



Designing Light-Duty Vehicle Incentives for Low- and Moderate-Income Households

Prepared by:

Gregory Pierce

J.R. DeShazo
(Principal Investigator)

Tamara Sheldon

Britta McOmber

Evelyn Blumenberg

UCLA Luskin Center for Innovation

DESIGNING LIGHT-DUTY VEHICLE INCENTIVES FOR LOW- AND MODERATE-INCOME HOUSEHOLDS

FINAL REPORT
CONTRACT NO. 15RD011

PREPARED FOR:
CALIFORNIA AIR RESOURCES BOARD
RESEARCH DIVISION
CALIFORNIA ENVIRONMENTAL PROTECTION AGENCY
1001 I STREET
SACRAMENTO, CALIFORNIA 95814

PREPARED BY:
GREGORY PIERCE, J.R. DESHAZO (PRINCIPAL INVESTIGATOR),
TAMARA SHELDON, BRITTA MCOMBER, EVELYN BLUMENBERG

LUSKIN CENTER FOR INNOVATION
UNIVERSITY OF CALIFORNIA, LOS ANGELES
LOS ANGELES, CA 90095
MARCH 12, 2019

DISCLAIMER

The statements and conclusions in this report are those of the contractor and not necessarily those of the California Air Resources Board. The mention of commercial products, their source or their use in connection with material reported herein is not to be construed as actual or implied endorsement of such products.

ACKNOWLEDGMENTS

Gregory Pierce, J.R. DeShazo (Principal Investigator), Tamara Sheldon, Britta McOmber and Evelyn Blumenberg (Co-Principal Investigator) are the authors of this study. Paul Ong also served as a Co- Principal Investigator for this study. Mara Burnstein copy edited the document. Nicholas Cuccia designed and formatted the report.

We thank CARB staffers and staff from other state agencies and the South Coast and San Joaquin Valley AQMDs for their support, review, and comments on draft versions of this report.

This report was submitted in fulfillment of CARB contract #15RD011 "Designing Light-Duty Vehicle Incentives for Low- and Moderate-Income Households" by the University of California under the partial sponsorship of the California Air Resources Board. Work was completed as of March 2019.

Cover photos courtesy of Valley Clean Air Now

TABLE OF CONTENTS

FIGURES

TABLES

ABSTRACT

This report informs future strategies to improve clean vehicle access and use by low- and moderate-income households in California. The research identifies effective policy approaches — using purchase incentives and financing programs — that promote the retirement of functional, high-emitting vehicles and the adoption of advanced clean vehicles by the target population. As a percentage of household earnings, lower-income populations face disproportionate costs to maintaining and operating a vehicle. Optimally priced incentives and financing options can therefore promote household economic well-being while generating broader environmental and public health benefits through greenhouse gas emission reductions.

Analysis of a statewide, representative survey of 1,604 low- and moderate-income households reveals that respondents own as many vehicles as higher-income households in the state, and despite the high costs of purchase and operation, relied upon them heavily for travel purposes. Respondents, however, did not express strong interest in transit or alternative travel modes. The results of choice experiments presented to respondents suggest that further investment in new and used clean vehicle purchase incentives for the target population would be cost-effective. Offering rebates of $2,500, $5,000, or $9,500 increased plug-in hybrid electric vehicle (PHEV) and battery electric vehicle (BEV) purchases incrementally by approximately 20%, 40%, and 60-80% respectively. For the policy scenarios considered, rebates had a much larger impact than offering guaranteed financing alternatives. We found that offering both together did not significantly increase purchase rates beyond the increases associated with offering the rebate alone. As anticipated by California Senate Bill 350, the persistence of multiple barriers, including a larger dependence on used vehicles and a lower reliance than higher-income households on traditional financing mechanisms, should inform future program design and adaptation.

Research assessing the design and implementation of the Enhanced Fleet Modernization Program Plus-Up deployed in the South Coast and San Joaquin Valley air management districts shows uniformly high demand for vehicle retirement and replacement incentives, despite regional differences in program implementation.

EXECUTIVE SUMMARY

Background

California will require a transformation of its light-duty vehicle fleet to help meet statewide air quality and climate change goals. In 2018 Governor Jerry Brown issued an executive order setting a goal of 5 million zero-emission vehicles (ZEVs) in the state by 2030. Financial incentives can play an important role by accelerating the retirement and replacement of older, high-polluting vehicles and increasing the adoption of clean vehicles. Yet several challenges persist in enabling low- and moderate-income households to adopt near-zero and zero-emission vehicles in California. While low-income households have participated in the retirement rebate element of the Enhanced Fleet Modernization Program (EFMP) since 2010, few of these participants chose to take advantage of the replacement rebate for lower-emitting vehicles until the creation of the EFMP Plus-Up pilot program in 2015 (California Air Resources Board, 2013). The Plus-Up component provides an additional replacement incentive amount, dependent upon household income and type of replacement car, for the purchase or lease of a new or used clean vehicle. The EFMP Plus-Up pilot was implemented in the San Joaquin Valley and South Coast air quality management districts, and is expanding to other areas of the state as the renamed Clean Cars 4 All program.

The other statewide vehicle incentive program, the Clean Vehicle Rebate Project (CVRP), has offered rebates for zero-emission plug-in hybrid electric, battery electric, and fuel-cell electric vehicles since 2010. As in the early stages of implementing the EFMP, few low- and moderate-income households applied for CVRP rebates to aid in the purchase of hybrid and zero-emissions vehicles (Center for Sustainable Energy, 2014). Low initial adoption by this subpopulation prompted recent revisions to the household income criteria that increased the incentive amounts offered through the project.

Clean vehicle financing programs are more recent in nature and limited in scope than incentive programs. For instance, the Community Housing Development Corporation's Financing Assistance Pilot Project has operated since 2015 at a limited scope in the Bay Area. In summer of 2018, however, the California Air Resources Board provided a grant to the Beneficial State Foundation to operate the first statewide financing program, the Clean Vehicle Assistance Program. The findings in this report can help inform optimal rebate and financing approaches that accelerate households' conversion to a cleaner light-duty vehicle fleet, or incentivize a shift to alternative transit modes. The focus of this report is responsive to California Senate Bill (SB) 350, which prioritized the identification of barriers (and strategies to overcome them) to clean transportation access for low- and moderate-income Californians.

Objectives and Methods

This report assesses current policies and informs future strategies intended to improve new and used clean vehicle access and use by low- and moderate-income California households, the adoption of which will also generate broader statewide environmental, health, and economic benefits. The research aims to identify effective policy strategies, using incentives and preferential financing, to promote the retirement of functional, high-emitting vehicles and increase adoption of advanced clean vehicles by the target population. A statewide representative survey of 1,604 low- and moderate-income households divided by income and race-ethnicity forms the primary basis of the study's research conclusions. Additionally, a case study of the first year of the EMFP Plus-Up program was conducted via interviews with CARB and AQMD staff, as well as a descriptive analysis of program participant demographics, retirement and replacement vehicle characteristics, and purchase incentive levels.

Results

Survey respondents exhibited a high level of vehicle dependence; they held as many vehicles as the statewide average of two vehicles per household. However, significant differences existed between low- and moderate-income respondents; survey respondents from the lowest income bracket ($25,000 or less) held less than half the number of vehicles as moderate-income households ($75,000 or more). The study also calculates the annual expenditure to maintain and retain the household's main vehicle. The subset of households who reported fuel, insurance, and repair expenditures had average aggregated expenditures equivalent to 16.2% of their reported income. This level of expenditure exceeds the 15% affordability threshold for transportation expenditures recommended by several leading organizations.

In terms of the vehicle search and decision-making process, males were much more likely than females to be identified as the main decision maker in vehicle purchase decisions. Households spent an average of over six months looking for a vehicle before purchasing. The average reported expenditure to purchase a vehicle was almost $14,000, or over 50% of the average yearly income of households surveyed; this level of expenditure shows the importance of vehicles to low- and moderate-income households. However, significant differences in expenditure levels existed among respondents.

About 40% of surveyed households reported buying new vehicles at an average price of $21,125, which is nearly triple the average price of the remainder of households who purchased used vehicles at an average price of $7,957. Households who bought their main vehicle used were much more likely to be lower income and to pay for their vehicle in cash rather than finance their purchase via loans (about 40% of all respondents paid in cash). Households who purchased vehicles used were more than twice as likely as new vehicle purchasers to buy their vehicle somewhere other than a dealer (62% vs. 16%).

Choice set modeling results suggest that further investment in new and used clean vehicle purchase incentives for the target population would be cost-effective. We find that offering rebates at all levels significantly increases the propensity to purchase hybrids, PHEVs and BEVs among low- and moderate-income consumers. Rebates of $2,500, $5,000, and $9,500 increased purchase rates from their baselines by approximately 20%, 40% and 60-80% respectively across vehicle types. Furthermore, we find that offering guaranteed loans (even at a low interest rate of 5%) has a much smaller and uneven effect on the propensity to purchase these vehicles.

In terms of additional barriers to vehicle access, rural and suburban households report traveling about 25% more miles by vehicle than urban households, and thus incur higher fuel expenditures. Moreover, racial and ethnic minorities pay substantially more for automobile insurance (ranging from 10% more for Asian respondents to nearly 40% more for Black respondents) than non-Hispanic Whites, although the reasons for this disparity are unclear and sample sizes were too small to determine statistical significance. Despite the substantial barriers to vehicle access and use, surveyed households did not express strong interest in transit or alternative modes. Only about 6% rode transit daily (although 18% did so when their main vehicle was being repaired), with mode shares of less than 10% for all other non-walk and vehicle modes. Indeed, about 60% of respondents said they would not seriously consider selling their main vehicle even if transit were made as convenient and inexpensive as operating their vehicle.

Results regarding households' awareness of and ability to utilize PEVs were mixed. More than one-third of respondents reported awareness of PEV purchase incentives. As previous studies have shown, respondents living in single-family detached homes are more likely (61%) to have convenient PEV charging potential as compared to respondents who reside in multi-unit dwellings (35%).

Finally, research assessing the design and implementation of the EFMP Plus-Up deployed in the South Coast and San Joaquin Valley air management districts shows that, while implementation of the program differed by region, both exhibited uniformly high demand for such incentives.

Conclusions

Multiple findings from this study, including evidence of low- and moderate-income households' greater dependence on used vehicles, lower reliance on traditional financing, and concerted disinterest in alternative travel modes, should inform the adaptation of a wide range of transportation subsidy programs and planning efforts for this population. Particularly encouraging with respect to the goal of transforming the existing vehicle fleet to zero or near-zero vehicles, our findings suggest additional investment in vehicle incentives targeted toward this population can produce substantial benefits.

INTRODUCTION

In order to achieve air quality and climate change goals in California, the state must transform its light-duty vehicle fleet. Most relevant to getting more clean vehicles on the road, Governor Jerry Brown issued an executive order in 2018 setting a goal of 5 million zero-emission vehicles (ZEVs) in the state by 2030. Financial incentives can play an important role by accelerating the retirement and replacement of older, high-polluting vehicles and by increasing the adoption of clean vehicles. Yet several challenges persist in enabling low- and moderate-income households, representing nearly 50% of the state's population and vehicle holdings, to adopt near-zero and zero-emission vehicles in California. Lower-income households are more likely to own higher-emitting vehicles (due to lower purchase costs), to hold on to these vehicles longer, and to then bear a disproportionate burden of transportation-related air pollution when compared to higher-income households (National Travel Household Survey, 2009; Bhat et al., 2009; Choo and Mokhtarian, 2004; Choo et al., 2007). Low- and moderate-income households are also less likely to be able to afford or finance advanced clean vehicles without financial incentive support.

While low-income households have participated in the retirement incentive element of the Enhanced Fleet Modernization Program (EFMP) since 2010, few of these participants chose to take advantage of the replacement rebate for lower-emitting vehicles until the creation of the EFMP Plus-Up pilot program in 2015 (California Air Resources Board, 2013). The Plus-Up component provides an additional replacement incentive amount, dependent upon household income and type of replacement vehicle, for the purchase of a new or used clean vehicle. The EFMP Plus-Up pilot was implemented in the San Joaquin Valley and South Coast air quality management districts, and is expanding to other areas of the state as the renamed Clean Cars 4 All.

A statewide incentive program, the Clean Vehicle Rebate Project (CVRP), has offered rebates for zero-emission plug-in hybrid electric, battery-electric, and fuel-cell electric vehicles since 2010. Like the early stages of the EFMP, at its outset few low- and moderate-income households applied for CVRP rebates to aid in the purchase of hybrid and zero-emissions vehicles (Center for Sustainable Energy, 2014). Low initial adoption by this population prompted recent revisions to the income criteria used for increased incentive amounts offered through the project. Finally, very few car-sharing, ride-sharing, and other mode-shifting programs that utilize near-zero or zero-emission vehicles in low- and moderate-income neighborhoods currently exist. There are, however, several pilot programs underway throughout the state, including the Car Sharing and Mobility Options Pilot Project. A new statewide financing assistance program, the Clean Vehicle Assistance Program, also launched recently to offer financing assistance to lower-income households for clean vehicle purchase. Given the recent nature of many of these efforts, however, this report helps respond to California Senate Bill 350, which prioritized the identification of barriers (and strategies to overcome them) to clean transportation access for low-income Californians.

This report assesses current policies and informs future strategies to improve clean vehicle access and use by low- and moderate-income households while generating broader environmental and economic benefits in California. The research primarily aims to identify effective policy strategies, using incentives and preferential financing, that promote the retirement of functional, high-emitting vehicles and the adoption of advanced clean vehicles by the target population. A statewide representative survey of 1,604 low- and moderate-income households helps to inform future strategies to improve access to and adoption of clean vehicles.

Report Road Map and Research Questions

Chapters 1 and 2 present an overview of the survey development and deployment process, survey data cleaning and coding methods, and basic descriptive results of the survey that generate the more targeted findings reported in Chapters 3-7. Chapter 3 describes and assesses how surveyed households search for vehicles and make decisions about vehicle purchase, including financing choices. Chapter 4 presents the results of choice set analyses investigating the effect of different incentive amounts on households' preferences for clean vehicle purchases. Chapter 5 describes current household vehicle holdings, fleet characteristics, and management, including the necessary expenditures to operate the household's main vehicle. Chapter 6 provides an assessment of additional barriers to meeting low- and moderate-income households' travel needs, including elements of vehicle ownership and alternative mode availability and preference. Chapter 7 analyzes household awareness of plug-in electric vehicles and barriers or opportunities to plug-in vehicle charging at respondents' places of residence.

Finally, Chapter 8 presents the results of research on the EFMP Plus-Up program deployed in the South Coast and San Joaquin Valley air districts. This chapter focuses on lessons learned from the design and implementation of the initial pilot program.

Below we provide a detailed outline of motivating gaps in knowledge and the research questions this report addresses to inform further policy development (Chapters 3-8).

Chapter 3. The Vehicle Purchase Process: Past and Future Decision Making, Search, Expenditure, and Financing

A few studies analyze how households search for automobiles, and how technology influences their search. Only one study, to our knowledge, focuses on potential differences in this search by income group (Klein and Ford, 2003). Each of the studies identified, however, focuses on marketing and information costs rather than aspects of the vehicle or transportation need (Punj and Staelin, 1983; Srinivasan and Ratchford, 1991). Additional studies demonstrate that the process of searching for a new or used vehicle is time-consuming and thus expensive (Klein and Ford, 2003), and this is especially true for PEV purchase (Taylor and Fujita, 2018).

Despite a lack of research on the magnitude of vehicle purchase expenditures and the vehicle search process for disadvantaged households, several studies document the obstacles faced by low-income and minority households in the vehicle purchase process. For one, they experience price discrimination in the form of higher purchase prices for new cars (Ayres and Siegelman, 1995). Minorities also have lower levels of financial literacy and savings (Babiarz and Robb, 2014) partly due to costly and unfair financing arrangements for vehicles (Charles, Hurst, and Stephens 2008; Sutton, 2007; Van Alst, 2009) while having less access to financial institutions (Blanco, et al., 2015). These factors, on their own and combined, result in high purchase prices for both used and new vehicles for disadvantaged households.

To understand and inform programs and policies to improve clean vehicle use and access among low- and moderate-income households in California, the survey asked a series of questions regarding the process of past and prospective vehicle purchase decision making and financing. The responses to these questions allow us to answer the following research questions:

1. How quickly and where do low- and moderate-income households search for and ultimately purchase vehicles? How do they expect to search in the future?
2. How much do households pay and how do they finance vehicle purchases? How do they expect to finance purchases in the future?

Chapter 4. Assessing the Effects of Rebates and Guaranteed Loans on Purchase Decisions

Several recent studies found that subsidizing plug-in electric vehicles is relatively expensive because there is a large portion of non-marginal or non-additional buyers who would purchase the vehicle in the absence of a subsidy and thus raise the marginal cost of incentivizing an additional vehicle via subsidies (e.g., Tal and Nicholas, 2016; DeShazo, Sheldon, and Carson, 2017; Li et al., 2017; Sheldon and Dua, 2018). However, these studies also found several options to reduce policy costs — for example, by simultaneously subsidizing public charging (Li et al., 2017) or by assigning subsidies according to income, vehicle type, or some other source of observable heterogeneity

(DeShazo, Sheldon, and Carson, 2017; Sheldon and Dua, 2018). These papers also focus only on the new vehicle market, which represents a fraction of the total market. Furthermore, new car buyers tend to be different than used car buyers (e.g., higher-income). Lastly, we are unaware of studies that examine financing as a form of clean vehicle adoption policy. In this chapter, we examine the impact of both subsidies and financing on clean vehicle adoption rates for all vehicles (both new and used). This is also one of the first such studies to focus on low- and moderate-income consumers.

Using the results from carefully designed choice sets, we provide answers to the following questions:

1. **What effect would various rebate incentive levels have on the purchase of different types of low- and zero-emission vehicles?**
2. **What effect would guaranteed loans with various interest rates have on the purchase of different types of low- and zero-emission vehicles?**
3. **How would the present status of related programs (e.g., EFMP Plus-up and CVRP) affect vehicle purchase rates?**
4. **How do respondent characteristics such as income, ethnicity, geography, and AQMD region attenuate the effects of these rebate and loan programs?**

Chapter 5. Current Fleet Characteristics, Management, and Expenditures

Most low- and moderate-income households own and use automobiles. For example, data from the 2016 American Community Survey shows that 92% of households below 300% of the Federal Poverty Level in California have at least one automobile in their household, with the average low- or moderate-income household owning two vehicles. Additionally, the ACS found that about 80% of workers in poor California households commute by automobile.

Despite surprisingly little published evidence on this topic, economic theory suggests that low- and moderate-income households are more likely to own older, high-polluting vehicles than higher-income households (National Travel Household Survey, 2009; Bhat et al., 2009; Choo and Mokhtarian, 2004). Policies that effectively incentivize the retirement of high-polluting vehicles with near-zero and zero-emission replacements would have an out-sized impact on emissions reductions. In addition to the environmental impact of vehicle use by low- and moderate-income households, we expect that these households must expend a disproportionately higher percentage of their incomes to maintain and operate their vehicles.

Despite the prevalence of automobile ownership and the expected degraded condition of these vehicles among lower-income groups, relatively little research examines the size, profile, and maintenance expenditure of low- and moderate-income households' vehicle fleets. To fill these research gaps, survey respondents answered questions about their general vehicle holdings and more detailed questions regarding their self-selected main vehicle. The results of these and other questions from the survey allow us to answer five related questions of interest:

1. **What factors influence vehicle access and the number of vehicles used by households within the sample?**
2. **What are the emissions-relevant characteristics of vehicles to which surveyed households have access?**
3. **How do households compose their fleets with respect to household structure?**
4. **How much money do households need to expend to maintain and operate the household's main vehicle?**
5. **What do households report regarding their intentions to keep or dispose of their main vehicle and what factors influence these responses?**

Chapter 6. Potential Barriers to Vehicle Access and Interest in Alternative Travel Modes

In addition to income and financing constraints to maintain or purchase a vehicle (detailed in Chapters 3 and 5 of this report), low- and moderate-income households may face additional barriers to vehicle access. These barriers include capacity to cope with vehicle breakdown, lack of information, as well as financial, resource, or budgeting challenges, and/or discrimination, which compound pure cash flow obstacles. Unless they can be made as convenient and timely as vehicle use, alternative travel modes can only be a second-best solution to meet household travel needs in the face of vehicle access deficits.

To inform programs and policies to better understand and enhance clean vehicle access and use among low- and moderate-income households in California, the survey asked a series of questions regarding current barriers to personal vehicle access. The survey also evaluated respondents' access to and interest in using alternative modes. This allows us to answer the following research questions:

1. **Do surveyed households face additional barriers in getting vehicle repairs, the price of fuel, or obtaining insurance or credit status? If so, what socioeconomic and geographic factors are associated with these challenges?**
2. **How often do surveyed households use alternatives to driving their own personal vehicle? How often would they consider alternative modes if they were made as convenient and affordable as using a personal vehicle?**

Chapter 7. Awareness of Plug-In Electric Vehicles and Factors Mediating Plug-In Vehicle Charging Potential

As found in previous research, in the absence of targeted program support, low- and moderate-income households have lower awareness and usage levels of plug-in electric vehicles (PEVs) than higher-income households (DeShazo et al., 2017). Long-distance travel patterns and built environment factors also make it difficult for households to charge plug-in vehicles, and thus inhibit PEVs as a primary mode of transportation (see DeShazo, Krumholz, Wong, and Karpman, 2017).

This survey asked questions regarding household awareness of PEVs and incentives for their purchase, as well as long-distance, weekly, and commute travel patterns. This information informs the diversity of PEVs suitable for a household's travel needs. Respondents also answered questions about attributes of their dwelling place, which impacts the ease of PEV charging. The responses to these questions allow us to answer the following research questions:

1. **Are surveyed households aware of PEVs, state incentives for PEVs, and high-occupancy vehicle (HOV) lanes?**
2. **Do these households have long-distance, weekly, and commute travel patterns that would make PEV charging difficult?**
3. **Do these households have ready access to potential PEV charging infrastructure, or would facilitating such access require additional support?**

Chapter 8. Design and Implementation of the Enhanced Fleet Modernization Plus-Up Pilot Program

Using data on the first year of program operation provided by CARB and the two participating districts, this chapter outlines how the Enhanced Fleet Modernization Program (EFMP) Plus-Up pilot was implemented in the San Joaquin Valley Air Pollution Control District and South Coast Air Quality Management District. This vehicle retirement and replacement program targets the placement of a range of clean vehicles (hybrids, plug-in hybrids, and battery-only electric vehicles) in low-income households in San Joaquin and South Coast air districts. This study first describes the origins of the EFMP Plus-Up program, its relation to other vehicle replacement incentive programs, and its funding sources. This chapter outlines how the EFMP Plus-Up pilot was implemented during the first year of operation, highlighting lessons learned for future implementation efforts.

Finally, we sought to evaluate the effects of the EFMP Plus-Up Program on increased clean vehicle purchases at the ZIP code level between 2015 and 2018 using vehicle registration data. We sought to exploit the differences in the timing and geographic rollout of this program, employing a difference-in-difference method to identify the additional increase in vehicle purchases associated with the program. Our early analysis showed that the treated and untreated ZIP code areas have the same pretreatment trend in clean vehicle purchases, satisfying the key assumption of the difference-in-difference method. However, further testing revealed that there was not existing data yet to support robust analyses. (As of July 1, 2018, the program had distributed 3,727 rebates). As a result, this report does not present any of these inconclusive analyses. We recommend revisiting this analysis using either ZIP-code level data in two years when the number of processed rebates has doubled or micro-data becomes available at the household level that we did not have.

References

Ayres, I. and Siegelman, P. (1995). Race and gender discrimination in bargaining for a new car. *The American Economic Review*, 85(3), 304-321.

Babiarz, P. and Robb, C. (2014). Financial Literacy and Emergency Saving. *Journal of Family and Economic Issues*, 35(1), 40-50.

Bhat, C. R., Sen, S. and Eluru, N. (2009). The impact of demographics, built environment attributes, vehicle characteristics, and gasoline prices on household vehicle holdings and use. *Transportation Research Part B,* 43, 1–18.

Blanco, L. R., Ponce, M., Gongora, A. and Duru, O. K. (2015). A Qualitative Analysis of the Use of Financial Services and Saving Behavior Among Older African Americans and Latinos in the Los Angeles Area. *Sage Open*. DOI: 10.1177/2158244014562388.

California Air Resources Board (2013). Enhanced Fleet Modernization Program Assessment. Staff Report. Accessed February 25, 2015 from http://www.arb.ca.gov/msprog/aqip/EFMP_Update _Staff_Report_ November_2013.pdf.

California Center for Sustainable Research (2014). What Drives California's Plug-in Electric Vehicle Owners? California Plug-in Electric Vehicle Driver Survey Results. Conducted May 2013. Accessed February 25, 2015 from https://energycenter.org/sites/default/files/docs/ nav/ transportation/cvrp/survey- results/California_PEV_Owner_ Survey_3.pdf.

Charles, K. K., Hurst, E. and Stephens, M. (2008). Rates for Vehicle Loans: Race and Loan Source. *American Economic Review: Papers & Proceedings*, 98(2), 315-320.

Choo, S. and Mokhtarian P.L. (2004). What type of vehicle do people drive? The role of attitude and lifestyle in influencing vehicle type choice. *Transportation Research Part A*, 38, 201–222.

Choo, S., Shafizdeh, K. and Niemeier, D. (2007). The development of a prescreening model to identify failed and gross polluting vehicles. *Transportation Research Part D,* 12, 208–218.

DeShazo, J.R., Sheldon, T. and Carson, R. (2017). Designing Policy Incentives for Cleaner Technologies: Lessons from California's Plug-in Electric Vehicle Rebate Program. *Journal of Environmental Economics and Management*, 84, 18-43.

DeShazo, J. R., Krumholz, S., Wong, N. and Karpman, J. (2017). Southern California Plug-in Electric Vehicle Readiness Atlas: 2017 Update. *UCLA Luskin Center for Innovation*.

Klein, L. R. and Ford, G. T. (2003). Consumer search for information in the digital age: An empirical study of prepurchase search for automobiles. *Journal of Interactive Marketing,* 17(3), 29-49.

Li, S., Tong, L., Xing, J. and Zhou, Y. (2017). The Market for Electric Vehicles: Indirect Network Effects and Policy Design. *Journal of the Association of Environmental and Resource Economists*, 4(1), 89-133.

Punj, G. N. and Staelin, R. (1983). A Model of Consumer Information Search Behavior for New Automobiles. *Journal of Consumer Research*, 9(4), 366-380.

Sheldon, T. L. and Dua, R. (2018). Gasoline savings from clean vehicle adoption. *Energy Policy*, 120, 418-424.

Srinivasan, N. and Ratchford, B. T. (1991). An Empirical Test of a Model of External Search for Automobiles. *Journal of Consumer Research*, 18(2), 233-242.

Sutton, R. (2007). Car financing for low- and moderate-income consumers. Baltimore, MD: Annie E. Casey Foundation.

Tal, G. and Nicholas, M. (2016). Exploring the Impact of the Federal Tax Credit on the Plug-In Vehicle Market. *Transportation Research Record: Journal of the Transportation Research Board*, 2572, 95-102.

Taylor, M. and S. Fujita (2018) Consumer Behavior and the Plug-In Electric Vehicle Purchase Decision Process: A Research Synthesis." Lawrence Berkeley National Laboratory. Report LBNL-2001122.

U.S. Census Bureau. (2016). American Community Survey 2012 – 2016. *American Factfinder*.

U.S. Department of Transportation Federal Highway Administration (2009). National Household Travel Survey.

Van Alst, J. (2009). Fueling fair practices: A road map to improved public policy for used car sales and financing. Boston, MA: National Consumer Law Center.

CHAPTER 1

SURVEY DESIGN AND DEPLOYMENT CONTENTS, PROCEDURES, AND TIMELINE

This chapter describes the methods and procedures used to design and deploy a survey to a representative sample of low- and moderate-income households in California in order to understand i) the effectiveness of alternative incentive designs for low- and zero-emission vehicle purchases, and ii) the role that enhanced financing options might play in increasing the purchase of new or used low- and zero-emission vehicles.

The major methods described here are the contents, procedures, and timeline of a) structured interviews among the target population that informed the statewide survey design, b) the selection process and contracting agreement with an outside vendor to deploy the survey, c) the soft launch of the survey, and d) the full launch of the survey. CARB staff was consulted during the undertaking of each of these steps. All procedures and points-of-contact with respondents were also approved by the UCLA Institutional Review Board (IRB) under IRB approval #17-001704, Designing Light-Duty Vehicle Incentives for Low- and Moderate-Income Households.

1.1. Structured Interviews

As envisioned in the research contract, we first conducted structured interviews with members of the target demographic to inform the development of the survey instrument. Structured interviews with individual respondents allowed the researchers to obtain targeted feedback on question design and interpretation. The target demographic included eligible or actual Enhanced Fleet Modernization Program (EFMP) Plus-Up participants.

Content

Each structured interview lasted approximately 90 minutes. We provided both an English and Spanish-language script to each group, and conducted discussions in both languages. CARB staff reviewed the Spanish-language script in advance.

The English Structured Interview Guide served as a tool to guide the interviewer and interviewee during the process, and was translated into Spanish. The Guide first asked questions about the characteristics of members and vehicles in the household. The remainder of the Guide contained three modules: Module 1 - Maintenance and Repair, Module 2 - Vehicle Purchase Process, and Module 3 - Alternative Modes of Transportation. These modules covered factors influencing a) the timing and determinant of vehicle retirement decisions, b) participants search process leading up to, and choice of, vehicle replacement, c) the role of financing or credit constraints in replacement decisions, d) the role informal ride-share services may play, and e) the effectiveness of the specific policy incentives.

Interviewees reviewed and authorized a Consent to Participate Form (which was also translated to Spanish). As outlined in the research contract, participants earned $140 for participating in the interview. After, participants initialed a form signaling their acknowledgment of a received payment.

We coordinated with Valley Clean Air Now (Valley CAN), the San Joaquin Valley Air Pollution Control District and the South Coast Air Quality Management District to interview past or prospective EFMP Plus-Up participants. In addition to the administrative synergies realized by working with the districts to conduct structured interviews, the collective representativeness of the districts in urbanization, socio-economic profile, and travel behavior vis-à-vis the entire state was deemed sufficient. While the same survey instrument was deployed across the two districts, the timing and setting of interviews was tailored to the two areas based on the districts' respective capacities to facilitate engagement with interviewees.

Structured Interviewee Timing and Setting in the San Joaquin Valley

Eleven structured one-on-one interviews were conducted at a "Tune In and Tune Up" event put on by Valley CAN held at the San Joaquin County Fairgrounds in the City of Stockton on February 25, 2017. "Tune In and Tune Up" events are one-day car cleanup efforts that provide free emissions tests, diagnostic inspections, and vouchers for smog repairs (for more details regarding this program, see Chapter 8).

Inspections for over 525 vehicles occurred for residents attending the February 2017 event. Valley CAN staff invited attendees to participate in the interviews after confirming them as income and vehicle eligible for EFMP Plus-Up via the general screening process for the event. If attendees confirmed interest in participating in an interview regarding their general transportation needs and habits, they were directed to an area set up to conduct the interviews. Six interviews were in Spanish and five were in English. Participants received the consent form for reference. Christina Hernandez conducted Spanish interviews. J.R. DeShazo and Evelyn Blumenberg conducted English interviews. Gregory Pierce was the facilitator.

Structured Interviewee Timing and Setting in the South Coast

Similarly, eight structured one-on-one interviews were conducted with past EFMP Plus-Up participants in the South Coast Air Quality Management District (SCAQMD) in April 2017. SCAQMD provided a list of past participants in the EFMP Plus-Up program who agreed to potentially participate in the study. An initial phone interview and script facilitated the conversation between the interviewer and potential interviewee. The potential participant received information about the study and logistics. If the individual agreed to participate, then an in-person interview was scheduled. Four interviews in English and four interviews in Spanish took place. Each of the interviews with SCAQMD participants took place at UCLA. In addition to the Structured Interview Guide, an EFMP Plus-Up Participant Survey was included during the interview to assess satisfaction with replacement vehicles and to understand the benefits and disadvantages of the replacement vehicle. The interviews took place over a roughly two-week period. Gregory Pierce, Evelyn Blumenberg, and Christina Hernandez completed the interviews.

1.2. Contracting With Survey Vendor

To carry out the administration of the full survey, we solicited bids from external vendors. Given the sophistication of the survey instrument, and to ensure that the household sample was representative, we subcontracted with a highly reputable market research firm to administer it. We requested and received a minimum of three competitive bids from market research firms, pursuant to the university's purchasing policies, consistent with SCM Vol. 1 Section 3.06E. We selected the firm Growth from Knowledge Custom Research LLC (GfK) based on the comprehensiveness and cost-competitiveness of its bid and proven track record of administering similar surveys.

We started a formal university contracting procedure with GfK in September 2017, and finalized the agreement in November 2017.

The agreement stipulated GfK to obtain a survey sample restricted to the following target population:

- General population adults, age 18+;
- Who are California residents;
- Who reside in households with an income at or below 300% of the Federal Poverty Level (with at least 50% coming from households at or below 225%);
- Who stated their intent to replace a vehicle within the next three years; and
- English-, Spanish-, and Chinese-language survey-takers

Upon requests from CARB, the research contract was revised to increase the targeted general sample from 1,400 to 1,600 (with an even split between English and Spanish speakers) and a separate sample of 100 Chinese-language speakers. All survey responses were recorded online.

GfK recruits potential survey panel members by using address-based sampling (ABS) methods (previously GfK relied on random-digit dialing [RDD] methods). Once household members are recruited for the panel and assigned to a study sample, they are notified by email for survey taking, or panelists can visit their online member page for survey taking (instead of being contacted by telephone or postal mail). This allows surveys to be fielded quickly and economically. In addition, this approach reduces the burden placed on respondents, since email notification is less intrusive than telephone calls and most respondents find answering online questionnaires more interesting and engaging than being questioned by a telephone interviewer. Furthermore, respondents have the convenience to choose what day and time to complete their assigned survey.

GfK's KnowledgePanel® is the largest online panel that relies on probability-based sampling techniques for recruitment in the U.S.; hence, it is the largest national sampling frame from which fully representative samples can be generated to produce statistically valid inferences for study populations. In order to carry out this particular survey, GfK invited individuals from its existing KnowledgePanel® sample, supplemented with respondents from external sample vendors where necessary, to participate in a web-enabled survey. Survey respondents received a $5-equivalent incentive for participating, provided by the survey subcontractor.

1.3. Soft Launch of Survey Instrument

In a series of iterative conversations facilitated by the UCLA research team in consultation with CARB and GfK over the period November 2017-April 2018, we produced and tested 10 different editions of an online survey instrument. GfK provided the programmed versions of the survey instrument and posted them to a password-protected website, which we reviewed before finalizing and deploying the instrument in the survey's soft launch. In addition to copy edits to clarify the survey logic, meaning of questions, and response options throughout the survey, numerous refinements occurred to enable the successful operation of the six choice set exercises. Chapter 4 of this report primarily discusses the results of the choice set exercises.

A "soft launch" targeting the completion of 200 surveys allowed for quality control and confirmation of survey length before proceeding with the collection of the remaining 1,500 surveys. Respondents who were not participants in GfK's KnowledgePanel® sample answered additional demographic questions. Both the soft and final launch of the survey contained over 80 questions[1] across seven different modules. These modules are summarized as follows:

Module 1: Household Characteristics

Module 2: Household Vehicles and Travel

Module 3: Next Vehicle Purchase or Transportation Needs and Preferences

Module 4: Currently Available Vehicles

Module 5: Vehicle Choice Experiment

Module 6: Demographic Questions

Module 7: Willingness to Consider Alternative Travel Modes

GfK conducted and completed the soft launch from April 11 to April 17, 2018 and obtained 211 unique survey responses. UCLA received the results in late April 2018. The UCLA research team analyzed the responses of every question in the survey. Generally, the quality of the responses was quite high, and only minor changes were made to the survey instrument between the soft and full launch.

1.4. Full Launch of Survey Instrument

In an additional series of iterative conversations facilitated by the UCLA research team in consultation with CARB and GfK during April and May 2018, we produced and tested two additional versions of an online survey instrument before finalizing and deploying the instrument in the full launch of the survey. GfK collected the remainder of the

[1] The exact number of questions asked of each respondent depended, in part, on the nature of their response to some questions (which determined skip patterns), so there was neither a uniform number of questions asked of each respondent nor a meaningful average number of questions to report.

survey responses in May and June 2018, with the exception of the unweighted Spanish-language responses noted below (conducted in July 2018). GfK delivered a self-documented dataset in Statistical Package for Social Sciences (SPPS) format for all survey data (from all open-ended and close-ended questions) with complete variable and value labels to the UCLA research team for analysis. The UCLA team detected no problems with the delivered data.

A total of 1,604 fully completed surveys, from both the soft and full launch, were assigned weights by GfK to allow representativeness of the survey to the statewide low- and moderate-income population.[2] The incidence rate of the survey was well below the anticipated 40%, and the average response time of the survey exceeded the projected time of 35 minutes. Chapters 2-7 of this report present and discuss the results of these survey responses.

[2] GfK encountered unanticipated difficulty in completing 100 Chinese-language surveys. Accordingly, only 24 Chinese-language responses were recorded, and 83 additional Spanish-language surveys were completed in order to comply with research contract terms (as discussed and agreed upon by CARB). However, these responses cannot be analyzed with the 1,604 other survey responses due to their lack of weighting with the main sample.

CHAPTER 2
DESCRIPTIVE SURVEY RESULTS AND VALIDATION

This chapter demonstrates the adherence of the survey to the desired sample characteristics; describes the processing and geocoding procedures of key stratification variables; reports key descriptive statistics for socioeconomic and spatial characteristics of the sample (and the correlations between these factors), and compares the sample characteristics to those of low- and moderate-income Californians more broadly. More detail on some of these considerations is provided in the Appendix to this chapter.

2.1. Adherence to Desired Sample Characteristics

Again, the desired sample stipulated in the contract was defined as:

- Adults, age 18+;
- Who are California residents;
- Who reside in households with an income at or below 300% of the Federal Poverty Level (with at least 50% coming from households at or below 225%);
- Who stated their intent to acquire a vehicle within the next three years; and
- English-, Spanish-, and Chinese-language survey-takers.

Recruitment of survey participants was conducted by GfK (see Section 1.2 for details). The original target sample size of 1,400 was based on experience from a similar survey conducted by the authors among new car buyers in California (Sheldon et al., 2017). The power calculations to ensure statistically significant results from this previous work were updated to reflect the greater number of choice attributes — and thus greater sample size needed — in the current study. The revision of the contract to increase the target sample size from 1,400 to 1,600 only further ensured that statistically significant results were obtainable from the analysis.

The final usable survey sample size comprised 1,604 respondents[1] from unique households, all of whom were adults residing in California and stated their intent to replace a vehicle within their household within the next three years. GfK's statisticians assigned weights to each respondent that, when used to generate statistics, ensure representativeness of the sample to the statewide population of individuals with the desired sample characteristics. We show and discuss weighted results throughout the report (including weighted sample sizes for subsamples), unless otherwise noted.

All respondents also reported household incomes below 300% of the Federal Poverty Level (FPL), with 68% of the weighted sample (60% of the unweighted sample) reporting household incomes below 225% of the FPL. Further, 52% of the weighted sample (36% of the unweighted sample) were Spanish-language speakers.[2]

2.2. Processing and Geocoding of Data

Upon receipt of the full set of survey responses from GfK, we checked each of the variable responses. We spent significant time recoding variable responses from the original survey data for the purpose of carrying out the analysis plan (described in Chapters 3-7). As detailed more fully in the appendices and summarized in Table 2-1,

[1] A total of 1,707 unique survey responses were completed.

[2] As noted in Chapter 1, an additional 24 Chinese-language responses were conducted with an initial aim of collecting 100 such responses. Due to inability to reach this sample size, 83 additional Spanish-language surveys were completed in order to comply with research contract terms (as discussed and agreed upon by ARB). However, neither the Chinese-language nor the additional Spanish-language responses can be analyzed with the 1,604 other survey responses due to their lack of weighting with the main sample.

we also collected, appended, and geocoded several additional data points and sources from outside the survey results. We used these to carry out the demographic and spatial analysis requested by CARB, which included the analysis of outcomes of interest by race-ethnicity, income, language, and geographic subgroups within the sample.

Table 2-1. Summary of Data Sources Joined to Survey Results

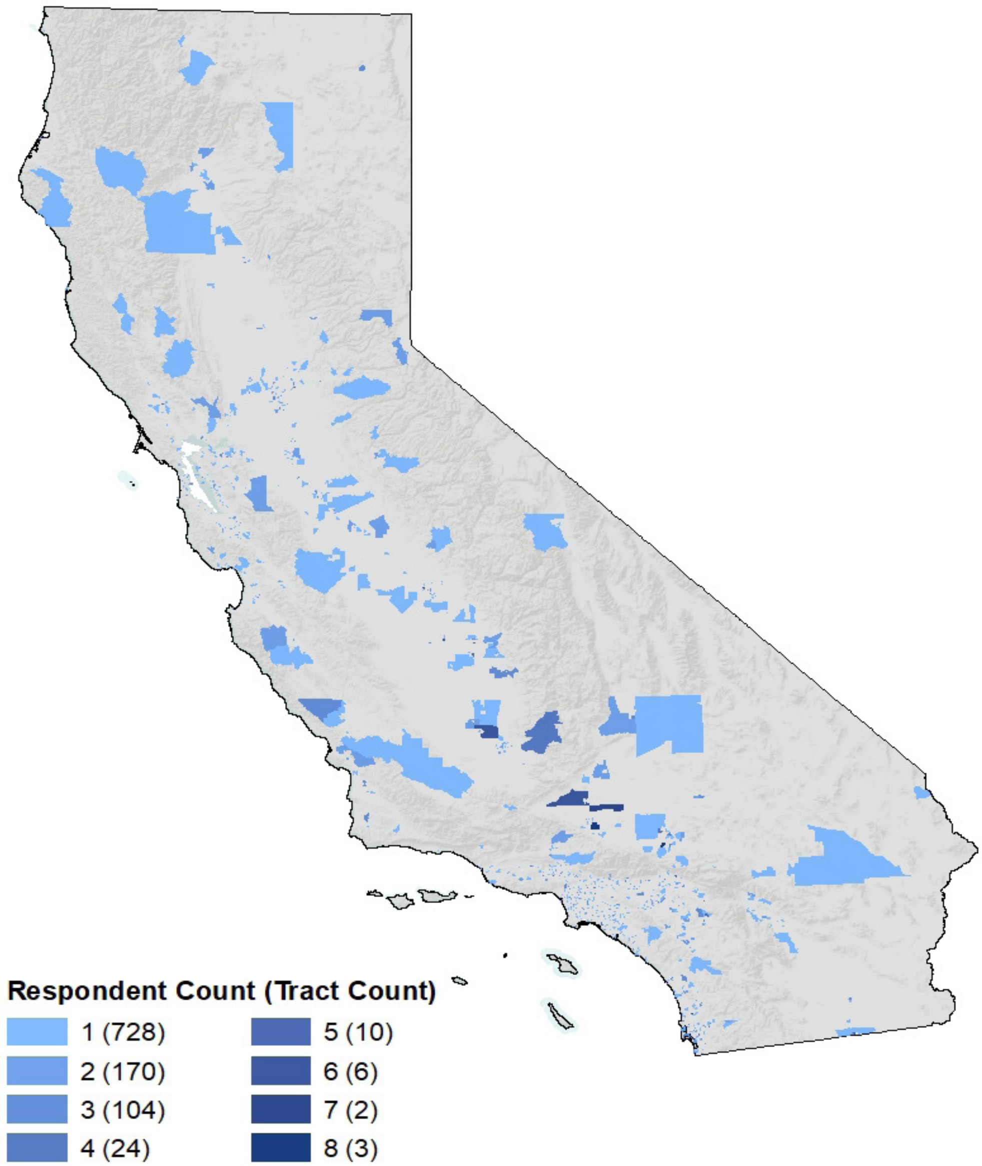
Data Type	Name	Source	Year
Survey	Ride & Replace	CARB	2018
Census	American Community Survey	American Factfinder	2012-2016
	Decennial Census	American Factfinder	2010
Shapefile	California Air Districts	CARB	2018
	Census Tracts	Census Bureau	2017
	Combined Statistical Areas	Census Bureau	2017
	Counties	Census Bureau	2016
	Disadvantaged Communities	CARB	2017
	Principal Cities	Census Bureau	2017
	Urban Areas	Census Bureau	2017

Geocoding is defined as a process of finding the mathematical representation of a geographic feature, such as a street address, street intersection, postcode, place, or point of interest, so that the feature can be mapped and spatially analyzed within a geographic information system (Shen, 2008). We used geocoding methods to assign a unique identification value to each data feature based on a certain set of geographic criteria. This process allowed us to spatially represent, stratify, analyze, and interpret the survey data. We classified the location of each survey respondent across six geographic categories, including census tract, county, air management district, consolidated statistical areas, urbanization, and disadvantaged community.

