Financial Impacts of RUC on Super-Commuters Study

Final Report

RUC America and California Department of Transportation

JANUARY 2024

RUC AMERICA
New paths to road funding

EBP

Executive Summary

In 2023, EBP conducted a Road Usage Charge (RUC) impact study on behalf of RUC America and Caltrans focused on the impact of a RUC on super-commuters in California. In this study, super-commuters are defined as car, truck, or van commuters who commute 90 or more minutes to work in one direction and make up approximately 3.7 percent of car, truck, or van commuters in California. These commuters travel long distances to work for a number of reasons, including but not limited to the high price of housing and cost of living in and adjacent to major metropolitan areas (e.g., Los Angeles and San Francisco Bay), the greater density of job opportunities in these metro areas compared to more limited job opportunities outside these areas, and the requirement of certain professions to travel long distances for work (e.g., workers in the construction, mining, extraction, or transportation industries).

In this report, we consider not only the impacts of a RUC on super-commuters by geography (e.g., rural vs. urban), but also by income, by race/ethnicity, and by occupation, to understand impacts of a RUC on different super-commuting groups (e.g., the impacts of a RUC on high vs. low-income super-commuters). The study areas for the analysis included Los Angeles and San Francisco Bay areas, which have a large percentage of workers who super-commute.

The study began by determining the geographic areas that super-commuters travel to and from and identifying counties that receive or send a high percentage of super-commuters. The study areas were confirmed as the Los Angeles and San Francisco Bay Areas by performing a geospatial analysis on employee home/work data.

The study determined the demographic characteristics (e.g., race/ethnicity, income, educational attainment, industry, occupation, etc.) of super-commuters in California compared to non-super-commuters (who drive less than 90 minutes to work). Super-commuter travel behavior and vehicle characteristics (e.g., fuel efficiency) were determined by evaluating and synthesizing several national and state-level data sources, including Construction industry apprentice and work site location data provided to the study team by the NorCal Carpenters Union and California Transportation Commission. We found that there are distinct groups of super-commuters that emerged from the analysis. Super-commuters are a diverse group that include a variety of road users with different demographic characteristics, travel behavior/patterns, and vehicle characteristics. Our analysis discovered the following patterns about super-commuter groups in the state of California:

- **Occupation:** Jobs in construction, extraction, repair, and maintenance have the highest representation of super-commuters (18.8 percent) followed by managerial roles (12.5 percent).
- **Occupation and Income:** Super-commuters with managerial roles had the greatest representation in higher personal earnings groups (38.4 percent making $200,000+ annually). Super-commuters with construction, extraction, repair, and maintenance roles had the greatest representation in low (less than $25,000 annually) and middle ($100,000 to $149,000 annually) income groups.
- **Race and Ethnicity**: Hispanic populations represent the largest percentage of super-commuters (42.4 percent), followed by White populations (34.9 percent) and Asian populations (12.9 percent).
- **Race, Ethnicity, and Income:** Asian super-commuters had the greatest representation in higher personal earnings groups (19.7 percent making $200,000+ annually). White super-commuters had the greatest representation in the mid-to-high personal earnings groups ($75,000-$199,000 annually). Hispanic super-commuters had the greatest representation in the lower income groups (53 percent making less than $25,000 annually; 45.1 percent making $50,000-75,000 annually).
- **Travel Behavior**: The 5+ person carpool category had the highest number of super-commuters as a percent of total car, truck, and van commuters (12.7 percent). This indicates that super-

A Tale of Two Super-Commuters

Overall, there are two typical types of super-commuters in California. One type drives a more fuel-efficient vehicle than the average Californian and is likely to work in managerial roles and be Asian or White.

This super-commuter may pay more in a shift to a road charge system because they are not currently contributing an equal amount to road maintenance in the gas tax system.

The second tends to work in the construction, transportation, mining, or extraction industries, be lower-income, more likely to be Hispanic, and drives a less fuel-efficient vehicle.

This super-commuter will pay less in a shift to a road charge system because they currently contribute more than average to road maintenance in the gas tax system.

commuters are more likely than non-super-commuters to carpool to work with several other commuters.

- **Vehicles:**
    - High mileage vehicles overall tend to be newer and have better fuel efficiency than their low and medium mileage counterparts. Electric cars are still uncommon but tend to have low- to -medium annual mileage (less than 20,000 miles per year). Super-commuters may not currently have confidence in the range of full electric vehicles.
    - Super-commuters are less likely to drive SUVs compared to non-super-commuters and are more likely to drive vans compared to non-super-commuters (8.3 vs. 5.7 percent).
    - The super-commuter group had a higher percent distribution in the 20 mpg or lower and 31 mpg or higher groupings, indicative of a diverging vehicle efficiency pattern for distinct types of super-commuters.
    - Super-commuters are more likely to own new or very old cars, compared to non-super-commuters.

A revenue equity analysis was conducted comparing the estimated amount that super-commuters (and non-super-commuters) pay in fuel taxes and registration surcharges versus a revenue-neutral RUC revenue.[1] The analysis shows that:

- **The largest determinant to the impact of a RUC on a given road user is the fuel efficiency of the car.** The second largest determinant is the annual mileage of the road user's vehicle.
- On average, super-commuter payments under a RUC will increase slightly, but when super-commuters are segmented by race, ethnicity, income, and occupation group, it is clear that **under a RUC, some super-commuters will experience payment increases and some will experience net savings.**
- The **commuters who save the most are those who currently drive fuel inefficient vehicles long distances.** Those that will see large increases drive highly efficient vehicles long distances. Commuters who drive more moderate distances or vehicles of more average efficiency see smaller impacts of a RUC transition.
- When considering disaggregate results, on average, **switching from existing gas taxes and surcharges to a RUC does not meaningfully increase the burden of revenue payments**, and in some cases, reduces payments for super-commuters.

[1] Mirroring the 2021-2022 Rural-Urban Equity analysis, the revenue neutral RUC rate was calculated as the sum of the statewide baseline revenue (fuel taxes and registration surcharges) divided by the sum of statewide vehicle miles traveled.

Contents

Introduction

This report provides data analysis results, visualizations, and insights related to the financial impact of a transition from fuel taxes to a road usage charge (RUC) on super-commuters – workers that commute more than 3 hours per day round trip. It explores whether super-commuters would pay more under a road charge than fuel taxes.[2] The analysis focuses on the metropolitan areas of San Francisco Bay and Los Angeles ("study areas"), where many workers are making the long commutes into employment centers. The study focuses on car, truck, and van commuters since these travelers directly pay fuel taxes while commuting.

Decision-makers need information on how household finances for key traveler types may change if a RUC replaces current revenue sources. From 2010 to 2019, the number of super-commuters in the US has increased 45 percent, with 33 percent of all super-commuting occurring in the New York City, Los Angeles, and San Francisco areas.[3] While super-commuters in the San Francisco Bay and Los Angeles areas are key constituencies, many of California's super-commuters live in other parts of the state, such as the Central Valley, which includes the two metros with the highest rates of super-commuting nationally (11.7% of Stockton's and 9.6% of Modesto's workforce).[4]

In California and elsewhere, the super-commuter population has diverse characteristics. Low housing stock and high housing prices drive workers to the periphery of metropolitan areas and beyond, but long commute times are attributed to factors beyond distance, including traffic congestion and limited public transit outside of metropolitan area cores. Super-commuters also include remote/hybrid workers who tend to be higher-income workers, raising a full range of potential equity considerations for how policy changes affect traveler types.

The study identifies study populations, geographies, demographics, vehicle characteristics, and travel behavior of super-commuters to determine the impact of a RUC transition on

[2] The fuel tax regime includes registration surcharges for electric vehicles. More information about applied registration surcharges can be found in the 'Payments Under Existing Policy' section.

[3] Salviati, C., and Warnock, R. Explosion of Super Commuters Offers Lessons for Sustainable Growth. 2021. https://www.apartmentlist.com/research/explosion-of-super-commuters-offers-lessons-for-sustainable-growth

[4] Salviati, C., and Warnock, R. 2021.

super-commuters in California. It looks at multiple data sources including the American Community Survey (ACS) summary tables and Public Use Microdata Sample (PUMS), the Longitudinal Employer-Housing Dynamics (LEHD) program, and the National Household Travel Survey (NHTS) and its large California sample, California Bureau of Automotive Repair smog check records, and California Department of Motor Vehicle sales transaction data. This variety of data sources allows us to understand super-commuters from different perspectives and compensate for weaknesses of some data sources. Moreover, as these datasets are available for different timeframes, there are slight variations that we observe across some characteristics throughout our analysis of super-commuters.

In addition to sections on the pattern of major factors in determining revenue burden, current policy and RUC revenue patterns, the report contains appendices providing supplemental materials and documenting the methodology applied during the analysis as well as details on supporting data and scripting.

Geography of Super-Commuters

Study Areas

Prior to identifying characteristics of super-commuters, it was first necessary to identify the areas in which super-commuters live and work. Though super-commuters are present across the state, the study aimed to identify areas in which high concentrations of super-commuters were present to better understand the spatial patterns of these long-distance commuters. Once these spatial patterns were identified, the study could dig deeper into the reasons behind the super-commuting patterns, and the characteristics of people (and their vehicles) that super-commute.

Using American Community Survey (ACS) summary table data from the US Census (2017-2021)[5], travel time to work by home geography and workplace geography was analyzed for commuters traveling >= 90 minutes one-way. These datasets are not segmented by mode, so this analysis was inclusive of all travel modes while other analysis focuses on super-commuters that drive cars, trucks, or vans.

Super-Commuter ‘Receivers’

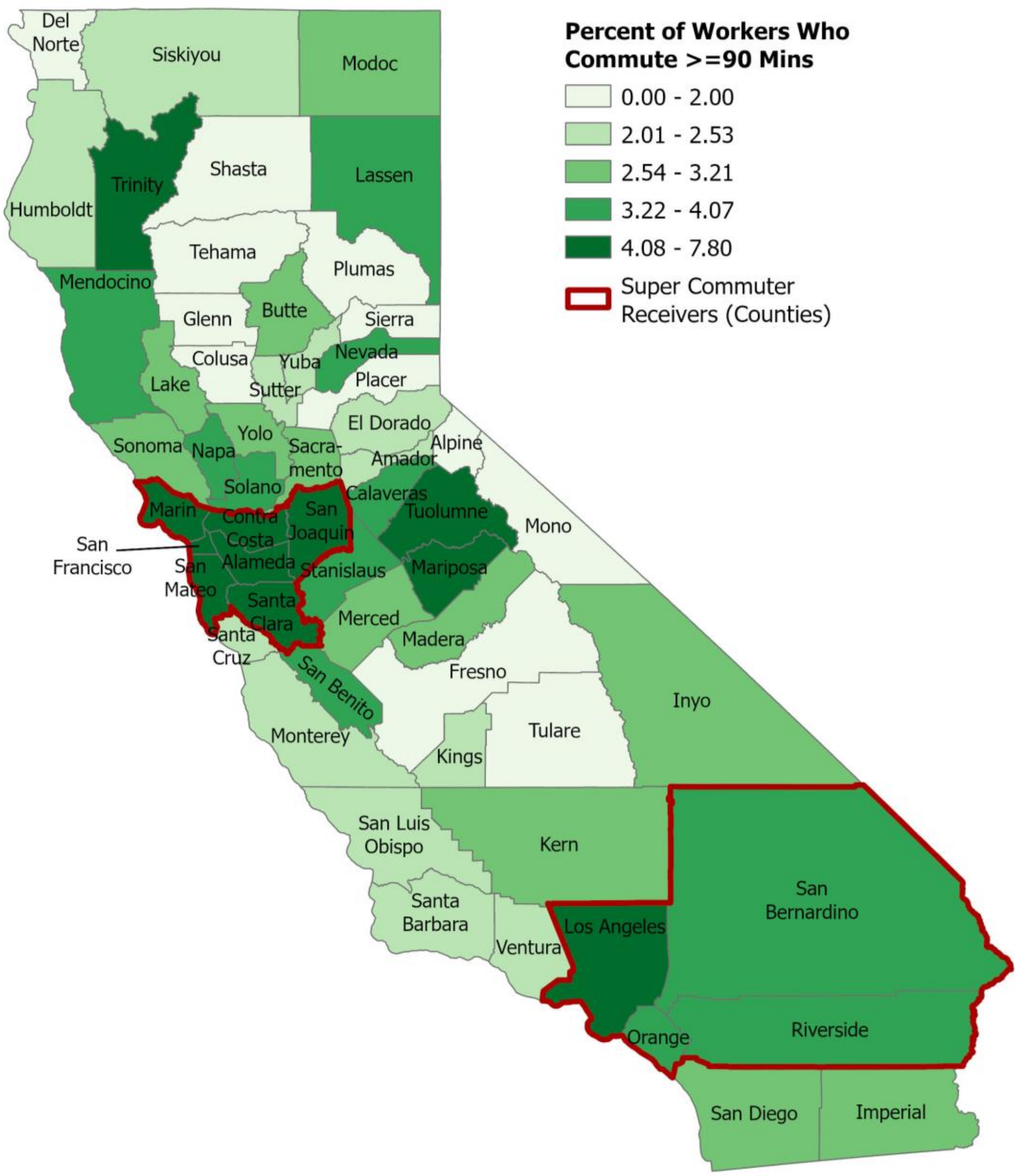
The assumption prior to the study was that the Los Angeles and San Francisco Bay areas were likely ‘receivers’ of high concentrations of super-commuters due to the high number of jobs in these locales combined with the cost of living in/near both areas. The ACS summary table analysis supported this assumption and found that 7.8 percent and 4.8 percent of commuters to San Francisco (SF) County and Los Angeles (LA) County, respectively, traveled >= 90 minutes one-way to work. Surrounding counties for both SF and LA counties additionally reported a high percent of workers who traveled >= 90 minutes one-way (Figure 1; Table 1).

Figure 1 highlights the determined study areas around LA and SF counties. The counties of Tuolumne, Mariposa, and Trinity also had a high percentage of workers who commuted >=

[5] US Census Bureau. 5-Year American Community Survey (ACS) Summary Tables. 2017-2021. https://www.census.gov/programs-surveys/acs/data/summary-file.2021.html#list-tab-1622397667

90 minutes. The scale of these employment markets and nature of commutes was determined to be sufficiently different that they were not highlighted in future study steps.

Figure 1. Percent of Workers with >= 90 Minute One-Way Commutes by Workplace (All Modes)



Source: EBP Analysis of American Community Survey (ACS) 5-Year Summary Tables (2021-2021), US Census Bureau.

Table 1. Percent of Study Area County Workers that Commute >= 90 Minutes One-Way (All Modes)

County Workplace	Percent >=90 Minute Commuters
San Francisco County	7.8%
San Mateo County	7.5%
Alameda County	6.5%
Santa Clara County	6.1%
San Joaquin County	4.9%
Contra Costa County	4.9%
Los Angeles County	4.8%
Marin County	4.2%
Riverside County	4.0%
San Bernardino County	3.9%
Orange County	3.7%

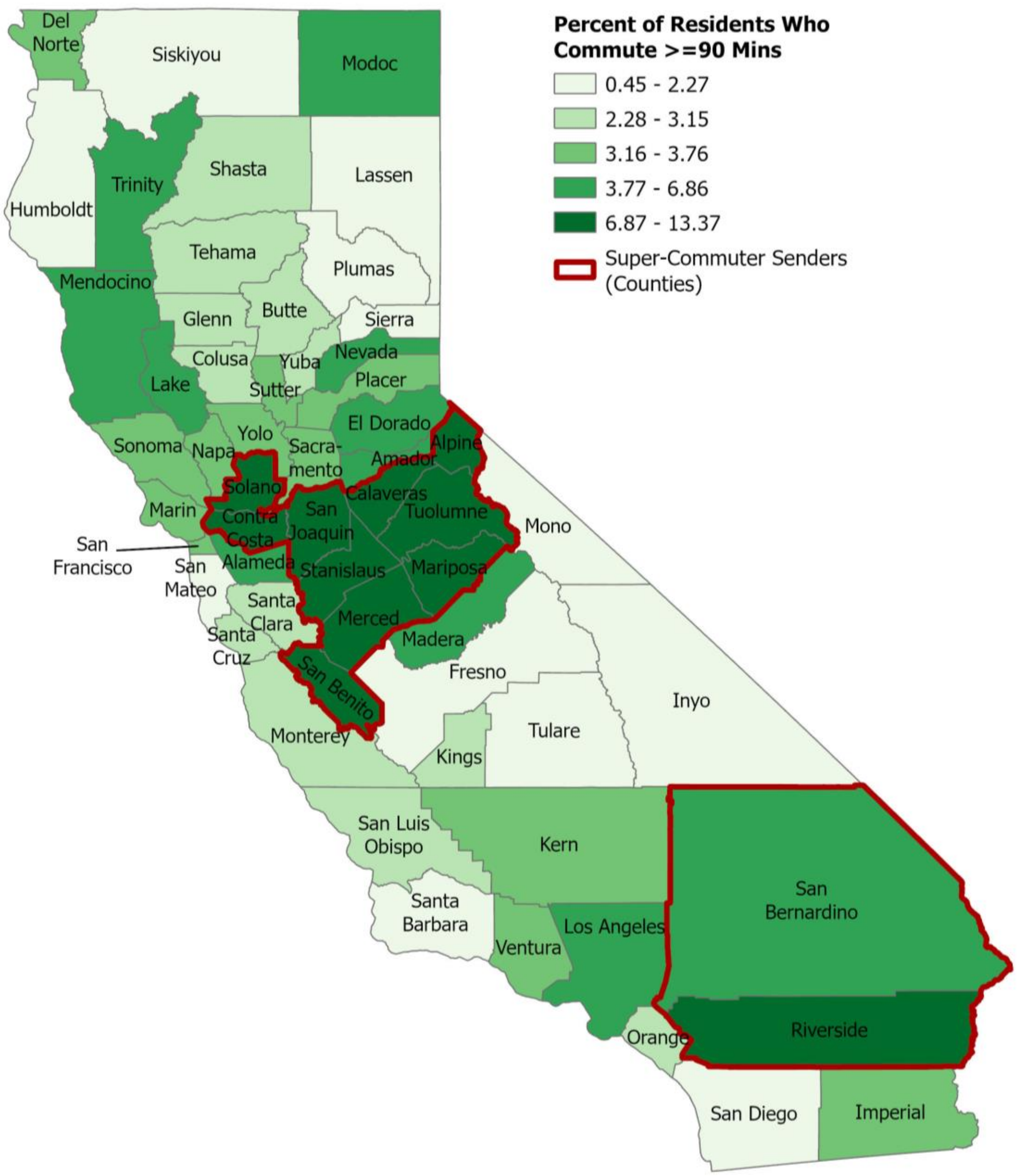
Source: EBP Analysis of American Community Survey (ACS) 5-Year Summary Tables (2021-2021), US Census Bureau.

Super-Commuter 'Senders'

The assumption prior to the study was that counties that surrounded SF and LA counties were likely 'senders' of high concentrations of super-commuters who worked in urban areas but lived outside due to the cost of living. It was anticipated that surrounding counties were the most likely to send super-commuters due to traffic considerations (a super-commuter could travel a short distance but be stuck in traffic for long periods of time) as well as distance considerations (particularly for LA county, the surrounding counties of Kern, San Bernardino, and Riverside are large, so traveling across one county could be sufficient in creating a commute >= 90 minutes).

The ACS summary table analysis supported this assumption for the Los Angeles area and found that 7.6 percent and 6.9 percent of residents in Riverside and San Bernardino Counties, respectively, traveled >= 90 minutes one-way to work. In the San Francisco study area, counties abutting San Francisco had a lower percent of long-distance commuters compared to counties in the Central Valley, such as San Joaquin, Stanislaus, and Merced counties, which were all found to have over 8 percent of residents commuting >= 90 minutes one-way. There were also a few SF Bay Area counties where over 7 percent of residents commuted long distance, including Solano, Contra Costa, and San Benito Counties. A unique outlier was found in Alpine County in central-eastern California, which features a small number of residents due to its mountainous terrain, but a high percentage of residents who commute >= 90 minutes, likely due to the low-density nature of the county (Figure 2; Table 2).

Figure 2. Percent of Residents with >= 90 Minute One-Way Commutes by County of Residence (All Modes)



Source: EBP Analysis of American Community Survey (ACS) 5-Year Summary Tables (2021-2021), US Census Bureau.

Table 2. Percent of Residents that Commute >= 90 Minutes One-Way (All Modes)

County Residence	Percent >=90 Minute Commuters
Alpine County	13.4%
San Joaquin County	10.9%
San Benito County	9.9%
Merced County	9.5%
Calaveras County	9.0%
Stanislaus County	8.8%
Contra Costa County	8.6%
Tuolumne County	7.9%
Riverside County	7.6%
Solano County	7.2%
Mariposa County	6.9%
San Bernardino County	6.9%

Source: EBP Analysis of American Community Survey (ACS) 5-Year Summary Tables (2021-2021), US Census Bureau.

Super-Commuter Travel Flow

To verify the ACS Summary Table analysis results of super-commuter 'sending' and 'receiving' counties and to better understand linked super-commuter travel flows, an additional analysis was performed using 2019 Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) data[6] . Like ACS summary tables, LEHD data does not differentiate between commute mode. LEHD data links worker residence information with their employer's address which may not represent the actual location where a given employee performs their work. Both remote workers and workers that travel to job sites may therefore appear as flows that are not true commutes. As a result, percent representation of super-commuters is higher than in the ACS summary table analysis, and there are a few counties such as Monterey and San Diego that have a high percentage of super-commuters according to LEHD, but not for ACS.

The LEHD analysis used origin-destination data for workers whose work locations were within the study area counties (and whose work locations were >= 90 minutes and < 150

[6] LEHD Origin-Destination Employment Statistics. 2019. https://lehd.ces.census.gov/data/.

minutes[7] from their place of residence (Table 3). Travel distance to workplace in minutes was determined using ArcGIS Pro's Service Area tool under the Network Analyst extension[8]. The results largely verified the ACS Summary Table results and displayed a high percentage of super-commuting residents in San Bernardino (15 percent) and Riverside (13 percent) for the LA study area, and counties in the Central Valley, including Stanislaus (13 percent), Merced (12 percent), San Joaquin (11 percent), and Calaveras (9 percent) for the SF study area (Figure 3; Table 3).

Table 3. Percent of Residents that Commute 90 – 150 Minutes One-Way to LA or SF Study Areas (All Modes)

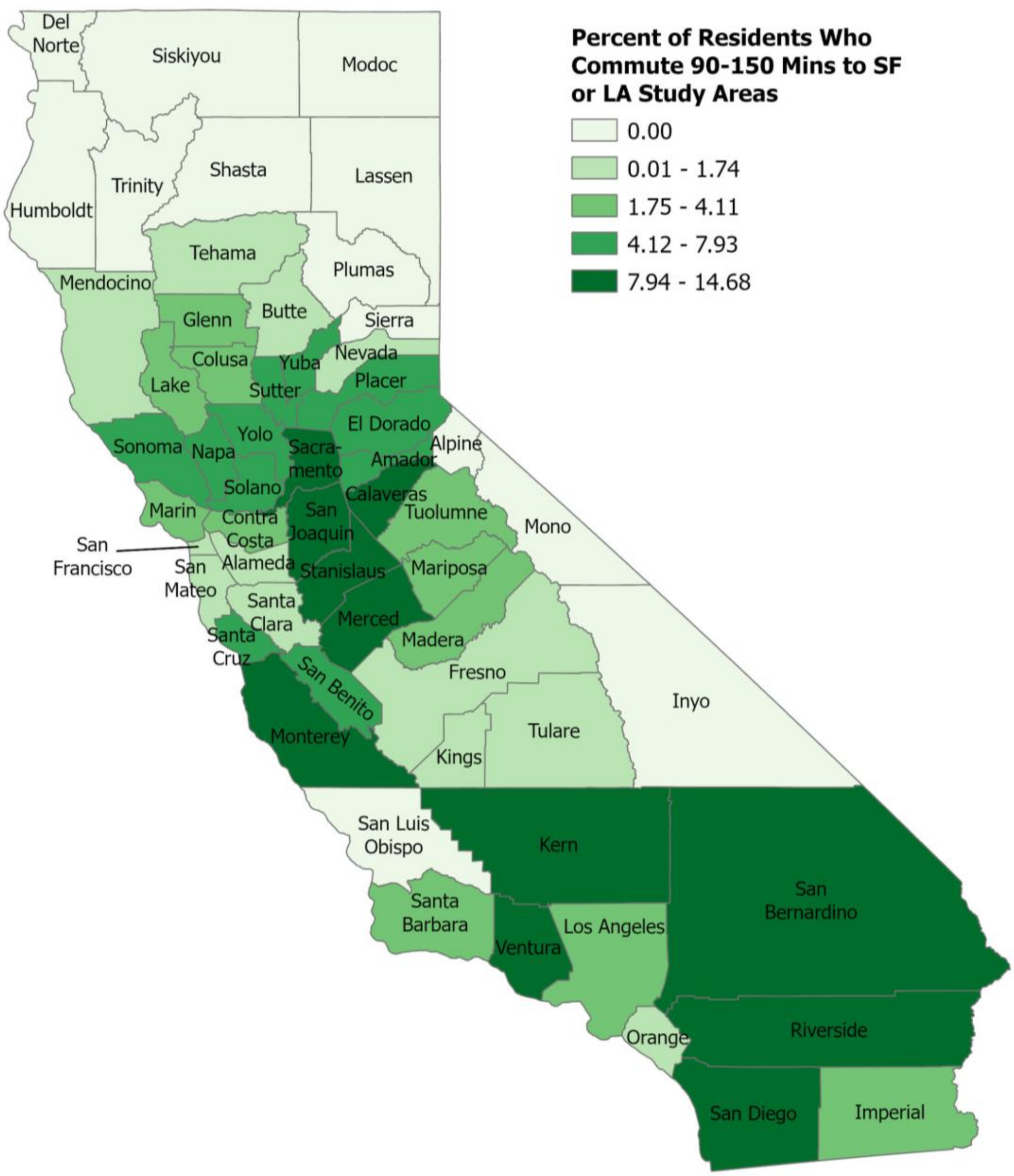
Residence County Name	Percent 90-150 Minute Super-Commuters
San Bernardino	15%
Stanislaus	13%
Riverside	13%
Merced	12%
San Joaquin	11%
Kern	11%
Monterey	10%
Calaveras	9%
Sacramento	9%
Ventura	8%
San Diego	8%
Amador	8%
San Benito	7%

Source: EBP Analysis of Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) data, 2019.

[7] This threshold was chosen based on assumptions of a feasible commute time for most professions (2.5 hours one-way) to provide an upper bound to exclude remote workers who worked 3 hours away and likely never commuted into the office.

[8] Esri. ArcGIS Pro: Network Analyst Extension. Service Area Analysis. https://pro.arcgis.com/en/pro-app/latest/help/analysis/networks/service-area-analysis-layer.htm

Figure 3. Percent of Residents who Travel 90-150 Minutes One-Way to LA or SF Study Area Counties (All Modes)



Source: EBP Analysis of Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) data, 2019.

