Update and Expansion of Financial Impacts of RUC on Urban and Rural Households Study

Final Report

RUC America

SEPTEMBER 2022

Executive Summary

Participating States
Alaska
California
Colorado
Hawaii
Idaho
Montana
Nebraska
New Mexico
Oklahoma
Oregon
Texas
Utah
Washington
Wyoming

One of the first questions people ask when introduced to the concept of a road usage charge (RUC) is, "How does this impact rural drivers?" This question is of interest across states large and small, as rural drivers generally drive longer distances for day-to-day activities and have limited access to transit alternatives. RUC America aims to address that question through this research effort with detailed, state-specific numbers.

This study draws on 65 million vehicle registration records and thorough statistics research on travel behavior to provide a geographically detailed analysis of how much households pay in current fuel taxes (and complementary registration fee surcharges) compared with a possible road usage charge (RUC) (i.e., a fee charged for each mile driven on roads). The study evaluates differences in household payments for varying geographic areas across fourteen states. The goal of the study is to assess how household payments change geographically if fuel taxes are replaced with a state RUC that collects the same amount of state revenue as the policies it replaces. We do not consider commercial vehicles in this analysis. Our analysis is conducted for the average household in each of 22,193 census tracts, capturing substantial variation within the five geographic groups analyzed for each state.

This work updates and expands earlier work conducted for ten RUC America member states between 2016 and 2018.

Revenue burden decreases for rural drivers under a RUC

We estimate a 6.4 percent decrease in payments, on average, for households in census tracts identified as "Rural Independent"[1] areas. This is balanced by a 2.9 percent increase in payments for households that live in census tracts we classify as "Large Urban Dense" areas across fourteen RUC America states participating in this study. Large urban areas with moderate density also see increases across all states, although average increases are smaller than in denser neighborhoods. Households in census tracts designated as Small Urban areas and rural areas with strong commuting ties to urban centers are forecasted to have different experiences depending upon the state being considered. On average, most states' "Rural Commuter" households experience overall savings.

[1] Geographic classifications are defined in the '2022 Geographic Classifications' section of the report.

These changes are very small in dollar terms. The largest average increase in collected revenue is for households in Large Urban Dense areas of Oregon, who pay $1.35 more per month. California households from Rural Independent areas save $3.32 per month. Different tracts within these categories have larger average household changes, and some tracts experience changes in the opposite direction of their groups average change. Specific households within a tract will also experience larger or smaller differences than the average household. However, these findings remind us that in general, transportation revenue produced from fuel taxes make up a small cost for households and a RUC will not be especially different from a fuel tax-based system for most drivers.

These results arise because rural drivers have less fuel-efficient vehicles than urban drivers on average

This is the primary finding that leads to the shift in revenue burden. Rural drivers consume more fuel per mile traveled than urban drivers for a variety of reasons: they drive larger, less efficient vehicles; they drive older vehicles; they choose engine types with lower efficiency ratings. These differences may be due to preferences of rural drivers or just out of necessity.

This difference is far more important to the findings of this analysis than differences in travel behavior between urban and rural drivers. Our analysis does not consider any change in travel behavior due to revenue policy changes. Rural drivers on average drive more than urban drivers, although only slightly more than drivers living in “Large Urban Moderate” density locations. These differences in levels of driving mean total payments are higher for rural drivers under current fuel tax policies when compared to a RUC, but less for urban drivers under a RUC.

The gap between what rural and urban drivers pay in fuel taxes is increasing over time

Between the analysis of the 2016-2018 data and 2022 data, we see a general trend of revenue per mile under current policies becoming increasingly unequal across geographies. We estimated that the percent decrease in household payments for Rural Independent and Rural Commuter populations from a transition today would be larger than a transition made with the prior vehicle fleet. This trend provides an opportunity for a RUC policy to better align revenue payments with road usage.

Using 2016-2018 data on vehicles and travel and using updated vehicle processing methodology and geographic analysis, we estimate only a one-percent increase and a 2.2-percent decrease in household payments for Large Urban Dense and Rural Independent populations, respectively. This is roughly one-third of the magnitude of changes estimated for 2022.

Vehicle electrification and improved fuel efficiency contribute to this shift

In the vehicle data collected, we see a substantial expansion of VMT attributable to full electric, plug-in hybrid, and standard hybrid vehicles in all states between the prior study and the 2022 study. The share of VMT from full electric vehicles increases by roughly six times, while the prevalence of normal hybrids and plug-in hybrids doubles.

The vehicles found in urban areas five years ago were more efficient than those found in rural areas and this disparity has increased over time. Efficiency improved in rural areas, but not fast enough to prevent the existing gap in revenue payments per mile under current policies from widening.

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This report provides insights, data, and visualizations related to the effect of states transitioning from a fuel tax-based transportation revenue policy framework[2] to a road usage charge (RUC) framework for household passenger vehicles in fourteen states.[3] Several states involved in this study are interested in such a transition from a research basis only and are not actively pursuing or implementing a RUC in their state.[4] Many states (beyond those participating in this study) are studying the possibility of a RUC to increase the long-term financial sustainability of the transportation funding system as increases in fuel efficiency and increased deployments of electric vehicles reduce fuel consumption. A secondary benefit of a RUC framework based on distance traveled would be to equalize the revenue generated for each mile traveled between vehicles, which currently can contribute very different amounts of revenue per mile of travel due to differences in fuel efficiency.

This report focuses specifically on shifts in the geographic patterns of revenue within states and a variety of the key inputs to that analysis. Conventional wisdom suggests that rural households may be worse off under a RUC because they must drive further to reach key destinations. But this viewpoint does not take into consideration the relative fuel efficiencies of the types of vehicles involved in rural household travel. This research seeks to provide data-driven evidence that disproves this conventional wisdom and shows how a RUC would actually be beneficial for rural households relative to the current transportation revenue policies dominated by fuel tax revenue.

We test a “revenue-neutral” RUC rate that collects the same amount of revenue from households as we estimate is collected under current policy. This differs from other studies that might use an independently set RUC rate or attempt to account for changes in collection and enforcement costs relative to current policy.

[2] In addition to fuel taxes across all types of fossil fuels and biofuels, the analysis also includes a variety of vehicle registration surcharges implemented across the participating states. In California, the fuel sales tax components that are periodically set and included in the prices of fuel (similar to excise taxes in other states) are also included. The analysis does not at any time consider other revenue streams such as vehicle purchase sales taxes, driver licensing revenue, commercial vehicle fees, etc.

[3] An Arizona revenue-neutral RUC is also evaluated in some report sections, but Arizona did not provide the vehicle registration data to support later analysis components.

[4] These states include Alaska, Arizona, Idaho, Montana, Nebraska, Nevada, New Mexico, North Dakota, Oklahoma, Texas, and Wyoming.

The key inputs to analyzing geographic patterns of revenue include:

- a geographic classification system that will be used for reporting results
- travel behavior estimates for households
- allocation of travel to different fuel types based on analysis of vehicle registration data
- fuel efficiency profiles of different areas within each participating state

The first part of this report covers these attributes for the 2022 data before providing details on current policy revenue estimates, RUC revenue estimates, and changes in the balance of payments between geographies. The vehicle analysis component represents the most important component of the study in terms of leveraging complete vehicle population data at a high level of spatial detail and vehicle characteristic specificity. This component does not rely on any survey data or statistical estimation like the other pieces of the study and other studies that attempt to address these research questions. Instead, this component uses geocoded vehicle registrations for registered vehicles in each participating state to assess specific fuel type and fuel consumption profiles for each of over 22,000 geographic areas in the 14 participating states.

A later section compares this data to that collected and prepared for 2016-2018 studies EBP conducted for RUC America. The goal of making this comparison is to understand how changes in travel behavior, settlement patterns, and the vehicle fleet may have changed revenue contribution patterns under in-force policy frameworks and the tested RUC framework for each time period. Over the five years between studies, fuel efficiency trends are expected to have been affected significantly by state and federal mileage regulations, incentives for alternative fuel vehicles, and by increased penetration of electric vehicles.

The 2016-2018 studies did not include Alaska, Nebraska, New Mexico, Oklahoma, or Wyoming, which therefore are not discussed in that section. The 2022 geographic classifications and travel behavior analyses leverage more current data sources and provide more granular reporting of differences between urban settings within states. Many factors affect estimates of travel behavior including shifting settlement patterns and demographics as well as updated survey data for estimation of household behavior. When appropriate the prior analysis is updated for improved comparability.

In addition to sections on the pattern of major input factors, current policy and RUC revenue patterns, and comparisons across study years, the report also contains appendices providing supplemental materials and documenting the methodology applied during the analysis as well as details on supporting data and scripting.

2022 Geographic Classifications

The geographic classification system used in this project is important because it affects how results are presented and how residents of each state can be compared to their peers. The geographic classes in this analysis were based on the latest available data on population density, total size of labor market areas, and localized commuting patterns. The system uses data that is expected to be updated regularly in the future – allowing the geographic classifications to capture evolving trends.

The analysis is primarily based on census tracts, which roughly represent a neighborhood of 4,000 people. This level of detail provides a good basis for differentiation between areas within counties and metropolitan areas with different population densities and commuting patterns. While numerous urban-rural classifications exist at the county level, greater resolution allows differentiation of important characteristics that are often missed when large counties contain both very rural and very urban areas.

We define five classes for the 2022 analysis (Table 1). The classes use the same data as FHWA does for urban and rural area definitions[5] and break them into subclasses with different types of travel behavior and regional scale. Overall, about 27 percent of the fifteen[6] classified states' census tracts fall in rural classes, compared with 34 percent of census tracts outside the fifteen states included in the geographic classification section.

[5] Consistent with research referenced by the Bureau of Transportation Statistics (BTS) in the Local Area Transportation Characteristics of Households (LATCH) products, EBP includes all communities with more than 10,000 residents in Small Urban or Large Urban classifications. The Census Bureau definition of an urban areas starts from communities with more than 2,500 people. FHWA limits urban areas to those with more than 5,000 (see HPMS Field Manual for definitions https://www.fhwa.dot.gov/policyinformation/hpms/fieldmanual/page11.cfm).

[6] It is important to note that Arizona was included in the initial stages of the analysis but did not submit vehicle registration data and was thus excluded from the later stages of the analysis. As such, references to '15 RUC America States' in the geographic classification section refer to the 14 RUC America states that comprise the bulk of the analysis in addition to Arizona.

Table 1. Class Definitions

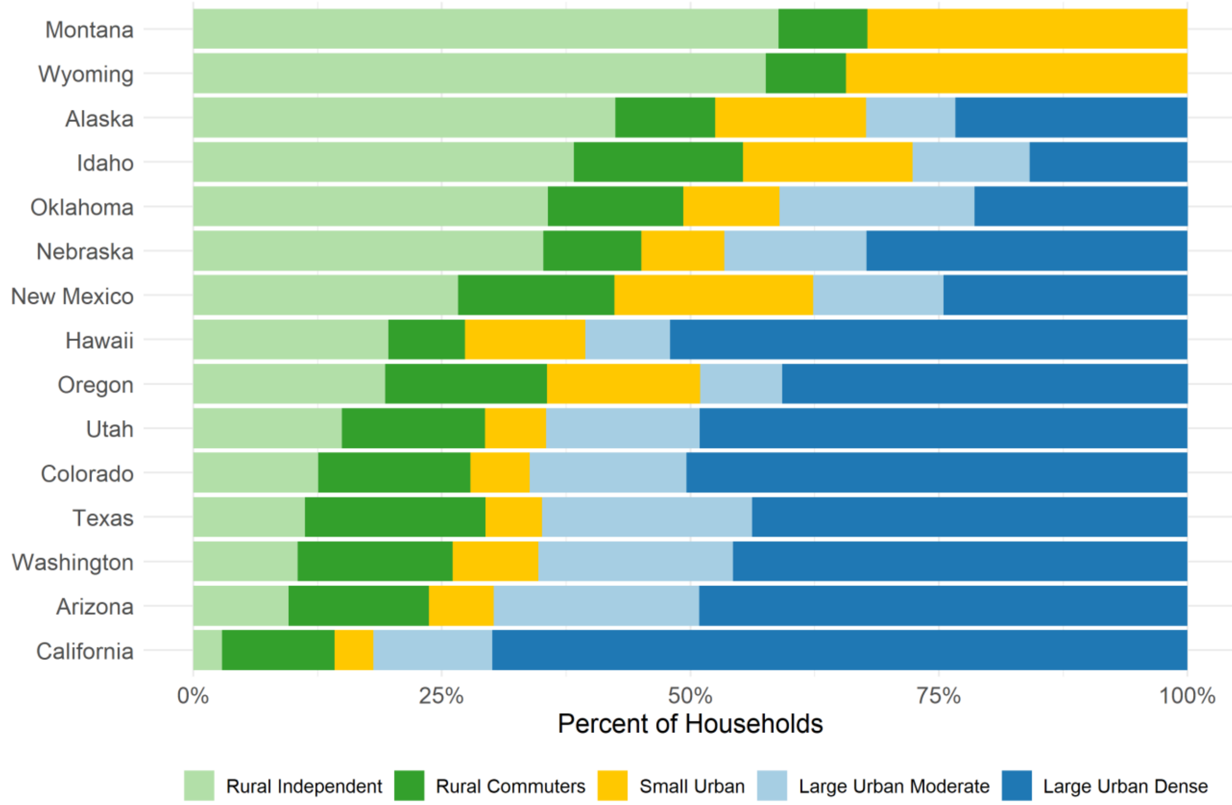
Class Name	Working Definition	Tracts in 15 RUC America States	Tracts in 35 Other US States + DC
Large Urban Dense	Metro population > 250,000; Primary commute flow is within urban areas; Densest 40% of census tracts in the US	11,097 (50%)	16,922 (34%)
Large Urban Moderate	Metro population > 250,000; Primary commute flow is within urban areas; Density less than top 40% of US census tracts	3,543 (16%)	12,194 (24%)
Small Urban	Metro population < 250,000; Primary commute flow is within urban areas > 10,000 population	1,582 (7%)	4,007 (8%)
Rural Commuter	Majority of commuters (>=50%) travel into urban areas	2,892 (13%)	6,665 (13%)
Rural Independent	All other tracts (<50% of commuters travel into urban areas)	3,079 (14%)	10,755 (21%)

Source: EBP analysis of ACS 2014-2019 5-year data, 2019 LEHD LODES data, and the Urban Areas from the 2010 Decennial Census.

Compared to the rest of the US (excluding RUC America states) where 34 percent of tracts are Large Urban Dense, the fifteen participating RUC America states have a much larger share of Large Urban Dense tracts (50 percent). Conversely, there is a much smaller share of Large Urban Moderate tracts (16 percent in RUC America states vs 24 percent for remaining states), indicating Large Urban regions are denser on average than similar size metropolitan areas in other parts of the country. The participating RUC America states also have a much lower share of Rural Independent tracts than the rest of the country (14 percent vs 21 percent).

There is significant variation in the patterns of settlement and commuting across the participating states. In Figure 1 and Table 2, we show the number of households residing in each geographic classification across the fifteen participating RUC America states. Two states (Montana and Wyoming) have no metropolitan areas with populations over 250,000, while in California, less than four percent of residents live in Small Urban areas and less than three percent live in Rural Independent areas. With over eleven percent of California households in Rural Commuting areas, even in rural settings, commuting to Large Urban areas is the norm. Arizona, Oklahoma, Texas, and Washington have around twenty percent of their population living in Large Urban Moderate settings, whereas this class represents less than ten percent of households for Alaska, Hawaii, and Oregon.

Figure 1. Percentage of State Households by Geographic Classification



Source: EBP analysis of ACS 2014-2019 5-year data, 2019 LEHD LODES data, and the Urban Areas from the 2010 Decennial Census.

Table 2. Households by Reporting Class by State

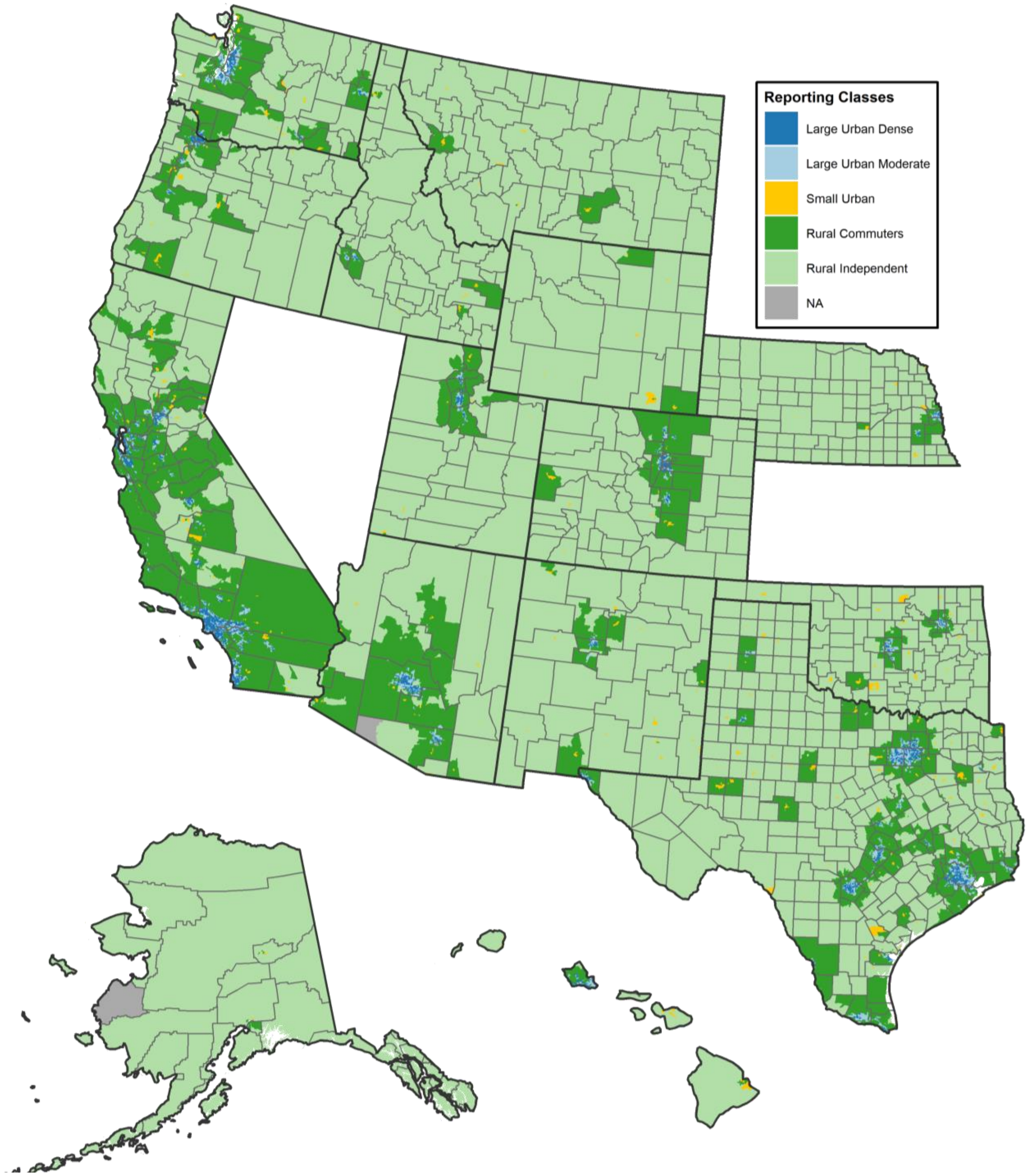
State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.
Alaska	23.4%	9.0%	15.2%	10.0%	42.5%
Arizona	49.1%	20.7%	6.5%	14.1%	9.6%
California	69.9%	12.0%	3.9%	11.3%	2.9%
Colorado	50.4%	15.7%	6.0%	15.3%	12.6%
Hawaii	52.0%	8.5%	12.1%	7.7%	19.6%
Idaho	15.9%	11.8%	17.1%	17.0%	38.3%
Montana			32.2%	9.0%	58.9%
Nebraska	32.3%	14.3%	8.4%	9.9%	35.2%
New Mexico	24.6%	13.1%	20.0%	15.7%	26.6%
Oklahoma	21.4%	19.6%	9.7%	13.6%	35.7%
Oregon	40.8%	8.2%	15.4%	16.3%	19.3%
Texas	43.8%	21.2%	5.7%	18.2%	11.2%
Utah	49.1%	15.5%	6.1%	14.4%	15.0%
Washington	45.7%	19.6%	8.6%	15.6%	10.5%
Wyoming			34.3%	8.1%	57.6%
15-State Weighted Average	**50.9%**	**15.7%**	**7.1%**	**14.2%**	**12.0%**

Source: EBP analysis of ACS 2014-2019 5-year data, 2019 LEHD LODES data, and urban area boundaries developed from the 2010 Decennial Census.

The geographic classification patterns can be seen visually in the map in Figure 2. When reviewing fifteen states on a single map, it can be difficult to identify the urban areas even though 74 percent of the households across the fifteen states are located in these areas. Appendix A provides an inventory of the state level maps produced for this study and delivered to the project participants as packages of graphics files. The goal of these graphics is to help readers identify the settlement and commuting patterns for their own state and possibly compare with other states. The state-level maps are not included in this report due to the impact inclusion would have on file size and page count.

Not all Small Urban areas have neighboring rural census tracts that send 50 percent of their rural workers into the adjacent Small Urban tracts. However, almost all Large Urban areas have clear commuter sheds extending into the rural portions of the metropolitan counties and beyond. A few exceptions include Native American lands where economies are more self-sufficient despite being in proximity to larger urban economies.

Figure 2. 15 State Geographic Classification Map



Source: EBP analysis of ACS 2014-2019 5-year data, 2019 LEHD LODES data, and urban area boundaries developed from the 2010 Decennial Census.

2022 Travel Behavior Estimates

Travel estimates are based on the Bureau of Transportation Statistics' analysis of the 2017 National Household Travel Survey as documented in their Local Area Transportation Characteristics of Households (LATCH) product.[7] The local area referenced in the title of LATCH is a census tract, consistent with this study's other components. LATCH estimates daily vehicle travel for households in a tract based on the Census Division a tract falls in, its density characteristics, and other information about the overall characteristics of the tract's households, including median income and household structure variables (for example, whether the household contains retirees). We update these values slightly by applying the estimators of census tract travel to the latest demographic data.[8]

The census tract estimates for daily household vehicle miles traveled (VMT) are tabulated across the fifteen participating states and shown graphically in Figure 3 grouped by which geographic class the tracts fall in. LATCH reveals a range of household VMT across tracts of a particular classification, but several patterns are visible on average:

- Households in Large Urban Dense and Small Urban areas tend to travel less (as measured by VMT) than households in rural areas
- Households in Large Urban Moderate areas travel almost as much as those in Rural Independent tracts
- Households in Rural Commuter areas travel the most by a wide margin

LATCH also provides equations for estimating the trip-making behavior of households. These estimates for the fifteen participating states' census tracts are shown in Figure 4. Rural Independent households take a very similar number of trips when compared to Large Urban Dense and Small Urban households, while Large Urban Moderate and Rural Commuter households make more trips per day. Considering the differences in VMT, differences in number of trips are consistent with rural households taking longer trips on average than urban residents.

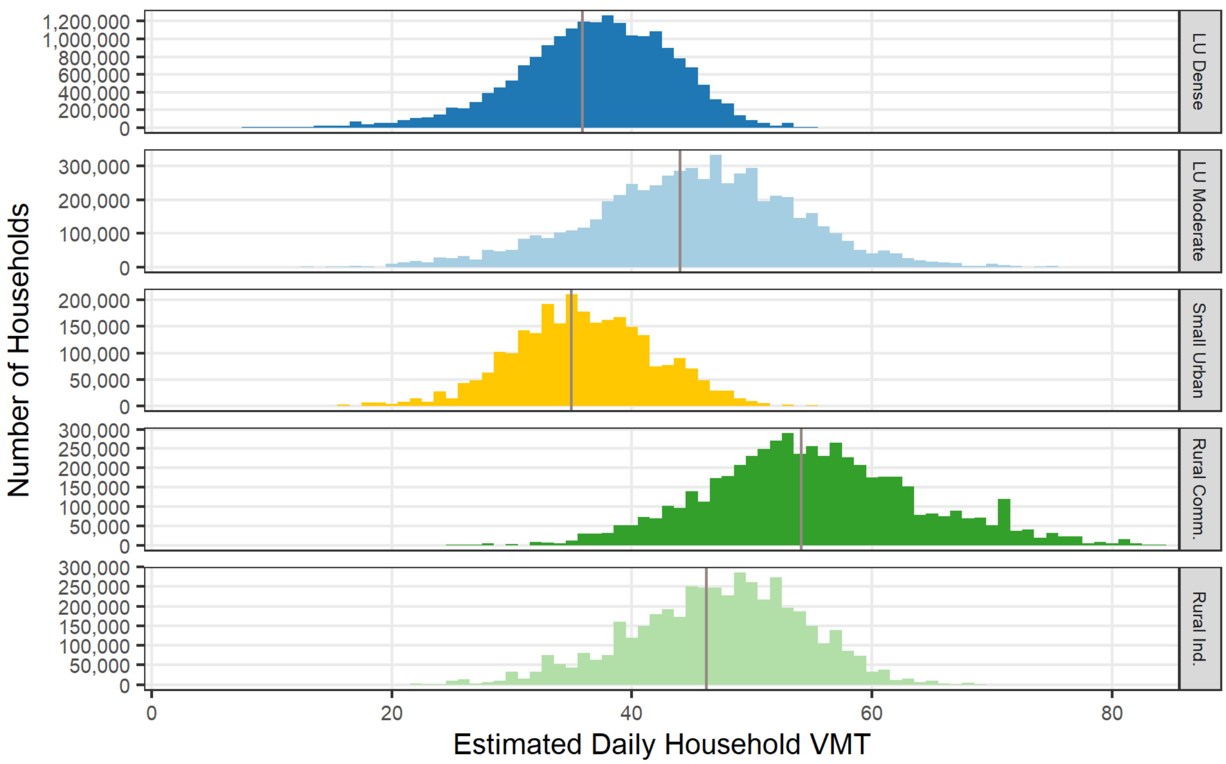
Results of subsequent analysis of RUC effects for the states will depend on their unique travel behavior and vehicle patterns. While not all trends and patterns are visible while viewing all fifteen states in the region at once, we do see lower levels of travel in the urban areas, higher levels in the Large Urban Moderate and Rural Commuter tracts around cities

[7] LATCH is available at Local Area Transportation Characteristics for Households (LATCH Survey) | Bureau of Transportation Statistics (bts.gov) and was originally released November 2018.
[8] LATCH used 2013-2017 American Community Survey (ACS) data which we were able to update with 2015-2019 ACS data.

(especially clear in Texas), and some variation between states within and across Census Divisions (Figure 5). Figure 6 maps trips showing spatial patterns corresponding to the data from Figure 4. It is important to remember when viewing maps that each census tract has roughly the same population (about 4,000) but that they can have very different land areas – some of the large rural areas estimated to have relatively low levels of travel may represent only a few thousand residents of those states.

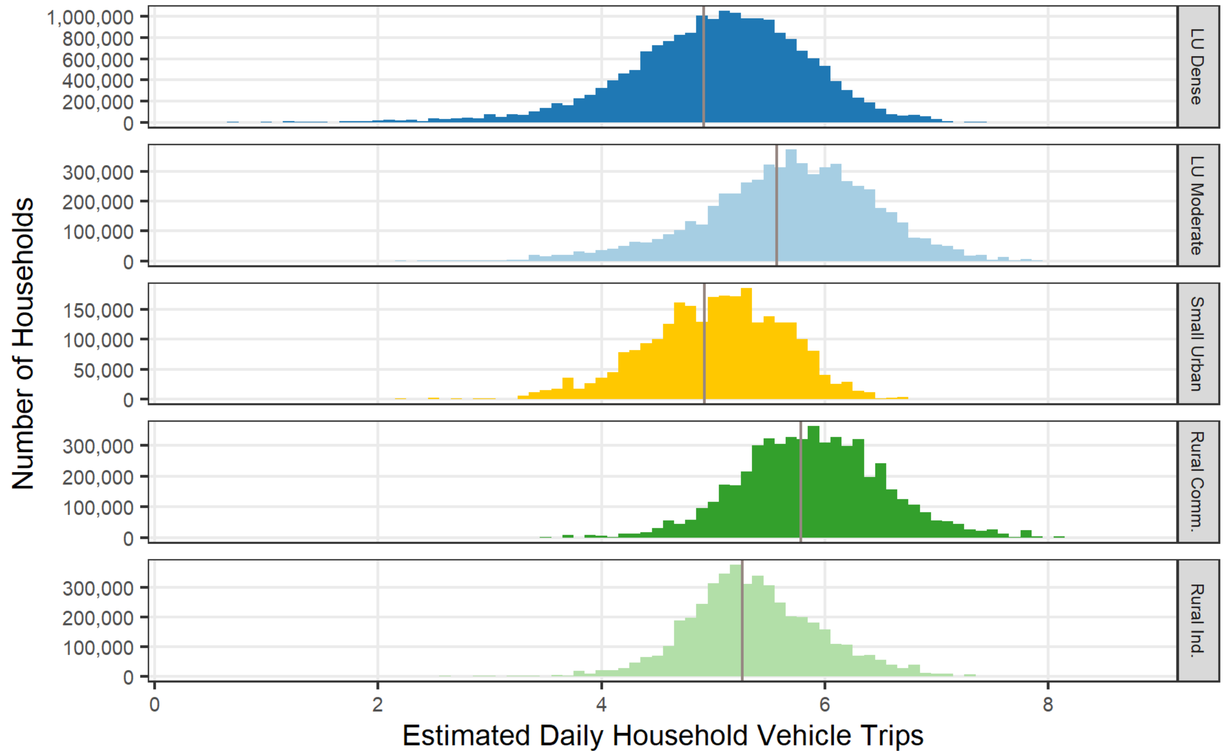
The box-and-whisker plots in Figure 7 show some of the differences and similarities between states. In all states, Rural Commuter households travel the most on average. However, in California, Hawaii, Oregon, and Washington, Large Urban Moderate households drive almost as much. In multiple states, Rural Independent households drive less than Large Urban Moderate Households.

Figure 3. Distribution of Daily Household VMT in the Study Region



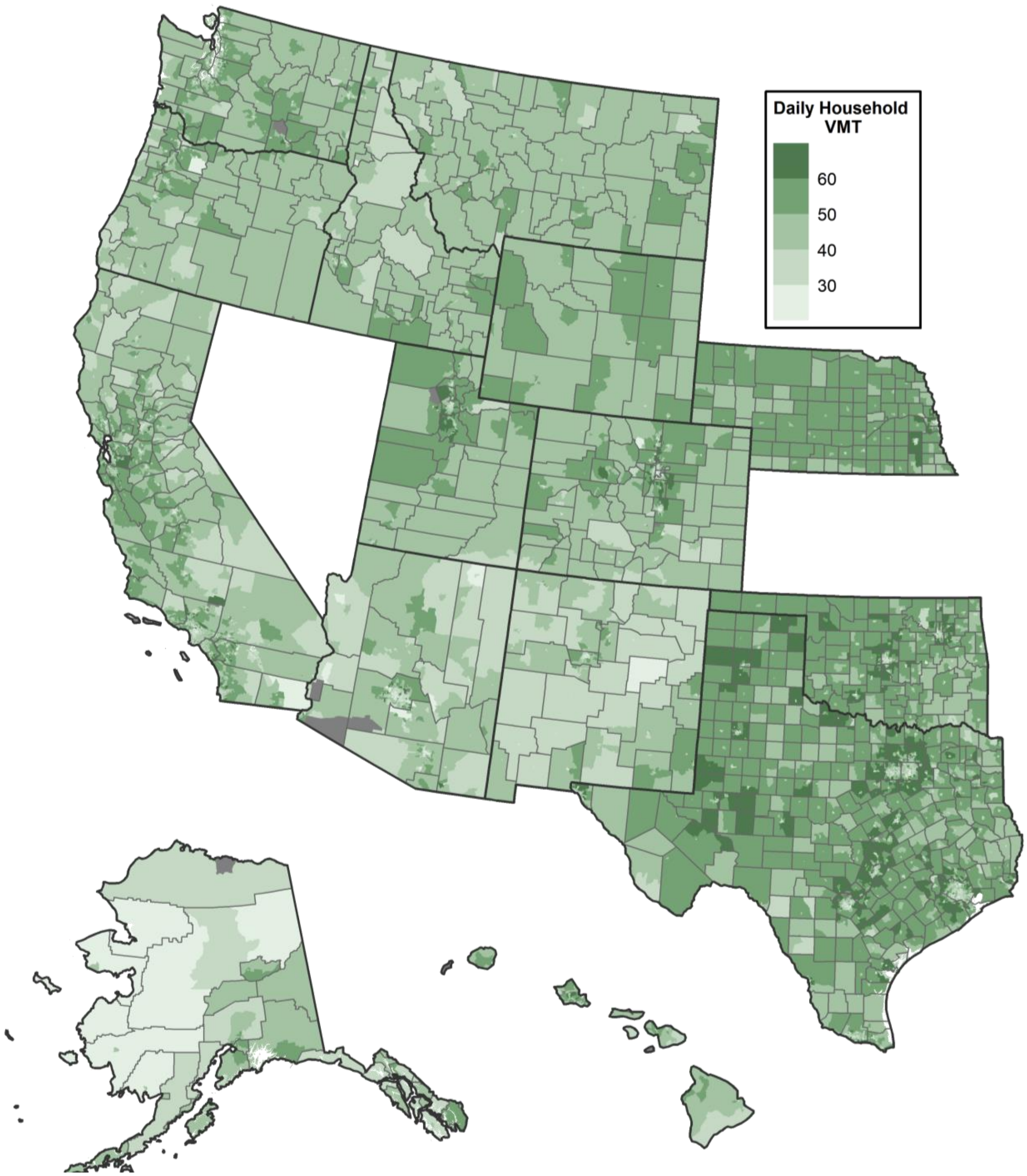
Source: EBP analysis of ACS 2015-2019 5-year data and BTS's LATCH product developed from ACS (2012-2016) and NHTS (2017) data.

Figure 4. Distribution of Daily Household Vehicle Trips in the Study Region



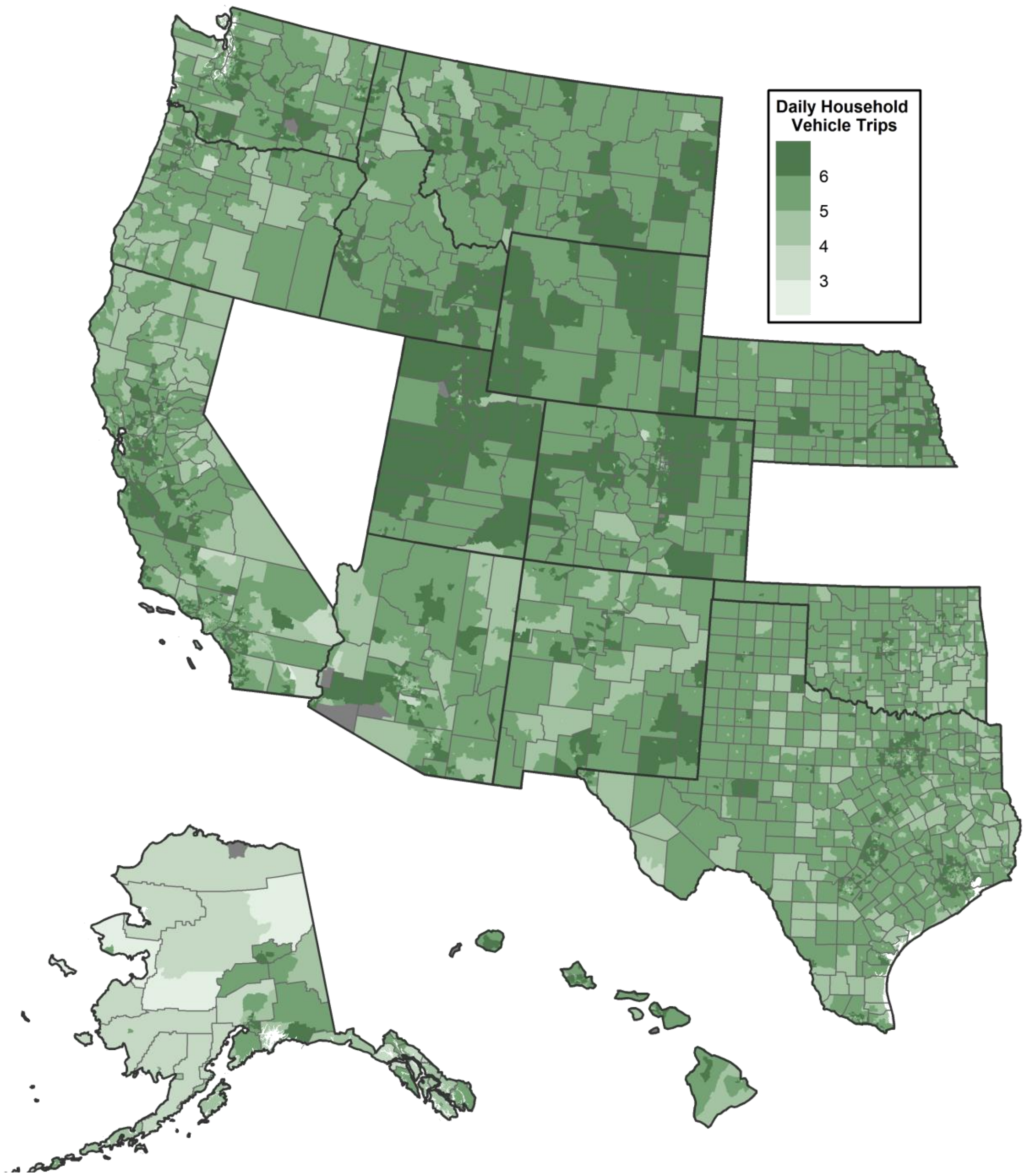
Source: EBP analysis of ACS 2015-2019 5-year data and BTS's LATCH product developed from ACS (2012-2016) and NHTS (2017) data.