Additionally, these methods permitted the appending of census data to each census tract, and thus each unique line of survey data. The American Community Survey 2012-2016 and 2010 Decennial Census provided data on the sociodemographic and neighborhood characteristics of each tract, spanning variables of race, ethnicity, income, housing, transportation, and total population.

The Ride and Replace Survey has 1,604 unique lines of data representing the survey answers of low- and moderate-income individuals in California. Of these, GfK provided census tract identifiers for a total 1,581 survey responses. This allowed the data to be geographically represented across 1,047 census tracts, as shown in Figure 2-1. Individual addresses are suppressed to protect the privacy of respondents. All geocoding methods were performed within the ArcGIS platform, and utilized the join, spatial join, intersect, symmetrical difference, dissolve, merge, and table statistics functions of ArcToolbox.

Figure 2-1. Number of Survey Respondents by Census Tract



2.3. Key Descriptive Socioeconomic and Spatial Characteristics of the Sample

Before discussing the key transportation and financing outcomes of interest, stratified by socioeconomic and spatial factors, here we report key univariate socioeconomic and spatial characteristics of the sample. The Appendix for this chapter contains the correlations between these characteristics, which we reference in subsequent analysis when interpreting the correlative factors that explain outcomes of interest.

Age, Sex, and Household Size

The age of survey respondents ranged from 18 to 91 years, with an average age of about 42 years old (with a standard deviation of 16 years). Slightly more men (53%) than women (47%) participated in the survey. The average household size was about 3.5 people (with a median size of 3, and a range of 1 to 12 persons).

Race-Ethnicity and Language

As shown in Table 2-2, the majority (52%) of the respondents in the sample population identified as Hispanic. The non-Hispanic racial and ethnic composition of the survey takers comprised White (27%), Black (9%), Asian (5%), other (5%), and two or more races (2%).

Table 2-2. Race-Ethnicity of Respondents

Category	Weighted Sample Size	Percent of Sample Respondents
White, Non-Hispanic	434	27%
Black, Non-Hispanic	148	9%
Asian, Non-Hispanic	82	5%
Other, Non-Hispanic	76	5%
2+ Races, Non-Hispanic	36	2%
Hispanic	828	52%
Sample Total	1,604	100%

The survey also asked Hispanic respondents about their language proficiency or preference. Of the Hispanic respondents, 472 were bilingual, 209 were English proficient, and 107 were Spanish proficient. As Table 2-3 shows, among all survey respondents, 29% were bilingual, 13% were English proficient, 7% were Spanish proficient, and 48% were not asked about their language proficiency.

Table 2-3. Language Proficiency of Hispanic Respondents

Category	Weighted Sample Size	Percent of Sample Respondents
English Proficient	209	13%
Bilingual	472	29%
Spanish Proficient	107	7%
Hispanics with missing data; re-asked in field	40	3%
Non-Hispanics, not asked	776	48%
Sample Total	**1,604**	**100%**

Educational Attainment and Employment Status

Most of the sample population had a high school-level education, with 46% having completed high school, 27% having completed some (but not all) of college, and 12% having attained a bachelor's degree or higher. About 15% of respondents did not complete high school.

Table 2-4. Highest Level of Education of Respondents

Category	Weighted Sample Size	Percent of Sample Respondents
Less than high school	244	15%
High school	729	46%
Some college	431	27%
Bachelor's degree or higher	195	12%
Sample Total	**1,600**	**100%**

The employment status of respondents differentiates between those working as a paid employee (51%) or those who are self-employed (11%). Those who are not working was due to not looking for work (10%), a temporary layoff (2%), disability (6%), retirement (12%), or other unspecified reason (8%).

Table 2-5. Employment Status of Respondents

Category	Weighted Sample size	Percent of Sample Respondents
Working - as a paid employee	814	51%
Working - self-employed	181	11%
Not working - on a temporary layoff from a job	31	2%
Not working - looking for work	163	10%
Not working - retired	193	12%
Not working - disabled	94	6%
Not working - other	129	8%
Sample Total	**1,604**	**100%**

Income, Poverty Status, and Disadvantaged Community Status

As noted above, all respondents reported household incomes below 300% of the FPL, with 68% reporting incomes below 225% of the FPL. While the FPL gives a measure of absolute poverty, we added a calculation to assess the relative poverty of respondents as well. Relative poverty is often measured as the ratio of a household's income to the area median income, which is typically the county median income. Using the U.S. Housing and Urban Development Department's income classification, households are considered Low-Income if they earn 80% of the Area Median Income (AMI), Very Low-Income if they earn 50% of the AMI, and Extremely Low-Income if they earn 30% of the AMI (2017).

Table 2-6. Relative Poverty Status of Respondents

Category	Weighted Sample Size	Percent of Sample Respondents
Extremely Low-Income	285	18%
Very Low-Income	264	17%
Low-Income	427	27%
Household Income Above 80% AMI	627	39%
Sample Total	**1,604**	**100%**

The survey did not ask for exact household income, but rather for bracketed income data, so no exact average or median income of the sample is reportable. Using the midpoints of the income brackets, however, we report an approximate household average income of $38,350 for 1,604 respondents. About two-thirds of respondents surveyed reported an annual household income of less than $25,000 (31%) or between $25,000 and $49,999 (37%), compared to 23% of respondents making $50,000 to $74,999 and just 9% of households reporting more than $75,000 in income. Around 38% of the sample live in a disadvantaged community.[3]

Table 2-7. Income Category of Respondents

Category	Weighted Sample Size	Percent of Sample Respondents
Less than $25,000	500	31%
$25,000 - $49,999	598	37%
$50,000 - $74,999	366	23%
$75,000 or more	140	9%
Sample Total	**1.604**	**100%**

[3] Using Cal EnviroScreen 3.0 DAC scores

Housing Type and Tenure

Over half of respondents (55%) report living in a detached single-family home. Other housing types reported include attached single-family homes (13%), multi-family dwellings (25%), and mobile homes (6%). Less than 1% of respondents live in a recreational vehicle (RV), boat, van, or other form of residence.

Table 2-8. Housing Type of Respondents

Category	Weighted Sample Size	Percent of Sample Respondents
Single-Family, detached	882	55%
Single-Family, attached	209	13%
Multi-Family dwelling	392	25%
Mobile Home	101	6%
Other	13	1%
Sample Total	**1,597**	**100%**

In terms of ownership status, about 54% of respondents are renters; 42% own their home, and 3% neither paid rent nor owned their home.

Geographic Location and Type Within California

Finally, using our method of delineating urban, suburban, and rural areas in California (described in the geocoding section), urban and suburban areas each contain about 43% of the sample respondents, while the remaining 14% are in rural areas.[4]

Table 2-9. Urbanization Geography of Residents

Category	Weighted Sample Size	Percent of Sample Respondents
Urban	679	43.0%
Suburban	670	42.5%
Rural	229	14.5%
Sample Total	**1,577**	**100**

In terms of residence in major population areas of the state, nearly half the sample live in the South Coast, with around 10% each from the San Joaquin Valley, Bay Area, and San Diego County air quality management district (AQMD) areas, 3% in Sacramento, and 19% in other AQMD geographies.

Table 2-10. AQMD Geography of Respondents

Category	Weighted Sample Size	Percent of Sample Respondents
Bay Area	169	11%
Sacramento Metro	47	3%
San Diego	146	9%
San Joaquin Valley	186	12%
South Coast	730	46%
Other	298	19%
Sample Total	**1,577**	**100%**

[4] Using American Community Survey (ACS) population data and geocoding methods, a total of 17,034,449 people reside in principal cities, 16,774,426 in suburbs, and 5,584,301 in rural areas.

2.4. Comparison of Sample to Statewide Low-Moderate Income Population

Finally, using available and contemporary administrative data on socioeconomic characteristics and spatial location, we compare the representativeness of the survey respondents to both the general California population and the low-moderate income population of California. To profile the state's (low-moderate) income population, we collected data from the 2016 American Community Survey (ACS) Integrated Public Use Microdata Series (IPUMS) micro-sample for California, the best available contemporary source for the state, which allows differentiation by income and other key characteristics.

Table 2-11 shows all available sample characteristics that are comparable to characteristics that can be derived from the 2016 ACS IPUMs data. In terms of race-ethnicity, we find that the survey sample is representative in terms of non-Hispanic White and Hispanic individuals, but oversamples Black individuals and undersamples Asian individuals.

In terms of education, the survey sample respondents are much more likely than the general population or low-moderate income populations to have a high school degree, but are less likely to have some college education or a college degree. The higher degree of high school attainment may reflect the fact that survey respondents needed to be aware and have access to a computer or mobile device in order to take the survey. Reported household size in the survey is also smaller than in low-moderate income populations in the ACS, and residential ownership is slightly higher. This may be attributable to the higher average age of respondents to the survey (42 years old) versus the general California population (35 years old).

Table 2-11. Sample Demographics Compared to Low- and Moderate-Income California Population

Characteristic	Sample Statistic (2018)	Entire California Population (2016 ACS)	Population Under 225% of FPL (2016 ACS)	Population Under 300% of FPL (2016 ACS)
Race/Ethnicity				
White, Non-Hispanic	27.1%	37.5%	25.1%	26.1%
Black, Non-Hispanic	9.2%	5.5%	6.9%	6.5%
Asian, Non-Hispanic	5.1%	14.3%	10.8%	11.2%
Other, Non-Hispanic	4.7%	3.7%	3.1%	3.1%
2+ Races, Non-Hispanic	2.2%	NA	NA	NA
Hispanic	51.6%	38.9%	54.1%	53.1%
Education				
High school degree	45.6%	20.4%	26.4%	26.3%
Some college	26.9%	29%	26.7%	28%
College or more	12.2%	33%	14.2%	15.5%
Other Comparable Characteristics				
Household size	3.5	3.7	4.0	4.1
Ownership of residence	42%	54.6%	33.1%	37.4%
Number of vehicles owned[5]	2.0	2.2	1.9	2.0
Total Respondents	**1,604**	**376,035**	**137,058**	**176,681**

Most important, however, the average number of vehicles per household (2.0) in the survey sample exactly corresponds to the average number of vehicles in the 2016 ACS. We compare and contextualize the extent of vehicle reliance, vehicle characteristics and travel behavior reported in the survey sample to data points derived for the general and low-moderate income California population using the 2013 California Household Travel

[5] This question, in both the ACS and our survey, allowed respondents to report only up to "6 or more vehicles." In both cases, we count a response of "6 or more" as 6 vehicles for reporting results.

Survey. This similarity in vehicle access, however, gives us confidence that our restriction of the survey sample to respondents intending to purchase a vehicle within the next three years has not markedly skewed the vehicle holding profile of our sample.

Further, Table 2-12 shows the spatial representativeness of the sample by comparing respondent locations to the share of the state's population across California's major AQMD areas. Excepting underrepresentation of the Bay Area AQMD and slight overrepresentation of the South Coast AQMD in the sample compared to the population, the correspondence between the sample location and the concentration of the state population is nearly linear.[6] The same holds true for the representativeness of the urban-suburban-rural population. The geocoding methods employed on 2012-2016 ACS total population data resulted in an estimated 43.2% of the state's residents living in urban areas, 42.6% in suburban areas, and 14.2% in rural areas. This almost exactly matches the location of survey respondents along these categories, with 43.0% residing in urban areas, 42.5% in suburban areas, and 14.5% in rural areas.[7]

Table 2-12. Comparison of Sample Population to California Population

Air Quality Management District	Share of Sample Population	Share of State Population (2012-2016 ACS)
Bay Area	11%	19%
Sacramento Metropolitan	3%	4%
San Diego	9%	8%
San Joaquin Valley	12%	10%
South Coast	46%	42%
All Other Districts	19%	16%

2.5. Format of Descriptive Tables in Chapters 3-7

In the following chapters (3-7), which report the core findings from the survey, we present a series of tables and graphics displaying descriptive results. We note statistically significant findings between means or categories as footnotes in each table. If no statistically significant differences are found at P<0.05 or P<0.10 (95% and 90% confidence levels, respectively), no table footnote is provided. Moreover, sample sizes change between some tables due to missing data or outliers excluded on one or more of the variables analyzed. The sample sizes in tables and figures are reported as whole numbers, and therefore may not add up to the sample total due to rounding. Where possible, we use the largest valid sample to analyze each variable.

To test differences in means for continuous variables, we used adjusted Wald tests with adjusted Bonferroni p-values. This option allows for simultaneous testing of all pairwise comparisons of means in a given table, and accounts for the sample weights within the survey design. The adjusted Wald test operates under a null hypothesis that the two means are equal, with the alternative hypothesis that they are unequal. The null hypothesis is rejected when the test statistic, or p-value, is less than the chosen threshold of either 0.05 or 0.10, indicating a statistically significant difference in means.

We also test the relationship between categorical variables. To determine if two variables have a relationship or if they are independent, we used a Pearson's chi-squared test. While the normal chi-square test function in Stata does not account for the survey weights, after defining the dataset as a complex survey design, Stata is able to compute the chi-square relationship by converting the test-value into an F-statistic. The null hypothesis for this test is that there is no relationship between two variables, and the alternative hypothesis is that there is a relationship (though

[6] Using ACS population data and geocoding methods, a total of 7,504,159 people are in the Bay Area AQMD, 1,581,093 in the Sacramento Metropolitan AQMD, 3,338,274 in San Diego County Air Pollution Control District (APCD), 4,149,288 in San Joaquin Valley APCD, 16,843,293 in South Coast AQMD, and 6,404,050 in another district.

[7] Using ACS population data and geocoding methods, a total of 17,034,449 people reside in principal cities, 16,774,426 in suburbs, and 5,584,301 in rural areas.

the direction and magnitude is unknown). The null hypothesis is rejected when the test statistic, or p-value, is below the chosen threshold of either 0.05 or 0.10, indicating a statistically significant relationship between the two variables. Importantly, the test for independence gets less reliable when cell sizes approach 0, and these cases are noted in the footnotes of two-way tables.

References

California Air Resources Board (2018). Air District Boundaries. *California Open Data Portal*. See https://data.ca.gov/dataset/california-air-resources-board-gis-datasets.

California Air Resources Board (2018). Disadvantaged and Low-Income Communities Investments. See https://www.arb.ca.gov/cc/capandtrade/auctionproceeds/communityinvestments.htm.

Department of Housing and Community Development (2017). Income Limits. See http://www.hcd.ca.gov/grants-funding/income-limits/index.shtml.

Ratcliffe, M. (2013). 2010 Census Urban Area Delineation Program. *U.S. Census Bureau, Geography Division*. See https://www2.census.gov/about/partners/sdc/events/steering-committee/2013-04/2013-ratcliffe.pdf.

Sheldon, T. L., DeShazo, J.R., Carson, R. T. and Krumholz, S. (2017). Factors Affecting Plug-in Electric Vehicle Sales in California. *UCLA Luskin Center for Innovation Report*.

Shen, X. (2008). Geocoding. In K. K. Kemp (Ed.), *Encyclopedia of Geographic Information Science*, 165-167. Thousand Oaks, CA: SAGE Publications, Inc. DOI: 10.4135/9781412953962.n75.

U.S. Census Bureau (2016). American Community Survey 2012 – 2016. American Factfinder.

U.S. Census Bureau (2017). Cartographic Boundary Shapefiles – Metropolitan and Micropolitan Statistical Areas and Related Statistical Areas. *The U.S. Census Bureau, Geography Division*. See https://www.census.gov/geo/maps-data/data/cbf/cbf_msa.html.

U.S. Census Bureau (2017). Cartographic Boundary Shapefiles – Urban Areas. The *U.S. Census Bureau, Geography Division*. https://www.census.gov/geo/maps-data/data/cbf/cbf_ua.html.

U.S. Census Bureau (2016). MAF/TIGER Shapefiles: CA County Boundaries. *California Open Data Portal*. See https://data.ca.gov/dataset/ca-geographic-boundaries.

U.S. Census Bureau (2017). TIGER/Line Shapefiles: Census Tracts. *U.S. Census Bureau, Geography Division*. See https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2017&layergroup=Census+Tracts.

U.S. Census Bureau (2017). TIGER/Line Shapefiles: Places. *U.S. Census Bureau, Geography Division*. See https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2018&layergroup=Places.

CHAPTER 3

THE VEHICLE PURCHASE PROCESS: PAST AND FUTURE DECISION MAKING, SEARCH, EXPENDITURE, AND FINANCING

As discussed in the Introduction and Chapters 2 and 6 of this report, the vast majority of low- and moderate-income households own and use automobiles despite the substantial financial burden of vehicle ownership and operation. About half of surveyed low- and moderate-income households also reported planning to keep their main household vehicle for two years or less, although this high level of vehicle turnover intent may reflect the survey selection criteria that allowed households to participate only if they intended to purchase a vehicle within the next three years. Unlike a house or other place of dwelling, which a typical household purchases once or twice over a lifetime (if they ever purchase rather than rent), low- and moderate-income households purchase vehicles more frequently.

The magnitude and relative frequency of vehicle purchases suggest that differential outcomes by income, race, or language in the vehicle search and buying process may have important implications for differences in wealth and financial well-being. Moreover,the frequent turnover observed in vehicle fleets represents an opportunity for policy makers to support a faster transition to cleaner vehicles than might typically be chosen by low- and moderate-income households in the absence of financial support. On the other hand, if informal transactions and methods of payment for vehicle purchase are preferred by low- and moderate-income households, supporting these vehicle purchases through public sector programs may prove challenging.

To inform programs and policies that seek to better understand and support more widespread access to and use of clean vehicles among low- and moderate-income households in California, our survey asked a series of questions regarding the process of past and prospective vehicle purchase decision making and financing. The responses to these questions allow us to answer the following research questions:

1. **How quickly and where do low- and moderate-income households search for and ultimately purchase vehicles? How do they expect to search in the future?**
2. **How much do households pay and how do they finance vehicle purchases? How do they expect to finance purchases in the future?**

Additional results on each of these topics, requested in CARB's analysis plan, are provided in the Appendix to this chapter.

3.1. Vehicle Search Leading to Purchase: Who Decides, How Long, and Where Do They Search?

A handful of studies have analyzed how households search for automobiles, and how technology (particularly, access to and use of the Internet) influences the search. Only one study, to our knowledge, focuses on potential differences in search by income groups (Klein and Ford, 2003).[1] Moreover, each of the studies identified focuses on marketing and information costs, not aspects of the vehicle or transportation needs (Punj and Staelin, 1983; Srinivasan and Ratchford, 1991). These studies demonstrate that the process of searching for a new or used vehicle is time costly, with the most recent study indicating the average household spends 19 hours searching (Klein and Ford, 2003). Taylor and Fujita find that the time invested in PEV purchase decision making is greater than that

[1] We note that this dearth of research contrasts with a voluminous literature on low-income housing search, particularly among publicly assisted housing voucher recipients, and the obstacles in these households' housing lease or purchase (for instance, see Shroder, 2002; Turner, 1998).

invested in ICE vehicle purchases (2018). Klein and Ford also report a consistently negative relationship between hours of search and income. Conversely, the authors find that income level does not influence the number of sources used in the search process, nor whether searchers visited an automobile dealership in person (2003).

Intra-Household Decision Making

To add evidence to existing knowledge, we first analyze who within the household in our survey was the primary decision maker regarding the purchase of their main vehicle. Not surprisingly, the respondent or their partner/spouse made the vast majority of vehicle purchasing decisions (86%). However, as shown in Table 3-1, there is a clear difference in influence over the decision between males and females. Males were more likely to be the primary decision maker, regardless of whether a male or female was the survey respondent.

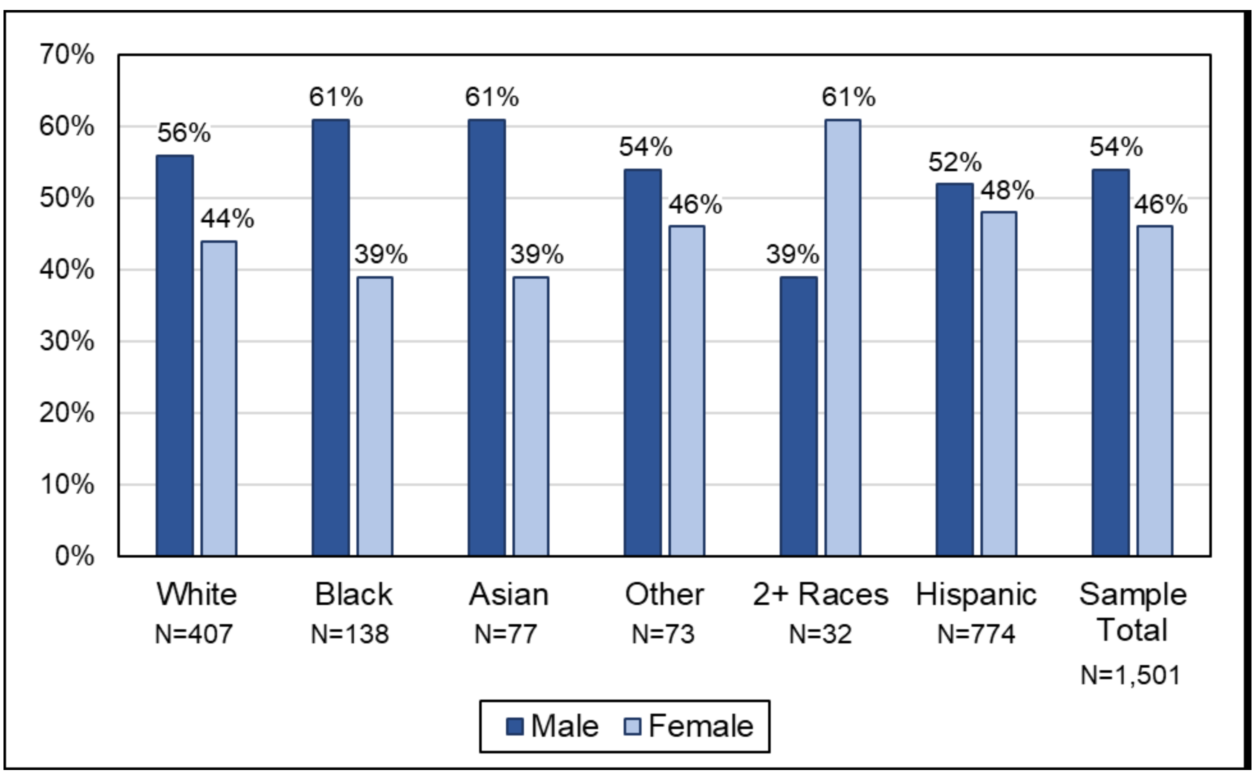
Table 3-1. Who Was the Primary Decision Maker in the Purchase of Your Main Vehicle, by Sex of Respondent

	Male		Female		Sample Total	
	N.	Pct.	N.	Pct.	N.	Pct.
Myself	556	68%	340	50%	896	60%
Partner/Spouse	15 0	18%	239	35%	388	26%
Older family member	96	12%	84	12%	180	12%
Other person in household	12	1%	12	2%	24	2%
Adult outside household	3	0%	11	2%	13	1%
Sample Total	**816**	**100%**	**685**	**100%**	**1,501**	**100%**

[1] There is a statistically significant relationship between the two variables at P<0.05, and it should be noted the table has cell sizes that approach 0.

We further explored gendered differences in decision making across racial-ethnic groups. Except for multi-racial respondents, all other groups reported a higher proportion of males as the primary decision maker in the purchase of the household's main vehicle (Figure 3-1).

Figure 3-1. Who Was the Primary Decision Maker in the Purchase of Your Main Vehicle, by Sex and Race/Ethnicity of Respondent



Months Spent Searching for Main Vehicle Before Purchasing

We also analyze how long respondents searched for the primary household vehicle before purchasing it (Table 3-2). The length of the search, measured in months, ranges from the date the search began to the date the vehicle was purchased. We cannot say anything, based on our data, regarding the intensity of the search. The average time spent searching was 5.7 months. Again, we see differences by sex, with females who were the primary decision maker facing longer searches (5.0 vs. 6.5 months).

Table 3-2. Number of Months Spent Searching for Past Purchase, by Sex of Respondent

	N.	Mean	S.D.
Male	797	5.0	6.8
Female	683	6.5	14.6
Sample Avg.	**1,480**	**5.7**	**10.5**

Interestingly, as Table 3-3 shows, we see a non-monotonic relationship between household income and time of search. The highest-income households surveyed spent nearly double the time searching as the sample average (10.2 months), and the lowest-income households spent the second most time searching (6.9 months). There are likely different reasons underpinning the longer search time between the two groups. Respondents earning less than $25,000 are more financially constrained, and may have to search longer to find a vehicle in their price range that also meets their needs. The higher-income group, or those making more than $75,000 a year, may spend more time searching for a vehicle that fits their personal preferences in terms of make, model, or year. This is supported by our finding that households with more vehicles (who are also higher income) spend longer searching. This non-monotonic relationship also largely holds when looking at racial-ethnic subgroups within income categories, excluding Asian households where the lowest- and highest-income groups spend the least time searching. We also find that, controlling for income level, households spend about two more months on average looking for new vehicles than used ones.

Table 3-3. Number of Months Spent Searching for Past Purchase, by Income

	N.	Mean[1]	S.D.
<$25,000	440	6.9	11.2
$25K-$50K	548	4.5	9.8
$50K-$75K	353	4.4	6.1
>$75,000	139	10.2	12.8
Sample Avg.	**1,480**	**5.7**	**10.5**

[1] The difference in mean months spent searching is statistically significant at P<0.05 between <$25K and $25-$50K, and <$25K and $50-$75K.

We also explored reported months of search for the household's main vehicle across racial-ethnic groups (Table 3-4). While White respondents appear to spend less time searching for vehicles than all but one other group, these differences are not statistically significant at the 95% confidence level.

Table 3-4. Number of Months Spent Searching for Past Purchase, by Race and Ethnicity

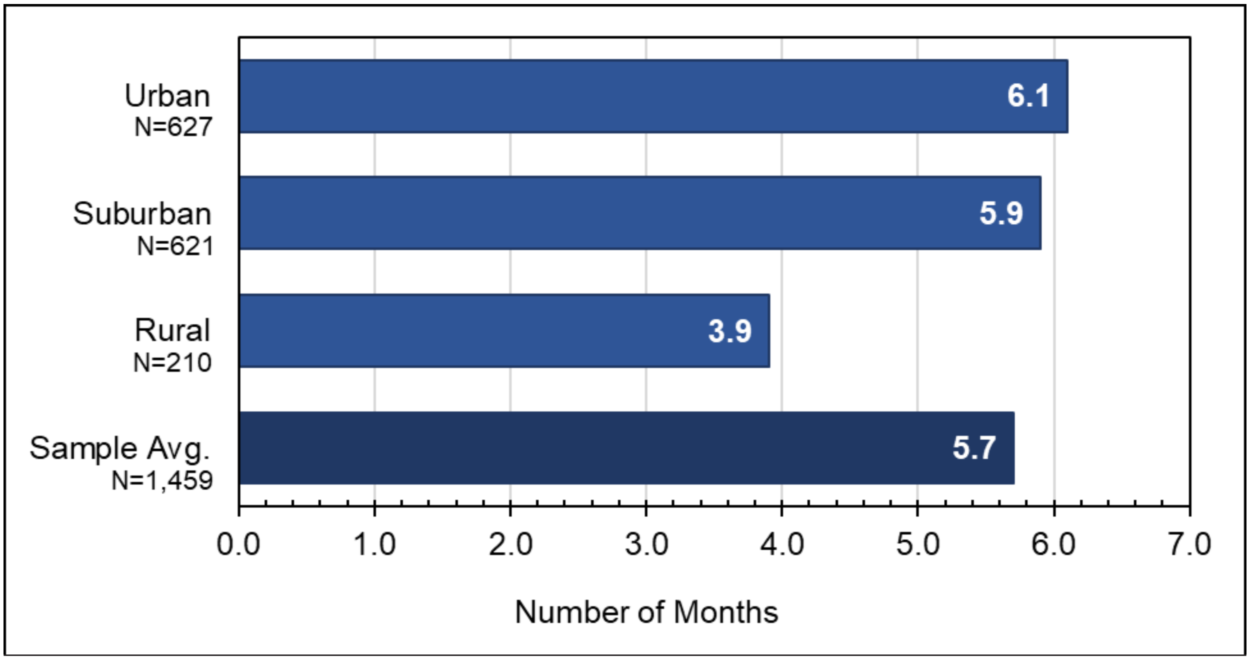
	N.	Mean[1]	S.D.
Non-Hispanic	720	4.9	10.4
White	400	4.6	11.8
Black	138	5.6	9.7
Asian	77	5.9	8.0
Other	73	3.9	4.2
2+ Races	32	5.8	9.0
Hispanic	760	6.5	9.7
English Proficient	184	3.8	5.7
Bilingual	446	7.0	12.8
Spanish Proficient	99	6.1	5.9
Sample Avg.	**1,480**	**5.7**	**10.5**

[1] The difference in mean months spent searching is statistically significant at $P<0.05$ between English Proficient and Bilingual, and at $P<0.10$ between Other and Hispanic.

Hispanic households, on the other hand, clearly report spending the most time searching for vehicles as compared to all other groups. Hispanic respondents in the lowest- and highest-income categories spent the most time (8.7 and 11.8 months, respectively) searching for their current vehicle, compared to all other non-Hispanic racial groups and income levels. There is also large variation across Hispanic households that appears to be explained by self-reported language proficiency differences. English-proficient Hispanic households report spending significantly less time on vehicle searches than the average surveyed households, while non English-proficient households spend nearly double the time of English-proficient households.

There are clear differences in vehicle search length by urbanization geography, with households in urban and suburban areas much more likely to spend significantly longer on their search than rural households (Figure 3-2). This may be, although we cannot say conclusively, because car ownership is more of a necessity and time-sensitive issue in rural areas, where amenities, services, institutions, and destinations are more spread out than in urban areas. Transit agencies in California cite a lack of density, longer and less direct distances, lower speeds, and higher costs for infrastructure improvements as the major reasons transit is less effective and efficient in rural areas (Association of Monterey Bay Area Governments 2017, 24). As such, rural areas have fewer alternative transit modes, making alternative modes less of a potential substitute for car access even in the short term. There are no significant differences in time spent searching for a vehicle across the major AQMD areas.

Figure 3-2. Number of Months Spent Searching for Past Purchase, by Urbanization Geography



The difference in mean months spent searching is statistically significant at P<0.05 between Suburban and Rural, and at P<0.10 between Urban and Rural.

Where Did Households Purchase Their Main Vehicle

We also analyze where (from what type of seller) households purchased their main vehicle, and their intentions about where to purchase a vehicle in the future. While 10 response categories were made available to surveyed households (as shown in Table 3-5), given the low response in many categories, we condensed these original response categories into five groups (social network, formal seller, semi-formal seller, Internet, all other) for analysis. By far the most common seller (60%) of vehicles to surveyed households were formal (i.e., dealerships, etc.) with purchases from social networks the second-largest category (17%). No other seller category represents more than 10% of sales.

Table 3-5. Seller Type of Main Vehicle Purchase and Expected Future Vehicle Purchase

Seller type	Past Main Vehicle		Expected Future Vehicle	
	N.	Pct.	N.	Pct.
1. Social network	**310**	**19.8%**	**130**	**8.4%**
Friend, family, or acquaintance	265	16.9%	130	8.4%
Received car as a gift/inheritance	45	2.9%	0	0%
2. Formal seller	**945**	**60.3%**	**1,080**	**69.7%**
Dealership	933	59.5%	1,051	67.9%
A credit union or purchasing service	13	0.8%	29	1.9%
3. Semi-formal seller	**135**	**8.6%**	**126**	**8.1%**
Local repair shop or garage	19	1.2%	47	3.0%
On-street advertiser	75	4.8%	41	2.6%
"Buy Here Pay Here" used dealer	41	2.9%	39	2.5%
4. Internet	**155**	**9.9%**	**179**	**11.6%**
Large seller (e.g., CarMax)	59	3.7%	93	6.0%
Individual seller (e.g., Craigslist)	96	6.1%	86	5.5%
5. Other	**22**	**1.4%**	**35**	**2.2%**
Sample Total	**1,567**	**100%**	**1,549**	**100%**

We also note that there are major differences between past purchase and expected future purchase. Households expect to buy more often through formal channels, much less often through social networks, and slightly more often via the Internet. To the extent that households rely on social networks to acquire vehicles due to discrimination from external sellers, however, this lower expectation of purchases through social networks may not be realized.

As Table 3-6 shows, the proportion of respondents who purchased their main vehicle through a formal channel (dealership, etc.) increases substantially as income increases (just 47% of those making less than $25,000 compared to about 75% of those making over $50,000). Among racial-ethnic groups, by far the most likely group to purchase their main vehicle through a formal channel were Non-Hispanic Asian respondents (74%).

Table 3-6. Seller Type of Main Vehicle Purchase, by Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Sample Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Social network	129	27%	117	20%	48	13%	16	11%	310	20%
Formal	222	47%	345	58%	274	75%	104	74%	945	60%
Semi-formal	49	10%	62	11%	19	5%	5	4%	135	9%
Internet	60	13%	57	10%	22	6%	15	11%	155	10%
Other	9	2%	12	2%	1	0%	0	0%	22	1%
Sample Total	**470**	**100%**	**593**	**100%**	**364**	**100%**	**140**	**100%**	**1,567**	**100%**

There is a statistically significant relationship between the two variables at P<0.05, and it should be noted the table has cell sizes that approach 0.

As shown in Table 3-7, we also examine how households purchased their main vehicle by language proficiency. English-language proficiency may be related to the ability or comfortability to negotiate and purchase a vehicle at a formal institution (dealership, etc.). We find noticeably higher reliance on semi-formal sellers (local repair shop, garage, on-street advertiser, or "Buy Here Pay Here" used dealer) and Internet sellers among Spanish-only speaking households, although we note that the small sample sizes do not allow us to determine whether these differences are significant. Even more pronounced than in the general sample of households, we find a major jump in expectation among Hispanic households (especially Spanish-language only, from 41% to 63%) to buy more often through formal channels, much less often through social networks, and slightly more often via the Internet.

Table 3-7. Seller Type of Main Vehicle Purchase, by Language (Hispanic Respondents Only)

	English		Bilingual		Spanish		Sample Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Social network	38	19%	93	20%	24	22%	155	20%
Formal	120	61%	290	63%	44	41%	453	59%
Semi-formal	19	10%	47	10%	18	17%	85	11%
Internet	19	10%	30	7%	18	17%	67	9%
Other	2	1%	1	0%	3	3%	6	1%
Sample Total	**197**	**100%**	**462**	**100%**	**107**	**100%**	**766**	**100%**

Interestingly, although again the sample sizes are small, higher proportions of rural respondents purchased their current main vehicle through local and semi-formal channels (repair shop, garage, on-street advertiser, buy here dealer) and the Internet than urban or suburban respondents. Rural respondents were also less likely to purchase their vehicle from social networks, such as family, friends, or acquaintances. Similar trends were observed in terms of future purchase plans. Finally, differences across AQMDs are not noticeable, except in the higher reliance on semi-formal channels in the South Coast and on Internet sellers for households in the San Diego County AQMD.

Table 3-8. Seller Type of Main Vehicle Purchase, by Urbanization Geography

	Urban		Suburban		Rural		Sample Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Social network	144	22%	136	21%	29	13%	309	20%
Formal	397	60%	406	62%	130	59%	933	60%
Semi-formal	51	8%	52	8%	27	12%	130	8%
Internet	63	9%	58	9%	31	14%	152	10%
Other	11	2%	7	1%	2	1%	20	1%
Sample Total	**665**	**100%**	**660**	**100%**	**219**	**100%**	**1,543**	**100%**

3.2. Magnitude of Vehicle Purchase Expenditure and Experience With Vehicle Finance

As opposed to home purchase, very few studies have examined the financial burden of vehicle purchases for low- and moderate-income households. Despite a lack of research regarding the magnitude of vehicle purchase expenditures and the vehicle search process for disadvantaged households, several studies[2] document the obstacles faced by low-income and minority households in the vehicle purchase process. For one, they face price discrimination in the form of higher purchase prices for new cars (Ayres and Siegelman, 1995). Minorities have lower levels of financial literacy and savings (Babiarz and Robb, 2014). This is partly related to these households having more costly and unfair financing arrangements for vehicles (Charles, Hurst, and Stephens; Sutton, 2007; Van Alst, 2009) and having less access to financial institutions (Blanco, et al., 2015). These factors, on their own

[2] Again, however, the literature on vehicle finance is very sparse compared to that for housing finance, especially for low-income households.

and combined, may result in high purchase prices for used and new vehicles for disadvantaged households.

Vehicle Status at Time of Purchase

First, we examine whether households bought new or used vehicles as their main vehicle. Only half of surveyed households provided this information in response to a direct question (N=819). For households that were not directly asked, the survey asked respondents for the year they obtained their primary vehicle, as well as the model year of that vehicle. Respondents were shown the new vs. used question if the year they reported getting the vehicle minus the vehicle's model year was greater than one. For example, a respondent who reported purchasing a 2015 or 2016 model vehicle within the 2015 calendar year was not asked the new vs. used question; we count this as a new vehicle purchase.

Using this response coding, we were able to raise the subsample substantially (N=1,550). After computing the difference between these two dates (N=731, Range= -1 to 1 Years) we assume that vehicles purchased within the same year of the vehicle's model year represent new car purchases, and vehicles purchased one year after the model year are used car purchases. It should also be noted that respondents who answered the new vs. used question may have interpreted it differently, which leads to some counterintuitive results when stratified by the place of purchase or seller type (Figure 3-3). Some respondents may consider a vehicle to be "new" based on a certain mileage, a recent model year, or if it is replacing an existing vehicle, despite being purchased secondhand.

As shown in Table 3-9, surveyed households were more likely to purchase their vehicle used (61%) rather than new (39%). This trend is stratified by income, with a larger proportion of the lowest-income households purchasing used vehicles, and a larger proportion of higher-income households purchasing new vehicles. For example, just 31% of respondents earning less than $25,000 a year purchased their primary vehicle new, compared to more than 44% of respondents earning above $50,000 a year. There are significant differences among racial and ethnic groups as well, as roughly 66% of Non-Hispanic Asian respondents purchased a new vehicle, while just 28% of Black respondents did. White and Hispanic households were about as likely to have purchased a new vs. used vehicle as the sample average.

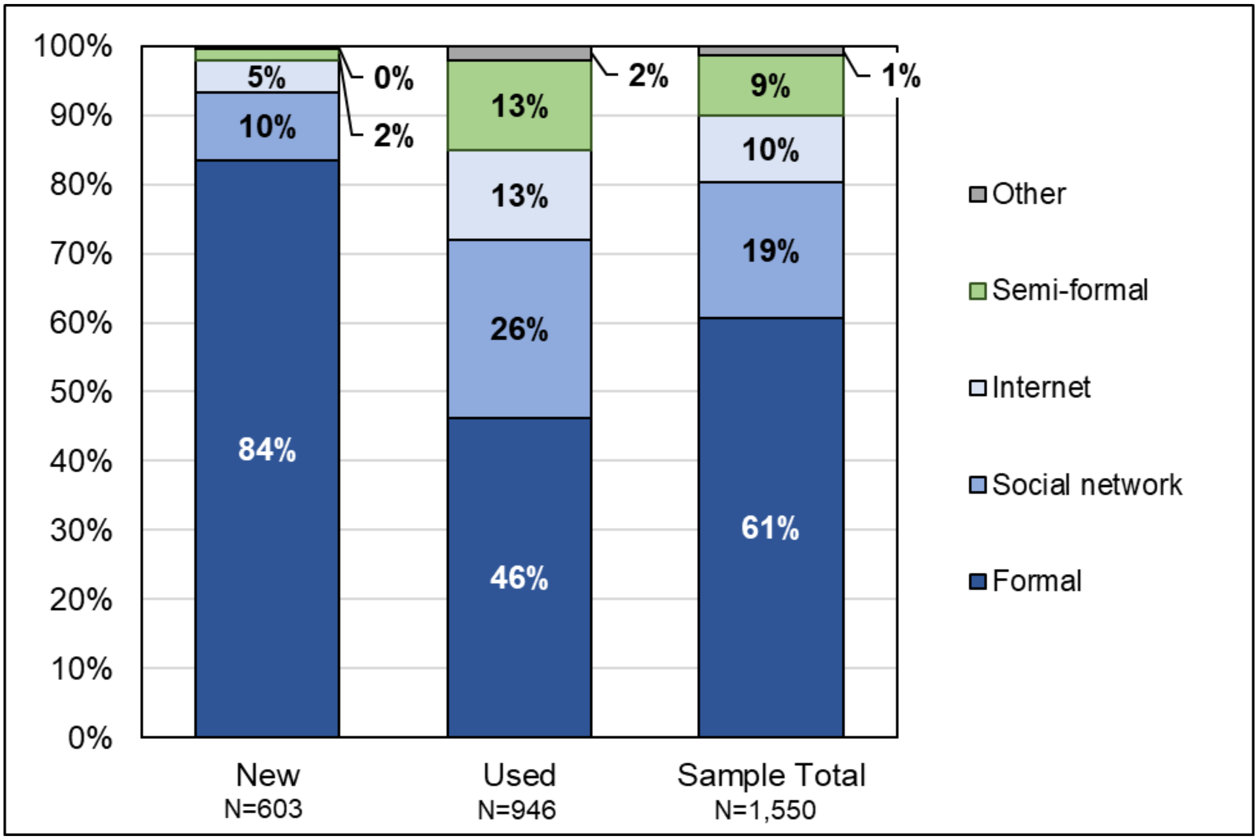
Table 3-9. Proportion of Households Who Buy New vs. Used Vehicles, by Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Sample Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
New	144	31%	239	41%	171	47%	50	36%	603	39%
Used	318	69%	348	59%	193	53%	88	64%	947	61%
Sample Total	461	100%	587	100%	364	100%	138	100%	1,550	100%

[1] There is a statistically significant relationship between the two variables at P<0.10.

