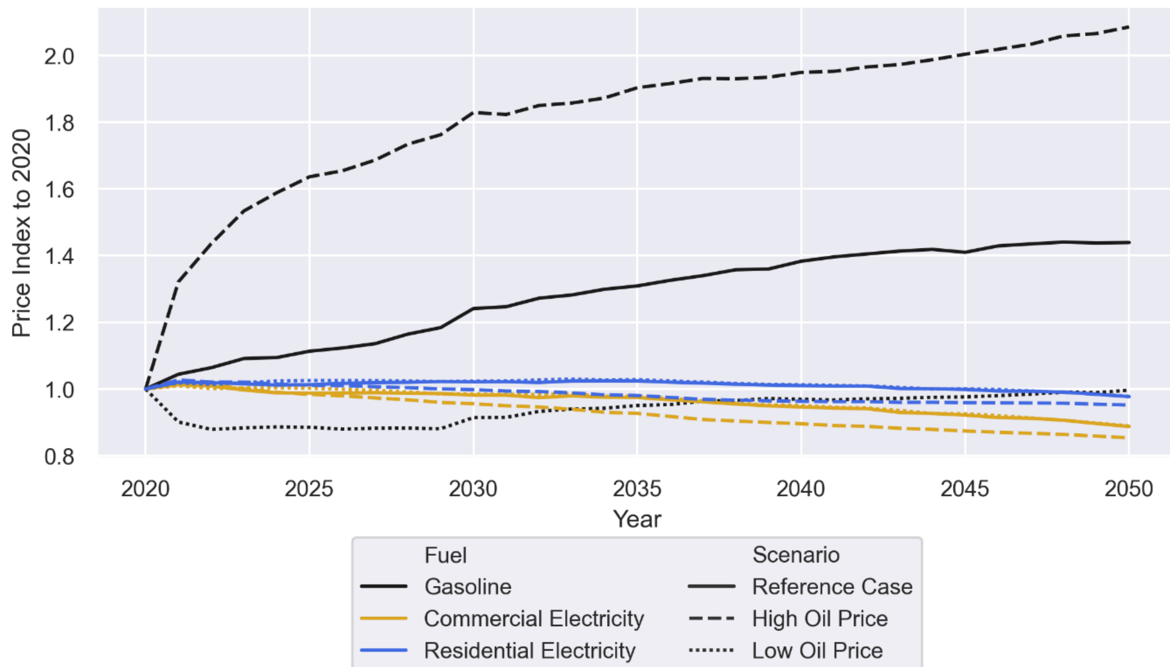

Figure S2. *Fuel price projections from the 2021 Annual Energy Outlook, indexed to 2020. Source: U.S. Energy Information Administration [50].*

S1.8 Life Cycle GHG Emissions

As discussed in the main text, county-level lifecycle GHG emissions factors of three ICEV and BEV classes were calculated with data and methods from Woody et al. [4,5]. The vehicle cycle and ICEV use-phase emissions assumptions are summarized in Table S8.

Table S8. *Life cycle GHG assumptions from Woody et al. [4,5].*

Life Cycle Phase	ICEV			BEV		
	Sedan	SUV	Pickup	Sedan	SUV	Pickup
Batteries	0.04	0.06	0.06	5.52	7.35	8.89
Fluids	0.76	1.14	1.14	0.18	0.31	0.31
Components	4.40	5.43	6.92	3.83	4.82	6.06
Assembly	0.73	0.73	0.73	0.73	0.73	0.73
Use Phase Emissions Factor	10.67 $kgCO_2e$/gallon			Varies by county; see S1.8.1		
Disposal	0.19	0.22	0.28	0.19	0.22	0.28

Note: GHG emissions units are in tCO_2e unless otherwise specified.

BEV = battery electric vehicle; GHG = greenhouse gas; ICEV = internal combustion engine vehicle; $kgCO_2e$ = kilograms of carbon dioxide equivalents; SUV = sport utility vehicle; tCO2e = metric tons of carbon dioxide equivalents

S1.8.1 Electricity Grid GHG Emission Factors

Current and future electricity grid GHG emission factors for 134 balancing areas in the contiguous United States were obtained from the National Renewable Energy Laboratory (NREL)'s Cambium 2021 tool for three scenarios: Mid Case (No New Policy), Mid Case (95%

Decarbonization by 2035), and High Renewable Energy Cost [52] (Figure S3). Mid Case (No New Policy) was used in the two baseline scenarios, while Mid Case (95% Decarbonization by 2035) was used in the best case for BEV scenario since it represents the lowest projected GHG emissions in the Cambium tool's suite of scenarios [95]. Likewise, the High Renewable Energy Cost scenario was used in the worst case for BEV scenario since it represents the highest projected GHG emissions among all scenarios [95].

Alaska and Hawaii are not included in the Cambium dataset. As such, we used the Cambium data to project Alaska and Hawaii's 2020 Emissions & Generation Resource Integrated Database (eGRID) emissions factors [53] into the future. Because Alaska does not have a Renewable Portfolio Standard (RPS) in place, we assumed that grid emissions factors in Alaska follow similar trajectories to other states without RPSs (i.e., Alabama, Arkansas, Florida, Georgia, Idaho, Kentucky, Louisiana, Mississippi, Nebraska, Tennessee, West Virginia, Wyoming). State-level RPS status was obtained from the EIA [96]. Hawaii's RPS established in 2001 requires 100% renewable energy by 2045 [97]. As such, we assumed that Hawaii's grid emissions factors follow trajectories of states with similar RPS goals (i.e., 100% renewable energy by 2045 or 2050). These states included California, Washington, New Mexico, Virginia, Colorado, Nevada, and Maine [97]. We acknowledge that this is a simplification of the many factors that influence future grid decarbonization in these two states; however, we believe this is reasonable for our purposes.

To estimate the trajectories, we calculated the percent change from the previous year from 2022-2050 for each state deemed to have similar renewable energy policies to Alaska or Hawaii. We then assigned the median percent change for each year for Alaska and Hawaii's trajectories. With the eGRID emissions factor as the seed, we used the trajectories to estimate future grid emissions factors for Alaska and Hawaii. Figure S4 shows the electricity grid GHG emission projections for Alaska and Hawaii.

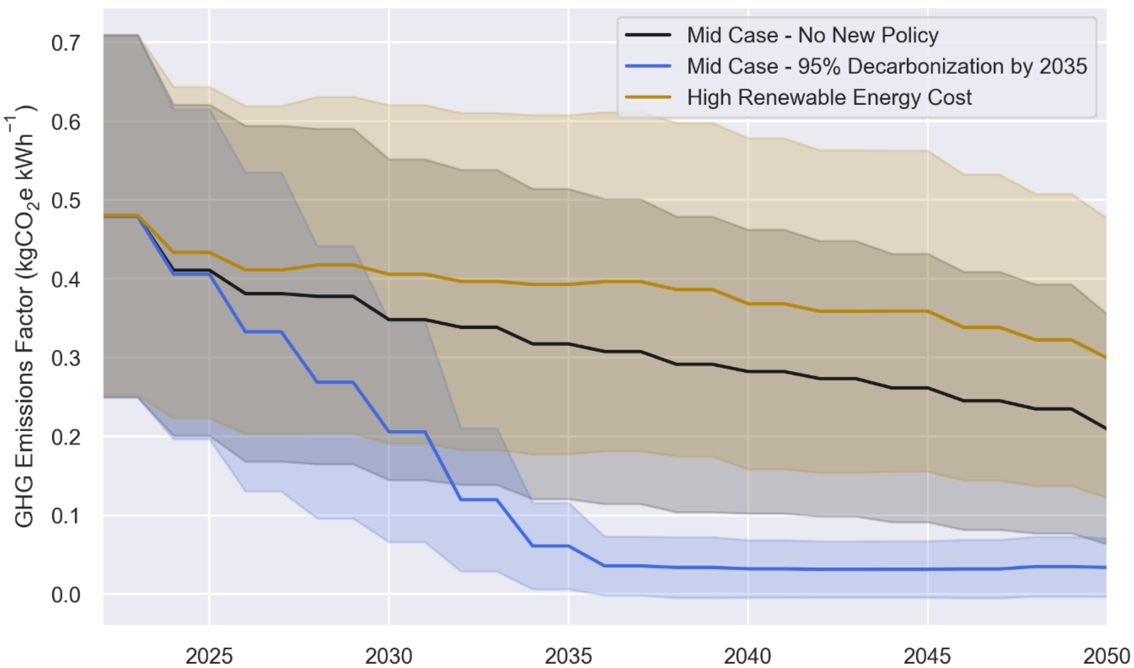

Figure S3. *Temporal variation (2022-2050) of greenhouse gas (GHG) emissions factors (kilograms of carbon dioxide equivalents per kilowatt-hour [kgCO2e kWh^{-1}]) for three electricity grid decarbonization scenarios from the National Renewable Energy Laboratory's Cambium 2021 tool [52]. Lines represent the mean emissions factor for the U.S. and shaded areas represent the standard deviation.*