Figure 5. Map of Daily Household VMT



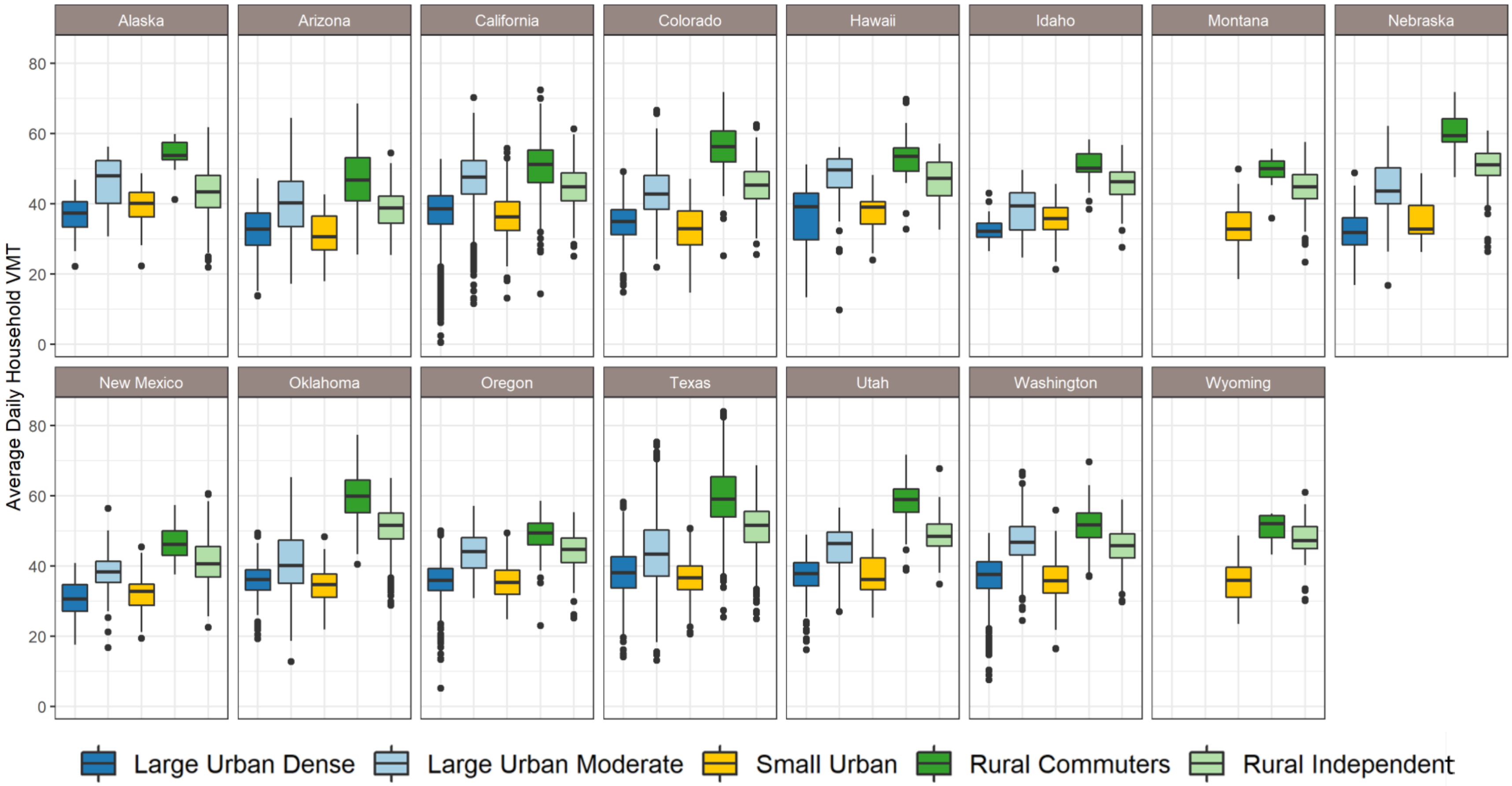
Source: EBP analysis of ACS 2015-2019 5-year data and BTS's LATCH product developed from ACS (2012-2016) and NHTS (2017) data.

Figure 6. Map of Daily Household Vehicle Trips



Source: EBP analysis of ACS 2015-2019 5-year data and BTS's LATCH product developed from ACS (2012-2016) and NHTS (2017) data.

Figure 7. Distribution of Daily Household VMT by State



Source: EBP analysis of ACS 2014-2019 5-year data, 2019 LEHD LODES data, urban area boundaries developed from the 2010 Decennial Census, and BTS's LATCH product developed from ACS (2012-2016) and NHTS (2017) data. Notes: Montana and Wyoming only include Small Urban, Rural Commuter, and Rural Independent geographies. Box-and-whisker plots are a much more compact version of the histograms from Figure 3. Whereas the histograms counted all households estimated to have a certain level of daily VMT and showed the mean/average for each category with a vertical bar, Figure 7 reveals the median daily VMT for each category in each state, plus the 25th and 75th percentile at the top and bottom of the boxes. This means that 50 percent of all observations are within the box. The whiskers cover the remaining 50% of observations, with "outliers" shown as dots.

2022 Vehicle Usage Estimates

We worked with each state to acquire registration data including vehicle identification numbers (VINs) and location information across the household light duty vehicle fleet and motor homes.[9] The analysis did not include commercial passenger vehicles (neither taxis nor buses), small vehicles (motorcycles, etc.), or non-passenger trucks (e.g., delivery and freight vehicles).

After receiving data, we standardized it, eliminated invalid records, and applied the NHTSA vPIC VIN decoding application programming interface (API). The methodology is described in Appendix D. VIN decoding identified standardized fuel types and data for matching fuel efficiency information from EPA records. A range of location attributes from different states were standardized to census tracts for further analysis and reporting. Appendix B records the number of vehicles records received, included after each intermediate step, and used in generating results.

Fuel Types

Use of the phrase "fuel types" in this section and the study overall represents a minor simplification. Reporting is done for six categories, which represent differences in primary fuel, as well as different drivetrain technologies. Several categories use gasoline and some use more than one type of fuel (e.g., hybrids use gasoline and have an electric motor; flex fuel uses gasoline and ethanol or diesel and biodiesel). Fuel type definitions follow to ensure transparency in reporting.

In many cases, the type of fuel is identified by the VIN's decoding using the NHTSA vPIC API, but where that is not available (or provides no information), the fuel reported with the registration is used, if available.

Gas. This category includes vehicles identified as being gasoline only.

Diesel. This category includes vehicles identified as being diesel only.

Hybrid. Hybrid vehicles are primarily vehicles that use gasoline but also have electric motors that provide some drive functions. However, the battery supplying these electric

[9] Arizona did not provide 2022 vehicle data despite participating in the other study components and the original study.

motors is only charged by the combustion engine or other sources like regenerative breaking. They cannot be charged when the internal combustion engine is not turned on.

Plug-in Hybrid. Plug-in hybrids are sufficiently different from standard hybrids or fully electric vehicles to be categorized distinctly. They can operate for a much longer period of time than standard hybrid vehicles in electric-only mode. The battery can be charged via an electrical connection when the vehicle is not active. They also have a fuel tank, but the internal combustion engine is typically only used when the battery is beginning to run low or to provide additional torque, etc.

Full Electric. Full electric vehicles are those that can only be propelled by electric motors with no back-up internal combustion engine. The great majority are battery electric vehicles, and in this study, we refer to battery electric vehicles as full electric, and category fuel cell electric vehicles as "other".

Flex Fuel. Flex fuel vehicles include gas/ethanol vehicles and diesel/biodiesel vehicles and represent the majority of vehicles that are not encompassed by the previously listed fuel categories in the analysis.

Other fuel types decoded and analyzed include fuel cell, CNG- and LPG-fueled vehicles. These are included when looking across all fuel types but are otherwise noted only in footnotes. For all fuel types, because we rely on NHTSA VIN decoding for standardized reporting across states, we may not capture vehicles converted from standard drivetrains to alterative fossil fuels. We use registration-provided fuel type if NHTSA does not know the fuel type and it is available.

Estimates of VMT by Fuel Type

The fleet mix in this report is presented in terms of the share of vehicle miles traveled (VMT) attributable to each fuel type. This controls for differences within geographic classes and states by how much the average household in each tract travels. Within geographic classes there is significant variation in travel behavior as reported in Figure 3. Based on the number of households in each geographic class, we calculated each state's total annual VMT as presented in Table 3.

This section analyzes how this total VMT for states can be assigned to fuel types as well as geographies. For exhibits like Figure 8 and Figure 9, we show differences in fuel mix for non-gas vehicles between geographic classes and states. We account for some of the substantial variation between tracts within geographic classes by representing findings using VMT rather than vehicle counts.

Revenue estimates depend on the mix of fuels and average travel behavior at the census tract level. Trends in vehicle fleet composition are best understood by looking within each geographic class by state. However, displaying these dimensions requires over 75 rows of data. In this section, we summarize the data two different ways for discussion. The detailed table of each state's variation in fuel mix across geographic classes can be found in Table 40 of Appendix C. Appendix C also includes maps of the prevalence of different fuel types in the regional VMT mix, with one map for each of the fuel type categories. Maps have also been prepared for each state to review the distribution of fuel types in their state as discussed in Appendix A.

State	Geographic Class	DVMT, Millions	Gas	Diesel	Hybrid	Plug-in Hybrid	Full Electric	Flex Fuel
Alaska	LU Dense	2.2	85.8%	3.6%	2.1%	0.1%	0.2%	8.1%
	LU Mod.	1.1	84.4%	4.9%	2.1%	0.1%	0.3%	8.2%
	Small Urb	1.6	81.8%	7.0%	1.6%	0.1%	0.2%	9.3%
	Rural Comm.	1.4	81.5%	8.0%	1.9%	0.1%	0.3%	8.2%
	Rural Indep.	4.8	81.2%	7.9%	1.5%	0.1%	0.5%	8.7%
California	LU Dense	342.0	87.0%	1.0%	5.8%	1.1%	2.3%	2.8%
	LU Mod.	73.6	85.5%	1.4%	5.8%	1.2%	2.8%	3.2%
	Small Urb	18.7	88.2%	2.0%	3.9%	0.6%	0.8%	4.6%
	Rural Comm.	75.6	86.2%	1.8%	5.1%	1.0%	2.0%	3.8%
	Rural Indep.	16.9	88.1%	2.9%	3.3%	0.5%	0.5%	4.7%
Colorado	LU Dense	37.2	88.6%	2.2%	2.7%	0.2%	0.8%	5.5%
	LU Mod.	14.6	86.5%	3.6%	2.8%	0.3%	1.1%	5.7%
	Small Urb	4.3	85.6%	6.0%	1.5%	0.1%	0.2%	6.6%
	Rural Comm.	18.6	82.1%	8.2%	2.3%	0.3%	1.0%	6.1%
	Rural Indep.	12.3	80.6%	10.4%	1.4%	0.1%	0.3%	7.2%
Hawaii	LU Dense	8.6	90.3%	1.1%	3.4%	0.4%	1.6%	3.2%
	LU Mod.	1.9	88.2%	1.4%	4.2%	0.5%	2.8%	2.8%
	Small Urb	2.1	90.4%	2.7%	2.3%	0.2%	1.0%	3.4%
	Rural Comm.	1.8	89.8%	1.9%	3.2%	0.4%	1.5%	3.4%
	Rural Indep.	4.3	88.8%	4.0%	2.5%	0.2%	1.0%	3.4%
Idaho	LU Dense	3.3	86.7%	4.0%	2.7%	0.2%	0.4%	5.9%
	LU Mod.	2.9	84.6%	5.6%	2.6%	0.2%	0.4%	6.6%
	Small Urb	3.9	84.6%	6.2%	1.8%	0.1%	0.1%	7.2%
	Rural Comm.	5.5	82.4%	7.9%	2.3%	0.2%	0.4%	6.8%

State	Geographic Class	DVMT, Millions	Gas	Diesel	Hybrid	Plug-in Hybrid	Full Electric	Flex Fuel
	Rural Indep.	11.2	79.8%	11.2%	1.4%	0.1%	0.1%	7.4%
Montana	LU Dense							
	LU Mod.							
	Small Urb	4.7	86.8%	3.9%	1.6%	0.1%	0.2%	7.5%
	Rural Comm.	1.9	84.2%	6.4%	1.5%	0.1%	0.2%	7.6%
	Rural Indep.	11.3	83.0%	7.2%	1.3%	0.1%	0.2%	8.3%
Nebraska	LU Dense	7.9	88.5%	1.2%	2.0%	0.1%	0.2%	8.0%
	LU Mod.	4.9	87.8%	1.6%	2.1%	0.1%	0.3%	8.0%
	Small Urb	2.3	84.9%	2.4%	1.0%	0.1%	0.1%	11.6%
	Rural Comm.	4.5	83.8%	4.1%	1.9%	0.2%	0.4%	9.7%
	Rural Indep.	13.5	79.2%	7.2%	0.9%	0.0%	0.0%	12.6%
New Mexico	LU Dense	5.8	87.1%	3.2%	2.7%	0.2%	0.3%	6.5%
	LU Mod.	4.0	84.3%	5.7%	2.6%	0.2%	0.5%	6.6%
	Small Urb	5.1	83.9%	5.1%	1.9%	0.1%	0.2%	8.8%
	Rural Comm.	5.8	83.2%	6.5%	2.4%	0.2%	0.5%	7.2%
	Rural Indep.	8.6	80.7%	8.4%	1.4%	0.1%	0.1%	9.2%
Oklahoma	LU Dense	11.5	86.2%	1.8%	1.8%	0.1%	0.2%	9.8%
	LU Mod.	12.4	85.1%	2.6%	1.8%	0.1%	0.3%	9.9%
	Small Urb	5.1	83.4%	3.2%	1.5%	0.1%	0.1%	11.7%
	Rural Comm.	12.2	81.1%	5.7%	1.6%	0.1%	0.2%	11.3%
	Rural Indep.	26.8	78.7%	7.0%	1.1%	0.0%	0.1%	13.1%
Oregon	LU Dense	23.1	86.9%	2.7%	5.1%	0.6%	1.3%	3.3%
	LU Mod.	5.9	85.5%	4.1%	4.6%	0.5%	1.4%	3.9%
	Small Urb	9.2	85.8%	5.8%	3.0%	0.3%	0.5%	4.5%
	Rural Comm.	12.9	82.7%	8.7%	3.0%	0.4%	0.7%	4.5%
	Rural Indep.	13.7	81.8%	10.4%	2.1%	0.2%	0.2%	5.3%
Texas	LU Dense	164.3	87.4%	2.1%	1.8%	0.2%	0.8%	7.7%
	LU Mod.	93.1	86.1%	3.1%	1.9%	0.2%	1.0%	7.8%
	Small Urb	20.5	82.6%	5.1%	1.1%	0.1%	0.2%	10.9%
	Rural Comm.	108.3	83.1%	5.7%	1.5%	0.1%	0.6%	8.9%
	Rural Indep.	55.2	78.6%	8.7%	1.0%	0.1%	0.1%	11.5%
Utah	LU Dense	17.7	86.5%	4.4%	2.2%	0.2%	0.5%	6.1%
	LU Mod.	6.8	85.0%	5.4%	2.2%	0.2%	0.5%	6.5%
	Small Urb	2.2	84.6%	6.5%	1.9%	0.2%	0.3%	6.4%
	Rural Comm.	8.3	84.4%	6.3%	2.0%	0.2%	0.4%	6.4%
	Rural Indep.	7.1	79.7%	11.0%	1.5%	0.1%	0.2%	7.2%
Washington	LU Dense	47.0	87.4%	2.0%	5.1%	0.4%	1.6%	3.5%
	LU Mod.	26.0	86.1%	3.8%	4.0%	0.4%	1.4%	4.3%
	Small Urb	9.0	87.9%	3.7%	2.7%	0.2%	0.5%	5.0%
	Rural Comm.	22.7	83.8%	7.3%	2.9%	0.3%	0.8%	4.9%
	Rural Indep.	13.7	84.0%	7.6%	2.3%	0.2%	0.4%	5.4%
Wyoming	LU Dense							
	LU Mod.							
	Small Urb	2.8	82.6%	7.4%	1.2%	0.1%	0.1%	8.7%
	Rural Comm.	0.9	77.9%	12.2%	1.3%	0.1%	0.1%	8.4%
	Rural Indep.	6.4	75.4%	14.1%	1.0%	0.0%	0.1%	9.4%

Table 3. Annual VMT by Geography and State (Millions)

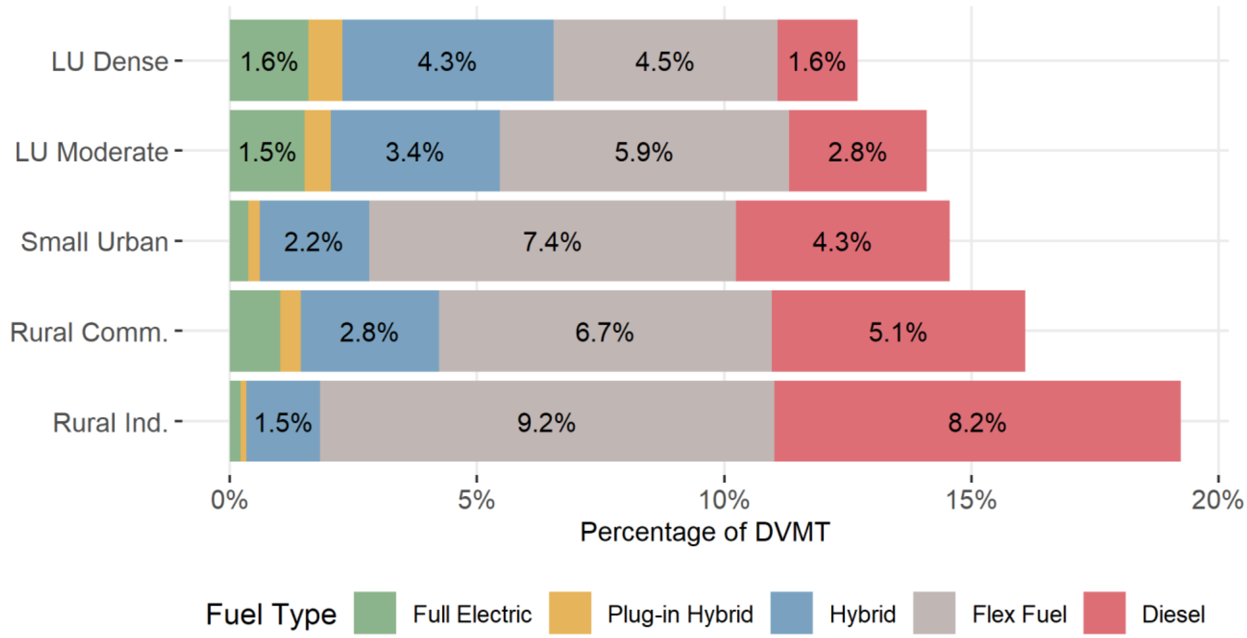
State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	Total
Alaska	796	396	570	497	1,767	4,025
California	124,844	26,864	6,830	27,584	6,167	192,288
Colorado	13,574	5,338	1,573	6,779	4,478	31,743
Hawaii	3,135	690	784	674	1,551	6,835
Idaho	1,191	1,076	1,410	1,998	4,076	9,751
Montana			1,699	695	4,126	6,520
Nebraska	2,896	1,796	830	1,652	4,930	12,104
New Mexico	2,128	1,451	1,844	2,112	3,149	10,683
Oklahoma	4,185	4,527	1,847	4,446	9,772	24,776
Oregon	8,429	2,153	3,356	4,700	5,008	23,646
Texas	59,978	33,996	7,466	39,523	20,152	161,114
Utah	6,470	2,500	816	3,031	2,602	15,420
Washington	17,160	9,494	3,290	8,304	4,997	43,244
Wyoming			1,036	347	2,326	3,709
Total	**244,785**	**90,281**	**33,350**	**102,342**	**75,101**	**545,859**

Source: 2015-2019 American Community Survey Data applied to the 2017 LATCH models.

In Figure 8, we summarize daily VMT data for all fourteen states across geographic classes. We see that gas vehicle's share of use is highest for Large Urban Dense areas and decreases as the geographic classes become more rural. This decreasing prevalence of gas VMT among less urban households is primarily due to increased fleet share for diesel and other category fuels – primarily flex fuels. Electric motor VMT (collectively full electric, plug-in hybrid, and regular hybrid vehicle VMT) are most prevalent in the Large Urban areas. Use of vehicles with electric motors is not common in Small Urban areas. The geographic classification with the third highest share of electric motor VMT (following Large Urban Dense and Large Urban Moderate) is Rural Commuter.

Full electric and plug-in hybrid vehicles are more than seven times as common in Large Urban areas as they are in Rural Independent areas. Conversely, diesel use is more than five times higher in Rural Independent areas than in Large Urban Dense areas (but slightly less than three times higher than in Large Urban Moderate areas). Flex Fuel vehicles are more than twice as common in Rural Independent areas than in Large Urban Dense areas. Diesel use grows consistently as areas become less dense and less tied to urban jobs.

Figure 8. Percent of Daily VMT by Fuel Type (Excluding Gasoline and Other) by Geographic Class



Source: EBP analysis of state registration data, LATCH-based estimates of VMT, and geographic classification outcomes. Data labels omitted for segments that account for 1.0% or less of DVMT.

Table 4. Percent of Daily VMT by Fuel Type by Geographic Class[10]

Geographic Classification	Gas	Diesel	Hybrid	Plug-in Hybrid	Full Electric	Flex Fuel
Large Urban Dense	87.2%	1.6%	4.3%	0.7%	1.6%	4.5%
Large Urban Mod.	85.9%	2.8%	3.4%	0.5%	1.5%	5.9%
Small Urban	85.4%	4.3%	2.2%	0.2%	0.4%	7.4%
Rural Commuter	83.9%	5.1%	2.8%	0.4%	1.0%	6.7%
Rural Independent	80.7%	8.2%	1.5%	0.1%	0.2%	9.2%
All Class Total	**85.4%**	**3.5%**	**3.3%**	**0.5%**	**1.2%**	**6.0%**

Source: EBP analysis of state registration data, LATCH-based estimates of VMT, and geographic classification outcomes.

Fuel mix varies quite a bit between states, although only one of the fourteen states has a gas share of VMT that is outside the 80-90 percent range (Wyoming, see Figure 9). Diesel penetration is as high as 12 percent in Wyoming data and as low as 1.3 percent in California. While the scale of California decreases the all-state average to 3.5 percent, ten

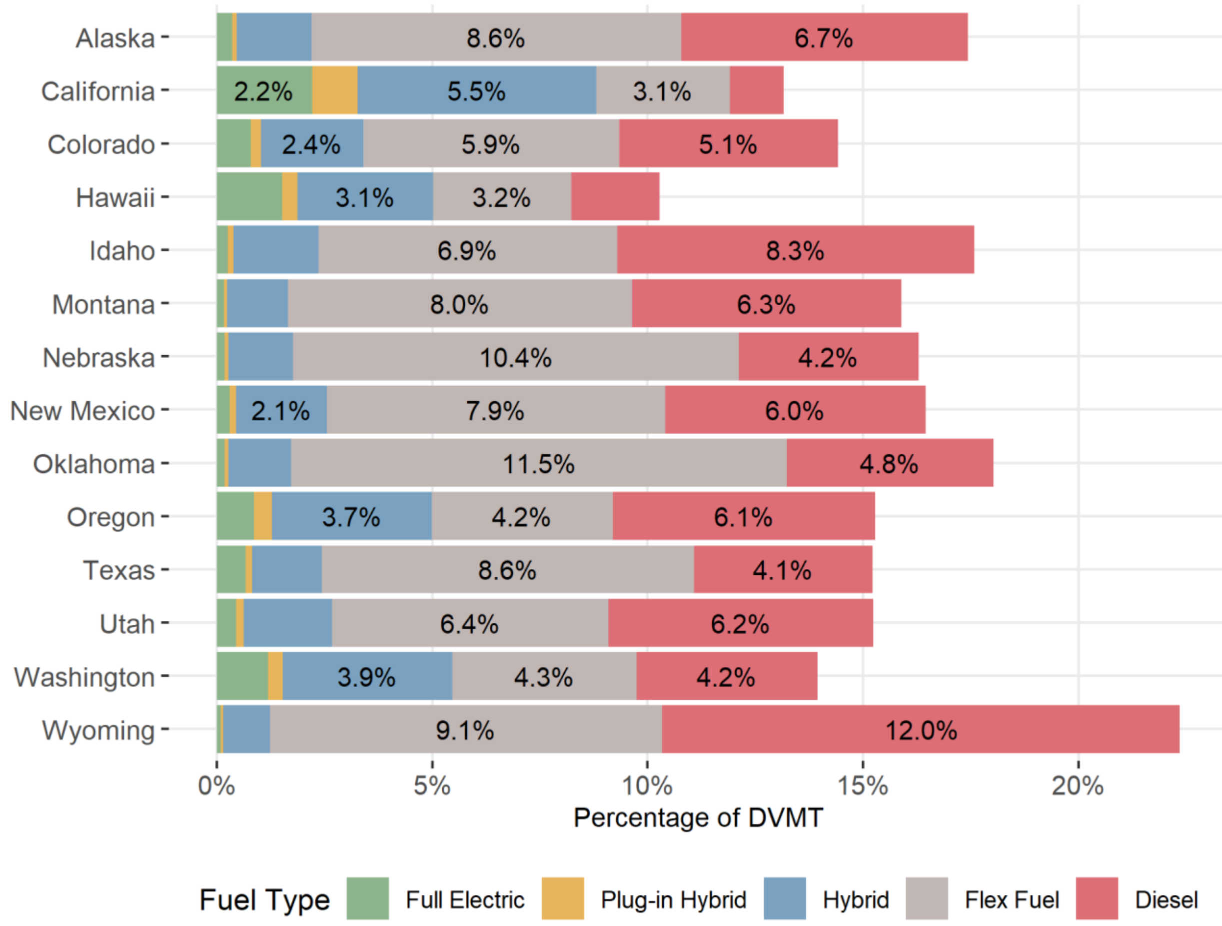
[10] Another category comprising other fossil fuels like propane, compressed natural gas (CNG) as well as fuel cells accounts for <0.1% of vehicles in each row.

states are in the range of four to seven percent diesel. The next highest of the 14 states for diesel VMT share is Idaho at 8.3 percent.

Three states exceed full electric shares of one percent (California, Hawaii, and Washington). California's share is more than ten times those in four of the other states. Only one state has more than one percent of VMT from plug-in hybrid vehicles (California). Eight of the fourteen states have roughly one-tenth that level of plug-in hybrid prevalence. Regular hybrid vehicles remain much more common in all states than plug-in hybrids and full electric vehicles. Six states see less than two percent of VMT from regular hybrids, but all have more than one percent shares. Only California has more than four percent of VMT in regular hybrids.

California is the only state where the share of VMT from vehicles with electric motors exceeds that from diesel and flex fuel vehicles. Hawaii has close to equal shares from these two groupings. In Oregon and Washington, VMT from vehicles with electric motors exceeds flex fuel vehicles. While flex fuel use is relatively low in these four states, it accounts for over 10 percent of VMT in Nebraska and Oklahoma. The VMT ascribed to flex fuel vehicles may actually be fueled by conventional diesel or gas, since these vehicles take both conventional and alternative fuels, but there is not a precise way to know. The likely mix of fuels in flex fuel vehicles will be considered in revenue estimation.

Figure 9. Percent of Daily VMT by Fuel Type (Excluding Gasoline and Other) by State



Source: EBP analysis of state registration data, LATCH-based estimates of VMT, and geographic classification outcomes. Data labels omitted for segments that account for 2.0% or less of DVMT.

Table 5. Percent of Daily VMT by Fuel Type by State[11]

State	Gas	Diesel	Hybrid	Plug-in Hybrid	Full Electric	Flex Fuel
Alaska	82.6%	6.7%	1.7%	0.1%	0.4%	8.6%
California	86.8%	1.3%	5.5%	1.1%	2.2%	3.1%
Colorado	85.6%	5.1%	2.4%	0.2%	0.8%	5.9%
Hawaii	89.7%	2.0%	3.1%	0.4%	1.5%	3.2%
Idaho	82.4%	8.3%	2.0%	0.1%	0.3%	6.9%
Montana	84.1%	6.3%	1.4%	0.1%	0.2%	8.0%
Nebraska	83.7%	4.2%	1.5%	0.1%	0.2%	10.4%
New Mexico	83.5%	6.0%	2.1%	0.1%	0.3%	7.9%
Oklahoma	81.9%	4.8%	1.5%	0.1%	0.2%	11.5%
Oregon	84.7%	6.1%	3.7%	0.4%	0.9%	4.2%
Texas	84.8%	4.1%	1.6%	0.1%	0.7%	8.6%
Utah	84.6%	6.2%	2.0%	0.2%	0.4%	6.4%
Washington	86.1%	4.2%	3.9%	0.3%	1.2%	4.3%
Wyoming	77.6%	12.0%	1.1%	0.1%	0.1%	9.1%
All State Total	**85.4%**	**3.5%**	**3.3%**	**0.5%**	**1.2%**	**6.0%**

Source: EBP analysis of state registration data, LATCH-based estimates of VMT, and geographic classification outcomes.

[11] The "other" category comprising other fossil fuels like propane, compressed natural gas (CNG) as well as fuel cells, accounts for <0.1% of vehicles in each row, except Utah, where they totaled 0.14% of vehicles.

2022 Vehicle Fuel Efficiency Summaries

Fuel efficiency is one of the primary determinants of fuel consumption and fuel tax revenue. It is of specific interest in this study as a RUC removes the influence of fuel efficiency on revenue contributions. We also assume that implementing a RUC has no impact on VMT, the other variable affecting fuel tax, and RUC payments. Each state's overall average fuel efficiencies are depicted in Table 6 and Figure 10. California and Hawaii have the greatest overall fuel efficiencies (23.5 MPGe[12] and 21.6 MPGe respectively), and Wyoming and Montana have the lowest overall efficiencies (17.7 MPGe and 18.1 MPGe, respectively). Average fuel efficiencies were estimated within each tract and then weighted by tract-level VMT to calculate aggregate metrics that provide a more accurate representation of a state's average fuel efficiency as it impacts fuel consumption. Appendix B summarizes the vehicle data leveraged for this analysis.

Diesel fuel contains around 20-30% more energy than gasoline fuel, but typically powers larger trucks which have lower fuel efficiencies, which is why fuel efficiency for gas is higher than diesel in Table 6. As diesel vehicles primarily represent a narrow group of larger pick-up trucks, the diesel efficiency is highly consistent across states with the exception of California (which contains more diesel automobiles – popular for their higher fuel efficiency before they struggled to comply with particulate emissions regulations).

While flex fuel vehicles are able to use a variety of different fuel mixes, for this study we assume they use E85 (a blend of 85 percent ethanol and 15 percent gasoline) about 33 percent of the time.[13] In contrast to diesel, E85 is less energy dense than gasoline resulting in their lower averages. The mix of vehicle types makes them more efficient than the included diesel vehicles.

Hybrid efficiency is also relatively consistent between states and about twice the efficiency of general gas vehicles.[14] Plug-in hybrids are only slightly more efficient than standard hybrids based on our assumption that they travel about 56 percent of the time on

[12] MPGe stands for miles-per-gallon-equivalent and includes conversion of the energy used by electric motors and non-liquid fuels (like CNG) to gallons-of-gasoline-equivalents.

[13] This number was determined using flex fuel vehicle models reported both in EPA fueleconomy.com (providing E85 and gasoline fuel efficiencies) and Fuelly (providing effective MPG). These vehicles' efficiencies were averaged using the count of vehicles reported in Fuelly as a weight for each make-model-year record.

[14] US Department of Energy: Alternative Fuels Data Center. Hybrid Electric Vehicles. https://afdc.energy.gov/vehicles/electric_basics_hev.html

electricity and the rest on their gasoline engines.[15] Their gas engines tend to be less efficient than non-plug-in hybrid engines and their electric drivetrains less efficient than full EVs.

Throughout this report, averages are influenced by the contribution of the participating states. Fourteen-state weighted averages (e.g., in Table 6) are higher than an unweighted average would be due to the disproportionate amount of VMT in California (which also has the highest overall average fuel efficiency).

Figure 10 illustrates the differences among states in average fuel efficiency, based on VMT-weighted harmonic means for all fuel types. While some states have quite similar average efficiencies, states with large numbers of pick-up trucks and larger SUVs like AK, MT, and WY have lower average efficiencies, while CA and HI stand out as much higher than other states.