Unsurprisingly, over 80% of new vehicles were purchased from a formal seller, whereas over 50% of used vehicles were purchased from other sellers (Figure 3-3). Nearly one-third of used vehicles were purchased from social networks such as family, friends, or acquaintances.

Figure 3-3. Proportion of Households Who Buy New Versus Used Vehicles, by Seller Type



There is a statistically significant relationship between the two variables at P<0.05, and it should be noted the figure has cell sizes that approach 0.

Main Vehicle Purchase Price

Next, we examine the amount households reported paying for their main vehicle. Detailed purchase price data were reported for about two-thirds of the sample. As shown in Table 3-10, after removing outliers, the average price households reported paying was $13,956, or roughly 53.5% of their annual income (N=1,124; with a range of $0-$50,000; and a standard deviation of $10,464). Variation in expenditures on vehicles is clearly positively correlated with income; higher-income households report paying 80% more for their main vehicle than the lowest-income bracket.

This level of expenditure is remarkable when considering the reported incomes[3] of surveyed households, and demonstrates previous findings in the literature of lower-income households' strong motivations to convert even small amounts of capital into vehicle purchase (Blumenberg and Pierce, 2012). For households within the lowest-income bracket of the sample, this expenditure represents over 100% of present annual income, and even among the highest-income bracket, it represents over 20% of annual income.[4]

[3] While some previous studies have shown evidence that some low-income households may suppress either data on their income levels or vehicle holdings to comply with the asset requirements of public assistance programs, we have no reason to assume that this is taking place in our survey responses.

[4] We note that we cannot observe whether these self-reported large vehicle purchase prices were financed by unreported income, financial support in lieu of income, wealth, or by debt. The last explanation seems the most likely, given the rise and relative ubiquity of automobile-related debt across U.S. households to an average of $20,000 in 2007, per the Survey of Consumer Finances (Pressman and Scott, 2010).

Table 3-10. Amount Paid for Main Vehicle, by Income

	N.	Mean[1]	S.D.	Mean Pct. Inc.
<$25,000	322	$10,007	$9,297	104.2%
$25K-$50K	420	$13,453	$11,687	38.1%
$50K-$75K	279	$17,704	$8,199	29.5%
>$75,000	103	$18,236	$8,053	22.4%
Sample Avg.	**1,124**	**$13,956**	**$10,464**	**53.5%**

[1] The difference in mean amount between all combinations of income groups is statistically significant at P<0.05, except between $25-$50K and >$75K, and $50-$75K and >$75K.

As expected, there is substantial variation in purchase price between new and used vehicles, with households paying nearly three times as much for the former (Table 3-11). Households also report paying substantially more for larger vehicles (Table 3-12), but higher-income households within the sample tend to purchase larger vehicles so the relative affordability burden is lower for these households.

Table 3-11. Amount Paid for Main Vehicle, by New vs. Used Vehicle Status and Race/Ethnicity

		New				Used				Sample Avg.			
		N.	Mean	S.D.	Mean Pct. Inc.	N.	Mean	S.D.	Mean Pct. Inc.	N.	Mean	S.D.	Mean Pct Inc.
Non-Hispanic	White	84	$21,864	$10,227	73.2%	213	$9,224	$8,040	27.4%	297	$12,796	$9,640	40.3%
Non-Hispanic	Black	27	$16,140	$9,370	157.0%	77	$8,583	$7,132	60.2%	104	$10,531	$8,589	85.2%
Non-Hispanic	Asian	41	$18,830	$11,483	55.3%	14	$10,487	$4,644	49.1%	55	$16,663	$10,570	53.7%
Non-Hispanic	Other	22	$22,270	$5,108	64.7%	18	$8,286	$9,380	91.4%	40	$15,909	$10,398	76.9%
Non-Hispanic	2+	7	$23,804	$4,923	41.9%	12	$15,744	$9,085	57.6%	18	$18,680	$8,506	51.9%
Hispanic		196	$21,753	$8,653	75.2%	401	$11,273	$9,451	42.6%	597	$14,711	$10,957	53.3%
Sample Avg.[1]		**376**	**$21,125**	**$10,046**	**77.2%**	**736**	**$10,379**	**$8,830**	**41.6%**	**1,112**	**$14,015**	**$10,443**	**53.7%**

[1] The difference in mean amount paid between new and used status is statistically significant at P<0.05.

There is some variation in the purchase price of respondents' main vehicles across race and ethnicity, with non-Hispanic Asian and Hispanic households paying more than White and Black households do. Despite paying the lowest outright price for their main vehicles, non-Hispanic Black respondents have the highest expenditure burden for vehicle purchase (85.2%) compared to the samplewide average of 53.7%.

Table 3-12. Amount Paid for Main Vehicle, by Body Type

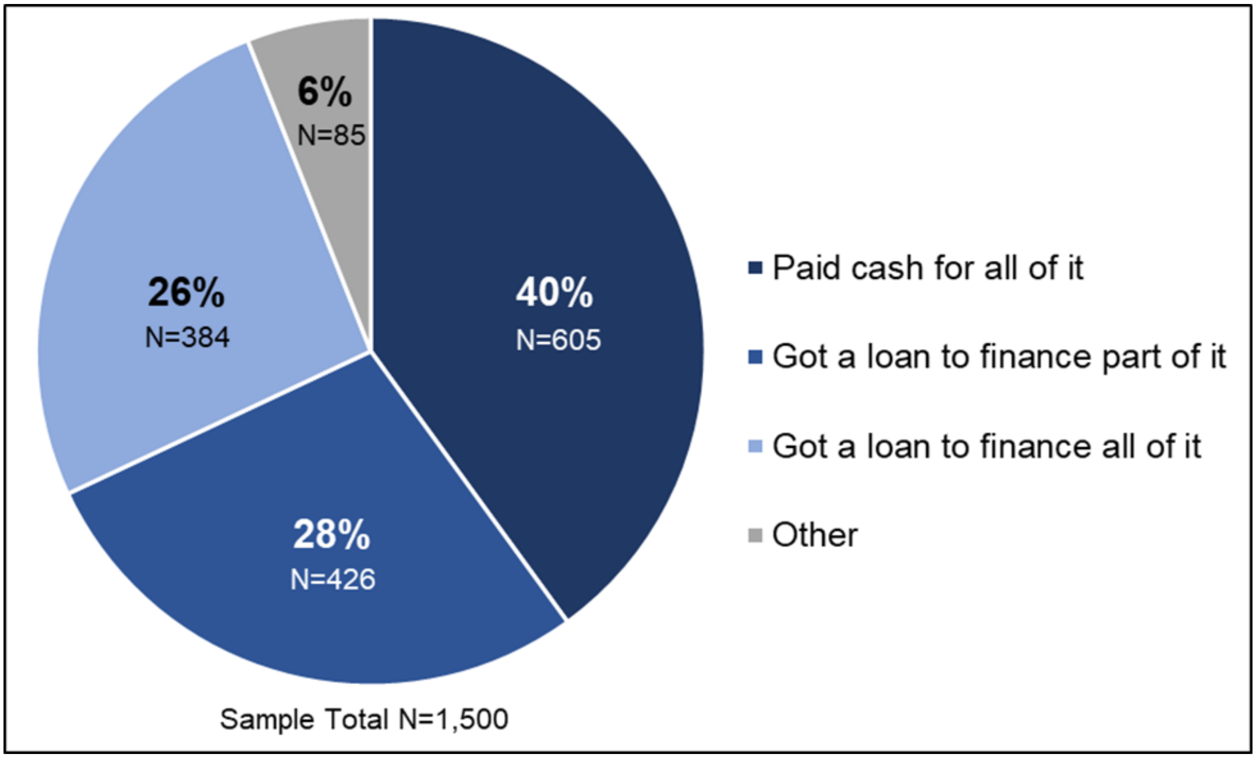
	N.	Mean[1]	S.D.	Mean Pct. Inc.
Small	490	$12,743	$9,824	58.3%
Medium	388	$13,559	$10,589	53.3%
Large	238	$17,113	$10,328	44.1%
Sample Avg.	**1,115**	**$13,958**	**$10,462**	**53.5%**

[1] The difference in mean amount paid is statistically significant at P<0.05 between Small and Large, and between Medium and Large vehicles.

Method of Payment and Purchase Price for Main Vehicle

Using the survey responses, we also analyze the financial means low- and moderate-income households use to pay for vehicle purchases. Forty percent of households indicate that they paid for their main household vehicle in cash, whereas roughly one-quarter of households reported getting a partial loan, and one-quarter reported getting a loan for the full purchase price (Figure 3-4).

Figure 3-4. Method of Payment for Vehicle



Unsurprisingly, as Table 3-13 shows, households were much more likely to pay in cash for used rather than new vehicles (46% v. 30%).[5] Conversely, they were much more likely to take out a loan to finance the entire purchase price if the vehicle was new rather than used (33% vs. 21%).

Table 3-13. Method of Payment for Vehicle, by New Versus Used Vehicle Status

	New		Used		Sample Total	
	N.	Pct.	N.	Pct.	N.	Pct.
Paid cash for all of it	178	30%	418	46%	596	40%
Got a loan to finance part of it	171	29%	251	28%	422	28%
Got a loan to finance all of it	192	33%	189	21%	381	26%
Other	42	7%	42	5%	84	6%
Sample Total	**584**	**100%**	**900**	**100%**	**1,483**	**100%**

There is a statistically significant relationship between the two variables at $P<0.05$.

In Tables 3-14 and 3-15, we further examine the method of payment used by the total purchase price of the vehicle, and the income level and other socioeconomic and geographic characteristics of households. Households that paid in cash for their main vehicle paid a significantly lower purchase price (less than half, on average) than those who financed part or all of their purchase.

[5] Not all households reported a vehicle age; thus, the sample size in Table 3-17 is lower than in Table 3-16.

Table 3-14. Method of Payment for Main Vehicle, by Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Sample Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Cash	199	62%	191	45%	89	32%	29	28%	508	45%
Partial Loan	59	18%	116	28%	81	29%	45	44%	301	27%
Full Loan	48	15%	92	22%	95	34%	25	25%	261	23%
Other	16	5%	20	5%	14	5%	4	3%	54	5%
Sample Total	**322**	**100%**	**420**	**100%**	**279**	**100%**	**103**	**100%**	**1,123**	**100%**

There is a statistically significant relationship between the two variables at P<0.05, and it should be noted the table has cell sizes that approach 0.

Moreover, the lowest-income households were significantly more likely to pay for their vehicle purchase in cash (62%) than higher-income households (no higher than 45%) surveyed. This may be indicative of the lowest-income households surveyed having trouble applying, qualifying, or being approved for a loan.

Table 3-15. Amount Paid for Main Vehicle, by Income and Method of Payment

	<$25,000			$25K-$50K			$50K-$75K			>$75,000			Sample Avg.[2]		
	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.
Cash	199	$6,995	$7,236	191	$9,382	$9,532	89	$12,531	$11,770	29	$9,191	$8,165	508	$8,990	$9,424
Partial Loan	59	$17,613	$10,454	116	$16,787	$10,589	81	$16,826	$6,964	45	$22,019	$9,031	301	$17,738	$9,559
Full Loan	48	$12,482	$8,075	92	$17,761	$9,118	95	$22,427	$6,095	25	$24,179	$13,994	261	$19,121	$9,010
Other	16	$12,403	$7,544	20	$13,076	$9,328	14	$23,766	$4,295	4	$1,847	$3,875	54	$14,855	$9,369
Avg.[1]	**322**	**$10,023**	**$9,032**	**420**	**$13,453**	**$10,465**	**279**	**$17,704**	**$9,407**	**103**	**$18,236**	**$12,358**	**1,123**	**$13,963**	**$10,463**

[1] The difference in mean amount paid between all combinations of income groups is statistically significant at P<0.05, except between $25-$50K and >$75K, and $50-$75K and >$75K.

[2] The difference in mean amount paid is statistically significant at P<0.05 between Cash and Partial Loan, Cash and Full Loan, and Cash and Other, and at P<0.10 between Full Loan and Other.

Future Affordable Purchase Price and Characteristics

The survey also asked respondents about how much they estimated they could afford to pay per month to replace their current main vehicle. The phrasing of the question, however, led to apparent confusion among respondents because it asked for either a purchase price or a down payment. After removing outliers clearly too small or too large to be a down payment or outright purchase of vehicle,[6] the average expected future vehicle purchase price or down payment was $8,793 (N=1,467, Range=$100-$50,000).

This amount is much lower than the total past purchase price for the main vehicle, likely partly reflecting that a vehicle down payment is usually 20% or less of the total vehicle price (Einvan et al. 2012). While we do not place great confidence in the estimate of expected purchase price, Table 3-16 suggests that there is a positive trend between household income and expected price or down payment.

[6] Some respondents entered a percentage or very low dollar amount as a down payment/purchase price instead of dollar amount because of the phrasing of the question. We excluded these responses from our analysis.

Table 3-16. Amount of Money Respondents Anticipate Spending to Purchase or Put a Down Payment on Future Vehicle, by Income

	N.	Mean[1]	S.D.
<$25,000	422	$7,195	$8,653
$25K-$50K	554	$9,515	$11,471
$50K-$75K	357	$8,582	$8,932
>$75,000	133	$11,427	$7,413
Sample Avg.	**1,467**	**$8,794**	**$9,915**

[1] The difference in mean amount between <$25K and $25-$50K is statistically significant at $P<0.05$.

Future Affordable Monthly Payments

The survey also asked respondents about how much they estimated they could afford to pay to replace their current main vehicle. Responses to this question appear more consistent (Table 3-17). After removing outliers, the average expected monthly affordable payment was $275, which annualized represents 14.6% of the average household's yearly income (N=1,450, Mean=$253, Range=$0-$500). As with past purchase price, this large stated willingness to pay illustrates the degree to which low- and moderate-income households want automobiles.

As with past vehicle purchases and as expected, we observe a positive trend in the level of self-reported ability to pay a monthly car payment and household income. The amount respondents state they could pay as a percent of household income is markedly higher among lower-income households, so the relative affordability burden of monthly payments decreases as income increases. This trend also holds for racial-ethnic groups across income categories, except among Asian households.

Table 3-17. Monthly Payments Households Report They Could Afford to Finance the Purchase of a Future Vehicle, by Income

	N.	Mean[1]	S.D.	Mean Pct. Inc.
<$25,000	452	$224	$174	31.2%
$25K-$50K	532	$248	$197	8.5%
$50K-$75K	334	$284	$116	5.8%
>$75,000	132	$289	$96	4.2%
Sample Avg.	**1,450**	**$253**	**$164**	**14.6%**

[1] The difference in mean monthly payment is statistically significant at $P<0.05$ between <$25K and $50-$75K, <$25K and >$75K, and between $25-50K and $50-$75K.

References

Association of Monterey Bay Area Governments (2017). Transportation Alternatives for Rural Areas – A Regional Study. See http://ambag.org/programs/Planning/TransportationAlternativesForRuralAreasFinalDraft_April%20 2017.pdf.

Ayres, I. and Siegelman, P. (1995). Race and gender discrimination in bargaining for a new car. *The American Economic Review*, 85(3), 304-321.

Babiarz, P. and Robb, C. A. (2014). Financial literacy and emergency saving. *Journal of Family and Economic Issues*, 35(1), 40-50.

Blanco, L. R., Ponce, M., Gongora, A. and Duru, O. K. (2015). A qualitative analysis of the use of financial services and saving behavior among older African Americans and Latinos in the Los Angeles area. *SAGE open*, 5(1). DOI: 2158244014562388.

Blumenberg, E., & Pierce, G. (2012). Automobile ownership and travel by the poor: Evidence from the 2009 National Household Travel Survey. Transportation Research Record: Journal of the Transportation Research Board, 2320, 28-36.

Charles, K. K., Hurst, E. and Stephens, M. (2008). Rates for vehicle loans: race and loan source. *The American Economic Review*, 98(2), 315-320.

Einav, L., Jenkins, M. and Levin, J. (2012). "Contract pricing in consumer credit markets." Econometrica, 80(4). 1387-1432.

Klein, L. R. and Ford, G. T. (2003). Consumer search for information in the digital age: An empirical study of prepurchase search for automobiles. *Journal of interactive Marketing*, 17(3), 29-49.

Pressman, S. and Scott, R. H. (2010). Consumer debt and poverty measurement. *Focus*, 27(1), 9-12.

Punj, G. N. and Staelin, R. (1983). A model of consumer information search behavior for new automobiles. Journal of consumer research 9(4), 366-380.

Shroder, M. (2002). Locational constraint, housing counseling, and successful lease-up in a randomized housing voucher experiment. *Journal of Urban Economics*, 51(2), 315-338.

Srinivasan, N. and Ratchford, B. T. (1991). An empirical test of a model of external search for automobiles. *Journal of Consumer Research*, 18(2), 233-242.

Sutton, R. (2007). Car financing for low- and moderate-income consumers. Baltimore, MD: Annie E. Casey Foundation.

Taylor, M. and S. Fujita (2018) Consumer Behavior and the Plug-In Electric Vehicle Purchase Decision Process: A Research Synthesis." Lawrence Berkeley National Laboratory. Report LBNL-2001122.

Turner, M. A. (1998). Moving out of poverty: Expanding mobility and choice through tenant-based housing assistance. *Housing Policy Debate*, 9(2), 373-394.

Van Alst, J. (2009). Fueling fair practices: A road map to improved public policy for used car sales and financing. Boston, MA: National Consumer Law Center.

CHAPTER 4

ASSESSING THE EFFECTS OF REBATES AND GUARANTEED LOANS ON PURCHASE DECISIONS

Policymakers have recently focused on increasing the adoption of clean technology, hybrid, near-zero, and zero-emissions vehicles by low- and moderate-income households. These households tend to drive older and higher-polluting vehicles, hold on to these vehicles longer, and often drive them farther distances than higher-income households (National Travel Household Survey, 2009; Bhat et al., 2009; Choo and Mokhtarian, 2004; Choo et al., 2007). As a result, policymakers are piloting several programs that aim to induce these consumers to adopt innovative technologies that reduce vehicle emissions, thereby reducing environmental and health damages within low- and moderate-income communities.

In this chapter we evaluate the effectiveness of implementing two such policies. The first is a policy that would provide rebate purchase incentives of varying levels to households that make, respectively, less than 225% and between 225% and 300% of the federal poverty limit when they adopt a cleaner vehicle. This is similar to the EFMP Plus-Up or Clean Cars 4 All program that in addition requires the scrapping of a functioning, older, high-polluting vehicle. The second policy, similar to CARB's financing assistance pilot project, would offer guaranteed financing to these same households when they purchase cleaner vehicles. For both of these policies we evaluate the effects of progressively higher levels of rebates ($0, $2,500, $5,000, and $9,500) and guaranteed financing at interest rates of 0%, 5%, 7.5% and 15%. At the request of the California Air Resources Board, we also explore how the effects of these programs vary by two income categories (less the 225% of the FPL and 225-300% of the FPL), as well as by race and ethnicity, urban, suburban, and rural geography, and AQMD region. The following research questions guide our analyses:

1. **What effect would various rebate incentive levels have on the purchase of different types of low- and zero-emission vehicles?**
2. **What effect would guaranteed loans with various interest rates have on the purchase of different types of low- and zero-emission vehicles?**
3. **How would the present status of related programs (e.g., EFMP Plus-up and CVRP) affect vehicle purchase rates?**
4. **How do respondent characteristics such as income, ethnicity, geography, and AQMD region attenuate the effects of these rebate and loan programs?**

Additional results on each of these topics, requested in CARB's analysis plan, are provided in the Appendix to this chapter.

In order to evaluate the effectiveness of these policy designs, we first developed and estimated an innovative empirical model of consumer vehicle choice. This enabled us to predict consumer choices across all vehicle makes and models currently available in the California market. Among the statewide representative survey of low- and moderate-income households in California, a total of 1,604 respondents provided information on their individual preferences for conventional and alternative vehicle attributes. This allowed us to estimate price elasticities of demand and the respondent's willingness to pay for different vehicles. We then integrated data on vehicle sales and market structure to predict the effect of alternative rebate and financing policy designs on our policy performance metrics.

We used this model to simulate the performance of four rebate levels: $0, $2,500, $5,000, and $9,500 for households with incomes below 225% of the Federal Poverty Limit or between 225% and 300%. We find that the rates of purchase with no subsidy was 26% for HEVs, about 4.5% for PHEVs and nearly 5% for BEVs.[1] Purchase rates did not vary greatly between low- and moderate-income levels. Additionally, all of the incentive levels demonstrated a positive and substantive impact on the propensity to purchase hybrids, PHEVs and BEVs. Offering rebates of $2,500, $5,000, or $9,500 increased purchases incrementally by approximately 20%, 40%, and 60-80% respectively, with small but significantly larger increases in the low-income group. When we evaluated how the responsiveness of respondents to rebates varied by geography, ethnicity and AQMD region, we found very little variation in purchases rates.

We also used the consumer vehicle choice model to simulate respondents' propensity to purchase hybrids, PHEVs and BEVs when respondents are offered guaranteed loans. As part of this evaluation we assessed the impacts of three interest rates (5%, 7.5% and 15%) on respondents' propensity to purchase a cleaner vehicle. Similar to the rebate level analysis, we included a scenario where respondents were not guaranteed a loan at a certain interest rate, in which case rates of purchase are 26% for HEVs, about 4.5% for PHEVs and about 5% for BEVs.

When considering the maximum impact of the guaranteed financing, we focus on the case of a guaranteed loan with the minimum interest rate (5%) in order to illustrate its effects on purchase rates for hybrids, PHEVs or BEVs. For hybrids, this loan offer increased purchases rates by 12% raising them from a base of about 26% to 27-29% (varying by income and demographics). For PHEVs, offering a loan increased purchased rates by about 16% from base purchase rates of 4-5% to 5-6% (also varying by income and demographics). For moderate-income consumers, receiving financing at a 5% interest rate results in PHEV adoption rates equivalent to those given a $2,500 subsidy. However, for respondents considering BEVs, the presence of a subsidized loan did not appreciably affect respondents purchase rates. When we evaluated how the responsiveness of respondents to subsidized financing varied by ethnicity, geography, and AQMD region, we found very little variation in purchases rates.

Finally, we explored possible interactions between offering both rebates and guaranteed financing. We found that offering both together did not significantly increase purchase rates beyond the increases associated with offering the rebate alone. The effect on purchase rates does not appear to be significantly impacted by income, race, geography or AQMD region.

For the simulation ranges considered, rebates had a much larger impact than offering guaranteed financing alternatives. This difference reflects not only each population's preference for financing (which is lower for low-income consumers) but also the price elasticities of demand. Rebates reduce the upfront price by lowering both the down payment and total payment as well as any monthly financing payment, if there are such payments. With financing, the upfront payment goes down, which increases utility, but the monthly payment goes up, decreasing utility. For low-income consumers, the decrease in utility due to the increase in monthly payments (which are higher for BEVs since BEVs are generally more expensive than other vehicle types) outweighs the increase in utility due to lowering the upfront payment.

4.1. Relevant Literature and Economic Theory

Several recent studies have evaluated subsidizing PEVs (e.g., Tal and Nicholas, 2016; DeShazo, Sheldon, and Carson, 2017; Li et al., 2017; Sheldon and Dua, 2018). These studies find that policy costs can be reduced in several ways, such as by simultaneously subsidizing public charging (Li et al., 2017) or by assigning subsidies according to income, vehicle type, or some other source of observable heterogeneity (DeShazo, Sheldon, and Carson, 2017; Sheldon and Dua, 2018). However, these papers focus on the new vehicle market, which represents a fraction of the total vehicle market. Furthermore, new car buyers tend to be different than used car buyers (e.g., higher-income).

[1] We do not have the numbers for the general public since the survey was administered only to low- and moderate-income consumers. Industry reports state the HEV/EV share of the new vehicle market, but we do not have the data on all annual new and used vehicle purchases to determine what the shares in the general population are.

We are unaware of papers that examine financing as clean vehicle adoption policy. In this study, we examine the impact of both subsidies and financing on clean vehicle adoption rates for all vehicles (both new and used). We are also one of the first such studies to focus on low- and moderate-income consumers.

Recent studies have shown that in order to maximize the cost-effectiveness of public revenues, higher rebates should be assigned to consumers with higher marginal utility of income and/or lower *ex ante* (expected) value for PEVs (DeShazo, Sheldon, and Carson, 2017; Sheldon and Dua, 2018).

The intuition for this result is shown in Fig. 4-1. Probability of purchasing the PEV is proportional to utility for the PEV. Let β be marginal utility of income, v be a consumer's ex ante[2] value for a PEV, and p be the price of a PEV. As shown in Fig. 1a, we can plot utility of the PEV versus rebate level as a linear function where the y-intercept is utility without the rebate, $v- \beta p$ and the slope of the function is the marginal utility of income. Although the probability of purchasing the PEV increases with the rebate, there is positive probability that the consumer will purchase the PEV in the absence of the rebate. If the consumer purchases the PEV in the absence of the rebate, the purchase is non-marginal in the sense that the purchase was not induced by the rebate policy. Area A is a proxy for the non-marginal purchase probability. Area B is a proxy for the marginal purchase probability; that is, by how much the rebate increases the probability of the consumer purchasing a PEV. The higher the consumer's expected (*ex ante*) value for the PEV, the higher non-marginal purchase probability. The higher the consumer's marginal utility of income, the more responsive they will be to the rebate and the higher their marginal purchase probability.

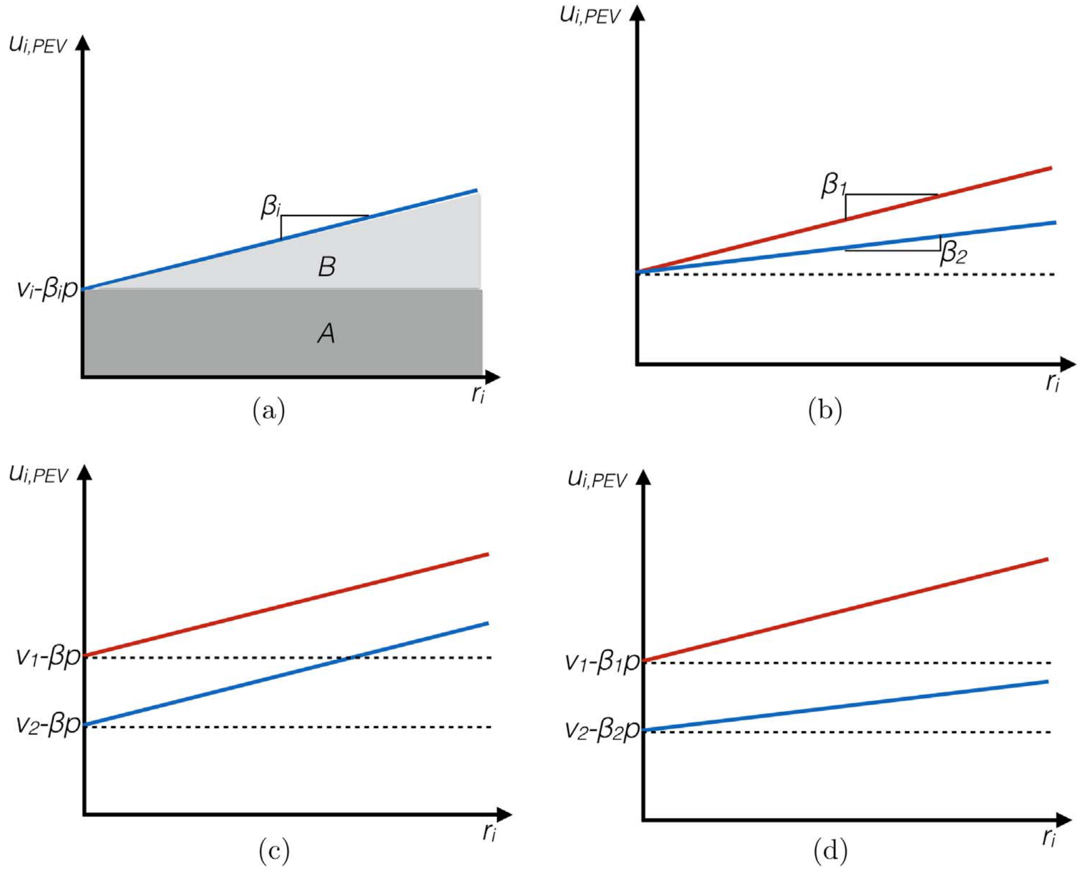
Rebates are more cost-effective when they target consumers with a higher ratio of marginal to non-marginal purchase probability; i.e., lower ex ante values and higher marginal utilities of income. Fig. 1b shows that if two consumers have the same probability of purchasing the PEV in the absence of the rebate, the policymaker should target the rebate toward consumer 1, who has the higher marginal utility of income and thus has a higher ratio of marginal to non-marginal purchase probability.

Fig. 1c shows that if two consumers have the same marginal utility of income, the policymaker should target the rebate toward consumer 2, who has the lower ex ante value and thus has a higher ratio of marginal to non-marginal purchase probability.

In Fig. 1d consumer 1 has a higher ex ante value for the PEV and a higher marginal utility of income, whereas consumer 2 has a lower ex ante value and a lower marginal utility of income. In this case, the policymaker would want to assign rebates r1 and r2 such that the ratio of consumer 1's marginal purchase probability to non-marginal purchase probability equals that of consumer 2.

[2] I.e., expected utility of the PEV.

Figure 4-1. Marginal Versus Non-Marginal PEV Purchase Probability



We can consider Figure 4-1 a demand curve, since PEV utility on the y-axis is proportional to quantity demanded and rebate on the x-axis is a measure of price. Therefore, our theoretical results suggest that rebates should be targeted toward consumer segments with lower market share and steeper demand curves. Targeting consumer segments and/or products with lower market share is cost-effective because it results in fewer rebates being allocated to infra-marginal purchases. Targeting consumer segments and/or products with steeper demand curves is more cost-effective because the rebates stimulate additional marginal purchases.

4.2. Background on Survey Instrument

As noted in earlier chapters, we contracted with the survey firm GfK to administer a survey to approximately 1,604 respondents within California. These respondents qualified as low- or moderate-income households and intended to purchase a vehicle within the next three years.

In the survey, we first collected preferences on the attributes of vehicles respondents preferred for their next intended purchase. Respondents selected their two most preferred body types and three most preferred makes for their next vehicle purchase. Respondents also indicated the anticipated amount they plan to spend on a down payment as well as a maximum monthly payment (were the purchase to be financed) and loan term (two to five years).

We then collected respondents' preferences on both brown and green vehicles. We did this by first guiding them through several sets of vehicle choices in which they were shown all vehicles in the "brown" vehicle universe[3] that are one of the preferred body types, one of the preferred makes, and have a market price less than 130% of the maximum amount the respondent could afford. This was calculated based on their chosen down payment, monthly

[3] The "brown" vehicle universe is populated with the most popular 50 used vehicle models by market share for 2010, 2015, and 2017. Three versions of each model are included (when information was available) for 2010 and 2015 model years — one with 50,000 miles, one with 100,000 miles, and one with 150,000 miles. Two versions of each model are included for 2017 model years — one brand new and one with 50,000 miles. Market prices were obtained from www.Edmunds.com.

payment, and loan term, assuming a 10% interest rate.[4] Respondents were then shown five vehicles per screen, including a thumbnail picture, the make, model, year, mileage, cost per mile, fuel economy, and market price (see Appendix Figure A4-1). They chose the vehicle they would most prefer to purchase out of sets of five. Finally, the survey asked them to choose which two vehicles they would be most likely to purchase out of the vehicles chosen in the previous sets. We refer to these vehicles as "brown1" and "brown2."

Next, respondents were asked to pick the vehicle they would most prefer out of a set of five vehicles from the "green" vehicle universe.[5] This random selection of vehicles included those that were among the most preferred body types and brands and had market prices less than 230% of the maximum amount the respondent could afford. If any BEVs (PHEVs) meet these criteria, then at least one BEV (PHEV) was included in the selection of five.[6] Respondents were shown a thumbnail picture, the make, model, year, mileage, engine type, cost per mile, fuel economy, electric range (if applicable) and price after incentives. The price after incentives is the market price less current statewide incentives. Respondents chose their two most preferred vehicles out of the set of five. We refer to these as "green1" and "green2."

Based on their preferences for "brown" and "green" vehicles, we then constructed a final choice set. In the final choice experiment, respondents were shown six choice sets with four vehicles in each set (see Appendix Figure A4-1). The first vehicle was always brown1 at market price. The other three vehicles were a mix of green1 and green2 with varying prices and with varying financing as well as hypothetical hybrid, PHEV, and BEV versions of brown1 with varying cost per mile, price, and financing. Finally, respondents were asked to choose their most preferred vehicle out of the vehicles chosen in the preceding six choice sets. We refer to this vehicle as "overall1."

4.3. Vehicle Choice Model and Policy Simulations

Using the choice experiment data, we estimated a vehicle choice model. To increase statistical power and variation in alternatives, we also include the data from the initial choice exercises (choosing amongst vehicles from the "brown" and "green" vehicle universe). Specifically, we estimated a conditional logit model, where utility is a function of upfront cost, monthly cost, vehicle age, vehicle mileage, whether or not the vehicle is financed, and indicators for if the vehicle is of the respondent's most preferred brand, most preferred body, brown1, green1, a BEV, or a PHEV. We also included indicators for body type (SUV, small car, midsize car, large car, or van/truck) and make category (American, European, Asian, or luxury). The upfront cost was the vehicle price (if not financed) or down payment (if financed). The monthly cost was the monthly refuel cost (cost per mile multiplied by monthly miles driven by the respondent) plus a monthly loan payment (if financed). Upfront cost, monthly cost, the financing indicator, and the BEV and PHEV indicators are all interacted with income level (above or below 225% of the federal poverty level) to allow for heterogeneity in preferences along these dimensions.

The estimated coefficients of the conditional logit model are all of the expected sign and highly statistically significant (except for the interaction coefficient between PHEV and low income, which is not statistically different from zero, indicating no significant preference of these respondents for PHEVs relative to ICEVs). Estimated price coefficients are negative and are larger in magnitude for low-income respondents, consistent with their being more price-responsive. The coefficients on age and odometer mileage are negative. Respondents prefer SUVs to cars and prefer trucks to SUVs. Respondents also prefer European and Asian makes to American makes. All else (e.g., upfront payment) equal, respondents prefer not to finance their purchase (lower-income respondents more so than moderate-income respondents).

[4] If fewer than five vehicles meet these criteria, the choices are populated with a random selection of vehicles that fit within 130% of the respondent's budget and are of a preferred brand or a preferred body.

[5] The "green" vehicle universe is populated with the most popular 30 hybrids by market share for 2010, 2011, 2013, 2016, and 2017. Also included in this vehicle universe are the 2011 Chevrolet Volt and Nissan Leaf, the 10 most popular PEVs in 2013, the 15 most popular PEVs in 2016, and all PEVS in 2017 with price data available. When market price was available, versions of each model are included with mileages of 0, 50,000, 100,000, and 150,000 miles.

[6] If fewer than five vehicles meet the criteria, then five vehicles choices are randomly selected that fit within 230% of the respondent's budget and are of a preferred brand or a preferred body.

Vans and trucks are the most preferred body type, followed by SUVs, large cars, small cars, and finally midsize cars. Both income groups prefer ICEVs to BEVs, the moderate-income group slightly more so than the low-income group. The moderate-income group, however, favors PHEVs to ICEVs.

Predicted Clean Vehicle Market Shares Across Policy Scenarios

Using the estimated coefficients from the vehicle choice model described above, we predicted vehicle choice and clean vehicle uptake in various scenarios. The set of vehicles for respondents to choose from in the simulations included all vehicles from the “brown” and “green” vehicle universes with MSRPs less than 120% of the respondent’s down payment plus 48 times the respondent’s maximum monthly payment. This restriction was implemented for computational ease but results are robust to this restriction.

First, we predicted baseline purchase probabilities without subsidies or financing for clean vehicles. Then, we predicted probabilities of the representative sample purchasing HEVs, PHEVs, and BEVs assuming various subsidy and financing scenarios. Aggregating the purchase probabilities across respondents gave the predicted market share of each vehicle type in each scenario.

Table 4-1 shows HEV, PHEV, and BEV market share for various consumer groups assuming no subsidy and subsidies of $2,500, $5,000, and $9,500. In these simulations, financing is not available. At the baseline (with no subsidy), approximately one quarter of the representative sample would purchase a new or used HEV. Over 4% would purchase a PHEV, and over 5% would purchase a BEV.

At the highest subsidy level ($9,500), 43.3% of the sample would purchase an HEV, 7.5% would purchase a PHEV, and 8.1% a BEV. At the baseline, a slightly larger share of moderate-income consumers would purchase an HEV than low-income consumers. A higher share of moderate-income consumers would purchase a PHEV, but a slightly higher share of low-income consumers would purchase a BEV. This reflects the stronger preference of moderate-income consumers for PHEVs relative to low-income consumers and vice versa for BEVs as estimated in the choice model. These predictions also reflect the brand and body preferences of individuals in these two income groups.

Table 4-1. Effect of Rebate Levels on Purchase Rate, by Income and Vehicle Type

By Income: Percent of Weighted Sample Choosing HEV/PHEV/BEV by Subsidy				
HEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Below 225% FPL	25.5%	30.5%	35.8%	43.9%
Above 225% FPL	25.9%	30.2%	34.8%	41.9%
PHEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Below 225% FPL	3.7%	4.5%	5.2%	6.8%
Above 225% FPL	5.4%	6.3%	7.3%	9.1%
BEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Below 225% FPL	5.4%	6.5%	7.6%	8.3%
Above 225% FPL	5.1%	5.9%	6.8%	7.6%

Table 4-2 shows clean vehicle adoption rates by location (urban, suburban, and rural), vehicle type, and subsidy. Differences in baseline adoption rates and responsiveness to subsidies are driven by the income composition of each subpopulation as well as the individual make and model preferences of constituents. For example, subpopulations with more low-income respondents are more responsive to the subsidies.

Table 4-2. Effect of Rebate Levels on Purchase Rate, by Geography, Subsidy and Vehicle Type

By Geography: Percent of Weighted Sample Choosing HEV/PHEV/BEV by Subsidy				
HEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Urban	25.7%	30.5%	35.6%	43.4%
Suburban	25.6%	30.4%	35.4%	43.2%
Rural	25.7%	30.5%	35.5%	43.4%
PHEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Urban	4.2%	5.0%	5.8%	7.4%
Suburban	4.3%	5.1%	5.9%	7.5%
Rural	4.3%	5.1%	6.0%	7.6%
BEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Urban	5.4%	6.4%	7.4%	8.1%
Suburban	5.4%	6.4%	7.4%	8.1%
Rural	5.2%	6.1%	7.1%	7.9%

Table 4-3 shows HEV, PHEV, and BEV market share for various consumer groups assuming no subsidy and financing available at three different interest rates. Financing with interest rates of 15%, 7.5%, and 5% increase the lower-income population's probability of purchasing a PHEV by 10%, 13%, and 14%, respectively. Financing with the three rates increases the moderate-income population's probability of purchasing a PHEV by 11%, 15%, and 17%, respectively. While financing increases the moderate-income population's probability of purchasing a BEV by up to 7%, it does not increase the lower-income population's probability of purchasing a BEV.

Table 4-3. Effect of Financing Alternatives on Purchase Rate, by Income and Vehicle Type

By Income: Percent of Weighted Sample Choosing HEV/PHEV/BEV by Financing/Interest Rate				
HEV	**None**	**15.0%**	**7.5%**	**5.0%**
Below 225% FPL	25.5%	26.3%	26.9%	27.0%
Above 225% FPL	25.9%	27.9%	28.7%	29.0%
PHEV	**None**	**15.0%**	**7.5%**	**5.0%**
Below 225% FPL	3.7%	4.1%	4.2%	4.3%
Above 225% FPL	5.4%	6.0%	6.3%	6.3%
BEV	**None**	**15.0%**	**7.5%**	**5.0%**
Below 225% FPL	5.4%	5.4%	5.4%	5.4%
Above 225% FPL	5.1%	5.3%	5.4%	5.4%

These differences reflect not only each population's preference for financing (which is lower for low-income consumers) but also price elasticities of demand. With financing, the upfront payment goes down, which increases utility, but the monthly payment goes up, decreasing utility. For low-income consumers, the decrease in utility due to the increase in monthly payments (which are higher for BEVs since BEVs are generally more expensive than other vehicle types) outweighs the increase in utility due to lowering the upfront payment.

Again, differences in responsiveness to subsidies are driven by the income composition of each subpopulation as well as the individual make and model preferences of constituents. For some subpopulations, receiving financing at a 5% interest rate results in adoption rates equivalent to those in Table 1 with no financing but a $2,500 subsidy (e.g., PHEV adoption for moderate-income consumers).

Tables 4-4 and 4-5 show the market shares for HEVs, PHEVs, and BEVs for various consumer groups at the three different subsidy levels ($2,500, $5,000, and $9,500), assuming guaranteed financing is available with a 15% interest rate (Table 4-5) or a 7.5% interest rate (Table 4-4). In many cases, particularly at the higher interest rate of 15%, financing does not increase clean vehicle uptake.

Table 4-4. Effect of Rebates and Financing at 7.5% Interest Rate on Purchase Rates

By Income: Percent of Weighted Sample Choosing HEV/PHEV/BEV by Subsidy (Financing at 7.5%)				
HEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Below 225% FPL	26.9%	30.5%	35.8%	43.9%
Above 225% FPL	28.7%	32.0%	35.5%	42.0%
PHEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Below 225% FPL	4.2%	4.7%	5.2%	6.8%
Above 225% FPL	6.3%	6.9%	7.6%	9.2%
BEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Below 225% FPL	5.4%	6.5%	7.6%	8.3%
Above 225% FPL	5.4%	6.1%	6.8%	7.6%

Table 4-5. Effect of Rebates and Financing at 15% Interest Rate on Purchase Rates

By Income: Percent of Weighted Sample Choosing HEV/PHEV/BEV by Subsidy (Financing at 15%)				
HEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Below 225% FPL	26.3%	30.5%	35.8%	43.9%
Above 225% FPL	27.9%	31.4%	35.2%	41.9%
PHEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Below 225% FPL	4.1%	4.6%	5.2%	6.8%
Above 225% FPL	6.0%	6.7%	7.5%	9.1%
BEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Below 225% FPL	5.4%	6.5%	7.6%	8.3%
Above 225% FPL	5.3%	6.0%	6.8%	7.6%

Financing increases uptake the most at the lowest subsidy level ($2,500) and the least at the highest subsidy level ($9,500). This is because the greater the subsidy, the more clean vehicles' purchase prices fall below the respondent's planned down payment. All else equal, respondents prefer to purchase their vehicle upfront. The most notable increases in clean vehicle uptake due to the financing are for moderate-income consumers' purchasing PHEVs. Financing with a 15% or 7.5% interest rate increases uptake by nearly 7% and 10%, respectively, when there is a $2,500 subsidy.