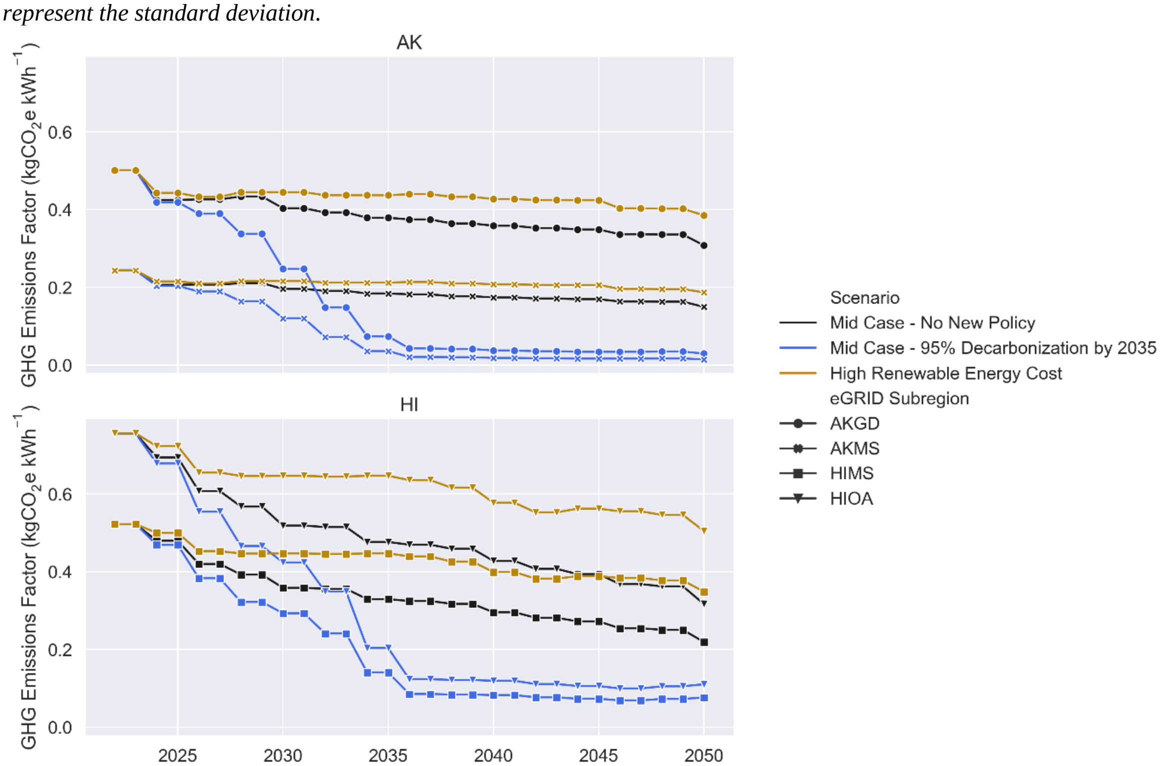

Figure S4. *Temporal variation (2022-2050) of greenhouse gas (GHG) emissions factors (kilograms of carbon dioxide equivalents per kilowatt-hour [kgCO2e kWh^{-1}]) for Alaska and Hawaii. Estimates are derived from the electricity grid decarbonization scenarios from National Renewable Energy Laboratory's Cambium 2021 tool and shown for the Emissions & Generation Resource Integrated Database (eGRID) subregions in each state.*

Appendix II – Supplementary Results

In this section we provide additional results to support our findings.

S1.9 LCOC Results

As expected, median LCOC is highest in the worst case for BEV scenario, followed by baseline-public charging, baseline-residential charging, and best case for BEV (Figure S5).

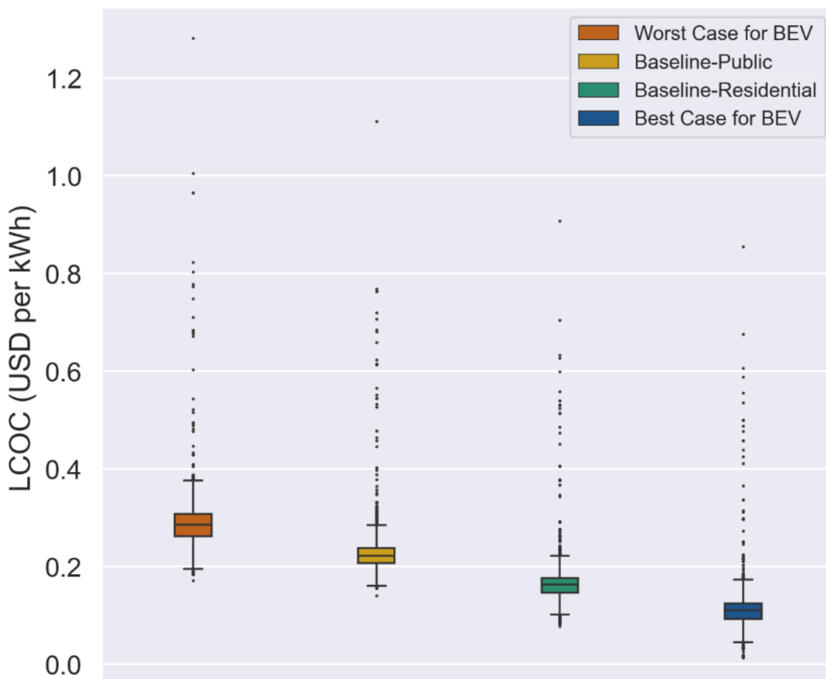

Figure S5. *Boxplots of the levelized cost of charging (LCOC in U.S. dollars per kilowatt-hour [USD per kWh]) for all four scenarios. Whiskers represent 1.5 times the interquartile range. BEV = battery electric vehicle.*

Figure S6 shows the median LCOC and standard deviation for each state. Alaska has the highest and most variable LCOC values for all four scenarios and is followed by Hawaii, Rhode Island, and California. Maine has the lowest median LCOC, followed by Washington, D.C., Nevada, and New York.

We also compare our state-level LCOC results to those from Borlaug et al. [31] and find that our LCOC estimates are generally higher than those from Borlaug et al., which was expected (Figure S7). The main reason for this is that we use updated EVSE cost estimates, which are generally higher than those assumed from the 2020 study. The differences can also be attributed to more recent EIA electricity prices, an updated version of the URDB database, and different assumptions for annual vehicle VMT and residential and public EVSE lifespans. We find that the percent changes in LCOC from Borlaug et al. to this study are highest for the Best Case for BEV scenario (Figure S8). This scenario assumes 100% residential L1 charging and no EVSE-related costs, which indicates that the residential electricity prices from the EIA and URDB are driving the changes. Additionally, we assumed opportunistic charging for the Best Case for BEV scenario (i.e., minimum between EIA and URDB), while Borlaug et al. assumed 100% TOU charging, which could also be contributing to the higher estimates in this study.

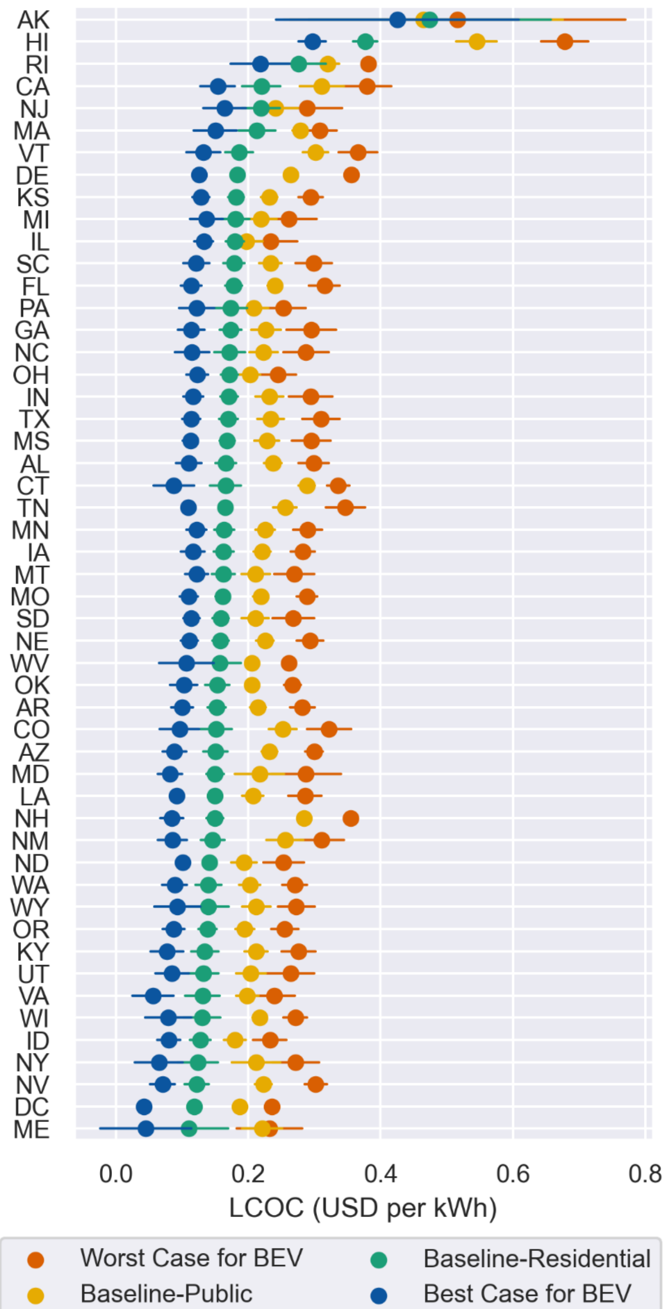

Figure S6. *Median levelized cost of charging (LCOC in U.S. dollars per kilowatt-hour [USD per kWh]) for each state. States are sorted by the LCOC from the baseline-residential charging scenario. Other three scenarios shown for comparison. Dots represent median values, while the lines represent the standard deviation. BEV = battery electric vehicle.*