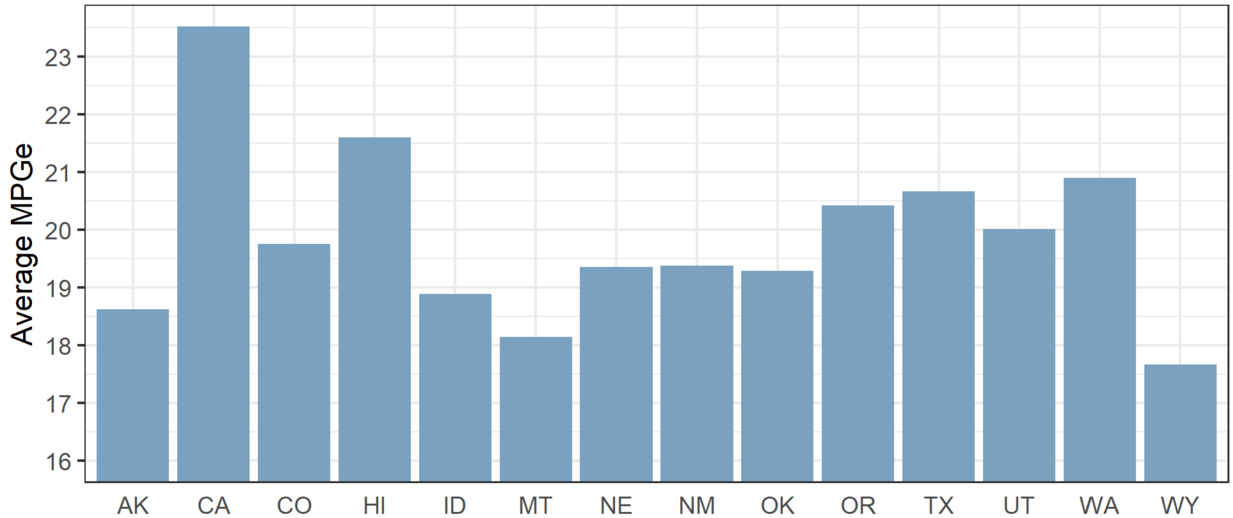
Table 6. Average[16] Fuel Efficiency by Fuel Type by State and Overall (MPG or MPGe)

State	Gas	Diesel	Hybrid	PHEV*	Full EV*	Flex Fuel	All
Alaska	19.0	14.9	36.6	49.5	111.7	16.1	18.6
California	22.6	18.3	40.8	59.4	113.1	18.2	23.5
Colorado	20.0	15.0	36.6	50.4	111.6	16.0	19.8
Hawaii	21.3	15.2	40.4	54.8	113.1	16.8	21.6
Idaho	19.4	14.8	36.6	49.3	113.7	16.2	18.9
Montana	18.5	15.5	35.0	48.4	109.3	15.7	18.1
Nebraska	19.9	14.8	34.9	49.2	111.6	16.6	19.4
New Mexico	19.9	14.8	37.9	52.2	112.5	16.3	19.4
Oklahoma	19.9	14.9	35.2	52.8	113.6	16.3	19.3
Oregon	20.5	15.2	39.5	58.1	113.3	16.5	20.4
Texas	21.2	15.3	38.0	50.0	115.1	16.4	20.7
Utah	20.5	14.9	37.8	55.1	109.7	16.5	20.0
Washington	20.8	15.5	39.2	54.2	112.7	16.7	20.9
Wyoming	18.4	14.5	33.6	50.6	110.3	15.6	17.7
14-State Avg	**21.3**	**15.5**	**39.6**	**57.5**	**113.3**	**16.7**	**21.3**

Source: EBP analysis of state vehicle registration data using EPA fueleconomy.com and Fuelly with precursor analysis dependent on NHTSA vPIC and VMT-weights based on LATCH. Notes: Weighted by tract VMT to recognize the fuel efficiency of vehicles used more frequently consistently in later analysis. "Full EV" refers to only electric vehicles using electric charging and batteries; fuel-cell driven vehicles are included in All. * MPGe for PHEV and Full EV is not used in estimating fuel consumption. Only the efficiency of PHEV's gasoline motors is used for estimation of gasoline consumption adjusted for the percentage of time that the average PHEV operates on gasoline. Electric motor use does not consume any taxable fuel.

[15] This number was based on EPA estimates, weighted by vehicles reported in EPA's My MPG reporting.
[16] The average used is typically the harmonic mean, which is most appropriate for combining ratios.

Figure 10. Weighted Average Fuel Efficiency by State (All Fuel Types)



Source: EBP analysis of state vehicle registration data using EPA fueleconomy.com and Fuelly with precursor analysis dependent on NHTSA vPIC and VMT-weights based on LATCH.

The average fuel efficiencies by geographic class and overall are shown in Table 7. California and Hawaii have the greatest average fuel efficiencies across all geographies, and Wyoming and Montana have the lowest average efficiencies across Small Urban, Rural Commuter, and Rural Independent geographies. Since Wyoming and Montana do not have census tracts that are classified as Large Urban Dense or Large Urban Moderate, Alaska and Idaho have the lowest average fuel efficiency for large urban geographies.

As was shown in Table 5, California and Hawaii have the greatest percentages of VMT represented by full electric and plug-in hybrid cars (2.2 percent and 1.5 percent, respectively), and the lowest percentages of diesel VMT represented by diesel vehicles (1.3 percent and 2.0 percent), which have lower average fuel efficiency. In addition to the highest gasoline fuel efficiencies (which represents more than 80 percent of VMT in almost all states), these vehicle usage mixes lead California and Hawaii to have high efficiency overall and across geographies.

Table 7. Average Fuel Efficiency by Geographic Class by State and Overall (MPGe)

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	All
Alaska	19.4	19.1	19.0	18.6	18.1	18.6
California	23.8	23.5	22.4	23.0	21.6	23.5
Colorado	20.6	20.4	19.0	19.2	17.9	19.8
Hawaii	22.4	22.5	20.7	21.6	20.2	21.6
Idaho	20.1	19.7	19.1	19.3	18.1	18.9
Montana			18.9	18.4	17.8	18.1
Nebraska	21.1	20.9	19.0	19.9	17.9	19.4
New Mexico	20.7	20.0	19.3	19.4	18.4	19.4
Oklahoma	20.6	20.3	19.6	19.3	18.4	19.3
Oregon	22.1	21.3	20.0	19.6	18.7	20.4
Texas	21.5	21.2	19.7	20.2	18.9	20.7
Utah	20.6	20.3	19.7	20.1	18.5	20.0
Washington	22.1	21.1	20.2	19.8	19.2	20.9
Wyoming			18.4	18.0	17.3	17.7
14-State Avg	**22.6**	**21.6**	**20.1**	**20.6**	**18.7**	**21.3**

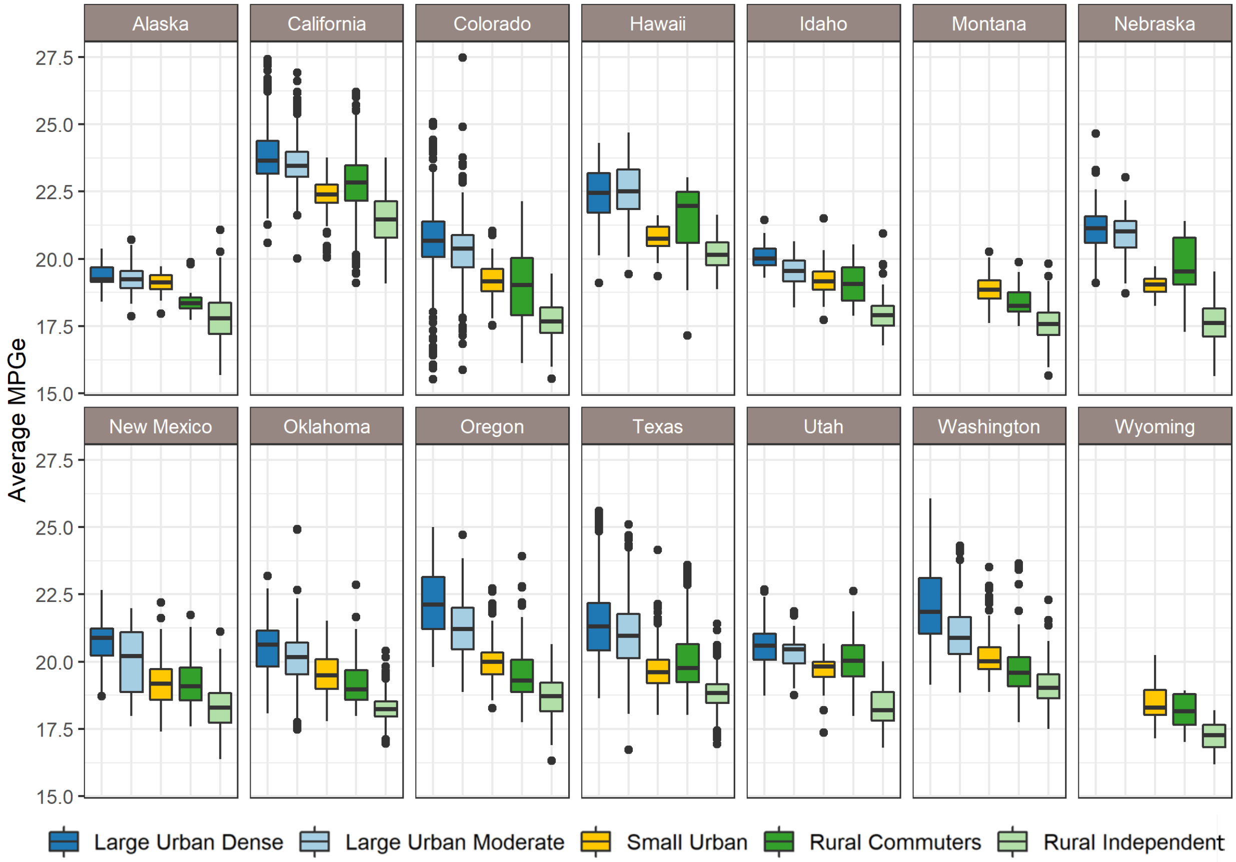
Source: EBP analysis of state vehicle registration data using EPA fueleconomy.com and Fuelly with precursor analysis dependent on NHTSA vPIC and VMT-weights based on LATCH. Notes: Weighted by tract VMT.

Figure 11 adds detail to Figure 10 on differences between geographic classes and shows the distribution across tracts within each geographic class. California, Colorado, Texas, Oregon, and Washington have a wide spread of average fuel efficiencies within geographic classes, with Large Urban Dense, Large Urban Moderate, and Rural Commuter geographies experiencing the greatest ranges including outliers.[17] This speaks to a diversity of preferences within different parts of these states, most of which are the larger population states participating in the study.

The tract-level average fuel efficiencies are mapped in Figure 12, which illustrates higher average MPGe (22 and above) in Large Urban Dense tracts in and around major cities (e.g. Seattle, WA; Portland, OR; Salt Lake City, UT; Denver, CO; Honolulu, HI; and Austin, Houston, and Dallas, TX) and much of western California. Low average MPGe (17.5 and below) can be seen in Rural Independent tracts in the central RUC America states (Wyoming, Nebraska, Montana, and Colorado, where census tracts are also larger due to lower density). Appendix A provides maps for each state, allowing better review of state specific patterns.

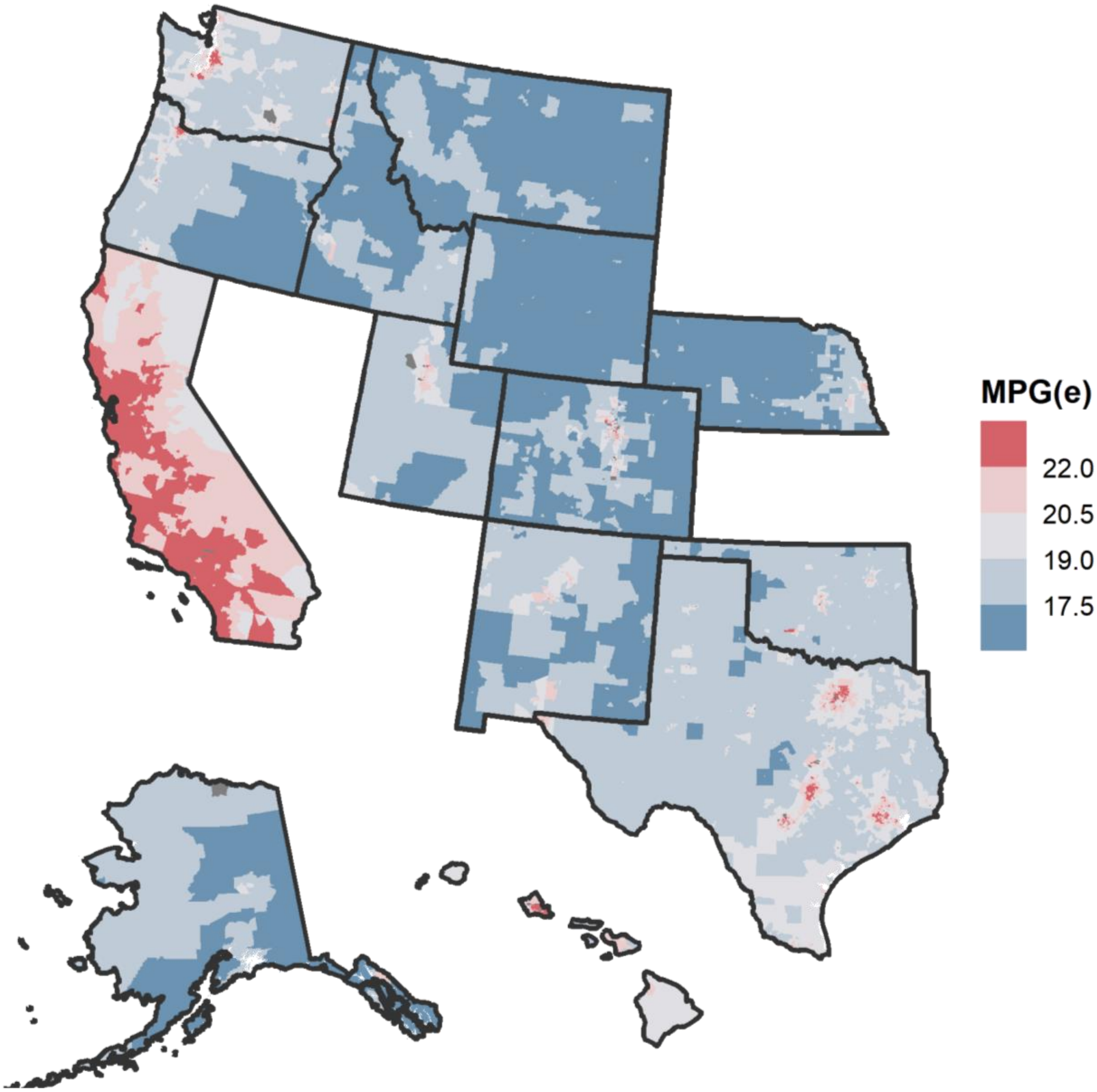
[17] Outliers on the box-and-whisker plots are shown as points beyond the bars that represent 1.5x the interquartile range (the distance between 25-percentile and 75-percentile metrics.

Figure 11. Distribution of Average Fuel Efficiency across Tracts within Geographic Classes



Source: EBP analysis of state vehicle registration data using EPA fueleconomy.com and Fuelly with precursor analysis dependent on NHTSA vPIC. Notes: 10 tracts are beyond the range of the Y-axis, primarily in Colorado.

Figure 12. Fourteen-State Map of Tract-Level Average Fuel Efficiencies for Vehicles of All Fuel Types



Source: EBP analysis of state vehicle registration data using EPA fueleconomy.com and Fuelly with precursor analysis dependent on NHTSA vPIC.

Vehicle Age

Vehicle age is strongly correlated with fuel efficiency, interesting on its own, and a key component of other vehicle analysis steps.[18] States with the highest average fuel efficiency (i.e., California, Hawaii) have the second and third lowest average vehicle age (see Table 8). In comparison to the fuel efficiency patterns displayed in Figure 12, we see essentially the inverse pattern depicted for vehicle age in Figure 14. Rural Independent tracts in the northern RUC America states (e.g., Montana, Idaho, and Oregon) have the highest average vehicle age (15+ years). Vehicles of households in Large Urban Moderate tracts tend to have the newest vehicles. Texas is a distinct outlier compared with the other states, in which no tract in the state has an average vehicle age that exceeds 11 years.

Texas has the lowest average vehicle age by a significant margin (average age of 7.9, compared to California and Hawaii's 10.1 and 10.2). This leads to relatively high fuel efficiencies by fuel type for Texas in Table 6. As we would expect, the states with low average fuel efficiency (e.g., Montana, Wyoming) have the highest average vehicle age out of the 14 states (15.0 and 12.9, respectively).

Across all states, the Rural Independent vehicles are on average the oldest (12.7) while the Large Urban Moderate vehicles are on average the newest (9.5). A distinct trend is that Rural Commuter vehicles are on average newer than Small Urban vehicles, with exceptions only in Alaska and Montana although a few other states are close. Figure 13 provides visual information on differences between classes and states as well as showing variability within the classes for each state.

In comparison to the fuel efficiency patterns displayed in Figure 12, we see essentially the inverse pattern depicted for vehicle age in Figure 14. Rural Independent tracts in the northern RUC America states (e.g., Montana, Washington, and Oregon) have the highest average vehicle age (14+ years). Vehicles of households in Large Urban Moderate tracts tend to have the newest vehicles. Texas is a distinct outlier compared with the other states, in which no tract in the state has an average vehicle age that exceeds 11 years.

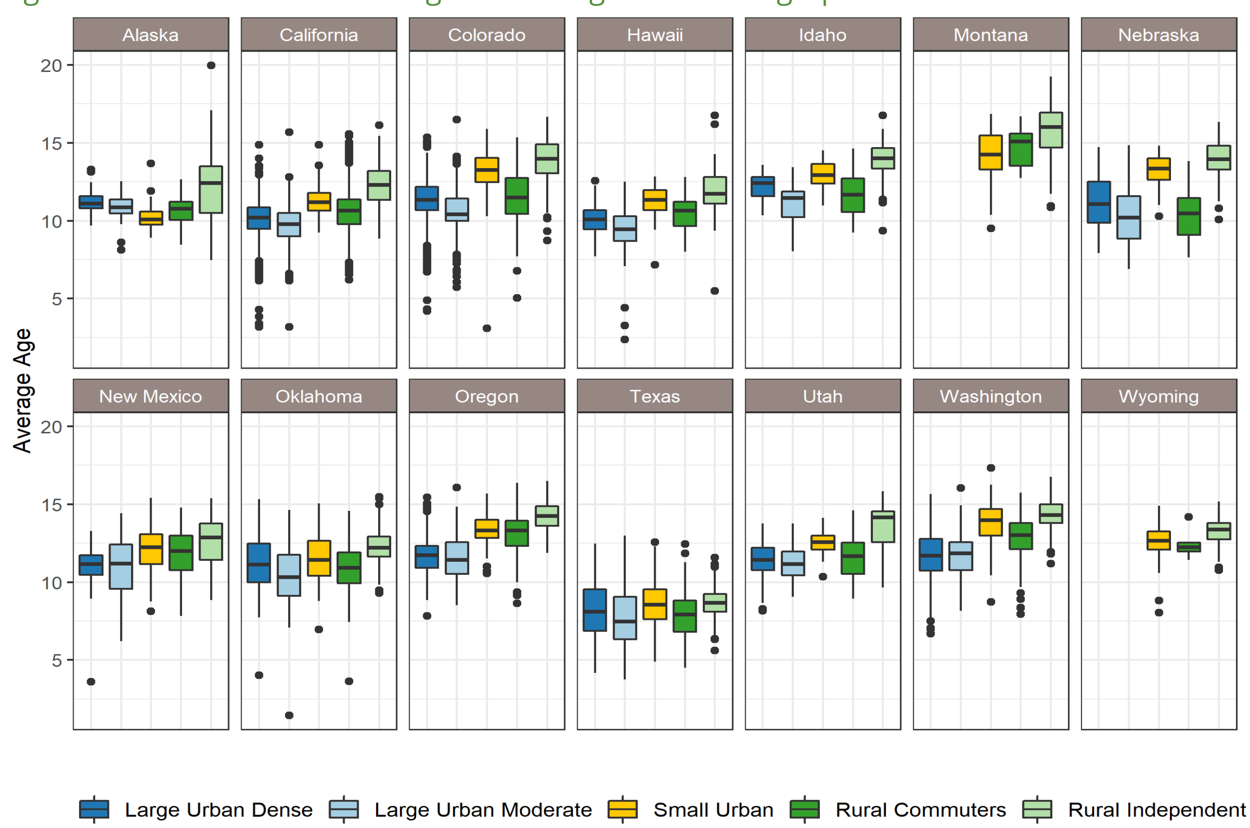
[18] To match vehicle records to EPA or Fuelly fuel efficiencies, vehicle age was derived from NHTSA vPIC decoding and the consulting team's analysis of vehicle registration data.

Table 8. Average Vehicle Age by Geography for Fourteen States and Overall

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	All
Alaska	11.2	10.5	10.3	10.4	12.0	11.2
California	10.0	9.6	11.2	10.4	12.2	10.1
Colorado	11.3	10.4	13.1	11.4	13.6	11.7
Hawaii	10.0	8.0	10.9	10.7	11.4	10.2
Idaho	12.0	10.9	12.8	11.2	13.8	12.6
Montana			14.2	14.5	15.4	15.0
Nebraska	10.8	10.0	13.0	10.3	13.8	12.0
New Mexico	10.9	10.9	12.0	11.5	12.7	11.7
Oklahoma	10.8	10.0	11.1	10.4	12.0	11.0
Oregon	11.6	11.4	13.1	12.9	14.2	12.7
Texas	8.0	7.4	8.3	7.6	8.7	7.9
Utah	11.3	11.1	12.5	11.6	13.3	11.8
Washington	11.6	11.6	13.7	12.7	14.2	12.4
Wyoming			12.5	12.4	13.1	12.9
14-State Avg	**10.1**	**9.5**	**11.8**	**10.4**	**12.7**	**10.5**

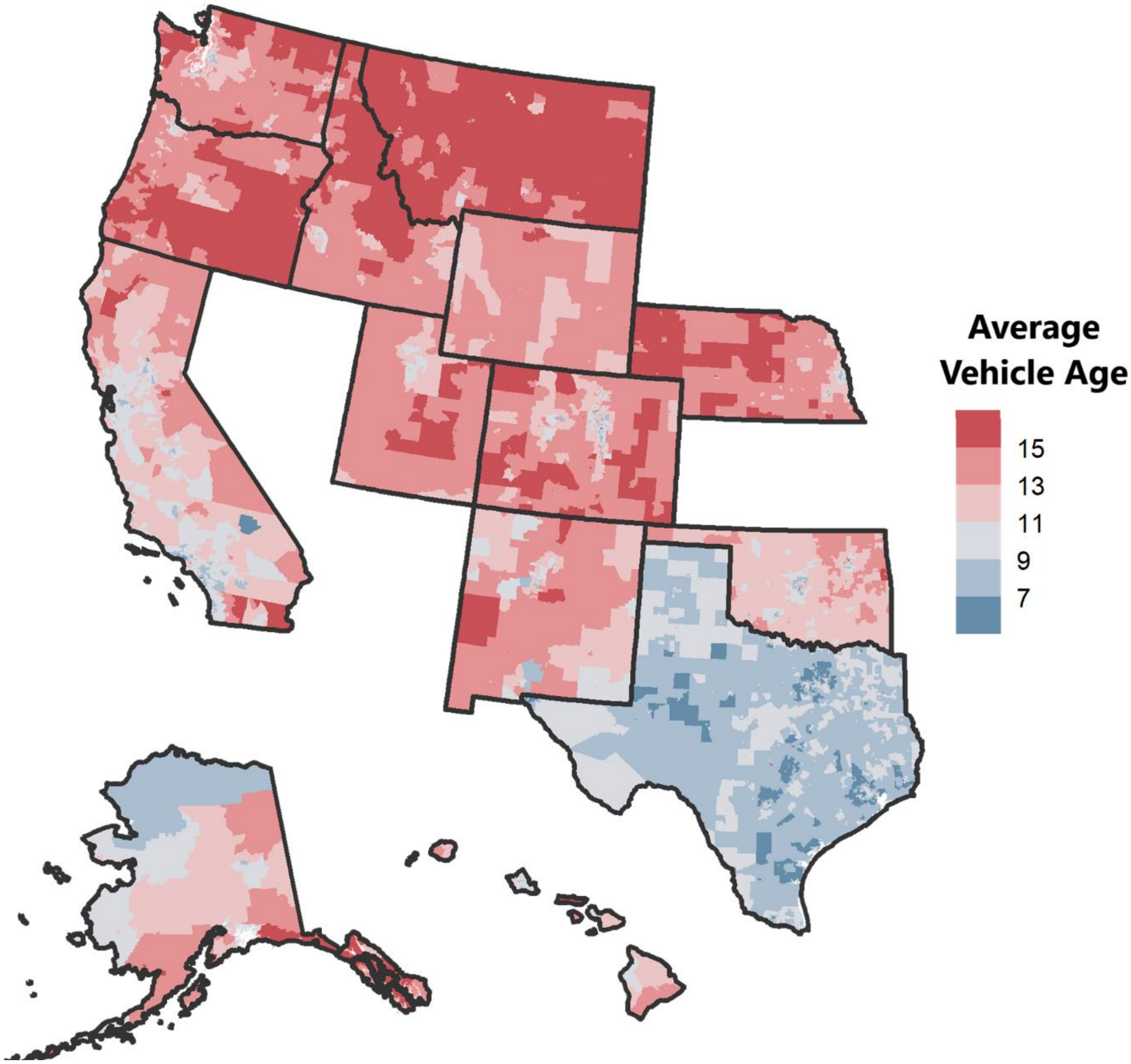
Source: EBP analysis of state vehicle registration data and NHTSA vPIC analysis.

Figure 13. Distribution of Average Vehicle Age within Geographies for Fourteen States



Source: EBP analysis of Vehicle registration data and NHTSA vPIC analysis.

Figure 14. Fourteen-State Map of Tract-Level Average Vehicle Age for All Fuel Types



Source: EBP analysis of state vehicle registration data and NHTSA vPIC analysis.

2022 Current Policy Payments

Estimating current revenue is the foundation for calculation of a 'revenue-neutral' RUC rate and identification of differences in revenue contribution between geographies under current policy. Current policy revenue includes annual fuel tax payments from all in-scope vehicle types as well as annual registration fee surcharges in the states for which they exist. Table 9 shows the annual revenue estimated per household in each geographic classification. The distribution of revenue per household by geographic class are displayed in Figure 15for each state.

Table 9. Annual Current Policy Revenue Per Household by Geographic Class and State

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	Statewide
Alaska	$63	$82	$71	$96	$81	$77
California	$334	$424	$349	$473	$445	$365
Colorado	$143	$183	$152	$253	$217	$176
Hawaii*	$232	$310	$226	$342	$290	$258
Idaho	$197	$245	$227	$320	$309	$271
Montana			$218	$324	$303	$278
Nebraska	$146	$206	$179	$288	$267	$214
New Mexico	$87	$117	$100	$146	$137	$116
Oklahoma	$129	$155	$132	$230	$202	$174
Oregon	$228	$297	$262	$353	$332	$279
Texas	$126	$150	$131	$212	$185	$154
Utah	$212	$263	$223	$345	$309	$254
Washington	$301	$405	$330	$471	$432	$364
Wyoming			$171	$249	$244	$220
14-State Average	**$252**	**$267**	**$221**	**$329**	**$262**	**$264**

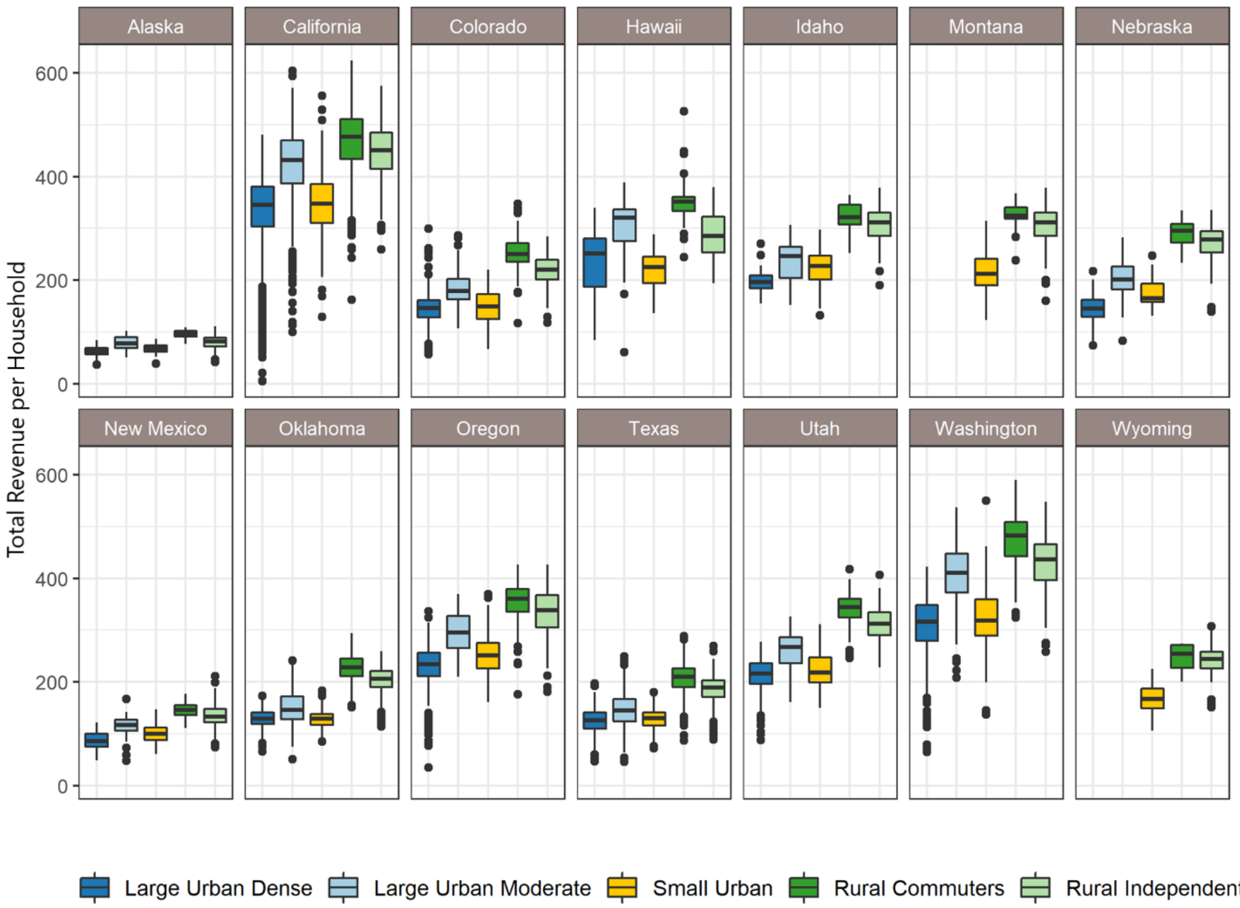
Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUC America state representatives; household data from ACS. Notes: * Hawaii includes state and county fuel taxes.

California and Washington produce the greatest revenue per household on a statewide basis when it comes to current fuel taxes ($365 for California, $364 for Washington). For both states, Rural Commuter tracts contribute the highest average household revenue ($473 and $471), followed by Rural Independent tracts ($445 and $432). These states' high current policy revenue per household can be attributed to high gas (CA: $0.59[19]; WA: $0.49)

[19] California gasoline fuel taxes consider both excise taxes and sales taxes. All other states are only excise taxes. Only state taxes are considered – not federal or local taxes.

and diesel (CA: $0.76[20]; WA: $0.49) taxes. California and Washington have the greatest variability between tracts within geographic classes for revenue contributions per household (Figure 15). Alaska's low fuel tax rate produces a lower per household burden, also seen in New Mexico, Texas, and Oklahoma.

Figure 15. Distribution of Annual Revenue per Household by Geographic Class and State



Supporting Analysis

To calculate fuel tax revenues, we calculated gallons (or gallon-equivalents) of fuel consumed by fuel type in each tract. Average fuel efficiencies were multiplied by annual VMT attributable to each fuel type. The state-level results of this calculation are reported in

[20] California diesel fuel taxes are generated primarily from the sales tax and secondarily from the excise tax. We base the value of the sales tax (which is charged as a set amount recalculated periodically rather than continuously) on the average price of diesel in 2020, 2021, and January and February of 2022 to avoid being influenced by atypically high and low prices.

Table 10. Gallons of each fuel consumed were multiplied by each fuel's tax rate[21] (as confirmed by RUC America state representatives) to obtain the revenue generated by fuel taxes (Table 11).

California and Texas produce the greatest amount of revenue from gas, diesel, other, and total fuel taxes. However, Texas does not tax E85 fuel, of which Texas vehicles consume an estimated 3.4 million gallons per year (Table 10). For E85 fuel, Washington and Oklahoma exceed California's revenues for E85, because they have higher E85 tax rates (Washington charges $0.49 and Oklahoma charges $0.20, while California charges only $0.09, much less than for gasoline).

Table 10. Annual Gallons Consumed (by Fuel Type)

State	Gasoline (millions of gallons)	Diesel (millions of gallons)	E85 (millions of gallons)	Other (gasoline gallon-equivalents)
Alaska	189.6	18.1	8.7	9,000
California	7,860.5	138.0	132.8	3,731,000
Colorado	1,449.4	108.1	47.7	138,000
Hawaii	300.8	9.2	5.3	20,000
Idaho	444.8	54.6	16.9	35,000
Montana	320.5	28.7	13.4	48,000
Nebraska	560.7	34.3	30.5	108,000
New Mexico	486.6	44.3	20.8	67,000
Oklahoma	1,133.0	80.5	70.6	553,000
Oregon	1,036.1	94.9	24.2	69,000
Texas	7,007.5	436.7	343.1	310,000
Utah	680.8	63.5	24.3	1,215,000
Washington	1,901.2	117.1	44.8	118,000
Wyoming	170.5	30.9	8.7	28,000
14-State Total	**23,541.9**	**1,258.9**	**791.7**	**6,447,000**

Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding. Note: Totals may not equal the sum of columns due to rounding. Other fuels include CNG and LPG.

In addition to fuel tax rates, RUC America representatives provided updated annual vehicle registration surcharges to estimate payments. Surcharge payments were tabulated by multiplying the estimated number of vehicles of the relevant types per tract (derived from ACS estimates)[22] by the relevant registration surcharges (Table 12). Registration surcharges

[21] Fuel tax rates for states included in the former and current analysis can be found in Appendix D (Table 48).

[22] Direct counts of alternative fuel vehicle registrations were not used due to the potential for geocoding errors and missing registration data to have especially high impacts on these revenues from a small subset of vehicles. Instead EBP scaled vehicle counts up or down to align with the statistically smoothed estimates of vehicle ownership from the US census bureau. We still directly used the % of vehicles in each tract of the relevant fuel type.

are most common for full EVs, moderately common for PHEVs, and uncommon for other vehicles.

Table 11. Annual Revenue Generated by Fuel Taxes (by Fuel Type)

State	Gas ($M)	Diesel ($M)	E85 ($M)	Other^ ($)	All ($M)
Alaska	$17.1	$1.6	$0.8	$1,000	$19.5
California	$4,637.7	$104.9	$11.9	$330,000	$4,754.9
Colorado	$341.5	$23.9	$11.2	$24,000	$376.6
Hawaii*	$113.9	$3.3	$0.6	$3,000	$117.8
Idaho	$146.8	$18.0	$5.6	$11,000	$170.4
Montana	$105.8	$8.6	$4.4	$3,000	$118.8
Nebraska	$145.8	$8.6	$7.9	$27,000	$162.3
New Mexico	$77.8	$9.3	$3.3	$9,000	$90.5
Oklahoma	$226.6	$16.1	$14.1	$27,000	$256.8
Oregon	$393.7	$36.1	$9.2	$26,000	$439.0
Texas	$1,401.5	$87.3	$0.0	$44,000	$1,488.9
Utah	$217.8	$20.3	$7.8	$219,000	$246.2
Washington	$931.6	$57.4	$21.9	$0	$1,010.9
Wyoming	$40.9	$7.4	$2.1	$7,000	$50.4
14-State Total	**$8,798.5**	**$402.8**	**$100.9**	**$731,000**	**$9,303.0**

Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges confirmed by RUC America state representatives. Note: Totals may not equal the sum of columns due to rounding. * Hawaii includes state and county fuel taxes. ^ Other is CNG and LPG and is included in the "All" fuels total column but presented last because in almost all states it does not affect the totals when presented in millions of dollars. This is the only column not in millions.

Washington produced the greatest estimated vehicle surcharge ($9.2 million) for full EVs. Its $150 full EV vehicle surcharge is the second highest among the 14 states (only Wyoming has a higher rate, at $200 per vehicle). Washington also collects surcharge revenue for PHEVs ($1.3 million) as well as hybrid vehicles ('other', $15.9 million), due to the second highest PHEV registration rate and highest hybrid registration rate out of the 14 states. Alaska, Montana, New Mexico, and Texas do not currently require registration surcharges of any kind.

Total current policy revenue was tabulated by summing revenue generated by fuel taxes (Table 11) and registration surcharges (Table 12) and is reported by geographic class in Table 13. California and Texas have the greatest current policy revenue ($4.8 billion and $1.5 billion). Much of California and Texas's revenue originates in Large Urban Dense tracts. Alaska produced the least revenue statewide with almost half of the revenue in Rural Independent tracts.