Super-Commuters by RUC America Geographic Classifications of Home Location

The ACS summary table and LODES data analyses confirmed that the San Francisco and Los Angeles study areas receive a high concentration of super-commuter workers and appropriate super-commuter 'receiving' study areas for the analysis. The analyses identified super-commuter 'sending' counties, which included counties in the Central Valley for the SF study area, and counties surrounding Los Angeles for the LA study area. These designations are helpful for the purposes of the analysis to discern general geographic patterns.

To provide more detail on the settings in which super-commuters live, geographic classifications were assigned to all census tracts in the state, updating the methodology applied in previous RUC America geographic analysis using 2020 urban area designations from the Decennial Census, 2019 LEHD data to estimate travel flows between tracts, and using 2021 ACS data to estimate population density (Table 4).

Table 4. Geographic Classification Designations

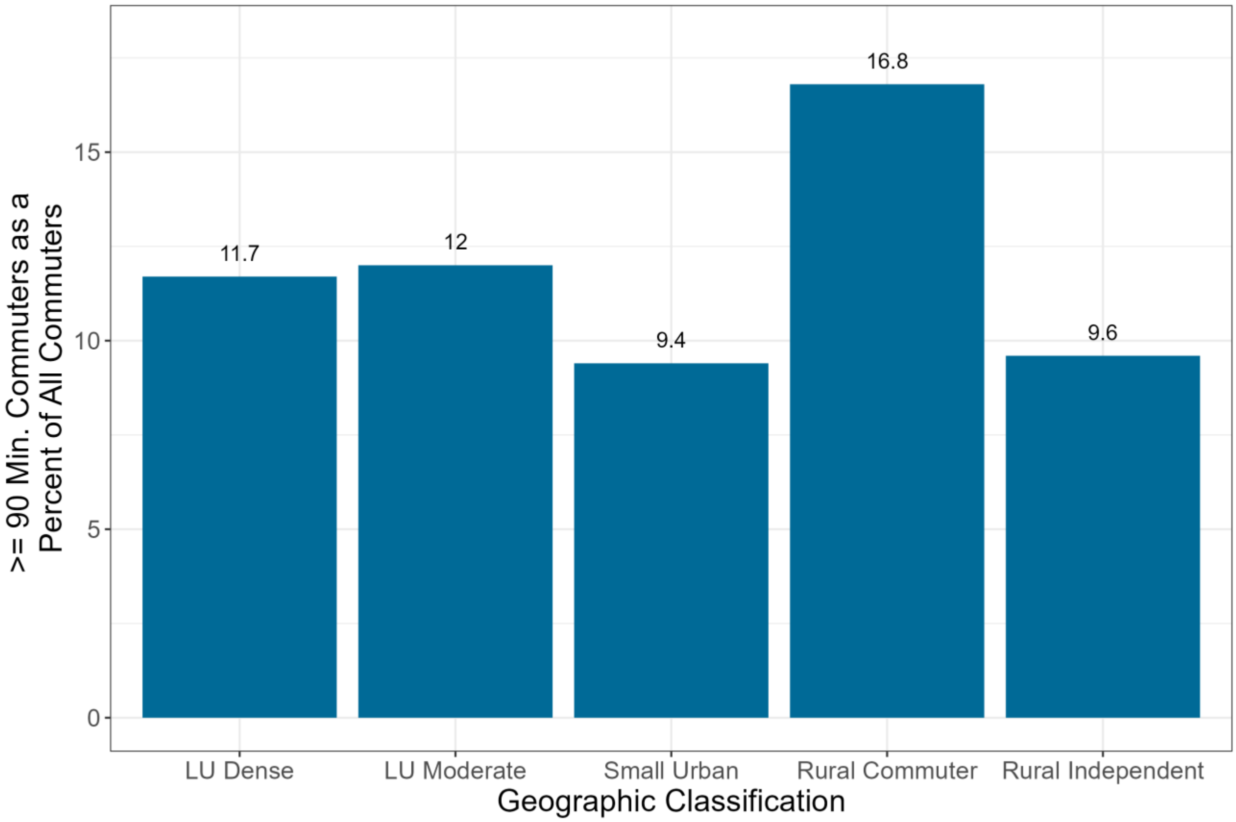
Class Name	Definition	Resident Tract of Car/Truck/Van Super-Commuters	Resident Tract of All Car, Truck, Van Commuters
Large Urban Dense	Metro population > 250,000; Primary commute flow is within urban areas; Densest 40% of census tracts in the US	35%	43%
Large Urban Moderate	Metro population > 250,000; Primary commute flow is within urban areas; Density less than top 40% of US census tracts	38%	36%
Small Urban	Metro population < 250,000; Primary commute flow is within urban areas > 10,000 population	3%	3%
Rural Commuter	Majority of commuters (>=50%) travel into urban areas	20%	13%
Rural Independent	All other tracts (<50% of commuters travel into urban areas)	4%	4%

Source: EBP analysis of ACS 2017-2021 5-year data, 2019 LEHD LODES data, and the Urban Areas from the 2020 Decennial Census.

Compared to all commuters, commuters who commute >= 90-minutes one-way are relatively more prevalent in Large Urban Moderate and Rural Commuter census tracts, and relatively less prevalent in Large Urban Dense tracts. This aligns with expectations, as super-commuters must travel long distances to work, so likely aren't concentrated in Large Urban Dense cities, but outside these cities, in Large Urban Moderate areas, or Rural Commuter areas. Both Small Urban and Rural Independent classifications have the same percent distributions when looking at the two groups (both represent small proportions of the California workforce).

Although the relative percent of long-distance commuters is greater than all commuters in both Large Urban Moderate and Rural Commuter tracts, long distance commuters are represented by a full 7 percentage points higher than overall commuters in Rural Commuter tracts (verses only a 2-percentage point difference in Large Urban Moderate tracts). This pattern is also apparent when considering the percent of >=90-minute one-way commuters as a percentage of all commuters (including the >= 90-minute commuters). We find that the greatest percent representation is found in the Rural Commuter geographic grouping (6.5 percent of all commuters). Considering that the estimated super-commuter population size using the ACS Summary Table data is approximately 3.7 percent, it is evident that super-commuters are represented to a higher degree in the Rural Commuter classification compared to the other classifications (Figure 4).

Figure 4. Geographic Groupings of Commuters Who Travel >= 90-Minutes One-Way as a Percent of All Commuters (Car, Truck, or Van Commuters)



Source: EBP analysis of ACS 2017-2021 5-year data, 2019 LEHD LODES data, and the Urban Areas from the 2020 Decennial Census.

While this analysis focuses on car, truck, and van commuters, Large Metro Urban tracts may have a significant number of commuters who travel more than 90 minutes via public transit, which was not a focus of this study since these travelers do not directly pay fuel taxes while commuting.

Demographics of Super-Commuters

To understand the demographic characteristics of super-commuters, we looked at two datasets: the 2017-2021 5-Year Public Use Microdata Sample (PUMS) conducted by the U.S. Census and the 2017 National Household Travel Survey (NHTS) conducted by the Federal Highway Administration.[9] While the results of these two datasets overlap, they convey different pieces of information necessary for our analysis of Super-Commuters. NHTS records primarily focus on travel behavior and vehicle characteristics, but also includes key demographic data including race and ethnicity, household income, and educational attainment. NHTS contained 26,000 households, 53,600 people, 52,200 vehicles and a means to expand this sample to account for the 12.8 million households, 36.6 million people, and 25.1 million vehicles considered in this study in the state of CA.[10] . PUMS data records largely focus on demographic characteristics of individual people or housing units. It contained 769,000 households and 1.8 million people and similar to NHTS data, a means to expand this sample to account for the 14.3 million households and 39.4 million people considered in this study in the state of CA.[11]

The PUMS unit of analysis is the super-commuter (or non-super commuter), while the NHTS unit of analysis can be either the super-commuter or the super-commuting household. The latter refers to households with at least one super-commuter. Non-super-commuting households therefore are households with no super-commuters. We expect similar demographic results in both datasets with slight variation based on differences in survey sampling.

Race and Ethnicity

Among all commuters, Hispanic populations make up the largest group of commuters in California followed by White populations. However, we can see from Figure 5 and Table 5 that the highest percentage of super-commuters (4.6 percent) is represented by Native

[9] 2017 was the last year the full NHTS was conducted (As of 2020, the NHTS began releasing NextGen NHTS results which include origin and destination data for passenger vehicles and trucks).

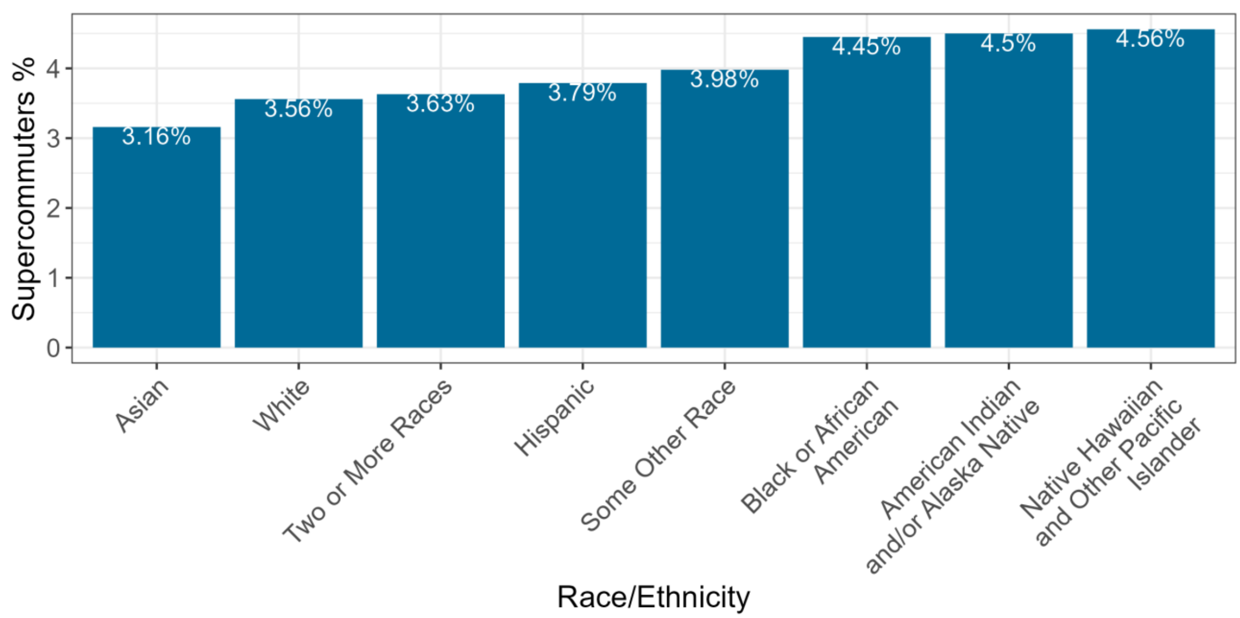
[10] The weighted totals account for data excluded during data cleaning and transformation that weren't relevant for the purposes of the analysis.

[11] The weighted totals account for data excluded during data cleaning and transformation that weren't relevant for the purposes of the analysis.

Hawaiian and Other Pacific Islander populations followed by American Indian and/or Alaska Native (4.5 percent) and Black or African American (4.5 percent) populations. For American Indian and/or Alaska Native and Native Hawaiian and Other Pacific Islander populations, this is likely a result of small sample sizes resulting in an overall higher percentage of super-commuting populations.

As expected, we observed similar patterns in the NHTS dataset (Table 6). For analysis purposes, we grouped all races except for Asian, Black, Hispanic, and White in an 'All Others' category, and we observe that the highest percentage of super-commuter households is represented by All Other racial groups (6.5 percent).

Figure 5. Super-Commuters as a Percentage of All Car, Truck, and Van Commuters by Race/Ethnicity



Source: EBP Analysis of Public Use Microdata Sample (PUMS), 2017-2021.

Within the super-commuter group, roughly 42 percent of super-commuters are Hispanic and 34 percent are White owing to the large population counts of these racial groups in California. The distributions of these two groups are dominant and there is less representation in other racial groups. A similar pattern of overall distribution is seen in the non-super-commuter group, where approximately 40 percent of non-super-commuters are Hispanic and 36 percent are White. Compared to non-super-commuters, super-commuters are slightly less likely to be Asian or White, and slightly more likely to be Hispanic or Black or African American (Table 5).

Table 5. Super-Commuters by Race (PUMS)

Race/Ethnicity	Super-Commuter Count	Non-Super-Commuter Count	Super-Commuters as Pct of Commuters*	Super-Commuter Distribution**	Non- Super-Commuter Distribution**
American Indian and/or Alaska Native	1,713	36,336	4.5%	0.3%	0.3%
Asian	68,444	2,100,344	3.2%	12.9%	15.0%
Black or African American	31,691	680,170	4.5%	6.0%	4.9%
Hispanic	223,151	5,669,572	3.8%	42.2%	40.5%
Native Hawaiian and Other Pacific Islander	2,391	50,086	4.6%	0.5%	0.4%
Some Other Race	1,798	43,413	4.0%	0.3%	0.3%
Two or More Races	15,154	402,526	3.6%	2.9%	2.9%
White	184,846	5,004,860	3.6%	34.9%	35.8%

Source: EBP Analysis of Public Use Microdata Sample (PUMS), 2017-2021. Note: *Super-Commuters as Pct of Commuters refers specifically to car, truck, or van commuters, or the value derived by adding super-commuters and non-super-commuters. **Super-Commuter Distribution and Non-Super-Commuter Distribution refers to the percent breakdown of each distinct grouping into the categories in the first column.

From the NHTS survey, we see that Hispanic and White commuters are most prevalent within the super-commuter (45.8 and 34.4 percent, respectively) and non-super-commuter (38.4 percent and 38.2 percent respectively) groups. In both PUMS and NHTS datasets, we see that Hispanic commuters are the most prevalent racial/ethnic group, but the NHTS dataset shows a 7.4 percentage point difference between super-commuters and non-super-commuters, compared to the 1.7 percentage point difference between the two groups in the PUMS dataset (Table 6).

Table 6. Super-Commuters by Race (NHTS)

Race / Ethnicity	Super-Commuter Count	Non-Super-Commuter Count	Super-Commuters as Pct of All Commuters *	Super-Commuter Distribution**	Non- Super-Commuter Distribution**
All Other	33,388	661,067	4.8%	7.2%	5.2%
Asian	30,522	1,673,089	1.8%	6.5%	13.2%
Black	28,445	633,013	4.3%	6.1%	5.0%
Hispanic	213,962	4,858,444	4.2%	45.8%	38.4%
White	160,749	4,835,672	3.2%	34.4%	38.2%

Source: EBP Analysis of National Household Travel Survey (NHTS) 2017. Note: *Super-Commuters as Pct of All Commuters refers specifically to car, truck, or van commuters, or the value derived by adding super-commuters and non-super-commuters. **Super-Commuter Distribution and Non-Super-Commuter Distribution refers to the percent breakdown of each distinct grouping into the categories in the first column.

Sex

The representation of super-commuters by sex in California confirmed our initial hypothesis. There are more male super-commuters (4.6 percent) than female super-commuters (2.5 percent) in California and we see that men are nearly twice as likely as women to be super-commuters.

Within the super-commuter group, we observe that roughly 2/3 of the population is male (69 percent), indicating that there are more males undertaking longer commutes of 90 minutes or more than females owing to multiple factors, including but not limited to gender disparities in specific industries and occupations. Within the non-super-commuter group, we see a similar pattern of a greater number of male work commuters, but we see a more even split between the two sexes (Table 7).

Table 7. Sex of Super-Commuters

Sex	Super-Commuter Count	Non- Super-Commuter Count	Super-Commuters as Pct of All Commuters*	Super-Commuter Distribution**	Non- Super-Commuter Distribution**
Female	161,838	6,326,373	2.5%	30.6%	45.3%
Male	367,350	7,660,934	4.6%	69.4%	54.8%

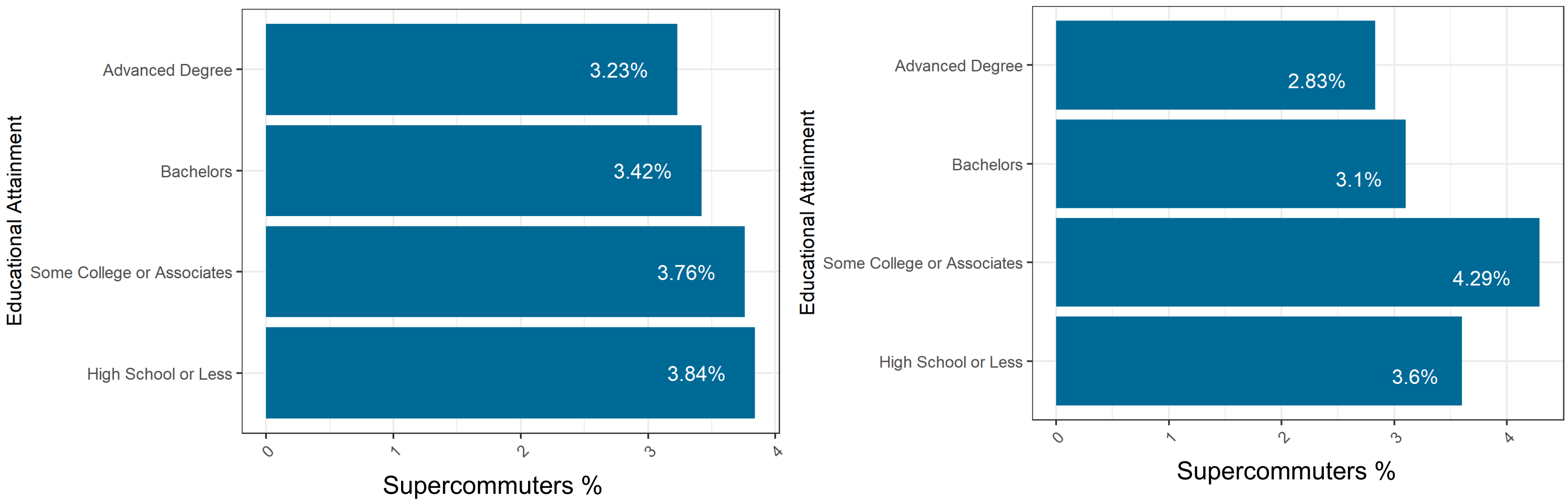
Source: EBP Analysis of Public Use Microdata Sample (PUMS), 2017-2021. Note: *Super-Commuters as Pct of All Commuters refers specifically to car, truck, or van commuters, or the value derived by adding super-commuters and non-super-commuters. **Super-Commuter Distribution and Non-Super-Commuter Distribution refers to the percent breakdown of each distinct grouping into the categories in the first column.

Educational Attainment

When considering the distribution of education attainment level for super-commuters and non-super-commuters (Figure 6), both groups have the greatest representation in 'some college or associate's degree' education group (34.7 and 33.7 percent, respectively). However, when considering super-commuters as a percent of total car, truck, and van commuters, 3.8 percent are found in the ‘high school diploma or high school diploma/equivalent’ level of education group followed by ‘some college or associate’s degree’ level group. Despite the small margins, we see a trend of super-commuters having a higher percent representation in the lower education groupings when comparing super-commuters to all car, truck, and van commuters (Figure 6).

Looking at NHTS data, we see similar results with slight variation. We found a higher percentage of super-commuters with ‘some college or associate’s degree’ (4.3 percent) among all educational attainment levels than what was observed in PUMS data where we observed the highest percentage of super-commuters in ‘less than high school diploma or high school diploma/equivalent’ (3.8 percent).

Figure 6. Super-Commuters as a Percentage of All Car, Truck, and Van Commuters by Educational Attainment Level (PUMS-left, NHTS- right)



Source: EBP Analysis of Public Use Microdata Sample (PUMS) (left), 2017-2021, EBP Analysis of National Household Travel Survey (NHTS) 2017 (right).

The distribution of commuters across different education levels within super-commuter and non-super-commuter groups are similar, with roughly a third of super-commuters and non-super-commuters having 'some college or associate's degree' (34.7 and 33.7 percent, respectively) followed closely by approximately a third of super-commuters and non-super-commuters having 'less than high school diploma or high school diploma equivalent' (33.9 and 32.1 percent, respectively). Although both groups display similar patterns, super-commuters are slightly more likely than non-super-commuters to be in either the 'less than high school diploma or high school diploma/equivalent' or the 'some college or associate's degree' educational grouping. Alternatively, non-super-commuters are slightly more likely to be in either the 'bachelor's degree' or 'post-baccalaureate, master's, or doctorate degree' educational grouping. This suggests that the average super-commuter has slightly lower educational attainment compared to that of non-super-commuters (Table 8).

Table 8. Education Attainment Level of Super-Commuters (PUMS)

Education Level	Super-Commuter Count	Non-Super-Commuter Count	Super-Commuters as Pct of All Commuters*	Super-Commuter Distribution**	Non- Super-Commuter Distribution**
Less than high school diploma or high school diploma /equivalent	179,473	4,491,796	3.8%	33.9%	32.1%
Some college or Associate's degree	183,652	4,707,069	3.8%	34.7%	33.7%
Bachelor's degree	107,849	3,044,246	3.4%	20.4%	21.8%
Post-Baccalaureate, Master's, or Doctorate Degree	58,214	1,744,196	3.2%	11%	12.5%

Source: EBP Analysis of Public Use Microdata Sample (PUMS), 2017-2021. Note: *Super-Commuters as Pct of All Commuters refers specifically to car, truck, or van commuters, or the value derived by adding super-commuters and non-super-commuters. **Super-Commuter Distribution and Non-Super-Commuter Distribution refers to the percent breakdown of each distinct grouping into the categories in the first column.

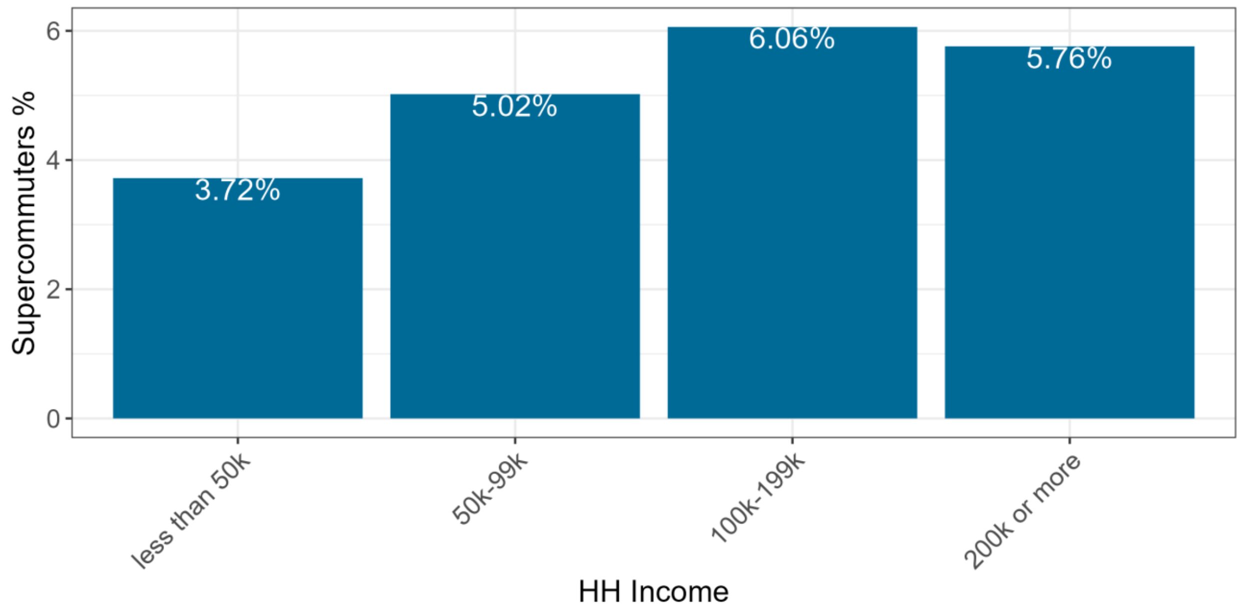
Household Income

Household income includes the summation of personal earnings (wages/salary) for all household members in addition to other income sources such as social security payments, pensions, public assistance, and interest and dividends.[12] Considering that transportation taxes, fees, and payments are typically pooled at the household level, we consider household-level income when evaluating the revenue equity of baseline versus RUC payments.

Commuters in California are spread over a spectrum of different income groups. We can see that higher income groups have a greater proportion of super-commuter households out of all commuter households but the difference between middle- and higher-income groups is relatively small. From Figure 7, we can see that households who take home $100k-$199k in annual income have the highest percentage of super-commuters (6.06 percent) followed by households with incomes of $200k or more (5.76 percent). These results were confirmed by NHTS.

[12] US Census Bureau. Income vs. Earnings. https://www.census.gov/newsroom/blogs/random-samplings/2010/09/income-vs-earnings.html

Figure 7. Super-Commuter Households as a Percentage of All Car, Truck, and Van Commuter Households by Household Income



Source: EBP Analysis of Public Use Microdata Sample (PUMS), 2017-2021.

Within respective super-commuter and non-super-commuter groupings, we observe a similar pattern where we have a higher proportion of super-commuter and non-super-commuter households in the middle-income groups. In the $50k-$99k and $100k-$199k groupings, we find ~67 percent of super-commuter households and ~62 percent of non-super-commuter households. We also observe that there is a greater proportion of non-super-commuter households represented in the low and lower-middle income groups, and a greater proportion of super-commuter households represented in the upper-middle- and higher-income groups. This suggests that the average super-commuter household makes a slightly higher income compared to the average non-super-commuter household (Table 9).

Table 9. Household Income of Super-Commuters (PUMS, 2017 $)

Household Income ($)	Super-Commuter Household Count	Non-Super-Commuter Household Count	Super-Commuter Households as Pct of All Commuters Households*	Super-Commuter Household Distribution**	Non- Super-Commuter Household Distribution**
less than $50k	76,668	1,983,670	3.7%	17.0%	23.8%
$50k-$99k	139,347	2,638,587	5.0%	30.8%	31.6%
$100k-$199k	164,539	2,549,399	6.1%	36.4%	30.6%
$200k or more	71,220	1,165,767	5.8%	15.8%	14.0%

Source: EBP Analysis of Public Use Microdata Sample (PUMS), 2017-2021. Note: *Super-Commuter Households as Pct of All Commuters Households refers specifically to households with car, truck, or van commuters, or the value derived by adding super-commuter households and non-super-commuter households. **Super-Commuter Household Distribution and Non-Super-Commuter Household Distribution refers to the percent breakdown of each distinct grouping into the categories in the first column. PUMS household income data converted into 2017-dollar value for comparison with 2017 NHTS data (NHTS data couldn't be converted to 2021-dollar value).

Within the NHTS data, we observe a similar pattern when considering super-commuter households as a percent of all commuters' households. For both PUMS and NHTS, the greatest percentages of super-commuter households as a percentage of all commuters' households were found in the $100k-$199k and $200k or more groupings. Both datasets saw the highest percentage in the $100k-$199k grouping (6.1 percent for PUMS, 6.3 percent for NHTS), followed by the $200k or more grouping (5.8 percent for PUMS, 5.1 percent for NHTS). From these verified results we can conclude that super-commuter households, as a percent of all commuter households, are more likely to have upper middle ($100k-$199k) or high incomes ($200k or more) (Table 10).