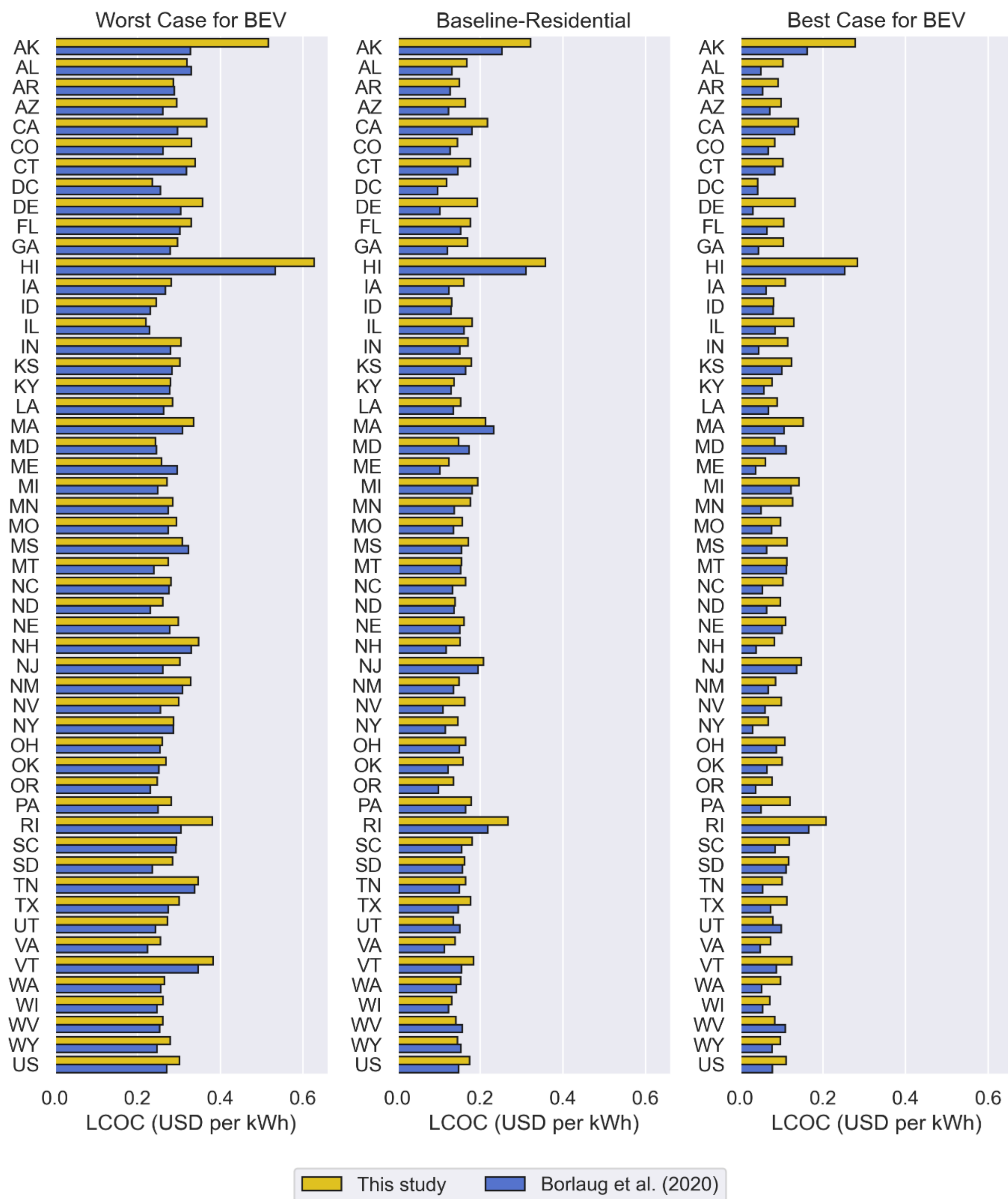

Figure S7. *Comparison of state-level levelized cost of charging (LCOC in U.S. dollars per kilowatt-hour [USD per kWh]) results from this study to those in Borlaug et al. (2020) [31]. BEV = battery electric vehicle.*

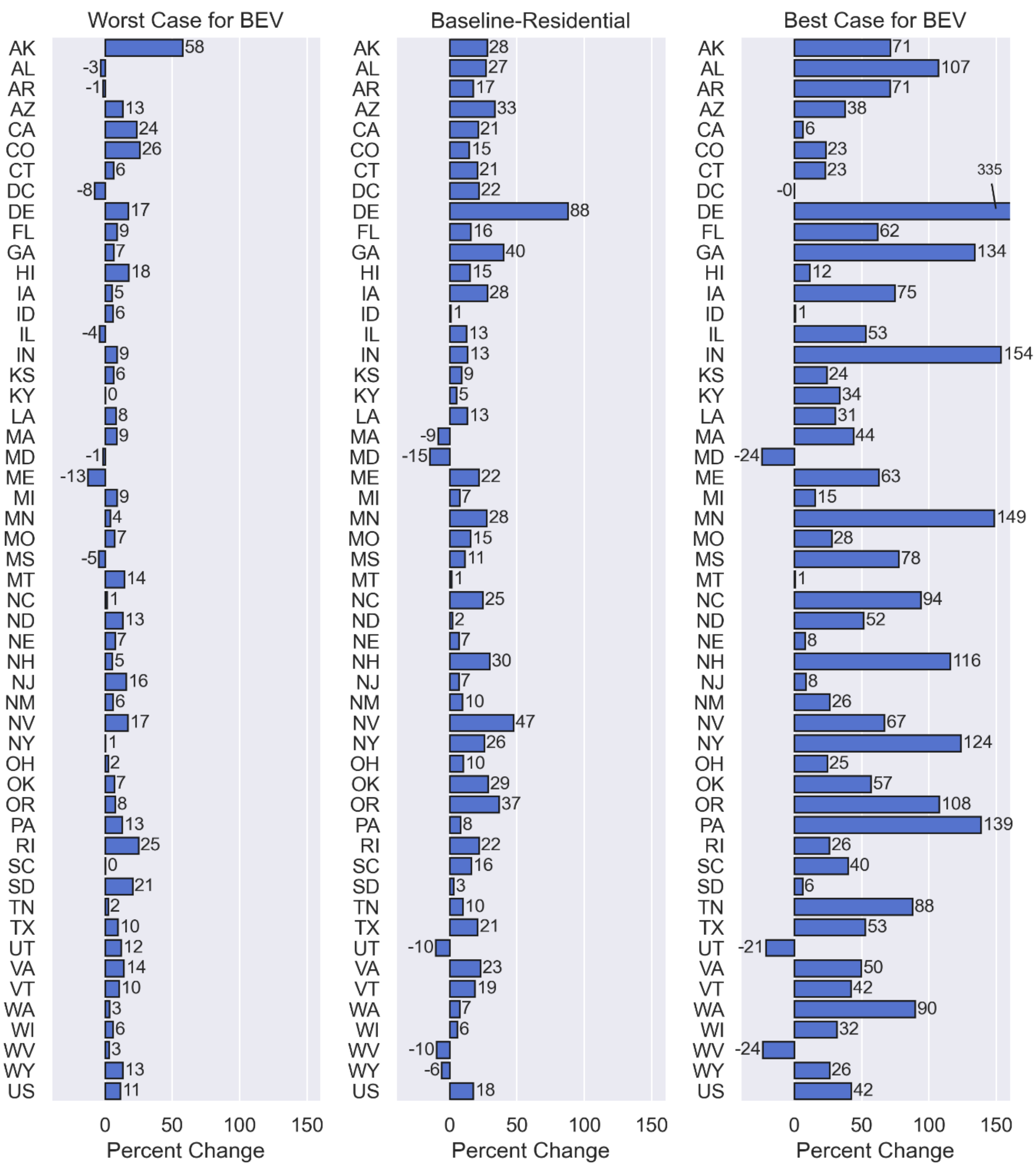

Figure S8. *Percent change in state-level levelized cost of charging (LCOC in U.S. dollars per kilowatt-hour [USD per kWh]) results from Borlaug et al. (2020) to this study. BEV = battery electric vehicle.*

S1.10 Underlying Variables

To better understand the geographic variation in energy burden and GHG savings, we map the underlying variables for ICEV and BEV models for the baseline-residential scenario (Figure S9 and Figure S10). For easier interpretation, we converted the variables to the same energy basis, namely gallons of gasoline equivalent (GGE). We assume 1 kWh equates to 0.031 GGE [98].