Table 12. Estimated Annual Vehicle Registration Surcharge Payments by Type

State	Full EV	PHEV	Other	All Vehicles
Alaska	$0	$0	$0	$0
California	$920,000	$0	$0	$920,000
Colorado	$1,570,000	$0	$0	$1,570,000
Hawaii	$630,000	$0	$0	$630,000
Idaho	$450,000	$130,000	$0	$580,000
Montana	$0	$0	$0	$0
Nebraska	$180,000	$0	$0	$180,000
New Mexico	$0	$0	$0	$0
Oklahoma	$530,000	$190,000	$1,400	$721,400
Oregon	$2,470,000	$22,000	$8,300,000	$10,792,000
Texas	$0	$0	$0	$0
Utah	$1,090,000	$210,000	$860,000	$2,150,000
Washington	$9,230,000	$1,320,000	$15,860,000	$26,420,000
Wyoming	$85,000	$0	$0	$85,000
14-State Total	**$17,150,000**	**$1,870,000**	**$25,010,000**	**$44,030,000**

Source: EBP calculations fuel efficiencies from EPA or Fuelly (for Oregon); fuel type percentages from decoded vehicle records or raw agency coding; fuel taxes and vehicle surcharges confirmed by RUC America state representatives. Note: Totals may not equal the sum of columns due to rounding. Vehicles to which surcharges are applied are estimated from fuel mix percentages applied to Census Bureau estimates of total vehicles in each tract to reduce the effect of location assignment errors in the calculations.

Table 13. Total Annual Current Policy Revenue by Geographic Class ($ Millions)

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	All
Alaska	$4	$2	$3	$2	$9	$19
California	$3,048	$663	$178	$699	$168	$4,756
Colorado	$155	$62	$19	$83	$59	$378
Hawaii*	$56	$12	$13	$12	$26	$118
Idaho	$20	$18	$24	$34	$74	$171
Montana			$30	$12	$76	$119
Nebraska	$36	$22	$11	$22	$72	$162
New Mexico	$17	$12	$16	$18	$28	$90
Oklahoma	$41	$45	$19	$46	$107	$258
Oregon	$150	$39	$65	$93	$103	$450
Texas	$535	$308	$72	$373	$202	$1,489
Utah	$102	$40	$13	$49	$45	$248
Washington	$392	$226	$81	$209	$129	$1,037
Wyoming			$14	$5	$32	$51
14-State Total	**$4,553**	**$1,449**	**$558**	**$1,657**	**$1,130**	**$9,347**

Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUCW state representatives. Note: Total current policy revenue includes state fuel taxes and vehicle registration fees (Table 11 and Table 12). Totals may not equal the sum of columns due to rounding. Estimated revenue is expected to be less than total revenue receipts in each state as only some vehicles are captured in this work. * Hawaii includes state and county fuel taxes.

2022 Changes in Payments under RUC

To evaluate the magnitude of difference in revenue contribution per household by geographic class, we calculate the annual raw dollar change (Table 14) as well as annual percent change (Table 15) between policies. The distributions of percent change per household by state and geographic class are visualized in Figure 16. Averaged across all states, on an annual basis, the smallest absolute difference in revenue contributions is seen in Large Urban Moderate tracts ($3.40 increase, 1.8%), whereas the largest absolute difference by far is seen in Rural Independent tracts ($17 decrease, 6.4%). There is a decreasing pattern of average annual revenue changes as tracts become more rural: Large Urban Dense household payments increase $6 (2.8%), Large Urban Moderate's increase $3.40 (1.8%), Small Urban's decrease $5.50 (2%), Rural Commuter's decrease $7.70 (2.1%), and Rural Independent's decrease $17 (6.4%) (Table 14 and Table 15).

For an individual state and geographic class, the largest percentage increase is for households in Nebraska's Large Urban Dense tracts (8.8%). The largest percent decrease is for households in Colorado's Rural Independent tracts (9.1%). New Mexico experienced the smallest absolute percent change in both directions, with a 0.1 percent decrease in revenue contributions for Small Urban households, and a 0.1 percent increase in contributions for Rural Commuter households. The greatest variability within a geographic class is seen for Colorado's large urban households, while the lowest variability is seen in Wyoming, Idaho, and Alaska (Figure 16). For an individual state and geographic class, the largest dollar increase in revenue contribution per household is in Oregon, where the average increase for Large Urban Dense tracts is $16. The largest average decrease is for California Rural Independent tracts of almost $40 (Table 14).

There is considerable variation between tracts within geographic classes around the average changes reported in Table 15 (Figure 17). The geographic classification's average changes are represented by the shift in the distribution towards decreases as the geographies move from Large Urban Dense (top) to Rural Independent (bottom). Although the ranges differ and Small Urban and Rural Commuter distributions are visually similar, the overall trend of decreased contributions for rural areas and increased contributions for urban areas is evident. Another way to consider the data in Figure 16 and Figure 17 is as summarized in Table 16, which shows the percent of tracts in any geographic class estimated to experience savings from implementing a RUC. Data presented in this table sacrifices details on the relative size of increases and decreases but provides a more concise metric focused on the distribution of savings by geographic class under a RUC when compared to the current fuel tax.

State-specific graphics containing the same information as Figure 17 are described in Appendix A. The graphics allow states to understand the distribution of changes estimated in their state without having to consider the impact of large states or significantly different states when grouped together in Figure 17.

The juxtaposition between percent change in Large Urban Dense and Rural Independent geographies is starkly apparent in Figure 18, which shows that tracts in and around major cities generally experience increases under a RUC policy, whereas Rural Independent tracts experience decreases. State-specific maps that allow readers to better observe the patterns within any individual state are described in Appendix A.

Table 14. Dollar Change in Annual Revenue Contribution Per Household

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	Statewide
Alaska	$2.40	$2.10	$1.50	-$0.10	-$2.30	$0.00
California	$4.40	$0.80	-$18.00	-$11.50	-$39.90	$0.00
Colorado	$6.00	$5.40	-$5.50	-$7.10	-$19.70	$0.00
Hawaii*	$0.80	$2.80	$2.40	-$6.40	-$2.40	$0.00
Idaho	$11.80	$9.90	$3.20	$6.50	-$12.30	$0.00
Montana			$7.00	$6.30	-$4.80	$0.00
Nebraska	$12.90	$16.10	-$3.10	$8.40	-$19.90	$0.00
New Mexico	$7.10	$3.50	-$0.10	$0.10	-$8.30	$0.00
Oklahoma	$8.30	$7.60	$2.20	-$0.50	-$9.60	$0.00
Oregon	$16.20	$11.70	-$4.90	-$12.20	-$25.00	$0.00
Texas	$4.60	$3.10	-$4.90	-$4.40	-$14.30	$0.00
Utah	$5.50	$3.50	-$3.60	$2.10	-$22.20	$0.00
Washington	$14.90	$3.00	-$8.00	-$22.30	-$30.90	$0.00
Wyoming			$7.20	$4.40	-$4.90	$0.00
14-State Average	**$6.00**	**$3.40**	**-$5.50**	**-$7.70**	**-$17.00**	**$0.00**

Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUCW state representatives; household data from ACS. * Hawaii accounts for state and county fuel taxes.

Table 15. Percent Change in Annual Revenue Contribution Per Household

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	Statewide
Alaska	3.9%	2.6%	2.2%	-0.2%	-2.8%	0.0%
California	1.3%	0.2%	-5.2%	-2.4%	-9.0%	0.0%
Colorado	4.2%	3.0%	-3.6%	-2.8%	-9.1%	0.0%
Hawaii	0.4%	0.9%	1.1%	-1.9%	-0.8%	0.0%
Idaho	6.0%	4.1%	1.4%	2.0%	-4.0%	0.0%
Montana			3.2%	1.9%	-1.6%	0.0%
Nebraska	8.8%	7.8%	-1.7%	2.9%	-7.5%	0.0%
New Mexico	8.1%	3.0%	-0.1%	0.1%	-6.0%	0.0%
Oklahoma	6.4%	4.9%	1.7%	-0.2%	-4.7%	0.0%
Oregon	7.1%	3.9%	-1.9%	-3.5%	-7.5%	0.0%
Texas	3.7%	2.1%	-3.7%	-2.1%	-7.7%	0.0%
Utah	2.6%	1.3%	-1.6%	0.6%	-7.2%	0.0%
Washington	4.9%	0.8%	-2.4%	-4.7%	-7.2%	0.0%
Wyoming			4.2%	1.8%	-2.0%	0.0%
14-State Average	**2.8%**	**1.8%**	**-2.0%**	**-2.1%**	**-6.4%**	**0.0%**

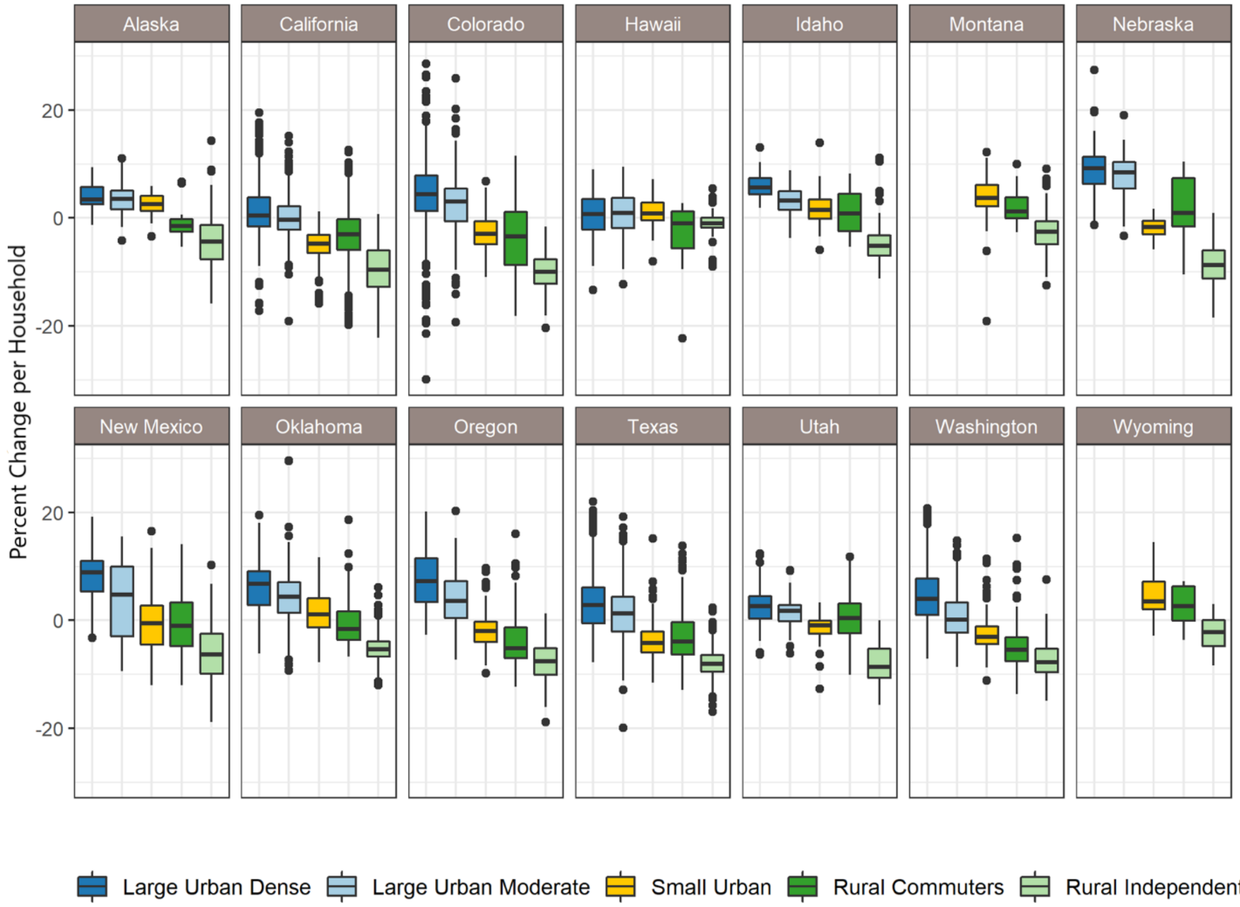
Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUCW state representatives; household data from ACS.

Table 16. Percent of Tracts with Annual Savings from RUC Transition

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	Statewide
Alaska	3.3%	23.1%	14.3%	75.0%	83.3%	48.2%
California	45.0%	54.8%	99.7%	77.6%	99.6%	53.6%
Colorado	18.5%	27.3%	80.5%	67.9%	100.0%	41.4%
Hawaii	44.0%	36.8%	35.7%	61.5%	73.1%	49.5%
Idaho	0.0%	7.7%	25.9%	48.6%	91.9%	48.8%
Montana			9.7%	25.0%	79.0%	51.9%
Nebraska	6.4%	6.0%	89.5%	37.2%	98.6%	48.8%
New Mexico	4.7%	41.1%	53.8%	56.8%	87.8%	49.6%
Oklahoma	14.5%	17.8%	39.0%	58.5%	95.5%	52.4%
Oregon	6.3%	22.4%	78.8%	82.5%	97.3%	48.8%
Texas	29.0%	40.1%	90.7%	76.7%	99.7%	51.4%
Utah	16.4%	26.9%	82.9%	45.1%	98.8%	38.6%
Washington	16.9%	47.1%	82.4%	91.1%	97.7%	48.5%
Wyoming			11.4%	25.0%	75.9%	49.6%
14-State Average	**33.6%**	**41.1%**	**72.5%**	**74.0%**	**94.9%**	**50.7%**

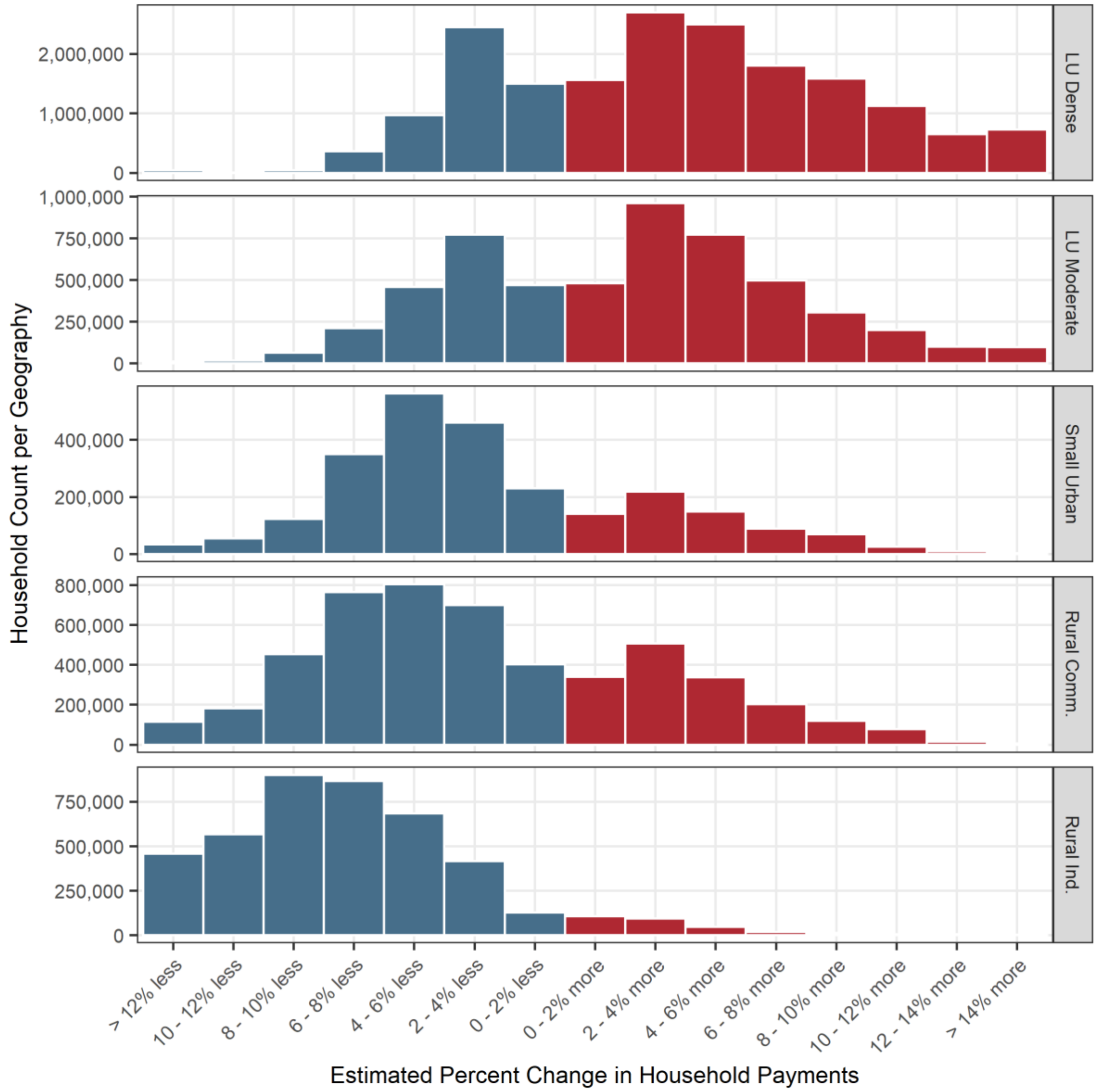
Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUCW state representatives; household data from ACS.

Figure 16. Distribution of Percent Change in Annual Revenue Contributions per Household



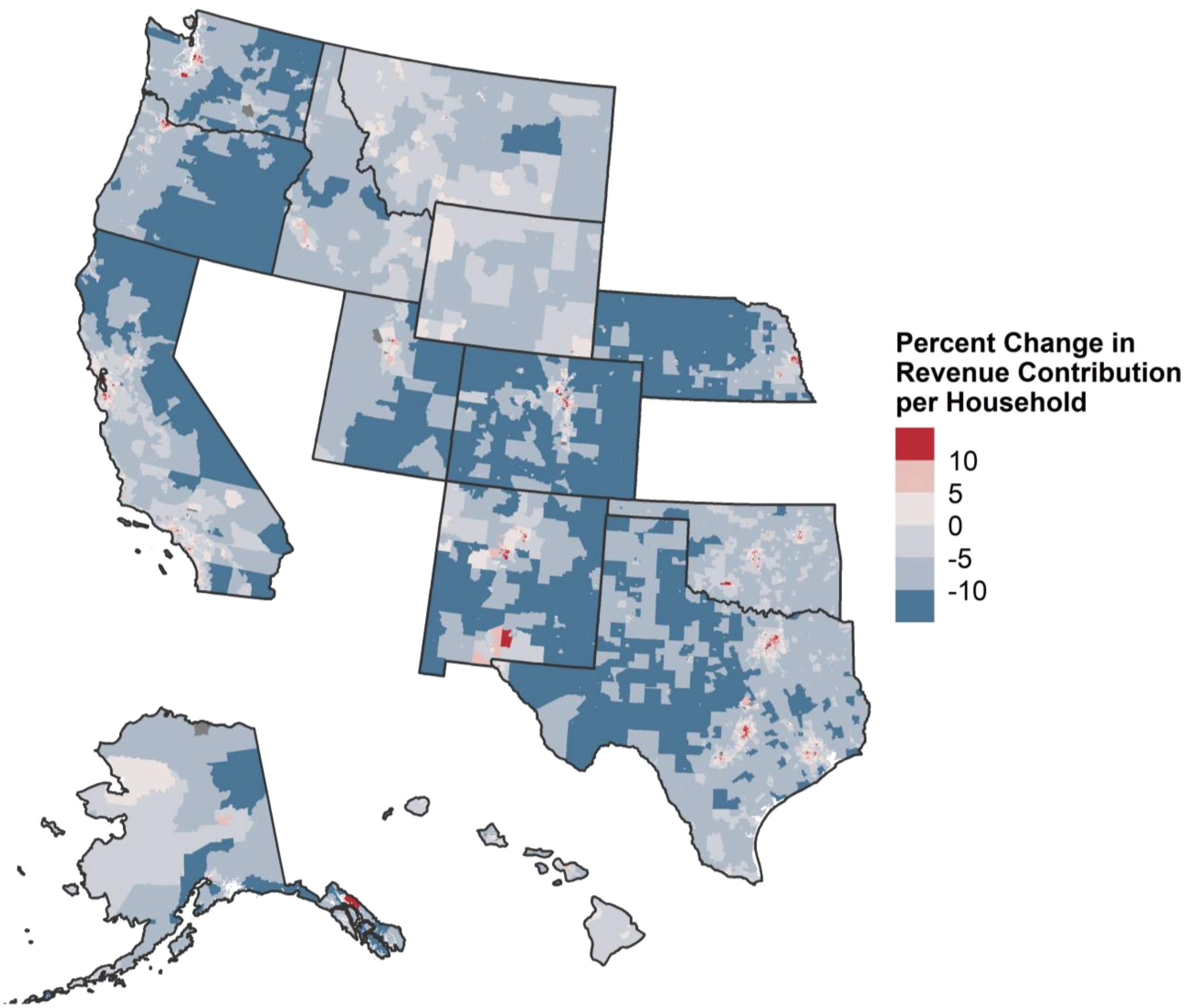
Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUCW state representatives; household data from ACS.

Figure 17. Distribution of Percentage Changes in Annual Revenue Contribution Per Household by Geographic Class for the Fourteen-State Region



Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUCW state representatives; household data from ACS.

Figure 18. Fourteen-State Map of Percentage Changes in Annual Revenue Contribution Per Household



Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUCW state representatives; household data from ACS.

Supporting Analysis

To calculate changes, per household annual revenues under a RUC were estimated (Table 17). Statewide averages remain consistent with the current policy revenue per household tabulations (Table 13) due to the revenue-neutral nature of the RUC. We see a similar geographic pattern as the current policy, with greater revenues in rural areas.

To determine the changes in state, geographic class, and household-level payments under a proposed RUC policy, the state-based, revenue-neutral RUC rates were calculated by dividing total annual state revenue by total annual state VMT and are reported in cents per mile (Table 18). California and Washington have the highest RUC rates (2.47 and 2.40, respectively), while Alaska and New Mexico have the lowest RUC rates (0.48 and 0.85).

Table 17. Total Annual RUC Policy Revenue Per Household by Geographic Class and State

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	Statewide
Alaska	$66	$85	$72	$96	$79	$77
California	$339	$425	$331	$462	$405	$365
Colorado	$149	$188	$146	$246	$197	$176
Hawaii*	$233	$313	$228	$336	$288	$258
Idaho	$209	$255	$230	$326	$296	$271
Montana			$225	$331	$298	$278
Nebraska	$159	$222	$176	$297	$247	$214
New Mexico	$94	$120	$100	$146	$128	$116
Oklahoma	$137	$162	$134	$229	$193	$174
Oregon	$244	$309	$257	$341	$307	$279
Texas	$131	$153	$126	$208	$171	$154
Utah	$217	$266	$219	$347	$287	$254
Washington	$316	$408	$322	$449	$401	$364
Wyoming			$179	$253	$239	$220
14-State Average	**$258**	**$270**	**$216**	**$321**	**$245**	**$264**

Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUCW state representatives; household data from ACS. * Hawaii includes state and county fuel tax replacement.

Table 18. RUC Rate Estimation for this Analysis by State (or County)[23]

State	Current Policy Revenue ($ Millions)	Annual VMT (Millions)	RUC Rate (cents/mi)
Alaska	$19	4,025	0.48
California	$4,756	192,288	2.47
Colorado	$378	31,743	1.19
Hawaii: Hawaii	$17	1,079	1.61
Hawaii: Honolulu	$80	4,487	1.78
Hawaii: Kauai	$8	393	1.93
Hawaii: Maui	$14	875	1.57
Idaho	$171	9,751	1.75
Montana	$119	6,520	1.82
Nebraska	$162	12,104	1.34
New Mexico	$90	10,683	0.85
Oklahoma	$258	24,776	1.04
Oregon	$450	23,646	1.90
Texas	$1,489	161,114	0.92
Utah	$248	15,420	1.61
Washington	$1,037	43,244	2.40
Wyoming	$51	3,709	1.36

Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUC AMERICA state representatives.

RUC rates are influenced significantly by fuel efficiency and fuel tax rates. With the exception of the vehicle registration surcharge component (which is included in the revenue analysis but represent no more than 2.5 percent of studied revenues in any state), the RUC rate can be calculated as:

$$RUC\ rate = \frac{Fuel\ tax\ rate\ per\ gallon}{MPG}$$

The goal of this analysis is to capture the tax rates of a variety of available fuels and apply them to the fuel efficiency (MPG) of different vehicles in different locations (accounting for the relative use of vehicles). The variation between tax rates between states is much higher than the variation in average fuel efficiency, so differences in RUC rates are primarily due to tax rate differences. Registration surcharges and efficiency become much more important in terms of the relative geographic burden within states.

The state-based RUC rates were multiplied by the annual VMT to determine the total RUC policy revenue by state and by geographic class (Table 19). The RUC policy revenues are

[23] RUC rates reported for HI counties instead of HI state-wide estimated rate.

revenue-neutral by state, illustrated by the consistency between the statewide and overall totals in Table 13 and Table 19.

Table 19. Total Annual RUC Policy Revenue by Geographic Class and State ($ Millions)

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	All
Alaska	$4	$2	$3	$2	$9	$19
California	$3,088	$664	$169	$682	$153	$4,756
Colorado	$162	$64	$19	$81	$53	$378
Hawaii*	$56	$12	$13	$12	$26	$118
Idaho	$21	$19	$25	$35	$71	$171
Montana			$31	$13	$75	$119
Nebraska	$39	$24	$11	$22	$66	$162
New Mexico	$18	$12	$16	$18	$27	$90
Oklahoma	$44	$47	$19	$46	$102	$258
Oregon	$160	$41	$64	$89	$95	$450
Texas	$554	$314	$69	$365	$186	$1,489
Utah	$104	$40	$13	$49	$42	$248
Washington	$412	$228	$79	$199	$120	$1,037
Wyoming			$14	$5	$32	$51
14-State Total	**$4,661**	**$1,468**	**$544**	**$1,619**	**$1,056**	**$9,347**

Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUCW state representatives. Note: Totals may not equal the sum of columns due to rounding. * Hawaii includes state and county fuel tax replacement.

Comparisons to the 2016-2018 Analyses

EBP provided RUC America with assessments of geographic differences in the burden of fuel tax revenue starting in 2016 with additional states added to the analysis in 2017 and 2018 for a total of ten states participating in the original study. The original study depended on geographic classifications, travel behavior estimates, and vehicle analysis conceptually similar to that being undertaken for this study, although they differ slightly in execution.

Comparing Geographic Classifications

The original study considered three geographic classes instead of the current five. The three classes were derived from the US Department of Agriculture (USDA) Economic Research Services' Rural-Urban Commuting Area (RUCA) codes.[24] The RUCA code methodology continues to inform EBP's method for the updated classification system but has only historically been updated by USDA a few years after each decennial census and may not be updated in this cycle. The assignment of tracts from the original ten states is shown in Table 20.

Table 20. Original 2016-2018 Report Classification Data Summary (Ten Original States)

UMR Classification	RUCA Codes Included	Census Tracts
Urban	1, 4	12,203 (86%)
Mixed	2, 3, 5	1,122 (8%)
Rural	6, 7, 8, 9, 10	926 (6%)

Source: EBP analysis of state registration data with respect to USDA ERS RUCA classifications.

One of the objectives of the updated classification system was to create a geographic classification system that would not represent 86 percent of tracts with a single class. Additionally, the "Mixed" moniker was ambiguous since it included primarily rural areas where residents commuted to urban areas. Suburban areas as traditionally thought of were mostly included within the Urban class.

To meet these objectives and leverage more current data, the new geographic classification system was created. The relationship between the original classification system and that being used for the 2022 study is shown in Table 21. To make a complete comparison, the five new participating states' census tracts were also classified using the original (2016)

[24] USDA Economic Research Service. Rural-Urban Commuting Area Codes. https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/

system, so Table 21 covers all 15 states. The original classification system is also mapped in Figure 19 for comparison with Figure 2.

In the maps it is apparent how many additional less-dense urban fringe tracts were classified as Urban in 2016-2018 and how the definition has now been narrowed, with nine percent of Urban tracts moving to Rural Commuter and three percent to Rural Independent. A few formerly Mixed tracts are assigned to one of the three urban classes. Three of the primary reasons for this are:

- The RUCA codes considered a tract within one urban area that had a primary commute flow to a different area to be a subordinate geography to the larger urban area, whereas we count it as an urban class because its cumulative flows are still within urban areas.
- Some tracts that had some population within the urban area boundary but the majority outside in 2010 had significantly grown by 2019 within the urban portion, such that the population-weighted centroid of the tract now justifies an urban classification.[25]
- Some Urban Clusters[26] may have grown from populations below 10,000 to populations above 10,000, leading to their new inclusion in Small Urban based on 2019 ACS population estimates.

Almost all tracts that were classified as Rural in 2016-2018 became Rural Independent in 2022, while there is a mix of how formerly Mixed tracts are allocated given the commuting thresholds imposed in the new system and how they differ from the RUCA code methodology.

[25] Some population-weighted centroids may also fall outside of the area covered by a census tract due to irregular shapes. This centroid could then fall within an urban area boundary even if none of the tract's area is within the boundary. This is a consequence of leveraging precalculated centroids to work within the schedule and budget conditions of the project rather than custom tabulations of block-level population relative to urban area boundaries.

[26] The 2010 Urban Area boundaries have two types of urban areas: urbanized areas with population 50,000 or greater and urban clusters with population 2,500 or greater. Census micropolitan areas now have a minimum threshold of 10,000, so RUCA Codes and EBP's system establish a 10,000 minimum threshold for some classes.

Table 21. Geographic Classification System Comparison (Tracts in the Ten Original States)

Expanded 2016-2018 Class*	2022 Class	Census Tracts
Urban	Large Urban Dense	10,980 (61%)
Urban	Large Urban Moderate	3,423 (19%)
Urban	Small Urban	1,469 (8%)
Urban	Rural Commuter	1,608 (9%)
Urban	Rural Independent	621 (3%)
Mixed	Large Urban Dense	117 (5%)
Mixed	Large Urban Moderate	91 (4%)
Mixed	Small Urban	105 (5%)
Mixed	Rural Commuter	1,093^ (50%)
Mixed	Rural Independent	799 (36%)
Rural	Large Urban Dense	0 (0%)
Rural	Large Urban Moderate	4 (0%)
Rural	Small Urban	3 (0%)
Rural	Rural Commuter	168 (9%)
Rural	Rural Independent	1,653 (90%)

Source: EBP analysis of ACS 2014-2019 5-year data, 2019 LEHD LODES data, and urban area boundaries developed from the 2010 Decennial Census. Notes: * Original classification methodology, expanded to 15 states. ^ Mixed to Mixed includes one census tract in Maricopa County, AZ that was classified as NA in the previous study but was deemed 'Mixed' in the current study.

Comparing Travel Behavior

The original study utilized regression equations developed for the Bureau of Transportation Statistics' (BTS) 2009 National Household Transportation Survey (NHTS) Transferability Statistics report. These equations were applied at the census tract level using data from the 2009-2013 American Community Survey (ACS).[27] Table 22 shows these original estimates, by state and geography, and current study estimates using the 2017 NHTS Local Area Transportation Characteristics for Households models and 2015-2019 American Community Survey Data. As discussed in the previous section, the LU Dense, LU Moderate and Small Urban classifications are roughly comparable to the Urban classification of the original study. Rural Commuter tracts roughly correspond with Mixed tracts, and Rural Independent closely matches with Rural in the original study.

[27] Most state estimates utilize 2009-2013 ACS data. CO, HI, and TX use 2011-2015 data that became available at the time those analyses were added to the report.

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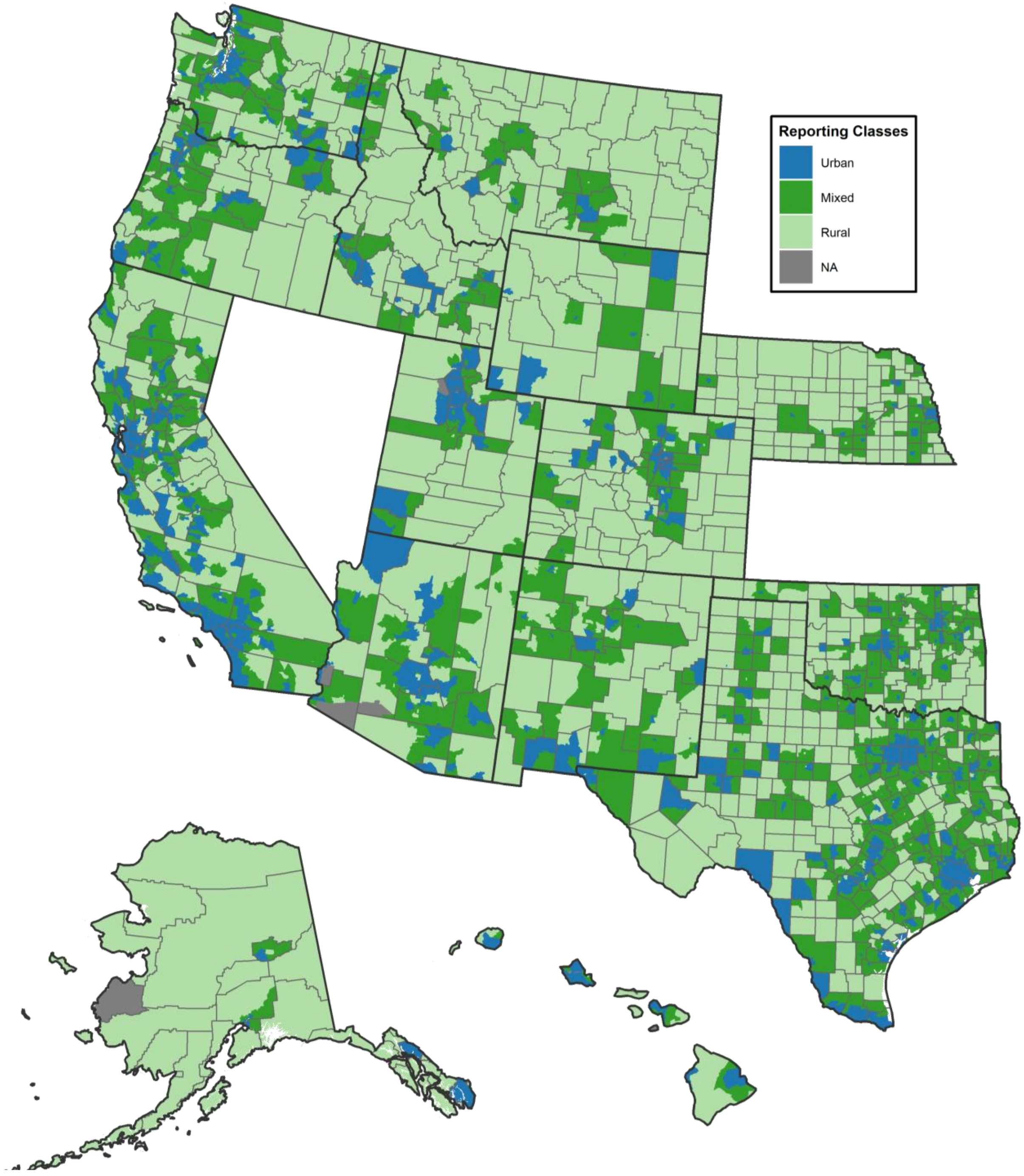
Figure 19. Original 2016-2018 Classification Map for 15 States[28]



Source: EBP analysis of USDA ERS RUCA codes, developed from the 2010 Decennial Census and 2010 ACS data.

[28] This map depicts the original classification methodology from the 2016-2018 analysis expanded for 15 states for geographic classification comparison purposes only.