Following the choice experiment, respondents were asked if they would make the same purchase decision if their current vehicle were replaced or retired. Out of the full representative sample, 84% would make the same decision if replacing their current vehicle and 61% if retiring. Yet 94% would make the same purchase decision if paid a $1,500 incentive to retire their current vehicle. More respondents were willing to retire their current vehicle if their current vehicle is older.

4.4. Conclusions

In this chapter we evaluated the effectiveness of two policies in increasing the adoption of clean technology vehicles for low- and moderate-income households. The first is a policy that would offer rebate incentives of varying levels to households that make less than 225% and between 225% and 300% of the Federal Poverty Limit when they purchase clean vehicles. Purchase rates did not differ greatly between low- and moderate-income levels. We find that all incentive levels create a positive and substantive impact on the propensity to purchase hybrids, PHEVs and BEVs. Offering rebates of $2,500, $5,000, and $9,500 increased clean vehicle purchases incrementally by approximately 20%, 40% and 60-80% respectively, with only small differences in these rates across the two income groups.

The second is a policy that would offer guaranteed financing (at 5%, 7.5% and 15%) to these same households when they purchase cleaner vehicles. For purposes of illustration, we focus on the case of a guaranteed loan with the maximum interest rate (15%) in order to demonstrate its effects on purchase rates for hybrids, PHEVs and BEVs. For hybrids, this loan offer increased purchase rates by 12%, raising them from a base of about 26% to about 29%. For PHEVs, offering a loan increased purchase rates by about 16% from base purchase rate of 4-5% to 5-6%. For this subpopulation, receiving financing at a 15% interest rate results in adoption rates equivalent to those when receiving a $2,500 subsidy (e.g., PHEV adoption for moderate-income consumers). However, for respondents considering BEVs, the presence of a subsidized loan did not significantly affect respondents' purchase rates.

Rebates had a much larger impact than did offering guaranteed financing alternatives. This difference reflects not only each population's preference for financing (which is lower for low-income consumers) but also the price elasticities of demand. Rebates reduce the upfront price, lowering both the down payment and total payment as well as any monthly financing payment, if there are such payments. With financing, the upfront payment goes down, which increases utility, but the monthly payment goes up, decreasing utility. For low-income consumers, the decrease in utility due to the increase in monthly payments (which are higher for BEVs since BEVs are generally more expensive than other vehicle types) outweighs the increase in utility due to lowering the upfront payment.

References

Bhat, C. R., Sen, S. and Eluru, N. (2009). The impact of demographics, built environment attributes, vehicle characteristics, and gasoline prices on household vehicle holdings and use. *Transportation Research Part B,* 43, 1–18.

Choo, S. and Mokhtarian P.L. (2004). What type of vehicle do people drive? The role of attitude and lifestyle in influencing vehicle type choice. *Transportation Research Part A*, 38, 201–222.

Choo, S., Shafizdeh, K. and Niemeier, D. (2007). The development of a prescreening model to identify failed and gross polluting vehicles. *Transportation Research Part D,* 12, 208–218.

DeShazo, J. R., Sheldon, T. L. and Carson, R. T. (2017). Designing policy incentives for cleaner technologies: Lessons from California's plug-in electric vehicle rebate program. *Journal of Environmental Economics and Management*, 84, 18-43.

Diamond, D. (2009). The impact of government incentives for hybrid-electric vehicles: Evidence from US states. *Energy Policy*, 37(3), 972-983.

Gallagher, K. S. and Muehlegger, E. (2011). Giving green to get green? Incentives and consumer adoption of hybrid vehicle technology. *Journal of Environmental Economics and Management*, 61(1), 1-15.

Holland, S.P., Mansur, E.T., Muller, N.Z. and Yates, A. J. (2016). Environmental benefits from driving electric vehicles? *American Economic Review*, 106(12). 3700-3729.

Jin, L., Searle, S. and Lutsey, N. (2014). Evaluation of state-level U.S. electric vehicle incentives. *The International Council on Clean Transportation*. See http://www.theicct.org/ evaluation-state-level-us-electric-vehicle-incentives.

Li, S., Linn, J. and Spiller, E. (2013). Evaluating "Cash-for-Clunkers": Program effects on auto sales and the environment. *Journal of Environmental Economics and Management*, 65(2), 175-193.

Li, S., Tong, L., Xing, J. and Zhou, Y. (2017). The market for electric vehicles: indirect network effects and policy design. *Journal of the Association of Environmental and Resource Economists*, 4(17), 89-133.

Mian, A. and Sufi, A. (2012). The effects of fiscal stimulus: Evidence from the 2009 Cash for Clunkers Program. *The Quarterly Journal of Economics*, 127(3), 1107-1142.

Sheldon, T. and Dua, R. (2018). Measuring the Cost-effectiveness of Clean Vehicle Subsidies. KAPSARC Discussion Paper KS—2018—DP033. DOI: 10.30573/KS—2018-DP033. See https://www.kapsarc.org/wp-content/uploads/2018/05/KS-2018-DP033-Measuring-the-Cost-effectiveness-of-Clean-Vehicle-Subsidies.pdf.

Sierzchula, W., Bakker, S., Maat, K. and van Wee, B. (2014). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, 68, 183-194.

Tal, G. and Nicholas, M. (2016). Exploring the impact of the federal tax credit on the plug-in vehicle market. *Transportation Research Record: Journal of the Transportation Research Board*, 2572, 95-102.

Zhang, X., Xie, J., Rao, R. and Liang, Y. (2014). Policy incentives for the adoption of electric vehicles across countries. *Sustainability*, 6(11), 8056-8078.Tal, G. and Nicholas, M. (2016). Exploring the impact of the federal tax credit on the plug-in vehicle market. *Transportation Research Record: Journal of the Transportation Research Board*, 2572, 95-102.

Zhang, X., Xie, J., Rao, R. and Liang, Y. (2014). Policy incentives for the adoption of electric vehicles across countries. *Sustainability*, 6(11), 8056-8078.

Zivin, G., Joshua, S., Kotchen, M. J. and Mansur, E. T. (2014). Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies. *Journal of Economic Behavior & Organization*, 107, 248-268.

CHAPTER 5

CURRENT FLEET CHARACTERISTICS, MANAGEMENT, AND EXPENDITURES

Most low- and moderate-income households own and use automobiles. For example, data from the 2016 American Community Survey (ACS) show that 92% of households below 300% of the Federal Poverty Level (FPL) in California have at least one automobile in their household, and that the average low- or moderate-income household owns about two vehicles. Additionally, the ACS data show that about 80% of workers in low-income (below 225% of FPL) California households commute by automobile.

While there is little published evidence on this topic, economic theory suggests that low- and moderate-income households are more likely to own older, high-polluting vehicles than higher-income households. Policies that effectively incentivize the retirement of high-polluting vehicles with near-zero and zero-emission replacements would have an outsized impact on emissions reductions. In addition to the environmental impacts of vehicle use by low- and moderate-income households, we might expect that low-moderate income households spend a high percentage of their incomes to maintain and operate their vehicles.

Despite the prevalence of automobile ownership, and the expected lower quality of vehicles operated among lower-income groups, relatively little research examines the size, profile, and maintenance expenditure of low- and moderate-income households' vehicle fleets. To fill these research gaps, survey respondents were asked about their general vehicle holdings as well as more detailed questions regarding their self-selected main vehicle. The results of these and other questions from the survey allow us to provide answers, with varying degrees of certainty, to five related questions of interest:

1. **What factors influence vehicle access and the number of vehicles used by household structure within the sample?**
2. **What are the emissions-relevant characteristics of vehicles in which surveyed households have access?**
3. **How do households compose their fleets with respect to household structure?**
4. **How much money do households need to spend to maintain and operate the household's main vehicle?**
5. **What do households report regarding their intentions to keep or dispose of their main household vehicle and what factors influence these responses?**

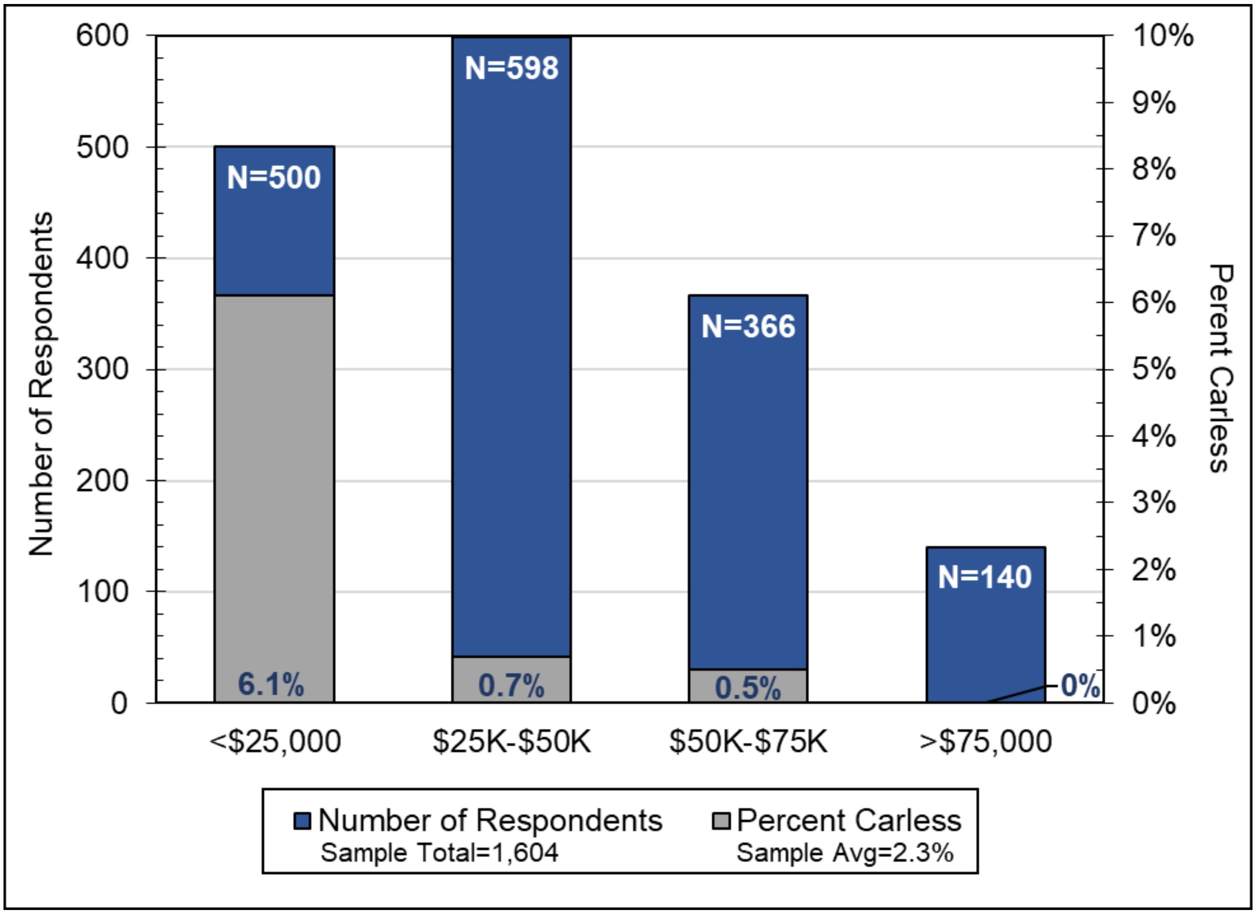
Where possible, we compare the results from the sample to findings on the entire California population and/or low-moderate income households from administrative data sources, previous studies or other sources. Additional results on each of these topics, requested in CARB's analysis plan, are provided in the Appendix to this chapter.

5.1. Vehicle Ownership and Number of Vehicles by Household Structure

There are three main findings from our survey regarding vehicle access. First, nearly all low- and moderate-income households have access to and use at least one vehicle, at levels above the entire California population of households. Second, the average number of vehicles to which surveyed households have access is comparable to both the low-moderate income and the general population of California. Third, the expected socioeconomic and geographic correlations of higher vehicle access are borne out in our survey results.

Figure 5-1 shows that, of 1,604 respondents, only 2.3% (or 36 households) indicated that their household does not currently have access to and use a vehicle. The vast majority of the non-car using respondents earn less than $25,000 a year (83%). This contrasts with nearly 8% of all households in California not reporting vehicle access in the 2016 ACS, and 15.5% of households not having access to a vehicle and making less than $50,000 in the 2013 California Household Travel Survey (CHTS). These disparities likely reflect the screening question regarding prospective vehicle purchase in our survey.

Figure 5-1. Households Who Do Not Have Access to a Vehicle



Moreover, the average household in the sample had access to 2.0 vehicles. As Table 2-11 in Chapter 2 shows, this average corresponds to the average number of vehicles held by households under 300% of the FPL in California using data from the 2016 ACS, and is only slightly below the average of 2.2 vehicles held by the average California household.

As expected, the number of vehicles per household also notably increases as household income increases, with households with incomes below $25,000 holding an average of 1.4 vehicles, as compared to those with incomes above $75,000 in the sample who hold an average of 3.1 vehicles. The descriptive differences in mean vehicle holdings across income groups shown in Table 5-1 are statistically significant.

To understand vehicle holdings per household and whether they meet basic transportation needs, however, it is essential to account for household structure. The number of vehicles available for use adjusted for household size, or for the number of licensed drivers in the household, may paint a more accurate picture of vehicle access for individuals within a given household. The average number of persons in surveyed households was 3.5, and the average number of licensed drivers per household in the sample was 2.3, with household sizes and number of license drivers increasing by income group.

In terms of the representativeness of the survey sample to the state of California, the mean number of vehicles per person is 0.73 in the sample and 0.77 across all households in the state (per the 2013 CHTS). The mean number of vehicles per licensed driver is even more similar, with an average of 0.98 in the sample and 1.0 across the state.

Table 5-1 also shows that vehicle holdings tend to increase with household size, even within the same income categories. For instance, within households making between $25,000 and $50,000, the number of vehicles held varies from 1.5 in one-person households to 2.3 in 6+ person households. The correspondence between household size and vehicle holdings, however, seems to level off among the larger households in the sample.

Table 5-1. Mean Vehicle Holdings, by Household Size and Income

HH	<$25,000			$25K-$50K			$50K-$75K			>$75,000			Sample Avg.[2]		
Size	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.
1	164	1.1	0.5	63	1.5	0.9	N/A	N/A	N/A	N/A	N/A	N/A	228	1.2	0.6
2	125	1.2	0.6	189	1.6	0.9	N/A	N/A	N/A	N/A	N/A	N/A	314	1.4	0.8
3	101	1.6	0.8	119	2.0	0.9	90	2.0	1.2	N/A	N/A	N/A	310	1.9	1.0
4	54	2.3	1.2	132	2.2	1.0	134	3.0	1.2	N/A	N/A	N/A	320	2.5	1.2
5	41	1.4	1.3	55	2.1	1.1	63	2.0	0.7	55	2.8	0.8	215	2.2	1.1
6+	16	2.0	1.5	39	2.3	1.7	79	3.0	1.1	84	3.2	1.1	218	2.9	1.4
Avg[1]	**500**	**1.4**	**0.9**	**598**	**1.9**	**1.0**	**366**	**2.6**	**1.3**	**140**	**3.1**	**1.2**	**1,604**	**2.0**	**1.2**

[1] The difference in mean vehicle holdings between all combinations of income groups is statistically significant at P<0.05 except $50K-$75K and >$75K, which is significant at P<0.10.

[2] The difference in mean vehicle holdings between all combinations of household size categories is statistically significant at P<0.05, except between 1 and 2, 3 and 5, 4 and 5, and 4 and 6. The difference between 4 and 5 is significant at P<0.10.

As shown in Table 5-2, nearly 50% of all households in the sample reported having two licensed drivers in their household. The average vehicle holdings increase even more dramatically when assessed in terms of the number of licensed drivers, rather than by household size, although the sample sizes for each response category tend to be too small to allow for tests of statistical significance. Generally, households hold fewer vehicles than licensed drivers.

Table 5-2. Mean Vehicle Holdings, by Number of Licensed Drivers and Income

# HH	<$25,000			$25K-$50K			$50K-$75K			>$75,000			Sample Avg.[2]		
Drivers	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.
0	4	0.6	0.5	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	4	0.6	0.6
1	94	1.1	0.7	140	1.3	0.5	39	1.2	0.4	1	1.9	1.4	273	1.2	0.5
2	180	1.5	0.7	292	1.9	0.8	153	2.1	0.5	49	2.2	0.5	673	1.9	0.8
3	51	2.1	1.1	68	2.6	0.9	77	2.9	0.7	47	3.0	0.4	243	2.6	0.8
4	20	3.2	0.7	19	3.4	1.3	51	3.1	1.2	25	4.0	0.5	115	3.4	0.9
5+	2	4.0	1.9	14	4.7	0.9	41	4.7	1.2	16	4.7	1.7	73	4.7	1.0
Sample Avg.[1]	**351**	**1.6**	**1.0**	**532**	**1.9**	**1.1**	**361**	**2.6**	**1.2**	**137**	**3.1**	**0.9**	**1,382**	**2.1**	**1.2**

[1] The difference in mean vehicle holdings between all combinations of income groups is statistically significant at P<0.05 except $50K-$75K and >$75K, which is significant at P<0.10.

[2] The difference in mean vehicle holdings between all combinations of licensed driver categories is statistically significant at P<0.05.

Similar as to what has been found in past research (Blumenberg and Pierce, 2012) among racial-ethnic groups, non-Hispanic Black households tend to own the fewest cars per household. This holds true when adjusting for household size, or as shown in Table 5-3, when adjusting for the number of licensed drivers per household.

Table 5-3. Mean Vehicle Holdings, by Number of Licensed Drivers and Race/Ethnicity

	Non-Hispanic															Hispanic			Sample Avg.[2]		
	White			Black			Asian			Other			2+ Races								
	N.	Mean	S.D.	N.	Mean	S.D	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.
0	1	0.0	N/A	0.2	0.0	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	3	0.9	0.4	4	0.6	0.6
1	49	1.1	0.4	36	0.9	0.4	16	1.0	0.2	2	1.3	0.8	10	1.6	1.0	161	1.3	0.5	273	1.2	0.5
2	198	1.9	1.0	69	1.6	0.4	31	1.6	0.6	26	2.1	0.5	13	1.9	0.7	335	1.9	0.7	673	1.9	0.8
3	71	2.7	0.9	8	2.4	1.2	12	2.7	0.5	9	2.3	0.5	5	2.7	0.6	138	2.7	0.8	243	2.6	0.8
4	38	3.4	1.0	6	4.4	0.5	8	1.5	1.0	7	3.8	0.3	N/A	N/A	N/A	56	3.5	1.0	115	3.4	0.9
5+	5	3.1	0.4	1	2.0	0.0	5	3.7	0.8	10	3.6	1.9	N/A	N/A	N/A	52	5.2	0.9	73	4.7	1.0
Avg.	**362**	**2.1**	**1.3**	**120**	**1.6**	**0.8**	**72**	**1.8**	**1.0**	**55**	**2.6**	**1.1**	**28**	**1.9**	**1.0**	**745**	**2.3**	**1.1**	**1,382**	**2.1**	**1.2**

[1] The difference in mean vehicle holdings is statistically significant at P<0.05 between Black and White, Black and Other, and Black and Hispanic, and at P<0.10 between Asian and Other, Asian and Hispanic, and 2+ Races and Hispanic.

[2] The difference in mean vehicle holdings between all combinations of licensed driver categories is statistically significant at P<0.05.

There are no notable differences in vehicle holdings by urbanization geography or by major AQMD geographies, as shown below. Our findings on vehicle ownership cohere with the existing literature. Previous research shows that income influences several aspects of household fleet management. Most notably, income influences whether households own a vehicle (Jong et al., 2004) and how many vehicles are in a household (Fang, 2008; Mitra and Saphores, 2017).

5.2. The Condition of Fleet Vehicles: Age, Odometer, and Fuel Economy

Next, we examine the emissions-relevant characteristics of vehicles that surveyed households have access to, as compared to known characteristics of the California and U.S. vehicle fleet. Given that only low- to moderate-income households participated in the survey, we generally expect them to have older vehicles with more mileage and worse fuel economy than the general vehicle fleet.

We expect this due to previous research demonstrating that income influences vehicle type and the ways in which households manage their vehicle fleets. Income is also associated with the purchase of certain types of vehicles. Low-income families tend to purchase large, likely "secondhand" vehicles (Bhat et al., 2009; Choo and Mokhtarian, 2004). Additionally, data from the 2009 National Household Travel Survey show that low- and moderate-income households tend to own their vehicles longer than higher-income households, who have the resources to replace aging automobiles (Figure 5-2). A CARB report suggests that the highest-emitting group of vehicles were 20 years or older (Cackette, Wallauch, Hedglin, & Ford, 2012), and a RAND Corporation report shows that 39% of reactive organic gas and nitrogen oxide emissions come from 15-year-old or older vehicles (Dixon and Garber, 2001).

Emissions not only tend to be higher in older vehicles, but these vehicles are also more likely to fail smog checks and be gross polluters (Choo et al., 2007), and to be unregistered (Pierce and Connolly, 2018).[1] While new vehicles have benefited from the steady improvements in pollution-control equipment, including the development of near-zero and zero-emission vehicles, older vehicles' pollution-control equipment deteriorates over time, once again contributing to higher levels of emissions and impeding progress toward California's air quality and climate change goals.[2]

Vehicle Characteristics by Income Level of Household

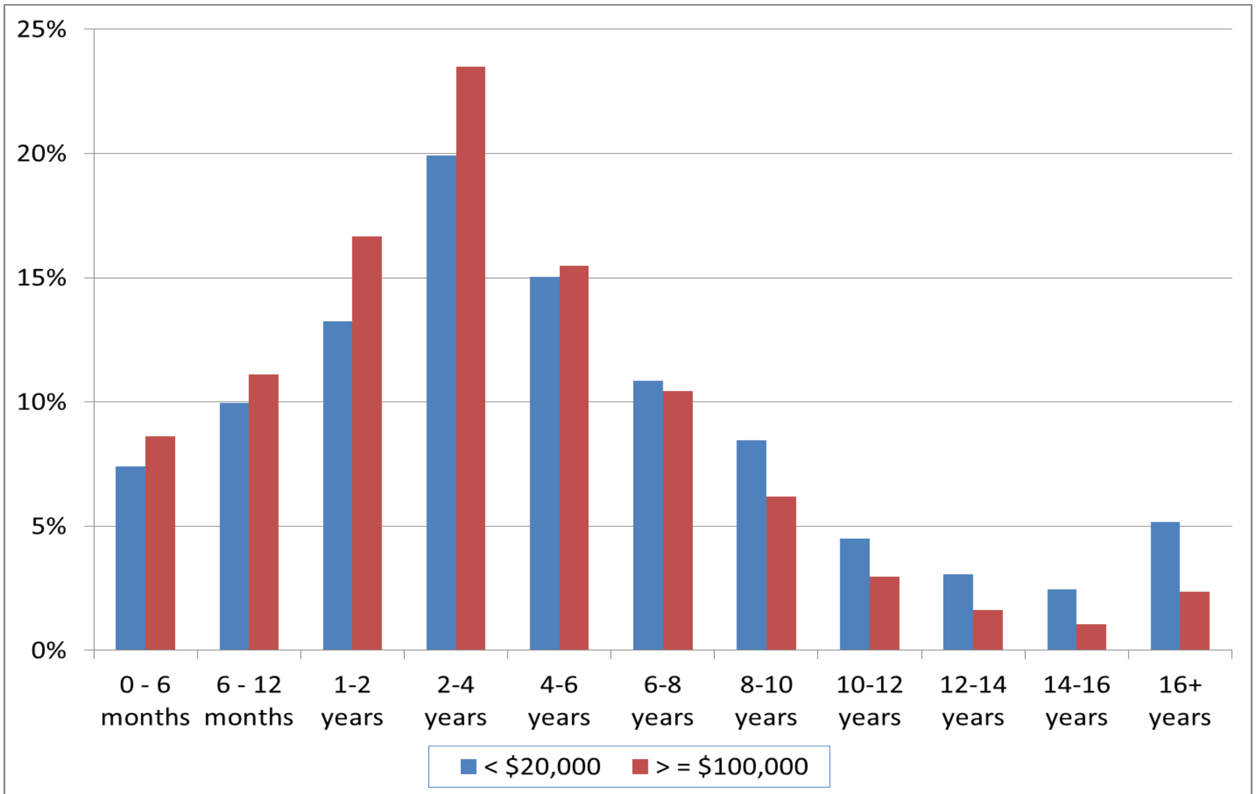
Existing evidence suggests that low- and moderate-income households are more likely to drive older vehicles

[1] We note that while we included a question regarding vehicle registration in the soft launch of the survey, it was omitted in the full launch due to the lack of accuracy in initial responses.

[2] Lower-income households own fewer automobiles and their members take fewer trips and travel fewer miles than higher-income households (Murakami and Young, 1997; Santos et al., 2011). Therefore, their per-household contribution to emissions from these old vehicles relative to higher-income households remains uncertain.

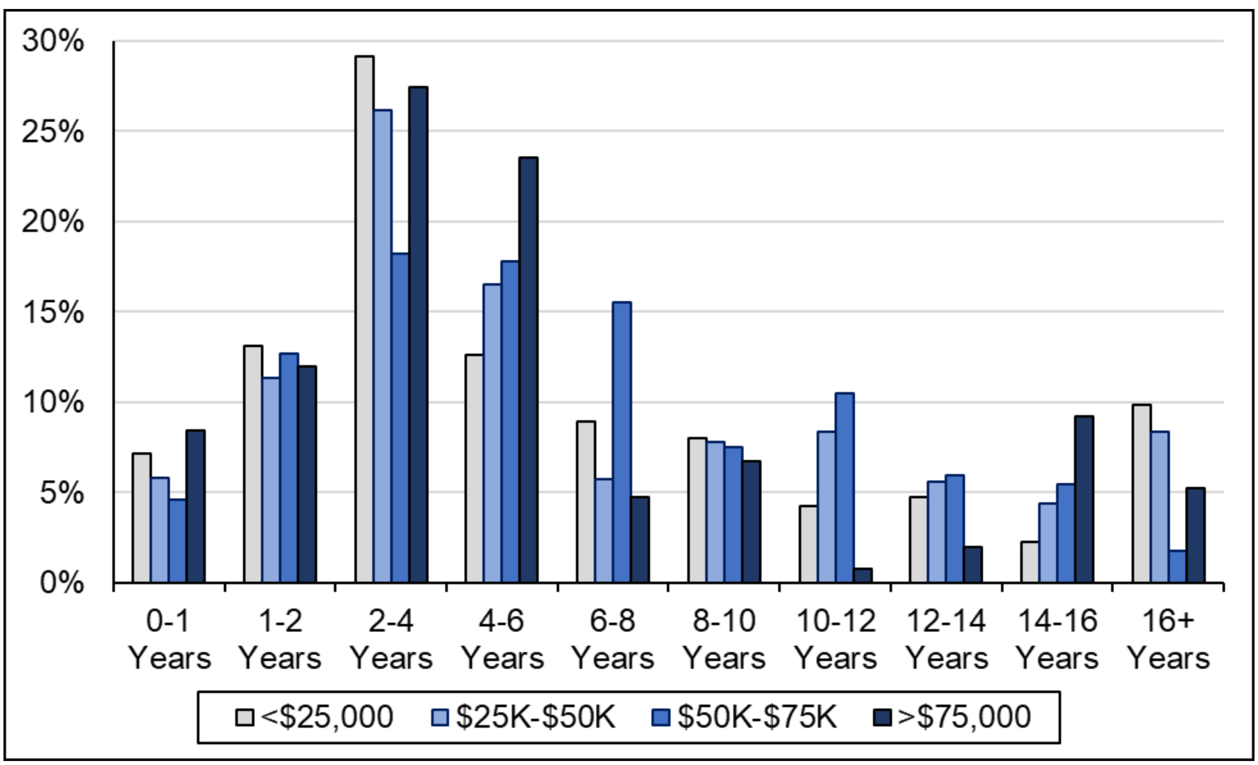
than higher-income households. For instance, Figures 5-2 and 5-3 show the relationship between vehicle years of ownership and household income groups in the 2009 NHTS and our 2018 survey. Both figures suggest that low-income households tend to own older vehicles.

Figure 5-2. Vehicles by Years of Ownership and Household Income (2009 National Household Travel Survey)



Source: 2009 National Household Travel Survey.

Figure 5-3. Vehicles by Years of Ownership and Household Income (2018 Ride and Replace Survey)



As shown in Table 5-4, however, the average vehicle year of all vehicles in the sample was 2007, or about 11 years old at the time of the survey. Given that the average age of all light-duty vehicles in California (2013 CHTS) was 10.9 years and for households with incomes below $50,000 was 12.8 years, vehicles held by surveyed households do not appear to be noticeably older than the general vehicle fleet.[3] The average mileage of all vehicles in the sample was 88,832, and the average mileage per gallon (MPG) was 23.5. While higher-income households within the sample appear to have slightly newer vehicles with less mileage, there are no statistically significant differences in means for fleet age, mileage, MPG across income groups at the 95% confidence level.

Table 5-4. Vehicle Fleet Characteristics, by Income

	Vehicle Holdings			Fleet Age			Fleet Mileage			Main Vehicle MPG		
	N.	Mean[1]	S.D.	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.
<$25K	500	1.4	0.9	468	2006.7	7.9	444	85,123	102,606	459	22.4	8.6
$25K-$50K	598	1.9	1.1	589	2006.8	8.8	566	90,284	96,061	588	24.3	9.2
$50K-$75K	366	2.6	1.1	364	2007.7	5.9	344	93,215	64,388	364	23.6	6.8
>$75K	140	3.1	0.8	140	2007.7	6.5	127	88,945	51,224	364	23.6	6.8
Sample Avg.	**1,604**	**2.0**	**1.2**	**1,561**	**2007.2**	**7.6**	**1,481**	**89,788**	**82,622**	**1,551**	**23.5**	**8.3**

[1] The difference in mean vehicle holdings is statistically significant at P<0.05 for all combinations of income groups, except $50-$75K and >$75K which is significant at P<0.10.

Vehicle Characteristics by Race-Ethnicity of Household Head

As suggested in Table 5-5, there appear to be more clear differences in vehicle fleet characteristics across racial-ethnic groups of households. White, non-Hispanic respondents have the oldest and highest-mileage fleets. Asian, non-Hispanic respondents have the youngest fleets, and Multiracial non-Hispanics have the lowest-mileage fleets. Non-Hispanic Black and Hispanic individuals seem to drive the least fuel-efficient vehicles, while non-Hispanic Multiracial and Other respondents own the most efficient vehicles overall. The difference in mean fleet age between non-Hispanic White, Asian, and Hispanic households is significant at the 95% confidence level.

Table 5-5. Vehicle Fleet Characteristics, by Race and Ethnicity

		Vehicle Holdings			Fleet Age			Fleet Mileage			Main Vehicle MPG		
		N.	Mean[1]	S.D.	N.	Mean[2]	S.D.	N.	Mean[3]	S.D.	N.	Mean[4]	S.D.
Non-Hispanic	White	434	1.9	1.3	425	2005.9	10.2	406	100,881	108,314	427	24.2	10.5
Non-Hispanic	Black	148	1.5	0.8	142	2007.6	5.5	138	99,847	68,668	131	22.7	6.8
Non-Hispanic	Asian	82	1.7	1.0	82	2009.6	7.8	82	69,743	83,912	82	23.1	9.0
Non-Hispanic	Other	76	2.2	1.1	76	2007.6	5.6	76	84,428	83,761	76	25.6	7.5
Non-Hispanic	2+ Races	36	2.1	1.0	34	2008.7	10	34	60,501	79,360	34	26.6	8
Hispanic		828	2.1	1.1	801	2007.4	6.4	746	86,572	67,675	801	23.0	7.0
Sample Avg.		**1,604**	**2.0**	**1.2**	**1,561**	**2007.2**	**7.6**	**1,481**	**89,788**	**82,622**	**1,551**	**23.5**	**8.3**

[1] The difference in mean vehicle holdings is statistically significant at P<0.05 between White and Black, Black and Hispanic, and Asian and Hispanic, and at P<0.10 between Black and 2+ Races.

[2] The difference in mean fleet age is statistically significant at P<0.05 between White and Asian, and at P<0.10 between White and Hispanic, and Asian and Hispanic.

[3] The difference in mean fleet mileage is statistically significant at P<0.05 between White and Asian, White and 2+ Races, and 2+ Races and Hispanic, and at P<0.10 between Black and Asian, and Asian and 2+ Races.

[4] The difference in mean MPG is statistically significant at P<0.05 between 2+ Races and Hispanic.

Vehicle Fleet Characteristics by Geography

We also examine fleet characteristics by urbanization status of the household's residential location. Although household size, number of licensed drivers, and vehicle holdings remain fairly constant, Table 5-6 shows differences

[3] The average age of vehicles in the United States was 11.6 years (IHS Markit, 2016).

in mean fleet age and mileage across urban, suburban, and rural areas. Households in rural areas have the oldest fleets, while those in suburban areas have the highest-mileage fleets. Mean fleet mileage is higher in both suburban and rural areas. While urban households tend to have slightly more fuel-efficient fleets than suburban or rural households, these differences are not statistically significant.

Table 5-6. Vehicle Fleet Characteristics, by Urbanization Geography

	Vehicle Holdings			Fleet Age			Fleet Mileage			Main Vehicle MPG		
	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.
Urban	680	1.9	1.2	663	2007.2	7.3	631	84,912	81,628	652	22.9	8.0
Suburban	671	2.1	1.2	656	2007.3	7.4	616	92,417	84,342	658	23.9	8.7
Rural	229	2.0	1.2	219	2006.6	9.1	211	91,914	76,133	216	23.9	7.7
Sample Avg.	**1,580**	**2.0**	**1.2**	**1,537**	**2007.2**	**7.6**	**1,458**	**89,280**	**82,387**	**1,527**	**23.5**	**8.3**

Finally, Table 5-7 shows vehicle fleet characteristics across air quality management district (AQMD) geographies. Generally, differences across regions are small, except in terms of fleet age and mileage. For example, households in the San Joaquin Valley AQMD have the oldest and highest-mileage fleets, while those in San Diego County have the youngest and second-highest mileage fleets. Households in Sacramento Metropolitan have the second-youngest, lowest-mileage, and most fuel-efficient fleets.

Table 5-7. Vehicle Fleet Characteristics, by AQMD Geography

	Vehicle Holdings			Fleet Age			Fleet Mileage			Main Vehicle MPG		
	N.	Mean	S.D.	N.	Mean[1]	S.D.	N.	Mean[2]	S.D.	N.	Mean	S.D.
Bay Area	170	2.0	1.4	166	2006.3	8.3	162	87,060	82,099	165	24.9	8.7
Sacramento	48	2.1	1.1	48	2008.3	8.8	48	68,744	90,285	48	25.1	9.8
San Diego	147	1.7	1.1	137	2008.8	6.9	134	92,015	99,424	137	24.0	8.0
SJV	186	2.0	1.2	176	2005.9	8.7	156	108,243	96,394	175	24.6	9.5
South Coast	732	2.0	1.1	715	2007.5	7.1	681	86,014	76,302	712	22.7	8.2
Other	298	2.1	1.2	296	2006.9	7.4	277	90,028	77,549	290	23.5	7.1
Sample Avg.	**1,580**	**2.0**	**1.2**	**1,537**	**2007.2**	**7.6**	**1,458**	**89,280**	**82,387**	**1,527**	**23.5**	**8.3**

[1] The difference in mean fleet age is statistically significant at P<0.05 between San Diego and SJV.

[2] The difference in mean fleet mileage is statistically significant at P<0.05 between SJV and South Coast, and at P<0.10 between Sacramento and SJV.

5.3. Vehicle Body Type and Fleet Composition

We also examine the body type of vehicles held by low- and moderate-income households and the composition of household-level vehicle fleets. We try to examine whether there are trends in the complementarity of vehicles held by a given household. For example, in the previous section our analysis revealed the trend that household vehicle holdings increase as household size increases, across different incomes, ethnicities, urbanization geographies, and AQMDs. One might expect households with four or more vehicles to own at least one large-sized vehicle such as a van. However, there are no known studies or data points to which we can compare these results.

The likely reason for this lack of previous research is due to the inaccessibility of vehicle body type data in other data sources. In order to examine body type and fleet composition among survey vehicles, we had to undertake significant recoding of data on vehicle makes/models and recategorize that data into vehicle body types. As shown in Table 5-8, we first used unique make/model vehicle combinations in the dataset (3,188 vehicles) to manually code each vehicle into one of 13 different body type classifications.

Table 5-8. Vehicle Body Type Classifications

	N.	Pct.
1. Small Vehicle	**1,320**	**41%**
1. Subcompact Car	237	7%
3. Compact Car	954	30%
12. Sports Car	129	4%
2. Medium Vehicle	**1,126**	**35%**
2. Small SUV/Crossover	596	19%
5. Midsize Car	282	9%
7. Large Car	214	7%
9. Small Station Wagon	0	0%
11. Midsize/Large Station Wagon	34	1%
3. Large Vehicle	**718**	**23%**
4. Midsize/Large SUV	190	6%
6. Minivan	127	4%
8. Pickup Truck	350	11%
10. Van	51	2%
4. Other	**24**	**1%**
Total	**3,188**	**100%**

These options were modeled after the body type class options offered to respondents in the vehicle choice set portion of the survey (the results of which are discussed in Chapter 4).[4] Using these categories, compact cars were the most common category, representing nearly one-third of all vehicles held by surveyed households. Small SUVs or crossovers represented nearly one-fifth of all vehicles. While comparison points from outside data sources are few, it does appear that surveyed households held fewer large vehicle and SUVs than shown in U.S. new vehicle purchase patterns, according to recent estimates (IHS, 2014).

For the analysis, we further condensed these categories to three broader vehicle groups based on vehicle size and estimated fuel economy, as shown in Table 5-9. This table also shows the most common vehicle and its average vehicle age and fuel economy in each of the 13 categories for illustration purposes.

[4] In doing this manual classification we accounted for model year as some body types of a make/model change over the years. We also added a category class for sports cars.

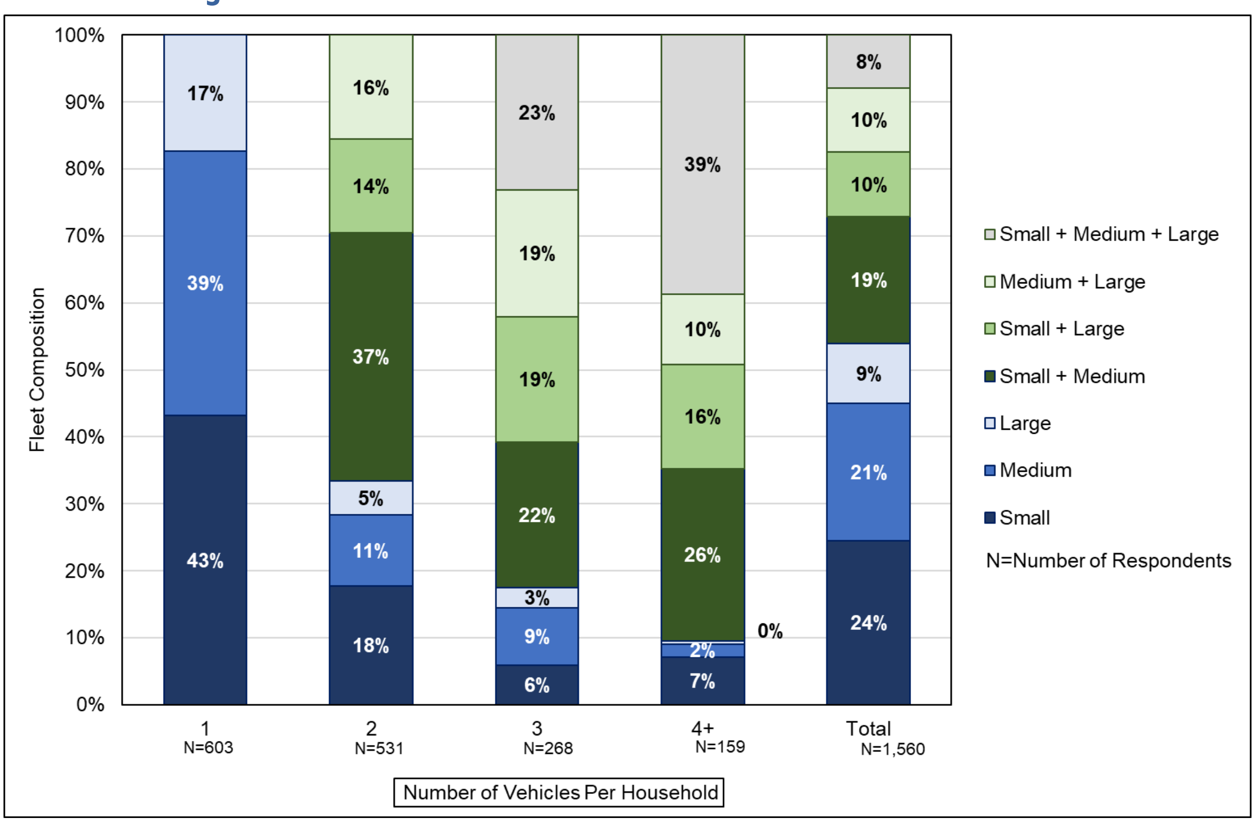
Table 5-9. Condensed Vehicle Body Type Categories and Example Vehicles

Type Category	Type	Example Vehicle	Avg. MPG	Avg. Year
1. Small Vehicle (N=1,320, 41% of sample)	Subcompact Car	Honda Civic	26	2008
	Compact Car	Toyota Corolla	26	2008
	Sports car	Ford Mustang	20	2003
2. Medium Vehicle (N=1,126, 35% of sample)	Small SUV/Crossover	Honda CRV	20	2008
	Midsize Car	Chevy Malibu	24	2008
	Large Car	Chrysler 300	21	2005
	Midsize/Large Station Wagon	Subaru Outback	23	2005
3. Large Vehicle (N=718, 23% of sample)	Midsize/Large SUV	Chevy Tahoe	16	2005
	Minivan	Toyota Sienna	19	2006
	Pickup Truck	Ford F-150	14	2006
	Van	Chevy Astro	16	2004

Having condensed vehicle types into three categories, we were then able to describe the prevalence of different fleet packages across households with different numbers of vehicles. Figure 5-4 shows the presence of at least one body type of vehicle present depending on the combination category.