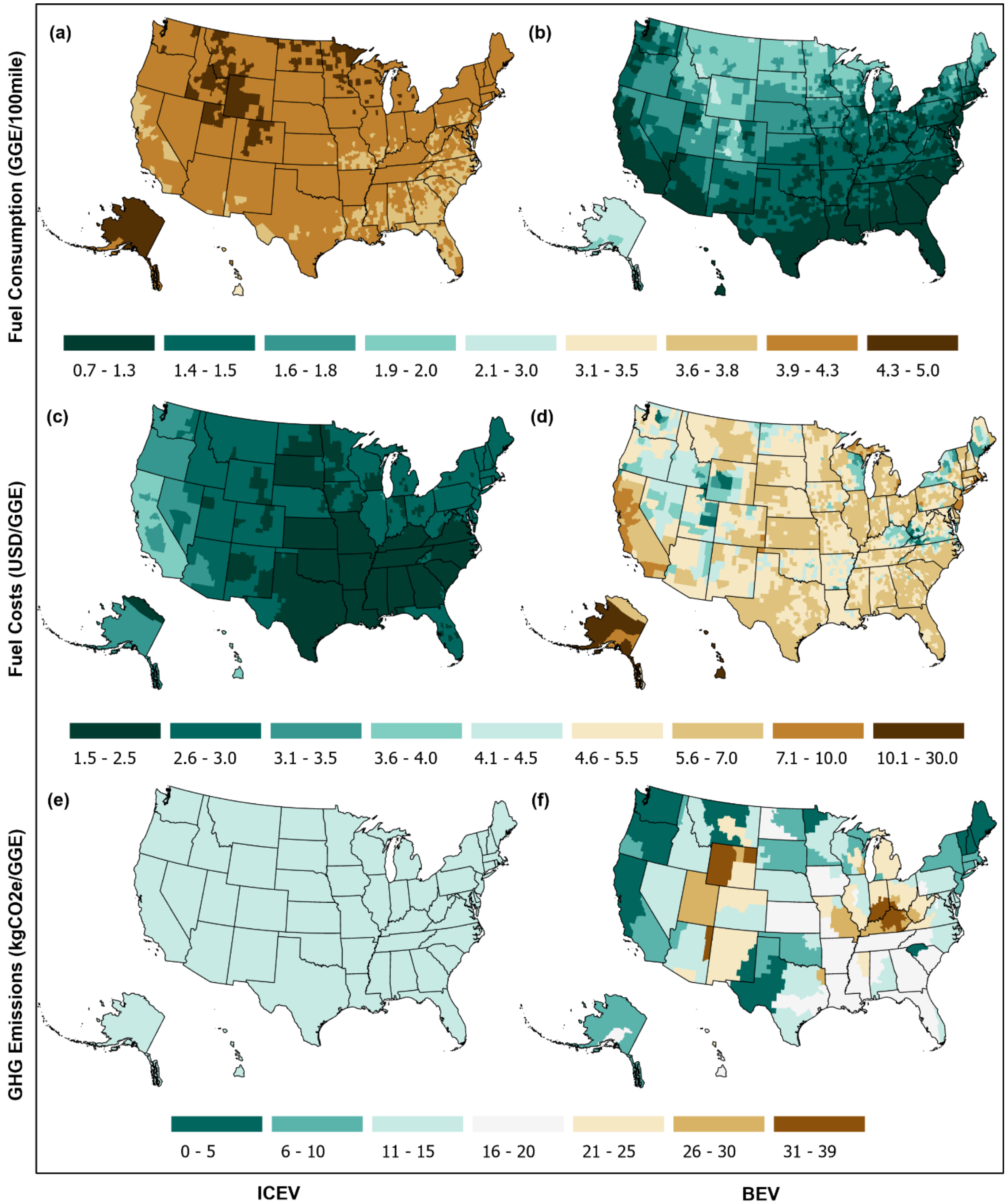

Figure S9. *Geographic distribution of underlying variables normalized to GGE by powertrain.* ***(a-b)*** *Fuel consumption (GGE per 100 miles).* ***(c-d)*** *Fuel costs (USD per GGE).* ***(e)-(f)*** *Use-phase GHG emissions (kgCO_2e per GGE). Notes: In this study, the GHG emissions of a new ICEV remain constant throughout the U.S. and is therefore included for illustration purposes only. BEV = battery electric vehicle; GGE = gallons of gasoline equivalent; GHG = greenhouse gas; ICEV = internal combustion engine vehicle; kgCO_2e = kilograms of carbon dioxide equivalents; USD = U.S. dollars.*

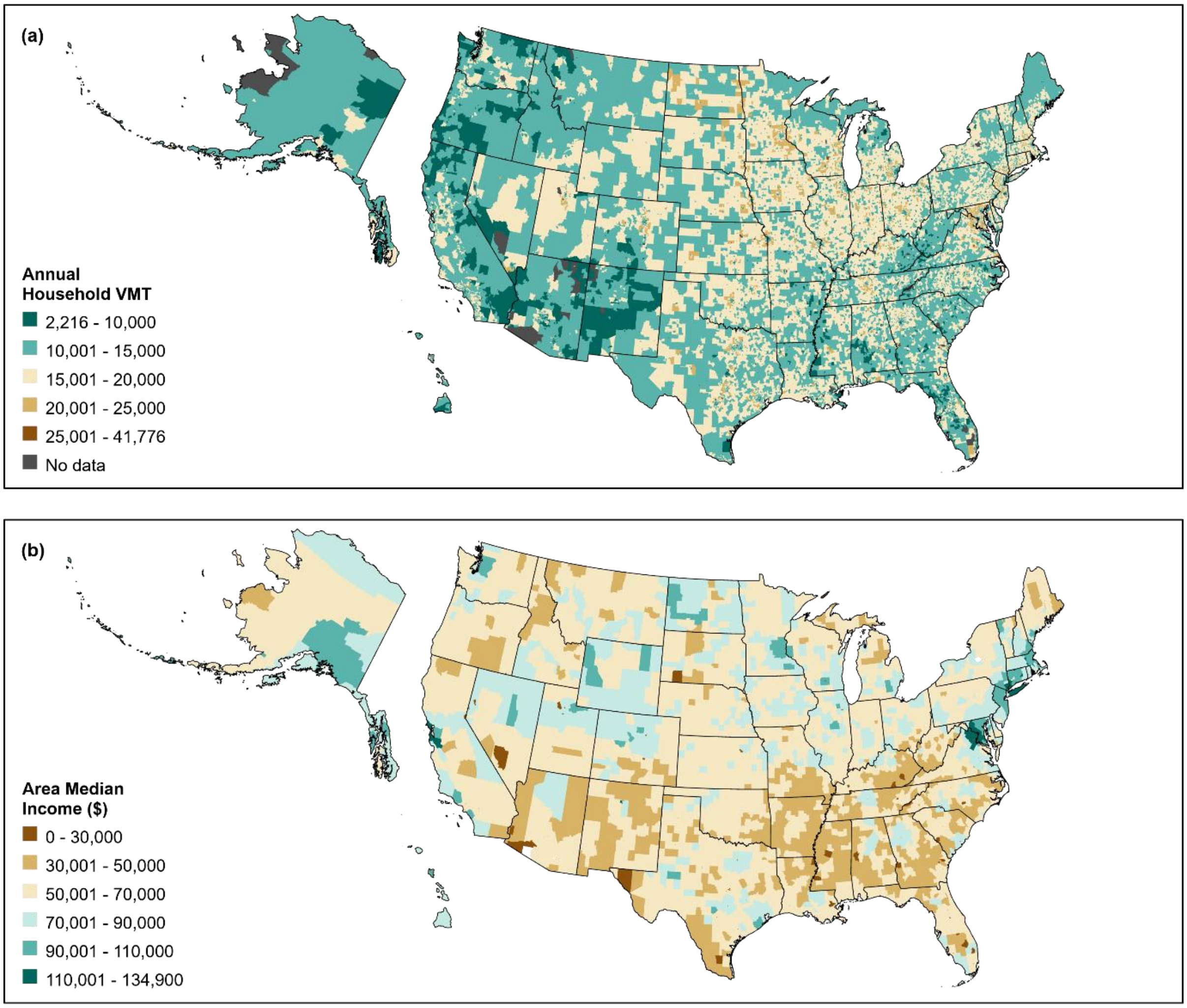

Figure S10. *Geographic distribution of household level variables.* ***(a)*** *Annual household vehicle miles traveled (VMT; weighted to tract-level). Source: Zhou et al. [40].* ***(b)*** *Area median income. Source: U.S. Department of Housing and Urban Development [55].*

S1.10.1 Fuel Consumption

Fuel consumption varies geographically due to differences in drive cycle and temperature. State-level fuel consumption results for both powertrains are shown in Figure S11. Clearly, ICEV fuel consumption is much higher than BEV fuel consumption across the country; however, the difference in fuel consumption between the two powertrains varies.