Table 22. Daily VMT per Household (Original Geographies and Travel Estimates Compared with Updated Geographies and Travel Estimates)

	Original 2016-2018 Study			Current Study				
	Urban	Mixed	Rural	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.
Arizona	37.3	45.8	41.4	32.4	39.4	31.8	47.4	39.1
California	42.1	46.0	39.4	32.4	47.1	36.7	51.2	44.9
Colorado	42.7	58.0	46.3	34.3	43.3	33.6	56.4	45.4
Hawaii	45.4	47.7	45.4	35.9	48.3	38.6	52.4	47.1
Idaho	44.5	52.6	44.8	32.6	39.8	35.9	51.0	46.3
Montana	41.0	51.6	42.8			33.8	49.7	44.9
Oregon	38.2	42.6	38.6	35.1	44.4	37.0	49.0	44.2
Texas	47.4	54.1	44.0	38.7	45.4	37.3	61.6	50.7
Utah	47.7	59.9	52.6	37.0	45.3	37.3	59.0	48.8
Washington	41.1	46.3	39.7	36.1	46.6	36.8	51.2	45.8

Source: Original Study: Bureau of Transportation Statistics' (BTS) 2009 National Household Transportation Survey (NHTS) Transferability Statistics report & 2009-2013 American Community Survey (ACS). Current Study: 2017 NHTS Local Area

The biggest difference between the estimation systems is the creation of the three urban classifications – with LU Dense and Small Urban VMT estimates lower than the original Urban estimates. In most cases, LU Moderate VMT estimates are higher than original Urban estimates, but not in all cases, which may be due to changes in travel behavior as surveyed at the Census Division and Urbanicity Index category level. Alternatively, some of the tracts originally classified as Urban have been included in Rural Commuter or Rural Independent in the improved classification. In general, Rural Commuter VMT estimates are higher than original Mixed estimates for the Pacific Census division and Texas, and lower for the Mountain division. This same pattern holds for Rural Independent compared to original Rural tracts. The patterns from 2017 NHTS summarized by the LATCH research show less significant variation between the states than was reported by the Transferability Statistics analysis of the 2009 NHTS. We use the 2017 data under the assumption that it is just as reliable as the 2009 data and much more current. During the 2016-2018 study and in work for other organizations, we have validated that the LATCH estimates are reasonable compared to other sources including state-level surveys with higher sample counts and odometer readings from vehicle inspections.

Table 23 shows the total VMT from household daily travel estimated for each state for the original and current studies. For this study, 2015-2019 American Community Survey Data was applied to the 2017 LATCH models to estimate VMT using the most recent available data. Remember that these VMT totals do not include light duty commercial VMT or medium and heavy duty VMT.

Table 23. Daily Household Vehicle Miles Traveled Estimates by State (Nine States Common to Both Studies)

State	2016-2018 Study Methodology	2022 Study Methodology
Arizona	91,022,898	94,211,412
California	529,820,872	526,817,750
Colorado	89,499,266	86,967,238
Hawaii	20,632,590	18,726,556
Idaho	26,520,657	26,715,847
Montana	17,516,539	17,862,780
Oregon	58,921,026	64,784,141
Texas	443,356,784	441,408,857
Utah	42,952,381	42,245,699
Washington	109,500,321	118,475,998

Source: 2015-2019 American Community Survey Data applied to the 2017 LATCH models.

We show a relatively stable amount of VMT being captured in most states. The largest percentage point differences in VMT included a 10% increase for Oregon and an approximately 10% decrease for Hawaii. The largest total difference in VMT included a roughly 9 million VMT increase for Washington and an approximately 3 million VMT decrease for California. However, considering that California and Washington are two of the greatest VMT producing study states (California is first, Washington is third), this only amounts to a 7.6% increase in overall VMT for Washington, and a 0.6% decrease in overall VMT for California.

These changes arise from the updated daily VMT estimates from the 2017 NHTS LATCH and differential population growth rates by states. The study methodology focuses on relative changes in costs between geographies and the validity of estimates is not expected to be affected by slight changes in coverage of VMT. The travel universe for this study is designed to capture revenue for a specific segment of road usage rather than all travel, something that must be remembered when interpreting these results.

Comparing Fuel Type Patterns

This section tabulates the VMT by fuel type from the 2016-2018 studies using the new geographic classifications and fuel type categories. VMT per tract before allocating to fuel types is taken directly from the 2016-2018 studies. Figure 20 shows how fuel mixes differed between geographic classes in the 2016-2018 data compared with the updated 2022 data for the nine states where there are data available for both.[29] Figure 21 shows how fuel mixes have evolved over roughly five years in the data delivered by each state for the two studies.[30] Table 41in Appendix C provides multidimensional detail on the prior study's data using the current geographic classes and fuel type groups, which can be directly compared to Table 40(also in Appendix C).

Differences are affected not only by different vehicle fleet composition but also by the VMT assigned to each vehicle from the two different NHTS derivatives (2009 and 2017 data) and associated demographic characteristics of tracts.

For the nine states from which we have data for the 2016-2018 study and the 2022 study, we calculate large percentage increases in the amount of plug-in hybrid (0.2% to 0.5%) and full electric VMT (0.2% to 1.3%) over the last five years. There is a moderate increase in the amount of diesel VMT (2.7% to 3.3%) and hybrid VMT (2.5% to 3.5%) in the dataset and a decrease in the share of gas (87.1% to 85.7%) and flex fuel vehicles (6.9% to 5.5%).[31]

Overall, the geographic pattern of VMT by fuel type remains very consistent across time. Plug-in hybrid and full electric vehicle use is most common in the Large Urban areas, and then amongst Rural Commuter. These vehicle use types are less popular in Small Urban areas and Rural Independent areas. This same pattern holds for regular hybrid vehicles across geographic classes and time. Full electric vehicle adoption has been faster than plug-in hybrid vehicles, a trend that is expected to continue into the future. Across the five years between study periods, diesel vehicles became more common the more rural the geographic classification. Rural Independent areas have more than five times as large a diesel share as Large Urban Dense areas in both studies.

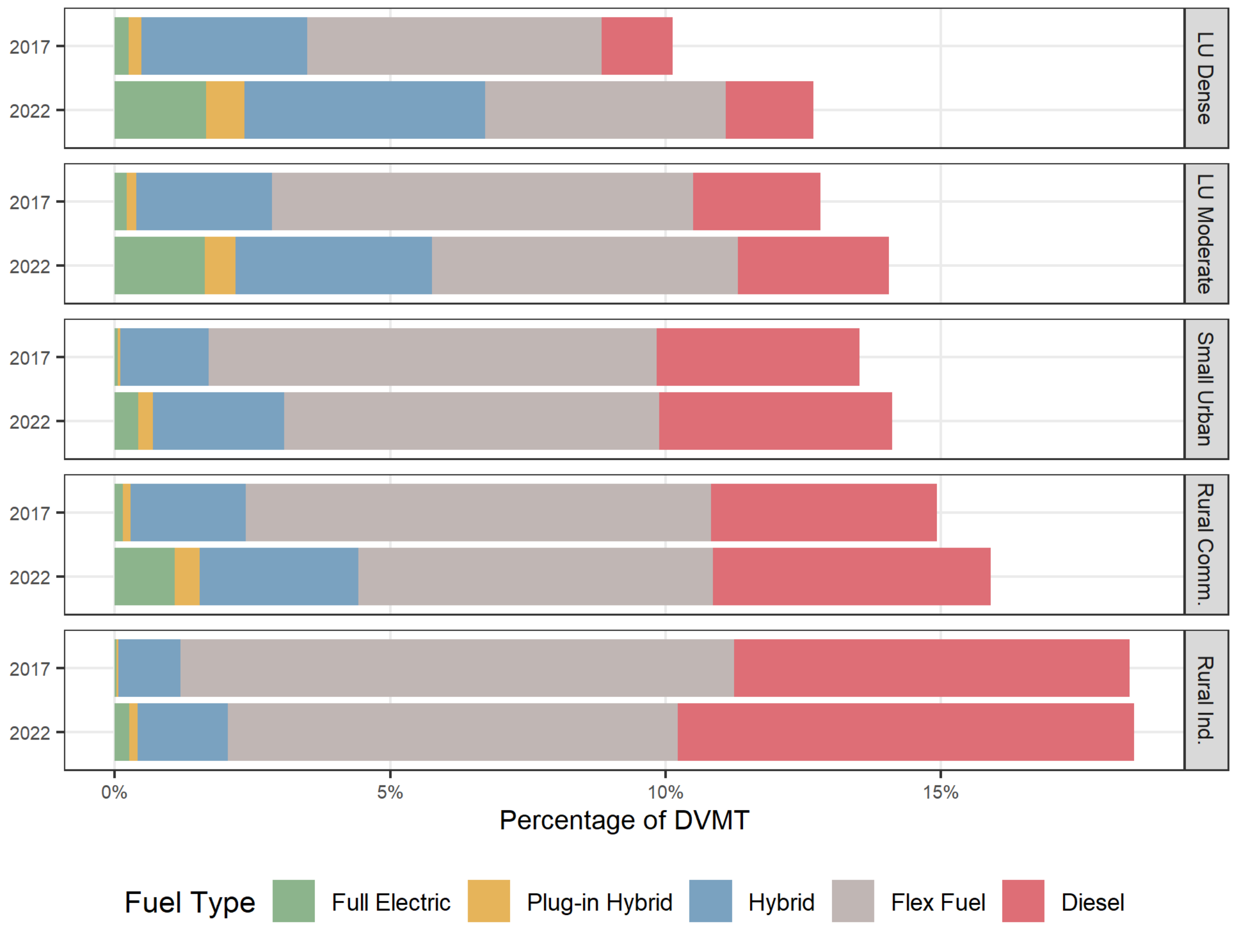
[29] The data displayed corresponds to the 2016-2018 data from Table 24 and is complemented by the direct differences calculated for Table 25.

[30] The original study's data is reported in Table 26 and we provided calculations of differences from Table 5 in Table 27.

[31] Changes noted are only between the 9 states with data in both years.

Full electric, plug-in hybrid, regular hybrid, and diesel shares of VMT increase between the original study and 2022 study in every geographic class. Flex fuel use decreases in all five geographic classes although this fuel type is still roughly twice as common in Rural Independent areas as in Large Urban Dense areas. Flex fuels are the only type for which the ordering between geographic classes changes between study years (based on other fuel share of total VMT). Rural Commuter households' other fuel use falls somewhat faster than Small Urban areas' flex fuel use (a drop of 2 percentage points vs a drop of 1.3), so that in 2022 Small Urban areas now have a higher share of flex fuel use than Rural Commuter areas.

Figure 20. Percent of Daily VMT by Fuel Type (Excluding Gasoline and Other) by Geographic Class (Nine States Common to Both Studies)[32]



Source: EBP analysis of state registration data, LATCH-based estimates of VMT, and geographic classification outcomes.

[32] California, Colorado, Hawaii, Idaho, Montana, Oregon, Utah, Texas, and Washington.

Table 24. Percent of Daily VMT by Fuel Type by Geographic Class (Nine States Common to Both Studies; Percents Reported for Original Study)[33]

Geographic Class	Gas	Diesel	Hybrid	Plug-in Hybrid	Full Electric	Flex Fuel
Large Urban Dense	89.5%	1.3%	3.0%	0.2%	0.3%	5.3%
Large Urban Mod.	86.7%	2.3%	2.5%	0.2%	0.2%	7.6%
Small Urban	85.9%	3.7%	1.6%	0.1%	0.0%	8.1%
Rural Commuter	84.5%	4.1%	2.1%	0.1%	0.1%	8.4%
Rural Independent	80.8%	7.2%	1.1%	0.0%	0.0%	10.1%
Total	**87.1%**	**2.7%**	**2.5%**	**0.2%**	**0.2%**	**6.9%**

Source: EBP analysis of state registration data, LATCH-based estimates of VMT, and geographic classification outcomes.

Table 25. Change in Percentage Points of Daily VMT by Fuel Type by Geographic Class (Nine States Common to Both Studies)[34]

Geographic Class	Gas	Diesel	Hybrid	Plug-in Hybrid	Full Electric	Flex Fuel
Large Urban Dense	(2.3%)	0.3%	1.4%	0.5%	1.4%	(1.0%)
Large Urban Mod.	(0.8%)	0.4%	1.1%	0.4%	1.4%	(2.1%)
Small Urban	(0.1%)	0.5%	0.8%	0.2%	0.4%	(1.3%)
Rural Commuter	(0.4%)	0.9%	0.8%	0.3%	0.9%	(2.0%)
Rural Independent	0.7%	1.1%	0.5%	0.1%	0.2%	(1.9%)
Total	**(1.4%)**	**0.6%**	**1.1%**	**0.4%**	**1.1%**	**(1.4%)**

Source: Difference of Table 4 filtered to the nine 2022 states that also participated in the 2016-2018 study and Table 24.

All states experience growth in full electric, plug-in hybrid, hybrid, and diesel VMT. This suggests somewhat consistent trends in fuel technology adoption across the nine states included in both the 2016-2018 study and the 2022 analysis, with the exception perhaps of flex fuels. However, this could also be affected by updated estimates of VMT for the tracts based on changing demographics and the updated NHTS data.

Idaho, Montana, Oregon, and Washington are the only states that saw increases in the share of VMT using flex fuels, with the increase much larger in Idaho and Montana than the other northwest states. Texas saw a decrease in flex fuel VMT of over four percentage points, a shift that is itself larger than the total flex fuel share of some other states. This appears to be somewhat balanced by Texas's regular gas share increasing by four percentage points as well as growing the state's full electric share. Texas and Montana are

[33] California, Colorado, Hawaii, Idaho, Montana, Oregon, Utah, Texas, and Washington. Not reported are "Other", i.e., biofuel, and other fossil fuels like propane, compressed natural gas (CNG), etc. These are <1% of vehicles in all geographies and overall.

[34] Excludes the "Other" category, which Includes biofuel, and other fossil fuels like propane, compressed natural gas (CNG), etc. This was less than a 1 percentage-point change in all cases.

the only states where the gas VMT share increases. In Montana, this appears to be balanced by a falling share of diesel.

California gains 1.8 percentage points of full electric VMT share, while Hawaii and Washington each gain 1.1 percentage points. Oregon gains 0.9 percentage points, followed by Colorado (0.7-point gain) and Texas (0.6 points). The gains in share for PHEVs are smaller but exhibit a similar pattern of gains across states. Those with higher VMT shares in the 2016-2018 study tended to see bigger increases over the last five years.

Changes in diesel use also exhibit quite a range of change despite a consistent direction for the trend of growing VMT from this source in the newer dataset. Colorado and Hawaii see diesel VMT shares more than double (2.2% to 5.1% and 0.6% to 2.1%) while Idaho's share increases by more than 67 percent (4.9% to 8.3%). In contrast, between datasets, the increase in Texas diesel share is only two-tenths of one percent (from 4.0% to 4.2%).

The states with the highest full electric, plug-in hybrid, and regular hybrid fleet utilization shares are also the states with the highest gas vehicle fleet utilization shares in both study years. States where vehicles with electric motors are popular and increasingly common are also those with the lowest level of diesel and other category fuel use for household transportation. Increasing levels of electrification have decreased the share of pure gas VMT in some states, but gas is still the dominant fuel type for all study states.

Table 26. Percent of Daily VMT by Fuel Type by State (Nine States Common to Both Studies, Original Study Values)[35]

State	Gas	Diesel	Hybrid	Plug-in Hybrid	Full Electric	Flex Fuel
California	91.2%	0.7%	4.1%	0.4%	0.4%	3.2%
Colorado	88.6%	2.2%	0.9%	0.1%	0.1%	7.6%
Hawaii	93.2%	0.6%	1.2%	0.1%	0.4%	4.2%
Idaho	89.4%	4.9%	0.9%	0.0%	0.0%	4.7%
Montana	79.7%	13.0%	1.4%	0.0%	0.0%	5.8%
Oregon	87.7%	5.5%	2.8%	0.1%	0.0%	3.8%
Texas	80.8%	4.0%	1.2%	0.0%	0.0%	12.7%
Utah	86.0%	5.5%	1.7%	0.1%	0.1%	6.6%
Washington	90.8%	3.1%	2.3%	0.0%	0.1%	3.6%

Source: EBP analysis of state registration data and LATCH-based estimates of VMT.

[35] Excludes the "Other" category, which Includes biofuel, and other fossil fuels like propane, compressed natural gas (CNG), etc. This was less than a 1% of vehicles everywhere except Texas, where they accounted for 1.2% of vehicles.

Table 27. Change in Percentage Points of Daily VMT by Fuel Type by State (Nine States Common to Both Studies)[36]

State	Gas	Diesel	Hybrid	Plug-in Hybrid	Full Electric	Flex Fuel
California	(4.5%)	0.6%	1.5%	0.7%	1.8%	(0.1%)
Colorado	(3.0%)	2.9%	1.5%	0.1%	0.7%	(1.7%)
Hawaii	(3.5%)	1.5%	2.0%	0.2%	1.1%	(1.0%)
Idaho	(7.0%)	3.4%	1.1%	0.1%	0.2%	2.2%
Montana	4.3%	(6.8%)	0.0%	0.1%	0.2%	2.1%
Oregon	(3.0%)	0.5%	0.9%	0.3%	0.9%	0.4%
Texas	4.0%	0.2%	0.4%	0.1%	0.6%	(4.1%)
Utah	(1.3%)	0.7%	0.3%	0.1%	0.4%	(0.2%)
Washington	(4.7%)	1.1%	1.6%	0.3%	1.1%	0.6%

Source: Difference between Table 5 and Table 26.

[36] Excludes the "Other" category, which Includes biofuel, and other fossil fuels like propane, compressed natural gas (CNG), etc. This was less than a 1 percentage-point change in all cases except Texas, where it was a -1.2 percent-point change.

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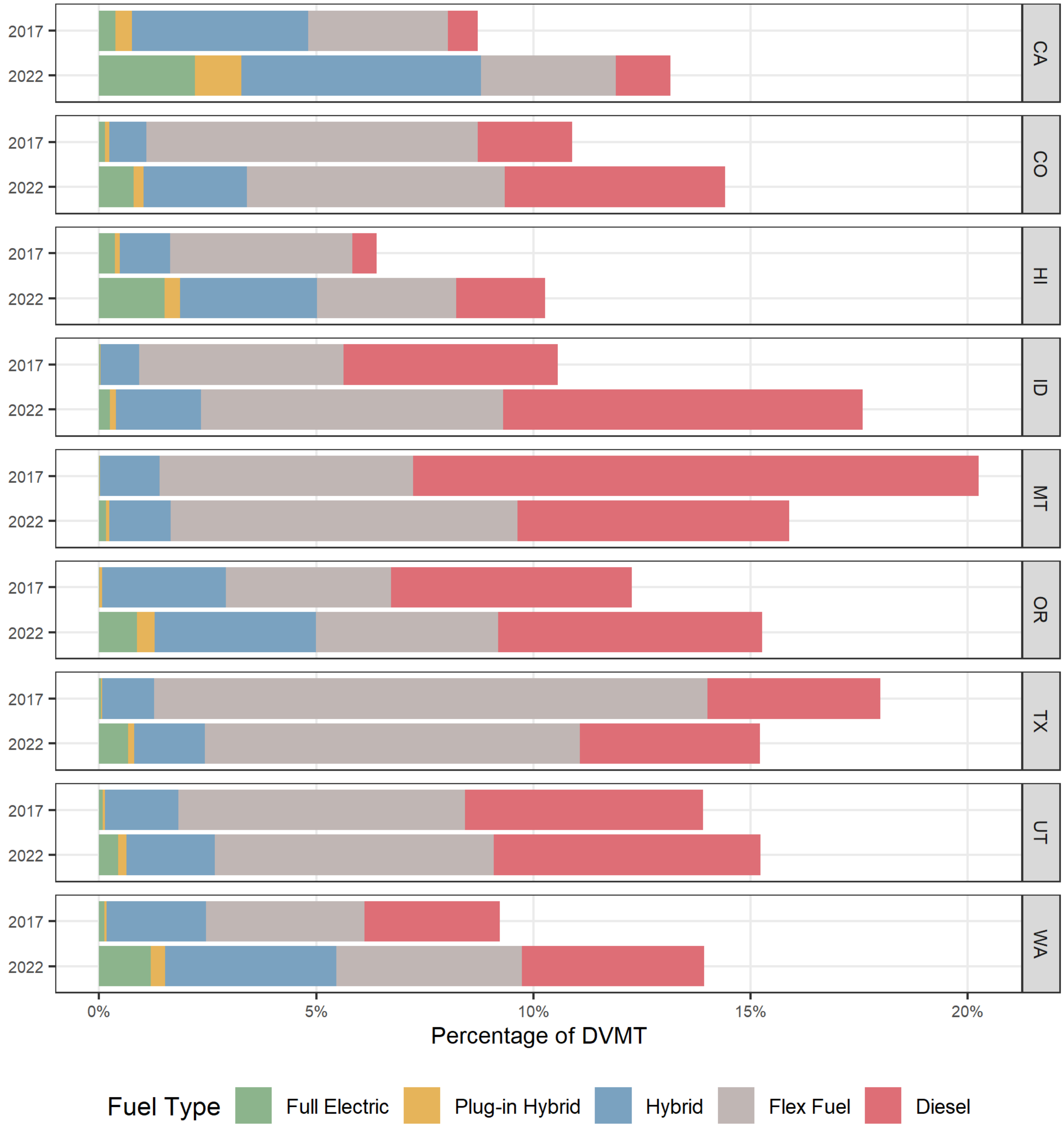
Figure 21. Percent of Daily VMT by Fuel Type (Excluding Gasoline and Other) by State (Comparing Original States)



Source: EBP analysis of state registration data and LATCH-based estimates of VMT

Comparing Fuel Efficiency

The results of the updated 2016-2018 analysis show that California had the highest overall fuel efficiency (21.7 MPGe), as well as the highest fuel efficiency for all fuel types with the exception of full EVs (the second lowest fuel efficiency at 81.7 MPGe) and Hybrids, (second highest – tied with Colorado). In comparison, Idaho had the lowest overall fuel efficiency (18.6 MPGe), but the state with the lowest fuel efficiency per fuel type varied based on the fuel type (Table 28).

Table 28. MPGe for Updated 2016-2018 Study Vehicles by Fuel Type (VMT-Weighted[37], Nine States Common to Bost Studies, Original Data)

State	Gas	Diesel	Hybrid	PHEV	Full EV	Flex Fuel	All
California	21.3	27.0	40.7	60.1	81.7	18.7	21.7
Colorado	19.5	16.4	40.7	54.1	103.9	16.1	19.2
Hawaii	20.7	19.9	43.9	56.3	106.9	17.6	20.7
Idaho	18.9	14.6	37.6	57.1	105.4	16.2	18.6
Montana	19.8	14.2	36.5	56.0	48.2	15.7	18.7
Oregon	19.8	15.4	39.2	54.7	116.2	16.4	19.6
Texas	19.6	14.7	35.7	53.9	97.4	16.0	18.8
Utah	19.9	14.7	35.7	56.6	106.7	16.4	19.4
Washington	19.9	15.7	39.3	54.7	100.4	16.0	19.8

Source: EBP calculations using fuel efficiencies from EPA and Fuelly. Notes: Weighted by VMT.

In comparison to the former (2016-2018) study, the current (2022) study reflects significant gains in full EV fuel efficiency across all states with the exception of Oregon (see Table 29). Most states had very few EVs in the original study. In comparison, PHEVs saw a general decrease in fuel efficiency across all states except for Oregon. The number of PHEVs in fleets has also grown and the type of vehicles available expanded. Five out of nine of the states saw decreases in diesel efficiencies, while the remaining four saw modest increases.[38] Apart from Montana (-1.3 MPG), all states saw a slight increase in average MPG for gas.[39] Overall, Texas saw the greatest increase in efficiency (1.9 MPGe) while Montana saw the greatest decrease in efficiency (-0.5 MPGe).

[37] Fuel efficiencies reported in this table are significantly lower than those reported in the original study. This arises due to the very minor differences in vehicle inclusion in order to leverage a consistent methodology when making comparisons, but primarily due the weighting by VMT as well as application of the harmonic mean rather than arithmetic mean when presenting averages. The updated methodology more accurately describes the effective efficiency that contributes to fuel consumption.

[38] Some of these findings may result from states sharing different vehicle populations with the study team.

[39] It appears the 2022 study includes a much more complete set of vehicles from Montana, so this result like represents improved data quality rather than a true trend in vehicle technology for Montana.

Table 29. Change in Average MPGe for Vehicles between Studies for Nine Common States (by Fuel Type)

State	Gas	Diesel	Hybrid	PHEV	Full EV	Flex Fuel	All
California	1.3	-8.8	0.0	-0.7	31.4	-0.5	1.8
Colorado	0.5	-1.4	-4.1	-3.7	7.6	-0.1	0.6
Hawaii	0.7	-4.7	-3.5	-1.6	6.2	-0.8	0.9
Idaho	0.5	0.2	-1.1	-7.8	8.3	0.0	0.3
Montana	-1.3	1.3	-1.5	-7.6	61.2	0.0	-0.5
Oregon	0.7	-0.2	0.3	3.3	-2.9	0.2	0.8
Texas	1.7	0.7	2.3	-3.9	17.7	0.4	1.9
Utah	0.6	0.3	2.0	-1.4	3.0	0.0	0.7
Washington	0.9	-0.2	-0.1	-0.5	12.3	0.7	1.1

Source: EBP calculations using fuel efficiencies from EPA and Fuelly.

Average efficiencies are summarized by geographic class in Table 30. Montana has the lowest difference in average MPGe across the five geographies, with an MPGe range of 0.8. Oregon has the greatest difference in MPGe across geographies, with a range of 2.2. California reported the highest average fuel efficiencies within each of the five geographies, while Texas had the lowest fuel efficiencies for Small Urban, Rural Commuter, and Rural Independent geographies, and Idaho had the lowest fuel efficiencies for Large Urban Dense and Large Urban Moderate geographies.

Table 30. MPGe for Updated 2016-2018 Study Vehicles by Geographic Class (VMT-Weighted[40], Nine States Common to Bost Studies, Original Data)

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	All
California	21.9	21.7	21.1	21.4	20.6	21.7
Colorado	19.8	19.5	18.6	18.9	17.7	19.2
Hawaii	21.1	21.1	20.2	20.6	19.7	20.7
Idaho	19.3	18.9	18.8	18.7	18.1	18.6
Montana			19.2	18.9	18.4	18.7
Oregon	20.6	20.0	19.3	19.1	18.4	19.6
Texas	19.4	19.1	17.9	18.4	17.4	18.8
Utah	19.8	19.5	19.1	19.4	18.2	19.4
Washington	20.6	19.8	19.5	19.1	18.9	19.8

Source: EBP calculations using fuel efficiencies from EPA and Fuelly.

Texas saw the greatest increase in average MPGe across all five geographies, while Montana experienced the greatest decrease in MPGe for Small Urban, Rural Commuter,

[40] Fuel efficiencies reported in this table are significantly lower than those reported in the original study. This arises due to the very minor differences in vehicle inclusion in order to leverage a consistent methodology when making comparisons, but primarily due the weighting by VMT as well as application of the harmonic mean rather than arithmetic mean when presenting averages. The updated methodology more accurately describes the effective efficiency that contributes to fuel consumption.

and Rural Independent geographies (Table 31). Idaho, Utah, and Colorado tied for lowest increase in MPGe for Large Urban Dense and Large Urban Moderate geographies. However, the most significant information revealed in Table 31 is that fuel efficiency improved faster over time in the more urban parts of the states than the more rural parts of the states. This initial result leads us to expect that rural areas will bear an increasing share of fuel tax revenue over time.

Table 31. Change in Average MPGe for Vehicles between Studies for Nine Common States (by Geographic Class)

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	All
California	1.9	1.9	1.3	1.6	0.9	1.8
Colorado	0.8	0.9	0.4	0.3	0.1	0.6
Hawaii	1.3	1.5	0.5	1.0	0.5	0.9
Idaho	0.8	0.8	0.4	0.6	0.0	0.3
Montana*			-0.4	-0.5	-0.5	-0.5
Oregon	1.4	1.3	0.7	0.6	0.3	0.8
Texas	2.1	2.1	1.8	1.8	1.5	1.9
Utah	0.8	0.8	0.6	0.7	0.4	0.7
Washington	1.6	1.3	0.7	0.7	0.3	1.1

Source: EBP calculations using fuel efficiencies from EPA and Fuelly. Notes: * Montana's fuel efficiency decreases on average, largely because we are analyzing a much more complete set of vehicle registrations in the 2022 study than the 2016-2018 analyses.

Comparing Vehicle Age

Average vehicle age was reviewed in Table 32. In the original study, Idaho had the greatest overall vehicle age (14.9 years; closely followed by Montana at 14.3 years), whereas Texas had the lowest (9.2 years). Idaho had the greatest vehicle age for all geographies except for Rural Commuter tracts, in which Montana had the greatest age (13.8 compared to 14.3 years). Texas had the lowest vehicle age across all geographies. In terms of age disparities among geographies, Montana had the least range in vehicle age (0.1 years) while Oregon had the greatest (3.9 years).

Table 32. Average Vehicle Age for Updated 2016-2018 Study Vehicles by Geographic Class

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	All
California	10.5	10.0	11.6	10.7	12.1	10.5
Colorado	10.4	9.7	12.0	9.8	12.2	10.5
Hawaii	10.0	10.2	10.7	10.7	11.9	10.5
Idaho	14.9	14.0	15.0	13.8	15.5	14.9
Montana			14.2	14.3	14.3	14.3
Oregon	10.7	10.2	13.4	13.0	14.1	12.2
Texas	9.2	8.8	9.4	9.0	9.8	9.2
Utah	10.4	10.3	11.2	10.6	11.2	10.6
Washington	13.1	12.8	14.5	13.6	14.4	13.4

Source: EBP calculations from registration records.

Between the 2016-2018 study and the 2022 study, Idaho experienced the greatest overall decrease in vehicle age (-2.3 years) while Colorado and Utah tied for the greatest overall increase in vehicle age (1.2 years) (Table 33). Utah produced the greatest increases in age for Large Urban Moderate, Small Urban, and Rural Independent tracts, while Colorado saw the greatest increases in Large Urban Dense and Rural Commuter tracts. Texas went from having the newest vehicle fleet to being even more of an outlier with the second greatest decrease in average age.[41]

Table 33. Change in Average Vehicle Age for Vehicles between Studies by Geographic Class

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	All
California	-0.5	-0.4	-0.4	-0.3	0.1	-0.4
Colorado	1.0	0.7	1.1	1.6	1.4	1.2
Hawaii	0.1	-2.2	0.2	-0.1	-0.5	-0.3
Idaho	-2.9	-3.1	-2.2	-2.6	-1.7	-2.3
Montana			-0.1	0.2	1.2	0.8
Oregon	0.9	1.2	-0.3	-0.1	0.0	0.5
Texas	-1.2	-1.5	-1.1	-1.5	-1.1	-1.3
Utah	0.9	0.8	1.3	1.0	2.1	1.2
Washington	-1.5	-1.2	-0.9	-0.9	-0.2	-1.1

Source: EBP calculations from registration records.

Comparing the Geographic Balance of Revenue

For the purposes of revenue estimates, the former (2016-2018) RUC America study featured fuel tax rates for gas, which were also applied to E85 purchases, whereas the current (2022) study includes tax rates for diesel, CNG, LPG, and E85 explicitly. Tax rates

[41] This is despite the fact that the timing of the vehicle data receipt for Texas (as the final addition to the 2016-2018 study) may bias down the results for Texas in Table 33.

(confirmed by RUC America state representatives) are reported in Table 48 in Appendix D and include excise taxes charged per gallon or gallon equivalent. [42] Hawaii is the only state for which local option taxes (e.g., county-specific taxes) are considered. In Hawaii, the county-specific rates are considered because they completely cover all of the populated areas of the state. All states except Texas raised gas taxes between study periods. The updated methodology recognizes actual E85 rates and results in a decrease of assessments for California, Texas, and Maui in E85 taxes. In addition to updated tax rates, VMT estimates, household characteristics and spatial patterns, and vehicle fleets changed between the study periods, resulting in the production of differing RUC rates in the 2022 study compared to the 2016-2018 study (Table 34). While most states experienced an increase in RUC rates, Texas experienced a decrease in rates (0.99 to 0.92). This may be attributable to the decrease in the E85 fuel tax rate applied (given Texas's considerable use of E85). The remaining states' increased rates can be attributed mainly to increases in gas tax rates.

The state that experienced the greatest absolute change in RUC rate was California, which increased by 1.1 cents per mile following a 12 cent per gallon increase, indexing of the gas tax rate, and inclusion of the diesel rate, which is significantly higher than the gas tax rate.

[42] California fuel taxes consider both excise taxes and sales taxes but exclude sales tax revenue directed to local government operations.

Table 34. Comparison of Estimated RUC Rates Across Analyses (cents/mile) (Nine States Common to Both Studies)

State	Original Study	Updated Original Data[43]	Current Study
California	1.10	1.37	2.47
Colorado	1.00	1.11	1.19
Hawaii: Hawaii	0.70	0.73	1.61
Hawaii: Honolulu	0.70	0.76	1.78
Hawaii: Kauai	0.70	0.83	1.93
Hawaii: Maui	0.70	1.12	1.57
Idaho	1.45	1.62	1.75
Montana	1.12	1.20	1.82
Oregon	1.39	1.42	1.90
Texas	0.87	0.99	0.92
Utah	1.25	1.40	1.61
Washington	1.95	2.15	2.40

Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUCW state representatives.

The fuel tax collections per household for the updated 2016-2018 analysis are reported in Table 35 by geographic class. The greatest state average for revenue contribution per household was found in Washington, with each household contributing an average of $312. Alternatively, the lowest state average was found in Hawaii, with each household contributing an average of $133. Washington also produced the highest average revenue contributions across all geographic classifications, and Hawaii produced the lowest average contribution across all classifications.

Similar to the fuel tax collections per household for 2022 described in Table 9, the greatest average revenue contributions were found in Rural Commuter tracts ($240), followed by Large Urban Moderate, Rural Independent, Small Urban large, and urban dense tracts ($186).

Consistent with the revenue-neutrality of the RUC revenue, the 2016-2018 RUC revenue contributions per state (Table 36) are the same as the fuel tax collections per state (Table 35). Also consistent between fuel tax collections and RUC collections is the pattern of greatest to lowest geographic class contribution: Rural Commuter tracts contributed the

[43] Original study rates are presented here for reference. The rates produced using the original travel data, vehicle records, and tax rates but improved vehicle processing methods are significantly different from the original rates. We suspect this is primarily due to improvements in the methodology for calculating average efficiency for vehicles within tracts and a few other adjustments to include diesel vehicles in both studies and additional review of data quality. Unfortunately, there are too many independent factors to be able to identify the specific causal roles in the update. We believe the updated rates are a better comparison to the current study rates.

most overall ($239), followed by Large Urban Moderate, Rural Independent, Large Urban Dense, and Small Urban ($183), with those final two urban groups switching places slightly.

Table 35. Annual Fuel Tax Collections per Household in Updated 2016-2018 Analysis by Geographic Class

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	All
California	$196	$232	$190	$237	$215	$205
Colorado	$146	$182	$152	$244	$202	$174
Hawaii*	$119	$147	$148	$155	$147	$133
Idaho	$194	$258	$243	$295	$273	$257
Montana			$157	$219	$192	$183
Oregon	$180	$219	$184	$219	$202	$194
Texas	$150	$177	$152	$207	$190	$170
Utah	$198	$265	$202	$319	$260	$235
Washington	$280	$354	$286	$363	$321	$312
9-State Average	**$186**	**$220**	**$188**	**$240**	**$217**	**$202**

Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUCW state representatives; household data from ACS. * Hawaii includes state and county fuel taxes.

Table 36. Annual RUC Collections per Household in Updated 2016-2018 Analysis by Geographic Class

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	All
California	$198	$231	$184	$233	$204	$205
Colorado	$149	$183	$148	$243	$191	$174
Hawaii*	$119	$147	$150	$153	$146	$133
Idaho	$195	$257	$242	$297	$272	$257
Montana			$153	$220	$194	$183
Oregon	$182	$218	$180	$220	$201	$194
Texas	$151	$177	$148	$207	$187	$170
Utah	$199	$266	$200	$321	$259	$235
Washington	$285	$352	$280	$361	$315	$312
9-State Average	**$188**	**$220**	**$183**	**$239**	**$212**	**$202**

Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUCW state representatives; household data from ACS. * Hawaii includes state and county fuel tax replacement.