For households with two vehicles, the most common fleet package was to have one small and one medium vehicle (37%), and the second most common fleet package was for a household to have two small vehicles (18%). On the other hand, among all households with three vehicles, 6% own only small vehicles, while 19% own a combination of medium and large vehicles (this could be two medium and one large or one medium and two large). Overall, most households have a fleet composition of small- and medium-sized vehicles (64%). The most common fleet composition for households with three and four or more vehicles tends to be at least one small, one medium, and one large vehicle.

Figure 5-4. Fleet Package Combinations



Steps for future research using this data involve examining how different types of fleet packages are assembled by households with respect to household structure (household size and the number of drivers), travel needs, and socioeconomic factors. This data exploration, however, is outside the scope of this report.

5.4. Main Vehicle Operational and Maintenance Expenditures

Moving beyond fleet management, we examine the necessary expenditures by households to operate their self-reported "main vehicle."

Summary of Necessary Household Expenditure to Operate Vehicles

While a single quantitative metric notion of transportation affordability itself is subject to debate, the 15% "affordability threshold" for the percent of household expenditure on transportation is commonly used (Rice, 2004; Sanchez, Makarewicz, Hasa, and Dawkins, 2007; Smart and Klein, 2018). Our estimates of the expenditure burden for the main vehicle, which excludes known but unquantified registration, depreciation and parking costs, much less the necessary expenditure to operate other vehicles or alternative modes, already approaches this threshold. This finding suggests that California low- and moderate-income households likely pay far more than 15% of their annual income for necessary transportation expenditures.

Our most inclusive formula for calculating the necessary expenditure to maintain the household's main vehicle adds the following itemized expenditure categories:

Annual Expenditure to Maintain and Retain Vehicle = Annual Insurance Cost + Annual Fuel Cost + Annual Repair Costs + Annual Interest Paid on Vehicle Loan

We describe our process for calculating each itemized expenditure and then the total annual expenditure below. We note that, due to non-responses for some of the survey's itemized expenditures, compared to the total vehicle-holding sample of 1,568 households, our primary annual expenditure formula incorporates only 1,322 households, while our secondary necessary annual expenditure formula includes 526 households, and our tertiary formula includes fewer than 200 households.

We also note that other known necessary expenditures for vehicle operation and maintenance, which we did not measure in our survey, include vehicle registration fees[5] and expenditures on vehicle parking. These expenditures would certainly increase our aggregate annual expenditure estimates.[6] Moreover, we note that the reference points cited below for itemized and aggregate vehicle operation expenditures are not specific to low- and moderate-income households, as previous studies or reports have typically not focused on this population.

Calculating Annual Main Vehicle Insurance Expenditure

The first step we took in determining the annual cost of insurance was to exclude outliers from the variable where respondents were asked to report the monthly cost of insurance for the main vehicle. This is necessary due to the possibility of misinterpretation of the question. The range of answers might reflect the annual cost of insurance rather than the monthly cost, or the cost of insuring all household vehicles instead of the primary vehicle alone. For example, it is extremely unlikely that the monthly cost of insuring one vehicle is $8,500 (the max in the data range). For these reasons, we bounded the range of monthly insurance costs between $0-$500, based on the natural breaks of the distribution of the data.

In cases where respondents did not know the exact amount they paid for insurance, they were able to select a range of prices using their "best guess." The mean of each price range was calculated and applied to the respondents

[5] The California DMV estimates typical registration and tax costs for a single operational vehicle as comprising a $58 registration fee, $25 California Highway Patrol fee, $16-47 County/District fees, $25-$175 Transportation Improvement Fee, and a Vehicle License Fee of 0.65% of the market value of the vehicle (2018). See https://www.dmv.ca.gov/portal/dmv/detail/pubs/brochures/fast_facts/ffvr34 and https://cloudfront.escholarship.org/dist/prd/content/qt6vs3v6wh/qt6vs3v6wh.pdf?t=paw748.

[6] Other estimates of the cost of ownership also include vehicle value depreciation as a cost, although depreciation cannot be considered an expenditure.

with missing data where possible. For example, if a respondent selected "$81-100" as their best guess, the value $90.50 was imputed as their monthly insurance cost. Finally, we generated a new variable to calculate the yearly cost of insurance from the reported monthly costs (multiply by 12 months). These bounds put the average annual expenditure of insurance for surveyed households at $1,317 for 1,420 households (Table 5-10). This average annual derived expenditure among surveyed households seems plausible given that recent California estimates of full coverage automobile insurance are $1,588 (Connick, 2018), $1,654 (Glover, 2018), $1,673 (Gusner, 2017), $1,713 (Johnson, 2018), and $1,962 (Jacobs, 2018). Glover also estimates minimum coverage automobile insurance expenditures to be about $629 per year in California (2018).

Table 5-10. Annual Insurance Expenditures, by Income

	N.	Mean	S.D.	Mean Pct. Income
<$25,000	416	$1,249	$1,058	18.4%
$25K-$50K	532	$1,326	$1,328	3.8%
$50K-$75K	347	$1,452	$ 1,068	2.5%
>$75,000	125	$1,130	$467	1.4%
Sample Avg.	**1,420**	**$1,317**	**$1,123**	**7.5%**

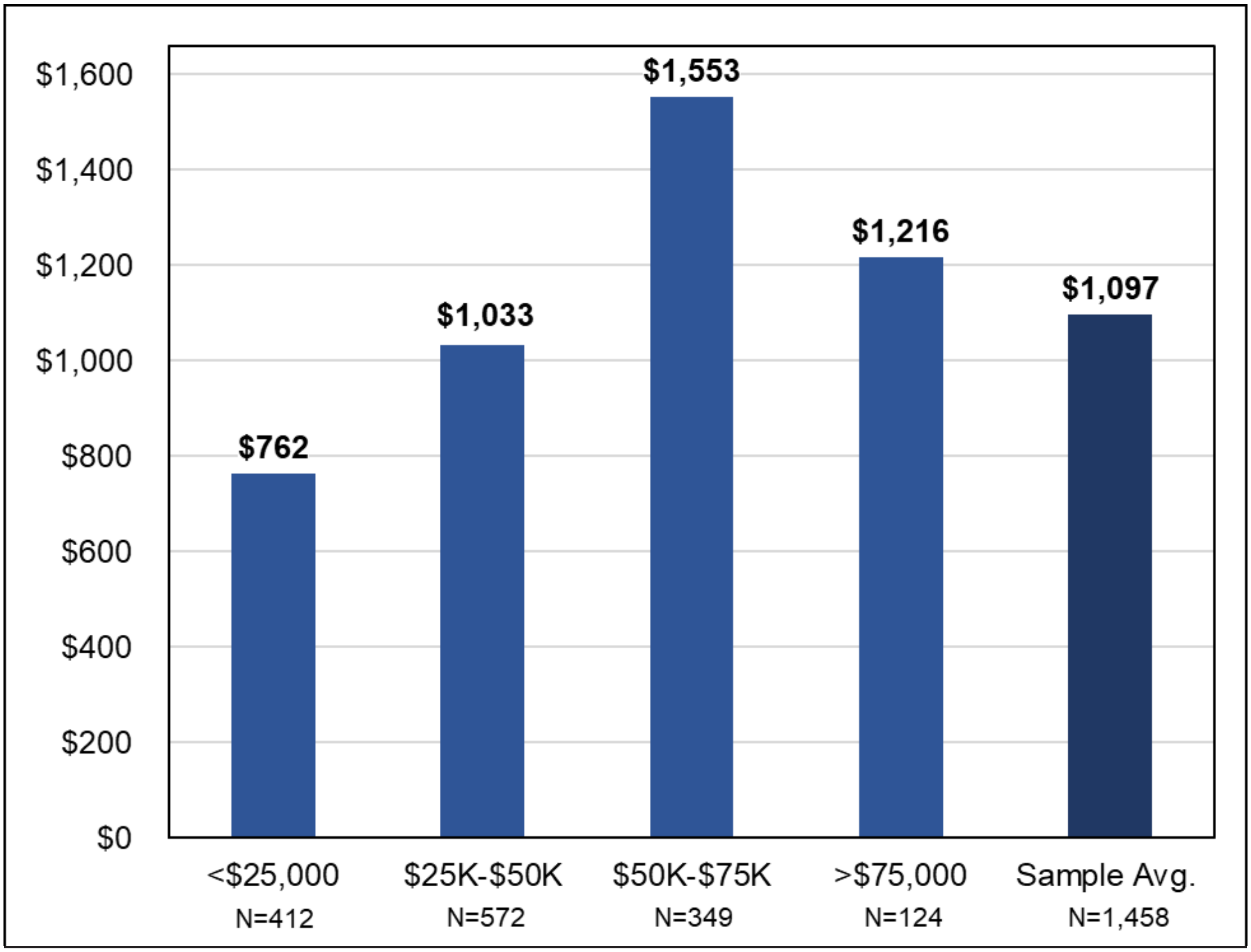
The difference in mean annual insurance expenditure is statistically significant at P<0.05 between $50-$75K and >$75K.

Calculating Annual Main Vehicle Fuel Expenditure

Calculating annual fuel cost required the cleaning and combination of several variables in the survey. We first removed outliers from data from questions asking survey respondents about their: a) self-reported cost of a gallon of gas in their area (N=1,538, Mean=$3.52, Range=$1.00-5.00), b) about their main vehicle's fuel economy in terms of miles per gallon (N=1,551, Mean=23.5, Range=1-70), and c) about the miles they drive their main vehicle per week (N=1,545, Mean=140, Range=0-800).7 Once outliers were removed, we combined these variables to estimate the annual expenditures on fuel per year. As Figure 5-5 shows, the final average annual expenditure on fuel which we calculate for the sample is $1,097 (N=1,458, Range=$0-$8,125).

[7] This calculates to 7,000 miles driven per year. It can be compared to per capita VMT (all income levels) in California of 9,000 (PPIC, 2011), 9,053 (Megna, 2016), 11,000 (Hymel, 2014), and 13,636 (Kandel, 2014).

Figure 5-5. Annual Fuel Expenditures, by Income



[1] The difference in mean annual fuel expenditure between all combinations of income groups is statistically significant at P<0.05, except between $25K-$50K and $75K, and $50-$75K and >$75K.

Calculating Annual Main Vehicle Repair Expenditure

A smaller set of households (N=613) reported needing to spend money on repairs for their main vehicle within the last year. After removing outlier responses deemed to be erroneous, the final reported average annual expense on major repairs was $715, with a range from $3 to $4,000. This compares to lower average household cost of vehicle maintenance and repairs (for all vehicles) reported of $384 per year (Palmer et al., 2018), $427 per year (Schmitz, 2016), and $524 per year (Gower, 2017).

1. Annual Aggregate Expenditure on Main Vehicle = Insurance + Fuel

To calculate an estimate of the annual expenditure to maintain and retain the household's main vehicle, we first include only those households that report valid insurance and fuel costs (Table 5-11), as adding repairs and loan payments drastically reduces our sample. In this most conservative estimation, the average expenditure per household on the main vehicle is $2,419, still representing above 10% of income. The percent of income expended on the main vehicle dramatically decreases as income levels rise.

Table 5-11. Annual Vehicle Expenditure, by Income

	N.	Mean[1]	S.D.	Mean Pct. Income
<$25,000	366	$1,935	$1,271	22.2%
$25K-$50K	513	$2,377	$1,874	6.8%
$50K-$75K	333	$3,020	$1,666	5.2%
>$75,000	111	$2,406	$782	3.0%
Sample Avg.	**1,322**	**$2,419**	**$1,652**	**10.3%**

[1] The difference in mean annual vehicle expenditure between all combinations of income groups is statistically significant at P<0.05, except between <$25K and >$75K, and $25-$50K and >$75K. The difference between <$25K and >$75K is significant at P<0.10.

2. Annual Aggregate Expenditure on Main Vehicle = Insurance + Fuel + Repairs

We can calculate an estimate of the annual expenditure to maintain and retain the household's main vehicle for only 526 households as a function of annual insurance expenditure + annual fuel expenditure + repair expenditure (in the past year only). The annual expenditure estimated for these households was $3,317, with a standard deviation of $2,151. This level of expenditure appears comparable to a 2013 "total cost of ownership" estimate for California households at $3,966 (Persaud, 2013).

The average percent of income expended on the main vehicle, or the proportional expenditure burden, is 16.2%. Interestingly, annual expenditures for large vehicle are pronouncedly higher than small or medium-sized vehicles, but income is higher for households who report their main vehicle as large so the proportional expenditure burden is less for these households.

As Table 5-12 shows, generally, higher-income households within the sample spend more on operating and maintaining their vehicles, but the percent of income expended on the main vehicle drops dramatically as income increases, from over 35% among households with incomes below $25,000 to less than 4% by households with incomes above $75,000.

Table 5-12. Annual Vehicle Expenditure (Including Repairs), by Income

	N.	Mean[1]	S.D.	Mean Pct. Inc
<$25,000	158	$2,513	$1,425	35.1%
$25K-$50K	198	$3,408	$2,397	9.5%
$50K-$75K	131	$4,211	$2,251	7.1%
>$75,000	39	$3,108	$935	3.7%
Sample Avg.	**526**	**$3,317**	**$2,151**	**16.2%**

[1] The difference in mean annual vehicle expenditure is statistically significant at P<0.05 between <$25K and $25-$50K, and <$25K and $50-$75K, and at P<0.10 between $50-$75K and >$75K.

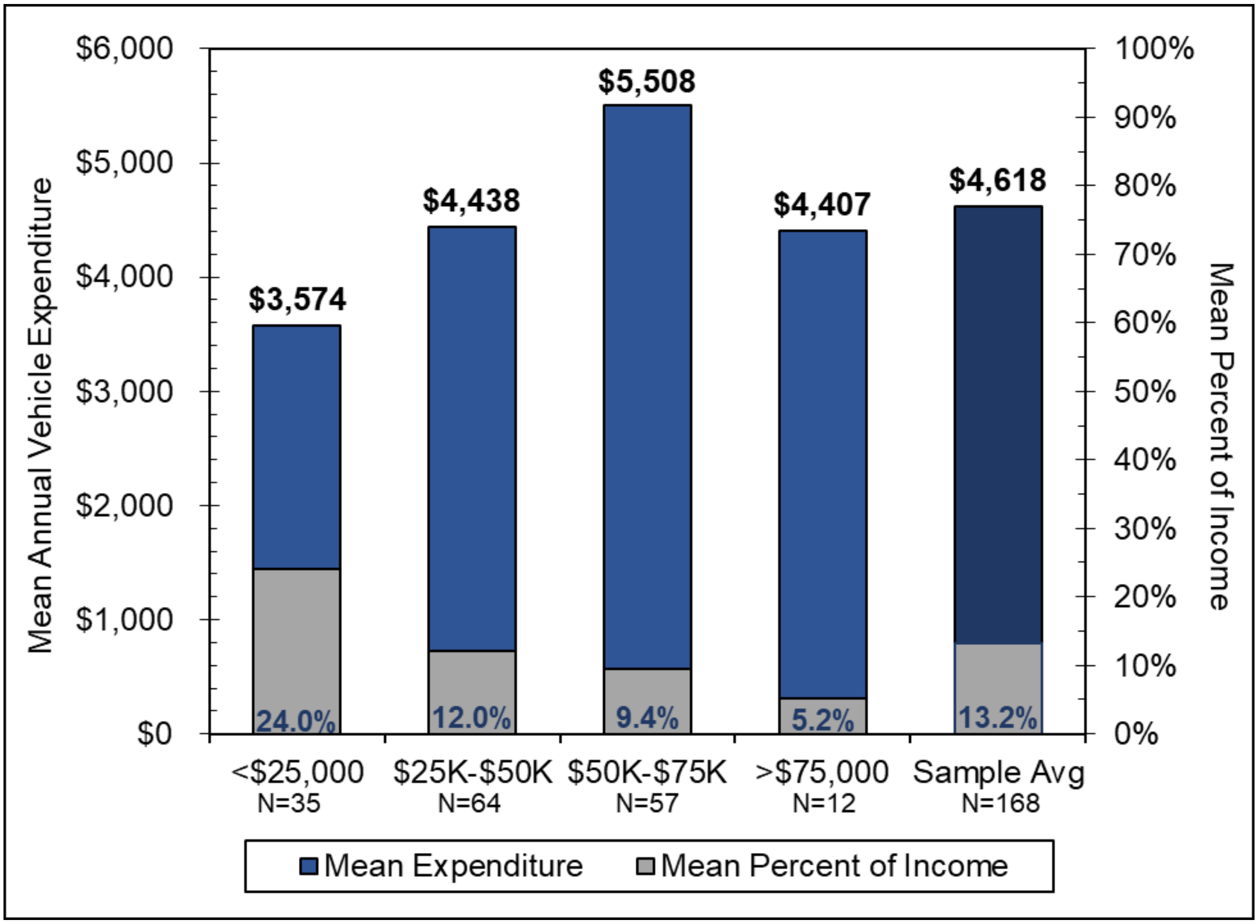
3. Annual Aggregate Expenditure on Main Vehicle = Insurance + Fuel + Repairs + Interest

We can calculate a more detailed annual expenditure figure and proportional expenditure burden for the subset of surveyed households who reported paying interest on an automobile loan in the last year.[8] After removing outliers, the 168 households in the survey reported paying an average of $592 in interest per year.

When adding interest to the aggregate expenditure and proportional expenditure burden calculations, however, the sample size of households with full data dropped considerably, and these households have both higher reported non-interest vehicle expenditures and higher incomes than households in our main expenditure calculation. Among the 168 households for which we have full data, we calculate an average annual expenditure of $4,618, with an average proportional expenditure burden of 13.2% (Figure 5-6).

[8] This involved the combination of five different variables in the survey.

Figure 5-6. Annual Vehicle Expenditure (Including Repairs and Interest Paid, Among Households Reporting This Data), by Income



5.5. Intention to Keep or Dispose of Main Vehicle

Finally, we examine what surveyed households report regarding their intentions to keep or replace their main household vehicle and what factors influence these responses. As with vehicle fleet packages, we are not aware of any previously published literature on this topic. However, understanding low- and moderate-income households' intentions regarding vehicle retention and replacement can help inform the operation of the state's vehicle scrappage and replacement incentive programs.

About half of the surveyed low- and moderate-income households reported that they only plan to keep their main household vehicle for two years, whereas more than 20% of households plan to keep their main vehicle for more than five years. This suggests that there is segmentation in vehicle retention plans within the surveyed population. Some of this variation may be explained by difference in income (Table 5-13), with higher-income households intending to keep their main vehicle for longer periods. Clear trends in vehicle retention intentions by race-ethnicity groups, or across urbanization geography or AQMD areas are not discernible, partly because the sample sizes for these subgroups were quite small.

Table 5-13. How Long Households Plan to Keep Main Vehicle, by Income

Years	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Sample Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
< 1	96	21%	105	18%	46	13%	24	17%	271	17%
1 - 2	175	37%	187	32%	102	28%	28	20%	492	32%
2 - 4	90	19%	145	25%	108	30%	43	31%	387	25%
5+	88	19%	127	22%	88	24%	42	30%	346	22%
Unsure	18	4%	23	4%		5%	2	1%	63	4%
Sample Total	**467**	**100%**	**588**	**100%**	**364**	**100%**	**140**	**100%**	**1,559**	**100%**

On other hand, households with older vehicles expressed a greater intent to dispose of their vehicle compared to households with newer vehicles (Table 5-14), except for 4% with older vehicles who are unsure. There is a difference in vehicle age of 2.5 years between households who intend to keep their vehicle less than a year as opposed to those who intend to keep their vehicle five or more years.

Table 5-14. Mean Vehicle Age, by How Long Households Plan to Keep Main Vehicle

Years	N.	Mean[1]	S.D.
< 1	267	2006.1	7.2
1 - 2	487	2007.1	6.4
2 - 4	387	2008.3	6.5
5+	344	2008.6	6.6
Unsure	63	2005.2	5.0
Sample Avg.	**1,548**	**2007.5**	**6.6**

[1] The difference in mean vehicle age is statistically significant at P<0.05 between 5+ Years and Unsure, and at P<0.10 between <1 and 2-4 Years, and <1 and 5+ Years.

Households are nearly evenly split in reporting that they have seriously considered getting rid of their main household vehicle, with 44% reporting that they have done so. Among those, however, vehicle preference, rather than expenditure, safety or need, appears to be the main driver of this consideration (Table 5-15).

Table 5-15. Main Reasons for Considering Getting Rid of Vehicle

	N.	Pct.	Mean (MY)	S.D.
Too expensive to maintain	131	19%	2005.6	6.4
Unreliable or unsafe	77	11%	2005.3	5.6
Need more seating or cargo space	106	16%	2007.5	6.1
Want a different or newer make/model	268	40%	2006.4	6.1
Can no longer afford vehicle	25	4%	2008.3	5.0
Other	69	10%	2006.9	7.0
Sample Avg.	**676**	**100%**	**2006.4**	**6.2**

By far the most common reason given by households who have considered getting rid of their current vehicle is that they want a different or newer make/model (40%). This indicates that, even among households with constrained resources, vehicle aesthetics, style, and personal preferences are extremely salient in household decision making. In fact, households with incomes below $25,000 are much more likely to report that their main consideration is vehicle make/model (46%) than households with incomes above $75,000.

When asked whether households would be willing to participate in a vehicle scrapping program without being offered a replacement vehicle, over 40% indicated willingness to accept $1,500 or less to scrap their main vehicle (Table 5-16). The $1,500 threshold is salient as it is the amount offered by the Bureau of Automotive Repair through its Customer Assistance Program to low-income households to scrap a vehicle if it has failed its last smog check test. Just less than 30% indicated they would accept between $2,000 and $3,000 to scrap their main vehicle, while the remaining 30% of the sample would not accept $3,000 and might not accept any amount offered to them.

Table 5-16. Lowest Amount of Money Households Would Accept to Participate in a Vehicle Scrapping Program

Amount offered	N.	Pct.
$250	49	4%
$500	102	8%
$750	68	5%
$1,000	179	14%
$1,500	145	11%
$2,000	88	7%
$2,500	64	5%
$3,000	208	16%
None of the above	191	15%
I would not participate	175	14%
Sample Total	**1267**	**100%**

When asked whether they would still choose their most preferred vehicle (derived from the choice experiments presented to them in Chapter 4) if it meant they had to dispose of their current main vehicle, more than four-fifths of survey respondents indicated they would. In this case, the method of disposal was not specified. The only clear difference in willingness to dispose of their main vehicle was seen among the highest-income households surveyed, as shown in Table 5-17.

Table 5-17. Percent of Households Who Would Choose the Choice Set Vehicle If Replacing Current Main Vehicle, by Income

	Yes		No		Sample Total	
	N	Pct	N	Pct	N	Pct
<$25K	409	84%	79	16%	488	100%
$25K-$50K	502	85%	88	15%	589	100%
$50K-$75K	304	85%	52	15%	355	100%
>$75K	103	74%	37	26%	140	100%
Sample Total	**1,317**	**84%**	**256**	**16%**	**1,573**	**100%**

Without being offered an incentive, 70% of respondents indicated that they would be willing to dispose of their vehicle by sending it to the junkyard if that was a condition of obtaining their preferred vehicle from the choice set experiments. There is some variation across income groups, with the highest proportion of respondents (74%) earning below $25,000 a year, and the second highest (71%) earning more than $75,000 a year.

If respondents indicated that they were not willing to scrap their main vehicle as a precondition, they were then asked if they would send their vehicle to the junkyard for $1,500. Overall, only 46 respondents (10%) indicated they would change their mind with this level of incentive. There was little discernible variation across income, race and ethnicity, urbanization geography, or air quality management districts, although this may be due to the very small sample sizes for these subgroups.

References

Bedsworth, L., Hanak, E. and Kolko, J. (2011). Driving change: Reducing vehicle miles traveled in California. *Public Policy Institute of California.* See https://www.reimaginerpe.org/files/PPIC%20Report%20-%20Driving%20Change%202-17-11.pdf.

Bhat, C. R., Sen, S. and Eluru, N. (2009). The impact of demographics, built environment attributes, vehicle characteristics, and gasoline prices on household vehicle holdings and use. *Transportation Research Part B,* 43, 1–18.

Blumenberg, E., & Pierce, G. (2012). Automobile ownership and travel by the poor: Evidence from the 2009 National Household Travel Survey. *Transportation Research Record: Journal of the Transportation Research Board*, 2320, 28-36.

Cackette, T., Wallauch, J., Hedglin, P. and Ford, T. (2012). California Smog Check and Vehicle Retirement Programs. Air Resources Board and Bureau of Automotive Repair.

Choo, S. and Mokhtarian P.L. (2004). What type of vehicle do people drive? The role of attitude and lifestyle in influencing vehicle type choice. *Transportation Research Part A*, 38, 201–222.

Choo, S., Shafizdeh, K. and Niemeier, D. (2007). The development of a prescreening model to identify failed and gross polluting vehicles. *Transportation Research Part D,* 12, 208–218.

Connick, W. (04 Oct 2018). Car insurance for low income households. *Insurify*. See https://insurify.com/blog/car-insurance/what-you-should-know-about-low-income-car-insurance.

Dixon, L. and Garber, S. (2001). Fighting air pollution in Southern California by scrapping old vehicles. *RAND Institute for Civil Justice.* See https://www.rand.org/content/dam/rand/pubs/monograph_reports/2007/MR1256.pdf.

Fang, H. A. (2008). A discrete-continuous model of households' vehicle choice and usage, with an application to the effects of residential density. *Transportation Research Part B: Methodological,* 42(9), 736-758.

Glover, L. (14 Jun 2018) Finding cheap full coverage car insurance. *Nerdwallet*. See https://www.nerdwallet.com/blog/insurance/car-insurance-basics/cheap-full-coverage-insurance.

Gower, J. (07 Sep 2017). Where do car repair costs put the most strain on budgets? *Repair Pal.* See https://repairpal.com/blog/car-repair-costs-by-county-sept-2017

Gusner, P. (28 July 2017). Car insurance rates by state, 2017 edition. *Insure, Quadrant Information Services.* See https://www.insure.com/car-insurance/car-insurance-rates.html.

Hymel, K. M. (2014). Factors influencing vehicle miles traveled in California: Measurement and analysis. *California State University, Northridge Department of Economics.* See https://www.csus.edu/calst/frfp/vmt_trends_hymel_report.pdf.

IHS Markit (2014). SUVs and Crossovers Overtake Sedans to Become Most Popular Vehicle Body Style in the U.S., IHS Automotive Finds. See https://news.ihsmarkit.com/press-release/automotive/suvs-and-crossovers-overtake-sedans-become-most-popular-vehicle-body-style-

Jacobs, S. (22 Mar 2018). Americans spend an average of $125 a month on car insurance. *Business Insider.* See https://www.businessinsider.com/average-cost-car-insurance-in-every-state-ranked-2018-3.

Johnson, C. (28 Feb 2018). Here are the most and least expensive states for car insurance in 2018. *Clark.* https://clark.com/cars/car-auto-insurance-rates-states-highest-lowest.

Jong, G., Fox, J., Daly, A., Pieters, M. and Smit, R. (2004). Comparison of car ownership models. *Transport Reviews*, 24(4), 379-408.

Kandel, A. (07 Feb 2014). Annual per-capita California driving 1.5 times the national average. *Air Quality Matters*. See https://alankandel.scienceblog.com/2014/02/07/annual-per-capita-california-driving-1-5-times-the-national-average.

Megna, M. (21 July 2016). Average miles driven per year by state. *Car Insurance.* See https://www.carinsurance.com/Articles/average-miles-driven-per-year-by-state.aspx.

Mitra, S. K. and Saphores, J. D. M. (2017). Carless in California: Green choice or misery? *Journal of Transport Geography*, 65, 1-12.

Murakami, E. and Young, J. (1997). Daily travel by persons with low income. Presented at the NPTS Symposium, Bethesda, Maryland, October 29-31.

Palmer, K., Tate, J. E., Wadud, Z. and Nellthorp, J. (2018). Total cost of ownership and market share for hybrid and electric vehicles in the UK, US and Japan. *Applied Energy*, 209, 108-119.

Persaud, C. (2013). Chart: Car-ownership costs by state. *Bankrate*. See https://www.co.washington.or.us/LUT/TransportationFunding/upload/Bankrate-Car-Ownership-Cost-by-State-August-2013.pdf.

Pierce, G., & Connolly, R. (2018). Can Smog Repairs Create Social Justice? The Tune In & Tune Up Smog Repair Program in the San Joaquin Valley. UCLA Luskin Center for Innovation report.

Rice, L. (2004). Transportation spending by low-income California households: Lessons for the San Francisco bay area. San Francisco, CA: Public Policy Institute of California.

Sanchez, T. W., Makarewicz, C., Hasa, P. M. and Dawkins, C. J. (2007). Transportation costs, inequities, and trade-offs. *Transportation Research Board 86th Annual Meeting*. Washington, DC. See https://www.academia.edu/download/44170484/Transportation_Costs_Inequities_and_Trad20160328-26414-1nq5u4i.pdf.

Santos, A., McGuckin, N., Nakamoto, H. Y., Gray, D. and Liss, S. (2011). Summary of Travel Trends: 2009 National Household Travel Survey. *FHWA, U.S. Department of Transportation*, Washington, D.C.

Schmitz, M. (15 June 2016). Survey: These 10 states have the highest repair costs. *USA Today*. See https://www.usatoday.com/story/money/cars/2016/06/15/survey-california-has-nations-highest-car-repair-costs/85938980/.

Smart, M. J. and Klein, N. J. (2018). Complicating the story of location affordability. *Housing Policy Debate*, 28(3), 393-410.

U.S. Census Bureau. (2016). American Community Survey 2012 – 2016. *American Factfinder*.

U.S. States Department of Transportation Federal Highway Administration (2009). National Household Travel Survey.

CHAPTER 6

POTENTIAL BARRIERS TO VEHICLE ACCESS AND INTEREST IN ALTERNATIVE TRAVEL MODES

Low- and moderate-income households face multiple barriers to robust levels of vehicle access and usage. In short, in addition to income and financing constraints to maintain or purchase a vehicle (detailed in Chapters 4 and 5 of this report), these households may face barriers to maintaining vehicle access. For instance, ongoing fees incurred to use a vehicle legally — for driver's license renewals, smog checks, automobile registration, insurance — by their very nature constitute a higher percentage of the budgets of low-income households when compared to higher-income households.

More broadly, we report results on a range of barriers which low- and moderate-income households face, including capacity to cope with vehicle breakdown, relative lack of information in decision making, as well as financial, resource or budgeting challenges, and/or discrimination, which compound pure cash flow obstacles. Relatedly, we consider whether households view use of alternative travel modes as not only a second-best solution to meet household travel needs in light of vehicle access deficits, but also as a best solution if it can be made as convenient and timely as vehicle use.

To inform programs and policies that seek to better understand and support more widespread access to and use of clean vehicles among low- and moderate-income households in California, our survey asked a series of questions regarding current barriers to personal vehicle access,[1] as well as questions regarding access to and interest in using alternative modes. The responses to these questions allow us to answer the following research questions:

1. **Do surveyed households face additional barriers compared to higher income households in getting vehicle repairs, the price of fuel, obtaining insurance or credit status? If so, what socioeconomic and geographic factors are these challenges associated with?**
2. **How often do surveyed households use alternatives to driving their personal vehicle? How often would they consider alternative modes if they were made as convenient and affordable as using a personal vehicle?**

Additional results on each of these topics, requested in CARB's analysis plan, are provided in the Appendix to this chapter.

6.1. Additional Barriers to Vehicle Access: Fuel, Insurance, Repairs, and Credit

We first explore the potential barriers to vehicle usage related to reported fuel, insurance, and repair expenditures for the main vehicle: the three main drivers of annual expenditure to operate a vehicle as calculated in Chapter 4. We next analyze credit as it relates to the ability to finance vehicle purchases, which occur less often, but are typically larger, as analyzed in Chapter 5.

Fuel Expenditures

Households in Sacramento ($3.36) and San Joaquin Valley ($3.43) do report slightly lower prices for a gallon of gasoline than the state average ($3.52). We find little variation in the price of fuel, however, across surveyed households, either by socioeconomic status or by geography.

[1] While we originally asked direct questions regarding difficulties in purchasing a vehicle and vehicle insurance in the soft launch of the survey (as described in Chapter 1), the responses to these questions were not informative. Accordingly, they were eliminated in the full launch of the survey. These questions included the following: "Has your household ever had any difficulty in purchasing car insurance? "Did you encounter any difficulty in purchasing your [main vehicle]? and "What challenges did you encounter when you tried to purchase your [main vehicle]"?

Accordingly, our focus is not on average fuel price but rather on fuel expenditures for the household's main vehicle (the survey average for which is around $1,100 on an annual basis). Fuel expenditure reflects not only fuel price but also the fuel economy of the vehicle driven, and the distance the vehicle is driven. All else equal, there is no strong body of evidence from previous studies to suggest whether we should expect low- and moderate-income households to drive less fuel-efficient vehicles or to drive more fuel-efficient vehicles as compared to higher-income households.

Table 6-1. Mean Weekly Mileage, by Income

	N.	Mean[1]	S.D.
<$25,000	457	95	122
$25K-$50K	589	126	147
$50K-$75K	362	193	148
>$75,000	126	147	91
Sample Avg.	**1,535**	**134**	**143**

[1] The difference in mean weekly mileage is statistically significant at P<0.05 between <$25K and $25-$50K, <$25K and $50-$75K, and $25-$50K and $50-$75K. The difference is significant at P<0.10 between <$25K and >$75K.

We do know, however, from past studies that lower-income households drive fewer miles than higher-income households (Blumenberg and Pierce, 2012). This trend appears to be supported by our data, as Table 6-1 suggests. The average vehicle miles traveled (VMT) reported by respondents was 134 miles weekly, or 19.1 miles daily. This daily VMT is very similar to the 18.9 miles reported by households earning less than $50,000 who participated in the 2013 California Household Travel Survey (CHTS).

There is a positive and statistically significant trend between income and average weekly mileage. Respondents earning between $50,000 and $74,999 drive the most in a week, or about 193 miles on average. Respondents located in suburban areas drive (an average of 45) more miles a week than respondents in urban areas. Drivers who live in urban areas have the lowest weekly mileages, on average (110 miles compared to 155 for suburban and 143 for rural).

Table 6-2. Annual Fuel Expenditures, by Urbanization Geography

	Annual Fuel Expenditures			VMT Per Week		Fuel Economy	
	N	Mean[1]	S.D.	Mean[2]	S.D.	Mean	S.D.
Urban	596	$941	$1,072	112	117	23.8	7.4
Suburban	627	$1,224	$1,256	156	156	24.2	8.2
Rural	212	$1,164	$1,070	144	129	23.8	7.7
Sample Avg.	**1,435**	**$1,097**	**$1,169**	**136**	**139**	**24.0**	**7.9**

[1] The difference in mean annual fuel expenditures is statistically significant at P<0.05 between Urban and Suburban.

[2] The difference in mean VMT per week is statistically significant at P<0.05 between Urban and Suburban.

In terms of annual fuel expenditures, as Table 6-2 shows, we find, as expected, that urban households spend significantly less (about 25%) on fuel than either suburban or rural households. This is mainly due to urban households driving far fewer miles per week (112 miles compared to 155 and 144), since there is little variation in the average fuel economy of the primary household vehicle across urbanization geographies. The differences in fuel expenditures and miles driven are even starker by AQMD area, with Bay Area residents spending an average of about two-thirds of the amount of residents outside major AQMD geographies (see Table 6-3).

Table 6-3. Annual Fuel Expenditures, by AQMD Geography

	Annual Fuel Expenditures N	Mean[1]	S.D.	VMT Per Week Mean[2]	S.D.	Fuel Economy Mean	S.D.
Bay Area	156	$857	$1,031	108	127	25.0	8.5
Sacramento Metro	46	$1,198	$1,543	157	183	25.3	9.3
San Diego	130	$1,148	$1,184	133	118	23.9	8.1
San Joaquin Valley	165	$927	$1,000	122	127	24.6	9.3
South Coast	660	$1,073	$1,152	130	137	23.5	7.6
Other	278	$1,351	$1,204	170	147	23.9	6.7
Sample Avg.	**1,435**	**$1,097**	**$1,169**	**136**	**139**	**24.0**	**7.9**

[1] The difference in mean annual fuel expenditures is statistically significant at P<0.05 between Bay Area and Other, and SJV and Other, and at P<0.10 between South Coast and Other.

[2] The difference in mean VMT per week is statistically significant at P<0.05 between Bay Area and Other, and South Coast and Other, and at P<0.10 between SJV and Other.

Insurance Cost

Previous research has found that automobile insurance rates also place a disproportionate burden on disadvantaged households due to the widespread use of flat rates as well as redlining in low-income and high-minority neighborhoods (Ong and Stoll, 2007). We find that average insurance expenditures ($1,317) for the household's main vehicle are about 20% higher than fuel expenditures. In terms of insurance expenditures for the main vehicle, however, we find that lower-income households pay much less than higher-income households. This may be due to the value of the insured vehicle being higher for higher-income households.

Moreover, we find a statistically significant and large difference in the insurance expenditures of households who report as non-Hispanic White and all other racial and ethnic groups. Non-Hispanic Whites pay 20% less than any other racial or ethnic minority group, and Blacks pay much higher percentages of their reported household income than any other group. This difference does not appear to be explained by differences in income within the sample.

Table 6-4. Annual Insurance Expenditures, by Race and Ethnicity

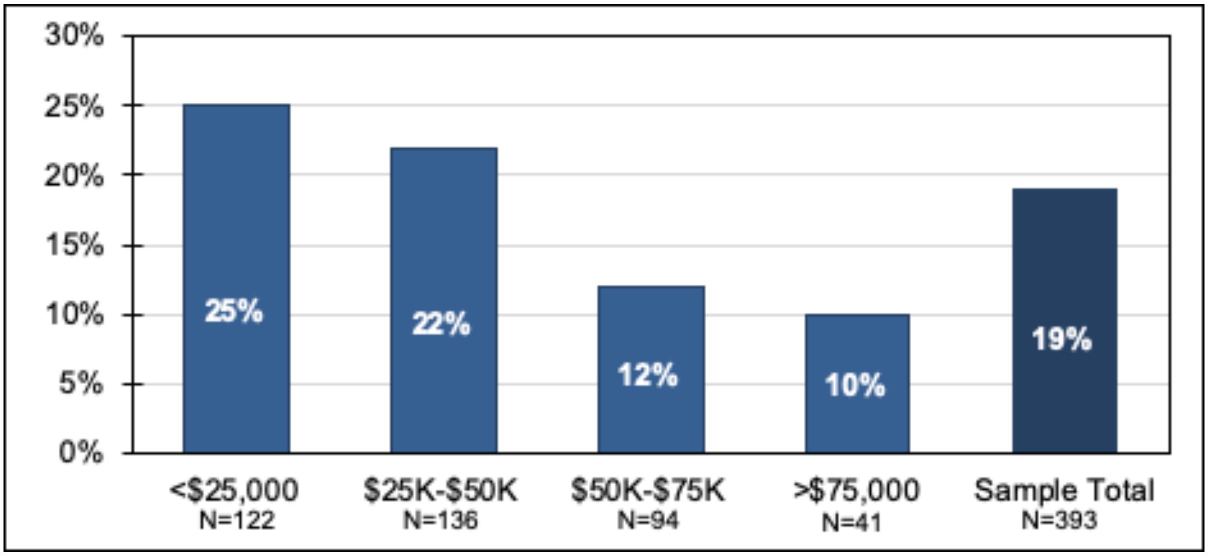
		N.	Mean[1]	S.D.	Mean Pct. Inc.
Non-Hispanic	White	401	$1,111	$1,245	4.1%
	Black	130	$1,525	$1,151	22.8%
	Asian	66	$1,221	$780	5.3%
	Other	64	$1,562	$1,275	9.6%
	2+ Races	31	$1,649	$1,430	5.6%
Hispanic		729	$1,367	$946	6.8%
Sample Avg.		**1,420**	**$1,317**	**$1,123**	**7.5%**

[1] There are no statistically significant differences in mean annual insurance expenditures, except when White is compared to all other race/ethnicities combined (P<0.05).

Given the high expenditure of households on insurance, we also asked survey participants whether they were aware of and participated in the California Department of Insurance's Low Cost Automobile Insurance Program. About 25% of all households surveyed were aware of the program, and about 20% of those households (or 5% of all surveyed households) purchased their insurance through the program.

We found little difference in awareness of the program by income subgroup within the sample, and no notable differences in awareness by racial or ethnic subgroup. As Figure 6-1 shows, while sample sizes were too small to determine statistically significant differences, it does appear that, among households aware of the program, the lowest-income households in the sample were more likely to enroll in the program (25%) than the highest-income households (10%). We also find that, among households aware of the program, minority households were more likely to be enrolled, perhaps reflecting the difficulty they encounter in purchasing affordable insurance on the open market.

Figure 6-1. Low-Cost Automobile Insurance Program Participation, by Income (Among Households Aware of the Program)



Main Vehicle Repairs and Mobility

We also asked questions regarding the nature of the last "costly"[2] repair to the household's main vehicle, how recently it occurred, how much the household had to spend to make the repair, how long the vehicle was unavailable, and whether the main vehicle currently needed any major repairs.

About one-third of respondents reported that they never had to make or pay for major repairs to their main vehicle. As Table 6-6 shows, among those that did need repairs, the most common types were brakes (20%) and ignition system (11%). The prevalence of past recent repairs contrasts with the nearly 90% of responding households who owned a vehicle reporting that their main vehicle currently needed major repairs. The most common repairs currently needed are brakes (18%) and body, bumper, or windows (15%). This suggests that necessary vehicle repairs are being deferred by low- and moderate-income households.

[2] The definition of "costly" was left to the respondent's discretion.

Table 6-5. Most Common Past Repairs Performed and Current Repairs Needed[3]

	Past Repairs Performed		Current Repairs Needed	
	N. (YES)	Pct.	N. (YES)	Pct.
Body, bumper, or windows	96	6%	214	15%
Timing belt	141	9%	61	4%
Transmission	106	7%	128	9%
Exhaust system	62	4%	77	5%
Ignition system (battery, starter)	167	11%	69	5%
Brakes	318	20%	259	18%
Cooling system (radiator)	161	10%	74	5%
Fuel pump	82	5%	45	3%
Electrical system	92	6%	91	6%
Engine	151	10%	70	5%
Catalytic converter	44	3%	24	2%
Other	140	9%	319	22%
Total itemized repairs needed	**1560**	**100%**	**1,431**	**100%**

Among those who did have their vehicle repaired within the past three years and recalled the specific monetary burden of repairs, the mean expenditure for repair was $755. Not surprisingly, households who had repairs done in this period had older vehicles than those who did not obtain repairs. On average, as shown in Table 6-6, vehicles that needed repairs were unavailable for nine days, and older vehicles were more likely to have needed repairs than newer vehicles. Respondents also reported spending more and losing access to their vehicle for a longer period on less recent repairs, although this may be related to the likelihood of persons to remember and report the details of only more severe repairs in the distant past.