The distributions within super-commuter and non-super-commuter households were slightly less consistent between datasets due to considerable differences in sample frames leading to differences in population estimates. For example, NHTS has approximately half the number of estimated super-commuter households making $200k or more but has estimated roughly 20,000 more super-commuter households making less than $50k. However, for both groups, the majority of super-commuter and non-super commuter households are found in the $50k-$99k and $100k-$199k groupings.

Table 10. Household Income of Super-Commuters (NHTS, 2017 $)

Household Income	Super-Commuter Household Count	Non-Super-Commuter Household Count	Super-Commuter Households as Pct of All Commuters-Household*	Super-Commuter Household Distribution **	Non-Super-Commuter Household Distribution **
less than $50k	96,465	2,111,916	4.4%	26.8%	29.8%
$50k-$99k	89,843	2,237,941	3.9%	24.9%	31.6%
$100k-$199k	135,125	2,011,798	6.3%	37.5%	28.4%
$200k or more	39,095	725,579	5.1%	10.8%	10.2%

Source: EBP Analysis of National Household Travel Survey (NHTS) 2017. Note: *Super-Commuter Households as Pct of All Commuters Households refers specifically to households with car, truck, or van commuters, or the value derived by adding super-commuter households and non-super-commuter households. **Super-Commuter Household Distribution and Non-Super-Commuter Household Distribution refers to the percent breakdown of each distinct grouping into the categories in the first column. PUMS household income data converted into 2017-dollar value for comparison with 2017 NHTS data (NHTS data couldn't be converted to 2021-dollar value).

Personal Earnings

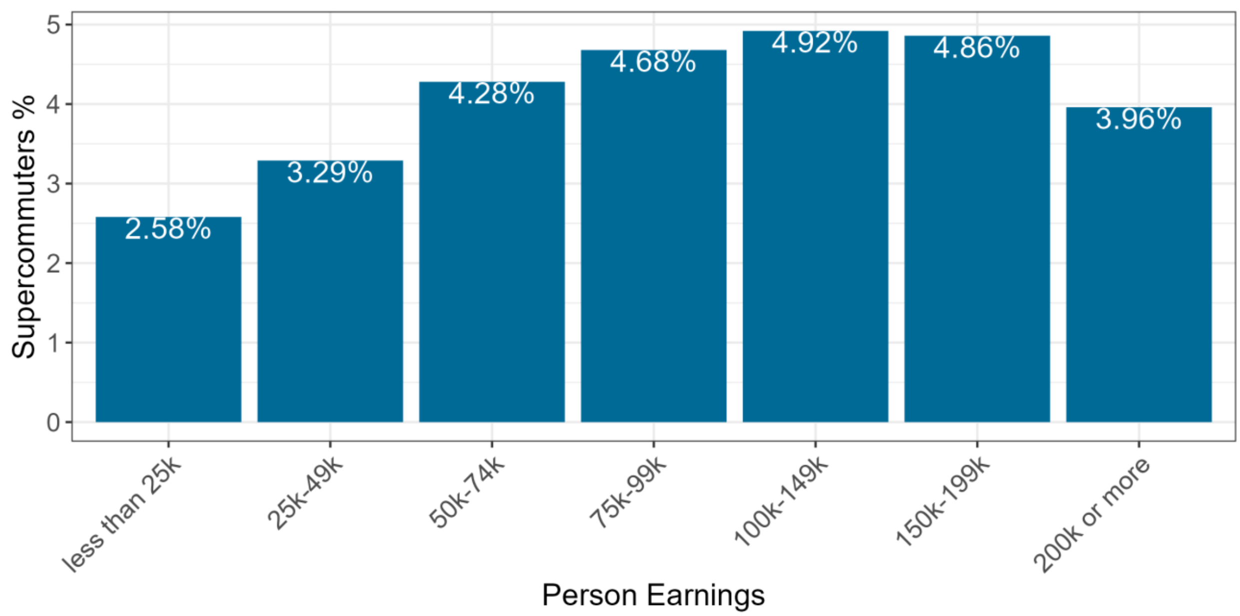
Although we consider income at the household-level when we evaluate the revenue equity of baseline versus RUC policies, it is important to also understand the personal earnings of super-commuters at the person-level. Personal earnings include wages and salaries, which typically amount to a large portion of a person or a household's income.[13] By considering the personal earnings of super-commuters we can isolate the typical salary of a super-commuter to better understand the likely impact of a RUC at the person-level.

From a personal earnings perspective, 56 percent of non-super-commuters earn less than $50k per year (Table 11). Only 45 percent of super-commuters fall in this group. We observe a higher proportion of super-commuters in all earnings groups above $50k.

Super-commuters make up a greater portion of these higher earning groups. From Figure 8, we can see that the $100k-$149k and $150k-$199k groups have the highest percentage of super-commuters (4.9 percent) followed closely by $75k-$99k earners (4.7 percent).

[13] US Census Bureau. Income vs. Earnings. https://www.census.gov/newsroom/blogs/random-samplings/2010/09/income-vs-earnings.html

Figure 8. Super-Commuters as a Percentage of All Car, Truck, and Van Commuters by Person Earnings



Source: EBP Analysis of Public Use Microdata Sample (PUMS), 2017-2021.

Table 11. Annual Person- Level Earnings of Super-Commuters (2021 $)

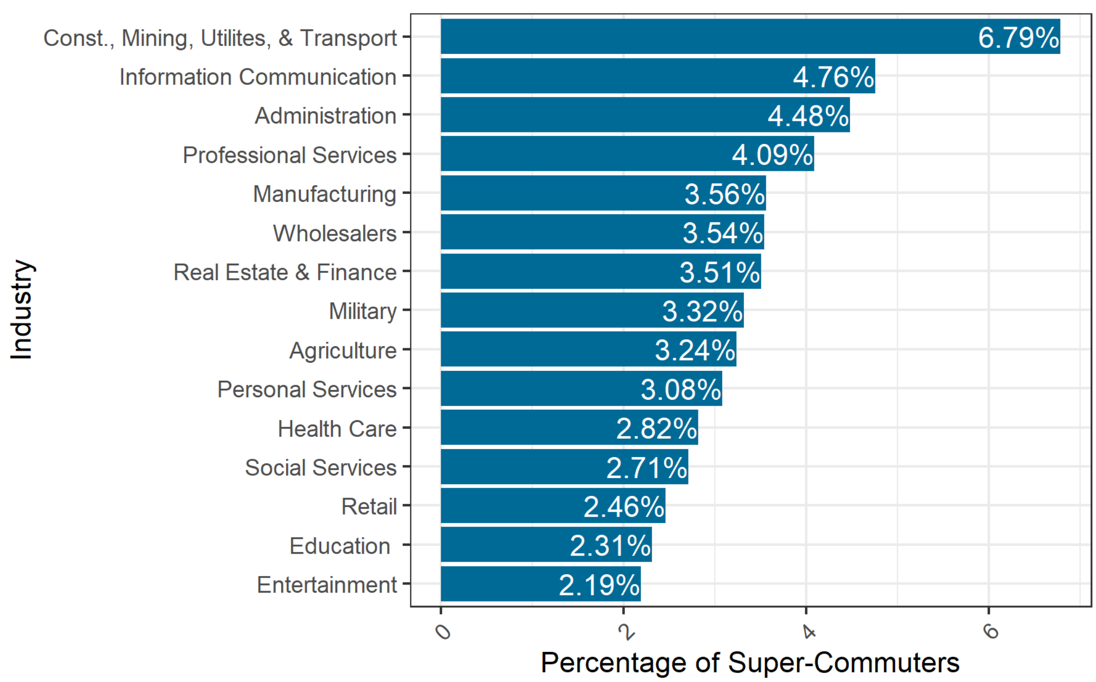
Person Earnings ($)	Super-Commuter Count	Non-Super-Commuter Count	Super-Commuters as Pct of All Commuters*	Super-Commuter Distribution**	Non- Super-Commuter Distribution**
less than 25k	101,162	3,817,764	2.6%	19.1%	27.3%
25k-49k	136,416	4,014,829	3.3%	25.8%	28.7%
50k-74k	106,130	2,375,688	4.3%	20.1%	17.0%
75k-99k	65,401	1,333,185	4.7%	12.4%	9.5%
100k-149k	71,443	1,381,600	4.9%	13.5%	9.9%
150k-199k	24,682	483,662	4.9%	4.7%	3.5%
200k or more	23,954	580,579	4.0%	4.5%	4.2%

Source: EBP Analysis of Public Use Microdata Sample (PUMS), 2017-2021. Note: *Super-Commuters as Pct of All Commuters refers specifically to car, truck, or van commuters, or the value derived by adding super-commuters and non-super-commuters. **Super-Commuter Distribution and Non-Super-Commuter Distribution refers to the percent breakdown of each distinct grouping into the categories in the first column.

Industry and Occupation

A key question that the study aims to answer is to understand the types of jobs and industries in which super-commuters work. Among all industry groups, we see that industries that involve on-site work such as construction, mining, power utilities and transportation have the largest proportion of super-commuters (6.8 percent) as shown in Figure 9.

Figure 9. Super-Commuters as a Percentage of All Car, Truck, and Van Commuters by Industry



Source: EBP Analysis of Public Use Microdata Sample (PUMS), 2017-2021.

Within the super-commuter group, we observe a similar trend and see ~25 percent of super-commuters in construction, mining and extraction, power utilities, transportation followed by 13.4 percent in professional services. While the distribution of industries within the non-super-commuter group is a bit more evenly spread out, we do observe similar patterns to those seen in the super-commuter group (Table 12).

Table 12. Super-Commuters by Industry

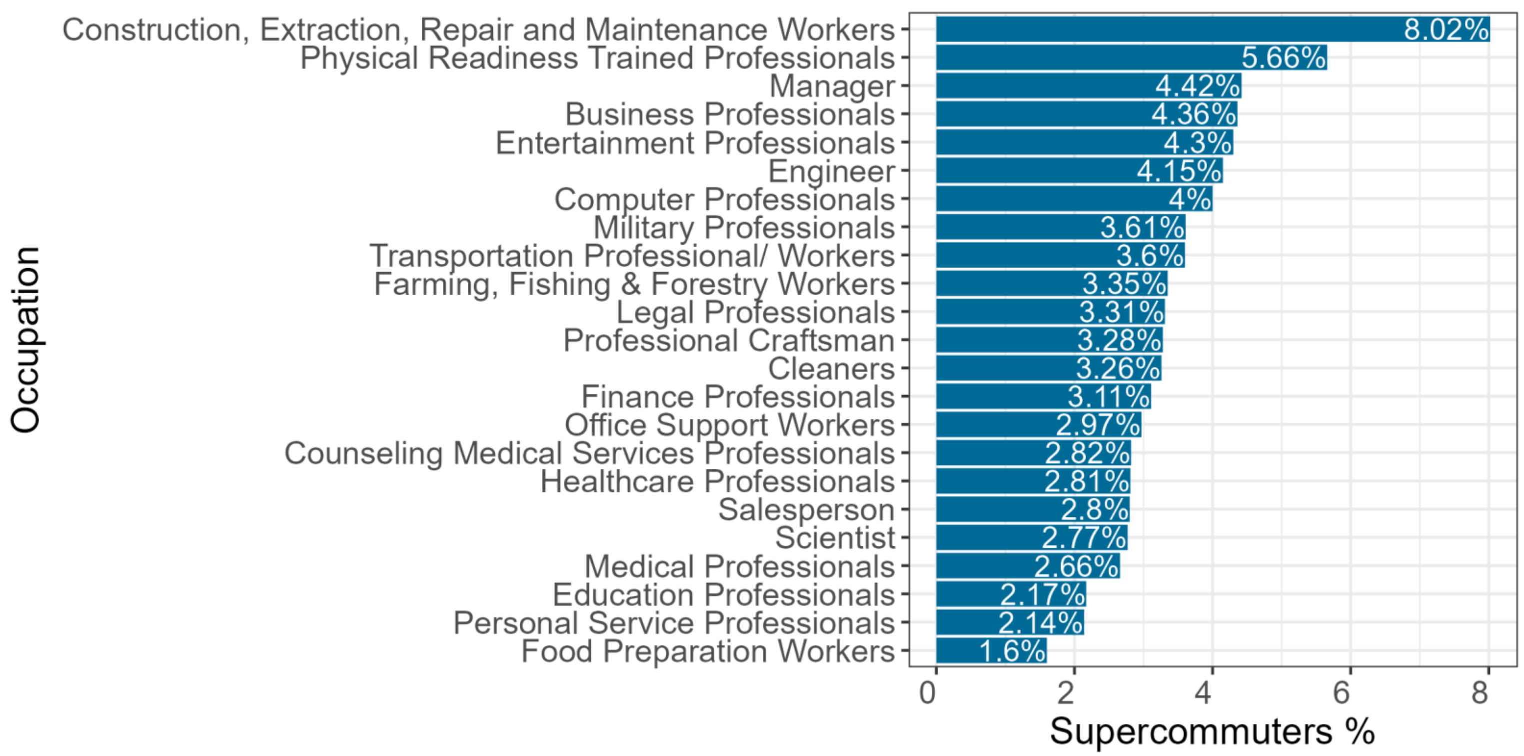
Industry	Super-Commuter Count	Non-Super-Commuter Count	Super-Commuters as Pct of All Commuters*	Super-Commuter Distribution**	Non- Super-Commuter Distribution**
Administration	30,387	647,902	4.5%	5.7%	4.6%
Agriculture	10,092	301,699	3.2%	1.9%	2.2%
Construction, Mining and Extraction, Power Utilities, Transportation	134,984	1,852,416	6.8%	25.5%	13.2%
Education	27,488	1,164,531	2.3%	5.2%	8.3%
Entertainment	31,278	1,397,770	2.2%	5.9%	9.9%
Real Estate & Finance	26,775	737,059	3.5%	5.1%	5.3%
Information Communication	16,201	324,189	4.8%	3.1%	2.3%
Health Care	43,966	1,516,674	2.8%	8.3%	10.8%
Manufacturing	49,194	1,331,569	3.6%	9.3%	9.5%
Military	3,520	102,394	3.3%	0.7%	0.7%
Professional Services	70,641	1,655,457	4.1%	13.4%	11.8%
Retail	37,777	1,499,461	2.5%	7.1%	10.7%
Social Services	9,756	349,940	2.7%	1.8%	2.5%
Personal Services	22,558	709,405	3.1%	4.3%	5.1%
Wholesalers	14,571	396,841	3.5%	2.8%	2.8%

Source: EBP Analysis of Public Use Microdata Sample (PUMS), 2017-2021. Note: *Super-Commuters as Pct of All Commuters refers specifically to car, truck, or van commuters, or the value derived by adding super-commuters and non-super-commuters. **Super-Commuter Distribution and Non-Super-Commuter Distribution refers to the percent breakdown of each distinct grouping into the categories in the first column.

As seen in Table 12, super-commuters are represented in higher proportions by the construction, extraction, and repair industries. As such, workers in occupations related to those industries also constitute the highest percentage of super-commuters (8 percent) across all occupations. The second highest occupation group for super-commuters is physical readiness trained professionals (5.7 percent), which primarily includes first-responders and correctional officers (Figure 10).

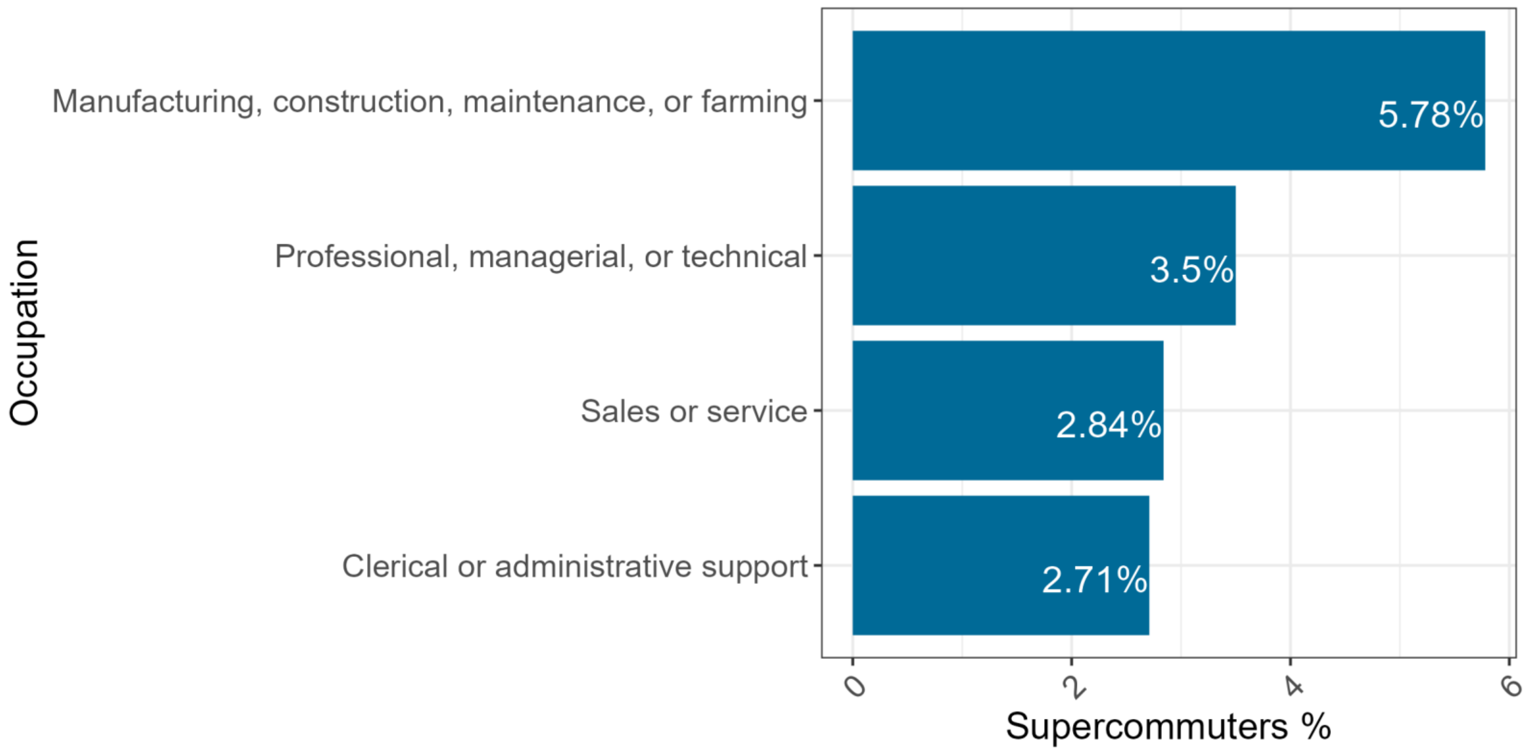
While the NHTS dataset had less detailed groupings than what were found in PUMS, we still observe similar patterns in which manufacturing, construction, maintenance, or farming occupations have the highest percentage of super-commuters (5.7 percent) followed by professional, managerial, or technical occupations (3.5 percent) which combines several categories from the PUMS analysis, including but not limited to Physical Readiness Trained Professionals, Business Professionals, Engineers, and Managers (Figure 11).

Figure 10. Super-Commuters as a Percentage of All Car, Truck, and Van Commuters by Occupation (PUMS)



Source: EBP Analysis of Public Use Microdata Sample (PUMS) 2017-2021

Figure 11. Super-Commuters as a Percentage of All Car, Truck, and Van Commuters by Occupation (NHTS)



Source: EBP Analysis of National Household Travel Survey (NHTS) 2017.

Within the super-commuter group, we observe a similar trend and see ~19 percent of super-commuters as construction, extraction, repair, and maintenance workers followed by 12.5 percent of super-commuters in managerial positions. Alternatively, within the non-super-commuter group, we see office support workers (11 percent) followed by salesperson (9.7 percent) as the occupations with the largest representation (Table 13).

Table 13. Super-Commuters by Occupation (PUMS)

Occupation	Super-Commuter Count	Non-Super-Commuter Count	Super-Commuters as Pct of All Commuters*	Super-Commuter Distribution**	Non- Super-Commuter Distribution**
Business Professionals	18,032	395,314	4.4%	3.4%	2.8%
Cleaners	18,987	563,399	3.3%	3.6%	4.0%
Computer Professionals	16,863	405,029	4%	3.2%	2.9%
Counseling Medical Services Professionals	7,039	242,405	2.8%	1.3%	1.7%
Construction, Extraction, Repair and Maintenance Workers	99,214	1,138,549	8.0%	18.8%	8.1%
Food Preparation Workers	12,822	788,903	1.6%	2.4%	5.6%
Education Professionals	16,787	755,751	2.2%	3.2%	5.4%
Engineer	14,065	324,807	4.2%	2.7%	2.3%
Entertainment Professionals	13,980	310,763	4.3%	2.6%	2.2%
Farming, Fishing & Forestry Workers	7,650	220,540	3.4%	1.5%	1.6%
Finance Professionals	8,947	278,722	3.1%	1.7%	1.9%
Healthcare Professionals	14,093	488,092	2.8%	2.7%	3.5%

Legal Professionals	5,202	152,048	3.3%	0.9%	1.1%
Medical Professionals	22,782	832,757	2.7%	4.3%	5.9%
Manager	65,945	1,426,588	4.4%	12.5%	10.2%
Military Professionals	1,821	48,553	3.6%	0.3%	0.4%
Office Support Workers	47,204	1,542,668	2.9%	8.9%	11.0%
Professional Craftsman	24,448	721,653	3.3%	4.6%	5.2%
Personal Service Professionals	8,382	382,950	2.1%	1.6%	2.7%
Physical Readiness Trained Professionals	18,956	316,132	5.7%	3.6%	2.3%
Salesperson	38,957	1,353,865	2.8%	7.4%	9.7%
Scientist	4,600	161,339	2.8%	0.9%	1.1%
Transportation Professional/ Workers	42,412	1,136,480	3.6%	8.0%	8.1%

Source: EBP Analysis of Public Use Microdata Sample (PUMS), 2017-2021. Note: *Super-Commuters as Pct of All Commuters refers specifically to car, truck, or van commuters, or the value derived by adding super-commuters and non-super-commuters. **Super-Commuter Distribution and Non-Super-Commuter Distribution refers to the percent breakdown of each distinct grouping into the categories in the first column.

Within the super-commuter groups in NHTS data, we see that there is a higher percentage of super-commuters in manufacturing, construction, maintenance, or farming groups (23.9 percent) followed by professional, managerial, or technical occupational groups (45.5 percent), which is the opposite of what was observed in PUMS where we found more super-commuters in construction, extraction, and maintenance work. Within non-super-commuter group, we observe that roughly half of non-super-commuters is found in professional and managerial roles (46.3 percent) however, the second highest percentage of non-super-commuters within are found in sales or services (26.8 percent). This reflects that super-commuters are mostly found in manufacturing, construction jobs that often requires long commute to on-site locations.

Table 14. Super-Commuters by Occupation (NHTS)

Occupation	Super-Commuter Count-Household	Non-Super-Commuter Count - Household	Super-Commuters as Pct of All Commuters-Household*	Super-Commuter Distribution-Household**	Non-Super-Commuter Distribution-Household**
Clerical or administrative support	44,088	1,581,285	2.7%	9.5%	12.5%
Manufacturing, construction, maintenance, or farming	111,298	1,815,338	5.8%	23.9%	14.4%
Professional, managerial, or technical	212,063	5,850,041	3.5%	45.5%	46.3%
Sales or service	98,834	3,384,677	2.8%	21.2%	26.8%

Source: EBP Analysis of National Household Travel Survey (NHTS) 2017. Note: *Super-Commuters as Pct of All Commuters refers specifically to car, truck, or van commuters, or the value derived by adding super-commuters and non-super-commuters. **Super-Commuter Distribution and Non-Super-Commuter Distribution refers to the percent breakdown of each distinct grouping into the categories in the first column.

Super-Commuter Intersectional Characteristics

Race/ Occupation

The Hispanic population group has the largest percent of super-commuter and non-super-commuter commuters in California, as seen in Table 5. This pattern was consistent as we looked at race/ethnicity across other demographic characteristics such as occupation and personal earnings. Across different occupations listed in Table 13, we observe that within the super-commuter group, the highest percentage of Hispanic commuters are found in construction, extraction, repair and maintenance occupations (28.5 percent) after cross tabulating race/ethnicity and occupation. While the most prevalent occupation across all races/ethnicities is construction, extraction, repair and maintenance (18.8 percent), managerial roles are the second highest represented group within super-commuters (12.5 percent) which is the most prevalent for most racial groups.

We observe some similarities between super-commuter and non-super-commuter groups after conducting a cross-tabulation analysis. Within the non-super-commuter group, we do see the highest percentage of Hispanic commuters in construction, extraction, repair and maintenance occupations (12 percent) but at a significantly lower share than what we observed within the super-commuter group. Moreover, we see more uniformity among the prevalence of non-super-commuters represented by different occupations such as managerial roles (10 percent) and office support workers (11 percent), which are the most prevalent occupation across all race/ethnic groups except for Asian commuters.

Race/ Personal Earnings

We observe that across different personal earning groups, super-commuters are mostly represented in Asian, White, and Hispanic racial/ethnic groups. Within the Asian racial group, the highest percent of super-commuters are found in the higher personal earnings groups (19.7 percent in $150k-$199k and 18.3 percent in $200k or more). Despite the prevalence of Hispanic populations as super-commuters, we see Hispanics mostly dominating lower income groups (53 percent in less than $25k and 45.1 percent in $50k-$74k). After Hispanics, White populations seem to have the highest percent of super-commuters in the middle to higher income level ranges ($75k to $199k).

We observe some similarities between super-commuter and non-super-commuter groups from the cross-tabulation analysis. Hispanic populations, being in large numbers, have the highest percentage of non-super-commuters, but only in lower income groups (50.7 percent in less than $25k and 37.4 percent in $50k-$74k). White populations, on the other hand, tend to have the highest percentage of non-super-commuters across all personal earnings categories except for the less than $25k group. Like the super-commuter group, we observe that within the Asian racial group, a higher percent of non-super-commuters are found in the higher personal earnings groups, with the highest percentage in $150-$199k category (26.1 percent).

Personal Earnings/ Occupation

Workers in construction, extraction, repair, and maintenance occupations (18.8 percent) and managerial roles (12.46 percent) have the highest percentage of super-commuters across all personal earnings levels while office support workers (11 percent) and managers (10.2 percent) are the most popular occupations among non-super-commuters. As expected, within managerial roles, super-commuters are more highly represented in higher personal earning groups (38.4 percent in $200k or more) as managerial positions usually require a highly skilled workforce and tend to be compensated higher as a result for low and middle earnings groups (less than $25k to $100-$149k), super-commuters are highly represented in the construction, extraction, repair, and maintenance group followed by the office support workers group.

We observe the same patterns for managerial roles in the non-super-commuter group as well (e.g., a higher percentage of non-super-commuters in higher personal earning levels (32.7 percent in $200k or more)). However, the group with the highest percentages of non-super-commuters after the managerial group is medical professionals, with 14.7 percent in the $200k or more group. Interestingly, we see a lower percentage of non-super-commuters in construction, extraction, repair, and maintenance workers as opposed to the super-commuter group which reinforces our assumption that super-commuters are mostly found in lower to middle personal earnings groups working as construction, extraction, repair, and maintenance workers. In the lower to middle earnings groups, especially in the less than $25k and $50k-$74k groups, we see different occupation groups where non-super-commuters are highly represented including food preparation workers, salespersons, and office support workers.