Table 37. Annual Dollar Change in Revenue Contribution Per Household for the Updated 2016-2018 Analysis by Geographic Class and State

State	LU Dense	LU Mod.	Small Urban	Rural Comm.	Rural Indep.	All
California	$1.40	-$0.40	-$6.00	-$3.50	-$10.50	$0.00
Colorado	$2.90	$1.50	-$3.70	-$0.80	-$10.70	$0.00
Hawaii*	$0.50	$0.10	$1.50	-$1.90	-$1.50	$0.00
Idaho	$1.00	-$0.10	-$1.00	$2.00	-$0.80	$0.00
Montana			-$4.30	$0.90	$2.30	$0.00
Oregon	$2.00	-$0.60	-$4.40	$0.80	-$1.20	$0.00
Texas	$1.10	$0.30	-$4.10	$0.40	-$3.50	$0.00
Utah	$0.10	$0.50	-$2.50	$1.90	-$1.70	$0.00
Washington	$4.50	-$2.60	-$6.10	-$2.40	-$5.90	$0.00
9-State Average	**$1.60**	**-$0.20**	**-$4.50**	**-$1.10**	**-$4.20**	**$0.00**

Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUCW state representatives; household data from ACS. * Hawaii accounts for state and county fuel taxes.

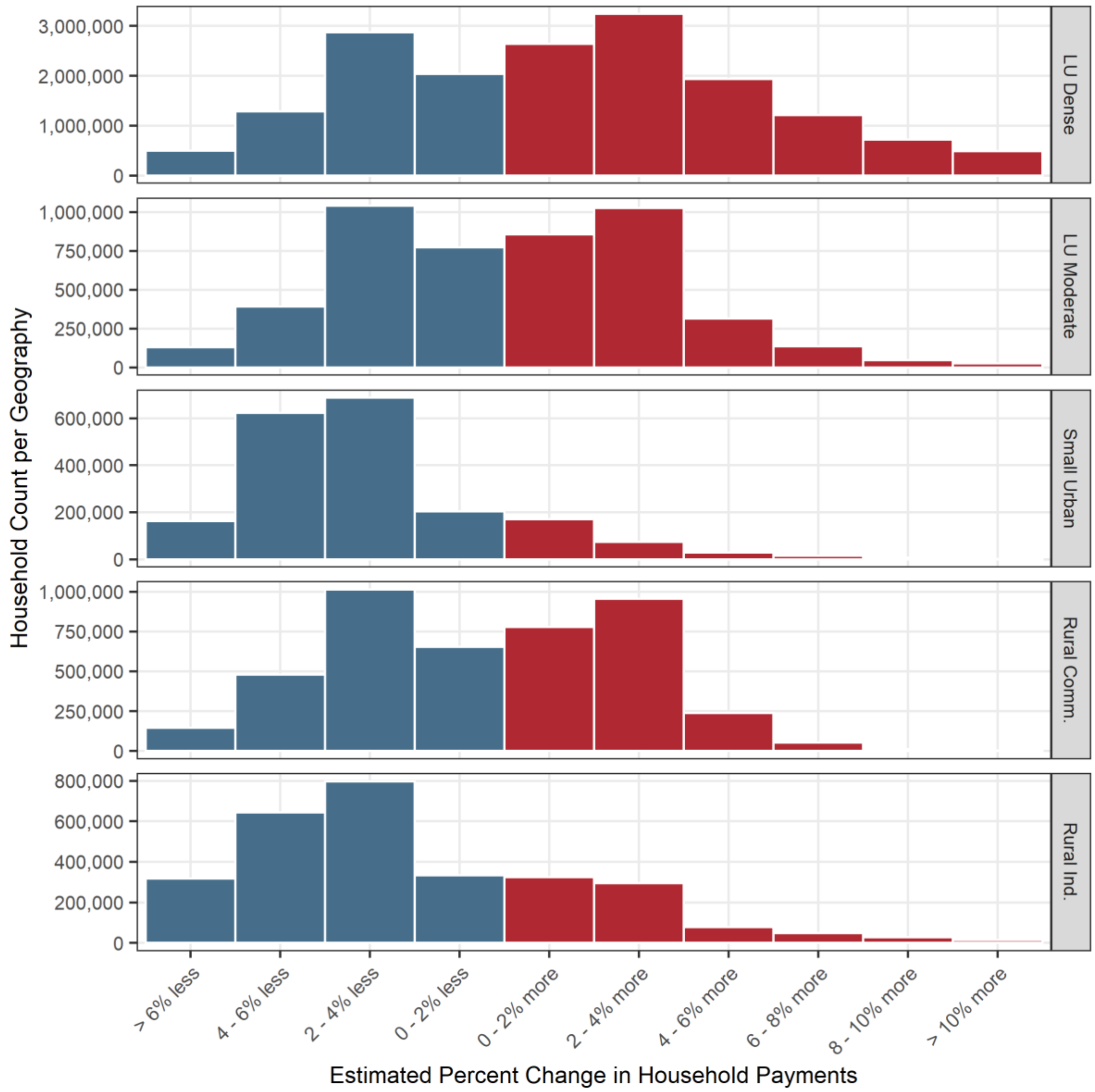
Rural Independent tracts experience the second greatest decrease in revenue contributions when moving from traditional fuel policies to RUC policies (-$4.20), with only Small Urban tracts producing a greater decrease in revenue contributions (-$4.50) (see Table 37). Meanwhile, only Large Urban Dense tracts show an increase in revenue contributions ($1.6). These updated estimates show even less significant changes were likely to result had a RUC been rolled out in 2017 than the original study analysis. The predicted average changes are less than a dollar a month in all states and geographic classes.

The distributions of percent changes in revenue contribution per household for the 2016-2018 study are illustrated in Figure 22, in which it is evident that the Large Urban Dense, Large Urban Moderate and Rural Commuter tract residents are more likely to experience increases in payments under a RUC compared to Small Urban and Rural Independent tract residents. However, almost all classes had a significant number of households on either side of the dividing line between increases and decreases. Over the past five years, the skewing of outcomes has become much more pronounced, showing an increasing likelihood of RUC to lessen the revenue share of rural areas compared to urban areas.

The updated 2016-2018 analysis also shows a significant value to separating the Small Urban households out from the previously larger urban group. The updated analysis shows that RUC would generate more revenue from households in Large Urban Dense settings and return that revenue to Small Urban households.

State-specific graphics showing each state's unique distribution of outcomes are described in Appendix A. These will be helpful to states since California and Texas represent a significant share of all households in Figure 22.

Figure 22. Distribution of Percentage Changes in Updated 2016-2018 Annual Revenue Contribution Per Household by Geographic Class for Nine-State Region[44]



Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; fuel taxes and vehicle surcharges from RUCW state representatives; household data from ACS. Note: Hawaii accounts for state and county fuel taxes

[44] California, Colorado, Hawaii, Idaho, Montana, Oregon, Utah, Texas, and Washington

Implications & Future Research

We find that for the fourteen states analyzed, a RUC-based policy shifts the revenue burden from rural populations towards urban populations when compared to current fuel tax-based revenue policies. This finding has become more pronounced over time and arises from rural drivers having less efficient vehicles compared to urban drivers. The electrification of vehicles and improved fuel efficiency of vehicles over time has widened the fuel efficiency gap between urban and rural households.

These findings are significant for state DOTs, policy makers, and drivers residing in all types of geographies. As vehicle electrification accelerates and more fuel-efficient vehicles are adopted, current fuel tax burdens will fall disproportionately on rural drivers. By shifting to a RUC policy, urban drivers will pay more than they currently do via fuel taxes, and rural drivers will pay less. Although rural drivers will continue to pay more overall due to higher VMT in rural areas versus urban areas, the burden of responsibility is better balanced under a RUC.

Future research could consider the impact of switching from baseline fuel tax policies to a RUC policy on commercial vehicles in addition to passenger vehicles, the latter of which this study focused on. A significant share of fuel tax revenue is not covered by this study as it is paid by light-, medium-, and heavy-duty commercial vehicles.

Geographic differences between fuel taxes and RUCs have been addressed quite robustly in the literature at this point but analysis to date has been less able to address how the balance of contributions may change between other groups such as those of different income levels, household structures (e.g., families), and disadvantaged populations. Few large data sources provide these details at a state-level, so analysis may require statistical integration of data sources using methods like this study.

Research could incorporate additional revenue considerations, such as local fuel taxes or fees on vehicles of varying fuel types to derive conclusions that paint a more complete local picture. This may include local RUC rates as well which may involve location of travel information to supplement the location of residence data used in this study. Analysis could also include a federal fuel tax replacement, and total costs of vehicle ownership and use as a share of household budgets.

Market penetration of electric vehicles and new, efficient vehicles will continue to be unequal geographically. Minimizing these geographic differences will be important for reasons other than revenue balance. The impacts of a RUC-based policy on urban and rural areas will continue to shift over time, and research should be conducted throughout this transitional period to capture and understand shifts in travel behavior, the vehicle market, and geographic differences in household payments. States further along in the electric transition may benefit from forecasting fleet penetration patterns to understand the urgency of RUC policy adoption to protect not only revenue amounts but also the balance of revenue collections between groups such as urban and rural households.

Appendix A: State Level Maps and Graphics

For each state, the following maps have been prepared based on 2022 data:

- Geographic Classification (comparable to Figure 2)
- Daily Household VMT (comparable to Figure 5)
- Gasoline Percentage of Vehicles
- Diesel Percentage of Vehicles
- Full Electric Percentage of Vehicles
- PHEV Percentage of Vehicles
- Hybrid Percentage of Vehicles
- Other Percentage of Vehicles
- All-Vehicles Fuel Efficiency (comparable to Figure 12)
- All-Vehicles Average Age (comparable to Figure 14)
- Percentage Changes in Annual Revenue Contribution Per Household at the Tract Level (comparable to Figure 18)

State-specific graphics have also been prepared based on 2016-2018 or 2022 data for:

- Distribution of Daily Household VMT (comparable to Figure 3)
- Distribution of Percentage Changes in Annual Revenue Contribution Per Household by Geographic Class (comparable to Figure 17).
- Distribution of Percentage Changes in Updated 2016-2018 Annual Revenue Contribution Per Household by Geographic Class (comparable to Figure 22)

Appendix B: Vehicles Analyzed

Of the approximately 74 million vehicle registration records that were received by the consulting team from RUC America state representatives and DMVs in 2022, about 57 million records from the 14 states that submitted vehicle registrations were determined appropriate for inclusion in the analysis, successfully decoded to determine fuel, geocoded to tracts, and matched to fuel efficiency information. Table 38 provides a breakdown of the records used for each state for the purposes of the analysis and where limitations may have occurred, prohibiting the use of some records. The methodology documentation describes the processes carried out to develop the final vehicle data set.

Table 38. Household Daily-Use Vehicle Records Analyzed in 2022 Study

State	Records Received	Valid Records for Decoding[45]	Fuel Determined[46]	Tract Assigned in State[47]	MPG Information Available
Alaska	2,381,059	477,021	375,842	373,947	345,584
California	29,061,733	25,162,913	24,131,106	23,919,821	22,947,266
Colorado	4,988,994	4,971,327	4,702,885	3,343,699	3,116,921
Hawaii	1,979,920	1,189,132	1,069,632	1,026,074	992,769
Idaho	1,014,818	1,014,697	968,886	966,047	906,735
Montana	1,392,743	1,392,551	1,217,006	1,211,415	1,143,019
Nebraska	1,682,630	1,682,630	1,606,355	1,604,775	1,503,419
New Mexico	1,885,278	1,885,016	1,788,234	1,774,072	1,690,498
Oklahoma	3,887,856	3,195,542	2,511,995	2,407,035	2,306,339
Oregon	3,484,642	3,298,094	3,142,655	3,128,840	2,909,178
Texas	12,676,407	11,508,276	11,210,802	11,172,062	10,582,911
Utah	2,539,729	2,539,729	2,472,996	2,413,333	2,332,030
Washington	6,262,375	6,262,375	6,125,344	6,090,351	5,689,570
Wyoming	703,690	694,096	605,201	564,111	514,601
14-State Total	**73,941,874**	**65,273,399**	**61,928,939**	**59,995,582**	**56,980,840**

Source: EBP analysis of state vehicle registration data using EPA fueleconomy.com and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding.

For comparison purposes, a summary of the data available from the 2016-2018 analysis and the records that were used in the updated comparison study are recorded in Table 39.

[45] Excludes records received where a VIN was duplicate or missing, and where registration information indicated that the vehicle was out-of-scope (such as commercial vehicles) and non-active registrations.

[46] Using vPIC API or given information to determine fuel type, and further screening for out-of-scope vehicles based on vPIC API. RVs were analyzed separately and are not counted in fuel determination, tract assignment, or efficiency assignment.

[47] Some addresses or ZIP codes suggest that the vehicle is located in another state or did not provide sufficient information to associate the vehicle to a census tract and its households. Colorado specifically is affected by the lack of ZIP Code data which limits our ability to proportionately assign vehicles that could not be uniquely coded to a census tract.

Table 39. Household Daily-Use Vehicle Records Analyzed in 2016-2018 Study

State	Records Received	Valid Records for Decoding	Fuel Determined	Tract Assigned in State	MPG Information Available
California	22,792,030	21,305,291	21,211,471	21,209,679	21,209,679
Colorado	5,516,550	4,017,313	4,013,928	3,968,579	3,968,579
Hawaii	1,101,737	969,758	969,415	969,415	969,415
Idaho	2,746,599	2,193,375	2,172,158	2,118,760	2,118,760
Montana	700,000	527,681	519,016	519,016	517,576
Oregon	3,782,752	2,517,375	2,502,082	2,502,076	2,502,076
Texas	24,203,117	18,051,018	17,963,290	17,963,290	17,963,290
Utah	2,330,849	1,970,018	1,959,629	1,959,629	1,959,629
Washington	5,130,385	4,302,908	4,288,290	4,288,285	4,288,285
9-State Total	**68,304,019**	**55,854,737**	**55,599,279**	**55,498,729**	**55,497,289**

Appendix C: State VMT by Fuel Type and Geographic Class

Table 40. Detailed Daily VMT by Fuel Type for 2022

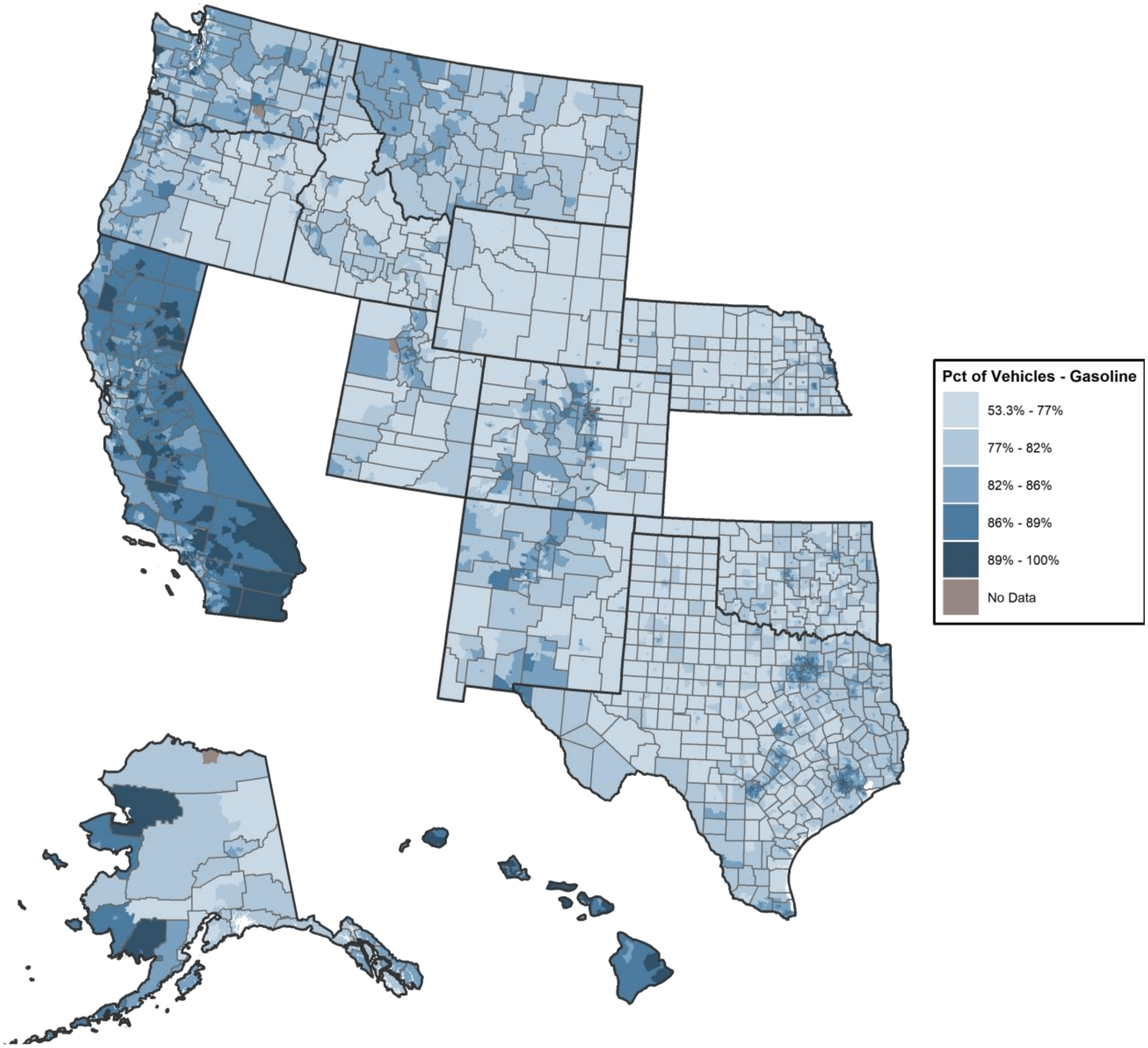
State	Geographic Class	DVMT, Millions	Gas	Diesel	Hybrid	Plug-in Hybrid	Full Electric	Flex Fuel
Alaska	LU Dense	2.2	85.8%	3.6%	2.1%	0.1%	0.2%	8.1%
	LU Mod.	1.1	84.4%	4.9%	2.1%	0.1%	0.3%	8.2%
	Small Urb	1.6	81.8%	7.0%	1.6%	0.1%	0.2%	9.3%
	Rural Comm.	1.4	81.5%	8.0%	1.9%	0.1%	0.3%	8.2%
	Rural Indep.	4.8	81.2%	7.9%	1.5%	0.1%	0.5%	8.7%
California	LU Dense	342.0	87.0%	1.0%	5.8%	1.1%	2.3%	2.8%
	LU Mod.	73.6	85.5%	1.4%	5.8%	1.2%	2.8%	3.2%
	Small Urb	18.7	88.2%	2.0%	3.9%	0.6%	0.8%	4.6%
	Rural Comm.	75.6	86.2%	1.8%	5.1%	1.0%	2.0%	3.8%
	Rural Indep.	16.9	88.1%	2.9%	3.3%	0.5%	0.5%	4.7%
Colorado	LU Dense	37.2	88.6%	2.2%	2.7%	0.2%	0.8%	5.5%
	LU Mod.	14.6	86.5%	3.6%	2.8%	0.3%	1.1%	5.7%
	Small Urb	4.3	85.6%	6.0%	1.5%	0.1%	0.2%	6.6%
	Rural Comm.	18.6	82.1%	8.2%	2.3%	0.3%	1.0%	6.1%
	Rural Indep.	12.3	80.6%	10.4%	1.4%	0.1%	0.3%	7.2%
Hawaii	LU Dense	8.6	90.3%	1.1%	3.4%	0.4%	1.6%	3.2%
	LU Mod.	1.9	88.2%	1.4%	4.2%	0.5%	2.8%	2.8%
	Small Urb	2.1	90.4%	2.7%	2.3%	0.2%	1.0%	3.4%
	Rural Comm.	1.8	89.8%	1.9%	3.2%	0.4%	1.5%	3.4%
	Rural Indep.	4.3	88.8%	4.0%	2.5%	0.2%	1.0%	3.4%
Idaho	LU Dense	3.3	86.7%	4.0%	2.7%	0.2%	0.4%	5.9%
	LU Mod.	2.9	84.6%	5.6%	2.6%	0.2%	0.4%	6.6%
	Small Urb	3.9	84.6%	6.2%	1.8%	0.1%	0.1%	7.2%
	Rural Comm.	5.5	82.4%	7.9%	2.3%	0.2%	0.4%	6.8%
	Rural Indep.	11.2	79.8%	11.2%	1.4%	0.1%	0.1%	7.4%
Montana	LU Dense							
	LU Mod.							
	Small Urb	4.7	86.8%	3.9%	1.6%	0.1%	0.2%	7.5%
	Rural Comm.	1.9	84.2%	6.4%	1.5%	0.1%	0.2%	7.6%
	Rural Indep.	11.3	83.0%	7.2%	1.3%	0.1%	0.2%	8.3%
Nebraska	LU Dense	7.9	88.5%	1.2%	2.0%	0.1%	0.2%	8.0%
	LU Mod.	4.9	87.8%	1.6%	2.1%	0.1%	0.3%	8.0%
	Small Urb	2.3	84.9%	2.4%	1.0%	0.1%	0.1%	11.6%
	Rural Comm.	4.5	83.8%	4.1%	1.9%	0.2%	0.4%	9.7%
	Rural Indep.	13.5	79.2%	7.2%	0.9%	0.0%	0.0%	12.6%
New Mexico	LU Dense	5.8	87.1%	3.2%	2.7%	0.2%	0.3%	6.5%
	LU Mod.	4.0	84.3%	5.7%	2.6%	0.2%	0.5%	6.6%
	Small Urb	5.1	83.9%	5.1%	1.9%	0.1%	0.2%	8.8%
	Rural Comm.	5.8	83.2%	6.5%	2.4%	0.2%	0.5%	7.2%
	Rural Indep.	8.6	80.7%	8.4%	1.4%	0.1%	0.1%	9.2%

State	Geographic Class	DVMT, Millions	Gas	Diesel	Hybrid	Plug-in Hybrid	Full Electric	Flex Fuel
Oklahoma	LU Dense	11.5	86.2%	1.8%	1.8%	0.1%	0.2%	9.8%
	LU Mod.	12.4	85.1%	2.6%	1.8%	0.1%	0.3%	9.9%
	Small Urb	5.1	83.4%	3.2%	1.5%	0.1%	0.1%	11.7%
	Rural Comm.	12.2	81.1%	5.7%	1.6%	0.1%	0.2%	11.3%
	Rural Indep.	26.8	78.7%	7.0%	1.1%	0.0%	0.1%	13.1%
Oregon	LU Dense	23.1	86.9%	2.7%	5.1%	0.6%	1.3%	3.3%
	LU Mod.	5.9	85.5%	4.1%	4.6%	0.5%	1.4%	3.9%
	Small Urb	9.2	85.8%	5.8%	3.0%	0.3%	0.5%	4.5%
	Rural Comm.	12.9	82.7%	8.7%	3.0%	0.4%	0.7%	4.5%
	Rural Indep.	13.7	81.8%	10.4%	2.1%	0.2%	0.2%	5.3%
Texas	LU Dense	164.3	87.4%	2.1%	1.8%	0.2%	0.8%	7.7%
	LU Mod.	93.1	86.1%	3.1%	1.9%	0.2%	1.0%	7.8%
	Small Urb	20.5	82.6%	5.1%	1.1%	0.1%	0.2%	10.9%
	Rural Comm.	108.3	83.1%	5.7%	1.5%	0.1%	0.6%	8.9%
	Rural Indep.	55.2	78.6%	8.7%	1.0%	0.1%	0.1%	11.5%
Utah	LU Dense	17.7	86.5%	4.4%	2.2%	0.2%	0.5%	6.1%
	LU Mod.	6.8	85.0%	5.4%	2.2%	0.2%	0.5%	6.5%
	Small Urb	2.2	84.6%	6.5%	1.9%	0.2%	0.3%	6.4%
	Rural Comm.	8.3	84.4%	6.3%	2.0%	0.2%	0.4%	6.4%
	Rural Indep.	7.1	79.7%	11.0%	1.5%	0.1%	0.2%	7.2%
Washington	LU Dense	47.0	87.4%	2.0%	5.1%	0.4%	1.6%	3.5%
	LU Mod.	26.0	86.1%	3.8%	4.0%	0.4%	1.4%	4.3%
	Small Urb	9.0	87.9%	3.7%	2.7%	0.2%	0.5%	5.0%
	Rural Comm.	22.7	83.8%	7.3%	2.9%	0.3%	0.8%	4.9%
	Rural Indep.	13.7	84.0%	7.6%	2.3%	0.2%	0.4%	5.4%
Wyoming	LU Dense							
	LU Mod.							
	Small Urb	2.8	82.6%	7.4%	1.2%	0.1%	0.1%	8.7%
	Rural Comm.	0.9	77.9%	12.2%	1.3%	0.1%	0.1%	8.4%
	Rural Indep.	6.4	75.4%	14.1%	1.0%	0.0%	0.1%	9.4%

Table 41. Detailed Daily VMT by Fuel Type for 2016-2018 Study States in Updated Study

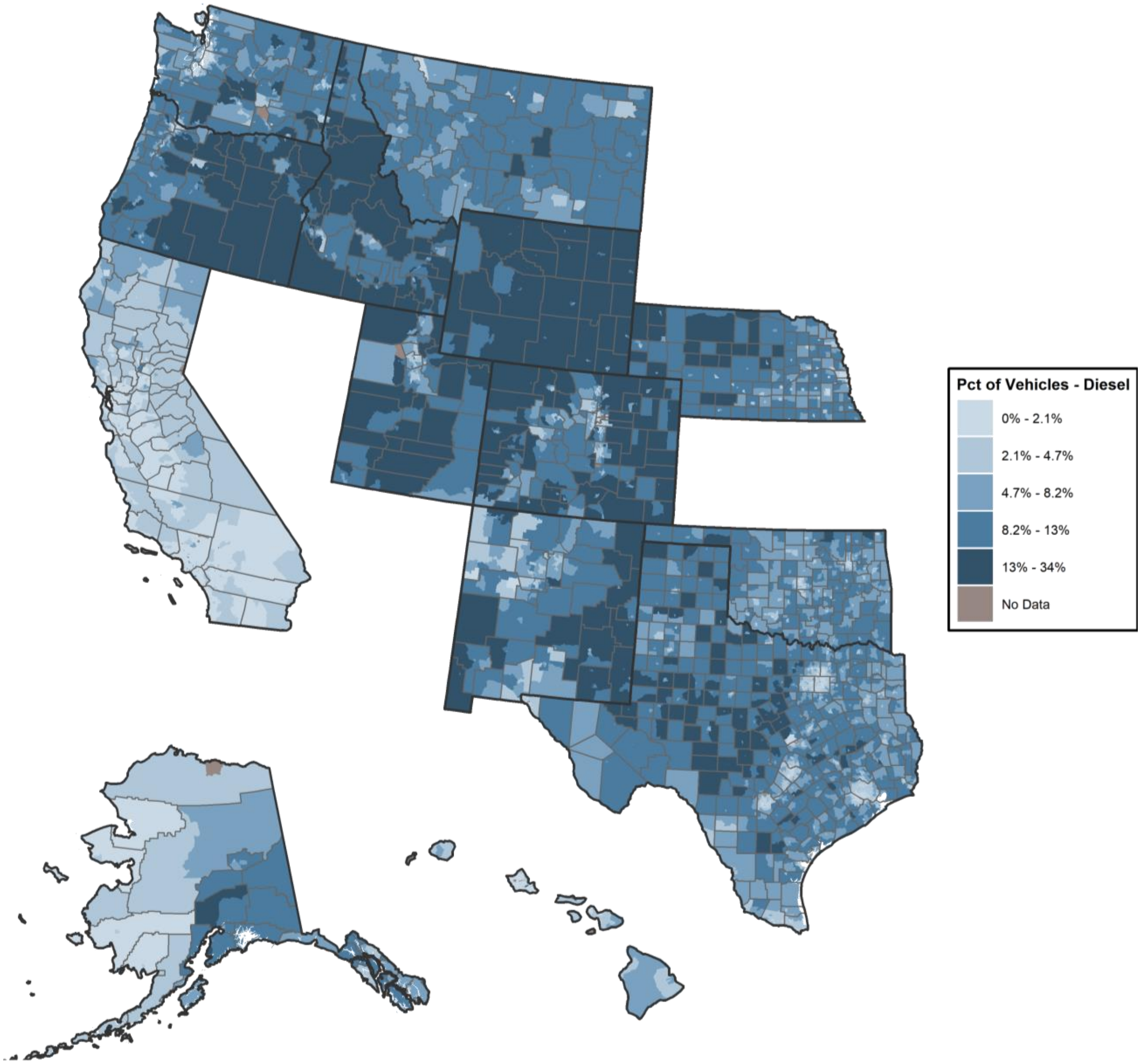
State	Geographic Class	DVMT, Millions	Gas	Diesel	Hybrid	Plug-in Hybrid	Full Electric	Flex Fuel
California	LU Dense	357.4	91.4%	0.6%	4.2%	0.4%	0.4%	2.9%
	LU Mod.	71.4	90.3%	0.8%	4.4%	0.4%	0.5%	3.4%
	Small Urb	18.6	91.9%	0.8%	2.8%	0.1%	0.1%	4.2%
	Rural Comm.	67.2	90.6%	0.9%	3.9%	0.4%	0.3%	3.8%
	Rural Indep.	15.2	92.1%	1.0%	2.3%	0.1%	0.1%	4.2%
Colorado	LU Dense	39.2	90.4%	1.3%	0.9%	0.1%	0.1%	6.7%
	LU Mod.	14.6	89.0%	1.6%	1.0%	0.1%	0.2%	7.6%
	Small Urb	4.6	87.9%	2.3%	0.5%	0.0%	0.0%	8.5%
	Rural Comm.	18.6	87.0%	3.2%	0.9%	0.1%	0.2%	8.1%
	Rural Indep.	12.5	85.1%	3.9%	0.5%	0.0%	0.1%	9.5%
Hawaii	LU Dense	10.2	93.4%	0.4%	1.2%	0.1%	0.4%	4.1%
	LU Mod.	2.1	93.3%	0.4%	1.5%	0.2%	0.6%	3.7%
	Small Urb	2.3	92.6%	0.7%	0.9%	0.1%	0.3%	4.9%
	Rural Comm.	2.0	93.2%	0.5%	1.0%	0.1%	0.3%	4.5%
	Rural Indep.	4.1	93.1%	1.0%	1.0%	0.1%	0.3%	4.0%
Idaho	LU Dense	3.3	92.7%	2.3%	1.2%	0.0%	0.0%	3.8%
	LU Mod.	3.1	90.7%	3.4%	1.2%	0.0%	0.0%	4.7%
	Small Urb	4.3	90.9%	3.7%	0.8%	0.0%	0.0%	4.5%
	Rural Comm.	5.0	88.6%	5.0%	1.2%	0.0%	0.0%	5.2%
	Rural Indep.	10.9	87.9%	6.6%	0.7%	0.0%	0.0%	4.8%
Montana	LU Dense							
	LU Mod.							
	Small Urb	4.8	84.1%	8.9%	1.5%	0.0%	0.0%	5.5%
	Rural Comm.	1.8	81.3%	12.1%	1.6%	0.0%	0.0%	5.1%
	Rural Indep.	10.9	77.6%	15.0%	1.3%	0.0%	0.0%	6.1%
Oregon	LU Dense	22.4	90.4%	2.8%	3.6%	0.1%	0.0%	3.1%
	LU Mod.	5.5	87.9%	4.0%	3.6%	0.1%	0.0%	4.3%
	Small Urb	8.3	88.9%	4.9%	2.3%	0.1%	0.0%	3.9%
	Rural Comm.	10.9	85.1%	7.9%	2.7%	0.1%	0.0%	4.2%
	Rural Indep.	11.8	84.1%	9.7%	1.7%	0.0%	0.0%	4.5%
Texas	LU Dense	174.1	84.4%	2.2%	1.4%	0.0%	0.1%	10.9%
	LU Mod.	96.6	82.4%	3.0%	1.3%	0.0%	0.1%	12.1%
	Small Urb	22.4	76.1%	5.3%	0.9%	0.0%	0.0%	16.3%
	Rural Comm.	94.6	78.4%	5.6%	1.1%	0.0%	0.0%	13.6%
	Rural Indep.	55.6	72.8%	8.1%	0.8%	0.0%	0.0%	16.6%
Utah	LU Dense	18.1	87.9%	3.8%	1.8%	0.1%	0.1%	6.2%
	LU Mod.	7.5	86.3%	5.0%	1.8%	0.1%	0.1%	6.5%
	Small Urb	2.2	86.2%	5.6%	1.6%	0.0%	0.0%	6.4%
	Rural Comm.	8.1	85.8%	5.6%	1.7%	0.1%	0.1%	6.6%
	Rural Indep.	7.0	80.7%	9.9%	1.4%	0.0%	0.0%	7.9%
Washington	LU Dense	45.6	92.4%	1.7%	2.7%	0.1%	0.2%	3.0%
	LU Mod.	24.1	90.6%	2.8%	2.4%	0.1%	0.2%	4.0%
	Small Urb	8.5	91.8%	2.8%	1.5%	0.0%	0.0%	3.8%
	Rural Comm.	19.6	88.2%	5.4%	1.9%	0.0%	0.1%	4.3%
	Rural Indep.	11.7	88.4%	5.5%	1.5%	0.0%	0.0%	4.5%

Figure 23. Percent of Gas Vehicles in 2022 by Tract Across Study States



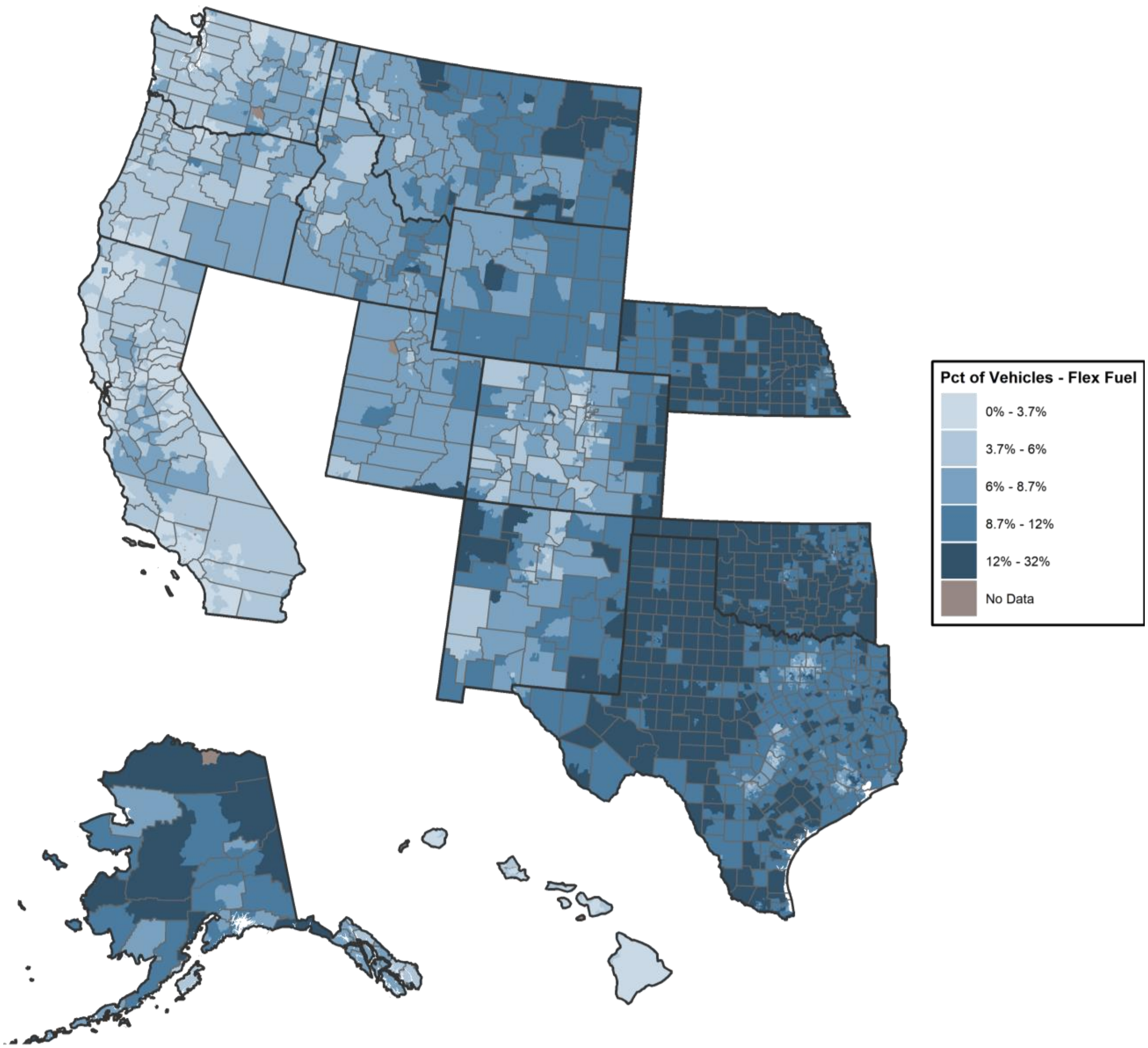
Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; household data from ACS.