Table 6-6. Vehicle Age and Repair Monetary and Time Burden

	Vehicle Age (MY)			$ Spent on Repair			Days Unavailable		
	N.	Mean[1]	S.D.	N.	Mean	S.D.	N.	Mean	S.D.
<= 6 Months	445	2006.6	6.0	377	$660	$755	445	5.8	13.9
<= 1 Year	303	2006.4	6.7	236	$804	$817	301	14.7	48.9
<= 3 Years	207	2003.7	6.4	172	$896	$789	208	7.2	34.2
Never	507	2010.4	6.2	N/A	N/A	N/A	N/A	N/A	N/A
Unsure	94	2007.1	5.1	N/A	N/A	N/A	N/A	N/A	N/A
Sample Avg.	**1,556**	**2007.5**	**6.6**	**785**	**$755**	**$788**	**954**	**8.9**	**33.9**

[1] The difference in mean vehicle age is statistically significant at P<0.05 between all combinations of when the vehicle was last repaired, except between <=6 Months and <=1 Year, <=6 Months and Unsure, and <=1 Year and Unsure.

[2] The difference in mean amount spent on repairs is statistically significant at P<0.10 between <=6 Months and <=3 Years.

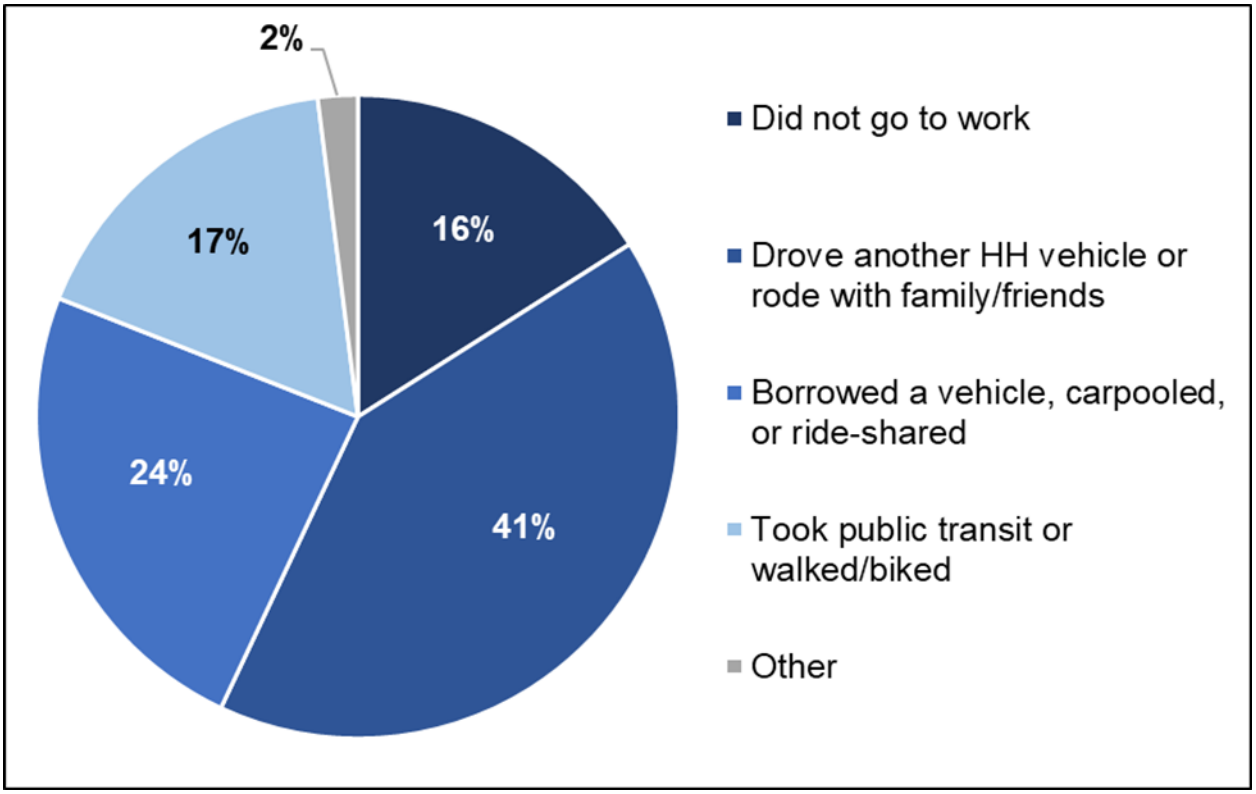
Among households reporting major repairs, about 35% said the inoperability of the vehicle prevented them from getting somewhere they needed to go. Within households surveyed, both lower-income and minority group status are correlated with more limited mobility during their main vehicle's unavailability, although neither difference is statistically significant. Households who were prevented from going to a destination because of their vehicle's inoperability were also asked about the nature of these destinations. The most common response was work, with errands being second most common (see Appendix).

Given that the work trip commute is often the main and self-reported most important trip for households, the survey also asked specifically how the respondent traveled to work while their main vehicle was being repaired (Figure 6-2). Over 50% reported still using a personal vehicle to get to work, although interestingly the highest

[3] Respondents were asked to indicate all necessary repairs needed, so multiple entries per vehicle were often specified.

share of respondents reported getting a ride with family or friends when their main vehicle was being repaired (29%), far outpacing driving another household vehicle (12%) and perhaps suggesting that no other household vehicle was available for this purpose. Nearly 20% of the sample reported using public transit (17%), far outpacing the use of transit on a regular basis, as shown below. Nearly one-sixth of the sample, however, reported not going to work (16%), suggesting the magnitude of the burden that vehicle breakdowns place on low- and moderate-income households.

Figure 6-2. Mode of Getting to Work While Main Vehicle Was Unavailable



Credit History and Assessment

Returning to barriers to vehicle purchase rather than maintenance, we also analyzed surveyed households' self-reported credit capacity and assessment, and the characteristics of their vehicle financing history. Low-income households may have little access to savings or credit. One study found that almost a third of low-income households have no bank account, just 17% have a FICO score above 600 — a typical cutoff for obtaining a bank loan — and 18% have no FICO score at all (Einav et al. 2012, 1393).

About 70% of all respondents reported having a credit card, but the lowest-income group in the survey (with incomes below $25,000) was much less likely (59%) than other income groups (73-76%) to hold one. Among racial and ethnic groups, Black households stand out as much less likely to hold a credit card (54% vs. a minimum of 64% for all other groups).

More important to the process of vehicle finance than the holding of a credit card is a household's credit score, although the two factors are related. Because of the sensitivities around asking households for their credit score, we instead asked them to self-assess their credit, despite the lack of specificity obtainable from this response. Lower-income households surveyed were again much more likely to assess their own credit as poor, or to have no credit history (Table 6-7).[4] Although the sample sizes for sub groups were small, Black households were also much less likely to assess their credit as "excellent" than all other groups.

[4] As shown in the Appendix to this chapter, low-income households were also less likely to have checked their credit, and thus have an accurate recall of their credit standing, than higher-income households.

Table 6-7. Credit Score Self-Assessment, by Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Excellent	83	17%	155	26%	93	26%	56	40%	387	24%
Good	128	26%	181	31%	171	47%	47	34%	527	33%
Fair	150	30%	161	27%	49	13%	10	7%	370	23%
Poor	76	15%	57	10%	35	9%	21	15%	189	12%
Unknown	29	6%	11	2%	10	3%	0	0%	49	3%
No history	32	6%	27	5%	8	2%	5	4%	73	5%
Sample Total	**498**	**100%**	**591**	**100%**	**366**	**100%**	**140**	**100%**	**1,595**	**100%**

There is a statistically significant relationship between the two variables at P<0.05, and it should be noted the table has cell sizes that approach 0.

Vehicle Finance Terms

As detailed in Chapter 5, 54% of respondents took out a loan to finance all or part of the purchase of their current vehicle, compared to 40% who paid cash. The high percentage who did not pursue vehicle financing may indicate difficulty in applying, qualifying, or getting approved for a loan; a lack of trust in financial intermediaries, or pure preference. Respondents with higher incomes were more likely to have taken out a loan to cover all or part of the price of their current vehicle, but we do not observe major differences across racial and ethnic groups (Table 6-8).

Table 6-8. Method of Payment for Main Vehicle, by Race and Ethnicity

	Non-Hispanic										Hispanic		Total	
	White		Black		Asian		Other		2+ Races					
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Cash	182	45%	53	38%	30	39%	36	49%	4	13%	300	39%	605	40%
Partial loan	107	26%	42	31%	30	39%	5	7%	6	19%	236	30%	426	28%
Full loan	79	19%	42	31%	13	17%	20	28%	18	55%	212	27%	384	26%
Other	40	10%	1	1%	4	5%	11	16%	4	13%	25	3%	85	6%
Sample Total	**407**	**100%**	**138**	**100%**	**77**	**100%**	**73**	**100%**	**32**	**100%**	**773**	**100%**	**1,500**	**100%**

[1] There is a statistically significant relationship between the two variables at P<0.05, and it should be noted the table has cell sizes that approach 0.

Credit scores, in turn, affect the favorability of the terms of loans taken out for vehicle purchase, as shown in Table 6-9. Respondents who assessed their credit as excellent or good obtained much better vehicle loan rates than those who assessed their credit as fair or poor. The average interest rate on a vehicle loan reported by surveyed households was 6.8%, which compares favorably to one scholarly estimate of the national average interest rate derived from the Consumer Expenditure Survey (Attanasio et al., 2008) and recent market estimates (Experian, 2018; Edmunds, 2018).

Table 6-9. Mean Interest Rate, by Credit Self-Assessment

	N.	Mean[1]	S.D.
Excellent	165	6.1%	6.3%
Good	288	5.3%	5.0%
Fair	203	8.9%	6.6%
Poor	78	10.2%	7.0%
Unknown	13	4.9%	3.5%
No credit history	22	3.3%	3.0%
Sample Avg.	**769**	**6.8%**	**6.3%**

[1] The difference in mean interest rate is statistically significant at P<0.05 between Good and Fair, Good and Poor, Fair and Unknown, Fair and None, Poor and Unknown, and Poor and None.

Of those who financed their vehicle purchase with a loan, the majority went to a bank, credit union, or finance company (58%), with a large minority financing through a dealership (37%). The average reported interest rate obtained from financial institutions and dealerships was very similar, as shown in Table 6-10. Less than 5% received a loan through less traditional means, such as from a friend or relative, although in these cases the reported rates were significantly lower.

Table 6-10. Mean Interest Rate and Length of Loan, by Type of Automobile Loan

	Interest Rate of Loan			Length of Loan (Years)		
	N.	Mean[1]	S.D.	N.	Mean	S.D.
Bank, credit union, or finance company	456	7.1%	6.2%	473	4.7	1.5
Dealership	282	6.7%	6.5%	296	4.5	1.6
From a friend or relative	26	2.9%	3.4%	28	3.1	1.5
Other	7	9.5%	9.3%	7	3.4	2.6
Sample Avg.	**772**	**6.8%**	**6.3%**	**804**	**4.6**	**1.6**

[1] The difference in mean interest rate is statistically significant at P<0.05 between Bank and Friend, and Dealer and Friend.

[2] The difference in mean loan length is statistically significant at P<0.05 between Bank and Friend, and Dealer and Friend.

We found that interest rates are higher on automobile loans taken out to cover the entire cost of the respondent's previous vehicle purchase, compared to partial loans. Interestingly, as shown in Table 6-11, we found the reported interest rates obtained from lower-income households are generally lower than for higher-income households.

Table 6-11. Mean Interest Rate by Method of Payment and Income

	Partial Loan			Full Loan			Sample Avg.[2]		
	N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.
<$25,000	103	4.5%	5.0%	72	5.2%	4.6%	174	4.8%	4.9%
$25K-$50K	153	7.6%	8.4%	121	9.2%	7.6%	274	8.3%	8.1%
$50K-$75K	92	5.5%	5.4%	138	7.3%	4.6%	229	6.6%	5.1%
>$75,000	55	6.0%	3.3%	38	8.1%	5.3%	94	6.9%	4.4%
Sample Avg.[1]	**403**	**6.1%**	**6.3%**	**369**	**7.6%**	**6.0%**	**772**	**6.8%**	**6.3%**

[1] The difference in mean interest rate is statistically significant at P<0.10 between Partial Loan and Full Loan.

[2] The difference in mean interest rate is statistically significant at P<0.05 between <$25K and $25-$50K.

Moreover, as Table 6-12 shows, non-Hispanic White respondents reporting paying the highest interest rates on auto loans on average compared to other racial/ethnic groups, partly because they are more likely to obtain a loan for the full value of the vehicle.

Table 6-12. Mean Interest Rate, by Method of Payment and Race/Ethnicity

		Partial Loan			Full Loan			Sample Avg.		
		N.	Mean	S.D.	N.	Mean	S.D.	N.	Mean	S.D.
Non-Hispanic	White	99	5.8%	6.1%	73	10.2%	10.1%	172	7.7%	8.7%
	Black	42	5.2%	6.4%	42	6.8%	3.0%	84	6.0%	4.8%
	Asian	30	5.5%	3.6%	13	3.0%	5.9%	44	4.7%	4.6%
	Other	4	6.8%	4.9%	20	5.0%	1.7%	25	5.3%	2.4%
	2+ Races	6	6.9%	7.7%	12	3.0%	2.6%	19	4.3%	4.8%
Hispanic		221	6.5%	5.8%	208	7.7%	5.1%	429	7.1%	5.5%
Sample Avg.[1]		**403**	**6.1%**	**6.3%**	**369**	**7.6%**	**6.0%**	**772**	**6.8%**	**6.3%**

[1] The difference in mean interest rate is statistically significant at P<0.10 between Partial Loan and Full Loan.

[2] The difference in mean interest rate is statistically significant at P<0.05 between White and Asian, and Asian and Hispanic, and at P<0.10 between 2+ Races and Hispanic.

6.2. Reliance on Alternative Travel Modes

In addition to examining the barriers to vehicle access, we also assess the use of alternative travel modes to the personal vehicle. While alternative modes are often considered not only as a second-best solution to meet household travel needs considering vehicle access deficits (such as mode of travel when vehicle is being repaired, as discussed above) they may also as a first-best solution if they can be made as convenient and timely as vehicle use.

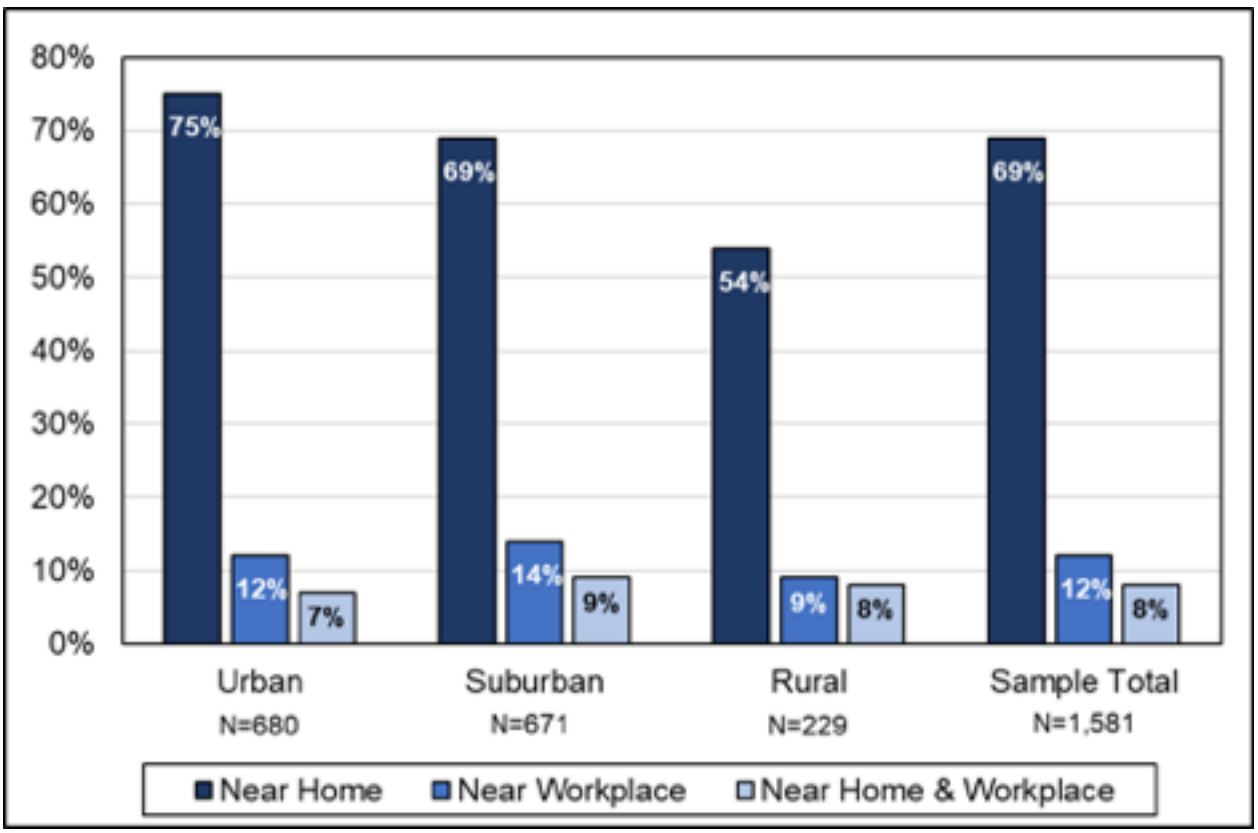
First, we analyze respondents' self-assessment of whether a transit stop (i.e., bus or rail) is located within a comfortable walking distance to either their home or workplace (see Table 6-13). More than two-thirds indicated that there was a walkable transit stop nearby their home, but less than 15% indicated such a stop near their workplace. Less than 10% indicated a transit stop near both locations. As seen in the Appendix to this chapter, differences in perceived proximity to a transit stop did not vary substantially by race or income.

Table 6-13. Walkable Transit Stop Near Both Home and Workplace

	No		Yes		Sample Total	
	N.	Pct.	N.	Pct.	N.	Pct.
Near Home	498	31%	1106	69%	1604	100%
Near Workplace	1404	88%	200	12%	1604	100%
Near Home & Workplace	1481	92%	123	8%	1604	100%

On the other hand, as expected, perceived walkable access to transit near the home was much higher in urban areas than in rural areas (Figure 6-3). Somewhat surprisingly, however, walkable transit access from both the home and workplace was no greater in urban areas than rural or suburban locations.

Figure 6-3. Walkable Transit Stop Near Both Home and Workplace, by Urbanization Geography



Second, we examine how often surveyed households use alternative modes to driving a personal vehicle available within the household. Table 6-14 shows the self-reported frequency of use of travel modes, with respondents able to select as many modes as they take, which again exhibit personal vehicle dominance. About 70% of respondents reported using a vehicle within their household daily, with 20% also reporting at least one walk trip. No other mode exceeded 6% of daily use.

Table 6-14. Frequency of Alternative Travel Mode Usage[5]

	Daily		Weekly		1x Per Wk		Monthly		Yearly		Never		Total
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.
Public transit	87	6%	75	5%	49	3%	118	8%	313	20%	898	58%	1,540
Vehicle in HH	1,097	70%	274	17%	70	4%	30	2%	18	1%	79	5%	1,568
Borrowed non-HH Vehicle	22	1%	47	3%	55	4%	57	4%	237	16%	1,085	72%	1,503
Carpool	23	1%	89	6%	66	4%	126	8%	199	13%	1,016	67%	1,518
Ride-share	33	2%	49	3%	56	4%	116	8%	295	19%	979	64%	1,528
Car-share	10	1%	23	2%	43	3%	36	2%	39	3%	1,365	90%	1,516
Rental Car	9	1%	15	1%	44	3%	51	3%	443	29%	943	63%	1,505
Govt-provided Vanpool	12	1%	32	2%	36	2%	46	3%	22	1%	1,365	90%	1,512
Govt-sponsored Dial-a-Ride	13	1%	33	2%	39	3%	33	2%	20	1%	1,381	91%	1,520
Work-provided Transportation	29	2%	36	2%	55	4%	54	4%	54	4%	1,291	85%	1,519
Bicycle	82	5%	68	5%	110	7%	106	7%	144	9%	1,003	66%	1,513
Walking	300	20%	251	16%	203	13%	175	11%	160	10%	443	29%	1,531
Other	22	3%	15	2%	34	4%	8	1%	22	3%	687	87%	788
Sample Total	**1,738**	**N/A**	**1,007**	**N/A**	**859**	**N/A**	**956**	**N/A**	**1,967**	**N/A**	**12,534**	**N/A**	**19,061**

Whereas the weekly percentage of respondents who took at least one walking trip is more than double the average reported by individuals with low-moderate incomes who took the 2013 CHTS (49% vs. 20%), the percentage of individuals taking at least one transit trip (14% vs. 18% for households with incomes of $50,000 to $100,000 and 26% for households with incomes below $50,000) or at least one biking trip (17% vs. 28% for households with incomes of $50,000 to $100,000 and 32% for households with incomes below $50,000) is much smaller than comparable households in the CHTS survey. Similarly small trends of usage of alternative modes were observed except on monthly or yearly intervals. More than 50% of respondents, however, indicated that they never took public transit or ride sharing.

We also examined the potential change in mode reliance if public transit were made free to respondents. Table 6-15 shows the percentage of respondents, by household income category, who indicate that they would take transit at least weekly if it were free, and the destination they would use transit to reach. In this case, just over 60% of respondents say they would use transit to go to work on a weekly basis, and nearly 60% say they would use transit to go to school.

[5] Respondents could select multiple choices at each time interval frequency.

Table 6-15. If Transit Rides Were Made Free to You, How Often Would You Use Them to Get to the Following Destinations?

	Work		School		Taking Children to School / Daycare / Activities		Shopping / Errands / Fitness		Healthcare		Entertainment / Social		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Daily	419	37%	252	30%	314	33%	304	22%	240	18%	263	19%	1,792	26%
Weekly	273	24%	232	27%	200	21%	490	36%	293	22%	420	31%	1,908	27%
Monthly	42	4%	32	4%	35	4%	92	7%	187	14%	162	12%	550	8%
Yearly	105	9%	42	5%	69	7%	97	7%	256	19%	144	11%	714	10%
Never	299	26%	295	35%	322	34%	370	27%	348	26%	380	28%	2,014	29%
Sample Total	**1,139**	**100%**	**854**	**100%**	**940**	**100%**	**1,353**	**100%**	**1,325**	**100%**	**1,369**	**100%**	**6,979**	**100%**

Finally, we examine responses by survey takers regarding whether they would seriously consider selling their main vehicle if transit were made as convenient and inexpensive as operating their vehicle (Table 6-16). Just less than 60% of respondents said they would choose to keep their vehicle in any case. The primary reason respondents gave for preferring to keep their vehicle was that they enjoyed driving (especially among higher-income households), with the second most common reason being that vehicle ownership provides an economic safety net. Despite the high necessary expenditure for vehicle operation, one-third of the sample combined preferred to keep their vehicle because they denied the premise that alternative modes could be as cheap or convenient for travel purposes as their main vehicle. This relative lack of use of or interest in transit reflects recent research on transit usage trends in Southern California (Manville, Taylor, and Blumenberg, 2018).

Table 6-16. Primary Reason Households Prefer to Own/Keep Vehicle Regardless of Alternative Travel Modes, by Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Ownership is an investment	62	23%	54	14%	28	13%	8	13%	152	16%
Ownership provides a safety net	60	22%	70	18%	73	34%	13	21%	216	23%
Ownership is valued by family/friends	10	4%	28	7%	14	6%	4	7%	56	6%
Alternative modes are more expensive	16	6%	11	3%	1	0%	0	0%	29	3%
Alternative modes are not as useful for my travel needs	33	12%	87	23%	28	13%	2	4%	150	16%
I enjoy driving	83	31%	107	28%	47	22%	25	42%	263	28%
Other	8	3%	27	7%	23	11%	7	11%	64	7%
Sample Total	**273**	**100%**	**383**	**100%**	**213**	**100%**	**60**	**100%**	**929**	**100%**

There is a statistically significant relationship between the two variables at $P<0.10$, and it should be noted the table has cell sizes that approach 0.

References

Attanasio, O. P., Koujianou Goldberg, P. and Kyriazidou, E. (2008). Credit constraints in the market for consumer durables: Evidence from micro data on car loans. *International Economic Review*, 49(2), 401-436.

Blumenberg, E., & Pierce, G. (2012). Automobile ownership and travel by the poor: Evidence from the 2009 National Household Travel Survey. *Transportation Research Record: Journal of the Transportation Research Board*, 2320, 28-36.

Edmunds (01 March 2018). Auto Loan Interest Rates Hit Highest Level in Eight Years in February, According to Edmunds Analysis. See.

Einav, L., Jenkins, M. and Levin, J. (2012). Contract pricing in consumer credit markets. *Econometrica*, 80(4), 1387-1432.

Experian (2018). State of the Automotive Finance Market: A look at loans and leases in Q2 2018. See https://www.experian.com/content/dam/marketing/na/automotive/quarterly-webinars/q2-2018-state-auto-finance-markets.pdf

Manville, M., Taylor, B. D. and Blumenberg, E. (2018). Falling Transit Ridership: California and Southern California. *Report for Southern California Association of Governments*. See http://www.scag.ca.gov/Documents/ITS_SCAG_Transit_Ridership.pdf

Ong, P. M., & Stoll, M. A. (2007). Redlining or risk? A spatial analysis of auto insurance rates in Los Angeles. *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management*, 26(4), 811-830.

CHAPTER 7

AWARENESS OF PLUG-IN ELECTRIC VEHICLES AND FACTORS MEDIATING PLUG-IN VEHICLE CHARGING POTENTIAL

Past research has found that low- and moderate-income households do not have as high an awareness of or usage levels of plug-in electric vehicles (PEVs) as higher income households (DeShazo et al., 2017). Moreover, long-distance travel patterns and built environment factors can make it impractical and difficult for households to charge plug-in vehicles to meet their travel needs, and thus to use PEVs as their primary mode of transportation (see DeShazo, Wong and Karpman, 2017; DeShazo, Krumholz, Wong and Karpman, 2017).

To inform programs and policies that seek to better understand and support more widespread access to and use of PEVs among low- and moderate-income households in California, our survey asked questions regarding household awareness of PEVs and incentives for PEV purchase. Additionally, questions were asked regarding long-distance, weekly, and commute travel patterns that affect the diversity of PEVs, which might fit household travel needs. Respondents were also asked questions regarding attributes of their place of residence that would make PEV charging more or less difficult. The responses to these questions allow us to answer the following research questions:

1. **Are surveyed households aware of PEVs, state incentives for PEVs, and nearby high-occupancy vehicle (HOV) lanes?**
2. **Do these households have long-distance, weekly, and commute patterns that would make home PEV charging difficult?**
3. **Do households live in residences that can easily accommodate PEV charging infrastructure, or would facilitating such access require additional support?**

Additional results on each of these topics, requested in CARB's analysis plan, are provided in the Appendix to this chapter.

7.1. Awareness of PEVs, PEV Incentives, and HOV Lane Access

We first analyze whether low- and moderate-income households have seen PEVs and are aware of existing state incentives offered to households to enable the purchase or lease of PEVs. While the PEV market is relatively new and awareness of PEVs in the general public is thus constantly evolving, it is safe to assume that gaps in awareness continue to be an obstacle to PEV adoption (Krause et al., 2013). We also assess households' self-reported access to HOV lanes. Drivers of PEVs currently retain special access to HOV lanes, and proximity to HOV lanes with this access has been shown to be a major inducement for PEV purchase in California (Sheldon and DeShazo, 2017).

In our survey, nearly 80% of respondents surveyed indicated that they had seen "all-electric or plug-in hybrid vehicles on the road or in parking lots." While both socioeconomic and geographic factors appear correlated with awareness levels, differences influenced by these factors appear relatively small. We note that this high level of self-reported basic visual awareness of PEVs does not necessarily translate to higher levels of awareness or knowledge of PEVs. Indeed, results of other recent surveys suggest that greater awareness may be much lower than basic awareness (Lambert, 2017; Kurani and Hardman, 2018), although each survey tends to phrase questions regarding PEV awareness slightly differently, and the variations may influence reported awareness results.

For instance, as shown in Table 7-1, there appears to be a positive relationship between household income and PEV awareness, with the highest-income group having a modestly larger proportion of respondents (83%) who have seen PEVs than the lowest-income group (75%). Moreover, non-Hispanic White and Asian households are slightly more likely to report having seen PEVs than Hispanic or Black households. There are also modest differences in awareness by urbanization geography, with suburban households (83%) more likely to have seen PEVs than rural (78%) or urban (74%) households. Differences across AQMD geographies are not particularly notable.

Table 7-1. Percent of Respondents Who Have Seen PEVs, by Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Sample Total	
	N.	Pct	N.	Pct	N.	Pct	N.	Pct	N.	Pct
Yes	376	75%	464	78%	294	81%	116	83%	1,250	78%
No	122	25%	130	22%	70	19%	24	17%	347	22%
Sample Total	**498**	**100%**	**594**	**100%**	**364**	**100%**	**140**	**100%**	**1,597**	**100%**

PEV Incentives Awareness

While nearly 80% of respondents were aware of PEVs, less than 40% of households surveyed reported that they were aware that "the State of California offered rebates that could lower your costs of purchasing" PEVs. As shown in Table 7-2, we again see a positive relationship between household income and awareness of incentives, although the relationship is less strong than between income and general PEV awareness. Differences in PEV incentive awareness are more notable across racial and ethnic groups, with Asian and Hispanic households demonstrating the least awareness of these rebates.

Table 7-2. PEV Incentives Awareness, by Race and Ethnicity

	Non-Hispanic										Hispanic		Sample Total	
	White		Black		Asian		Other		2+ Races					
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Yes	214	49%	68	46%	23	28%	21	27%	16	44%	246	30%	587	37%
No	220	51%	80	54%	60	72%	55	73%	20	56%	577	70%	1,011	63%
Sample Total	**434**	**100%**	**148**	**100%**	**82**	**100%**	**76**	**100%**	**36**	**100%**	**823**	**100%**	**1,599**	**100%**

There is a statistically significant relationship between the two variables at $P<0.05$, and it should be noted the table has cell sizes that approach 0.

While awareness of PEV incentives is remarkably consistent across urbanization geography, it is less so by air quality management district (AQMD) area (see Table 7-3). Although the sample sizes are too small to make claims about statistical significance between areas, households in the Sacramento Metropolitan area appear much more aware of PEV rebates than residents of other areas, with Bay Area households also being more aware than average, and San Diego County and San Joaquin Valley residents being less so.

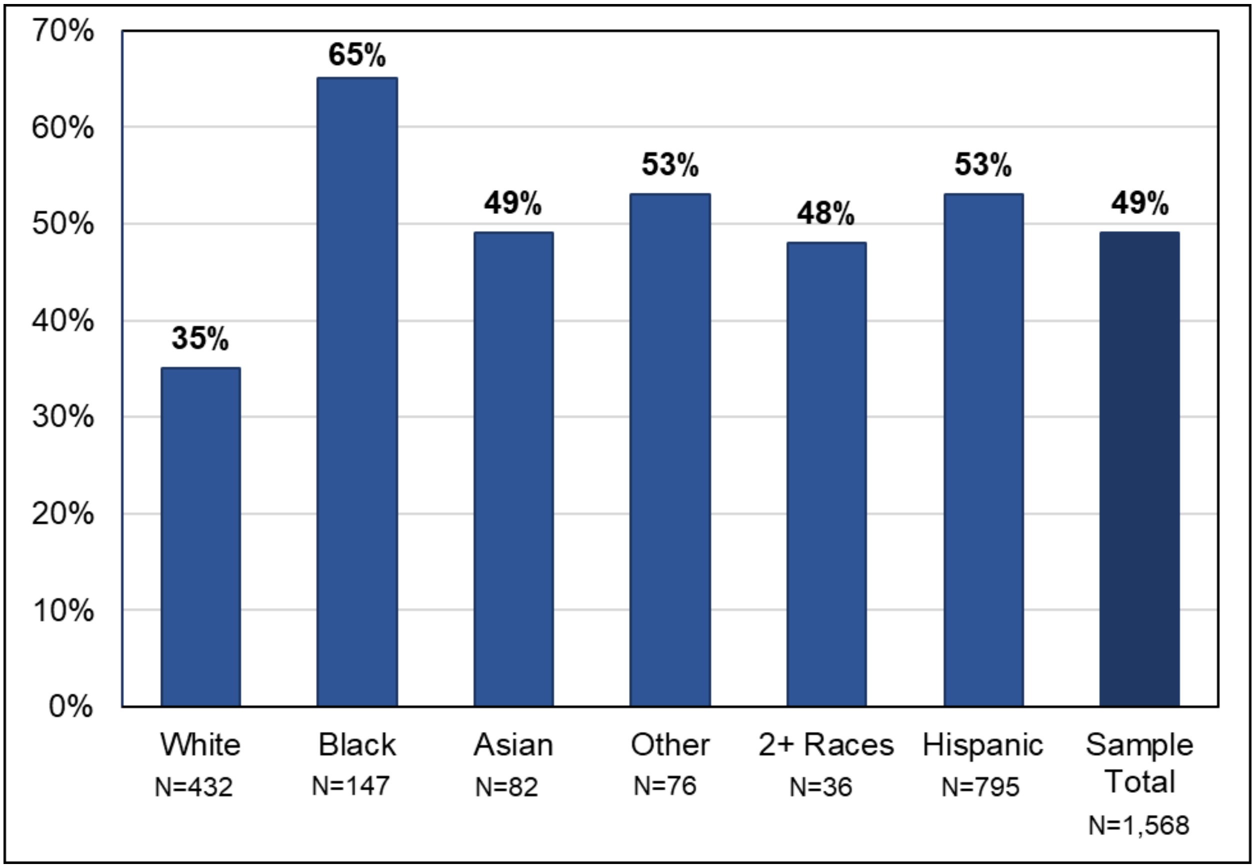
Table 7-3. PEV Incentives Awareness, by AQMD Geography

	Bay Area		Sacramento		San Diego		SJV		South Coast		Other		Sample Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Yes	71	42%	24	51%	44	30%	59	32%	261	36%	112	38%	572	36%
No	98	58%	23	49%	103	70%	127	68%	469	64%	183	62%	1,003	64%
Sample Total	**170**	**100%**	**48**	**100%**	**147**	**100%**	**187**	**100%**	**730**	**100%**	**295**	**100%**	**1,575**	**100%**

Awareness of HOV Lanes

Finally, awareness of HOV lanes is varied across racial-ethnic groups and by geographic factors. As Figure 7-1 shows, non-Hispanic Whites are significantly less likely than all other groups to report having HOV lanes nearby that they could use for commuting purposes. In particular, non-Hispanic Black respondents report nearly double the level of awareness of non-Hispanic Whites. Much of this difference may be attributable to the spatial proximity of racial-ethnic groups with respect to freeways within metropolitan areas. This proximity has negative health impacts on minority groups (Houston, Wu, Ong, and Winer, 2004), but may promote greater access to HOV lanes.

Figure 7-1. HOV Lanes Nearby That Could Be Used for Daily Commute, by Race and Ethnicity



There is a statistically significant relationship between the two variables at P<0.05, and it should be noted the table has cell sizes that approach 0.

Moreover, as Table 7-4 shows, we see substantial variation in awareness of nearby HOV lanes for commuting across AQMD areas. Residents of the Bay Area, Sacramento Metropolitan and South Coast AQMDs are much more likely than residents of San Diego County, San Joaquin Valley or smaller AQMDs to report close proximity.

Table 7-4. HOV Lanes Near You That You Could Use for Your Daily Commute, by AQMD Geography

	Yes		No		Sample Total	
	N.	Pct.	N.	Pct.	N.	Pct.
Bay Area	105	62%	65	38%	170	100%
Sacramento Metro	26	61%	17	39%	43	100%
San Diego	70	49%	74	51%	145	100%
San Joaquin Valley	75	40%	111	60%	186	100%
South Coast	400	57%	305	43%	705	100%
Other	83	28%	213	72%	296	100%
Sample Total	**760**	**49%**	**785**	**51%**	**1,544**	**100%**

There is a statistically significant relationship between the two variables at P<0.05, and it should be noted the table has cell sizes that approach 0.

7.2. Travel Patterns and Related Vehicle Needs

Households were also asked questions regarding their long-distance, weekly, and commute travel patterns. Each of these factors affects whether and what type of PEVs might fit their travel needs, with households making longer trips requiring PEVs that have longer travel ranges between charging times. We note that it is not only objectively measured PEV range and charging needs that affect PEV adoption, but also perceptions regarding (the lack of) range, or so-called range anxiety that influence adoption levels (see Franke and Krems, 2013).

The most important travel behavior element for the feasibility of use of PEVs by households is the frequency of long trips, which might exceed or test the electric range of some PEVs. We find, however, that only about 7% of respondents take a vehicle trip exceeding 100 miles (round trip per week), but about two-thirds of households take such a trip yearly or less frequently.[1] While non-Hispanic White households report taking fewer long-distance vehicle trips than minority groups, sample sizes and differences are not large enough to explain these differences. Moreover, and against expectations, as Table 7-5 shows, rural households appear to take long-distance trips slightly less often on a monthly or weekly basis than urban or suburban households.

Table 7-5. Frequency of Trips Longer Than 100 Miles, by Urbanization Geography

	Urban		Suburban		Rural		Sample Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Weekly	48	7%	47	7%	9	4%	104	7%
Monthly	197	30%	173	26%	54	25%	425	28%
Yearly	227	34%	238	36%	102	47%	567	37%
Rarely/Never	191	29%	202	31%	54	25%	446	29%
Sample Total	**663**	**100%**	**660**	**100%**	**219**	**100%**	**1,541**	**100%**

Similarly, as shown in Table 7-6, only 7% of respondents indicated that the expected most important use of the next vehicle they purchase would be for regular long trips. By far the most important expected use of their next vehicle purchase was for commuting purposes, and regular but short non-commuting trips were the next most valued use of the next vehicle they envisioned purchasing.

Table 7-6. Uses for Next Vehicle, by Expected Level of Importance

	Most Important		Moderately Important		Least Important		Sample Total
	N.	Pct.	N.	Pct.	N.	Pct.	N.
Commuting	976	56%	91	6%	161	9%	1,228
Regular Short Trips	438	25%	709	44%	246	14%	1,393
Regular Long Trips	117	7%	451	28%	593	34%	1,161
Occasional Long Trips	139	8%	282	18%	535	31%	956
Off Road Uses	79	5%	77	5%	192	11%	348
Sample Total	**1,749**	**100%**	**1,609**	**100%**	**1,727**	**100%**	**5,086**

Commute Distance

We also analyzed commute distance and patterns, as these factors relate to the ease and reliability of charging a PEV frequently (Pearre, Kempton, Guensler and Elango, 2011). After removing outliers, we find the self-reported average round-trip commute distance for respondents to be 22 miles (N=1166, Range=1-150). This is a longer commute distance than expected, given that reported vehicle miles traveled in Los Angeles and the Bay Area is 24-25 miles (Metropolitan Transportation Commission, 2015). There are few notable differences in commute distance by socioeconomics status factors (see Chapter 7 Appendix for details).

On the other hand, as one might expect, the farther respondents are located from urban areas, the more miles they commute during a typical workday, on average. Longer round-trip commute distances are particularly notable for residents of the San Joaquin Valley AQMD and for respondents residing outside a major AQMD area (see Table 7-7).

[1] By comparison, data from the 2013 CHTS show that of all one-way trips taken by all households, 3.1% (or 2.8% for households with incomes less than $50,000) were one-way trips of 50 miles (or 100 miles round trip) or more on a daily basis.

Table 7-7. Mean Commute Distance (Miles), by AQMD Geography

	N.	Mean[1]	S.D.
Bay Area	124	18	24
Sacramento Metro	42	16	12
San Diego County	104	21	19
San Joaquin Valley	126	27	27
South Coast	533	19	20
Other	206	29	27
Sample Avg.	**1,135**	**22**	**23**

[1] The difference in mean commute distance (miles) is statistically significant at P<0.05 between Sacramento and Other, and South Coast and Other, and at P<0.10 between Sacramento and SJV.

Even more than geography, however, the nature of employment and its locational stability influences commute distance.[2] Nearly a quarter of respondents do not report to the same primary work location each workday.[3] About half of these individuals commute to a different work site each day while the other half commute to multiple work sites or locations each workday. The 13% of respondents who commute to a different work site each day report commuting nearly double the distance of same-location commuters, and even more than those who travel to multiple sites a day (see Table 7-8). The fairly substantial levels of variability in workplace location among the low- and moderate-income population suggest that these households may not benefit as much in using workplace-located electric vehicle charging.

Table 7-8. Mean Commute Distance (Miles), by Commute Pattern

	N.	Mean[1]	S.D.
Same primary work location each workday	884	19	21
Different work site or location each workday	150	33	30
Multiple work sites or locations each workday	121	28	22
Sample Avg.	**1,155**	**22**	**23**

[1] The difference in mean commute distance (miles) is statistically significant at P<-0.05 between Same Location and Different Location, and Same Location and Multiple Locations.

Differences in commute pattern are not markedly different across socioeconomic or geographic stratifying variables (see Chapter 7 Appendix), although lower-income, Black, and respondents from the San Joaquin Valley are more likely to report not traveling to the same location each workday.