Travel Behavior of Super-Commuters

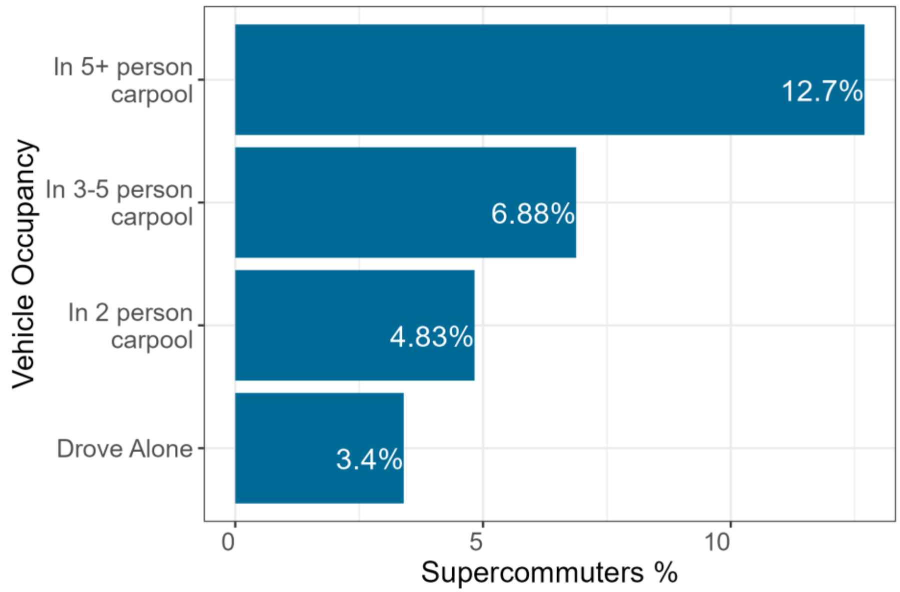
To understand the travel behavior of super-commuters, we looked the 2017-2021 5-Year Public Use Microdata Sample (PUMS) conducted by the U.S. Census and the 2017 National Household Travel Survey (NHTS) conducted by the Federal Highway Administration. From both datasets, we analyzed vehicle occupancy for super-commuters compared to non-super-commuters.

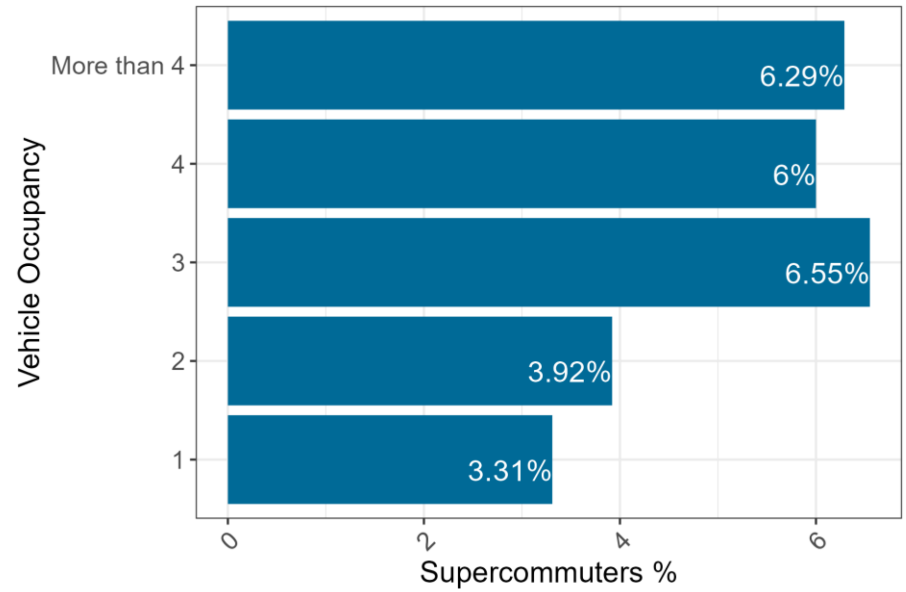
Vehicle Occupancy

For the PUMS analysis, we filtered the dataset to find super-commuters who travel to work via car, truck, or van. To determine travel behavior characteristics of super-commuters in cars, trucks, and vans, we analyzed vehicle occupancy and determined the likelihood of super-commuters to travel alone, in a 2-person carpool, in a 3–5-person carpool, or in a 5+ person carpool. It was discovered that the 5+ person carpool category has the highest number of super-commuters as a percent of total car, truck, and van commuters (12.7 percent). This indicates that super-commuters are more likely than non-super-commuters to carpool to work with several other commuters. This is likely a reflection of super-commuter industry and occupation trends in relation to non-super-commuter trends, considering that a high proportion of super-commuters are represented in the construction, mining, and extraction industry groups, in which workers frequently travel from a common business location to a worksite in a shared vehicle. Additionally, super-commuters likely carpool more than non-super-commuters due to the long commute lengths (Figure 12).

From the NHTS analysis, we observe that the 3-person carpool group has the highest number of super-commuters as a percent of total car, truck, and van commuters (6.6 percent) followed by the 5+ person carpool group. While there is some variation in results compared to what was observed in PUMS, we can still conclude that the results reflect the super-commuter industry and occupation trends in relation to non-super-commuter trends.

Figure 12. Super-Commuters as a Percentage of All Car, Truck, and Van Commuters by Vehicle Occupancy Level (PUMS- left, NHTS- right)





Source: EBP Analysis of Public Use Microdata Sample (PUMS) (left), 2017-2021, EBP Analysis of National Household Travel Survey (NHTS) 2017 (right).

Within the super-commuter group in PUMS data, we observe that the highest proportion of super-commuters drove alone to work (82.3 percent) followed by 11.4 percent in the 2-person carpool group. We see a similar distribution pattern in the non-super-commuter group, but we see a higher percentage of non-super-commuters driving alone (88.5 percent), and a lower percentage driving in a 2-person carpool (8.5 percent). Interestingly, we observe that super-commuters are more than twice as likely to commute in 3-5 person carpools (5.3 percent) compared to non-super-commuters (2.7 percent), and super-commuters are more than three times as likely to commute in 5+ person carpools compared to non-super-commuters (1.0 percent vs. 0.3 percent). For the latter group, we note that 12.7% of all commuters in 5+ person carpools are super-commuters, which is nearly four times the percent of super-commuters that drove alone (Table 15).

Table 15. Super-Commuters by Vehicle Occupancy (PUMS)

Vehicle Occupancy	Super-Commuter Count	Non-Super-Commuter Count	Super-Commuters as Pct of All Commuters*	Super-Commuter Distribution**	Non- Super-Commuter Distribution**
Drove Alone	435,269	12,378,643	3.4%	82.3%	88.5%
In 2-person carpool	60,555	1,193,080	4.8%	11.4%	8.5%
In 3–5-person carpool	27,961	378,433	6.9%	5.3%	2.7%
In 5+ person carpool	5,403	37,151	12.7%	1.0%	0.3%

Source: EBP Analysis of Public Use Microdata Sample (PUMS), 2017-2021. Note: *Super-Commuters as Pct of All Commuters refers specifically to car, truck, or van commuters, or the value derived by adding super-commuters and non-super-commuters. **Super-Commuter Distribution and Non-Super-Commuter Distribution refers to the percent breakdown of each distinct grouping into the categories in the first column.

Within the super-commuter group in NHTS data, we observe similar results as in PUMS where a high proportion of super-commuters drove alone to work (79.5 percent) followed by 11.7 percent in the 2-person carpool group (Table 16). We also see a similar pattern in the non-super-commuter group but an even higher percentage of non-super-commuters driving alone (84.8 percent), and 10.5 percent traveling in a 2-person carpool. Similar to the PUMS findings in Table 15, we see that super-commuters are represented to a greater degree in the 2+-person carpool groupings compared to non-super-commuters, and we observe that super-commuters are roughly twice as likely as non-super-commuters to commute to work in a 3-person carpool.

Table 16. Super-Commuters by Vehicle Occupancy (NHTS)

Vehicle Occupancy	Super-Commuter Count-Household	Non-Super-Commuter Count - Household	Super-Commuters as Pct of All Commuters-Household*	Super-Commuter Distribution-Household**	Non-Super-Commuter Distribution-Household**
Drove Alone	366,123	10,695,384	3.3%	79.5%	84.8%
In 2-person carpool	53,829	1,320,506	3.9%	11.7%	10.5%
In 3-person carpool	23,256	331,812	6.6%	5.1%	2.6%
In 4-person carpool	5,238	82,112	6.0%	1.1%	0.7%
In >4 person carpool	11,961	178,151	6.3%	2.6%	1.4%

Source: EBP Analysis of National Household Travel Survey (NHTS) 2017. Note: *Super-Commuters as Pct of All Commuters refers specifically to car, truck, or van commuters, or the value derived by adding super-commuters and non-super-commuters. **Super-Commuter Distribution and Non-Super-Commuter Distribution refers to the percent breakdown of each distinct grouping into the categories in the first column.

Vehicle Characteristics of Super-Commuters

Vehicle characteristics including vehicle type, fuel type, and fuel efficiency affect the costs road users incur for each mile traveled. As such, these characteristics play an instrumental role in determining the equity impacts of a potential RUC.

To understand these vehicle characteristics for super-commuters, we looked at three datasets: the 2017 National Household Travel Survey (NHTS) conducted by the Federal Highway Administration, odometer readings from the CA Bureau of Automotive Repair (BAR)'s vehicle smog inspections[14], and odometer readings from the CA Department of Motor Vehicles' vehicle sale/transfer data.

NHTS records contained 26,000 households, 53,600 people, 52,200 vehicles and a means to expand this raw sample to account for the 12.8 million households, 36.6 million people, and 125.1 million vehicles considered in this study in the state of CA.[15] Although the NHTS represents quite a large, comprehensive survey, it only observes 1 out of every 500 households for a snapshot in time during 2016 and 2017. To provide another perspective on the vehicle population, we collected administrative data (inspection and sale/transfer) from BAR and DMV. The use of administrative records to supplement survey data builds on previous RUC equity work for California through RUC America that leveraged every registration record for light duty household vehicles.

The BAR dataset included 49,534,280 vehicle smog check event records, and the DMV dataset contained 5,630,441 transaction records. The most recent six years of vehicle smog inspection data (2017 to 2023) were requested from BAR, which included vehicles ranging from Model Year (MY) 1976 to 2015. To complement this dataset, vehicle sale/transfer records from 2015 to 2023 were requested from CA DMV, which featured vehicles ranging from MY 2015 to 2023. These two data sources intentionally included different sets of model years to avoid double counting the same event. DMV removed older model years sold during the sample period as they are already covered by the BAR data. Vehicles newer

[14] Inspections occur every 2 years for vehicles older than 8 years, but if within those 8 years the vehicle is transferred and a change of ownership occurs, this 8-year exemption is reduced to 4 years.

[15] The weighted totals account for data excluded during data cleaning and transformation that weren't relevant for the purposes of the analysis.

than MY 2015 appearing in the BAR data (due to required smog checks for vehicles between ages four and eight) were also filtered out.

Both the BAR and DMV data had the possibility of observing a single vehicle multiple times. We considered each time window between events as potentially including super-commuting behavior or other high-mileage travel patterns. While the BAR data is a relatively comprehensive record of the in-service vehicles older than 8 years at any time, there is definitely some bias in the newer vehicles observed by DMV through the documentation of sales transactions. Still these data sources provide many more actual observations of vehicle usage without relying on survey responses.

From the NHTS data, we analyzed vehicle type, fuel type, fuel efficiency, and vehicle age for super-commuter household vehicles compared to non-super commuter household vehicles. For multiple vehicle records within a single household, vehicle records were weighted by VMT and summarized at the household level. From the BAR and DMV datasets, we analyzed the same variables as NHTS for high-mileage vehicles, those driven 20,000 or more miles per year, compared to low-/medium-mileage vehicles, those driven less than 20,000 miles per year.[16] For the BAR and DMV data, we are not able to isolate super-commuters specifically, but we are able to make conclusions about high- vs. low-/medium-mileage vehicles, which are still applicable for the scope of this analysis.

Vehicle Mileage

In our analysis of vehicle data from the Bureau of Automotive Repair (BAR) (which included vehicle records from MY 1976 to 2015), high-mileage vehicle usage – defined as vehicles driven over 20,000 miles per year between smog checks – only accounts for about 5% of the records. On the other hand, in our analysis of DMV vehicle data, more than one-third of newer vehicles (less than eight years old) sold in the last eight years, fell into this high-mileage category. This suggests that a very large number of drivers traveling large amounts per year, due to work commutes or other trip requirements, are selecting new vehicles and possibly selling them after just a few years of ownership.

[16] This threshold was informed from previous yearly mileage research conducted using data from NHTS that showed that the majority of non-super-commuters drove less than 20,000 miles per year.

Older, high-usage vehicles in the BAR data were only driven an average of 25,930 miles per year, compared with newer, high-usage vehicles that were sold and reported in the DMV data, which were driven an average of 31,458 miles. For both datasets, we capped the maximum number of miles accrued per year at 75,000 and assumed all greater amounts were due to data entry errors.

Older, low- and medium-mileage vehicles (vehicles driven less than 20,000 miles per year), were also driven much less than newer vehicles in this group: an average of 7,978 annual miles per year (Table 17) compared to 11,742 (Table 18).

Table 17. High- and Low-/Medium-Mileage Vehicles by Mileage (BAR)

Mileage Type	Count	Mean Yearly Miles
Low and Medium	46,799,232	7,978
High	2,734,889	25,930

Source: EBP Analysis of Bureau of Automotive Repair (BAR) data (2023).

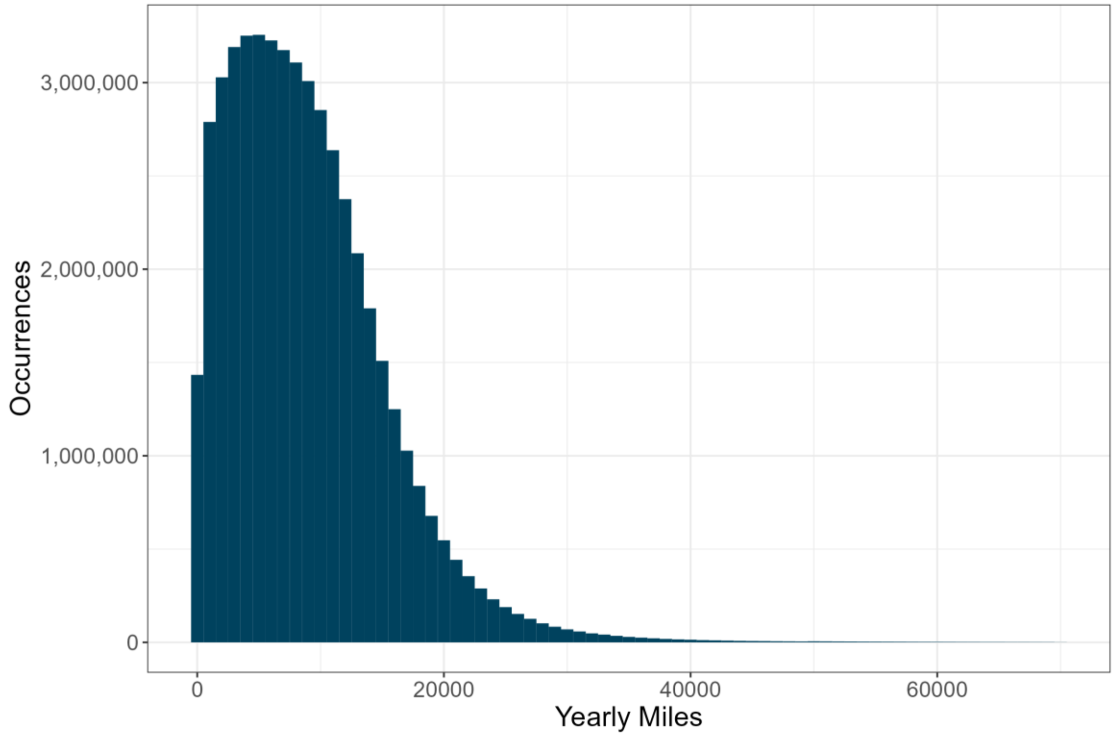
Table 18. High- and Low-/Medium-Mileage Vehicles by Mileage (DMV)

Mileage Type	Count	Mean Yearly Miles
Low and Medium	3,678,179	11,742
High	1,952,262	31,458

Source: EBP Analysis of Department of Motor Vehicles (DMV) data (2023).

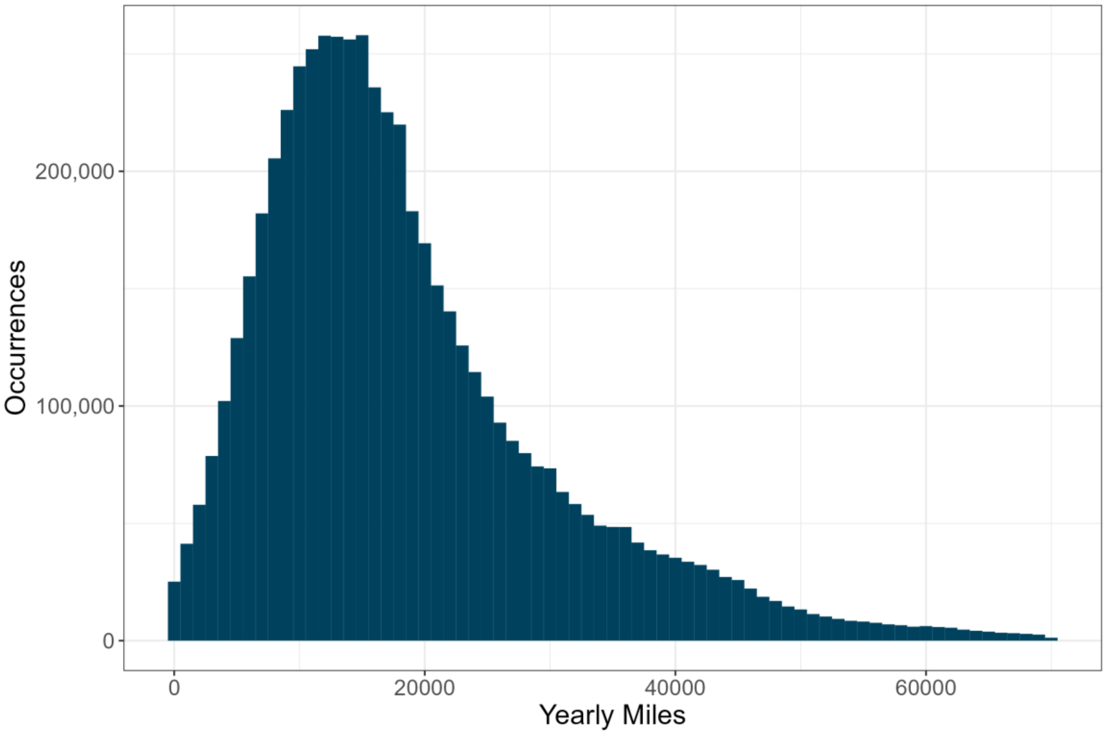
To provide additional insight on the relationship between vehicle mileage and vehicle age range, histograms of estimated annual vehicle mileage for BAR and DMV vehicles were visualized and broken into buckets of 1,000 miles (Figure 13 and Figure 14). In the BAR data (which includes vehicles from MY 1976 to 2015 that underwent smog checks from 2017-2023) we see there is a sharp increase in the occurrence of low mileage vehicles, and we see the dataset reaches its modal value in the 6,000-7,000 miles per year range. The DMV data (which includes vehicles from MY 2015-2023 that were sold or transferred between 2015 and 2023) has a slightly higher modal value around 14,000 miles, and a longer tail relative to BAR.

Figure 13. Yearly Miles Distribution (BAR)



Source: EBP Analysis of Bureau of Automotive Repair (BAR) data (2023).

Figure 14. Yearly Miles Distribution (DMV)



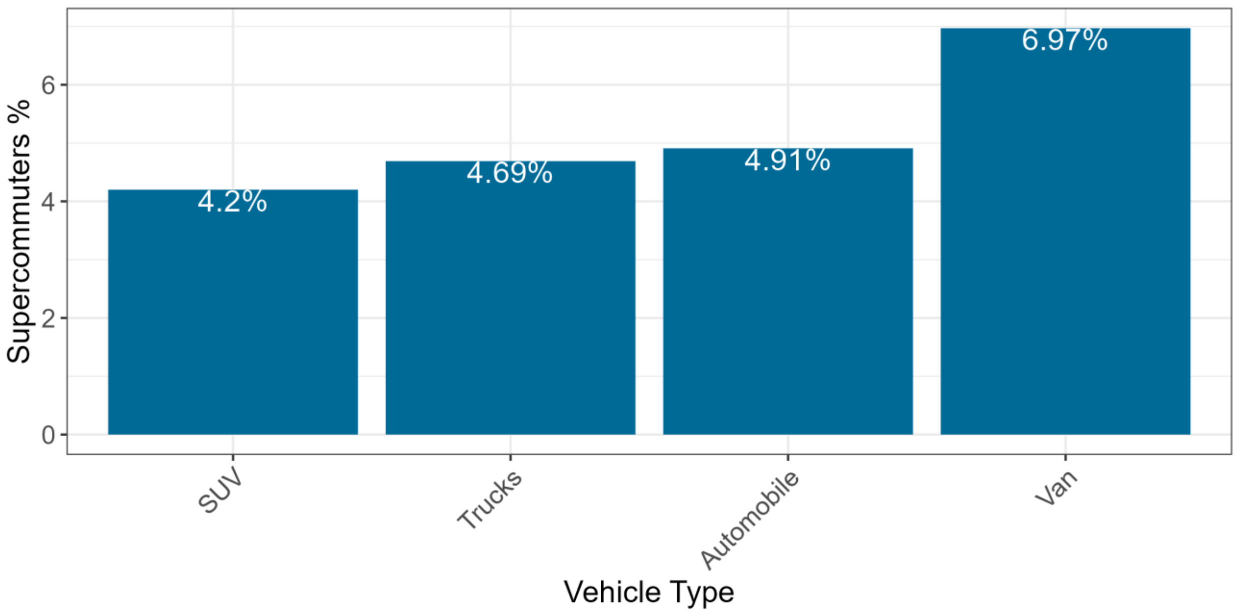
Source: EBP Analysis of Department of Motor Vehicles (DMV) data (2023).

These findings align with the mean yearly miles results in Table 17 and Table 18 as they reinforce the association between high-mileage and newer vehicles. With both a higher modal mileage value and more observations to the right of the 20,000 miles per year cutoff, the higher average mileage of the DMV dataset begins to make sense. Additionally, considering the low mileage of vehicles in model year 2023, the number of high-mileage vehicles in the DMV dataset can be considered an underestimate, as these vehicles will only gain more mileage as 2023 continues.

Vehicle Type

In NHTS data, as shown in Figure 15, vans have the highest percentage of VMT driven by super-commuter households (7 percent) followed by automobiles (4.9 percent) and pickup trucks (4.7 percent). As super-commuters are more likely to carpool compared to non-super-commuters, it makes sense that the vehicle with the highest passenger capacity has the greatest number of super-commuters as a percentage of all commuters.

Figure 15. VMT Driven per Vehicle Type by Super-Commuter Households as a Percentage of All VMT Driven per Vehicle Type by Car, Truck, and Van Commuter Households



Source: EBP Analysis of National Household Travel Survey (NHTS) 2017.

Within the super-commuter household group, we can see that most super-commuter households' mileage was driven in automobiles (62.2 percent) followed by SUVs (19 percent) in 2017. We see a similar pattern within the non-super-commuter household group, where most mileage was driven in automobiles (61.4 percent) followed by SUVs (22.1 percent). Notably, super-commuter households' mileage is less likely to be driven in SUVs compared to non-super-commuter households and is more likely to be driven in vans (8.3 vs. 5.7 percent) (Table 19).

Table 19. VMT Driven per Vehicle Type by Super-Commuter Households

Vehicle Type	Super-Commuter Households VMT as Pct of All Commuter Households' VMT*	Distribution of Super-Commuter Household VMT**	Distribution of Non-Super-Commuter Household VMT**
Van	7.0%	8.3%	5.7%
Automobile	4.9%	62.2%	61.4%
Trucks	4.7%	10.5%	10.9%
SUV	4.2%	19.0%	22.1%

Source: EBP Analysis of National Household Travel Survey (NHTS) 2017. Note: *Super-Commuter Household VMT as Pct of All Commuters' Household VMT refers specifically to households with car, truck, or van commuters. **Distribution of Super-Commuter Household VMT and Non-Super-Commuter VMT refers to the percent VMT breakdown of each distinct grouping into the categories in the first column.

When considering high- to low/medium-mileage vehicles in BAR and DMV data, we observe a similar difference in the distribution of vehicle types. Both sets have similar proportions of automobiles and crossovers in both mileage groups but see a shift from SUVs (more common in the low-/medium-mileage group) to trucks and vans (Table 20 and Table 21). This finding ties into our analysis of super-commuters' occupations, as trucks and vans are commonly used for both work and commuting by workers in industries like construction and agriculture. In the NHTS analysis, we see a higher prevalence of van usage for super-commuter households compared to non-super-commuter households, but in contrast we see a slightly lower prevalence of truck usage for super-commuters compared to non-super-commuter households (Table 19). That the administrative data is more consistent with other findings may be a factor of survey sample bias or that high-mileage trucks are used in a way that drivers typically do not consider "commutes."

The DMV set has a larger share of crossovers and SUVs and a smaller share of trucks and vans when compared to the BAR set. This is reflective of national fleet trends that have increased the prevalence of crossovers and SUVs relative to all other vehicle types.

Table 20. Number of Vehicles in Each Mileage Category by Vehicle Type (BAR)

Vehicle Type	High Mileage Count	Low Mileage Count	High Mileage Percent	Low Mileage Percent	Difference in Percentage
Automobile	1,241,847	21,055,943	45.41%	44.99%	0.42%
Crossover	478,096	8,395,412	17.48%	17.94%	-0.46%
SUV	356,445	7,346,684	13.03%	15.70%	-2.67%
Truck	534,232	8,207,843	19.53%	17.54%	2.00%
Van	124,269	1,793,350	4.54%	3.83%	0.71%
Total	**2,734,889**	**46,799,232**	**100.00%**	**100.00%**	

Source: EBP Analysis of Bureau of Automotive Repair (BAR) data (2023).