Figure 24. Percent of Diesel Vehicles in 2022 by Tract Across Study States



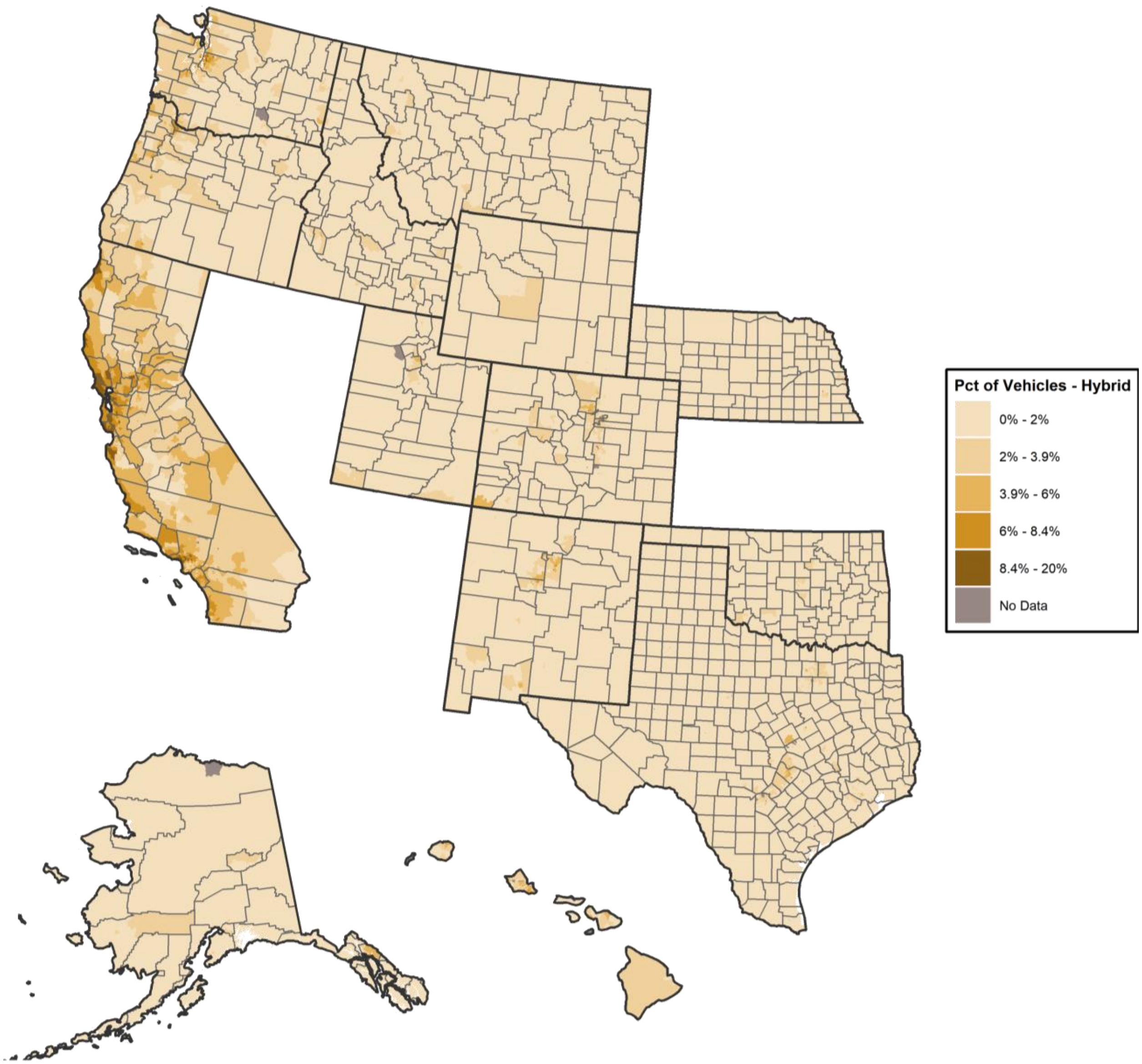
Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; household data from ACS.

Figure 25. Percent of Other Fuel Vehicles in 2022 by Tract



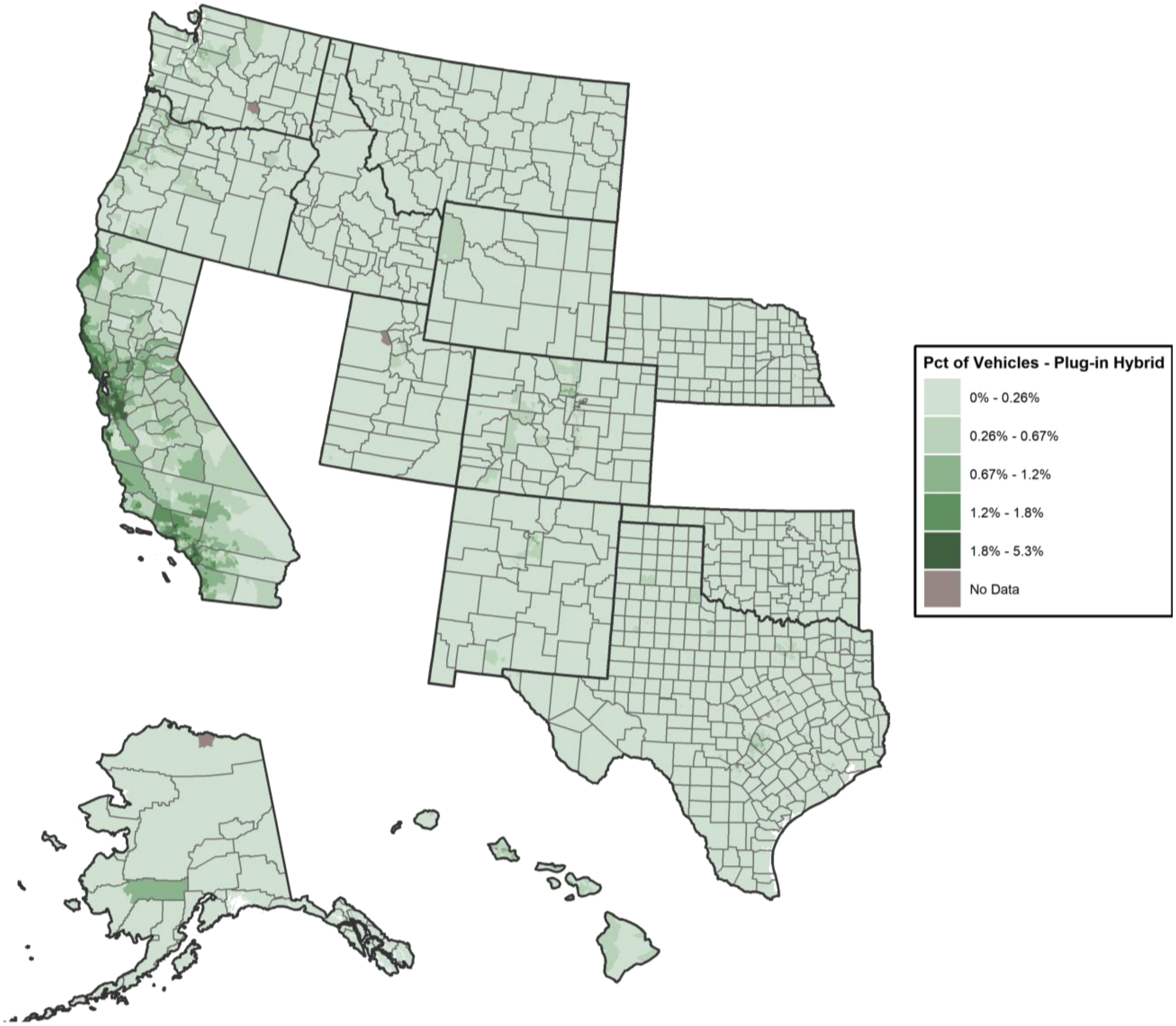
Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; household data from ACS.

Figure 26. Percent of Standard Hybrid Vehicles in 2022 by Tract Across Study States



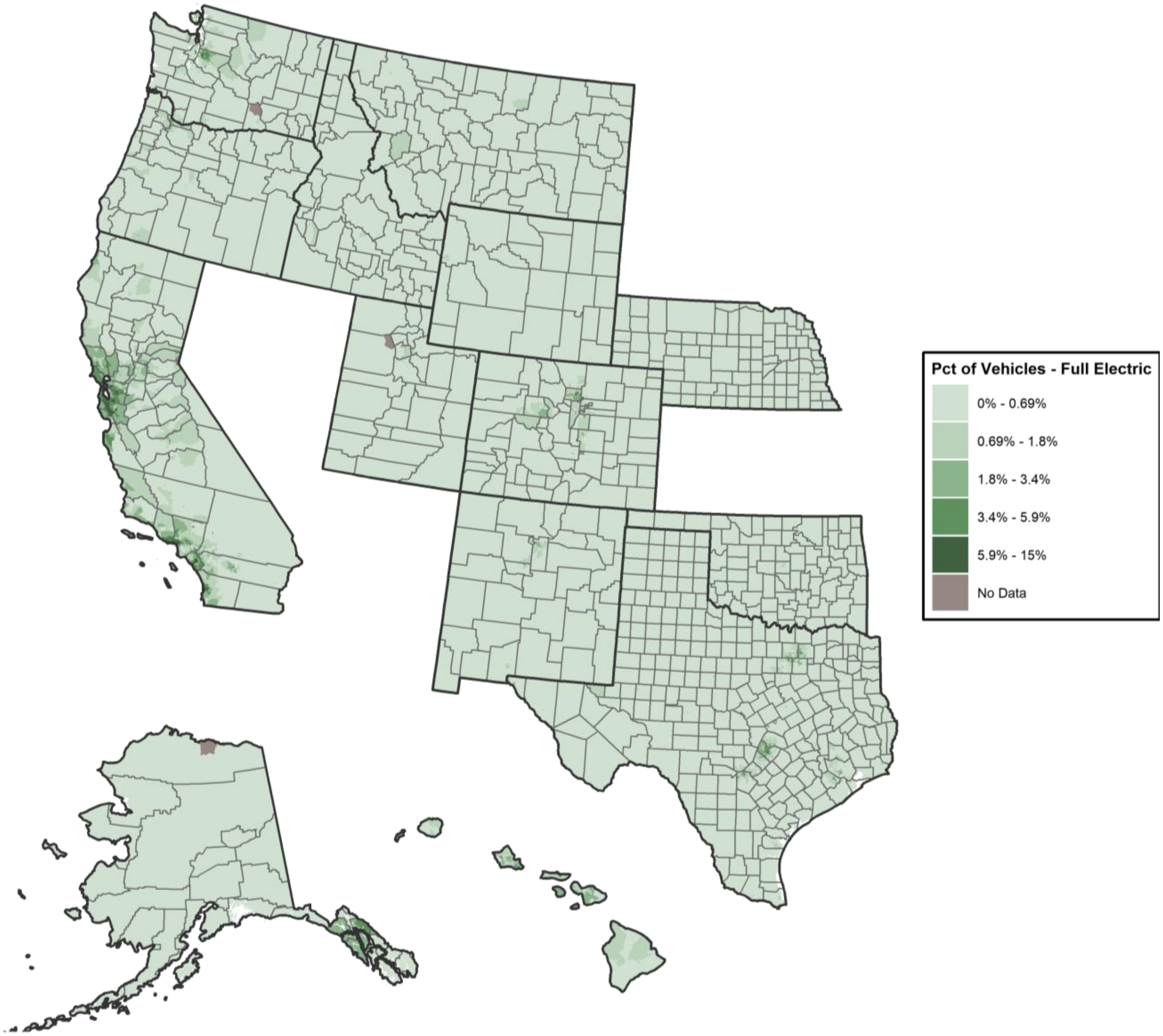
Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; household data from ACS.

Figure 27. Percent of Plug-in Hybrid Vehicles in 2022 by Tract Across Study States



Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; household data from ACS.

Figure 28. Percent of Full Electric Vehicles in 2022 by Tract Across Study States



Source: EBP calculations using VMT estimates from LATCH; fuel efficiencies from EPA and Fuelly; fuel type percentages from registration records decoded with NHTSA vPIC or raw agency coding; household data from ACS.

Appendix D: Methodology

Introduction

This document describes the methods used across fourteen RUC America states to compare 1) a baseline policy of fuel taxes and alternative fuel vehicle registration surcharges to 2) a road usage charge (RUC) policy that results in households in each state having the same out-of-pocket expenses under both policies. It is a companion for the reports that summarize and discuss the results of the analysis. It is descriptive in nature of how the team approached the analysis and is supplemented by a Data Documentation package that inventories the supporting data applied and the specific processing procedures contained in each analysis script. Each of the component steps taken to prepare data for the revenue policy comparisons are described, excluding the registration data collection process from the participating states. The component steps include:

- Geographic Classification
- Travel Behavior Analysis
- Vehicle Data Preparation
- Vehicle Usage Analysis

The most complex component of the analysis is the preparation of a common vehicle dataset across the participating states. This component recoded a variety of location information attributes provided by the different states to census tracts as the geographic unit and standardized fuel type and fuel efficiency information. The vehicle data preparation also updates data from analyses conducted between 2016 and 2018 and sets up comparisons of the two data vintages. Separate methods are described for addressing on-road recreational vehicles as a distinct group from the primary population of vehicles used for household daily travel.

All analysis components use 2010 Census Tracts and related geographic entities as most 2020 geographic entities had not been released at project initiation and were only slowing released at various times during the project.

Geographic Classification

To assess the effects of a RUC system on different kinds of travelers, we distinguish between areas with distinct travel, density, and demographic characteristics.

EBP previously aggregated the US Department of Agriculture Economic Research Service's Rural-Urban Commuting Area Codes[48] to three geographic classifications (urban, mixed, and rural). Because the RUCA Codes were last updated in 2013 using data from the 2010 decennial census, we base the current analysis on a new methodology and updated data sources but are inspired by the methods of the RUCA Codes.

We define the five geographic classifications of census tracts used in the study in Table 42. The classifications consider regional population, local density, and commuting relationships, including those between non-metropolitan areas and nearby metro areas. The unit for the geographic classification is the census tract, allowing us to identify rural portions of metropolitan areas (the OMB definitions of which are county-based).

We use US Census Bureau data products to classify census tracts, as listed in Table 43. These data products are applied at four steps to separate all census tracts into the five geographic classifications used in the study, as shown in Figure 29.

- **Step 1** divides tracts between Urban and Rural classification groups based on the Urban Area boundaries published after the 2010 census. At the time of this study, the updated Urban Area boundaries from the 2020 census had not been released. Tracts were considered to fall inside an Urban Area if their centroid was in the Urban Area. (Urban Areas are defined at the census block level and therefore not coterminous with tracts.) Urban Areas are defined by the Census Bureau to include areas with populations of 2,500 or greater. ACS data on Urban Area population was used to remove tracts from the Urban classification group if their centroid was within one of the Urban Area boundaries containing fewer than 10,000 people.
- **Step 2** divides the Urban classification group between Large Urban and Small Urban classification groups. This determination was made based on whether the tract was within a county belonging to a Core-Based Statistical Area with population over 250,000 based on the latest available ACS data at the time of the

[48] USDA Economic Research Service. Rural-Urban Commuting Area Codes. https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/

study. Census tract and county boundaries are coterminous. Small Urban tracts are one of the final geographic classifications.

- **Step 3** divides the Rural classification group between Rural Commuter and Rural Independent classifications (both final classifications used in the study). Commuting flows provided by LEHD LODES data were summarized to identify what percentage of commuters out of each census tract traveled to an Urban Area, excluding locations with less than 10,000 population. If a majority of a tract's commuters traveled to a Large Urban or Small Urban classification tract, that tract was considered Rural Commuter.
- **Step 4** divides the Large Urban classification group into Large Urban Dense and Large Urban Moderate tracts (both final classifications). To make this distinction, every tract in the US was ranked according to its population density (not only participating states and not only Large Urban tracts). If the tract was among the 40 percent of densest tracts in the US, it was classified as Large Urban Dense. All other Larger Urban tracts were assented as LU Moderate.

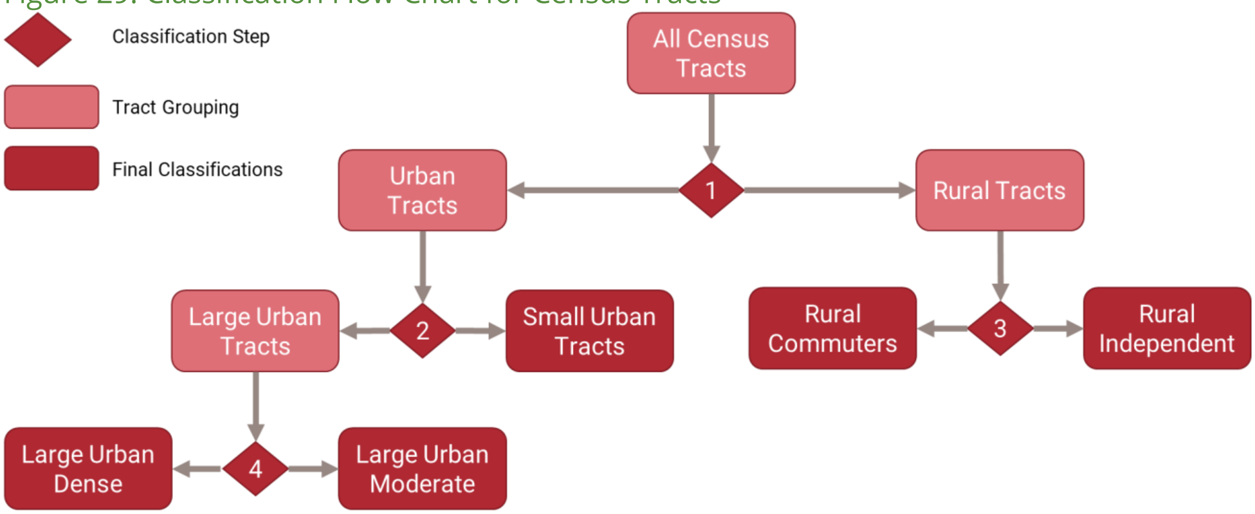
Table 42. Geographic Classifications

Class Name	Working Definition
Large Urban Dense	Metro population > 250,000; Among the densest 40% of US census tracts Primary commute flow is within urban areas;
Large Urban Moderate	Metro population > 250,000; Not among the densest 40% of US census tracts Primary commute flow is within urban areas;
Small Urban	Metro population < 250,000; Primary commute flow is within urban areas
Rural Commuter	Primary commute flow is >=50% into urban areas with population >10,000
Rural Independent	All other tracts

Table 43. Key Data Sources and Uses

Data Source		Classification Role
2010 Urban Area[49] boundaries		Differentiate between urban areas and non-urban areas
ACS 5-year sample data (2015-2019)	Census tract population	Split Large Urban tracts between Dense and Moderate classifications
	Core-Based Statistical Area (CBSA)[50] population	Separate Large Urban (Dense & Moderate) tracts from Small Urban tracts
	Urban Area population	Shift Tracts in urban clusters with less than 10,000 population to into Rural Commuter and Rural Independent geographies
Longitudinal Employer-Household Dynamics (LEHD)[51] Origin-Destination Employment Statistics (LODES) data		Separate Rural Commuter and Rural Independent tracts

Figure 29. Classification Flow Chart for Census Tracts



[49] Urbanized Areas (or UAs) are areas with 50,000 or more people and Urban Clusters (UCs) are areas with at least 2,500 and less than 50,000 people.

[50] CBSAs are geography types that are specifically used to analyze urban areas and adjacent surroundings. These areas have boundary definitions that are outlined by the Office of Management and Budget (OMB) and are updated approximately every decade. Currently, there are two types of CBSAs that are different only in the population size of their core areas. Metropolitan statistical areas have a core of at least 50,000 people while micropolitan areas have a core between 10,000 and 50,000 people.

[51] LEHD is a longitudinally linked employer-employee dataset created by the U.S. Census Bureau that provides detailed spatial distribution of workers' employment and residential locations and the relationship between the two at the census block group level (which is easily aggregated to census tracts). Details on age, earnings, industry distributions, and local workforce indicators are also available through this source.

Travel Behavior Analysis

We use the US Bureau of Transportation Statistics (BTS) Local Area Transportation Characteristics of Households (LATCH) product developed from ACS and NHTS data and especially its model coefficients.[52] BTS's LATCH development used 2012-2016 5-year ACS data (the most recent available at the time of their analysis). EBP leverages the findings of BTS's analysis along with 2015-2019 ACS (the most current available at the time of this analysis) to make more current estimates based on changing tract demographics. The ACS variables used in the analysis are shown in Table 44.

Table 44. ACS Variables Used in Travel Behavior Estimation

Variable	Formula (ACS Table ID | Variable)
Total Population	B01003
Household Income (Thousands $)	B19013e1 | HD01_VD01
1 vehicle available in household	B08201 | HD01_VD04
2 or more vehicles available in household	B08201 | HD01_VD05, HD01_VD06, HD01_VD07
1 worker household	B08202 | HD01_VD04
2 or more workers in household	B08202 | HD01_VD05, HD01_VD06
Life Cycle (1+ child <18)	B11005e2 | HD01_VD01
Life Cycle (1 person household, <65)	B11007e8 | HD01_VD08
Life Cycle (2+ person household, 0 65+)	B11007 | HD01_VD09
Life Cycle (2+ person household, 1+ 65+)	B11007 | HD01_VD04

Source: Table 7 from the LATCH Methodology document published by BTS

To use the appropriate modelling coefficients in the LATCH model, the Urbanicity Index classification was determined for each census tract in the fifteen states.[53] A tract's classification depends on whether its centroid is within an Urban Area (either a Census Urbanized Area or Urban Cluster) or Non-Urban area, and its population density percentile relative to all other tracts in the US using population reported in the ACS data. The Urbanicity Index includes a definition for suburban areas, which provides more detail than many systems that are simply use a binary urban-rural classification scheme. The definitions of the three classes of the Urbanicity Index were shown in Table 45.

[52] https://www.bts.dot.gov/latch/latch-methodology

[53] This follows the methodology described by the Bureau of Transportation Statistics (BTS) and used in the Local Area Transportation Characteristics for Households (LATCH) report. Table 5. Urbanicity Index: Count of 2010 Census Tracts by Category | Bureau of Transportation Statistics (bts.gov) (https://www.bts.gov/archive/subject_areas/national_household_travel_survey/methodology/list_of_figures_and_tables/table5)

The Urbanicity Index was determined using 2010 census tract and urban area boundaries. EBP used population estimates from the 2015-2019 ACS and census tract land area to compute the population density and density percentiles for all census tracts nationally.

Table 45. Urbanicity Index Definitions

Classification	UA/UC Designation	Population Density Centile
Urban	In UA	60 to 100
	In UCs	30 to 100
Suburban	In UAs	0 to 60
	In UCs	0 to 30
Rural	Not in UA or UC	N/A

The Urbanicity Index determination and demographic data from the 2015-2019 American Community Survey were then used in conjunction with the LATCH 2017 model coefficients for the appropriate census division[54] to estimate total daily household vehicle miles traveled (HH_DVMT) and total daily household vehicle trips.

Since the LATCH estimates represent average daily travel, each tract's estimated total VMT per household was annualized by multiplying by 294.11, the factor used in the 2016-2018 analysis, to facilitate comparisons to the published results. We also examined results based on higher annualization factors that resulted in a closer match of annual household VMT to other estimates of aggregate household travel. Total VMT generated in the tract was generated by multiplying the number of households by average annual household VMT. When estimating travel behavior there are 226 census tracts (out of 22,273 across the 15 states) with zero households for which not travel behavior is recorded.

Vehicle Data Preparation

There are four primary steps to develop data for the vehicle usage analysis:

- **Initial Screening for Valid Records**, where initial VIN registration records received from agencies are screened for being valid, with the resulting records intended to represent only registrations of state residents of their vehicles for personal passenger travel. Other records are eliminated from any further analysis.

[54] See LATCH 2017 Methodology Appendix A | Bureau of Transportation Statistics (bts.gov) (https://www.bts.gov/latch-2017-methodology-appendix), Northeast Region for Pennsylvania and New Jersey (Table_A1), South Atlantic Region for Delaware and North Carolina (Table_A3).

- **Fuel Type Determination**, where records are assigned a fuel type based on their match to either the NHTSA vPIC VIN decoding, or their own registration record. Where available, the NHTSA decoding is used because it provides a standardized source of fuel type data without the possibility for data entry errors as well as relating the records to appropriate make, model, and model years, which will become relevant later. Records without a recognized fuel type are eliminated from further analysis.
- **Vehicle Location Assignment to Census Tracts**, where records are associated with geographic locations. Where a record can be geocoded to a specific census tract, that tract is used; if not geocoded, a ZIP code provided in the registration data is used to allocate the vehicle proportionally to related census tracts.
- **Adding Fuel Efficiency Data**, where any record with a VIN decoding is associated if possible with fuel efficiency ratings. The result of the data preparation phase of the analysis is a series of files containing all vehicles that are used in revenue estimation, with their census tract identifier, fuel type, and fuel efficiency.

Initial Screening for Valid Records

Records are screened out of analysis for four key reasons: First, we remove records without any VIN provided. Second, we deduplicate the records by first ordering records by how likely they are to be eliminated by a subsequent step, favoring records that are not likely to be eliminated. Then, if a VIN appears more than once, we drop second and subsequent records, leaving the record most likely to be valid. The third screening is to remove records that were not in the scope of the study based on the registration data received, depending on the data definitions provided by states and the fields provided. (State-specific filters are recorded in the data processing scripts that will be transmitted as part of the Data Documentation.[55]) Fourth, if the best address data in the record indicates an out-of-state resident, the record is eliminated. Any record not eliminated via one of these screens passes on to subsequent steps; any record screened out does not and is no longer counted.

[55] As examples Texas included an 'Owner Type' column that required filtering to 'Individual' records, and Hawaii included a 'Status' column that required filtering to 'Active' records.

Fuel Assignment and Attribute Screening

To consistently identify make, model, year, and fuel type information, we use the National Highway Transportation Safety Administration (NHTSA) vPIC decoder.[56] A significant number of characteristics are recorded in a vehicle's VIN, which have been standardized since 1981. While most state's registration data includes similar information to that decoded by EBP using vPIC, vPIC use eliminates variation in how states record these fields and removes data entry errors during the registration process that can create inconsistencies.

The vPIC decoding uses 3 fields to indicate fuel type, "Primary Fuel"," Secondary Fuel", and "Electrification Level". This results in dozens of combinations of values. We created a lookup table to recode each combination of values to one of 10 distinct values: "Gasoline," "Diesel," "Hybrid," "Full EV," "Fuel Cell," "PHEV," "Natural Gas," "Flex Fuel," "LPG," and "Unknown." The table is called by the vehicle record processing scripts, both of which are included in the Data Documentation task. We combine Full EV (battery) and Fuel Cell in later analysis to Full EV, and Flex Fuel, Natural Gas, and LPG as "Other".

For vehicles where the fuel type is "Unknown", we use the fuel type provided by the state agency's data if available. As with fuel types decoded with vPIC, for each state, we recode fuel type codes to one of valid values (or none if indeterminate) and use a custom lookup table for each state's fuel codes to affect the recoding in record processing scripts. The crosswalks and scripts are included in the Data Documentation task.

At this stage, a record is eliminated from further analysis for one of the following reasons. First, if it had no NHTSA decoding. Second, if it was decoded but had poor quality in the make, model, or model year field. Third, if the record had no fuel type assigned to it after the process described above, it was eliminated. Finally, a record was eliminated if the body type as indicated by the NHTSA decoding was not in scope. The crosswalks and body type eliminated are provided in the Data Documentation task.

Vehicle Location Assignment to Census Tracts

This analysis seeks to represent the average characteristics of the vehicles in each census tract of a state for comparison to the census tract-based travel behavior estimates and

[56] https://vpic.nhtsa.dot.gov/

aggregate reporting using the census tract-based geographic classes. Most states do not maintain census tract information associated with their registration data. Instead, they provided other types of location data, which EBP used to identify or estimate the census tract with which vehicles were associated. This section describes the data types, tools and methods used for this assignment.

Types of Location Data Received

All states transmitted registrations including VIN data and some type of location information. We turn this location information into census tract information using a variety of methods. We summarize the approach for each state in Table 46.

Table 46. Each State's Provided Location Information and EBP's Method for Census Tract Allocation

State	Location Data	Method for Census Tract Allocation
Alaska	Street Number and Name, City, County, ZIP Code	Address Geocoding, Crosswalk of Failed Results
California	Street Number and Name, City, County, ZIP Code	Address Geocoding57, Crosswalk of Failed Results
Colorado	Street Number and Name, City, County	Address Geocoding
Hawaii	Street Number and Name, City, County, ZIP Code	Address Geocoding, Crosswalk of Failed Results
Idaho	Street Number and Name, City, County, ZIP Code	Address Geocoding, Crosswalk of Failed Results
Montana	ZIP+4 Code	ZIP+4 Geocoding, Crosswalk of Failed Results
Nebraska	Street Number and Name, City, County, ZIP Code	Address Geocoding, Crosswalk of Failed Results
New Mexico	Street Number and Name, City, County, ZIP Code	Address Geocoding, Crosswalk of Failed Results
Oklahoma	ZIP+4 Code	ZIP+4 Geocoding, Crosswalk of Failed Results
Oregon	Street Number and Name, City, County, ZIP Code	Address Geocoding, Crosswalk of Failed Results
Texas	Street Number and Name, City, County, ZIP Code	Address Geocoding, Crosswalk of Failed Results
Utah	ZIP Code	Crosswalk from ZIP to Census Tract
Washington	Census Tract	N/A
Wyoming	Street Number and Name, City, County, ZIP Code	Address Geocoding, Crosswalk of Failed Results

[57] Geocoding is the process of assigning geographic coordinates based on other types of location data. Most geocoding utilities produce outputs as geographic features with attributes, which can be used for mapping or spatial analysis.

Tools and Data Used

EBP applied a number of tools, both applications and data resources, during the workflow to assign VIN records to census tracts. Table 47 lists primary tools and summarizes their tools use.

Table 47. Tools and Sources Used for Census Tract Assignment

Tool	Application
R	Constructing address locators; preparing data for geocoding; spatial join of point locations to census tracts
ArcGIS Pro and ArcMap 10.8	Running geocoding utilities
TIGER/Line Files[58]	Constructing address locators;
ESRI StreetMap[59]	Postal extension address locator used to geocode states with ZIP+4 Codes
2010 ZCTA to Census Tract Relationship Files[60]	Proportionately allocating vehicles for which ZIP code data was available to census tracts if other geocoding processes failed

Geocoding Addresses

There are a number of steps involved in geocoding the address data.

Constructing Address Locators. EBP constructed distinct address locators considering relevant administrative boundaries in R for each RUC America state. The locates are based on 2019 US Census TIGER/Line data, dual range address shapefiles containing detailed street information,[61] town/city boundaries containing town/city and state names, and county boundaries containing county names (if county information was provided by the state).

Filtering Records. To exclude invalid records prior to geocoding, we filter each states' registration records for missing street addresses, PO boxes, or other non-physical

[58] The most recent available files were extracted during the analysis using the R package Tigris: Comprehensive R Archive Network (CRAN). Package 'Tigris': Load Census TIGER/Line Shapefiles. https://cran.r-project.org/web/packages/tigris/tigris.pdf

[59] Esri. ArcGIS StreetMap Premium. https://www.esri.com/en-us/arcgis/products/arcgis-streetmap-premium/overview

[60] US Census Bureau. Relationship Files. https://www.census.gov/geographies/reference-files/time-series/geo/relationship-files.html

[61] Dual range address files identify both sides of the street with information on Street Number and Name, City, State, and ZIP Code

addresses, addresses with invalid characters (e.g., %, /), out-of-state records,[62] and addresses that begin with 'BLDG'. All records that were filtered out were exported to a separate file and marked as excluded within a data tracking sheet.

Standardizing Data. Each state provided address data in a different structure, sometimes using a single field and sometimes using a variety of different fields. We condense each states' filtered records into two columns in R: 'VIN,' and 'Address,' the latter of which contained the street address, city, county (if applicable), state, and zip-code (if present) separated by commas.

Segmenting Data. The records containing address and VIN data were segmented into separate CSV files containing a maximum of 300,000 records. This was the number of records identified as functioning best with the version of ArcGIS and computing resources available to the team. These CSV files were then uploaded to ArcGIS to be geocoded.

Geocoding Records. We used the 'Geocode Addresses' tool in ArcGIS Pro or ArcMap to process the filtered, standardized, and segmented registration records through the state's address locator. The geocoding tool transforms the records into geographic point shapefiles if the registrant's address meets the 'minimum match score' and scores a high enough 'match score' when compared to the address locator's address listings. The 'minimum match score' is a geocoding setting that determines how well addresses must match their candidate in the address locator to be considered a match. A perfect match yields a score of 100. A match score between 75 to 100 can generally be considered a good match. Addresses that yield a match score lower than this threshold will not be considered and will result in an 'unmatched' result. To increase or decrease the flexibility of the address matching process, the minimum match score can be altered depending on the quality of the data. For the purposes of this project, we use a minimum match score of 75 to capture the maximum number of valid registrations while excluding clearly invalid/incomplete records.

Whether or not an address matches is determined by the detail and accuracy of the registration data, the completeness of the address locator, and the 'minimum match score' set by the geocoding options. If an input address falls below the minimum match score when being compared to the address locator, it results in an 'unmatched' result. However,

[62] Since address locators were state-specific, only in-state records can geocode successfully. By filtering out-of-state records earlier in the process for states with a disproportionate number of out-of-state records, this created a higher geocode success rate.

if an input address is above the 'minimum match score' but multiple addresses are feasible in the address locator, it results in a 'tied' result. Table 8 provides an example of possible geocoding match results and rationales for the subsequent matches.

Table 8: Geocoding Match Results and Explanations

<table>
<tr><th>Input Address</th><th>Address Locator Record(s)</th><th>Minimum Match Score</th><th>Actual Match Score</th><th>Result</th><th>Rationale</th></tr>
<tr><td>16 W Elm Street, Portland, OR, 01234</td><td>16 West Elm Street, Portland, OR, 01234</td><td>75</td><td>95</td><td>Matched</td><td>Input address and address locator record are above the minimum match score and are nearly identical (match score of 95/100).</td></tr>
<tr><td rowspan="3">16 Elm Street, Portland, OR, 01234</td><td>16 S Elm Street, Portland, OR, 01234</td><td rowspan="3">75</td><td rowspan="3">90</td><td rowspan="3">Tied</td><td rowspan="3">There are two or more address locator records with match scores above 75 that qualify as viable matches (match score of 90/100) for the input address.</td></tr>
<tr><td>16 W Elm Street, Portland, OR, 01234</td></tr>
<tr><td>16 N Elm Street, Portland, OR, 01234</td></tr>
<tr><td rowspan="3">Elm Street, Portland, OR, 01234</td><td>16 Olm Street, Portland, OR, 02134</td><td rowspan="3">75</td><td rowspan="3">70</td><td rowspan="3">Unmatched</td><td rowspan="3">Due to a lack of detail in the street address or incomplete address locator records, no record exists within the address locator that provides a 75%+ match for the input street address (match score of 70/100).</td></tr>
<tr><td>5 Elm Street, Portland, OR, 02134</td></tr>
<tr><td>70 E Street, Portland, OR, 02134</td></tr>
</table>

As depicted in Table 8, addresses commonly result in 'tied' results if the registration information lacks details present in the address locator's records, such as road directionality (e.g., 16 N Elm Street or 16 W Elm Street) or apartment number (e.g., 16 Elm Street, Apt. 5 or 16 Elm Street, Apt. 10). Addresses commonly result in 'unmatched' results if the registration information lacks key identification information (e.g., address number, address, city) or if the address locator's records are incomplete. On a small scale, 'tied' results could be manually reviewed and the appropriate address selected, if the reviewer is provided enough information to select. On a large scale, as was the case for RUC America, making manual corrections is not feasible. The 'tied' and 'unmatched' results were reviewed closely in aggregate, and common invalid address patterns were corrected (e.g., changing "N" to "North", adding additional administrative boundaries such as counties to improve matching) and the geocoding process was repeated. This maximizes the number of matches during the geocoding process.