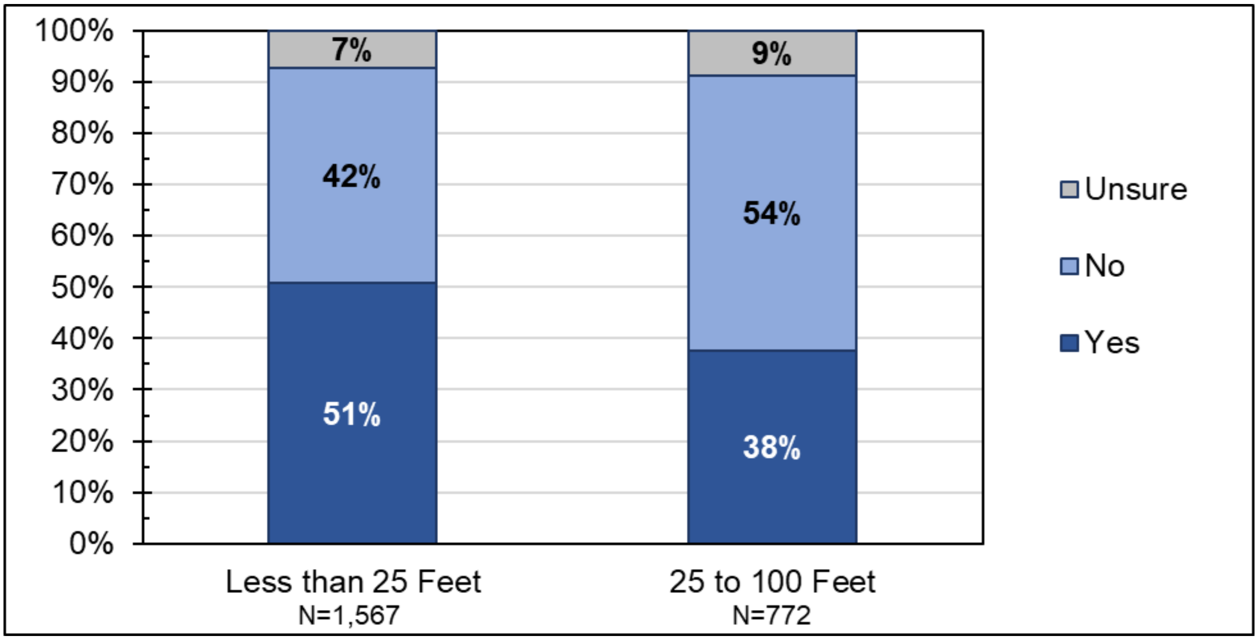
7.3. Built Environment Factors Affecting PEV Charging Potential

Finally, we analyze attributes of low- and moderate-income households' place of residence that would make PEV charging at home more or less difficult. The proximity of an existing electrical outlet to where vehicles are parked at home affects rates of PEV adoption. Past studies have found that the type and ownership status of residence affects charging proximity (DeShazo, Wong and Karpman, 2017; DeShazo, Krumholz, Wong, and Karpman, 2017). Among all respondents, as Figure 7-2 shows, a high proportion indicated there is an electrical outlet within 25 feet of where they usually park their car, which is ideal for PEV charging (51%). An additional 38% of respondents are aware of an outlet within 100 feet of where their main vehicle is parked.

[2] We did not ask questions regarding respondents' employment sector or specific job title.

[3] We searched for , but could not find, available reference points to contextualize this finding from other data sources or studies, in any U.S. context.

Figure 7-2. Presence of Electrical Outlet Where Vehicle Is Typically Parked



Over half of surveyed households reported parking their main vehicle in either a private garage (21%) or driveway (36%). Unsurprisingly, as Table 7-9 shows, private garages overwhelmingly have the most convenient charging potential, with 80% located within 25 feet of an electrical outlet. Driveways and multi-car garages also have high charging potential, with 60% and 61% respectively located with 25 feet of an electrical outlet. We note, however, that permission to use outlets in multi-car garages is likely to be more constrained than in private driveways.

Table 7-9. Presence of Electrical Outlet Within 25 Feet of Where Vehicle Is Typically Parked

	Yes		No		Unsure		Sample Total
	N.	Pct	N.	Pct	N.	Pct	N.
Private garage	260	80%	34	11%	30	9%	325
Carport	97	41%	128	54%	13	5%	239
Driveway	339	60%	200	36%	22	4%	560
Multi-car garage	48	61%	22	28%	9	11%	78
Parking lot	26	20%	91	69%	15	11%	132
Street	25	11%	178	77%	29	12%	232
Sample Total	**795**	**51%**	**654**	**42%**	**116**	**7%**	**1,565**

[1] There is a statistically significant relationship between the two variables at $P<0.05$, and it should be noted the table has cell sizes that approach 0.

As previous studies have shown, respondents living in single-family detached homes have the most convenient PEV charging potential, as 61% have an electrical outlet within 25 feet of their parking spot (see Table 7-10). Interestingly, residents of mobile homes and other less common residence types also have high charging potential, though these proportions may be a result of the small sample sizes. On the other hand, residents of multi-unit dwellings appear to have the lowest charging potential, with 65% of respondents reporting there are no electrical outlets near their parking spot. The results are quite similar when looking at the 100-foot threshold for a proximate electrical outlet.

Table 7-10. Presence of Electrical Outlet Within 25 Feet of Parked Car, by Housing Type

	Yes		No		Unsure		Sample Total
	N.	Pct	N.	Pct	N.	Pct	N.
Single-Family Detached	530	61%	283	32%	59	7%	872
Single-Family Attached	87	43%	102	51%	13	6%	202
Multi-Unit Dwellings	93	24%	246	65%	41	11%	380
Mobile Home	73	76%	21	21%	3	3%	97
Boat, RV, Van, etc.	12	88%	1.3	10%	0.2	2%	13
Sample Total	**794**	**51%**	**654**	**42%**	**116**	**7%**	**1,564**

There is a statistically significant relationship between the two variables at $P<0.05$, and it should be noted the table has cell sizes that approach 0.

Also, as expected, a higher share of respondents who own their home report the presence of an electrical outlet within 25 feet of their parking spot (65%), compared to those who rent (40%). While many, if not nearly all, of those households who own their own home live in single-family residences, the distinction is important. Residents who own their dwelling have more autonomy over the choice to install a PEV charger or the ability to run a charging cord between a proximate outlet and the location of their vehicle.

References

DeShazo, J. R., Krumholz, S., Wong, N. and Karpman, J. (2017). Siting Analysis for Plug-in Electric Vehicle Charging Stations in the City of Santa Monica. *UCLA Luskin Center for Innovation Report*.

DeShazo, J. R., Wong, N. and Karpman, J. (2017). Overcoming Barriers to Electric Vehicle Charging in Multi-Unit Dwellings: A Westside Cities Case Study. *UCLA Luskin Center for Innovation Report*.

Franke, T. and Krems, J. F. (2013). What drives range preferences in electric vehicle users? *Transport Policy*, 30, 56-62.

Houston, D., Wu, J., Ong, P. and Winer, A. (2004). Structural disparities of urban traffic in Southern California: implications for vehicle-related air pollution exposure in minority and high-poverty neighborhoods. *Journal of Urban Affairs,* 26(5), 565-592.

Krause, R. M., Carley, S. R., Lane, B. W. and Graham, J. D. (2013). Perception and reality: Public knowledge of plug-in electric vehicles in 21 US cities. *Energy Policy*, 63, 433-440.

Kurani, K. and S. Hardman (2018). Automakers and Policymakers May Be on a Path to Electric Vehicles; Consumers Aren't. See https://its.ucdavis.edu/blog-post/automakers-policymakers-on-path-to-electric-vehicles-consumers-are-not/

Lambert, F. (2017). Lack of awareness is surprisingly still the biggest problem for electric vehicle adoption. See https://electrek.co/2017/01/03/electric-vehicle-adoption-awareness/

Metropolitan Transportation Commission (2015). Daily Miles Traveled. See http://www.vitalsigns.mtc.ca.gov/daily-miles-traveled.

Pearre, N. S., Kempton, W., Guensler, R. L. and Elango, V. V. (2011). Electric vehicles: How much range is required for a day's driving? *Transportation Research Part C: Emerging Technologies*, 19(6), 1171-1184.

Sheldon, T. L. and DeShazo, J. R. (2017). How does the presence of HOV lanes affect plug-in electric vehicle adoption in California? A generalized propensity score approach. *Journal of Environmental Economics and Management*, 85, 146-170.

Sheldon, T. L., DeShazo, J.R., Carson, R. T. and Krumholz, S. (2017). Factors Affecting Plug-in Electric Vehicle Sales in California. *UCLA Luskin Center for Innovation Report*.

CHAPTER 8

DESIGN AND IMPLEMENTATION OF THE ENHANCED FLEET MODERNIZATION PLUS-UP PILOT PROGRAM

This research may be accessed online.

CONCLUSION

Early federal and state programs developed to increase the adoption of clean vehicle access were not widely accessed by low- and moderate-income households. Accordingly, this report analyzes policies and informs future strategies intended to improve new and used clean vehicle access and use by low- and moderate-income households in California and thus enable them to overcome barriers outlined in SB 350. Particularly, the research in this report focused on policy approaches that do or could use incentives and financing programs to promote the retirement of functional, high-emitting vehicles and the adoption of advanced clean vehicles by the target population. We analyzed the results of a statewide representative survey of 1,604 low- and moderate-income households to help inform future strategies to improve access to and adoption of clean vehicles among this population.

Understanding Low- and Moderate-Income Drivers' Vehicle and Travel Decisions in California

Our research confirms for California the findings of a small but important literature on low-income households' reliance on high-polluting vehicles (National Travel Household Survey, 2009; Bhat et al., 2009; Choo and Mokhtarian, 2004; Choo et al., 2007). We find that lower-income households are more likely to own higher-emitting vehicles (due to their lower purchase costs), to hold on to these vehicles longer, and thus are likely to bear a disproportionate burden of transportation-related air pollution when compared to higher-income households. Low- and moderate-income households are also less likely to be able to afford or finance advanced clean vehicles without financial incentive support.

We find that survey respondents, on average, own as many vehicles (2.0) as higher-income households in the state. Moreover, they spend significant amounts of their annual reported income on their last vehicle purchase (over 50%) and annual operation of their main vehicle (over 10%). We also find patterns of gendered influence regarding vehicle purchase, with men reporting a higher likelihood of being the primary decision maker.

Nevertheless, low- and moderate-income households report relying on vehicles for travel purposes nearly as much as higher-income households. Despite high levels of one-time and ongoing expenditure on vehicles, respondents generally did not express strong interest in transit or alternative travel modes. Only about 6% rode transit daily. When presented with the opportunity, nearly 60% of survey takers said they would not seriously consider selling their main vehicle even if transit were made as convenient and inexpensive as operating their vehicle.

The potential for influencing vehicle turnover rather than reductions in these households' vehicle fleets, however, appears more promising. About half of the surveyed low- and moderate-income households reported that they plan to keep their main household vehicle for only two years. When asked whether they would be willing to participate in a vehicle scrapping program without being offered a replacement vehicle, over 40% indicated willingness to accept $1,500 or less to scrap their main vehicle

Lessons Learned for California's PEV Incentive Policy Designs

Over the last several years California policymakers have increasingly focused on the adoption of clean technology, hybrid, near-zero, and zero-emissions vehicles by low- and moderate-income households. For example, the CVRP program is now income-tiered and the EFMP Plus-Up pilot program has evolved significantly to offer higher-tiered and targeted rebates for new and used vehicle purchases. In addition, California policymakers are piloting several financing programs that aim to induce low- and moderate-income consumers to adopt innovative technologies that reduce vehicle emissions, thereby reducing environmental and health damages within low- and moderate-income communities.

Our research finds that offering rebates had a much larger impact on new and used clean vehicle purchase propensity than offering guaranteed financing alternatives. This difference reflects not only each population's preference for financing (which is lower for low-income consumers) but also the price elasticities of demand. Rebates reduce both the upfront price by lowering the down payment and the total payment, as well as any monthly financing payment, if such payments exist. With financing, however, while the upfront payment declines, thereby increasing utility, the monthly payment goes up, which decreases utility. For low-income consumers, the decrease in utility due to the increase in monthly payments (which are higher for BEVs since BEVs are generally more expensive than other vehicle types) outweighs the increase in utility due to lowering the upfront payment. Importantly, we find that further investment in clean vehicle purchase incentives for low- and moderate-income households would be cost-effective.

Our modeling shows that offering varying levels of rebates significantly increases the propensity to purchase hybrids, PHEVs and BEVs among low- and moderate-income consumers. Rebates of $2,500, $5,000, and $9,500 increased purchase rates from their baseline rates by approximately 20%, 40% and 60-80% respectively across vehicle types. There were, however, substantial differences across clean vehicle types. For instance, at the highest subsidy level ($9,500), 43.3% of the sample would purchase an HEV, 7.5% would purchase a PHEV, and 8.1% a BEV. By contrast, we find that offering guaranteed loans, even at low interest rates, has a much smaller and more uneven effect on the likelihood of purchase.

Barriers to Access and PEV Awareness

Multiple remaining barriers to vehicle access, however, must be overcome to ensure that lower-income households in the state can benefit from incentive and financing programs. Households in the lowest-income group in the sample (with annual incomes below $25,000) reported consistently lower levels of vehicle access and travel, higher expenditure burdens, and reduced access to financing. Our analysis of the survey results also found that lower-income households had a greater dependence on used vehicles and a lower reliance on traditional financing mechanisms than those reported by higher-income households in other studies. Each of these factors should inform future incentive program design. Moreover, the reported differences in vehicle insurance expenditures by racial and ethnic minority groups should be further examined.

In terms of present PEV awareness among surveyed households, there was conflicting evidence. Nearly four-fifths reported having seen a PEV, but less than 40% were aware of currently offered PEV purchase incentives. There also appears to be remaining barriers to the ease of electric vehicle charging. About half of respondents reported the potential to charge a vehicle at home, although this ability was lower among renters. More surprisingly, nearly a quarter of respondents reported commuting to multiple work sites in a week, making siting for workplace charging potentially more challenging.

Finally, research assessing the design and implementation of the EFMP Plus-Up deployed in the South Coast and San Joaquin Valley Air Districts shows uniformly high demand for vehicle retirement and replacement incentives, despite regional differences in program implementation. We recommend revisiting our analysis of the broader effects of the Plus-Up program on clean vehicle adoption in the near future when more data becomes available as the program matures and expands.

Future Research Needs

Given the importance of transitioning ZEVs into the light duty fleet owned by low- and moderate-income households, several important questions remain that should be the focus of future research.

1. Perceived reliability, functionality and costs of operating aging PHEV and BEVs. Low- and moderate-income households will be adopting used PHEVs and BEVs and will bear the operational risks of these vehicles as they age. How will low- and moderate-income households experience the reliability, functional driving range and total ownership costs of these vehicles as they age? And will that experience and cost-benefit equation be superior when compared to aging ICE vehicles? When answering these questions, researchers should draw a distinction between first-generation BEVs (with limited ranges) versus emerging second-generation BEVs (with ICE equivalent ranges).

2. Optimal adjustments to incentive levels over time. While our research suggests that incentives currently have a significant impact on the purchase of additional PEVs, low- and moderate-income households may become less responsive to incentives in the future as vehicles' range performance increases, their purchase price decreases, and household trust that these vehicles will meet their travel needs increases. As these factors evolve, and the ability of incentives to induce additional vehicle purchases falls, incentives should be adjusted. Future research could identify how existing incentives should be adjusted or eligibility better targeted.

3. Average fuel efficiency of vehicle fleets of household of differing incomes. Researchers (Archsmith et al., 2017) have noted that households who purchase new PHEVs and BEV also appear to diversify their household fleet by subsequently purchasing less fuel-efficient vehicles with superior performance along other dimensions, such as passenger capacity or horsepower. It will be important to understand whether moderate to lower income households exhibit similar patterns of vehicle purchase. Specifically, how do households of differing incomes make incremental vehicle adoption decisions and how do these decisions affect fleet-average fuel economy?

4. Charging infrastructure needs of low- and moderate-income households. Comparatively speaking, how easy is it for low- and moderate-income households to meet their residential charging needs? Are such households relatively more or less dependent on publicly accessible charging infrastructure? Given that low- to moderate-income households are likely to purchase older used PEVs, will these vehicles be unable to use newer DC fast charging infrastructure because of technical and compatibility limitations?

5. Factors explaining new versus used vehicle purchase among low- and moderate-income households. One of the more surprising results found in this study is that 40% of respondents reported purchasing a new rather than used vehicle. This raises the question: Among EFMP eligible households, what explains the significant segmentation and differentiation in new and used vehicle expenditures that we observed? If respondents' stated intentions are acted upon, this opens up the possibility of the tailoring the CVRP and EFMP programs toward new vehicles. Precisely which types of households will purchase a new car, and what types of new cars, become an important question. We intend to undertake further research to answer this question.

GLOSSARY OF KEY TERMS

Acronym	Definition
ACS	American Community Survey
AQMD	Air Quality Management District
BEV	Battery Electric Vehicle
CARB	The California Air Resources Board
CHTS	California Household Travel Survey
CSA	Combined Statistical Areas are composed of adjacent metropolitan and micropolitan statistical areas.
CVRP	The Clean Vehicle Rebate Project is administered by the California Air Resources Board and provides rebates for qualifying individuals who purchase a new, clean-technology vehicle, such as a hybrid, plug-in hybrid electric, battery electric, or fuel-cell electric vehicle.
DAC	Disadvantaged Communities are identified by the California Environmental Protection Agency, and are communities that are most burdened and vulnerable to the effects of pollution from multiple sources (CEC, 2018).
EFMP and EFMP Plus-Up	The Enhanced Fleet Modernization Program is administered by the California Air Resources Board and provides rebates for qualifying individuals who scrap older, fuel inefficient vehicles. The Plus-Up pilot provides an additional incentive for qualifying individuals who replace their old vehicle with a new or used hybrid, plug-in hybrid electric, or battery electric vehicle.
FCEV	Fuel-Cell Electric Vehicles
FPL	The Federal Poverty Level is a fixed, income-based threshold that fluctuates depending on family size, household combination, and the annual Consumer Price Index, and does not account for in-kind income such as housing vouchers (Fritzell et al., 2015).
GfK	Growth from Knowledge Custom Research LLC is the market research firm that assisted in administering the Ride and Replace survey.
GHG	Greenhouse Gases are gases such as carbon dioxide, methane, nitrous oxide, and hydrofluorocarbons that trap heat in the atmosphere and contribute to the greenhouse effect (EPA, 2018).
HEV	Hybrid Electric Vehicle
HOV	High-Occupancy Vehicle Lane (also known as the carpool or diamond lane) is open to motorcycles, mass transits and vehicles with two or more occupants during their operational hours (Caltrans, 2018).
ICEV	Internal Combustion Engine Vehicle
NHTS	National Household Travel Survey
PEV	Plug-In Electric Vehicle includes both hybrid and battery-electric vehicles.
PHEV	Plug-In Hybrid Electric Vehicle
VMT	Vehicle Miles Traveled
ZEV	Zero-Emission Vehicle

References

California Energy Commission. (2018). "Disadvantaged Communities Definition." http://www.energy.ca.gov/commission/diversity/definition.html.

Caltrans. (2018). "High Occupancy Vehicle Systems." *California Department of Transportation*. http://www.dot.ca.gov/trafficops/tm/hov.html.

Fritzell, J., Rehnberg, J., Hertzman, J. and Blomgren, J. "Absolute or relative? A comparative analysis of the relationship between poverty and mortality. *Luxembourg Income Study Working Paper Series*, 637. 1 – 25.

U.S. Environmental Protection Agency. (2018). "Greenhouse Gas Emissions." https://www.epa.gov/ghgemissions/overview-greenhouse-gases.

APPENDICES

Chapter 2 Appendix

Section A. Correlations Between Key Socioeconomic and Spatial Variables

To allow for accurate interpretation of the causes and drivers of the results throughout this report, we ran a pairwise correlation among the key sociodemographic and geographic stratifying variables. Any pair of variables with a correlative value above 0.3 indicates a moderate-to-strong correlation. This means that the influence of one independent variable may be over- or understated during bivariate statistical analysis, due to the influence of the other highly correlated independent variable. We note and address concerns with omitted variable bias throughout the report.

The tables below show the direction and magnitude of the correlation between the selected variables of race and ethnicity, income, language, and geography. The format for each cell is the weighted number of respondents listed first, followed by the correlative value in the middle, and the column percentage at the bottom of the cell. An asterisk (*) denotes statistically significant correlative values at the 95% confidence level. Correlations above 0.3 are flagged in a bolded red font. Among survey respondents we find moderate-to-strong, statistically significant correlations between Hispanic ethnicity and English as a primary language, Hispanic ethnicity and Bilingual, non-Hispanic White and Bilingual, and rural geography and all other air quality management districts.

Table A2-1. Race-Ethnicity and Income Correlations

	White, Non-Hispanic	Black, Non-Hispanic	Asian, Non-Hispanic	Other, Non-Hispanic	2+ Races, Non-Hispanic	Hispanic	Total
< $25k	117 (-0.0543*)	71 (0.1177*)	31 (0.0315)	37 (0.0874*)	5 (-0.0582*)	238 (-0.0537*)	500
	27%	48%	37%	49%	13%	29%	31%
$25k - 50k	182 (0.0595*)	44 (-0.0489)	29 (-0.0133)	27 (-0.0079)	22 (0.0712*)	295 (-0.0364)	598
	42%	30%	35%	35%	60%	36%	37%
$50k - 75k	82 (-0.0584*)	27 (-0.0349)	22 (0.0203)	11 (-0.0421)	10 (0.0136)	215 (0.0770*)	366
	19%	18%	26%	15%	27%	26%	23%
> $75k	53 (0.0740*)	5 (-0.0575*)	1 (-0.0592*)	0 (-0.0673*)	0 (-0.0467)	80 (0.0361)	140
	12%	4%	2%	0%	0%	10%	9%
Total	**434**	**148**	**82**	**76**	**36**	**828**	**1604**
	100%	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Table A2-2. Race-Ethnicity and Language Correlations

	White, Non-Hispanic	Black, Non-Hispanic	Asian, Non-Hispanic	Other, Non-Hispanic	2+ Races, Non-Hispanic	Hispanic	Total
English	0 (-0.2356*)	0 (-0.1233*)	0 (-0.0901*)	0 (-0.0862*)	0 (-0.0585*)	**209 (0.3746*)**	209
	0%	0%	0%	0%	0%	25%	13%
Bilingual	**0 (-0.3934*)**	0 (-0.2059*)	0 (-0.1504*)	0 (-0.1440*)	0 (-0.0976*)	**472 (0.6253*)**	472
	0%	0%	0%	0%	0%	57%	29%
Spanish	0 (-0.1630*)	0 (-0.0853*)	0 (-0.0623*)	0 (-0.0596*)	0 (-0.0404)	107 (0.2590*)	107
	0%	0%	0%	0%	0%	13%	7%
Hispanic with missing data, re-ask	0 (-0.0970*)	0 (-0.0508*)	0 (-0.0371)	0 (-0.0355)	0 (-0.0241)	40 (0.1542*)	40
	0%	0%	0%	0%	0%	5%	2%
Not Hispanic, not asked	**434 (0.6291*)**	**148 (0.3293*)**	82 (0.2404*)	76 (0.2302*)	36 (0.1561*)	0 (-1)	776
	100%	100%	100%	100%	100%	0%	48%
Total	**434**	**148**	**82**	**76**	**36**	**828**	**1604**
	100%	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Table A2-3. Urbanization Geography and AQMD Region Correlations

	Bay Area	Sacramento Metro	San Diego County	San Joaquin Valley	South Coast	Other	Total
Urban	90 (0.0694*)	21 (0.0047)	80 (0.0760*)	65 (-0.0617*)	349 (0.0889*)	74 (-0.1757*)	679
	53%	44%	55%	35%	48%	25%	43%
Suburban	74 (0.0083)	25 (0.0398)	61 (-0.0027)	65 (-0.0549*)	350 (0.1027*)	94 (-0.1076*)	670
	44%	54%	42%	35%	48%	31%	42%
Rural	6 (-0.1092*)	1 (-0.0625*)	5 (-0.1030*)	56 (0.1639*)	31 (-0.2692*)	**130 (0.3981*)**	229
	3%	2%	3%	30%	4%	44%	15%
Total	**170**	**47**	**146**	**186**	**730**	**298**	**1577**
	100%	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Section B. Geocoding Methods

As noted in Chapter 2, we use geocoding methods to assign a unique identification value to each data feature based on a certain set of geographic criteria. This process allowed us to spatially represent, stratify, analyze, and interpret the survey data. We classified the location of each survey respondent across six geographic categories, including Census Tract, County, Air Quality Management District (AQMD), Consolidated Statistical Areas, Urbanization, and Disadvantaged Community (DAC). Refer to Table A2-4 for a summary of the demographic and geospatial data used in the geocoding process.

Table A2-4. Summary of Data Sources Joined to Survey Results

Data Type	Name	Source	Year
Survey	Ride & Replace	ARB	2018
Census	American Community Survey	American Factfinder	2012-2016
	Decennial Census	American Factfinder	2010
Shapefile	California Air Districts	ARB	2018
	Census Tracts	Census Bureau	2017
	Combined Statistical Areas	Census Bureau	2017
	Counties	Census Bureau	2016
	Disadvantaged Communities	ARB	2017
	Principal Cities	Census Bureau	2017
	Urban Areas	Census Bureau	2017

In order to view the spatial distribution of respondents, we first joined the survey data to the 2017 TIGER/Line California Census Tract shapefile. This created a polygon shapefile of survey respondents. Using the census tract identifier as the match field, the join output matched the survey data to 1,047 census tracts. This indicates the presence of census tracts containing more than one survey taker. To calculate the total number of respondents in each tract, we created a point shapefile with the centroids of the 1,047 tracts. We repeated the join process with the survey data and the census tract centroids, resulting in a point shapefile of survey respondents. Using a spatial join with summary statistics, we joined the point and polygon shapefiles of survey respondents. The result (Figure A2-1) was a shapefile of 1,047 tracts, with each containing the total number of respondents per tract. While the number of survey takers per tract ranged from one to eight, most tracts (70%) contained just one respondent.

After geocoding the survey respondents to census tracts, we performed a similar process to geocode respondents to counties, AQMDs, combined statistical areas (CSA), and DACs in California. By overlaying the census tract shapefile with those we wished to geocode and executing the spatial join function, we were able to assign unique values based on the respondent's location. For example, the range of county identifiers was 1 to 53, indicating that 5 of the total 58 counties in the state did not have any survey takers.

The AQMD identifiers ranged from 1 to 6, as we condensed the number of AQMDs to the five largest (Bay Area, Sacramento Metropolitan, San Diego County, San Joaquin Valley, and South Coast), and grouped all other AQMDs in an "Other" category using the merge function of ArcGIS. See Figure A2-2 for the condensed AQMD boundaries.

Similarly, geocoded respondents fell into 1 of 6 categories of CSAs based on the five largest (Los Angeles-Long Beach, San Jose-San Francisco-Oakland, San Diego, Sacramento-Roseville, and Fresno-Madera) and an "Other" category. Respondents who were located in a DAC were geocoded with a value of 1, while those located outside a DAC had a value of 2.

We also geocoded survey respondents based on the three urbanization categories of urban, suburban, or rural. The Census Bureau does not officially define "suburban," and therefore does not have a readily delineated shapefile, nor census data, for specifically suburban areas in California. The Bureau does, however, provide spatial boundaries and information on "Urban Areas" and on "Principal Cities," and promotes the generally accepted definition of suburban as areas located within an urban area and outside a principal city (Ratcliffe, 2013). It notes that this approach may underestimate the suburban population because it underbounds the suburban extent and excludes exurban development (Ratcliffe, 2013).

Using this approach, we overlaid the shapefile with all census tracts in California with the Census Bureau's "Places" (principal cities) shapefile, and performed a join using census tract identifiers as the match field. The result was all census tracts located in principal cities, in other words, all urban tracts. We repeated this process using the Bureau's "Urban Areas" shapefile and the intersect function of ArcGIS, to get a shapefile of census tracts located in urban areas. To identify suburban census tracts, we ran the symmetrical difference function on the urban areas and principal cities census tracts. To get the remaining rural tracts, we ran a symmetrical difference function on the urban areas and statewide census tracts. We then merged the three separate shapefiles together and assigned a unique value, or a 1 for urban tracts, 2 for suburban, and 3 for rural. See Figure A2-3 for urban, suburban, and rural census tracts in California.

Finally, we overlaid the shapefile geocoded with respondents' census tract, county, AQMD, CSA, and DAC identifiers with the urbanization shapefile and ran an intersect function. This process splits the census tracts up into partial tracts when intersected by urbanization boundaries, meaning a tract may fall in more than one urbanization category (e.g., 25% in rural and 75% in suburban). We addressed this discrepancy by assigning an urbanization category based on how the majority of the tract was characterized. Thus, if a tract were 25% rural and 75% suburban, it was classified as a suburban tract. To do this we used the dissolve function with the dissolve field based on the urbanization category with the maximum area. See Figure A2-4 for urban, suburban, and rural categorization of census tracts with survey respondents.

At the end of the geocoding process, we had a final shapefile titled "Geography of Survey Respondents," which included the spatial information of the census tract, county, AQMD, CSA, DAC, and urbanization category for each unique survey taker. The last step was to join selected sociodemographic variables from the 2012-2016 ACS to the geocoded shapefile "Geography of Survey Respondents." This was done using the join function of ArcGIS with the census tract identifier in the match field. Refer to Table A2-5 for a summary of the census variables used.

It is important to note that ACS 2012-2016 census data were unavailable for five census tracts where respondents are located.[1] We were able to partially impute data for these tracts, using older versions of the ACS (2011-2015 and 2010-2014) as well as the 2010 Decennial Census. All tracts with missing census data received a value of "-9999," to ensure it would be identified as null once uploaded into Stata. Additionally, we calculated the population density by dividing the total population (taken from census data) by the calculated area (in square miles) for each census tract. We exported the complete attribute table to Excel format and appended to the original data in Stata.

Table A2-5. Summary of Census Variables

Variable	Name
DC Table G001	Geographic Identifiers
ACS Table B03002	Hispanic or Latino Origin by Race
ACS Table B19001	Household Income in the Past 12 Months
ACS Table B08301	Means of Transportation to Work
ACS Table B25032	Tenure by Units in Structure
ACS Table B01003	Total Population

[1] Tracts 6037980001, 6037980003, 6037980004, 6071980100, and 6073009902.

Figure A2-1. Number of Respondents by Census Tract

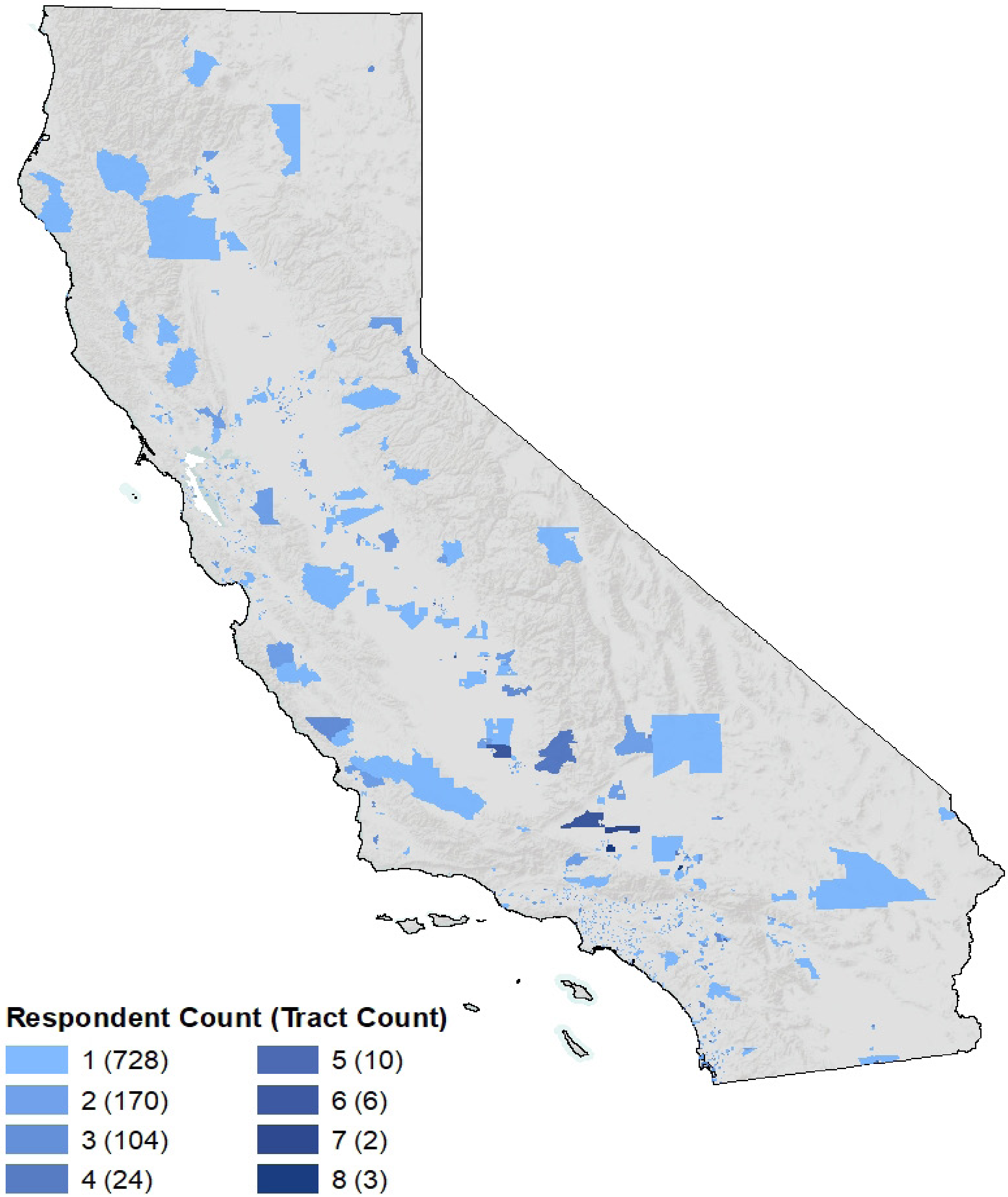


Figure A2-2. AQMD Categories

Figure A2-3. Geography of Urbanization Categories

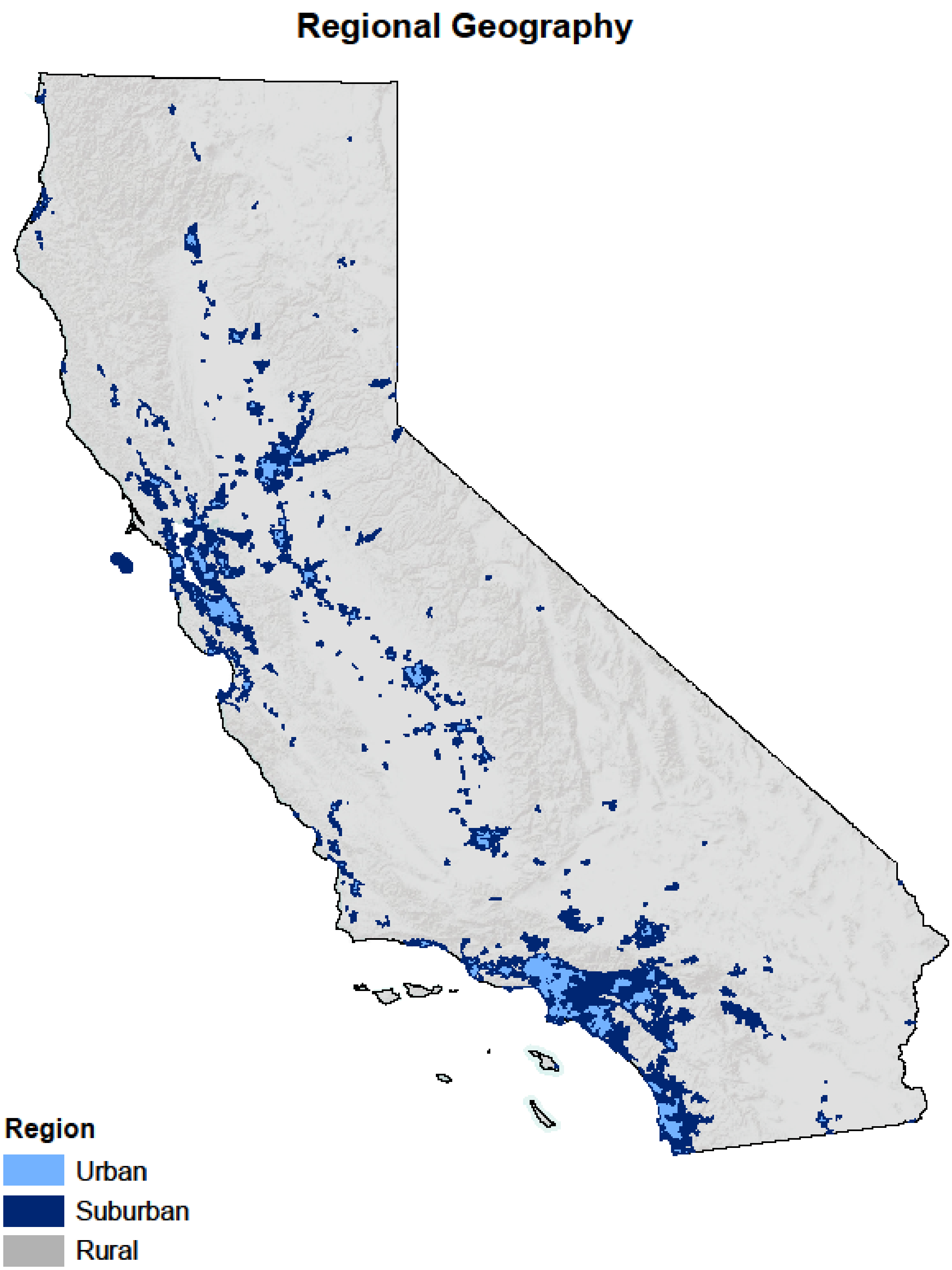
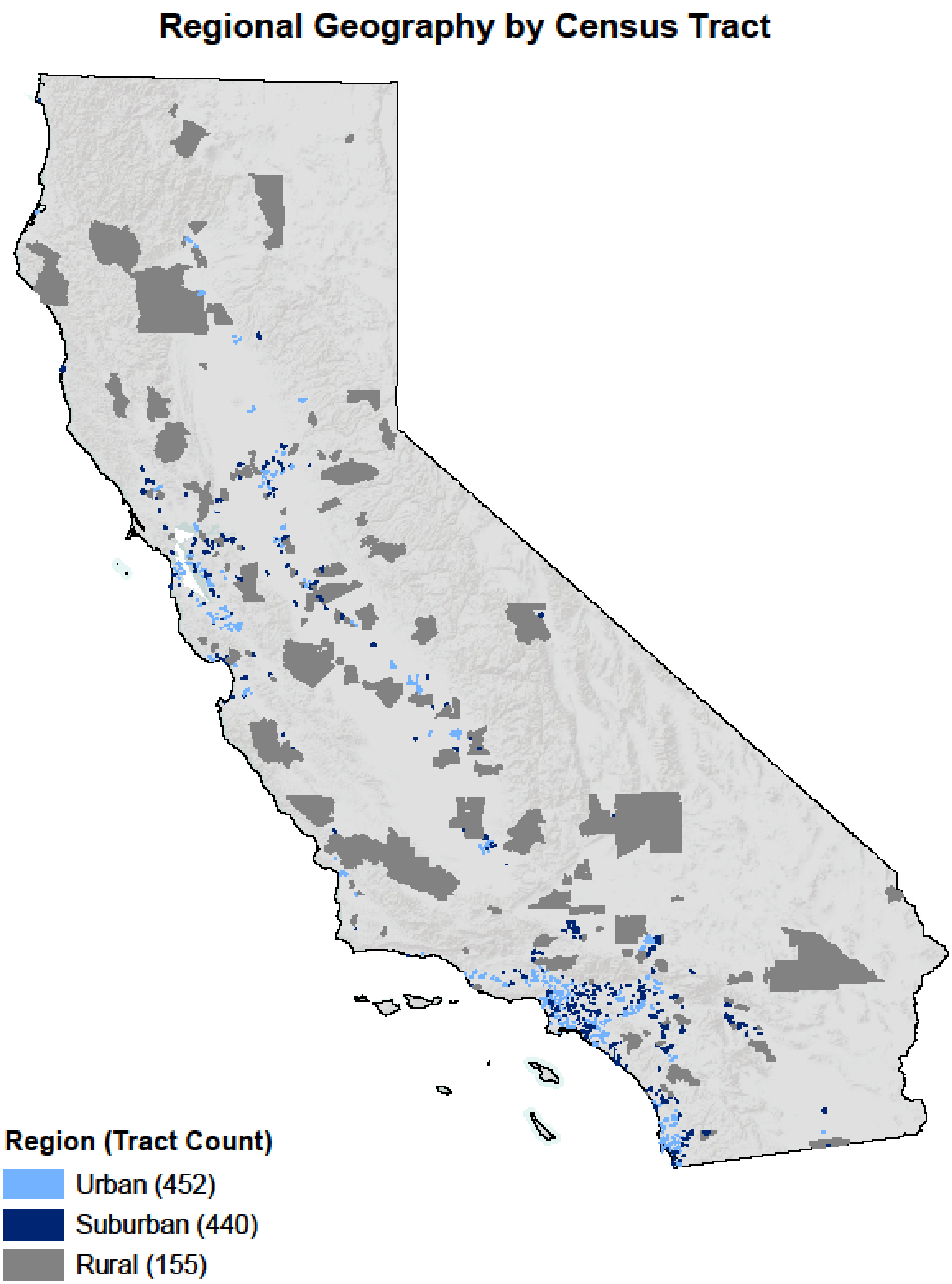


Figure A2-4. Urbanization Geography of Respondents



Chapter 3 Appendix

This appendix contains tables produced to address the research questions in Chapter 3 that were not included in the chapter. Additional tables in support of ARB's analysis plan are included below as well. For reference, the appendix will list the tables in the order they are discussed in the chapter, which is based on the guiding research questions. We then list the tables requested by ARB's analysis plan (if they are not already included or addressed by the guiding research questions for Chapter 3).

The research questions guiding this chapter are as follows:

1. How quickly and where do low- and moderate-income households search for and ultimately purchase vehicles? How do they expect to search in the future?
2. How much do households pay and how do they finance vehicle purchases? How do they expect to finance purchases in the future?

All tables requested by ARB's analysis plan can be found in Chapter 3 or in the tables below.