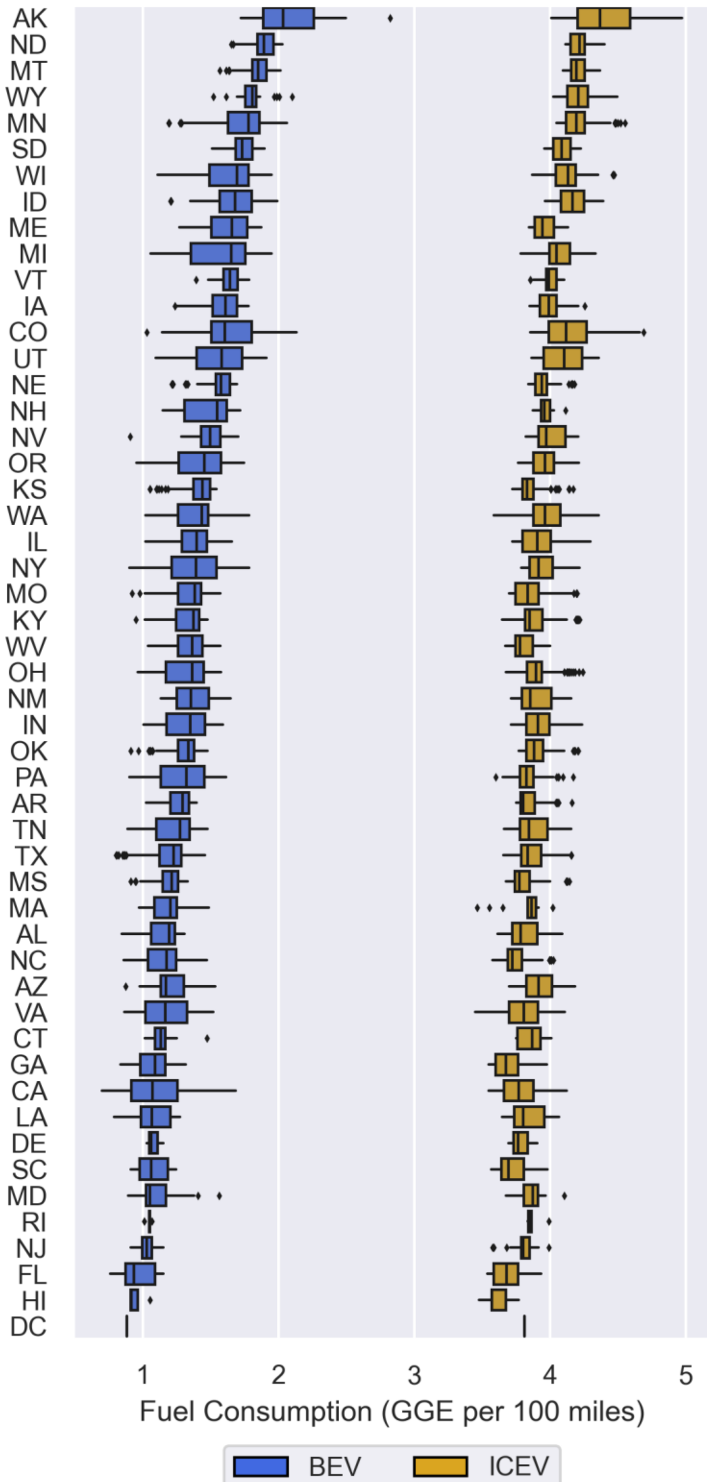

Figure S11. *Boxplots of fuel consumption for each state and powertrain. States are sorted by the median fuel consumption from the baseline-residential charging scenario. Whiskers represent 1.5 times the interquartile range. Units are in gallon of gasoline equivalent per 100 miles (GGE 100mile^{-1}). Note: Fuel consumption assumptions are the same across all scenarios. BEV = battery electric vehicle; ICEV = internal combustion engine vehicle.*

S1.10.2 Fuel Costs

In this study, fuel costs vary both geographically and temporally. Figure S12 and Figure S13 show the state-level median and standard deviation fuel costs for both powertrains for 2022 and 2040, respectively. Overall, on a per-energy unit basis, LCOC is generally higher than the cost of gasoline; however, this relationship does not hold in the best case for BEV scenario and for future projections, where gasoline prices are expected to increase significantly compared to electricity prices.

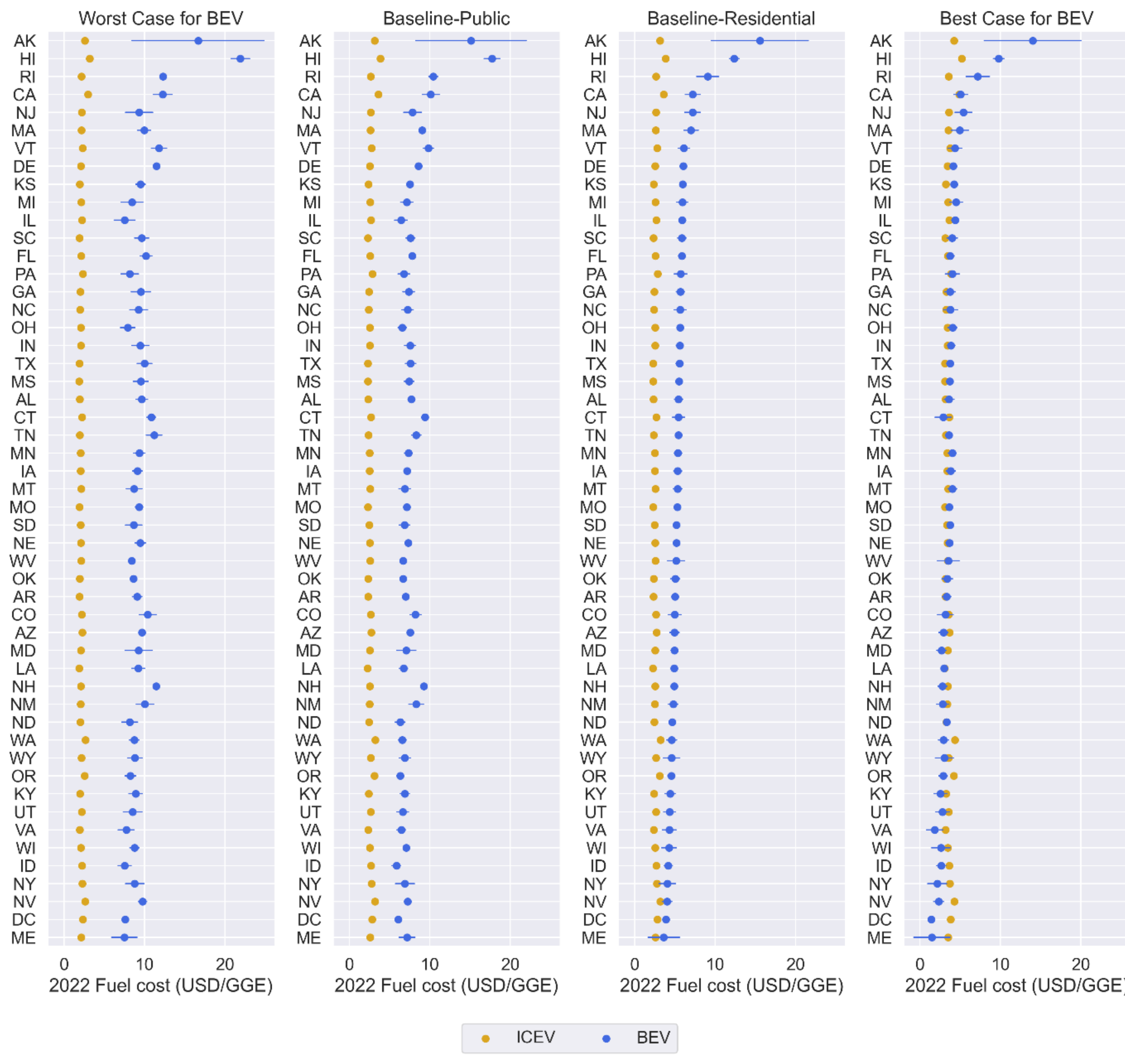

Figure S12. *Median 2022 fuel costs for each state and all scenarios. States are sorted by the fuel costs from the baseline-residential charging scenario. Dots represent median values, while the lines represent the standard deviation. Units are in U.S. dollars per gallon of gasoline equivalent (USD GGE^{-1}). BEV = battery electric vehicle; ICEV = internal combustion engine vehicle.*