Table 21. Number of Vehicles in Each Mileage Category by Vehicle Type (DMV)

Vehicle Type	High Mileage Count	Low Mileage Count	High Mileage Percent	Low Mileage Percent	Difference in Percentage
Automobile	902,501	1,676,010	46.23%	45.57%	0.66%
Crossover	418,866	838,647	21.46%	22.80%	-1.35%
SUV	368,542	805,148	18.88%	21.89%	-3.01%
Truck	211,676	297,164	10.84%	8.08%	2.76%
Van	50,677	61,210	2.60%	1.66%	0.93%
Total	**1,952,262**	**3,678,179**	**100.00%**	**100.00%**	

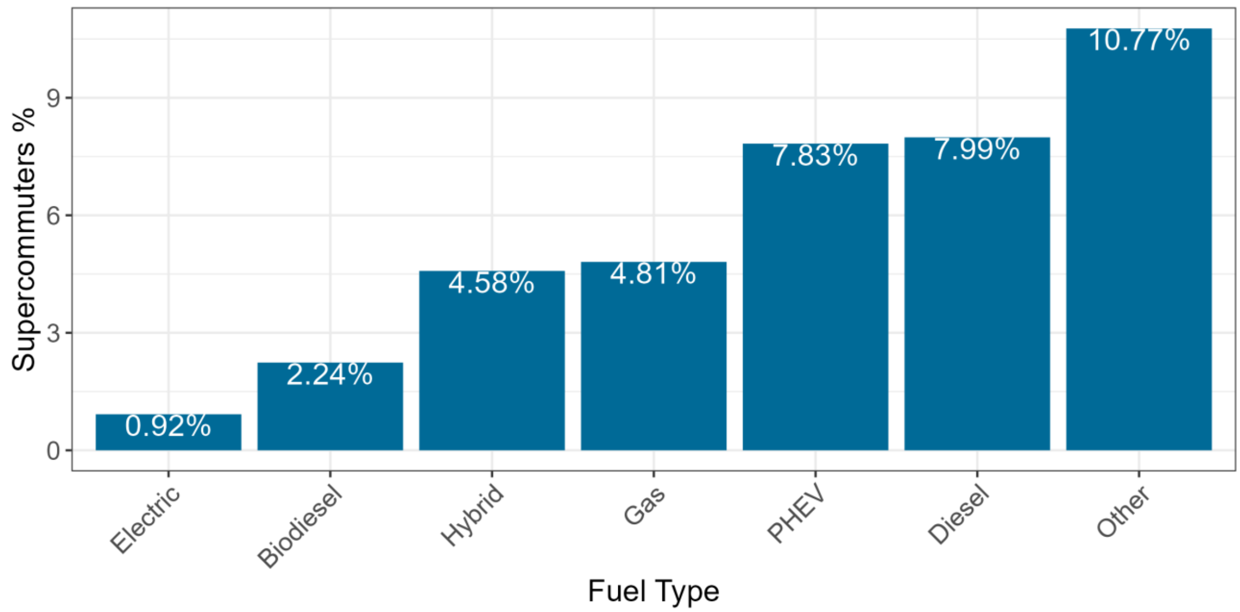
Source: EBP Analysis of Department of Motor Vehicles (DMV) data (2023).

Fuel Type

In NHTS, we observed the highest number of super-commuter households (as a percent of all car, truck, or van commuter households) using vehicles that rely on 'other fuel'[17] type (10.8 percent), followed by diesel (8 percent) and plug-in hybrid vehicles (7.9 percent). However, other fuel, biodiesel, electric, and PHEV vehicles all had small sample sizes, and their low or high percent representation may be driven by lack of observations in the data (Figure 16).

[17] 'Other' fuels include hydrogen, ethanol/flex fuel (e85), propane (LPG), and natural gas (CNG). Fuel type, economy, consumption, and cost in the 2017 NHTS were calculated using data provided by the Energy Information Administration. EIA Fuel Consumption Variables. https://nhts.ornl.gov/assets/EIA%20Fuel%20Consumption%20Variables.pdf. US Energy Information Administration. Alternative Fuel Vehicle Data 2017. https://www.eia.gov/renewable/afv/

Figure 16. VMT Driven per Vehicle Fuel Type by Super-Commuter Households as a Percentage of All VMT Driven per Vehicle Fuel Type by Car, Truck, and Van Commuters



Source: EBP Analysis of National Household Travel Survey (NHTS) 2017.

Most VMT driven by super-commuter households is fueled by gasoline (91.6 percent) and then the remaining ~ 8 percent of is dispersed across other fuel types (Table 22). We see a similar pattern across the distribution of VMT across super-commuter and non-super-commuter households, with 92.5 percent of VMT driven by non-super-commuter households also being fueled by gas. A greater percentage of super-commuter household VMT is powered by diesel, PHEV, and other vehicles, while a greater percent of non-super-commuter household VMT is fueled by gas, hybrid, and electric vehicles. It is possible that the vans and pickup trucks that super-commuter households use to commute with rely on diesel, and the automobiles that other super-commuter households use to commute with are PHEV vehicles. If so, this is an example of the varying types of super-commuters, who experience varying financial impacts as a result of driving different vehicles.

Table 22. VMT Driven per Vehicle Fuel Type by Super-Commuter Households

Fuel Type	Super-Commuter Household VMT as Pct of Commuters' Household VMT *	Distribution of Super-Commuter Household VMT**	Distribution of Non-Super-Commuter Household VMT**
Biodiesel	2.2%	0.0%	0.0%
Diesel	8.0%	2.8%	1.6%
Electric	0.9%	0.1%	0.7%
Gas	4.8%	91.6%	92.5%
Hybrid	4.6%	4.2%	4.4%
Other	10.8%	0.3%	0.1%
PHEV	7.8%	1.0%	0.6%

Source: EBP Analysis of National Household Travel Survey (NHTS) 2017. Note: *Super-Commuter Household VMT as Pct of Commuters' Household VMT refers specifically to car, truck, or van commuters. **Distribution of Super-Commuter Household VMT and Non-Super-Commuter VMT refers to the percent VMT breakdown of each distinct grouping into the categories in the first column.

When considering BAR and DMV data fuel type for both mileage classes, we similarly observe most vehicles are gasoline powered. In the BAR data (Table 23), there is a shift from gasoline towards diesel and (to a much greater extent) hybrid vehicles for high-mileage vehicles: older diesel and hybrid vehicles make up a surprisingly large number of older high-mileage vehicles. Their usage falls of slower than gasoline vehicles. (There are no EVs in the BAR data as they are exempt from smog checks and very few existed prior to MY 2015.)

In the DMV data (Table 24), the vehicle proportions between the two mileage groups are much closer than they are for the BAR data. Again though, administrative data corroborates survey data with electric vehicles going from about 2% of the low/medium group to about 1% of the high-mileage group, and diesel making up 50% more of the high mileage records than the low-mileage records.

Our NHTS analysis did not show a preference for hybrid vehicles, which was quite strong when looking specifically at the smog check record for older vehicles. These differences may be a result of the greater scope of the BAR and DMV datasets, as they capture a much higher proportion of all vehicles in the state of California. They also serve to highlight an important point to keep in mind about these analyses: super-commuters don't necessarily drive the highest mileage when considering all road travelers, and high-mileage vehicles don't necessarily belong to super-commuters.

Table 23. Number of Vehicles in Each Mileage Category by Fuel Type (BAR)

Fuel Type	High Mileage Count	High Mileage Percent	Low/Medium Mileage	Low Mileage Percent	Difference in Percentage
Diesel	111,695	4.08%	1,007,346	2.1%	1.9%
Gasoline	2,398,589	87.70%	43,979,650	93.9%	-6.2%
Hybrid	221,883	8.11%	1,786,866	3.8%	4.2%
Other	2,722	0.10%	25,370	< 0.1%	< 0.1%
Total	**2,734,889**	**100.00%**	**46,799,232**	**100.00%**	

Source: EBP Analysis of Bureau of Automotive Repair (BAR) data (2023).

Table 24. Number of Vehicles in Each Mileage Category by Fuel Type (DMV)

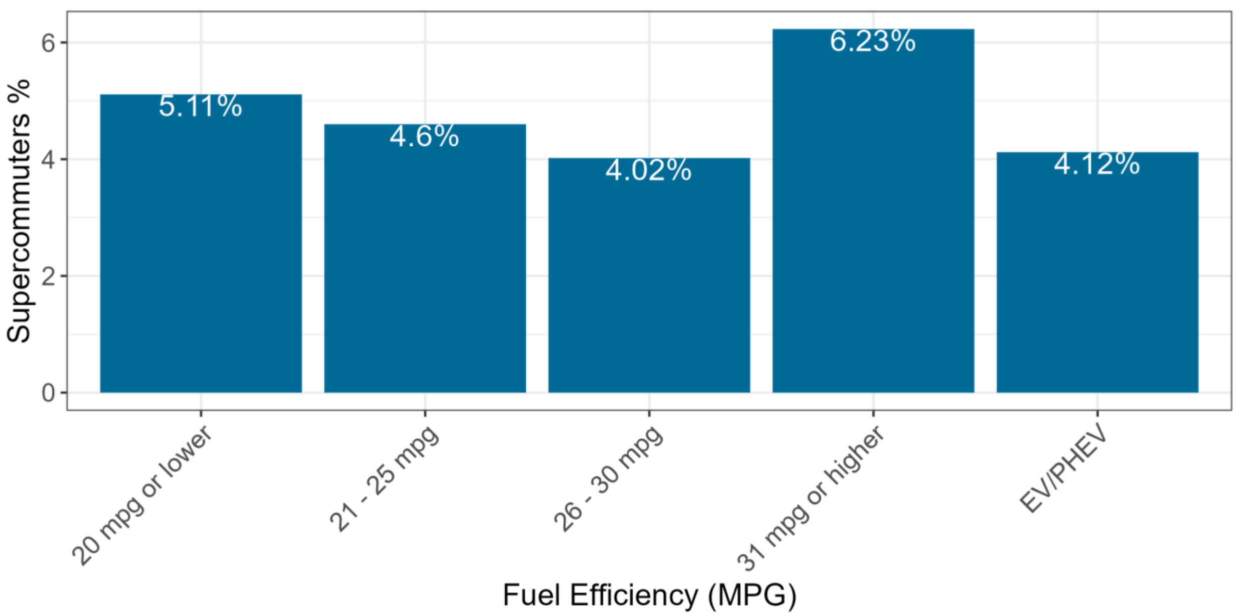
Fuel Type	High Mileage Count	High Mileage Percent	Low Mileage Count	Low Mileage Percent	Difference in Percentage
Diesel	37,763	1.9%	47,352	1.3%	0.6%
Electric	19,928	1.0%	79,659	2.2%	-1.2%
Gasoline	1,768,473	90.6%	3,323,584	90.4%	0.2%
Hybrid	126,019	6.5%	227,426	6.2%	0.3%
Other	79	0.0%	158	0.0%	0.0%
Total	**1,952,262**	**100.0%**	**3,678,179**	**100.0%**	

Source: EBP Analysis of Department of Motor Vehicles (DMV) data (2023).

Fuel Efficiency and Vehicle Age

Fuel efficiency of a vehicle is perhaps the most important factor impacting the amount a driver will pay under a fuel tax versus a RUC, and is often associated with vehicle age, as newer vehicle models are more fuel efficient.[18] The NHTS analysis discovered super-commuter households' vehicle usage makes up the greatest share of commuting households' vehicle use in the 31 mpg and higher category (6.2 percent) followed by the 20 mpg or lower category (5.1 percent). Low or high efficiency vehicles are more likely to be used by super-commuter households than middle efficiency vehicles. The bimodal distribution is indicative of the variation in super-commuters (Figure 17).

Figure 17. VMT Driven by Vehicle Efficiency by Super-Commuter Households as a Percent of All VMT Driven by Vehicle Efficiency by Car, Truck, and Van Commuters



Source: EBP Analysis of National Household Travel Survey (NHTS) 2017.

Within the super-commuter and non-super-commuter household groups, we observe that roughly 40 percent of vehicles have efficiencies of 20 mpg or lower, while roughly 30 percent have efficiencies of 21-25 mpg. The two groups are also similarly distributed (1.1 and 1.3 percent) for EV/PHEV vehicles (Table 25). Since efficiency is one of the largest

[18] More stringent vehicle fuel efficiency regulations have resulted in an upward trend in fuel efficiency over time.

determinants of the impacts of a RUC, some super-commuter households will see net savings, while others will see payment increases, depending on the efficiency of their vehicle.

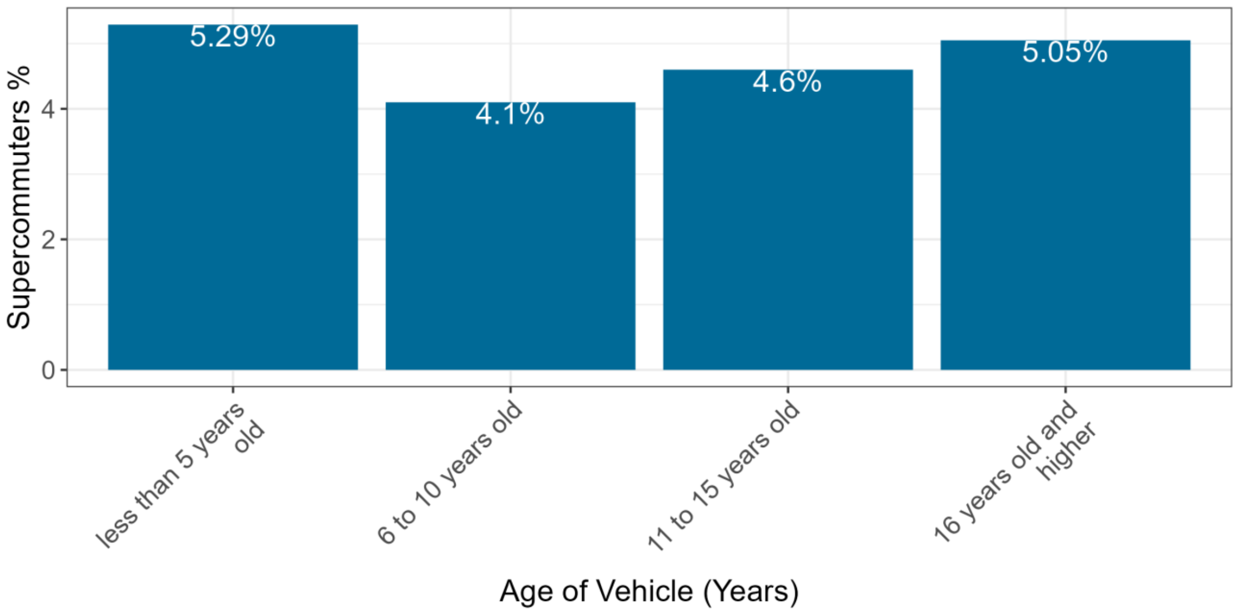
Table 25. VMT Driven by Efficiency by Super-Commuters

Vehicle Efficiency Grouping	Super-Commuter Household VMT as Pct of Commuters Household VMT*	Distribution of Super-Commuter Household VMT**	Distribution of Non-Super-Commuter Household VMT**
20 mpg or lower	5.1%	39.9%	37.8%
21 – 25 mpg	4.6%	29.6%	31.4%
26 – 30 mpg	4.0%	15.6%	19.0%
31 mpg or higher	6.2%	13.8%	10.6%
EV/PHEV	4.1%	1.1%	1.3%

Source: EBP Analysis of National Household Travel Survey (NHTS) 2017. Note: *Super-Commuter Household VMT as Pct of Commuters' Household VMT refers specifically to car, truck, or van commuters. **Distribution of Super-Commuter Household VMT and Non-Super-Commuter VMT refers to the percent VMT breakdown of each distinct grouping into the categories in the first column.

The age of a vehicle is correlated with fuel efficiency, and an aging vehicle stock is an important consideration in policy discussions about fuel tax-based transportation revenue policy or a road usage charge (RUC) framework. Among all commuters in the NHTS analysis, we observe that super-commuter households are most likely to use vehicles that are less than 5 years old (5.3 percent) followed by 16 years old and higher vehicles (5.1 percent) (Figure 18). Although the difference between the age groups is quite small, it is evident that super-commuter households are more likely to own new or very old cars, compared to non-super-commuter households. This provides further evidence of variance within the super-commuter group. The distribution of age between vehicle groups for super-commuters and non-super-commuters is quite similar, with only slightly more vehicles 6-15 years among non-super-commuters (Table 26).

Figure 18. VMT Driven by Vehicle Age by Super-Commuter Households as a Percent of All VMT Driven by Vehicle Age by Car, Truck, and Van Commuters



Source: EBP Analysis of National Household Travel Survey (NHTS) 2017.

Table 26. VMT Driven by Vehicle Age by Super-Commuter Households

Vehicle Age	Super-Commuters Household VMT as Pct of All Commuters Household VMT*	Distribution of Super-Commuter Household VMT**	Distribution of Non-Super-Commuter Household VMT**
less than 5 years old	5.3%	41.7%	37.9%
6 to 10 years old	4.1%	19.4%	23.0%
11 to 15 years old	4.6%	21.6%	22.7%
16 years old and higher	5.1%	17.2%	16.4%

Source: EBP Analysis of National Household Travel Survey (NHTS) 2017. Note: *Super-Commuter Household VMT as Pct of Commuters' Household VMT refers specifically to car, truck, or van commuters. **Distribution of Super-Commuter Household VMT and Non-Super-Commuter VMT refers to the percent VMT breakdown of each distinct grouping into the categories in the first column.

In the BAR data, high mileage cars are significantly newer than low and medium mileage ones (see Table 27). We do not see this pattern in the DMV data where the mean and median model year for both groups is 2017. (Consequently, model year was omitted from Table 28.) The mean fuel efficiency of the high mileage BAR vehicles is a full 1.63 miles per gallon (MPG) higher than that of the low-and-medium group. Interestingly, we do not see this same pattern in the DMV data, where high mileage vehicles tend to be slightly less efficient than their low mileage counterparts. This seeming anomaly can be explained by differences in the fleet composition of the DMV group, as we will see in the remainder of this section. Still, some of it may also be due to a bias in the data collection. The DMV dataset is composed of vehicles which have been sold, and we speculate that high efficiency, high mileage vehicles may be less likely to be sold than low efficiency, high mileage vehicles.

One factor contributing to this difference is the vehicle ages in each dataset. The BAR data has a much wider range of model years, and therefore a greater difference in efficiency between its oldest and newest vehicles. The DMV data has at most an eight-year gap with a fleet comprised of relatively newer vehicles, resulting in less difference in efficiency. The complete lack of model year 2023 vehicles in the DMV high mileage is not the cause of this difference, as excluding those vehicles from the data does not change this result.

Table 27. High- vs. Low- Efficiency and Age (BAR)

Mileage Type	Mean MPG	Mean Model Year	Median Model Year
Low	19.94	2005	2006
High	21.57	2009	2011

Source: EBP Analysis of Bureau of Automotive Repair (BAR) data (2023).

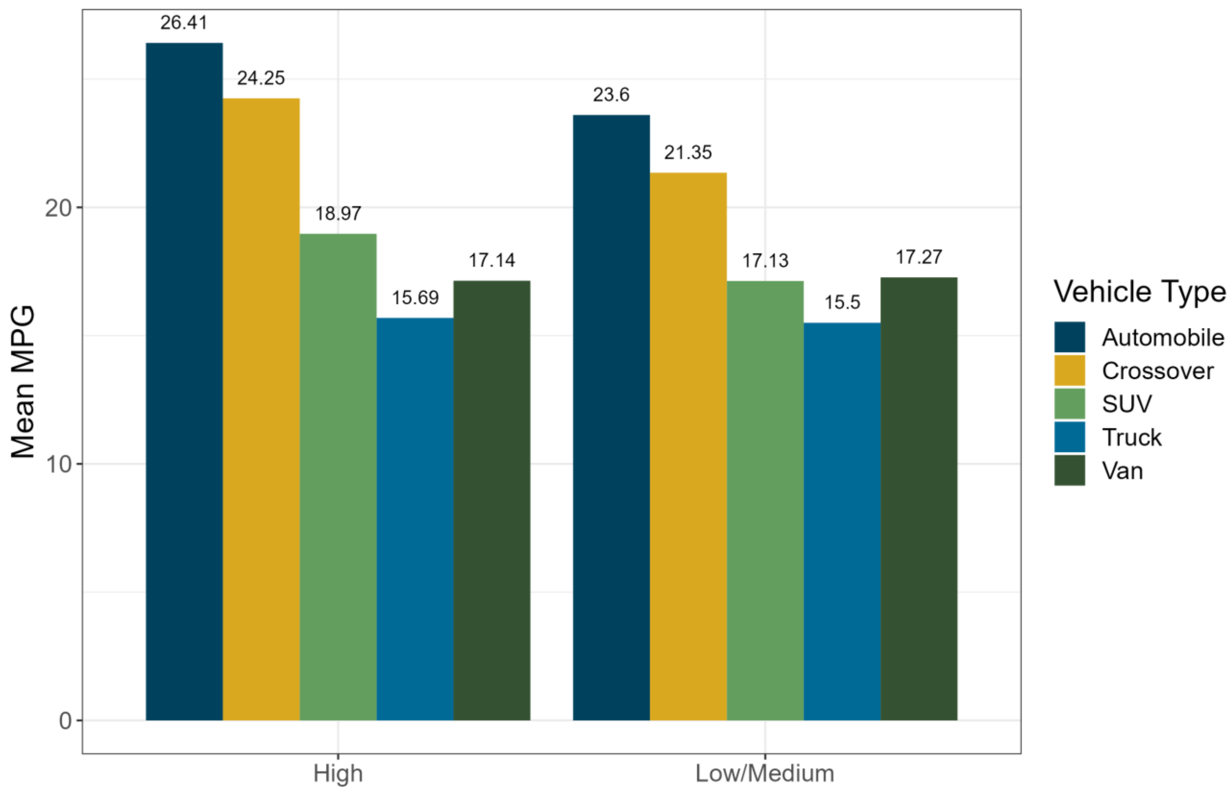
Table 28. High- vs. Low- Mileage Efficiency (DMV)

Mileage Type	Mean MPG
Low	25.11
High	24.96

Source: EBP Analysis of Department of Motor Vehicles (DMV) data (2023).

We also cross-tabulated fuel efficiency in each mileage group with vehicle and fuel type[19] (see Figure 19 and Figure 20). Looking at vehicle type trends in both datasets, we see a common pattern: automobiles are the most efficient vehicle type on average, followed by crossovers, SUVs, vans, and finally trucks. In the BAR dataset, we also observe that all vehicle types except for vans are more efficient in the high mileage group. This pattern is essentially reversed in the DMV data, where all vehicle types but automobiles are less efficient in the high mileage group. The fact that both trucks and vans are more common but less efficient among high-mileage vehicles explains a portion of our finding that high mileage vehicles are less efficient than low mileage vehicles on average in the DMV data.

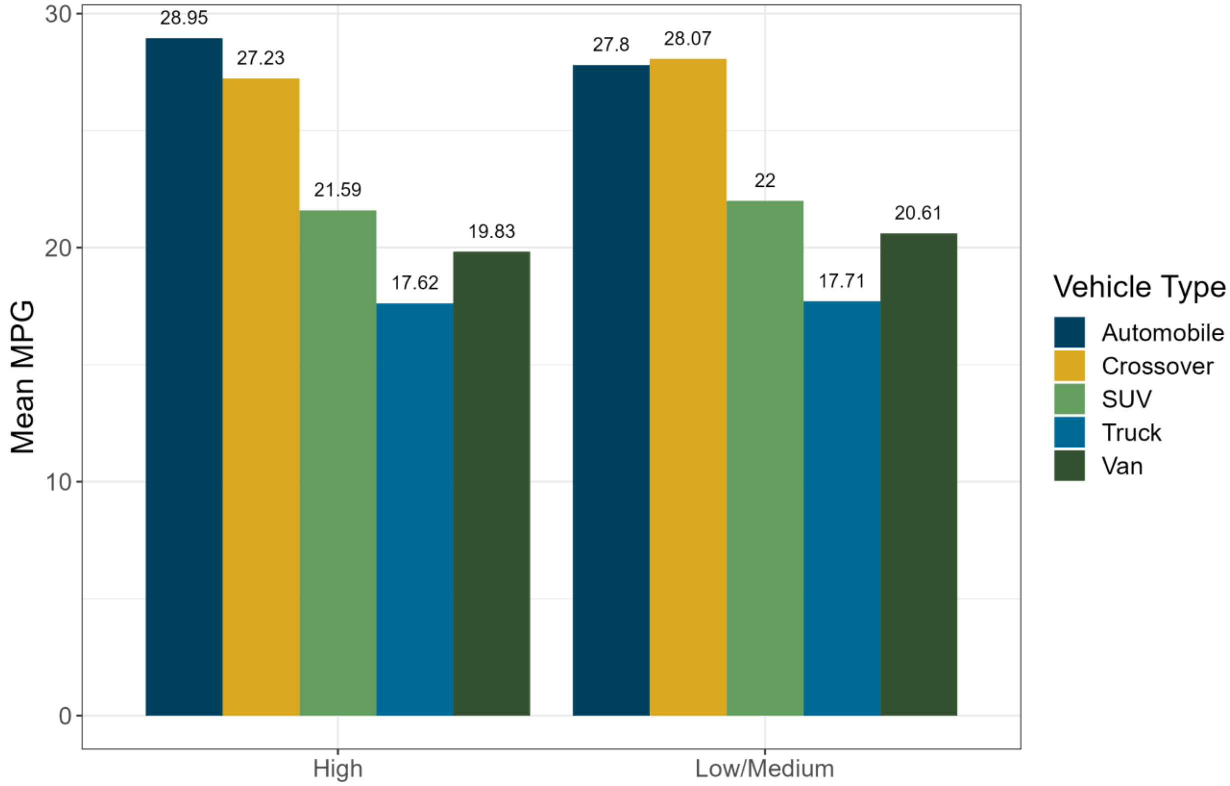
Figure 19. Mean MPG by Vehicle Type (BAR)



Source: EBP Analysis of Bureau of Automotive Repair (BAR) data (2023).

[19] From the BAR and DMV data, we were not able to separate out PHEV vehicles from hybrid vehicles in general. We were able to determine that in the BAR data, almost all the PHEV vehicles were denoted as Hybrids. In the DMV data, most were classified as Hybrids, but a small number were also marked as Gasoline or Electric.