Spatially Joining Records. After all records run through the geocoding tool, the point shapefiles (which include geometric data for the matched geocode records and attribute data for the tied and unmatched geocode records) are spatially joined to the respective state's census tracts using R functions. This resulted in the addition of a new column in the data table containing census tract IDs (GEOIDs) for which the matched VIN records were associated. All other location attributes are dropped from further analysis. The successfully geocoded and spatially joined GEOID & VIN data table was exported as a .RData file (similar to a csv file) to be used in the Vehicle Usage Analysis.

The tied and unmatched records are recorded in a separate file and marked as not geocoded within the data tracking sheet. A secondary census tract allocation method is applied to them as with other records without sufficient address information for geocoding (described below).

Geocoding ZIP+4 Data

For Oklahoma and Montana, based on the input data, the centroid of each ZIP+4 (ZIP code with additional delivery range information provided in the last 4 digits) is located and assigned XY coordinates using a geolocator developed by ESRI and acquired through their StreetMap product. This provides the approximate location of the registrant's address since the additional range information typically specifies the block on which someone resides. If geocoding fails, the first five digits of the ZIP+4 ID are used as described below. Like with point coordinates from address geocoding, we use a spatial join function in R to convert XY coordinates to census tract data.

Assigning Records Not Geocoded

The Census Bureau publishes a crosswalk that identifies the percent of households in each ZIP code tabulation area[63] that live in each census tract that intersects that ZIP code.

[63] ZIP code tabulation areas are a geography maintained by the Census Bureau that approximates the geographic areas as polygons based on the delivery route line files that ZIP codes represent. Many ZIP codes are not associated with any ZIP code tabulation areas because they represent a single delivery point (i.e., a bank, government, corporate, or university P.O. box).

Almost all ZIP code tabulation areas intersect multiple census tracts and almost all census tracts intersect multiple ZIP code tabulation areas.

Using the 2010 ZCTA to Census Tract Relationship File, a vehicle in a given ZIP code can be allocated to some number of associated census tracts using a weight.[64] We use the percentage of the population of the ZIP code in the census tract (the ZPOPPCT) as the weighting variable.

This method serves as the primary means for allocating vehicles to census tracts in Utah where only five-digit ZIP codes were available for location information. We also apply this method to all states that provided address and ZIP+4 information to include as many vehicles as possible for which those methods failed.

This results in assignment of fractional vehicles to census tracts. These fractional vehicles are interpreted as a probability that the vehicle is in one of these tracts or another and its characteristics can be proportionately included in summary statistics of each tract during vehicle usage analysis.

At this stage, records that had not been assigned a tract whatsoever were eliminated, as were records that were assigned a tract either not in any of the states of the study or not in the state the record was registered with.

Adding Fuel Efficiency data

We match decoded VIN data to fuel economy data from the EPA[65] to provide fuel economy. For dual-fuel vehicles such as plug-in hybrids and flex fuel vehicles, the fuel efficiency of both fuels was recorded for consideration. Combined fuel efficiency was recorded rather than the separate highway and city ratings. We do not adjust for different potential drive cycles of users in different geographic classifications.

[64] Some census tracts numbers needed to be updated, since the relationship file was produced in 2010 but updates to the 2010 census tract ID occurred to several census tracts following notes on changes in Arizona and California (https://www.census.gov/programs-surveys/acs/technical-documentation/table-and-geography-changes/2012/geography-changes.html) and Alaska (https://www.census.gov/programs-surveys/acs/technical-documentation/table-and-geography-changes.2015.html).

[65] Available at https://www.fueleconomy.gov/feg/download.shtm and https://www.fueleconomy.gov/feg/ws/index.shtml#vehicle.

EPA records are more detailed than NHTSA records and often contain trim and specific sub-model values. To match EPA data to the characteristics available from NHTSA, it is necessary to strip off some of these additional details from the model field. We adjust EPA data to match the naming conventions in the NHTSA data so there are common make, model, model year and fuel type attributes. This iterative improvement on naming consistency sometimes results in a one-to-one match between NHTSA-based processed registration and EPA data.

Approach when multiple possible matches

Where the modified EPA data has several records that repeat identical make, model, model year, and fuel type attributes, the efficiencies reported by the EPA are combined to create a single matchable record. Fuel efficiencies are consolidated using a harmonic mean[66] and one of two methods:

- If any of the individual records has associated data in EPA's My MPG[67] data sharing program, only those records were used. The number of responses for each record was used as a weight.
- Where there weren't any My MPG responses, no weights were applied when combining the efficiency for all records sharing the make, model, fuel type and model year.

Approach when no matches

For vehicles not covered in the EPA database, fuel economy information was matched from a databased developed from Fuelly.com's self-reported fuel efficiency.[68] The custom-developed look-up tables for vehicle make-model combinations filled with sources other than EPA data records are part of the Data Documentation delivery.

[66] There are three primary types of averages. The most common is the arithmetic mean. The alternatives, the geometric and harmonic means, are used for certain applications. In this case, because fuel efficiency is typically provided as miles-divided-by-gallons, the harmonic mean is the appropriate function for taking the average of ratios. This prevents bias towards higher efficiencies that would be produced by using the standard arithmetic mean.

[67] Vehicle owners self-report fuel efficiency to this program. In no case was the self-reported fuel efficiency used in our analysis, only the number of reports.

[68] https://www.fuelly.com/ provided a large database of user-reported fuel efficiencies for many of the vehicles for which EBP was seeking data. We were able to implement a web-scraping solution to efficiently leverage this data source.

Consideration of On-Road Recreational Vehicles

In addition to household vehicles for typical daily transportation purposes, EBP was also asked to consider on-road recreational vehicles (RVs) in revenue estimates. There are several components of the principal analysis that cannot be applied to RVs, so they are segregated from the general vehicle population for supplemental analysis. We analyzed RVs for all states except Hawaii, Oregon, Utah, and Washington, which did not provide significant numbers of RVs.

Determination of Annual Mileage

RVs are not covered by the LATCH travel behavior estimates. Most owners use RVs primarily for temporary travel rather than all daily trips. Because of this, they are not included in the definition of vehicles on which LATCH VMT estimates are based.

According to RV sellers, the industry average for RV VMT per year is approximately 5,000 miles,[69] although reported estimates by active users ranged from 4,000 – 8,000 miles per year.[70] After reviewing 20 vehicles on RV seller websites with vehicle years ranging from 1978 to 2022, the median miles/year was 3,700 miles, and the average miles/year was 3,864.[71] Due to the small sample size and presence of outliers (of the 20 vehicles the annual mileage ranged from 300 to 8,000), we apply the median RV vehicle miles per year.

As a point of comparison, the Federal Highway Administration's (FHWA) Highway Statistics Series (most recently updated in 2020) reports that single-unit trucks (which includes Class 5 (two-axle, six-tire vehicles – e.g. long-bed pickup trucks, sewage trucks, RVs) and Class 6 (three-axle vehicles – e.g. dump trucks, single tractors, and RVs) vehicles), averaged 12,278 miles traveled per vehicle in 2019 and 11,893 in 2020.[72] RVs are used less frequently than many of the other included vehicles.

[69] Bish's RVs. Understanding Miles per Gallon in an RV. 2021. https://www.guaranty.com/blog/understanding-miles-per-gallon-in-an-rv/#:~:text=The%20industry%20average%20for%20miles,a%20year%2C%20but%20it's%20rare.

[70] Bennett, Marc. RV Fuel and Mileage. 2020.; Renfro, Daniel. RV Mileage. 2020. https://www.metacamper.com/what-is-considered-high-mileage-for-an-rv/ ; Drivin & Vibin. High Mileage in an RV. 2021. https://drivinvibin.com/2021/12/03/high-mileage-rv/

[71] Craigslist. RVs for Sale by Owner. https://boston.craigslist.org/search/nos/sss?query=RVs ; RV Trader. Class A and Class C RVs for Sale. https://www.rvtrader.com/

[72] US DOT FHWA. Highway Statistics Series: 2019 and 2020. December 2021. https://www.fhwa.dot.gov/policyinformation/statistics/2020/vm1.cfm

Determination of Location

We geocode RVs using the same methods described above for other vehicles.

Recreational Vehicles (RVs) registered with addresses in RV parks do not produce successful address matches. This is because the addresses include RV park-specific address features (e.g., Space 5, Place 2, RV #3) that are not identified by street-based address locators. As with other failed matches, when possible, these are proportionately allocated using the ZCTA to Census Tract Relationship File.

Determination of Fuel Type

NHTSA vPIC is used to decode the RV VINs to determine fuel type. If vPIC is not successful, agency provided fuel type is used when possible. This methodology mirrors the methodology presented previously regarding VIN decoding.

As a final step, Flex Fuels were ignored because they were concentrated in a few low-quality records, and certain records where vPIC did not determine the fuel type were assigned to a type of Gasoline or Diesel because the make of the car was known to be only one or the other.

Determination of Fuel Efficiency

Light duty vehicles included in the study rely on fuel efficiency from EPA's fueleconomy.com or supplemental sources. RVs are not included in fueleconomy.gov and hence must always rely on a supplemental source.

RV sellers and active users report the average miles per gallon as 10-11 MPG of gas and 13-15 MPG of diesel for Class A (larger RV) and 13-20 MPG of gas and 16-25 MPG of diesel for Class C (smaller RV) vehicles.[73] (Both types are approximately equally represented in the RV buyers' market.[74]) The average of these ranges is 13.75 MPG for gas and 17.88 MPG for diesel, which we use as the baseline estimate for average RV fuel efficiency. Considering

[73] Southeast Financial. Average RV Class Miles per Gallon. March 2022. https://www.sefinancial.com/rv-loans/improve-rv-gas-mileage/#standardmpg ; RV Share. RV Gas Mileage. March 2022. https://rvshare.com/blog/rv-gas/ ; Top Notch Outdoor. Motorhome Gas Mileage. November 2020. https://topnotchoutdoor.com/motorhome-gas-mileage/

[74] RV Industry Association. RV Owner Demographic Profile. Oct 2021. https://www.rvia.org/news-insights/go-rving-rv-owner-demographic-profile-class-motorhomes#:~:text=One%20of%20the%20most%20common,66%25%20are%20ages%2055%2B.

that fuel efficiency is highly dependent on fuel type (e.g., diesel-powered RVs can get up to 30% greater fuel efficiency than standard, gas-powered RVs[75]), fuel efficiency is disaggregated by fuel type.

The FHWA's Highway Statistics Series reported the average miles traveled per gallon of fuel consumed for single-unit trucks as 7.5 in 2019 and 7.6 in 2020 (as a point of comparison).[76]

Updating Original Study Data

EBP was tasked with reviewing data from the previous study to ensure diesel vehicles were included in the revenue estimates because they had been explicitly excluded from the scope of the 2016-2018 study. During EBP's review of the 2016-2018 study it was determined that most states provided at least some diesel vehicle registrations and that EBP decoded the VINs associated with these records using vPIC. However, many of these vehicles were not assigned fuel efficiencies or included in further analysis. We add fuel efficiency data to these records to provide an updated dataset to input into a new vehicle usage analysis.

Vehicle Usage Analysis

The vehicle usage analysis includes incorporation of VMT information so that weighted results for geographic classes and statewide values reflect differences 1) the composition of the vehicle fleet across locations and 2) the relative intensity of use of any vehicle (of any fuel type) across locations.

Fuel type mix for each tract is calculated by the total count of vehicles in each fuel type category being divided by the total count of vehicles of any fuel type category. If a tract has households generating VMT but the registration data following census tract assignment contains less than ten registrations associated with that tract, its fuel mix is assigned as the average of all tracts in that state with the same geographic classification and sufficient vehicles for fuel mix calculation. Fuel type mix for geographic classifications is calculated as

[75] RV Share. RV MPG. March 2022. https://rvshare.com/blog/rv-gas/ ; Southeast Financial. Average RV Gas Miles per Gallon. March 2022. https://www.sefinancial.com/rv-loans/improve-rv-gas-mileage/

[76] US DOT FHWA. Highway Statistics Series: 2019 and 2020. December 2021. https://www.fhwa.dot.gov/policyinformation/statistics/2020/vm1.cfm

a weighted average of the fuel mix of each tract based on the total VMT of that tract (households times VMT per household). The state mix is calculated in the same manner.

Age metrics are also easily calculated by subtracting the Model Year from 2022 and calculating an average, weighted by the number of vehicles registered in each tract and geographic classification. Age metrics are not weighted by VMT.

Tract and class average fuel efficiency is calculated as a harmonic mean to accurately capture how ratios (miles-per-gallon) should be combined. The census tract-specific averages are a principal input to revenue estimates. Averages for geographic classifications are calculated as the harmonic mean of census tract values weighted by the total VMT of each tract.

To include alternative fuel registration surcharges in the revenue estimates, we estimate an adjusted count of vehicles per tract. This revenue component does not rely on VMT estimates (unlike the fuel tax component which used only vehicle mix information for estimation). Because there may be irregularities in the registration information available for analysis, we rely on ACS-based estimates of vehicles per tract. This should represent better matching between revenue from fuel tax and from registration surcharges.

Analyzing RV Records

RVs are excluded from all summarizations of fuel efficiency and fuel type that would be applied to LATCH-generated VMT. Instead, RV records were summarized by fuel type and fuel efficiency with their own aggregate VMT per tract calculated for inclusion in the revenue estimates.

Updating Original Study Data

The comparison data preparation included application of the original study's VMT estimates alongside the updated geographic classes (allowing comparison to geographic summaries of 2022 data). Tract-level fuel mixes and fuel efficiencies for fuel consumption estimation were re-calculated to include the previously excluded diesel vehicles.

Revenue Estimation

The final revenue estimation has three primary steps that leverage the data previously developed.

- Estimate Total Baseline Policy Revenue for tracts and states
- Estimate Revenue-Neutral RUC Rate for states
- Estimate Total RUC Revenue for tracts

Based on the data from these steps we report the revenue burden of baseline policies across the five geographic classifications and map contributions at the census tract level. We compare the baseline policy and RUC revenues at the tract level across geographic classifications, map them, and examine the distribution of revenue within geographic classifications.

To estimate the total baseline policy revenue for tracts and states, fuel tax rates reported by RUC America state representatives (Table 48) were multiplied by the estimated fuel use per fuel type per tract.

Table 48. Fuel Tax Rates Used Across Analyses ($/gallon or gallon-equivalent)

State	Study Vintage	Gas	Diesel*	CNG	LPG	E85
California**	2016-2018	$0.30	NA	$0	$0	$0.30
	2022	$0.59	$0.76	$0.09	$0.06	$0.09
Colorado	2016-2018	$0.22	NA	$0	$0	$0.22
	2022	$0.24	$0.22	$0.18	$0.14	$0.24
Hawaii, HI^	2016-2018	$0.15	NA	$0	$0	$0.02
	2022	$0.33	$0.33	$0.12	$0.11	$0.05
Honolulu, HI^	2016-2018	$0.17	NA	$0	$0	$0.02
	2022	$0.40	$0.40	$0.16	$0.17	$0.14
Kauai, HI^	2016-2018	$0.17	NA	$0	$0	$0.03
	2022	$0.39	$0.39	$0.15	$0.13	$0.06
Maui, HI^	2016-2018	$0.23	NA	$0	$0	$0.12
	2022	$0.33	$0.33	$0.12	$0.11	$0.05
Idaho	2016-2018	$0.32	NA	$0	$0	$0.32
	2022	$0.33	$0.33	$0.32	$0.23	$0.33
Montana	2016-2018	$0.27	NA	$0	$0	$0.27
	2022	$0.33	$0.30	$0.07	$0.05	$0.33
Oregon	2016-2018	$0.30	NA	$0	$0	$0.30
	2022	$0.38	$0.38	$0.38	$0.38	$0.38
Texas	2016-2018	$0.20	NA	$0	$0	$0.20
	2022	$0.20	$0.20	$0.15	$0	$0
Utah	2016-2018	$0.29	NA	$0	$0	$0.29
	2022	$0.32	$0.32	$0.18	$0.18	$0.32
Washington	2016-2018	$0.45	NA	$0	$0	$0.45
	2022	$0.49	$0.49	$0	$0	$0.49

Source: Fuel taxes from RUCW state representatives. Notes: * Diesel vehicles were excluded from the 2016-2018 analyses – it was assumed they would continue paying a gas tax. ** California fuel taxes consider both excise taxes and sales taxes but exclude tax revenue directed to local government operations for the purposes of this study. ^Local, county-based taxes reported for Hawaii.

We calculate fuel tax payments for each state by summing over all tracts in the state as shown in the formula below. Tract-level results are stored before aggregation. The fuel tax contribution of each fuel type is calculated individually for each fuel type as revenue policy rates differ by fuel type.

$$Total\ Baseline\ Policy\ Revenue = \sum_{tracts} \sum_{f} \left(Fuel\_Tax_f * \frac{VMT_{f,tract}}{FE_{f,tract}} + Reg\_Surcharge_f * N_{f,tract} \right)$$

WHERE: Fuel_Tax$_f$ is the fuel tax rate in cents/gallon , for the given state for fuel type **f***,*
VMT$_f$ is the annual VMT of all households in a tract for fuel type **f***,*
FE$_f$ is the fuel efficiency for fuel type **f** in each tract,
Reg_Surcharge$_f$ is a flat registration fee charged for some fuel types **f**, and
N$_f$ is the number of vehicles estimated by ACS for each tract allocated to each fuel type **f.**

The VMT by fuel type is developed in the early stages of the analysis from decoded VIN data aggregated to tracts in the Vehicle Usage Analysis stage. As a reminder, this summarization of the vehicle fleet results in all vehicles in a census tract producing the same VMT (as estimated using LATCH). The exception to this rule is the on-road recreational vehicles separated out in the vehicle data preparation and to which VMT was assigned separate from the LATCH-based analysis.

The fuel efficiencies for each fuel type are also summarized during the Vehicle Usage Analysis stage, including summarization using harmonic means for the various fuel types analyzed. Like with the VMT of vehicles of the same fuel type being set equal in this analysis, we apply the same average fuel efficiency to all VMT of a given fuel type. RVs represent an exception as they are assigned a different efficiency than vehicles that were matched to the EPA databases and the average of these RV efficiencies is applied to RV VMT.

To calculate the number of vehicles estimated by ACS per tract, we aggregated the following ACS variables and multiplied by number of households per tract: '1 Vehicle per Household', '2 Vehicles per Household', '3 Vehicles per Household', and '4+ Vehicles per Household'. We assume that '4+ Vehicles per Household' is equivalent to 4 vehicles for the purposes of the analysis, as the ACS does not provide granularity beyond the 4-vehicle threshold.

Fuel tax rates are zero for some fuel types (full electric vehicle VMT and the electric share of plug-in hybrid VMT as well as other fuel types in some states). Registration surcharges are only considered for full electric vehicles and plug-in hybrid vehicles.

For PHEVs, we assume that 56 percent of all miles were driven using only electricity.[77] This was incorporated into the calculation above by multiplying the VMT by the percentage of miles driven on conventional fuel (44 percent). For flex fuel vehicles, fuel consumption is adjusted to reflect the lower energy density of ethanol relative to gasoline. We assume that flex fuel vehicles are fueled by ethanol 33 percent of the time.[78] We do not adjust for the fact that most gasoline sold is E10.

We calculate a revenue-neutral RUC rate by dividing each states total baseline policy revenues by the state total annual VMT. This VMT calculation includes all fuel types without any weights and has no detail below the state-level. We assume all in-scope vehicles (including RVs) are covered by a single RUC rate. The rate assumes full policy compliance and is calibrated so that household costs are exactly equal under the baseline polices and RUC policies. There is no adjustment for collection costs or implementation costs (such as mileage recording equipment).

In the final step of revenue estimation (before results tabulations and visualizations), the state-specific RUC rates are applied to total VMT in each tract to estimate the total and per-household RUC payments for comparison to the baseline policy revenues. The analysis assumes all vehicles pay RUC and therefore all registration surcharges meant to replace fuel tax revenue are no longer applicable.

[77] This number was based on EPA estimates, weighted by vehicles reported in EPA's My MPG reporting.

[78] This number was determined using flex fuel vehicle models reported both in EPA fueleconomy.com (providing E85 and gasoline fuel efficiencies) and Fuelly (providing effective MPG). These vehicles' efficiencies were averaged using the count of vehicles reported in Fuelly as a weight for each make-model-year record.

Appendix E: Data Documentation

This documentation records the data sources, files, and scripts EBP leveraged. With the exception of vehicle registration data received, this document and accompanying data and code files should allow an analyst to reproduce EBP's analysis.

In this document, file names are italicized and an asterisk (*) is used in place of dates in file names, for example *MyRScript_*.R* or *MyData_*.xlsx.* Dates serve to version files with the date produced or updated. Dates are replaced by an asterisk (*) for simplicity in this document.

Scripts are presented in sequential order of EBP's workflow. Scripts use the *here* package's function *here()* to refer to a project workspace, providing indirect file paths. Unless otherwise indicated, every script documented uses the same root directory using *here()* calls. Inputs are saved within the subdirectories of the root folder and scripts also write outputs within the project workspace.

The subsections *Input Files* below describe required files that are not generated in the workflow of that section.

Classify Tracts

Input Files

CensusTracts_UAC-Revised.xlsx is an input table created by EBP in ArcGIS which identifies which tracts have centroids within urbanized areas or urban clusters.

The file *cbsa_to_county.xls* has reference tables showing core-based statistical area (CBSA) to county relationships from the Census.

Workflow and Scripts

DetermineUrbanicity.R

Purpose: Provide tract-level urbanicity classifications. 'Urbanicity' is a measure used in the travel behavior estimates and not a final metric used in results reporting.

- Takes as input CensusTracts_UAC-Revised.xlsx

- Uses the tidycensus package to download additional census data
- Produces *TractsUrbanicity_*.csv* file

CompileTractCharacteristics.R

Purpose: Classify each tract in the study states as one of five area types.

- Takes TractsUrbanicity_*.csv and cbsa_to_county.xls files
- Produces Geographic Classifications_50-50_*.xlsx file, which represents the geographic classifications for the current study

Estimate VMT by Tract

Input Files

The file *clean_latch_coefficients.xlsx* is manually prepared from Appendix A of the LATCH Methodology (https://www.bts.gov/latch-2017-methodology-appendix).

Tract_Data_For_Classification_50-50_*.csv is a copy of the Geographic Classifications tab in *Geographic Classifications_50-50_*.xlsx*, which is produced by *CompileTractCharacteristics.R*.

The file *nhts_2009_transferability.sas7bdat* is a SAS-formatted file downloaded from the NHTS 2009 archive (https://www.bts.gov/latch/latch-data).

OriginalStudyGeoClasses.xlsx is extracted from results files of EBP's 2016-2018 study data and provides tracts classifications as Urban, Mixed, and Rural.

CENSUS_TRACT_PATCH.xlsx was manually prepared to correct 2010 tracts that were renumbered to correct errors. This is necessary so that all input data of 2010, 2019, or other vintage uses the same census tract IDs. Less than 10 tracts have changed their official numbering.

The file *zcta_tract_rel_10.txt* shows the relationship between 2010 census ZIP-code tabulation areas (ZCTAs) and census tracts. It is downloaded from the Census Bureau. We use this to proportionately allocate vehicles for which only ZIP code location data is provided to census tracts. See https://www.census.gov/geographies/reference-files/time-series/geo/relationship-files.2010.html.

Workflow and Scripts

Estimating_VMT_v1.R

Purpose: Provide tract-level VMT estimates using LATCH methodology.

- Takes *TractsUrbanicity_*.csv* and *clean_latch_coefficients.xlsx*
- Applies the appropriate coefficients from LATCH to the characteristics of each census tract to estimate travel behavior
- Produces *t_tract_travel_characteristics_*.csv*

Compare_2009to2019LATCH.R

Purpose: Compare previous to current LATCH estimates, adjust if necessary.

- Takes the following input files:
    - nhts_2009_transferability.sas7bdat
    - OriginalStudyGeoClasses.xlsx
    - Tract_Data_For_Classification_50-50_*.csv
    - CENSUS_TRACT_PATCH.xlsx
    - t_tract_travel_characteristics_*.csv
- Produces *Updated_Travel_Behavior_Estimates_*.xlsx,* which is then manually adjusted for some census tracts that changed between 2010 and 2019. See notes in the *README* tab.

MakeTractsMaster.R

Purpose: Compare classified tracts to list of all existing/known tracts.

- Takes zcta_tract_rel_10.txt
- Calls an API to access TIGER products (using the R package tigris)
- Produces TractsMaster_*.xlsx, which includes a list of tracts associated with each state (corrected for documented changes in census tract definitions between 2010 and 2019)
- Includes a mapping of ZCTA codes allocated by percent to census tracts

FinalTractVmt.R

Purpose: Associate VMT with all tracts that have a geographic classification.

- Takes Updated_Travel_Behavior_Estimates_*.xlsx and TractsMaster_*.xlsx
- Produces Tracts with VMT *.xlsx, to combine the VMT and tract classifications into a single listing of all census tracts for the given states

Vehicle Analysis

The following process assigns registration records from the current and previous studies standardized vehicle attributes, including make, model, model year, fuel type, and fuel efficiency. Not all transmitted records are successfully assigned standardized attributes.

Years

The vehicle analysis refers to all VINs and files pertaining to the current year as “2021” (including in file naming conventions and scripts), and all files pertaining to previous studies as “2018”. This differs from other study components where “2022” and “2017” are used.

Registrations

“Record” refers to a single row of data, not necessarily a single vehicle or single VIN. For some states, a record represents multiple vehicles, given by the *veh_count* variable with VINs given in a truncated 11-digit form. For the majority of vehicles sold in the United States after about 1981, VINs are 17 alphanumeric characters. Positions 1-9 and 11 convey information about the attributes of the vehicle, so the NHTSA decoding API only requires a string with 11 characters. Position 10 is a check sum that is replaced with an asterisk for decoding.

Valid Records

Each script of the form *Step* operates on a list of records, and each script marks some of these records as not valid for further analysis. Once marked not valid, they are not analyzed further. (They are still tallied with an indicator that they were filtered out in a previous step.) “Valid” records means records that are not eliminated from further analysis.

Input Files

A series of *JoinedVINS_[ST].RData* files, so named because location information has been geocoded to points and then spatially joined to census tracts. In Texas and Colorado, these are broken in the files: *JoinedVINS_TX_Part1.RData*, *JoinedVINS_TX_Part2.RData*, *JoinedVINS_TX_Part3.RData*, and *JoinedVINS_CO_Part1.RData*, and *JoinedVINS_CO_Part2.RData*. These files are not transmitted with the data documentation as they include VINs from the states.

The file *vehicles.csv* is a file with EPA's estimate of fuel efficiencies for several thousands of vehicles.

*Vehicles Resources *.xlsx* includes several sheets that are used to recode registration data fields.

The file *zcta_tract_count_10.txt* shows the relationship between 2010 census ZIP-code tabulation areas (ZCTAs) and counties. See https://www.census.gov/geographies/reference-files/time-series/geo/relationship-files.2010.html.

FuellyEfficiency_*.xlsx is a collection of data points from Fuelly.com.

Registration files were obtained from 14 states. These are not included in this transmission, but the names of referenced files are in scripts. Most were in .csv or .xlsx format; sometimes these files are themselves pre-processed minimally so that they can be read easily by an R script. (e.g., parsing a file that was not in a .csv or .xlsx form.)

Registration files from previous studies were adjusted to be consistent with new data and named using the convention *[st]_2018_master_part_[xx].Rdata.* Scripts below are used on records from both years.

Workflow and Scripts

MakeStep1Masters.R

Purpose: Standardize registration data.

- Takes registration files as described in Input Files.

- Filters out records that are clearly not uniquely identified (that is, they have no VIN or a duplicated VIN) or not private passenger vehicles, based only on the registration data. (That is, no attempt to match data to NHTSA decodings is made at this stage.)
- Produces a series of .RData files representing all the records of VINs in a standardized format named using the convention [st]_2021_master_part_[xx].Rdata (examples include nm_2021_master_part_1.RData and tx_2021_master_part_23.RData). Parts have a fixed length to make processing feasible given memory constraints. No records are eliminated in this dataset.
- Produces a list of "partial" or "squished" VINs in the file squished_vins_byState_*.RData. Duplicate raw VINs are eliminated before being aggregated to unique squished VINs.
- Produces other_vins_*.RData for VINs that aren't 17 characters. This is for archival purposes and is not further processed.
- Produces Step 1 2021 Summary *.xlsx for auditing and informational purposes. For prior studies, Conversion *2018 Summary *.xlsx* is an analogous summary file.

*AssignVinsNhtsa *.R*

Purpose: Decode VINs with NHTSA API

- Takes squished_vins_byState_*.RData.
- Produces DecodedVins_*.xlsx, an offline database of all squished VINs needed to cover unique vehicles in the dataset.
- Assumes existence of a DecodedVins_*.xlsx file containing some previous decodings, but can be adapted to ignore this.
- It saves time to not requery the API but otherwise there's no functional reason to avoid doing so.

MakeStep2Masters.R

Purpose: Determine registration fuel types per NHTSA data.

- Takes as input the *.RData* files from *MakeStep1Masters.R* and files representing registrations from previous study in the format *[st]_2018_master_part_[xx].Rdata.*
- Takes as input the VIN attributes decoded with NHTSA vPIC and stored in *DecodedVins_*.xlsx* and lookup tables in *Vehicles Resources *.xlsx*.

- Filters out records that cannot be matched to a NHTSA decoding, have poor decoding data, or which are not in the scope according to the decoding. (The only exceptions are motorhomes, which are not filtered by decoding quality.)
- Marks remaining records valid and belonging to one of the following categories:
    - Has a NHTSA-determined fuel type
    - Has a fuel type indicated by the registration data
    - Is NHTSA-decoded and is a motorhome (in which case, the fuel type may or may not be indicated)
- Produces a new set of .Rdata files in the same format as those produced by *MakeStep1Masters.R.* To conserve memory, records that were not an in-scope or valid registration (at the end of Step 1) are dropped from the data. (In later steps, records are conserved even if they are not further analyzed.) This has no impact on further analysis other than to make loading data less memory-intensive.
- Produces a summary report, *Step 2 Summary *.xlsx*.

MakeStep3Masters.R

Purpose: Assign a Geocoded Census Tract

- Takes as input the .RData files produced in MakeStep2Masters.R, the JoinedVINS_[ST].RData files, and Vehicles Resources *.xlsx. Only for states geocoded to census tracts for this study.
- Filters the geocoded records for invalid tracts, a missing VIN, or a duplicate VIN.
- Joins the tract ID to the respective master vehicle record in the new field tract_geocoded.
- Does not filter the respective master vehicle records.
- Produces a set of .RData files in the "master" format described above.

MakeStep4Masters.R

Purpose: Assigning a Census Tract for non-geocoded records

- Takes as input the .RData files produced in MakeStep3Masters.R , Vehicles Resources *.xlsx, and the ZIP-to-tract allocation scheme of TractsMaster_*.xlsx
- If a record had a census tract provided by the state or as part of the previous study, the record is assigned to that tract
- If a record was successfully matched in MakeStep3Masters.R, it is assigned to that tract
- If a record's ZIP code has an associated ZCTA, the record is duplicated once for each of the matching tracts, and the ZIP code's vehicle count is allocated proportionally to each corresponding tract

- Not all ZIP codes correspond with a ZCTA, since some ZIP codes represent only a point-location of a post office or major commercial or institutional address
- The ZCTA-Tract relationship is many-to-many, which is causes the necessity for duplication and proportional allocation

- Filters out records where no tract was determined in any of these ways or if any tract allocated to any record was out of the state or otherwise invalid
- Produces a set of .RData files in the “master” format described above containing the field tract with the associated ID and the field geo_category recording which of the four assignment methods was used; the field tract_geocoded is dropped as it’s now redundant

GetMpgData.R

Purpose: Retrieve supplementary EPA data.

- Takes as input vehicles.csv
- For vehicle ids provided in the vehicles.csv file, Mpg_Data_*.xlsx provides data fetched from EPA website on data provided by My MPG participants
- Produces *Mpg_Data_*.xlsx*

AssignVpicEfficiency.R

Purpose: Match fuel efficiency to NHTSA VINs

- Takes as inputs *Vehicles Resources *.xlsx*, *FuellyEfficiency_*.xlsx*, *Mpg_Data_*.xlsx* and *DecodedVins_*.xlsx*
- Creates lists of vehicles uniquely identified by make, model, model-year and fuel type for the three data sources used, after recoding to harmonize the data sources:
    - NHTSA decodings, which have squished VINs that are references in master vehicle records
    - EPA fuel efficiency ratings
    - Fuelly fuel efficiency ratings
- Associates NHTSA’s squished VINs with fuel efficiencies by attempting to match to EPA rating first, then Fuelly rating
- Produces *Vpic Fuel *.xlsx*

MakeStep5Masters.R

Purpose: Assign fuel efficiency to master records.

- Takes as input the .RData files produced in MakeStep4Masters.R, Vehicle Resources *.xlsx, and Vpic Fuel *.xlsx
- If the registration record was associated with a NHTSA record (via the squished VIN), and the NTHSA record was associated with an EPA or Fuelly fuel efficiency (in the Vpic Fuel *.xlsx file), the registration record was assigned that fuel efficiency
- Failing that method, a match with the fuel type given by the registration record was used and a match attempted with the EPA fuel efficiencies then the Fuelly fuel efficiencies, in each case using make, model, model year and fuel types
- Produces a set of .RData files in the "master" format described above but containing fields indicating the estimated fuel efficiency of the primary fuel, the secondary fuel and the percent of miles travelled that relied on the primary fuel

SummarizeMpgByTract.R

Purpose: Summarize details.

- Takes as input the .RData files produced in Step 5, Vehicles Resources *.xlsx, and DecodedVins_*.xlsx
- Summarizes efficiency and age data by tract, as well as some special tabulations depending on the state that are needed to determine registration fees
- Produces efficiency_byTract_*.RData, special_bins_byTract_*.RData, and rvs_*.RData (and analogous .csv files for each)

ProcessMpgByTract.R

Purpose: Process Summary Files

- Takes as input Vehicles Resources *.xlsx, Tracts with VMT *.xlsx, efficiency_byTract_*.RData, special_bins_byTract_*.RData, and rvs_*.RData
- Reshapes and further processes efficiency data and age as well as some special tabulations depending on the state
- Produces Tracts Wide *.xlsx

Revenue Estimation

Input Files

*TaxRate_Surcharge_Inputs *.xlsx,* a table of all the confirmed fuel tax rates for each fuel type by state and each states registration surcharges as considered in the analysis.

The file *tracts15.xlsx*, a table of census tracts in Hawaii.

Workflow and Scripts

REA_Data_Prep.R

Purpose: Collates tract-level data to prepare for calculating financial impacts.

- Takes the following:
  - *Tracts Wide *.xlsx*
  - *TaxRate_Surcharge_Inputs *.xlsx*
  - *tracts15.xlsx*
  - *Updated_Travel_Behavior_Estimates_*.xlsx*
  - *Tracts with VMT *.xlsx*
- Merges vehicle, travel, geography, and tax and surcharge rate information for each tract and restructures data for further processing
- Produces *Tracts Compiled *.xlsx*

RevenueEquityAnalysis.R

Purpose: Calculate financial impacts by tract.

- Takes as input Tracts Compiled *.xlsx
- Calculates fuel consumption, fuel tax paid, and surcharges paid for each tract
- Calculates state-level current policy revenue and estimates a revenue-neutral RUC rate
- Calculates tract-level RUC paid and tract-level differences between policies
- Produces REA_by_Tract_*.xlsx and REA_by_State_*.xlsx.

RUCWest_UrbRur_Datasets_Phase2_Comp_*.xlsx is a formatted version of REA_by_State_*.xlsx.