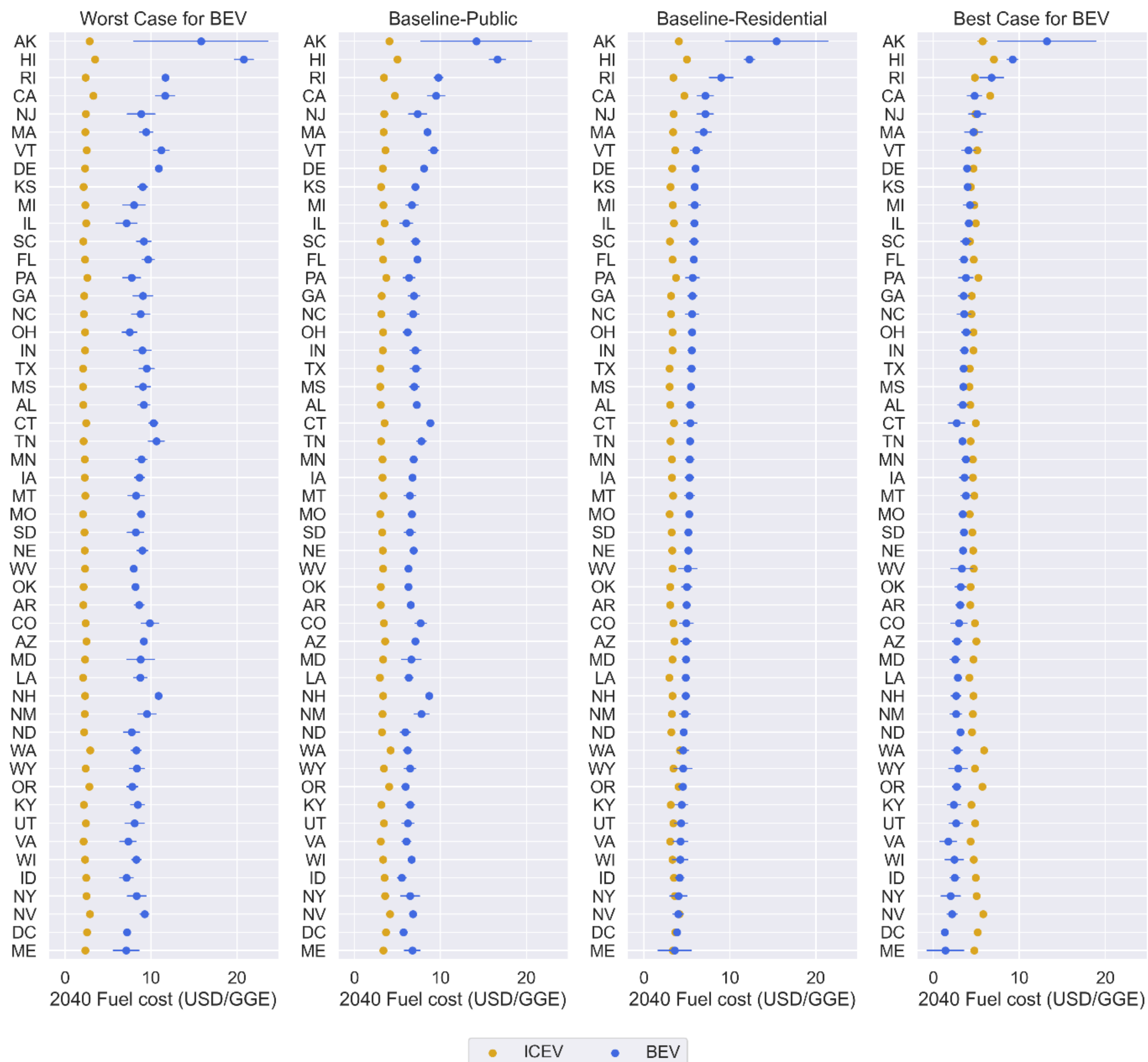

Figure S13. *Median 2040 fuel costs for each state and all scenarios. States are sorted by the fuel costs from the baseline-residential charging scenario. Dots represent median values, while the lines represent the standard deviation. Units are in U.S. dollars per gallon of gasoline equivalent (USD GGE^{-1}). BEV = battery electric vehicle; ICEV = internal combustion engine vehicle.*

S1.10.3 GHG Emissions Factors

Use phase electricity grid GHG emissions factors also vary geographically and temporally. Figure S14 shows the state-level median and standard deviation emissions factors for 2022 and 2040. Electricity grid emissions factors are essentially the same across all scenarios for 2022 and less than half of states have median electricity grid emissions factors lower than the gasoline emissions factor. By 2040, across all scenarios, grid decarbonization results in lower electricity grid emissions factors compared to gasoline for many more states.

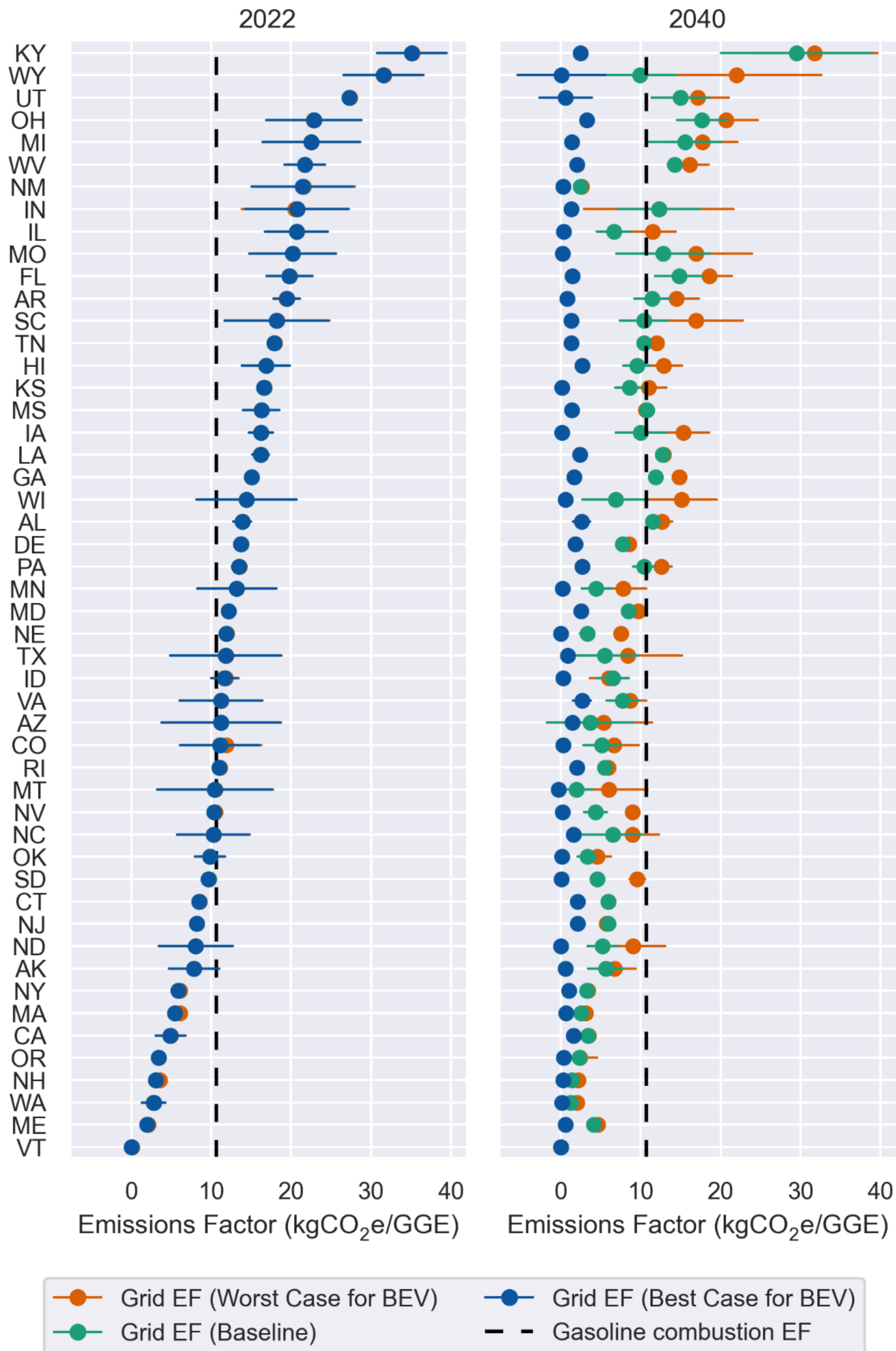

Figure S14. *Median 2022 and 2040 use phase greenhouse gas emissions factors (EFs) for each state and all scenarios. States are sorted by the EF from the baseline-residential charging scenario. Dots represent median values, while the lines represent the standard deviation. Units are in kilograms of carbon dioxide equivalents per gallon of gasoline equivalent (kgCO2e GGE*$^{-1}$*). Note: GHG assumptions for the two baseline scenarios are the same. BEV = battery electric vehicle.*

S1.11 Sensitivity Analysis

We conducted a parametric sensitivity analysis for 12 parameters in which each is adjusted ±10% while keeping the other parameters unchanged. The results are illustrated in Figure S15 using the population-weighted national average GHG and fuel cost savings. As noted in the main text, the fuel cost model is much more sensitive, with ICEV fuel consumption, gas price, and gas price projections resulting in the greatest changes (Figure S15a). For GHG savings (Figure S15a), the model less sensitive, with the only two parameters resulting in greater than 10% change: the gasoline combustion emissions factor and ICEV fuel consumption, both of which resulted in changes of ±17.2 percent.

Overall, the sensitivity to ICEV parameters is likely due to the increasingly greater difference between the ICEV and BEV fuel prices and GHG emission factors over time during the use phase (Figure S2 and Figure S3), which is exaggerated by higher ICEV fuel consumptions.

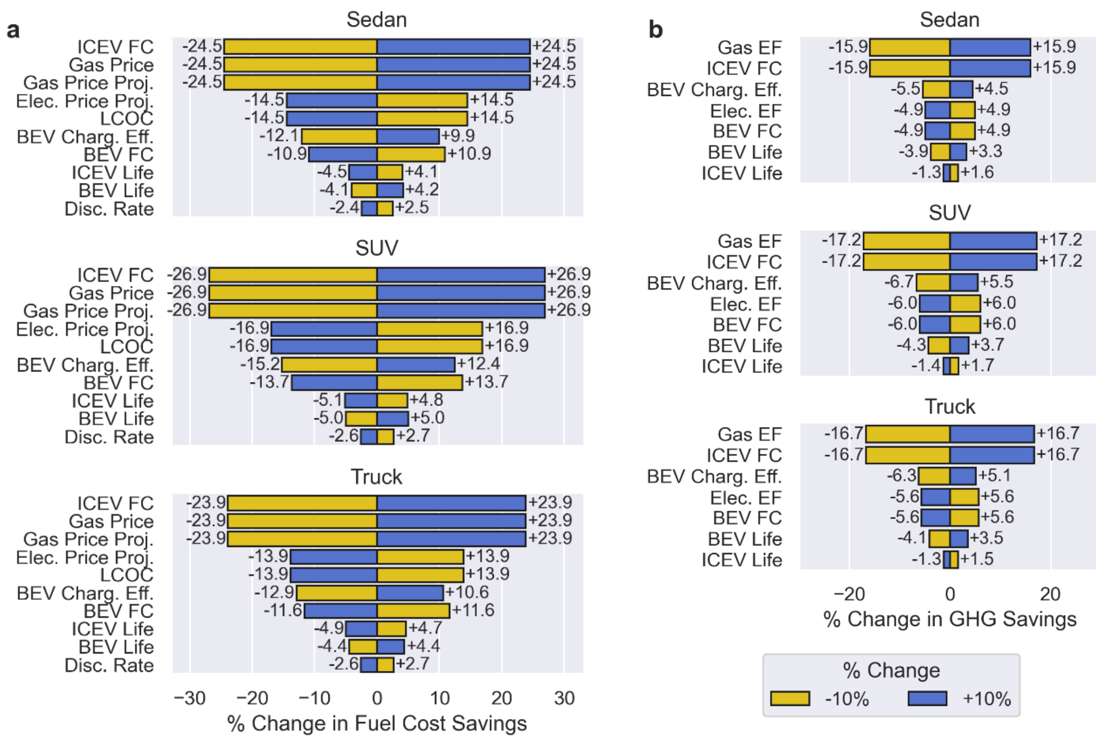

Figure S15. *Sensitivity analysis results indicating the percent change in national average savings when each parameter is adjusted by ±10% for sedan, sport utility vehicle (SUV) and truck vehicle classes.* ***(a)*** *Percent change in greenhouse gas (GHG) savings.* ***(b)*** *Percent change in fuel cost savings.*