Figure 20. Mean MPG by Vehicle Type (DMV)

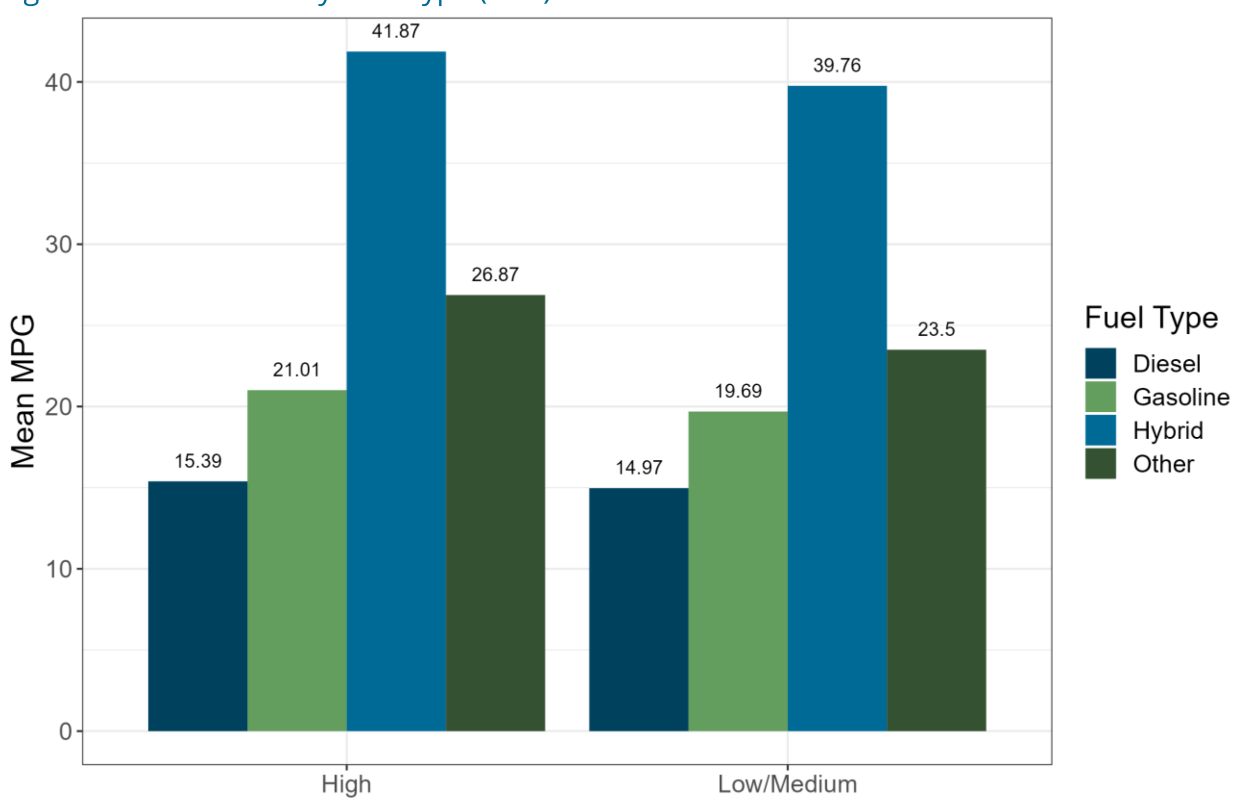


Source: EBP Analysis of Department of Motor Vehicles (DMV) data (2023).

When looking at efficiency by fuel types, we see a common set of trends in both datasets (Figure 21 and Figure 22): Electric (found only in the DMV dataset) and hybrid vehicles stand out as having comparatively high efficiency, followed by 'other' fuel types (encompassing flex fuel, CNG, and propane vehicles, among others), then gasoline. Diesel has the lowest average efficiency in both datasets. In the BAR data, we see uniformly higher MPG values for high mileage vehicles than for low/medium mileage vehicles. This trend is mirrored in the DMV data as well, with the exception of diesel vehicles, which are more efficient in the low mileage group. This is a clear example of Simpson's Paradox, wherein a trend in aggregate data is reversed in its subgroups. In this case, the reversal is likely due to differences in vehicle type between the groups.

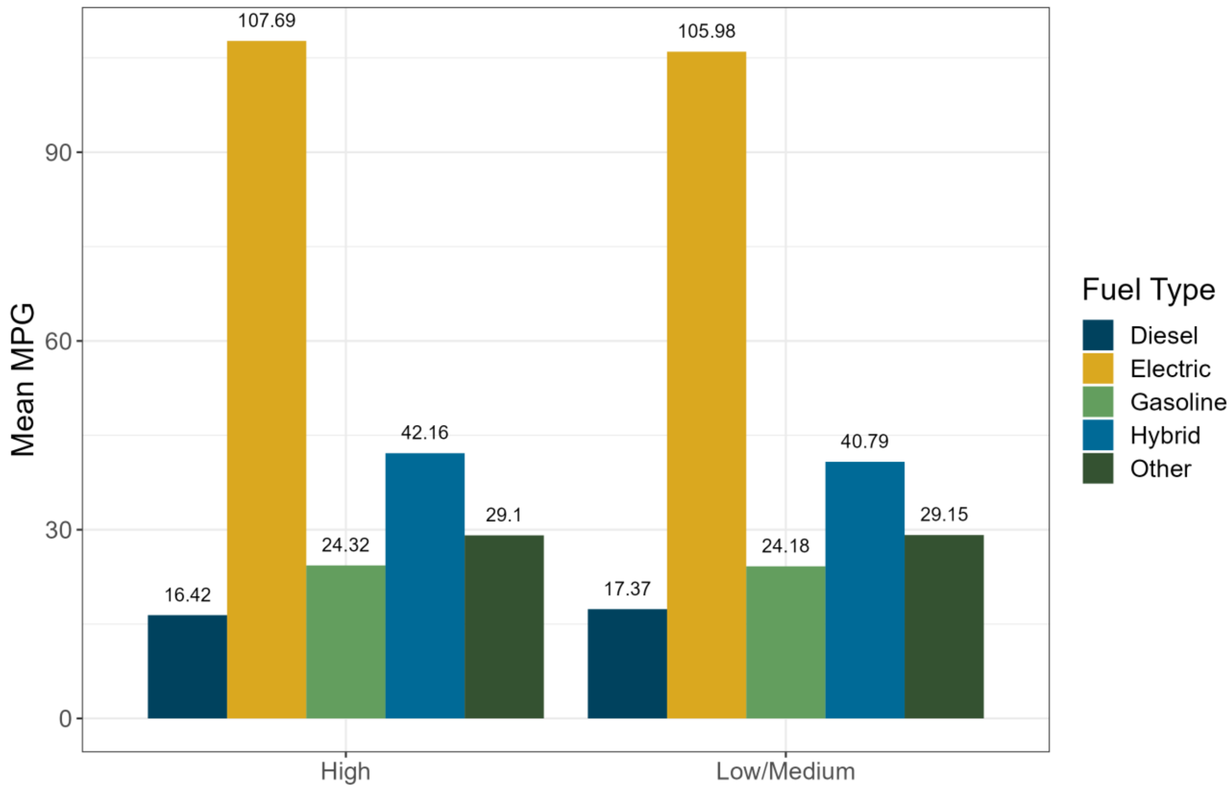
The lower miles-per-gallon average for high-mileage diesel vehicles compared to low-mileage diesel vehicles appears small, but it is in fact much larger than the difference between gasoline vehicles, partially because the common usage of miles-per-gallon instead of gallons-per-mile ratings in the US obscures fuel consumption rates. When considering the fuel consumption rates, high-mileage gasoline vehicles are only 0.58% more efficient than low-/medium-mileage gasoline vehicles, while diesel vehicles are 5.8% worse. While the hybrid efficiency change appears larger at 1.37 MPG, it is only a 3.2% improvement in fuel consumption given the higher starting point. These considerations plus the decreased electric and increased diesel share likely account for the difference.

Figure 21. Mean MPG by Fuel Type (BAR)



Source: EBP Analysis of Bureau of Automotive Repair (BAR) data (2023).

Figure 22. Mean MPG by Fuel Type (DMV)



Source: EBP Analysis of Department of Motor Vehicles (DMV) data (2023).

At the beginning of this section, we saw that there is a difference in the relationship between mileage group and fuel efficiency between the BAR and DMV datasets. We posited that this may be due to differences in vehicle age, vehicle type, and fuel type. To examine this further, we use a linear regression model to infer the relationship between mileage class and fuel efficiency, controlling for model year, fuel type, and vehicle type. The full results of this regression can be found in Appendix 1, but the major takeaway of the regression is that high mileage vehicles have, on average, a fuel efficiency 0.65 MPG higher than low mileage vehicles, all else equal.

More notably, we see a similar result for the DMV data, with high mileage vehicles having fuel efficiencies 0.39 MPG higher on average than the low mileage vehicles when attributes such as vehicle age, vehicle class, and fuel type are held constant. This supports the conclusion that high mileage vehicles are lower efficiency on average only because of differences in fleet composition.

In order to explore the characteristics of high mileage vehicles from one more avenue, we also constructed a logistic regression model which considers MPG, model year, vehicle type, and fuel type and attempts to classify vehicles as either high or low mileage based on these characteristics. From this, we can infer which attributes of a vehicle contribute most to the probability of it belonging to either mileage class. Overall, these results (detailed in Appendix 1) are very similar to those we see in the linear regression results above. Like with the linear regression, the effects we see in the logistic regression are overall statistically significant and tend only to differ in magnitude. With this in mind, several interesting patterns emerge. Fuel efficiency tends to have a relatively small effect on the mileage class in both datasets. Both model year and vehicle type are much stronger predictors of mileage class for the BAR dataset than for the DMV dataset. We assume this is because fuel efficiency has a wider range than model year and vehicle type. Finally, fuel type is a relatively strong predictor in both datasets, but slightly more so for the BAR data.

In summary, when considering both the BAR and DMV results, our findings indicate that higher mileage vehicles are slightly more fuel efficient than low mileage vehicles when controlling for model year, fuel type, and vehicle type. This will have implications for the amount that high mileage versus low mileage drivers will pay under a RUC, considering the significant impact of vehicle fuel efficiency on future RUC payments.

Payments Under Existing Policy

Unlike the RUC America revenue equity analysis,[20] which analyzed California DMV vehicle records, this revenue equity analysis focuses on vehicle records from the 2017 National Household Travel Survey that are already linked to NHTS household and person data. NHTS data was used to segment individual drivers by their commute mode, commute duration, and other demographic characteristics. The RUC America study did not contain these attributes as it used tract-level summary data on households in combination with the CA DMV data.

Prior analysis sections focused on super-commuters versus non-super-commuters specifically to highlight the demographic, travel behavior, and vehicle characteristic differences between these two groups of car commuters and to identify unique super-commuter characteristics. For the revenue equity analysis, an additional group, 'other auto travelers' are considered and reported on. This choice was made to provide a complete picture of the RUC impacts on all auto users, and to ensure revenue neutrality by describing the impacts for each of these distinct groups. The three segmented NHTS groups are displayed and defined in Table 29.

Table 29. Revenue Analysis Groupings

Group Label	Definition
Super-Commuters	Car, truck, or van commuters who travel >= 90 minutes to work, one-way
Non-Super-Commuters	Car, truck, or van commuters who travel < 90 minutes to work, one-way
Other Auto Travelers	All other car, truck, and van users. This includes teleworkers or those who commute by transit or other means but use car, truck, or van recreationally and reported annual vehicle mileage in the NHTS. This also includes NHTS respondents who left super-commuter identifying questions blank but reported annual vehicle mileage.

To calculate baseline revenue, vehicle fuel efficiency was applied to annual vehicle mileage to calculate the annual fuel consumed per vehicle. Only the efficiency of PHEV's gasoline

[20] https://caroadcharge.com/media/vktncxgu/rucamerica_urbrur_finalreport_2022-09-16.pdf

motors was used for estimation of gasoline consumption.[21] Fuel consumption for EVs was 0. Vehicle fuel consumption was then multiplied by the appropriate fuel tax based on the fuel type consumed by the vehicle. For electric vehicles, the EV surcharge was applied. The fuel tax and surcharge rates are consistent with the rates used during the RUC America 2021-2022 study. The fuel tax rates, and vehicle registration surcharges are displayed in Table 30.

Table 30. 2021-2022 California Vehicle Fuel Taxes and Registration Surcharges

Gas Tax ($/Gallon)	Diesel Tax ($/Gallon)	EV Surcharge ($/Vehicle)[22]
$0.59	$0.76	$100

Source: Fuel taxes and vehicle surcharges from Caltrans. Note: Fuel taxes consider both excise taxes and sales taxes. Only state taxes are considered – not federal or local taxes.

The baseline revenue was calculated at the person-level, which is shown in Table 31. The average and total vehicle miles traveled and average vehicle efficiency are included to provide context for the results.

In Table 31, super-commuters pay the highest annual baseline revenue, but produce a small percentage of the total baseline revenue due to the low prevalence of super-commuters. The same trend is evident for VMT, where super-commuters drive the greatest number of annual miles on average but comprise a small portion of total annual VMT. Notably, super-commuters on average drive the most fuel-efficient vehicles, compared to non-super-commuters, other auto travelers, and the statewide average.

[21] For PHEVs, the study assumes that 56 percent of all miles were driven using only electricity. This is based on EPA estimates, weighted by vehicles reported in EPA's My MPG reporting.

[22] Note: The 2021 policy attributes EV surcharges to vehicles that are MY 2020 and newer. Since NHTS data was produced in 2017, there are no MY 2020 EVs. As such, EV registration surcharges were attributed to all EVs. This methodological decision allows the 2017 microdata to better represent the impact of a RUC transition from current policy (as we are also using more current fuel tax rates, etc.)

Table 31. Annual Person-Level Baseline Revenue Estimates

Category of Traveler	Avg. Baseline Revenue (Per Person, $)	Total Baseline Revenue ($ Millions)	Avg. Annual VMT (Per Person)	Total Annual VMT (Billions)	Avg. Vehicle Efficiency (Per Person, MPG)
Non-Super-Commuter	$345	$4,072	12,814	151.6	21.9
Super-Commuter	$425	$184	16,059	7.0	22.2
Other Auto Travelers	$285	$3,145	10,336	114.4	21.3
All	**$318**	**$7,402**	**11,699**	**273.0**	**21.6**

Source: EBP calculations using VMT and fuel efficiencies from NHTS (2017) and fuel taxes and vehicle surcharges from Caltrans.

Payments Under RUC

To conduct the revenue equity analysis, we estimated a revenue-neutral RUC rate, in which the total hypothetical RUC payments by households were equivalent to the total estimated baseline payments at the state level. The benefit of using a revenue-neutral RUC rate is that the impacts of the RUC on different population groups are clear as overall changes are zero. Since the vehicle fleet analyzed differed from the RUC America analysis, a new RUC rate was calculated using baseline revenue and annual VMT derived from the NHTS vehicle fleet. The RUC America RUC rate and super-commuter study RUC rate are displayed in Table 32.

Table 32. RUC America RUC Rate vs. Super-Commuter Study RUC Rate

RUC America RUC Rate for CA (cents/mile)	Super-Commuter Study RUC Rate (cents/mile)
2.47	2.71

Source: EBP calculations using VMT from NHTS (2017) and fuel taxes and vehicle surcharges from Caltrans. RUC America RUC rate from 2021 EBP analysis.

The vehicle fleet used in the super-commuter study was from the 2017 NHTS, which contained less fuel-efficient vehicles overall compared to the 2021-2022 RUC America study which used 2021-2022 DMV vehicle sale/transfer data. As the fuel tax rates are held constant between studies, the difference in RUC rate is largely a factor of differences in fuel efficiency (and slight differences in fleet composition, since NHTS relied on weights to provide population estimates, while the DMV data represented the full population). It is notable to see the impact that increased fuel efficiency has had over a short period of time (2017 to 2022) on the RUC rate in the state of California.

The state-based RUC rate of 2.71 was multiplied by the annual VMT of each vehicle to determine the total RUC policy revenue by vehicle. Vehicles were linked to their primary drivers who had a category of traveler classification. These results are displayed in Table 33.

Table 33. Annual Person-Level RUC Revenue Estimates

Category of Traveler	Avg. RUC Revenue (Per Person, $)	Total RUC Revenue ($ Millions)
Non-Super-Commuter	$348	$4,112
Super-Commuter	$436	$189
Other Auto Travelers	$281	$3,101
All	**$318**	**$7,402**

Source: EBP calculations using VMT and fuel efficiencies from NHTS (2017) and fuel taxes and vehicle surcharges from Caltrans.

Similar to the baseline revenue estimates, super-commuters are predicted to pay the greatest amount of RUC revenue per person ($436), followed by non-super-commuters ($348), and other auto travelers ($281). Consistent with Table 31's estimate of the total statewide baseline revenue, the total statewide RUC revenue is estimated to be $7.4 billion (this excludes significant amounts of commercial and visitor travel).

Changes in Revenue

To calculate the change in revenue overall, and across different population groups with varying travel behavior, we calculated the annual raw dollar change and annual percent change between the estimated baseline and RUC payments. Table 34 displays the overall change in revenue contribution results for super-commuters, non-super-commuters, and other auto travelers.

Table 34. Annual Change in Revenue Contributions Under a RUC Policy Compared to Baseline Policy

Category of Traveler	Avg. Baseline Revenue (Per Person, $)	Avg. RUC Revenue (Per Person, $)	Total Baseline Revenue ($ M)	Total RUC Revenue ($ M)	Avg. Revenue Change (Per Person, $)	Average Revenue Change (Per Person, %)
Non-Super-Commuter	$345	$348	$4,072	$4,112	$3	1.0%
Super-Commuter	$425	$436	$184	$189	$11	2.5%
Other Auto Travelers	$285	$281	$3,145	$3,101	-$4	-1.4%
All	**$318**	**$318**	**$7,402**	**$7,402**	**$0**	**0%**

Source: EBP calculations using VMT and fuel efficiencies from NHTS (2017) and fuel taxes and vehicle surcharges from Caltrans.

Compared to non-super-commuters, we see that on average super-commuters will experience greater nominal ($11 vs. $3) and percent (2.5 percent vs. 1.0 percent) changes in revenue payments under a RUC policy. However, super-commuters can expect to pay less than $1 extra per month under a RUC policy, illustrating that the changes in revenue payments are minimal. These results reflect super-commuters as a group on average, but as we observed in the demographic analysis and travel behavior analysis, super-commuters are not a monolith.

Super-commuters include workers in the construction and extraction industries as well as software engineers, workers who make less than $50,000 per year and workers who make over $200,000, and workers who carpool and those who drive single occupancy vehicles. As a result, it is necessary to dig deeper into the overall results to understand the differential impacts of a RUC on different types of super-commuters. The impacts of a RUC transition will vary due to the travel behavior of groups and the efficiency of the cars they drive.

Changes by Occupation

Super-commuters travel such long distances by necessity for work, and/or as a result of the high price of living in urban areas or desire for amenities outside the urban area. The study analyzed different groups of workers by occupation to determine what the differential impact of a RUC would be on different types of super-commuters (and commuters, in general).

Super-commuters and non-super-commuters who work in manufacturing, construction, maintenance, or farming are all estimated to have moderate savings under a RUC policy ($37 for super-commuters and $44 for non-super-commuters). These are workers who are required to travel for work and must commute long distances to work sites. Alternatively, travelers in professional, managerial, or technical professions, presumably office work in more corporate settings, experience an increase in payments across the board ($40 for super-commuters and $14 for non-super-commuters). These groups could include workers who have the ability to work hybrid or remotely and might not even need to make the long commute more than a couple times a week (Table 35 and Table 36).

Clerical or administrative support professions produced similar results to the professional, managerial, or technical group. Lastly, sales or service careers, which also can require long commutes between work sites and client meetings, experienced net savings for super-commuters ($8) and only experience a slight increase in payments for non-super-commuters ($5).

Table 35. Annual Change ($) in Revenue Contributions Under a RUC Policy Compared to Baseline Policy by Occupation

Category of Traveler	Clerical or administrative support	Manufacturing, construction, maintenance, or farming	Professional, managerial, or technical	Sales or service
Non-Super-Commuter	$13	-$44	$14	$5
Super-Commuter	$29	-$37	$40	-$8

Source: EBP analysis of NHTS 2017 data. Note: Other auto travelers excluded from this table as this group does not travel to work by car, truck, or van, so it doesn't make sense to classify this group by occupation.

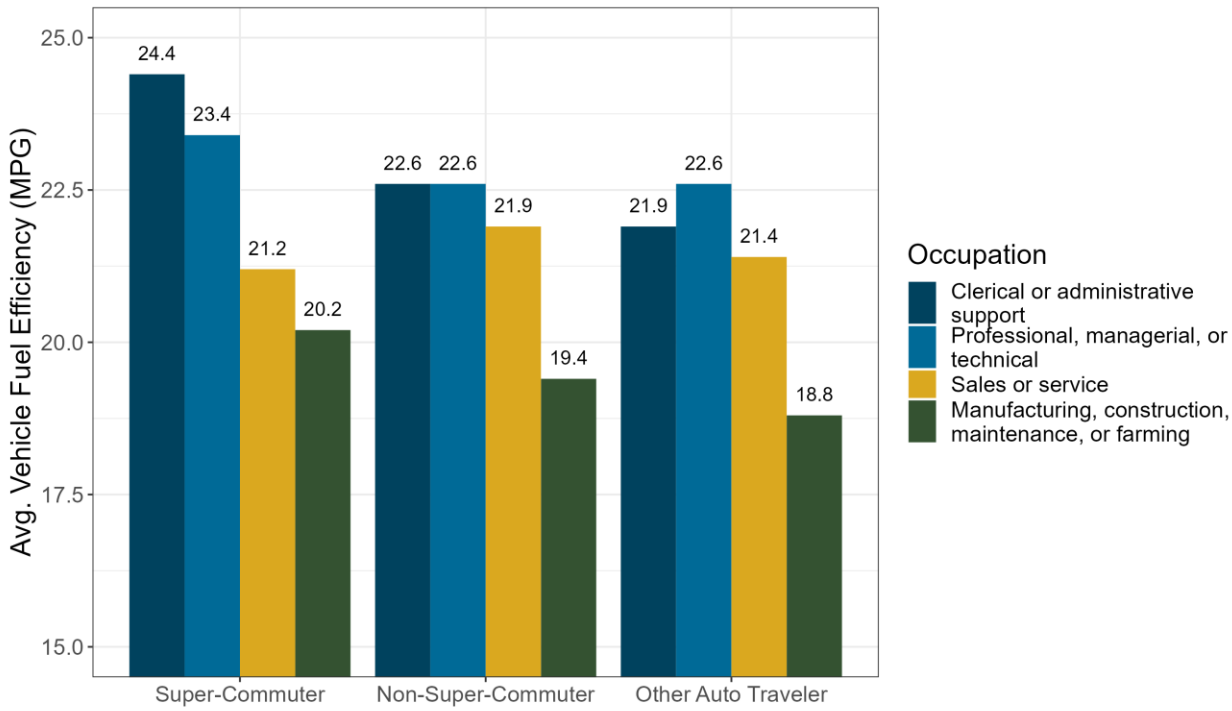
Table 36. Annual Change (%) in Revenue Contributions Under a RUC Policy Compared to Baseline Policy by Occupation

Category of Traveler	Clerical or administrative support	Manufacturing, construction, maintenance, or farming	Professional, managerial, or technical	Sales or service
Non-Super-Commuter	3.9%	-11.4%	4.2%	1.3%
Super-Commuter	7.6%	-7.8%	10.5%	-1.6%

Source: EBP analysis of NHTS 2017 data. Note: Other auto travelers excluded from this table as this group does not travel to work by car, truck, or van, so it doesn't make sense to classify this group by occupation.

Figure 23 provides further rationale for the occupation results, showing that travelers working in manufacturing, construction, maintenance, or farming occupations on average have the lowest vehicle fuel efficiency of the four groups. Both clerical or administrative support and professional, managerial, or technical occupation groups experience comparatively higher fuel efficiency, leading to slight (non-super-commuter; other auto travelers) or more substantial (super-commuter) increases in revenue payments.

Figure 23. Average Fuel Efficiency (MPG) by Traveler Type and Occupation



Source: EBP analysis of NHTS 2017 data.

Changes by Geographic Classification

Change in revenue results by traveler type and geography are depicted in Table 37 and Table 38. Super-commuters living in Small Urban areas have the greatest increase on average from a RUC transition (still only $4 per month more). Super-commuters experience minimal increases in Large Urban Dense areas, and slight increases in Large Urban Moderate and Rural Commuter areas (less than $3 per month in additional revenue).

There is an average decrease in payments for super-commuters, non-super-commuters, and other auto travelers in Rural Independent areas. Non-super-commuters and other auto travelers additionally experience savings for Small Urban and Rural Commuter areas. And other auto travelers also save in the less dense portions of Large Urban areas.

Table 37. Annual per Person Change ($) in Revenue Contributions Under a RUC Policy Compared to Baseline Policy by Geographic Classification

Category of Traveler	Large Urban Dense	Large Urban Moderate	Small Urban	Rural Commuter	Rural Independent
Non-Super-Commuter	$8	$8	-$10	-$19	-$41
Super-Commuter	$8	$24	$47	$33	-$13
Other Auto Travelers	$2	-$9	-$19	-$22	-$38

Source: EBP analysis of NHTS 2017 data, ACS 2017-2021 5-year data, 2019 LEHD LODES data, and Urban Area classifications from 2020 Decennial Census.

Table 38. Annual per Person Change (%) in Revenue Contributions Under a RUC Policy Compared to Baseline Policy by Geographic Classification

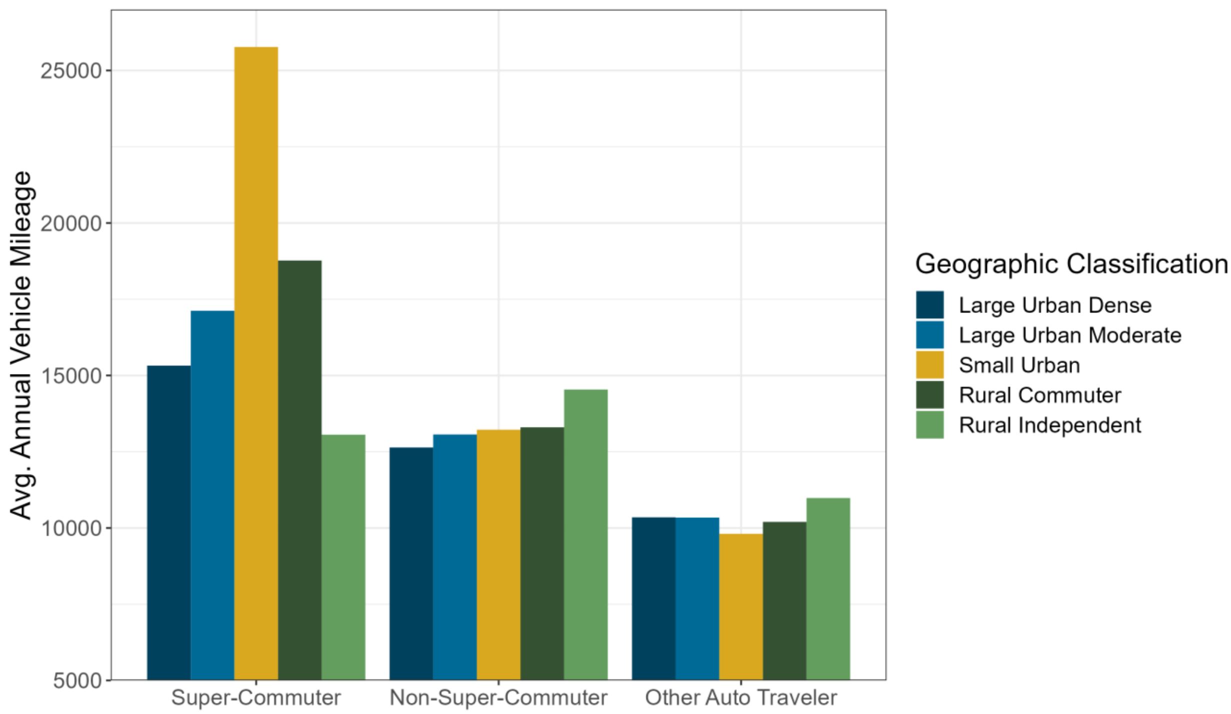
Category of Traveler	Large Urban Dense	Large Urban Moderate	Small Urban	Rural Commuter	Rural Independent
Non-Super-Commuter	2.3%	2.2%	-2.7%	-5.0%	-9.5%
Super-Commuter	1.2%	5.3%	7.2%	6.9%	-3.5%
Other Auto Travelers	0.7%	-3.2%	-6.7%	-7.4%	-11.4%

Source: EBP analysis of NHTS 2017 data, ACS 2017-2021 5-year data, 2019 LEHD LODES data, and Urban Area classifications from 2020 Decennial Census.