S1.12 Scenario Analysis

We ran the results for four different scenarios: baseline-residential charging, baseline-public charging, worst case for BEV, and best case for BEV. The most significant changes in the assumptions were related to the LCOC, fuel price projections, and electricity grid emissions factors (Table 1). At the national level, we see some level of savings across all scenarios, except for the worst case for BEV (Figure S16). Energy burden and GHG savings by state are shown in Figure S17 and Figure S18.

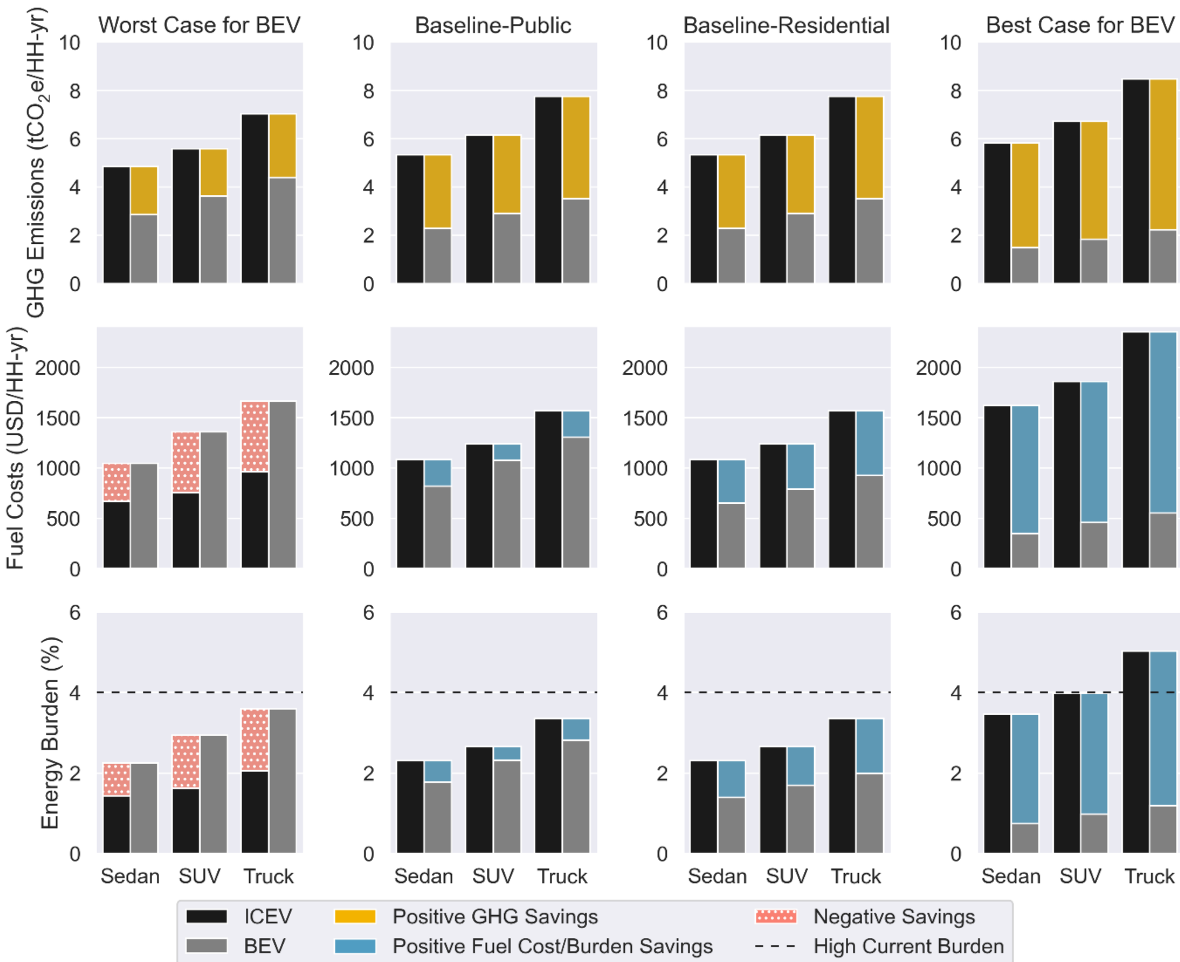

Figure S16. *National average GHG emissions (metric tons of carbon dioxide equivalents [tCO_2e] household-year^{-1}), fuel costs (U.S. dollars [USD] household-year^{-1}), and energy burden (%), by powertrain and vehicle class for all four scenarios. The colored bars represent the savings (or lack thereof) from a BEV relative to an ICEV. BEV = battery electric vehicle; GHG = greenhouse gas; ICEV = internal combustion engine vehicle; SUV = sport utility vehicle.*

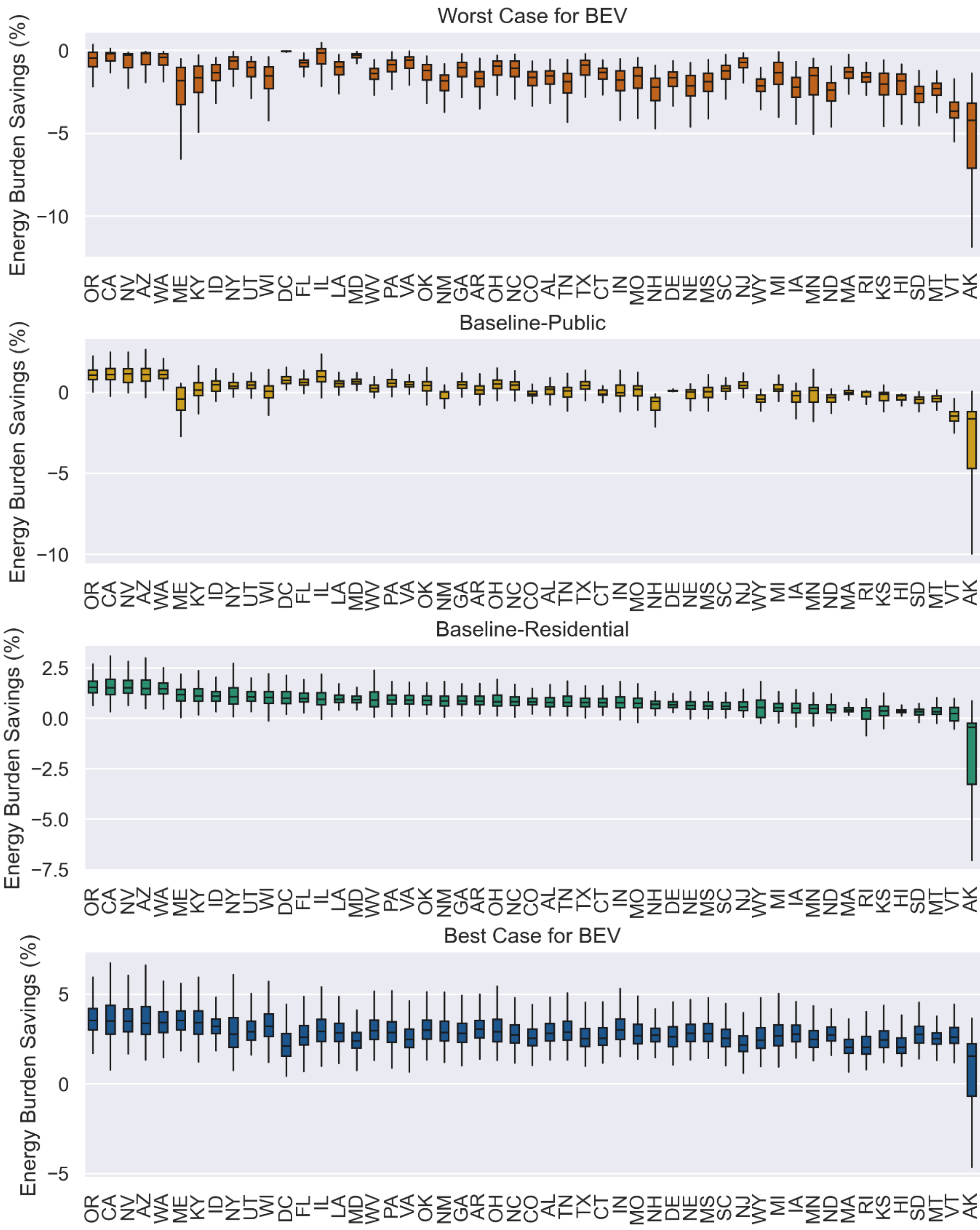

Figure S17. *Boxplots of annual energy burden savings (%) by state for all four scenarios. States are sorted by median energy burden savings for the baseline-residential charging scenario. Whiskers represent 1.5 times the interquartile range. Outliers are not shown. BEV = battery electric vehicle.*