These patterns can primarily be explained by differences in fuel efficiency for these groups, while the levels of changes and patterns between groups are also affected by total mileage.

Whereas annual mileage tends to increase as geographic density decreases for non-super-commuters and other auto travelers, super-commuters in Small Urban areas travel an average of over 25,000 miles per year (Figure 24), far more than other super-commuters. Super-commuters in Rural Independent areas have the lowest average annual mileage of all super-commuter groups (approximately 13,000 miles), even lower than non-super-commuter travelers (who may drive more for non-commute purposes). Annual mileage for super-commuters living in Large Urban areas is lower than Small Urban and Rural Commuter areas since their super-commuters are more likely to be caused by congestion than distance.

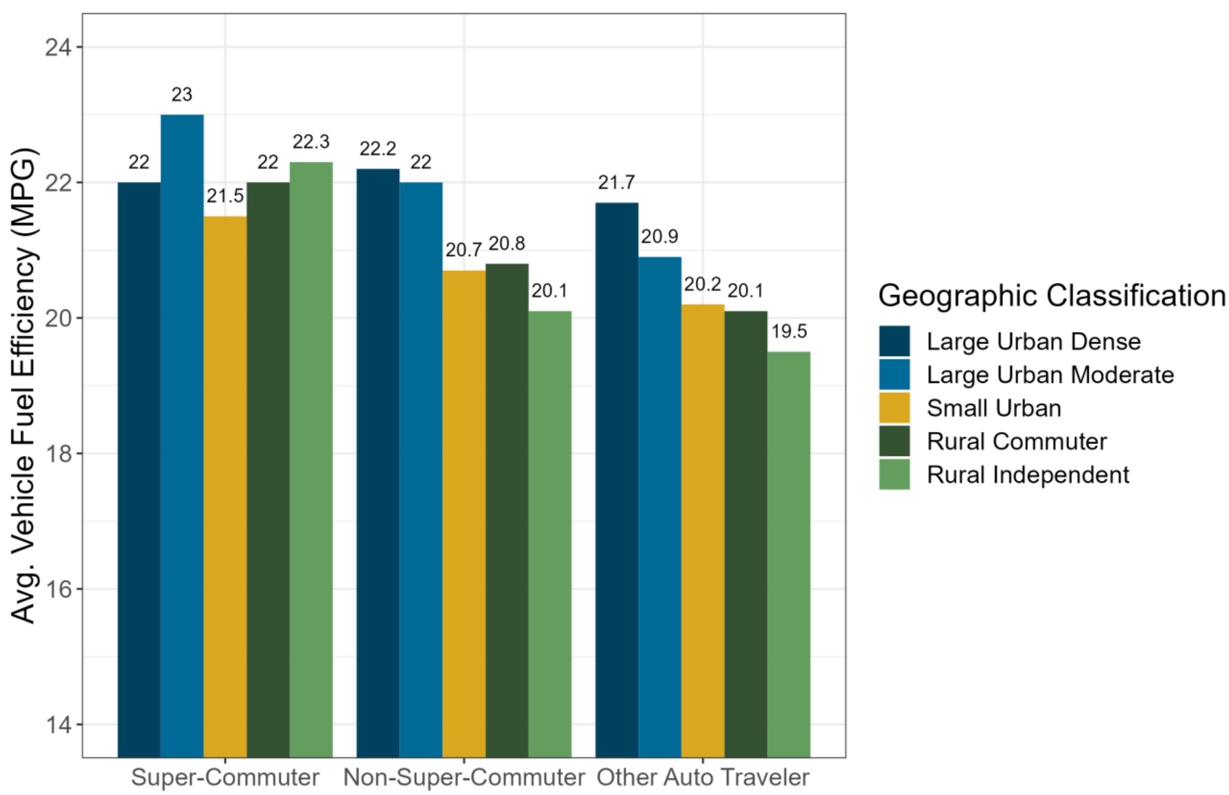
Figure 24. Average Annual Vehicle Mileage by Traveler Type and Geography



Source: EBP analysis of NHTS 2017 data, ACS 2017-2021 5-year data, 2019 LEHD LODES data, and Urban Area classifications from 2020 Decennial Census.

While non-super-commuter and other auto travelers have lower fuel efficiency as geographic density decreases, super-commuters again deviate from this trend. Super-commuters in Small Urban areas have the lowest fuel efficiency, and Large Urban Moderate and Rural Independent have higher fuel efficiency (Figure 25). However, super-commuters living in Small Urban areas have higher average fuel efficiency than all Small Urban, Rural Commuter, and Rural Independent non-super-commuters and Other Travelers.

Figure 25. Average Vehicle Fuel Efficiency (MPG) by Traveler Type and Geography



Source: EBP analysis of NHTS 2017 data, ACS 2017-2021 5-year data, 2019 LEHD LODES data, and Urban Area classifications from 2020 Decennial Census.

Changes by Race and Ethnicity

Super-commuters who self-identified as Black or Other[23] experienced annual savings ($9 and $17, respectively), while all other racial and ethnic groups experienced increases. The increases were slight for Hispanic ($8 annually) and White ($11 annually) super-commuters, but larger for Asian super-commuters ($62 annually).

Hispanic non-super-commuters were the only non-super-commuter group that experienced savings. Asian non-super-commuters also experienced a relatively large

[23] For the purposes of this study, 'All Other' includes the following pre-defined survey groups: American Indian or Alaska Native; Native Hawaiian or other Pacific Islander; Multiple responses selected; Some other race.

increase ($30 annually). The other auto travelers' group experienced savings across the board except for Asian travelers ($21 annually) (Table 39 and Table 40).

Table 39. Annual Change ($) in Revenue Contributions Under a RUC Policy Compared to Baseline Policy by Race/Ethnicity

Category of Traveler	Asian	Black	Hispanic	White	Other
Non-Super-Commuter	$30	$2	-$4	$1	$10
Super-Commuter	$62	-$9	$8	$11	-$17
Other Auto Travelers	$21	-$10	-$14	-$4	-$13

Source: EBP analysis of NHTS 2017 data.

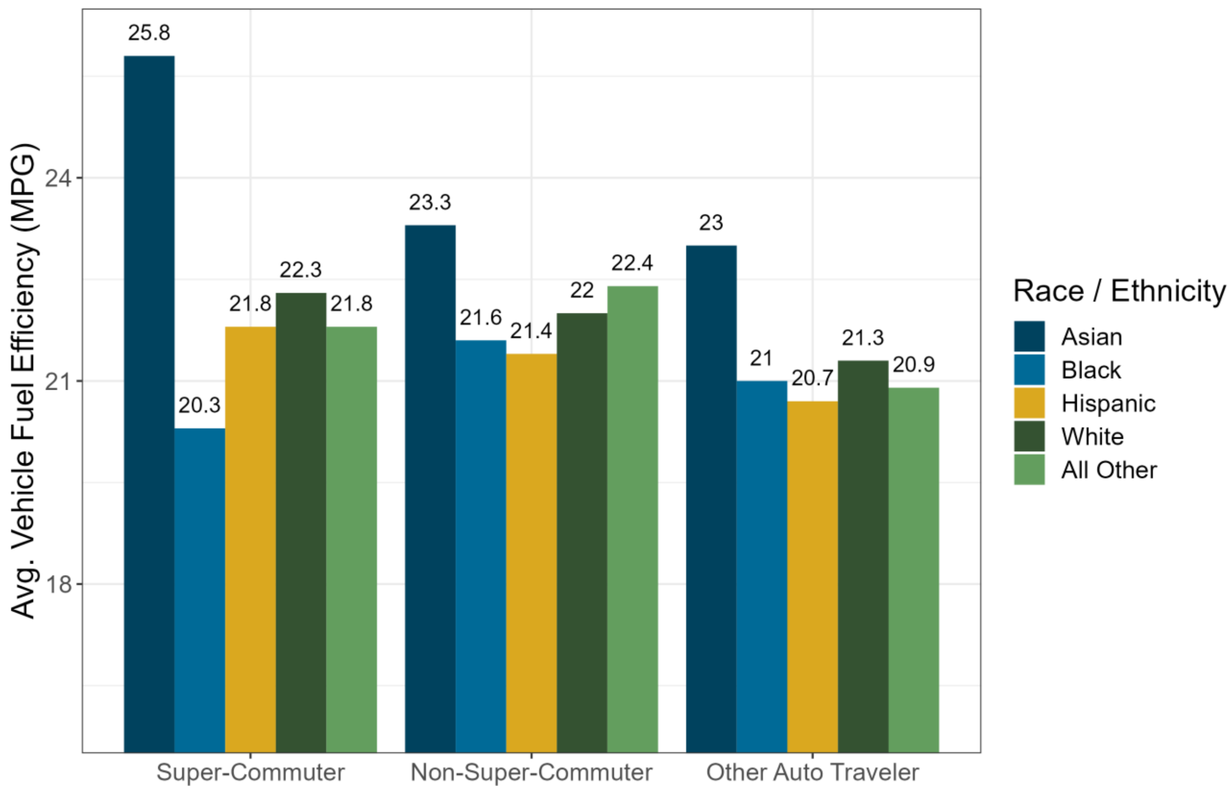
Table 40. Annual Change (%) in Revenue Contributions Under a RUC Policy Compared to Baseline Policy by Race/Ethnicity

Category of Traveler	Asian	Black	Hispanic	White	Other
Non-Super-Commuter	9.1%	0.7%	-1.2%	0.3%	3.0%
Super-Commuter	17.2%	-2.1%	2.2%	2.3%	-3.4%
Other Auto Travelers	8.0%	-3.2%	-4.5%	-1.3%	-4.3%

Source: EBP analysis of NHTS 2017 data.

The pattern of higher revenue payments for Asian travelers is attributed to vehicle choice and fuel efficiency. For super-commuters, non-super-commuters, and other auto travelers, Asian travelers on average have vehicles with the highest fuel efficiency (Figure 26). Since fuel efficient vehicles see an increase in payments under a RUC, it makes sense that Asian travelers would see an increase in revenue payments due to the high efficiency of Asian travelers' vehicles.

Figure 26. Average Vehicle Fuel Efficiency (MPG) by Traveler Type, Race, and Ethnicity



Source: EBP analysis of NHTS 2017 data, ACS 2017-2021 5-year data, 2019 LEHD LODES data, and Urban Area classifications from 2020 Decennial Census.

Changes by Household Income

One of the most important equity metrics that we consider in this study is the impact of a RUC on drivers with varying levels of household income, because a large increase in transportation costs for a lower income household will have different impacts than the same nominal increase for a high-income household. (Table 41 and Table 42).

The results of the analysis show that super-commuter households making $50,000-$99,999 are likely to save an average of $15 per year. Super-commuter households in the $100,000-$199,999 group will see a slight increase of $7 per year, and super-commuter households making $200,000 or more will experience an increase of $68 per year on average. Super-commuter households that make less than $50,000 per year experience an increase on average (roughly a $1 per month increase). This low-income group has the second highest efficiency for super-commuters (second only to the $200,000+ group) and third highest overall (behind high-income non-super-commuters), leading to a slight increase in revenue payments (Figure 27).

While for other auto travelers fuel efficiency strictly increases with income and is almost the same for the two lower income non-super-commuter groups (and lower than the higher income groups), for super-commuters, the lower income groups have higher efficiency vehicles than the upper-middle income group. This pattern has been observed in many other states, where the lowest income households have more efficient vehicles. Because these groups are most price sensitive to fuel costs, they own higher efficiency vehicles, even if those vehicles may be older. This trend is most clear for super-commuters in California as full costs can represent a significant share of their household budgets.

All non-super-commuter income groups see small increases, while all other auto travelers see small savings, except the ($100,000 – $199,999 group, which averages $0.20 per month in increases).

Table 41. Annual Change ($) in Revenue Contributions Under a RUC Policy Compared to Baseline Policy by Household Income

Category of Traveler	less than $50k	$50k-99k	$100k-199k	$200k or more
Non-Super-Commuter	$2	$1	$4	$13
Super-Commuter	$15	-$15	$7	$68
Other Auto Travelers	-$10	-$3	$2	-$2

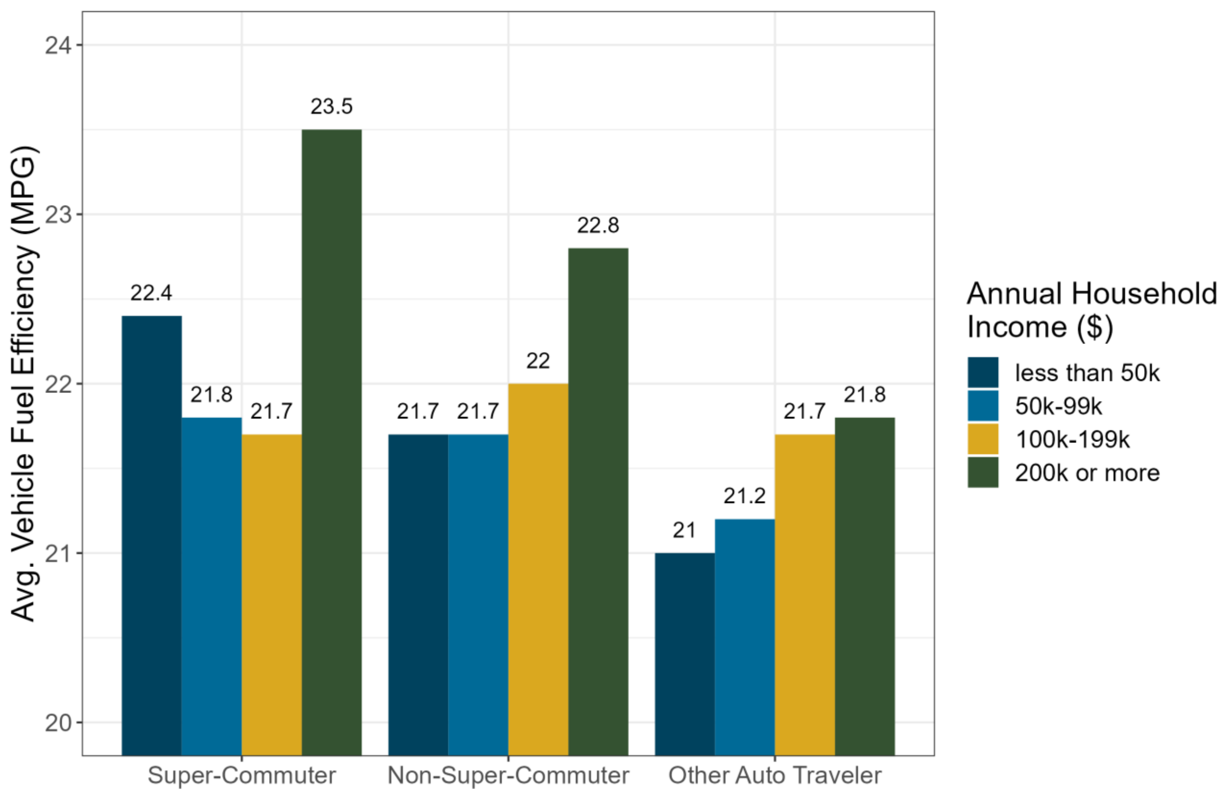
Source: EBP analysis of NHTS 2017 data.

Table 42. Annual Change (%) in Revenue Contributions Under a RUC Policy Compared to Baseline Policy by Household Income

Category of Traveler	less than $50k	$50k-99k	$100k-199k	$200k or more
Non-Super-Commuter	0.6%	0.3%	1.0%	3.8%
Super-Commuter	3.9%	-2.7%	1.8%	17.9%
Other Auto Travelers	-3.4%	-1.1%	0.8%	-0.5%

Source: EBP analysis of NHTS 2017 data.

Figure 27. Average Vehicle Fuel Efficiency (MPG) by Traveler Type and Household Income



Source: EBP analysis of NHTS 2017 data.

Conclusion

After a thorough review into the demographics, vehicle characteristics, and travel behavior of super-commuters, it is evident that the group is multifaceted and consists of vastly different road users. The odometer data analysis and revenue equity analysis allowed us to dig deeper into the nuances of the financial impacts of a RUC on these various road users. Analysis of these various components led us to the following conclusions:

There are distinct groups of super-commuters. Our analysis discovered the following patterns about super-commuter groups in the state of California:

- **Occupation:** Jobs in construction, extraction, repair, and maintenance have the highest representation of super-commuters (18.8 percent) followed by managerial roles (12.5 percent).
- **Occupation and Income:** Super-commuters with managerial roles had the greatest representation in higher personal earnings groups (38.4 percent making $200,000+ annually). Super-commuters with construction, extraction, repair, and maintenance roles had the greatest representation in low (less than $25,000 annually) and middle ($100,000 to $149,000 annually) income groups.
- **Race and Ethnicity**: Hispanic populations represent the largest percentage of super-commuters (42.4 percent), followed by White populations (34.9 percent) and Asian populations (12.9 percent).
- **Race, Ethnicity, and Income**: Asian super-commuters had the greatest representation in higher personal earnings groups (19.7 percent making $200,000+ annually). White super-commuters had the greatest representation in the mid-to-high personal earnings groups ($75,000+ annually). Hispanic super-commuters had the greatest representation in the lower income groups (53 percent making less than $25,000 annually; 45.1 percent making $50,000-75,000 annually).
- **Travel Behavior**: The 5+ person carpool category had the highest number of super-commuters as a percent of total car, truck, and van commuters (12.7 percent). This indicates that super-commuters are more likely than non-super-commuters to carpool to work with several other commuters.
- **Vehicles:**
    - High mileage vehicles overall tend to be newer and have better fuel efficiency than their low and medium mileage counterparts. Electric cars are still uncommon but tend to have low- to -medium annual mileage (less than 20,000

miles per year). Super-commuters may not currently have confidence in the range of full electric vehicles.
    - Super-commuters are less likely to drive SUVs compared to non-super-commuters and are more likely to drive vans compared to non-super-commuters (8.3 vs. 5.7 percent). These findings match the vehicle type patterns seen in high versus low mileage vehicles.
    - The super-commuter group had a higher percent distribution in the 20 mpg or lower and 31 mpg or higher groupings, indicative of a diverging vehicle efficiency pattern for distinct types of super-commuters.
    - Super-commuters are more likely to own new or very old cars, compared to non-super-commuters.

The revenue equity analysis produced the following results about the impact of a RUC on super-commuters (compared to non-super-commuters):

- **The largest determinant to the impact of a RUC on a given road user is the fuel efficiency of the car.** The second largest determinant is the annual mileage of the road user's vehicle.
- On average, super-commuter payments under a RUC will increase slightly, but when super-commuters are segmented by race, ethnicity, income, and occupation group, it is clear that **under a RUC, some super-commuters will experience payment increases and some will experience net savings.**
- Largely, the **super-commuters who save are those who currently drive fuel inefficient vehicles long distances.** Those who will see slight increases drive moderately efficient vehicles long distances. Those that will see large increases drive highly efficient vehicles long distances.
- When considering disaggregate results, on average, **switching from existing gas taxes and surcharges to a RUC does not meaningfully increase the burden of revenue payments**, and in some cases, reduces payments for super-commuters.

Opportunities for Future Analysis

The 2023 super-commuter study analyzed and synthesized data from a variety of national and state datasets, including ACS 5-Year Estimates (2017-2021, including PUMS data), LEHD Origin-Destination Employment Statistics (2019), NHTS data (2017), CA DMV sale/transfer data (2017-2023), and CA BAR inspection data (2015-2023). Each of these datasets used the most current data available at the time of analysis, which meant that the NHTS data and LEHD data represented pre-COVID-19 conditions. Given the scale of economic, behavioral, and technological change since the start of the pandemic, future analyses can build on the insights of this project by leveraging updated, post-COVID-19 data capturing current commuting patterns and vehicle ownership.

Future RUC analyses may be able to utilize more current travel surveys to estimate the impact of a RUC. These could include state or regional (e.g., MPO) sample populations. State sample frames could be surveyed in a state-specific effort such as the 2010-2012 California Household Travel Survey[24] (historically occurred roughly every 10 years) or a national survey with a state-specific sample frame (as California elected to collect in the 2017 NHTS and the 2022 NextGen NHTS). The 2022 travel survey component of NextGen NHTS was released in November of 2023, and will subsequently be released every two years. The 2022 origin-destination component using non-survey data was released in December of 2023, and will subsequently be released every year. MPO regions often conduct surveys independent from the state for calibration of their modeling tools. Integration of these surveys with state-wide samples offers the potential to better capture diverse populations that may be under-sampled by broader tools. Survey fusion also allows us to increase total sample observations after correcting weights and for different time periods.

This research only leveraged the sample household and vehicle populations from NHTS, whereas previous work by Caltrans and RUC America has used the full population of registered vehicles, which provides much more granular analysis. While that analysis only leveraged average demographic and travel behavior information for census tracts, states like New Jersey, North Carolina, Oregon, and Pennsylvania have leveraged synthetic

[24] Caltrans. California Household Travel Survey. https://dot.ca.gov/programs/transportation-planning/division-of-transportation-planning/data-analytics-services/transportation-economics/ca-household-travel-survey

household methods to match individual vehicles with individual households across those states for race/ethnicity, income, and geographic equity analysis. This allows usage of current vehicle fleet information and the annual ACS survey of demographic information to capture the rapid deployment of electric vehicles and other trends.

The California Energy Commission is currently conducting the next iteration of the California Vehicle Survey,[25] which also contains vehicle usage information as well as vehicle owner and vehicle characteristic information. While likely insufficient to provide all the data needed for a revenue equity analysis, this survey, the results of which should be published in 2025 (it will be fielded in 2024) could also supplement other state and regional sample frames, with specific applications to predicting the ownership patterns of different household segments. It should have a much larger sample of electric vehicles in California and their owners than either California's 2017 NHTS or 2022 NHTS samples.

These post-pandemic, national and state-based data sources will provide an up-to-date snapshot of the impact of a RUC on drivers based on current driving behavior. Moving forward, the NextGen NHTS, in particular, will allow for a more consistent database of vehicle data that will allow researchers to track the impacts of a RUC overtime, informing policy decisions.

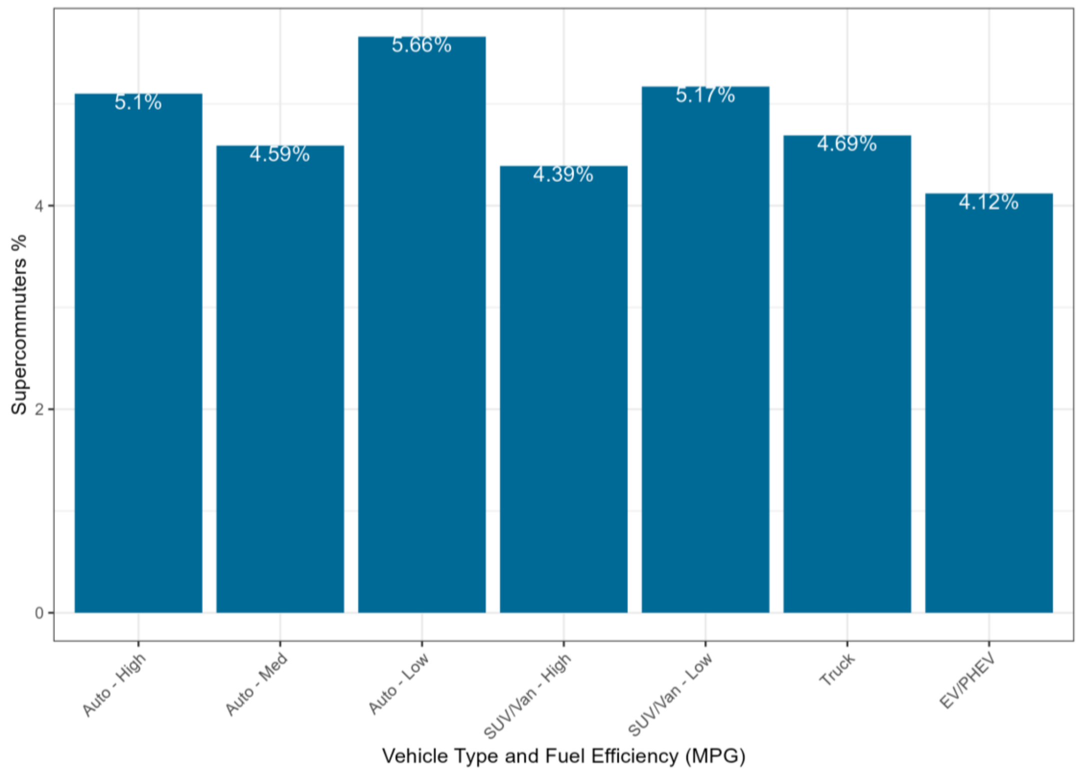
[25] California Energy Commission. California Vehicle Survey. https://www.energy.ca.gov/data-reports/surveys/california-vehicle-survey

Appendix 1: Supplementary Results

Combining Vehicle Type and Fuel Efficiency

From our analysis of vehicle types and fuel efficiencies, we observe that the highest percentage of super-commuters (as a percent of all commuters) is represented by super-commuters that drive low efficiency automobiles (5.7 percent) followed by low efficiency SUVs or vans (5.2 percent). However, we see the next highest percentage of super-commuters represented by super-commuters that drive high efficiency automobiles (5.1 percent). Electric/ plug-in hybrid vehicles have the lowest percentage of super-commuters which could primarily be due to the smaller sample size of EVs in the dataset. Overall, however, we observe a relatively even distribution of super-commuters across all fuel efficiency levels and vehicle types with a difference of 1.54 percentage points between the lowest and highest category with super-commuter population (Figure 28).

Figure 28. Super Commuters as a Percentage of All Car, Truck, and Van Commuters by Fuel Efficiency and Vehicle Type



Source: EBP Analysis of National Household Travel Survey (NHTS) 2017.

Within the super-commuter group, we observe a relatively dispersed distribution across different vehicle types and fuel efficiency levels. However, we do see most super-commuters driving automobiles of medium efficiency (29.8 percent) followed by automobiles with high efficiency (20.1 percent) (Table 43). Within the non-super-commuter group, we see a similar pattern where 31.5 percent of commuters drove automobiles with medium fuel efficiency (31.5 percent) followed by automobiles with high fuel efficiency (19 percent).

Table 43. Super Commuters' Fuel Efficiency by Vehicle

Vehicle by Efficiency Level	Super-Commuter Count-Household	Non-Super-Commuter Count-Household	Super-Commuters as Pct of Commuters-Household*	Super-Commuter Distribution-Household**	Non-Super-Commuter Distribution-Household**
Automobile (High)	73,618	1,369,891	5.1%	20.1%	19.0%
Automobile (Med)	109,113	2,265,906	4.6%	29.8%	31.5%
Automobile (Low)	41,117	685,686	5.7%	11.2%	9.5%
SUV/Van (High)	45,233	985,728	4.4%	12.3%	13.7%
SUV/Van (Low)	54,797	1,005,298	5.2%	15.0%	14.0%
Truck	38,610	785,005	4.7%	10.5%	10.9%
EV/PHEV	4,147	96,522	4.1%	1.1%	1.3%

Source: EBP Analysis of National Household Travel Survey (NHTS) 2017. Note: *Super-Commuters as Pct of Commuters refers specifically to car, truck, or van commuters, or the value derived by adding super-commuters and non-super-commuters. **Super-Commuter Distribution and Non-Super-Commuter Distribution refers to the percent breakdown of each distinct grouping into the categories in the first column.

Testing Relationship Between Mileage Class, Model Year, and Fuel Efficiency

We ran several regressions to test if mileage class has an effect on MPG, all else equal. To test this assumption, we ran a linear regression of the following type on both the BAR and DMV datasets:

$$y_i = \beta_0 + \beta_1 m_i + \beta_2 t_i + \vec{\upsilon} \cdot \vec{u_i} + \vec{\kappa} \cdot \vec{c_i} + \epsilon_i$$

Where y_i is the MPG, β_j are coefficients, m_i is the mileage class dummy variable[26], t_i is the model year, $\vec{\upsilon}$ is a vector of coefficients for $\vec{u_i}$, a vector of dummy variables for fuel type which assume gasoline as a default, and finally $\vec{\kappa}$ is a vector of coefficients for $\vec{c_i}$,

[26] 0 for low mileage, 1 for high mileage.

representing vehicle type which uses automobile as a default. ϵ_i is an error term. The results of these regressions are in Table 44 and Table 45, below.

Table 44. BAR Linear Regression Results (all active MY1976-MY2015 vehicles 2017-2023)

Variable	Coefficient Value	p-value
High Mileage	0.65	<0.001
Model Year	0.22	<0.001
Diesel	-1.12	<0.001
Hybrid	18.36	<0.001
Other	2.81	<0.001
Crossover	-2.49	<0.001
SUV	-6.22	<0.001
Truck	-7.45	<0.001
Van	-5.72	<0.001

Source: EBP Analysis of Bureau of Automotive Repair (BAR) data (2023).

Table 45. DMV Linear Regression Results (MY2015-MY2023 vehicles sold 2015-2023)

Variable	Coefficient Value	p-value
High Mileage	0.39	<0.001
Model Year	0.26	<0.001
Diesel	-0.69	<0.001
Electric	83.19	<0.001
Hybrid	16.01	<0.001
Other	6.17	<0.001
Crossover	-2.30	<0.001
SUV	-6.37	<0.001
Truck	-10.32	<0.001
Van	-7.63	<0.001

Source: EBP Analysis of Department of Motor Vehicles (DMV) data (2023).

In addition to that linear regression model, we also built a pair of logistic regression models to model the probability of a vehicle being in the high mileage class given its attributes. Using the same variable definitions as the above model, this model has the functional form:

$$P(m_i) = \text{logit}(\beta_0 + \beta_1 y_i + \beta_2 t_i + \vec{\upsilon} \cdot \vec{u_i} + \vec{\kappa} \cdot \vec{c_i} + \epsilon_i)$$

While these coefficients (which are shown in the table below) are in fact log-odds-ratios, we can interpret them as impacts on the probability of a given vehicle being a high mileage vehicle: positive coefficients are associated with a higher probability, while negative ones are associated with a lower probability. Similarly, larger coefficients have more of an impact than smaller ones.

Table 46. BAR Logistic Regression Results (all active MY1976-MY2015 vehicles 2017-2023)

Variable	Coefficient Value	p-value
MPG	0.03	<0.001
Model Year	0.17	<0.001
Diesel	0.40	<0.001
Hybrid	-0.08	<0.001
Other	0.38	<0.001
Crossover	-0.03	<0.001
SUV	-0.05	<0.001
Truck	0.74	<0.001
Van	0.59	<0.001

Source: EBP Analysis of Bureau of Automotive Repair (BAR) data (2023).

Table 47. DMV Logistic Regression Results (MY2015-MY2023 vehicles sold 2015-2023)

Variable	Coefficient Value	p-value
MPG	0.01	<0.001
Model Year	0.02	<0.001
Diesel	0.21	<0.001
Electric	-2.33	<0.001
Hybrid	-0.23	<0.001
Other	-0.16	0.23
Crossover	-0.02	<0.001
SUV	-0.05	<0.001
Truck	0.04	<0.001
Van	0.05	<0.001

Source: EBP Analysis of Department of Motor Vehicles (DMV) data (2023).

Appendix 2: Methodology

Introduction

This section describes the methods used in the various super-commuter analyses to determine the geographic classifications, demographics, travel behavior, vehicle characteristics, and vehicle mileage of super-commuters, and to determine the revenue equity impacts of a RUC on super-commuters.

This section serves as a companion for the reports that summarizes and discusses the results of the analysis. It is descriptive in nature of how the team approached the analysis, and each of the component steps taken to prepare data for the revenue policy comparisons are described.

All analysis components use 2020 Census Tracts with the exception of the LEHD analysis, which used 2010 Census Tracts, as 2020 LEHD data had not yet been released.

Geography of Super-Commuters

ACS Summary Table Methodology

Prior to classifying the census tract geographies in which super-commuters live, the study analyzed American Community Survey (ACS) 5-Year Estimate (2017-2021) data to determine where super-commuters live and work. Two distinct variables were analyzed: travel time to work by home geography, and travel time to work by workplace geography. These datasets allowed us to isolate commuters who traveled >= 90 minutes one-way but did not allow us to filter to only car, truck, and van users (the dataset was inclusive of all modes). As a result, this data source produced slightly larger estimates of super-commuters compared to other sources considered.

Using a combination of R and ArcGIS analysis, both datasets were analyzed at the county level, as census tract level detail was not available for these specific measures. The top counties for super-commuter residence and workplace were reported in tables and county-level results were mapped, showing the percent of workers and residents that commute >= 90 minutes to work. These analysis results provided evidence for the study's initial assumption: The SF Bay area and LA area are major focal points in the state of California for receiving super-commuters. The LEHD analysis was undertaken to confirm this assumption by considering disaggregate travel flow data.

LEHD Methodology

Whereas the ACS Summary Table analysis was only available at the county-level, Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics data (2019) is available at the census block-level. LEHD includes origin-destination flow data based on worker home and workplace locations allowing far more detailed analysis of where super-commuters are living and working. Similar to ACS Summary Tables, however, LEHD is also inclusive of all modes, meaning that the results slightly overrepresented super-commuters. Another limitation of the dataset is that LEHD data relies on employer's addresses for destination locations, which don't always align with workers' actual workplaces.

With these considerations in mind, the following analysis was undertaken. A service area analysis was conducted using ArcGIS Pro's Network Analyst extension, using the Service Area tool, on LEHD's linked origin-destination data. Travel distance in minutes was determined from workers homes to a selection of centroid points representing central locations for work destinations in the SF Bay and LA areas. These centroids were pre-determined by performing a spatial analysis of all destination locations in the two study areas and calculating geographically weighted centroids. Considering the millions of employment records, it was impossible to map each individual travel flow, and instead, common travel flow patterns were mapped and analyzed.

In order to limit the search area to super-commuters that could feasibly commute into work in the SF Bay or LA areas, the service area analysis was conducted for commutes within 90-150 minutes in one direction. This excluded non-super commuters (<90 minutes) as well as workers who couldn't feasibly commute to work from their home locations on a regular basis (>150 minutes, so either the work destination establishment was different from their actual workplace, or they were a teleworker). The LEHD results largely mirrored the ACS Summary Table results, showing that workers in the Central Valley were the most likely to super-commute into the Bay area, and that workers in LA county or surrounding counties were the most likely to super-commute into the LA area. This analysis confirmed the selected study areas, and provided additional evidence as to which counties were most likely to be super-commuter 'senders.'

Determining Geographic Classifications

After confirming the study areas for the analysis using ACS Summary Table and LEHD data, geographic classifications were assigned to all census tracts in the state, and the percent of super-commuters residing in each geographic classification was calculated. The methodology for determining geographic characteristics is described below.

We define the five geographic classifications of census tracts used in the study in the geographic classification section, in Table 4. 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 48. These data products are applied at four steps to separate all census tracts into the five geographic classifications used in the study.

- **Step 1** divides tracts between Urban and Rural classification groups based on the Urban Area boundaries published after the 2020 census. 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.) 2020 Urban Areas are defined by the Census Bureau to include at least 2,000 housing units or at least 5,000 people. 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 2,000 housing units and 5,000 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

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 2,000 housing units and 5,000 people. 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 48. Key Data Sources and Uses

Data Source	Classification Role
2020 Urban Area[27] boundaries	Differentiate between urban areas and non-urban areas
ACS 5-year sample data (2017-2021) Census Tract population	Split Large Urban tracts between Dense and Moderate classifications
ACS 5-year sample data (2017-2021) Core-Based Statistical Area (CBSA)[28] population	Separate Large Urban (Dense & Moderate) tracts from Small Urban tracts
ACS 5-year sample data (2017-2021) 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)[29] Origin-Destination Employment Statistics (LODES) data	Separate Rural Commuter and Rural Independent tracts

Demographics of Super-Commuters

Variable Selection from PUMS Dataset

The American Community Survey (ACS) Public Use Microdata Sample (PUMS) files are a set of untabulated records about individual people or housing units, released annually.[30] For the purposes of the Caltrans RUC (Road-User Charge) Super-commuter (super-commuter) analysis, the 2017-2021 5-Year PUMS estimates were used. The two record files used in the analysis include the housing record, where each row represents a housing unit with a unique identifier, "SERIAL NO", and the person record, where each row represents a person

[27] As of 2020, Urbanized Areas (or UAs) are areas with at least 2,500 people.

[28] 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.

[29] 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.

[30] Accessing PUMS Data (census.gov)

with identifier "SERIAL NO", reflecting individuals belonging to the same household. The variables used for the RUC analysis are described in Table 49 and Table 50.

Table 49. Selected Housing Record Variables

Housing Record Variable	Description
SERIAL NO	Housing unit/Group Quarter Unit person serial number
PUMA	Public use microdata area code (PUMA) based on 2020 Census definitions
ST	State code based on 2020 Census definitions
WGTP	Housing unit weight
NP	Number of persons associated with this housing record
HINCP	Household income (past 12 months, use ADJINC to adjust HINCP to constant dollars)
ADJINC	Adjusted income factor

Table 50. Selected Person Record Variables

Person Record Variable	Description
SERIAL NO	Housing unit/Group Quarter Unit person serial number
PUMA	Public use microdata area code (PUMA) based on 2020 Census definitions
PWGTP	Person weight
AGEP	Age
COW	Class of worker
EDUC	Educational attainment
RAC1P	Recoded detailed race code
HISP	Recoded detailed Hispanic origin
JWMNP	Travel time to work
JWRIP	Vehicle occupancy
JWTRNS	Means of transportation to work
PERNP	Total person's earnings
OCCP	Occupation
INDP	Industry
SEX	Sex

Objective (Proposed Analyses)

The initial step in the PUMS analysis was to filter the PUMS dataset using super-commuter characteristics and to perform an exploratory analysis to identify relevant demographic and travel behavior characteristics of super-commuters. The exploratory analysis began by calculating the number of super-commuters who pay fuel tax and their share of the commuting workforce by filtering by travel time to work and travel mode to work. Considering that estimated personal fuel tax revenue decreases when traveling with others, the number of super-commuters who drove to work individually and the number who carpooled were additionally calculated.

To better understand the demographic characteristics of Californian super-commuters, the exploratory analysis evaluated which racial and ethnic groups super-commuters are a part of, what the average/median income of super-commuters is, what level of education super-commuters typically have, what types of jobs do super-commuters have, and what kinds of industries do they work in.

Super-Commuter and Non-Super-Commuter Groups

The housing and person record files were joined using a unique identifier, SERIAL NO, so that each row represents each person's record and their associated household identifier. Based on this row-level data, our analysis included person weights (PWGTP) to get population estimates for super-commuters in the state of California. To filter the PUMS dataset to super-commuters, the travel time to work variable (JWMNP) was filtered to create a group of commuters who travel 90 or more minutes to work. Using the same variable, we identified non-super-commuters (car, truck, or van commuters with travel time less than 90 minutes). As discussed earlier, the focus of the analysis is on super-commuters who pay fuel tax and are going to be impacted by RUC. As a result, we used the means of transportation to work (JWTRNS) variable to further filter the super-commuter and non-super-commuter groups to individuals who use car, truck, or van to commute to work.

Data Cleaning

- **Vehicle Occupancy:** To understand travel behavior of super-commuters, JWRIP was used to calculate the share of super-commuters who travel individually or within a group via carpool. The categories were collapsed to the following: drove alone, 2-person carpool, 3–5-person carpool, and 5+ person carpool.

- **Race:** To minimize overlap in ethnicity and racial groupings, categories were created to separate those of Hispanic ethnicity from non-Hispanic groups using the HISP variable. As such, populations identifying as White, Black or African American, American Indian and/or Alaska Native, Asian, Native Hawaiian and Other Pacific Islander, some other race, or two or more races were all non-Hispanic designations, as Hispanic populations were filtered out prior to recoding the racial groups. Racial categories within PUMS data including "American Indian alone", "Alaska Native alone", "American Indian and Alaska Native tribes specified; or American Indian or Alaska Native, not specified and no other races", were collapsed to "American Indian and/or Alaska Native."
- **Educational attainment** levels were grouped based on general job qualification tiers including:
    - "Less than high school diploma or high school diploma/equivalent",
    - "Some college or Associate's degree",
    - "Bachelor's degree",
    - "Post-Baccalaureate, Master's, or Doctorate Degree"
- **Age groupings** were created by matching age brackets within LEHD data to maintain categorical consistency across datasets. These groupings include 29 or younger, 30-54 years, and 55 or older.
- **Income:** PUMS provides income levels at both the household and person level. With the understanding that household income is usually higher than individual income (for household sizes greater than 1), the following household income (HINCP) breaks were created which were adjusted for inflation through an adjustment factor (ADJINC):
    - less than 50k,
    - 50k-99k,
    - 100k-199k,
    - 200k or more

  Person earnings (PERNP) were also adjusted through an adjustment factor and were broken into the following groups:
    - less than 50k,

- 50k-75k,
- 50k-99k,
- 100k-150k,
- 150k-199k,
- 200k or more

Travel Behavior or Super-Commuters

Variable Selection from NHTS Dataset

The National Household Travel Survey (NHTS) is the main national source of data on how the travel behavior of the American public is changing as demographic, economic, and cultural changes are taking place in the country. The NHTS provides data on individual and household travel behavior trends linked to economic, demographic, and geographic factors that influence travel decisions and are used to forecast travel demand.[31]

For the purposes of the Caltrans RUC (Road-User Charge) Super-commuter (super-commuter) analysis, the 2017 NHTS estimates were used. The three record files used in the analysis include the housing record, where each row represents a housing unit with a unique identifier, "HOUSE ID", the person record, where each row represents a person with identifier "PERSON ID", and lastly, the vehicle record where each row represents a household vehicle with identifier "VEHID". Vehicle records are discussed under vehicle characteristics methodology section. The variables used for the RUC analysis are described in Table 51,

Table 52 and

Table 53.

[31] NHTS2017_UsersGuide_04232019_1.pdf (ornl.gov)

Table 51. Selected Household File Variables

Household File Variable	Description
HOUSEID	Household Identifier
WTHHFIN	Final Household Weight
HHFAMINC	Household Income
HH_RACE	Race of Household Respondent
HH_HISP	Hispanic Status of Household
HHSTATE	Household State
HHVEHCNT	Count of Household Vehicles
HBHUR	Urban/Rural Indicator- Block Group
PRICE	Price of Gasoline Affects Travel

Table 52. Selected Person File Variables

Person File Variable	Description
HOUSEID	Household Identifier
PERSONID	Person Identifier
CARRODE	Count of People in Vehicle to Work
R_AGE	Age
R_SEX	Gender
EDUC	Educational Attainment
OCCAT	Job Category
WTPERFIN	Final Person Weight
WRKTRANS	Mode to Work
TIMETOWK	Trip Time to Work in Minutes

Objective (Proposed Analyses)

The initial step in the NHTS analysis was to filter the NHTS dataset using super-commuter characteristics and to perform an exploratory analysis to identify relevant demographic and travel behavior characteristics of super-commuters. The exploratory analysis began by calculating the number of super-commuters who pay fuel tax and their share of the commuting workforce by filtering by travel time to work and travel mode to work. Considering that estimated personal fuel tax revenue decreases when traveling with others, the number of super-commuters who drove to work individually and the number who carpooled were additionally calculated.

To better understand the demographic characteristics of Californian super-commuters, the exploratory analysis evaluated which racial and ethnic groups super-commuters are a part of, what the average/median household income of super-commuters is, what level of education super-commuters typically have, what types of jobs do super-commuters have, and what kinds of industries do they work in. The labels in NHTS dataset were modified to match with PUMS dataset for easier comparison in analysis section.

Super-Commuter and Non-Super-Commuter Groups

The household and person files were joined using a unique identifier, HOUSE ID, after joining add-on sample from different files to NHTS dataset. Similarly, the household and vehicle files were joined using a unique identifier, HOUSE ID. In addition to this, we added new columns to vehicle file including total household miles, total household fuel consumption, average vehicle age per household, and average vehicle mpg per household. Based on this row-level data, our analysis included household weights (WTHHFIN) to get population estimates for super-commuters in the state of California. To filter the NHTS dataset to super-commuters, the travel time to work variable (TIMETOWK) was filtered to create a group of commuters who travel 90 or more minutes to work. Using the same variable, we identified non-super-commuters (car, truck, or van commuters with travel time less than 90 minutes). As discussed earlier, the focus of the analysis is on super-commuters who pay fuel tax and are going to be impacted by RUC. As a result, we used the means of transportation to work (WRKTRANS) variable to further filter the super-commuter and non-super-commuter groups to individuals who use car, truck, or van to commute to work.

Data Cleaning

- **Vehicle Occupancy:** To understand travel behavior of super-commuters, `carrode` was used to calculate the share of super-commuters who travel individually or within a group via carpool. The categories were collapsed to the following: drove alone, 2-person carpool, 3–4-person carpool, and 4+ person carpool.

- **Race:** To minimize overlap in ethnicity and racial groupings, categories were created to separate those of Hispanic ethnicity from non-Hispanic groups using the HISP variable. As such, populations identifying as White, Black, Asian were all non-Hispanic designations, as Hispanic populations were filtered out prior to recoding the racial groups. Racial categories within NHTS data including "American Indian or Alaskan Native", "Native Hawaiian or other Pacific Islander", "Multiple responses selected", and "Some other race' were collapsed to "All Other."

- **Educational attainment** levels were grouped based on general job qualification tiers including:
    - "Less than high school diploma or high school diploma/equivalent",
    - "Some college or Associate's degree",
    - "Bachelor's degree",
    - Graduate or Professional degree",

- **Occupation:** While PUMS dataset gives extensive detail on one's occupation, NHTS provides broad categories that capture different occupation groups listed in PUMS such as:
    - Sales or service,
    - Clerical or administrative support,
    - Manufacturing, construction, maintenance, or farming,
    - Professional, managerial, or technical

- **Travel Time to Work:** NHTS provides travel time to work in minutes in the range of 0-600 minutes. We created 30 minutes intervals to capture groups of commuters traveling less or more than 90 minutes and to calculate the number of commuters in each time interval.

- **Income:** NHTS provides income levels at the household level. The following household income (HINCP) breaks were created which were adjusted for inflation through an adjustment factor (ADJINC):

- less than 50k,
- 50k-99k,
- 100k-199k,
- 200k or more

Vehicle Characteristics of Super-Commuters

As mentioned in the section "Travel Behavior of Super-Commuters", we derived the vehicle characteristics from NHTS dataset using the vehicle records file. Variables shortlisted to understand vehicle characteristics of super-commuters are listed in

Table 53.

Table 53. Selected Vehicle File Variables

Vehicle File Variable	Description
VEHID	Household Vehicle Identifier Used on Trip
HOUSEID	Household Identifier
PERSONID	Person Identifier
WTHHFIN	Final Household Weight
OD_READ	Odometer Reading
ANNMILES	Self-reported Annualized Mile Estimate
BESTMILE	Best Estimate of Annual Miles
FUELTYPE	Fuel Type
FEGEMPG	Fuel Economy.gov EIA-Derived 55/45 Fuel Economy
FEGEMPGA	Fuel Economy.gov EIA-Derived 55/45 Alternative Fuel Economy
GSYRGAL	Annual Fuel Consumption in US Gallons
HFUEL	Type of Hybrid Vehicle
HYBRID	Hybrid Vehicle
MAKE	Vehicle Make
MODEL	Vehicle Model
VEHAGE	Age of Vehicle, Based on Model Year
VEHTYPE	Vehicle Type
VEHYEAR	Vehicle Year

Data Cleaning

- **Vehicle Mileage:** For the number of miles traveled by a vehicle, we used breaks of 10,000 as FHWA states that the average person drives around 13,500 miles per year. The breaks include:
  - Less than 10,000
  - 10,000- 20,000
  - 20,000- 30,000
  - 30,000 – 40,000
  - 40,000 – 50,000
  - 50,000 – 60,000
  - Greater than 60,000

- **Vehicle MPG:** We used different breaks within `fegempg` variable to categorize vehicles in different categories. These breaks include:
  - 10 mpg or lower
  - 11-20 mpg
  - 21-25 mpg
  - 26-30 mpg
  - 31 mpg or higher

- **Fuel Type:** NHTS dataset categorizes hybrid fuel types separately from regular fuel types hence both variables were used to create categories for fuels which were then grouped to be:
  - Biodiesel
  - Plug-in hybrid Vehicle (PHEV)
  - Electric
  - Hybrid
  - Gas
  - Diesel
  - Other

- **Vehicle Definition** categories were created by using vehicle types listed in NHTS dataset along with mpg levels to later estimate the types of vehicles traveled by super-commuters along with their fuel efficiency levels:
  - EV_phev (Electric or Plug-in Hybrid vehicle)
  - Auto-mid (Automobile and >=21 & <=27 mpg)
  - Auto-low (Automobile and <21 mpg)

- Auto-high (Automobile and >27 mpg)
- Suvvan_high (SUV/Van and >=20 mpg)
- Suvvan_low (SUV/Van and <20 mpg)
- Trucks

High vs. Low-Medium Vehicle Mileage

The purpose of the BAR and DMV vehicle mileage analysis was twofold: to confirm and supplement NHTS vehicle characteristic findings. The NHTS data featured small raw sample sizes that were expanded to represent the full CA population using survey weights, so the BAR and DMV records were sought to reinforce the findings from these small survey data. Additionally, the BAR and DMV vehicle records were sourced from different time periods to determine if vehicle characteristics differed between the two sets of data over time. The BAR analysis analyzed vehicle records from MY 1976 to 2015 for vehicles which underwent smog checks between calendar years 2017 and 2023, and the DMV analysis analyzed vehicle records from MY 2015 to 2023 that were sold or transferred between calendar years 2015 and 2023. These findings were used to supplement the 2017 NHTS vehicle characteristic findings which represent a snapshot in time of CA vehicle characteristics.

Variables selected for analysis in the BAR and DMV analysis are found in Table 54 and Table 55, respectively.

Table 54. Selected BAR Variables[32]

Vehicle File Variable (OIS)	Vehicle File Variable (EIS)	Description
VINID	VIN	Vehicle Identification Number
ODOMETERREADING	ODOMETER	Odometer reading at time of testing
TESTYEAR	N/A	Year in which test was done
TESTMONTH	N/A	Month in which test was done
N/A	END_DATE	Date on which test was completed
VEHICLEMODELYEAR	VEH_MOD_YR	Vehicle Model Year
FUELTYPE	FUEL_TYPE	Fuel used by vehicle

Table 55. Selected DMV Variables

Vehicle File Variable (OIS)	Description
VIN	Vehicle Identification Number
ODOMETER_READING	Odometer reading at time of sale
ODOMETER_CURRENT_DATE	Date of odometer reading
YEAR_MODEL	Vehicle Model Year
MOTIVE_POWER	Fuel used by vehicle

For both the BAR and DMV datasets, we calculated yearly miles driven on a per-vehicle basis. The first time a vehicle's VIN shows up in the data, we calculated its yearly miles as the odometer reading divided by the number of years since its production (i.e., the calendar year associated with its model year). For subsequent years, we calculated it as the odometer reading divided by the number of years since the date of the last reading.

We excluded from the data vehicles with invalid VINs, vehicles marked as having over 70,000 yearly miles, as well as any incomplete vehicles, and vehicles which are almost solely work vehicles, namely busses, (heavy) trucks, and limousines. Vehicles were segmented into 'high mileage' or 'low-medium mileage' vehicles depending on whether or not they drove over 20,000 miles per year (over = high, under = low-mid). This threshold was informed from previous yearly mileage research conducted using data from NHTS that showed that the majority of non-super-commuters drove less than 20,000 miles per year.

[32] The BAR data consisted of two subsets from two different kinds of smog inspections: Onboard Inspection System (OIS) and Emission Inspection System (EIS) with slightly different variable names/formats.

We were unable to isolate super-commuters in the data set but were still able to make conclusions about high-mileage drivers, which are applicable to this study.

To determine the vehicle type (i.e. body class) we merged the BAR or DMV data with vehicle data previously gathered from the NHTSA's VIN Decoder by EBP. Fuel efficiency was determined by merging vehicle data with efficiency estimates published by the EPA[33]. Additionally, the mean fuel efficiency published above is the harmonic mean of the miles-per-gallon figures.

Revenue Estimation

The final revenue estimation has three primary steps that leverage the NHTS data previously analyzed. For each travel group (super-commuters, non-super-commuters, and other auto travelers):

- Estimate Total Baseline Policy Revenue for CA
- Estimate Revenue-Neutral RUC Rate for CA
- Estimate Total RUC Revenue for CA

Based on the data from these steps we report the revenue burden of baseline policies and RUC revenue by geographic classification, income group, race/ethnicity group, and occupation group. We compare the baseline policy and RUC revenues for each travel group by geographic classification, income, race/ethnicity, and occupation, and examine the distribution within each of these groups.

To estimate the total baseline policy revenue for each travel group in CA, fuel tax rates reported by RUC America state representatives (Table 30) were multiplied by the estimated fuel use per reported NHTS vehicle per fuel type.

We calculate fuel tax payments and VMT for each travel group by summing over all NHTS dataset vehicles. The fuel efficiencies for each fuel type are summarized using harmonic means for the various fuel types analyzed.

[33] EPA. Vehicle Fuel Economy. https://www.fueleconomy.gov/feg/ws/index.shtml

The fuel tax contribution of each fuel type is calculated individually for each fuel type as revenue policy rates differ by fuel type. Fuel tax rates are zero for some fuel types (PHEV and hybrid vehicles). Registration surcharges are only considered for full electric vehicles.

For PHEVs, we assume that 56 percent of all miles were driven using only electricity. This was incorporated into the calculation above by multiplying the VMT by the percentage of miles driven on conventional fuel (44 percent).

We calculate a revenue-neutral RUC rate by dividing the state's total baseline policy revenues by the state's 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 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 for each travel group to estimate the total 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.