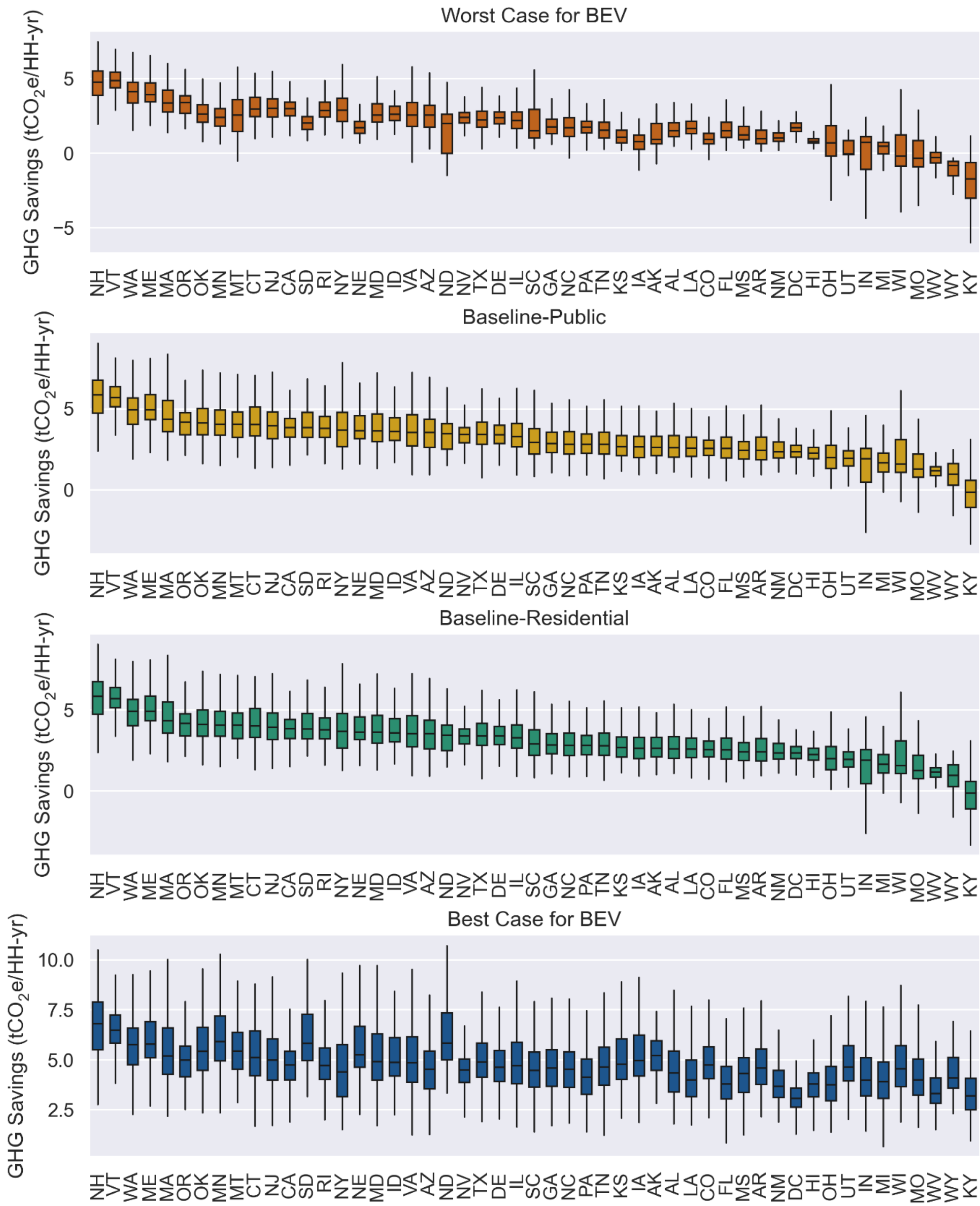

Figure S18. *Boxplots of annual household greenhouse gas (GHG) savings (metric tons of carbon dioxide equivalents [tCO_2e] household-year^{-1}) by state for all four scenarios. States are sorted by median energy burden savings for the baseline-residential charging scenario. Whiskers represent 1.5 times the interquartile range. Outliers are not shown. BEV = battery electric vehicle.*

S1.13 Energy Price Analysis

As noted in the main text, our results are sensitive to energy prices. "Current" transportation energy burden is based on pre-COVID-19 pandemic gasoline prices from February 2020. Gasoline prices have fluctuated and increased significantly since this time; though prices may have peaked in June 2022 (Figure S19) [99].

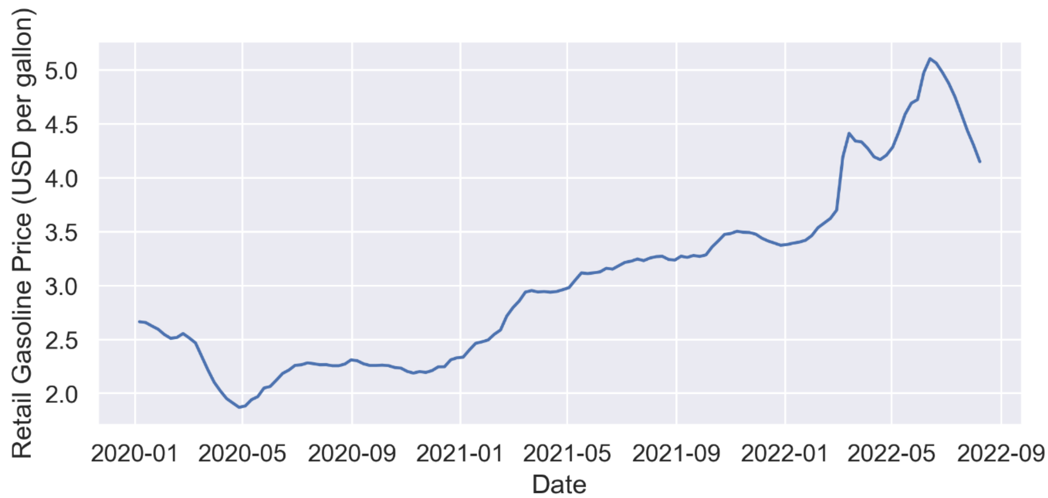

Figure S19. *Weekly U.S. retail gasoline prices (all grades, all formulations) in U.S. dollars [USD] per gallon from January 6, 2020 to August 8, 2022. Source: U.S. Energy Information Administration [99].*

We recalculated transportation energy burdens of the current on-road vehicle stock assuming state-level August 2022 gasoline prices from AAA (Figure S20) [100]. Our analysis indicates that August 2022 transportation energy burdens average almost 70% higher than 2020 burdens.

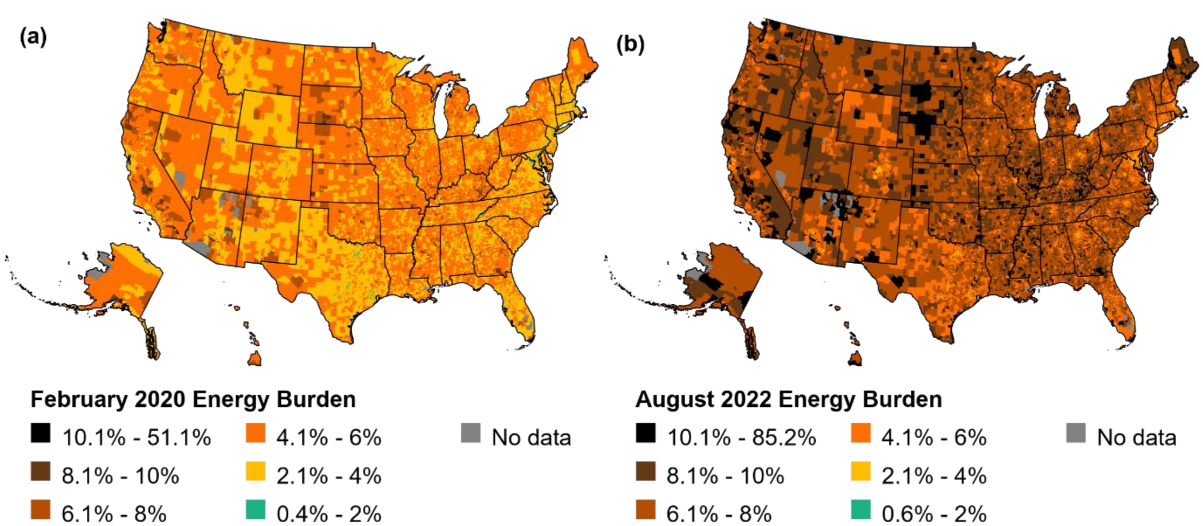

Figure S20. *Comparison between **(a)** February 2020 [40] and **(b)** August 2022 transportation energy burdens of the current on-road vehicle stock.*

References

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