1. Vehicle Search Leading to Purchase: Who Decides, How Long, and Where Do They Search?

Table A3-1. Number of Months Spent Searching for Past Purchase, by Income and New/Used

	New		Used		Total	
	N.	Mean	N.	Mean	N.	Mean
<$25,000	129	10.0	272	5.3	401	6.8
$25K-$50K	230	4.9	276	4.2	506	4.5
$50K-$75K	168	5.4	146	3.7	314	4.6
>$75,000	50	11.9	46	6.8	95	9.4
Total	**576**	**6.8**	**740**	**4.6**	**1,316**	**5.6**

Table A3-2. Number of Months Spent Searching for Past Purchase, by AQMD Geography

	N.	Mean
Bay Area	154	5.6
Sacramento Metro	39	5.0
San Diego	130	6.6
San Joaquin Valley	168	6.2
South Coast	681	6.0
Other	287	4.4
Total	**1,459**	**5.7**

Table A3-3. Past Purchase Seller, by Race/Ethnicity

	Non-Hispanic										Hispanic		Total	
	White		Black		Asian		Other		2+ Races					
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
Social network	80	19%	32	23%	11	13%	20	26%	4	13%	163	20%	310	20%
Formal	260	61%	90	63%	61	74%	44	58%	20	58%	471	58%	945	60%
Semi-formal	36	8%	3	2%	5	6%	1	2%	1	3%	89	11%	135	9%
Internet	47	11%	15	11%	1	1%	9	12%	9	26%	74	9%	155	10%
Other	5	1%	1	1%	5	6%	2	3%	0	0%	9	1%	22	1%
Total	**428**	**100%**	**142**	**100%**	**82**	**100%**	**76**	**100%**	**34**	**100%**	**806**	**100%**	**1,567**	**100%**

Table A3-4. Past Purchase Seller, by AQMD Geography

	Bay Area N.	Bay Area Pct.	Sacramento N.	Sacramento Pct.	San Diego N.	San Diego Pct.	SJV N.	SJV Pct.	South Coast N.	South Coast Pct.	Other N.	Other Pct.	Total N.	Total Pct.
Social network	48	29%	10	21%	35	25%	43	2 5%	127	18%	46	15%	309	20%
Formal	104	63%	31	65%	71	51%	97	55%	434	60%	196	66%	933	60%
Semi-formal	10	6%	1	2%	5	3%	5	3%	93	13%	16	5%	130	8%
Internet	3	2%	3	6%	27	19%	30	17%	57	8%	32	11%	152	10%
Other	1	1%	3	6%	1	1%	0	0%	9	1%	6	2%	20	1%
Total	**166**	**100%**	**48**	**100%**	**139**	**100%**	**175**	**100%**	**720**	**100%**	**297**	**100%**	**1,543**	**100%**

Table A3-5. Future Purchase Seller, by Income

	<$25,000 N.	<$25,000 Pct.	$25K-$50K N.	$25K-$50K Pct.	$50K-$75K N.	$50K-$75K Pct.	>$75,000 N.	>$75,000 Pct.	Total N.	Total Pct.
Social network	56	12%	33	6%	26	7%	14	10%	130	8%
Formal	276	59%	437	74%	267	76%	100	71%	1,080	70%
Semi-formal	58	12%	34	6%	15	4%	18	13%	126	8%
Internet	63	13%	72	12%	37	11%	6	5%	179	12%
Other	15	3%	12	2%	7	2%	2	1%	35	2%
Total	**469**	**100%**	**588**	**100%**	**352**	**100%**	**140**	**100%**	**1,549**	**100%**

Table A3-6. Future Purchase Seller, by Race/Ethnicity

	Non-Hispanic													
	White		Black		Asian		Other		2+ Races		Hispanic		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
Social network	27	6%	13	9%	10	12%	2	3%	0	0%	77	10%	130	8%
Formal	308	72%	113	79%	62	76%	52	69%	18	52%	527	67%	1,080	70%
Semi-formal	27	6%	8	6%	2	3%	10	13%	7	20%	72	9%	126	8%
Internet	56	13%	8	5%	7	9%	11	15%	10	28%	87	11%	179	12%
Other	9	2%	1	0%	0	0%	0	0%	0	0%	25	3%	35	2%
Total	**427**	**100%**	**142**	**100%**	**81**	**100%**	**76**	**100%**	**34**	**100%**	**789**	**100%**	**1,549**	**100%**

2. Magnitude of Vehicle Purchase Expenditure and Experience with Vehicle Finance

Table A3-7. Percent of Households Who Buy Used vs. New Vehicles, by Race/Ethnicity

	Non-Hispanic													
	White		Black		Asian		Other		2+ Races		Hispanic		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
New	151	40%	40	31%	54	68%	39	54%	18	67%	301	42%	603	43%
Used	274	60%	103	69%	28	32%	36	46%	16	33%	490	58%	947	57%
Total	**425**	**100%**	**142**	**100%**	**82**	**100%**	**76**	**100%**	**34**	**100%**	**791**	**100%**	**1,550**	**100%**

Table A3-8. Amount Paid for Main Vehicle, by Income and Race/Ethnicity

	Non-Hispanic										Hispanic		Total	
	White		Black		Asian		Other		2+ Races					
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
<$25K	76	$10,147	46	$8,210	22	$10,312	13	$10,181	3	$8,805	163	$10,417	322	$10,007
$25K-$50K	121	$12,462	33	$12,499	19	$21,357	19	$17,325	8	$18,690	219	$12,913	420	$13,453
$50K-$75K	56	$14,349	23	$12,850	14	$19,927	8	$21,809	7	$23,509	172	$18,862	279	$17,704
>$75K	46	$16,370	2	$3,000	1	$20,837	0	$35,000	N/A	N/A	54	$20,273	103	$18,236
Total	**299**	**$12,828**	**104**	**$10,531**	**55**	**$16,667**	**40**	**$15,909**	**18**	**$18,680**	**607**	**$14,579**	**1,124**	**$13,956**

Table A3-9. Amount Paid for Vehicle, by Urbanization Geography

	N.	Mean	Mean Pct Inc.
Urban	492	$14,062	62.1%
Suburban	452	$14,005	47.4%
Rural	167	$13,554	43.5%
Total	**1,112**	**$13,962**	**53.3%**

Table A3-10. Amount Paid for Vehicle, by Urbanization Geography and Vehicle Age

	New			Used			Total		
	N.	Mean	Mean Pct Inc.	N.	Mean	Mean Pct Inc.	N.	Mean	Mean Pct Inc.
Urban	154	$22,020	103.1%	328	$10,627	44.3%	482	$14,266	63.1%
Suburban	162	$19,890	52.9%	288	$10,575	43.6%	451	$13,934	47.0%
Rural	55	$23,090	78.1%	112	$8,861	26.4%	167	$13,554	43.5%
Total	**372**	**$21,248**	**77.4%**	**728**	**$10,335**	**41.3%**	**1,100**	**$14,022**	**53.5%**

Table A3-11. Amount Paid for Vehicle, by AQMD Geography

	N.	Mean	Mean Pct Inc.
Bay Area	124	$14,254	64.6%
Sacramento Metro	26	$15,491	56.3%
San Diego	94	$13,886	66.1%
San Joaquin Valley	140	$12,556	41.6%
South Coast	498	$13,957	54.4%
Other	230	$14,526	46.5%
Total	**1,112**	**$13,962**	**53.3%**

Table A3-12. Amount Paid for Main Vehicle, by Language (Hispanic Respondents Only)

	N.	Mean
English Proficient	158	$13, 785
Bilingual	344	$15,954
Spanish Proficient	80	$10,549
Total	**582**	**$14,624**

Table A3-13. Amount of Money Respondents Anticipate Spending to Purchase or Put a Down Payment on Future Vehicle, by Race/Ethnicity

		N.	Mean
Non-Hispanic	White	397	$9,512
	Black	122	$6,138
	Asian	76	$10,854
	Other	75	$10,096
	2+ Races	36	$8,335
Hispanic		761	$8,531
Total		**1,467**	**$8,794**

Table A3-14. Amount of Money Respondents Anticipate Spending to Purchase or Put a Down Payment on Future Vehicle, by Income and Race/Ethnicity

	Non-Hispanic													
	White		Black		Asian		Other		2+ Races		Hispanic		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
<$25K	103	$6,346	52	$4,904	28	$14,365	37	$5,944	5	$14,451	198	$7,295	422	$7,195
$25K-$50K	166	$11,125	39	$7,846	26	$14,176	27	$15,283	22	$10,000	275	$7,743	554	$9,515
$50K-$75K	81	$10,858	26	$2,625	22	$2,806	11	$11,311	10	$1,630	207	$9,213	357	$8,582
> $75K	46	$8,420	5	$22,634	1	$4,350	0	$9,541	N/A	N/A	80	$12,514	133	$11,427
Total	**397**	**$9,512**	**122**	**$6,138**	**76**	**$10,854**	**75**	**$10,096**	**36**	**$8,335**	**761**	**$8,531**	**1,467**	**$8,794**

Table A3-15. Amount of Money Respondents Anticipate Spending to Purchase or Put a Down Payment on Future Vehicle, by Language (Hispanic Respondents Only)

	N.	Mean
English Proficient	202	$7,143
Bilingual	434	$9,416
Spanish Proficient	94	$8,037
Total	**731**	**$8,609**

Table A3-16. Amount of Money Respondents Anticipate Spending to Purchase or Put a Down Payment on Future Vehicle, by Urbanization Geography

	N.	Mean
Urban	608	$9,264
Suburban	617	$7,968
Rural	219	$10,062
Total	**1,444**	**$8,831**

Table A3-17. Amount of Money Respondents Anticipate Spending to Purchase or Put a Down Payment on Future Vehicle, by AQMD Geography

	N.	Mean
Bay Area	157	$9,626
Sacramento Metro	41	$9,661
San Diego	136	$8,831
San Joaquin Valley	177	$6,709
South Coast	651	$8,776
Other	282	$9,724
Total	**1,444**	**$8,831**

Table A3-18. Monthly Payments Respondents Report They Could Afford to Finance the Purchase of a Future Vehicle, by Language (Hispanic Respondents Only)

	N.	Mean	Mean Pct Inc.
English Proficient	192	$240	11.2%
Bilingual	411	$276	14.8%
Spanish Proficient	105	$307	15.5%
Total	**708**	**$271**	**13.9%**

Table A3-19. Monthly Payments Respondents Report they Could Afford to Finance the Purchase of a Future Vehicle, by Urbanization Geography

	N.	Mean	Mean Pct Inc.
Urban	610	$244	14.9%
Suburban	592	$255	15.3%
Rural	225	$269	11.2%
Total	**1,427**	**$252**	**14.4%**

Table A3-20. Monthly Payments Households Report They Could Afford to Finance the Purchase of a Future Vehicle, by AQMD Geography

	N.	Mean	Mean Pct Inc.
Bay Area	147	$274	15.6%
Sacramento Metro	40	$215	9.6%
San Diego	134	$205	14.1%
San Joaquin Valley	168	$238	13.4%
South Coast	661	$256	16.2%
Other	278	$269	11.3%
Total	**1,427**	**$252**	**14.4%**

Chapter 4 Appendix

This appendix contains tables produced to address the research questions in Chapter 4 that were not included in the chapter. Additional tables in support of ARB's analysis plan are included below as well. For reference, the appendix will list the tables in the order they are discussed in the chapter, which is based on the guiding research questions. We then list the tables requested by ARB's analysis plan (if they are not already included or addressed by the guiding research questions for Chapter 4).

The research questions guiding this chapter are as follows:

1. What effect would various rebate incentive levels have on the purchase of different types low- and zero-emission vehicles?
2. What effect would guaranteed loans with various interest rates have on the purchase of different types low- and zero-emission vehicles?
3. How would the presence of both of these program affect vehicle purchase rates?
4. How do respondent characteristics such as income, ethnicity, geography, and AQMD region attenuate the effects of these rebate and loan programs?

All tables requested by ARB's analysis plan can be found in Chapter 4 or in the tables below.

Table A4-1. Percent of Weighted Sample Choosing HEV/PHEV/BEV, by Subsidy Level and AQMD Region

HEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Bay Area	25.3%	30.1%	35.1%	43.0%
Sacramento	26.2%	31.2%	36.5%	44.4%
San Diego	25.8%	30.7%	35.7%	43.3%
SJV	25.7%	30.6%	35.7%	43.5%
South Coast	25.6%	30.4%	35.4%	43.2%
Other	25.8%	30.6%	35.5%	43.3%
PHEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Bay Area	4.4%	5.2%	6.1%	7.8%
Sacramento	3.8%	4.5%	5.3%	6.7%
San Diego	4.1%	4.8%	5.6%	7.2%
SJV	3.9%	4.6%	5.4%	6.9%
South Coast	4.3%	5.1%	6.0%	7.6%
Other	4.4%	5.2%	6.1%	7.7%
BEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Bay Area	5.3%	6.3%	7.3%	8.2%
Sacramento	5.3%	6.3%	7.3%	8.0%
San Diego	5.6%	6.7%	7.7%	8.4%
SJV	5.3%	6.3%	7.3%	8.1%
South Coast	5.3%	6.2%	7.2%	8.0%
Other	5.4%	6.4%	7.4%	8.2%

Table A4-2. Percent of Weighted Sample Choosing HEV/PHEV/BEV, by Subsidy Level and Ethnicity

HEV	**$0**	**$2,500**	**$5,000**	**$9,500**
White	25.5%	30.2%	35.2%	42.8%
Black	25.4%	30.3%	35.4%	43.2%
Asian	25.2%	30.0%	35.1%	43.3%
Other	26.0%	31.0%	36.3%	44.3%
2+	25.6%	30.4%	35.5%	43.6%
Hispanic	25.8%	30.6%	35.6%	43.4%
PHEV	**$0**	**$2,500**	**$5,000**	**$9,500**
White	4.2%	5.0%	5.8%	7.4%
Black	3.8%	4.5%	5.3%	6.8%
Asian	4.1%	4.9%	5.7%	7.4%
Other	4.1%	4.9%	5.7%	7.3%
2+	4.2%	5.0%	5.8%	7.5%
Hispanic	4.4%	5.2%	6.1%	7.7%
BEV	**$0**	**$2,500**	**$5,000**	**$9,500**
White	5.5%	6.5%	7.5%	8.2%
Black	5.2%	6.2%	7.3%	7.9%
Asian	5.7%	6.8%	8.0%	8.8%
Other	5.1%	6.1%	7.1%	7.8%
2+	4.9%	5.9%	6.8%	7.6%
Hispanic	5.3%	6.3%	7.2%	8.0%

Table A4-3. Percent of Weighted Sample Choosing HEV/PHEV/BEV, by Financing Interest Rate and AQMD Region

HEV	**None**	**15.0%**	**7.5%**	**5.0%**
Bay Area	25.3%	27.0%	27.7%	27.9%
Sacramento	26.2%	27.4%	28.0%	28.2%
San Diego	25.8%	26.6%	27.2%	27.4%
SJV	25.7%	27.5%	28.3%	28.5%
South Coast	25.6%	26.5%	27.1%	27.3%
Other	25.8%	27.1%	27.8%	28.0%
PHEV	**None**	**15.0%**	**7.5%**	**5.0%**
Bay Area	4.4%	5.0%	5.1%	5.2%
Sacramento	3.8%	4.2%	4.4%	4.4%
San Diego	4.1%	4.5%	4.7%	4.7%
SJV	3.9%	4.4%	4.6%	4.6%
South Coast	4.3%	4.8%	4.9%	5.0%
Other	4.4%	4.9%	5.0%	5.1%
BEV	**None**	**15.0%**	**7.5%**	**5.0%**
Bay Area	5.3%	5.3%	5.4%	5.5%
Sacramento	5.3%	5.3%	5.3%	5.3%
San Diego	5.6%	5.6%	5.6%	5.6%
SJV	5.3%	5.3%	5.4%	5.4%
South Coast	5.3%	5.3%	5.3%	5.3%
Other	5.4%	5.4%	5.4%	5.5%

Table A4-4. Percent of Weighted Sample Choosing HEV/PHEV/BEV, by Subsidy Level (Financing at 15%) and Urbanization Geography

HEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Urban	26.8%	30.5%	35.6%	43.4%
Suburban	26.8%	30.4%	35.4%	43.2%
Rural	26.7%	30.5%	35.5%	43.4%
PHEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Urban	4.7%	5.2%	5.8%	7.4%
Suburban	4.8%	5.3%	5.9%	7.5%
Rural	4.7%	5.3%	6.0%	7.6%
BEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Urban	5.4%	6.4%	7.4%	8.1%
Suburban	5.4%	6.4%	7.4%	8.1%
Rural	5.2%	6.1%	7.1%	7.9%

Table A4-5. Percent of Weighted Sample Choosing HEV/PHEV/BEV, by Subsidy Level (Financing at 15%) and AQMD Region

HEV	**$0**	**$2,500**	**$5,000**	**$9,500**
Bay Area	27.0%	30.3%	35.1%	43.0%
Sacramento	27.4%	31.2%	36.5%	44.4%
San Diego	26.6%	30.7%	35.7%	43.3%
SJV	27.5%	30.6%	35.7%	43.5%
South Coast	26.5%	30.4%	35.4%	43.2%
Other	27.1%	30.6%	35.5%	43.3%
PHEV	$0	$2,500	$5,000	$9,500
Bay Area	5.0%	5.5%	6.1%	7.8%
Sacramento	4.2%	4.7%	5.3%	6.7%
San Diego	4.5%	5.0%	5.6%	7.2%
SJV	4.4%	4.9%	5.4%	6.9%
South Coast	4.8%	5.3%	6.0%	7.6%
Other	4.9%	5.4%	6.1%	7.7%
BEV	$0	$2,500	$5,000	$9,500
Bay Area	5.3%	6.3%	7.3%	8.2%
Sacramento	5.3%	6.3%	7.3%	8.0%
San Diego	5.6%	6.7%	7.7%	8.4%
SJV	5.3%	6.3%	7.3%	8.1%
South Coast	5.3%	6.2%	7.2%	8.0%
Other	5.4%	6.4%	7.4%	8.2%

Table A4-6. Percent of Weighted Sample Choosing HEV/PHEV/BEV, by Subsidy Level (Financing at 15%) and Ethnicity

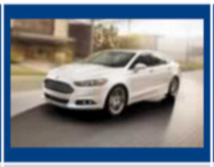
HEV	**$0**	**$2,500**	**$5,000**	**$9,500**
White	26.2%	30.2%	35.2%	42.8%
Black	25.9%	30.3%	35.4%	43.2%
Asian	27.1%	30.7%	35.1%	43.3%
Other	26.3%	31.0%	36.3%	44.3%
2+	27.9%	31.0%	35.5%	43.6%
Hispanic	27.3%	30.6%	35.6%	43.4%
PHEV	**$0**	**$2,500**	**$5,000**	**$9,500**
White	4.5%	5.1%	5.8%	7.4%
Black	4.1%	4.6%	5.3%	6.8%
Asian	4.8%	5.4%	5.9%	7.4%
Other	4.3%	4.9%	5.7%	7.3%
2+	5.0%	5.5%	6.1%	7.5%
Hispanic	5.0%	5.5%	6.1%	7.7%
BEV	**$0**	**$2,500**	**$5,000**	**$9,500**
White	5.5%	6.5%	7.5%	8.2%
Black	5.2%	6.2%	7.3%	7.9%
Asian	5.7%	6.8%	8.0%	8.8%
Other	5.1%	6.1%	7.1%	7.8%
2+	5.0%	5.9%	6.8%	7.6%
Hispanic	5.3%	6.3%	7.2%	8.0%

•

Figure A4-1. Example Vehicle Selection Questions from Survey

Below is a selection of vehicles that appear to match your preferences and fit within your budget. Please select which of the following vehicles you would be most likely to purchase if you were purchasing a vehicle now and these are your options. Assume the vehicles are different only in the ways we describe them below (in other words, assume they are all in similar, good condition). Prices shown are for the base models and do not include upgrades.

Select one answer from each row in the grid

					
Model Year	2017	2017	2015	2010	2010
Make & Model	Ford Fusion	Toyota Camry	Ford Fusion	Ford Focus	Ford Focus
Odometer	50,000 mi	0 mi (new)	150,000 mi	100,000 mi	50,000 mi
Cost per mile	$0.11	$0.11	$0.12	$0.11	$0.11
Fuel economy (MPG)	27	27	26	28	28
Price after incentives (if applicable)	$13,501	$17,323	$8,528	$5,038	$6,606
First Choice	○	●	○	○	○
Second Choice	○	○	○	○	●

Out of the following vehicles, please choose the vehicle that you would be most likely to purchase.

Select one answer only

				
Model Year	2017	2017	2013	2016
Make & Model	Toyota Camry	Toyota Camry	Toyota Avalon Hybrid	Ford Fusion Energi
Odometer	50,000 mi	50,000 mi	50,000 mi	100,000 mi
Engine Type	Gasoline	Gasoline	Hybrid	Plug-in Hybrid
Refueling cost per month **Fuel economy (MPG)**	$60 (27 mpg)	$60 (27 mpg)	$39 (42 mpg)	$24 (68 mpg)
Price after incentives (if applicable) **-Down payment** **=Loan amount**	$14,488* (pay in cash, no loan)	$13,039 -$8,000 =$5,039 loan	$13,032 -$8,000 =$5,032 loan	$10,338 -$8,000 =$2,338 loan
Monthly payment**	none	$128 *i*	$128 *i*	$65 *i*
Top choice	○	○	○	○

*This is the cash price of the vehicle
**Loan duration of 48 months

Previous | Next

Chapter 5 Appendix

This appendix contains tables produced to address the research questions in Chapter 5 that were not included in the chapter. Additional tables in support of ARB's analysis plan are included below as well. For reference, the appendix will list the tables in the order they are discussed in the chapter, which is based on the guiding research questions. We then list the tables requested by ARB's analysis plan (if they are not already included or addressed by the guiding research questions for Chapter 5).

The research questions guiding this chapter are as follows:

1. What factors influence vehicle access and the number of vehicles used by household structure within the sample?
2. What are the emissions-relevant characteristics of vehicles in which surveyed households have access?
3. How do households compose their fleets with respect to household structure?
4. How much money do households need to spend to maintain and operate the household's main vehicle?
5. What do households report regarding their intentions to keep or dispose of their main household vehicle and what factors influence these responses?

Additionally, tables requested by ARB's analysis plan can be found in Chapter 5 or in the tables below. ARB asked for the following:

6. Comparison of main vehicle with other household vehicles in terms of age, odometer reading, and fuel economy.

1. Vehicle Ownership and Number of Vehicles by Household Structure

Table A5-1. Mean Vehicle Holdings, by Household Size and Urbanization Geography

	Urban		Suburban		Rural		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean
1	101	1.2	97	1.2	21	1.6	219	1.2
2	121	1.4	120	1.4	64	1.6	305	1.5
3	133	1.7	146	2.1	30	1.4	309	1.9
4	126	2.3	138	2.9	53	2.2	317	2.5
5	102	2.2	84	2.0	28	2.1	215	2.1
6+	97	2.7	87	3.0	33	3.1	216	2.9
Total	**680**	**1.9**	**671**	**2.1**	**229**	**2.0**	**1,580**	**2.0**

Table A5-2. Mean Vehicle Holdings, by Household Size and AQMD Geography

	Bay Area		Sacramento		San Diego		SJV		South Coast		Other		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
1	35	1.1	3	1.0	46	1.1	34	2.0	77	1.1	24	1.4	219	1.2
2	29	1.3	9	1.5	20	1.4	23	1.8	146	1.4	78	1.4	305	1.5
3	44	2.2	6	1.3	22	2.0	33	1.6	150	1.8	54	2.0	309	1.9
4	19	3.2	9	3.0	23	2.2	38	2.4	151	2.4	77	2.7	317	2.5
5	21	1.8	8	2.0	16	1.6	23	1.3	110	2.3	38	2.6	215	2.1
6+	22	3.5	12	2.4	21	2.9	35	2.6	98	3.1	28	2.2	216	2.9
Total	**170**	**2.0**	**48**	**2.1**	**147**	**1.7**	**186**	**2.0**	**732**	**2.0**	**298**	**2.1**	**1,580**	**2.0**

Table A5-3. Mean Vehicle Holdings, by Number of Licensed Drivers and AQMD Geography

	Bay Area		Sacramento		San Diego		SJV		South Coast		Other		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
0	0	0.0	N/A	N/A	2	0.3	2	1.0	0	1.0	0	0.0	4	0.6
1	17	1.0	13	2.0	16	1.1	34	1.4	130	1.2	54	1.1	264	1.2
2	49	1.8	23	1.9	62	1.6	104	2.0	285	1.9	138	1.8	662	1.9
3	31	2.6	6	2.9	20	2.7	11	2.8	134	2.5	41	3.0	243	2.6
4	8	4.1	2	3.9	10	4.0	12	4.0	63	3.2	20	2.9	115	3.4
5+	20	3.9	N/A	N/A	3	3.7	2	4.0	29	5.3	19	4.9	73	4.7
Total	**127**	**2.4**	**43**	**2.2**	**113**	**2.0**	**164**	**2.1**	**642**	**2.2**	**642**	**2.2**	**1,361**	**2.2**

Table A5-4. Mean Vehicle Holdings, by Number of Licensed Drivers and Urbanization Geography

	Urban		Suburban		Rural		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean
0	3	1.0	0	0.0	2	0.0	4	0.6
1	120	1.2	99	1.1	46	1.4	264	1.2
2	285	1.8	259	2.0	119	1.7	662	1.9
3	97	2.4	115	2.7	31	3.2	243	2.6
4	42	3.3	59	3.3	13	3.9	115	3.4
5+	35	4.7	35	4.6	3	6.0	73	4.7
Total	**581**	**2.1**	**566**	**2.3**	**213**	**2.0**	**1,361**	**2.2**

2. The Condition of Fleet Vehicles: Age, Odometer, and Fuel Economy

Table A5-5. Mean Fleet Age, by Household Size and Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
1	156	2005.3	62	2006.6	N/A	N/A	N/A	N/A	218	2005.7
2	114	2006.4	185	2006.7	N/A	N/A	N/A	N/A	298	2006.6
3	99	2006.9	118	2006.2	90	2006.8	N/A	N/A	307	2006.6
4	52	2008.6	130	2006.8	134	2007.9	N/A	N/A	317	2007.6
5	31	2006.6	55	2006.3	63	2008.9	55	2009.3	205	2008.1
6+	15	2009.0	39	2009.3	77	2007.4	84	2006.7	216	2007.4
Total	**468**	**2006.7**	**589**	**2006.8**	**364**	**2007.7**	**140**	**2007.7**	**1,561**	**2007.2**

Table A5-6. Mean Fleet Age, by Household Size and Race/Ethnicity

	Non-Hispanic													
	White		Black		Asian		Other		2+ Races		Hispanic		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
1	70	2003.0	34	2006.5	10	2011.4	27	2008.1	2	2010.0	75	2006.3	218	2005.7
2	133	2005.3	31	2010.9	11	2005.5	12	2005.6	5	1997.8	105	2008.0	298	2006.6
3	78	2005.5	42	2006.3	23	2009.0	11	2010.4	2	2006.6	151	2006.6	307	2006.6
4	44	2005.4	20	2006.2	14	2010.2	15	2007.6	13	2009.0	211	2007.9	317	2007.6
5	36	2007.3	4	2010.2	6	2013.0	3	2008.0	2	2004.9	154	2008.1	205	2008.1
6+	64	2007.9	12	2008.2	18	2009.6	7	2007.9	9	2014.0	106	2006.4	216	2007.4
Total	**425**	**2005.9**	**142**	**2007.6**	**82**	**2009.6**	**76**	**2007.6**	**34**	**2008.7**	**801**	**2007.4**	**1,561**	**2007.2**

Table A5-7. Mean Fleet Age, by Household Size and Urbanization Geography

	Urban		Suburban		Rural		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean
1	95	2,006.0	92	2,005.6	21	2,006.4	209	2005.9
2	115	2,008.4	112	2,005.9	62	2,005.0	289	2006.7
3	132	2,006.9	145	2,006.5	29	2,005.6	306	2006.6
4	126	2,007.1	136	2,008.3	52	2,006.4	314	2007.6
5	99	2,008.1	84	2,008.8	21	2,006.4	205	2008.1
6+	95	2,006.5	86	2,007.7	33	2,009.1	214	2007.4
Total	**663**	**2007.2**	**656**	**2007.3**	**219**	**2006.6**	**1,537**	**2007.2**

Table A5-8. Mean Fleet Age, by Household Size and AQMD Geography

	Bay Area		Sacramento		San Diego		SJV		South Coast		Other		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
1	35	2,007.9	3	2,006.7	42	2,006.9	34	2,003.9	72	2,006.5	24	2,004.6	209	2005.9
2	25	2,004.8	9	2,005.7	17	2,009.7	21	2,004.4	140	2,007.5	77	2,006.0	289	2006.7
3	44	2,004.9	6	2,003.3	22	2,009.2	32	2,005.5	149	2,006.8	54	2,007.4	306	2006.6
4	18	2,006.7	9	2,006.4	23	2,008.9	38	2,007.1	149	2,008.0	76	2,007.1	314	2007.6
5	21	2,010.0	8	2,008.7	13	2,008.9	16	2,006.9	110	2,008.5	38	2,006.6	205	2008.1
6+	22	2,005.9	12	2,012.5	21	2,009.5	35	2,006.8	96	2,006.8	28	2,008.6	214	2007.4
Total	**166**	**2006.3**	**48**	**2008.3**	**137**	**2008.8**	**176**	**2005.9**	**715**	**2007.5**	**296**	**2006.9**	**1,537**	**2007.2**

Table A5-9. Mean Fleet Mileage, by Household Size and Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
1	149	109,858	62	99,398	N/A	N/A	N/A	N/A	211	106,303
2	113	83,143	180	82,088	N/A	N/A	N/A	N/A	293	82,445
3	87	78,389	115	100,301	84	103,727	N/A	N/A	287	95,946
4	51	62,239	123	92,909	119	97,274	N/A	N/A	293	89,808
5	28	83,464	51	88,690	63	78,539	48	66,611	190	77,825
6+	15	76,567	35	73,325	77	87,605	79	100,316	207	90,802
Total	**444**	**85,123**	**566**	**90,284**	**344**	**93,215**	**127**	**88,945**	**1,481**	**89,832**

Table A5-10. Mean Fleet Mileage, by Household Size and Race/Ethnicity

	Non-Hispanic										Hispanic		Total	
	White		Black		Asian		Other		2+ Races					
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
1	63	116,211	34	129,458	10	18,072	27	40,823	2	125,896	75	121,082	211	106,303
2	131	86,790	29	76,253	11	48,213	12	41,032	5	79,859	104	87,439	293	82,445
3	71	105,808	41	86,150	23	85,242	11	111,255	2	88,163	140	92,887	287	95,946
4	43	115,684	19	121,019	14	92,739	15	94,505	13	62,966	189	82,522	293	89,808
5	35	96,538	4	35,283	6	49,673	3	102,000	2	115,345	140	74,359	190	77,825
6+	64	100,308	12	102,026	18	67,498	7	153,933	9	26,660	97	87,956	207	90,802
Total	**406**	**100,959**	**138**	**99,847**	**82**	**70,020**	**76**	**84,428**	**34**	**60,501**	**746**	**86,581**	**1,481**	**89,832**

Table A5-11. Mean Fleet Mileage, by Household Size and Urbanization Geography

	Urban		Suburban		Rural		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean
1	89	104,693	91	108,504	21	87,982	202	104,106
2	115	87,049	109	84,410	60	62,302	284	80,584
3	123	83,335	134	107,744	29	75,849	286	95,653
4	116	86,707	122	86,749	52	106,819	290	89,924
5	94	71,178	80	72,847	15	132,905	190	77,780
6+	94	86,153	79	94,291	33	94,835	206	90,856
Total	**631**	**84,956**	**616**	**92,476**	**211**	**91,914**	**1,458**	**89,324**

Table A5-12. Mean Fleet Mileage, by Household Size and AQMD Geography

	Bay Area		Sacramento		San Diego		SJV		South Coast		Other		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
1	35	58,036	3	104,858	41	99,797	29	117,682	71	119,785	24	103,141	202	104,106
2	24	81,434	9	75,939	17	70,290	19	57,880	138	85,625	77	82,074	284	80,584
3	44	98,790	6	63,996	21	125,016	25	155,969	139	84,392	52	85,863	286	95,653
4	18	93,007	9	55,692	22	98,843	36	101,193	142	83,736	63	99,807	290	89,924
5	21	57,399	8	84,579	13	68,836	12	79,622	103	75,867	34	91,920	190	77,780
6+	21	100,285	12	65,550	21	76,194	35	116,027	89	88,709	28	78,859	206	90,856
Total	**162**	**87,060**	**48**	**68,744**	**134**	**92,015**	**156**	**108,243**	**681**	**86,014**	**277**	**90,028**	**1,458**	**89,324**

Table A5-13. Mean Fuel Economy, by Household Size and Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
1	155	23.4	62	30.8	N/A	N/A	N/A	N/A	217	25.5
2	107	23.2	185	24.1	N/A	N/A	N/A	N/A	292	23.8
3	98	21.0	119	23.8	90	23.0	N/A	N/A	307	22.7
4	53	21.2	127	21.9	134	23.6	N/A	N/A	313	22.5
5	31	18.6	55	23.2	63	24.7	55	24.1	205	23.2
6+	15	27.7	39	26.2	77	23.4	84	22.9	216	24.0
Total	**459**	**22.4**	**588**	**24.3**	**364**	**23.6**	**140**	**23.4**	**1,551**	**23.5**

Table A5-14. Mean Fuel Economy, by Household Size and Race/Ethnicity

	Non-Hispanic										Hispanic		Total	
	White		Black		Asian		Other		2+ Races					
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
1	70	27.8	34	20.8	10	16.1	27	26.7	2	25.2	74	26.4	217	25.5
2	134	23.1	25	23.9	11	26.7	12	18.9	5	20.2	105	25.0	292	23.8
3	79	23.3	42	23.4	23	18.5	11	25.6	2	27.6	150	22.5	307	22.7
4	44	23.8	14	21.9	14	23.4	15	28.6	13	27.6	213	21.5	313	22.5
5	35	22.9	4	32.2	6	22.8	3	28.0	2	22.8	154	22.9	205	23.2
6+	64	24.3	12	21.0	18	30.3	7	25.5	9	29.6	106	22.6	216	24.0
Total	**427**	**24.2**	**131**	**22.7**	**82**	**23.1**	**76**	**25.6**	**34**	**26.6**	**801**	**23.0**	**1,551**	**23.5**

Table A5-15. Mean Fuel Economy, by Household Size and Urbanization Geography

	Urban		Suburban		Rural		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean
1	94	26.0	92	24.0	21	30.0	208	25.5
2	109	23.5	113	24.1	61	23.5	283	23.7
3	133	21.7	145	23.6	28	22.6	306	22.7
4	121	22.2	137	22.7	52	22.9	310	22.5
5	100	23.2	84	23.7	21	20.8	205	23.2
6+	95	21.6	86	26.4	33	25.3	214	24.1
Total	**652**	**22.9**	**658**	**23.9**	**216**	**23.9**	**1,527**	**23.5**

Table A5-16. Mean Fuel Economy, by Household Size and AQMD Geography

	Bay Area		Sacramento		San Diego		SJV		South Coast		Other		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
1	35	23.3	3	28.6	40	25.8	34	30.8	72	26.0	24	18.8	208	25.5
2	25	27.5	9	20.1	18	24.1	20	21.0	134	23.1	77	24.7	283	23.7
3	44	21.7	6	20.7	22	24.8	32	24.3	149	22.1	53	23.8	306	22.7
4	18	25.0	9	31.7	23	20.6	38	20.9	151	21.9	71	23.6	310	22.5
5	21	30.1	8	19.9	13	27.1	16	26.9	110	21.3	38	22.5	205	23.2
6+	22	25.6	12	28.7	21	21.0	35	23.9	96	23.7	28	24.8	214	24.1
Total	**165**	**24.9**	**48**	**25.1**	**137**	**24.0**	**175**	**24.6**	**712**	**22.7**	**290**	**23.5**	**1,527**	**23.5**

3. Vehicle Body Type and Fleet Composition

No additional tables.

4. Main Vehicle Operational and Maintenance Expenditures

Table A5-17. Annual Vehicle Expenditure, by Race/Ethnicity

		N.	Mean	Mean Pct Inc.
Non-Hispanic	White	134	$3,170	12.6%
	Black	48	$2,721	9.9%
	Asian	31	$3,670	13.4%
	Other	30	$4,472	14.9%
	2+ Races	10	$2,679	8.3%
Hispanic		274	$3,349	19.7%
Total		**526**	**$3,317**	**16.2%**

Table A5-18. Annual Vehicle Expenditure, by Urbanization Geography

	N.	Mean	Mean Pct Inc
Urban	209	$2,862	16.5%
Suburban	233	$3,489	16.7%
Rural	74	$4,063	13.4%
Total	**517**	**$3,317**	**16.1%**

Table A5-19. Annual Vehicle Expenditure, by AQMD Geography

	N.	Mean	Mean Pct Inc
Bay Area	58	$3,329	10.5%
Sacramento Metro	11	$6,108	38.0%
San Diego	38	$2,634	16.3%
San Joaquin Valley	75	$2,877	10.9%
South Coast	234	$3,005	19.5%
Other	100	$4,308	12.9%
Total	**517**	**$3,317**	**16.1%**

Table A5-20. Annual Vehicle Expenditure, by Main Vehicle Body Type

	N.	Mean	Mean Pct Inc
Small	217	$3,075	18.8%
Medium	187	$3,026	15.1%
Large	113	$4,284	13.3%
Total	**518**	**$3,322**	**16.3%**

Table A5-21. Annual Vehicle Expenditure (Including Interest), by Race/Ethnicity

		N.	Mean	Mean Pct Inc
Non-Hispanic	White	34	$4,152	15.2%
	Black	22	$3,801	7.3%
	Asian	10	$5,600	12.8%
	Other	3	$2,795	9.9%
	2+ Races	3	$3,268	10.0%
Hispanic		97	$4,958	14.0%
Total		**168**	**$4,618**	**13.2%**

Table A5-22. Annual Vehicle Expenditure (Including Interest), by Urbanization Geography

	N.	Mean	Mean Pct Inc
Urban	69	$3,404	11.0%
Suburban	76	$5,224	13.4%
Rural	18	$6,936	18.6%
Total	**163**	**$4,645**	**13.0%**

Table A5-23. Annual Vehicle Expenditure (Including Interest), by AQMD Geography

	N.	Mean	Mean Pct Inc
Bay Area	14	$5,161	11.0%
Sacramento Metro	3	$3,359	7.3%
San Diego	7	$5,003	12.6%
San Joaquin Valley	19	$3,295	12.5%
South Coast	83	$3,698	11.8%
Other	36	$7,352	17.2%
Total	**163**	**$4,645**	**13.0%**

5. Intention to Keep or Dispose of Main Vehicle

Table A5-24. Mean Vehicle Age, by How Long Plan to Keep Current Vehicle and Income

Years	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
< 1	96	2004.8	101	2006.2	46	2006.3	24	2010.5	267	2006.1
1 - 2	174	2006.4	185	2007.1	102	2008.4	26	2006.6	487	2007.1
2 - 4	90	2007.8	145	2006.7	108	2009.5	43	2011.4	387	2008.3
5+	87	2008.1	126	2006.9	88	2010.1	42	2011.3	344	2008.6
Unsure	18	2003.9	23	2003.3	20	2008.9	2	2002.0	63	2005.2
Total	**465**	**2006.6**	**581**	**2006.6**	**364**	**2008.9**	**138**	**2010.2**	**1,548**	**2007.5**

Table A5-25. Mean Vehicle Age, by How Long Plan to Keep Current Vehicle and Race/Ethnicity

Years	Non-Hispanic													
	White		Black		Asian		Other		2+ Races		Hispanic		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
< 1	63	2006.2	42	2006.9	5	1994.8	15	2006.5	3	2005.0	139	2006.2	267	2006.1
1 - 2	110	2004.6	27	2005.5	34	2009.5	14	2007.5	10	2008.1	293	2007.8	487	2007.1
2 - 4	118	2006.1	32	2011.2	22	2008.8	23	2008.4	16	2010.5	175	2008.9	387	2008.3
5+	113	2007.0	36	2009.0	21	2012.3	14	2008.8	6	2015.0	155	2008.8	344	2008.6
Unsure	19	2000.2	5	2007.0	1	2006.6	9	2002.4	N/A	N/A	29	2009.0	63	2005.2
Total	**422**	**2005.7**	**142**	**2008.1**	**82**	**2009.1**	**76**	**2007.2**	**34**	**2010.2**	**791**	**2008.0**	**1,548**	**2007.5**

Table A5-26. Mean Vehicle Age, by How Long Plan to Keep Current Vehicle and Urbanization Geography

Years	Urban		Suburban		Rural		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean
< 1	123	2005.5	118	2007.0	24	2004.4	265	2006.1
1 - 2	186	2007.0	219	2007.3	75	2006.9	480	2007.1
2 - 4	179	2009.1	139	2008.9	62	2004.8	380	2008.3
5+	149	2009.0	141	2009.6	46	2005.3	337	2008.8
Unsure	20	2008.6	34	2004.5	9	2000.3	63	2005.2
Total	**657**	**2007.8**	**651**	**2007.9**	**216**	**2005.4**	**1,524**	**2007.5**

Table A5-27. Mean Vehicle Age, by How Long Plan to Keep Current Vehicle and AQMD Geography

Years	Bay Area		Sacramento		San Diego		SJV		South Coast		Other		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
< 1	31	2005.6	5	2011.8	33	2007.0	26	2005.8	122	2005.6	47	2006.4	265	2006.1
1 - 2	47	2007.9	20	2009.9	27	2006.1	59	2006.7	246	2007.0	81	2006.9	480	2007.1
2 - 4	31	2006.7	10	2006.1	44	2011.8	35	2005.2	181	2009.4	80	2006.3	380	2008.3
5+	53	2009.1	12	2010.4	21	2011.3	43	2004.3	136	2010.7	71	2006.5	337	2008.8
Unsure	2	2004.2	0	2008.7	11	2004.6	10	2008.1	27	2003.8	13	2006.3	63	2005.2
Total	**164**	**2007.6**	**47**	**2009.4**	**137**	**2008.8**	**173**	**2005.8**	**711**	**2008.0**	**291**	**2006.5**	**1,524**	**2007.5**

Table A5-28. How Long Respondents Plan to Keep Main Vehicle, by Race/Ethnicity

Years	Non-Hispanic													
	White		Black		Asian		Other		2+ Races		Hispanic		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
< 1	63	15%	42	30%	5	6%	15	20%	3	8%	143	18%	271	17%
1 - 2	110	26%	27	19%	34	41%	14	19%	10	29%	297	37%	492	32%
2 - 4	118	28%	32	23%	22	27%	23	31%	16	47%	175	22%	387	25%
5+	114	27%	36	25%	21	25%	14	19%	6	17%	155	19%	346	22%
Unsure	19	5%	5	4%	1	1%	9	12%	0	0%	29	4%	63	4%
Total	**425**	**100%**	**142**	**100%**	**82**	**100%**	**76**	**100%**	**34**	**100%**	**800**	**100%**	**1,559**	**100%**

Table A5-29. How Long Respondents Plan to Keep Main Vehicle, by Urbanization Geography

Years	Urban		Suburban		Rural		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
< 1	124	19%	121	18%	24	11%	269	18%
1 - 2	190	29%	220	34%	75	35%	485	32%
2 - 4	179	27%	139	21%	62	29%	380	25%
5+	150	23%	142	22%	46	21%	338	22%
Unsure	20	3%	34	5%	9	4%	63	4%
Total	**662**	**100%**	**657**	**100%**	**217**	**100%**	**1535**	**100%**

Table A5-30. How Long Respondents Plan to Keep Main Vehicle, by AQMD Geography

Years	Bay Area		Sacramento		San Diego		SJV		South Coast		Other		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
< 1	31	19%	5	11%	34	24%	26	15%	126	18%	47	16%	269	18%
1 - 2	48	29%	20	43%	28	20%	61	35%	248	34%	81	28%	485	32%
2 - 4	31	19%	10	20%	44	32%	35	20%	181	25%	80	27%	380	25%
5+	53	32%	12	26%	22	16%	43	24%	136	19%	71	24%	338	22%
Unsure	2	1%	0	0%	11	8%	10	6%	27	4%	13	4%	63	4%
Total	**164**	**100%**	**47**	**100%**	**139**	**100%**	**176**	**100%**	**717**	**100%**	**292**	**100%**	**1,535**	**100%**

Table A5-31. Main Reasons for Getting Rid of Vehicle, by Race/Ethnicity

	Non-Hispanic										Hispanic		Total	
	White		Black		Asian		Other		2+ Races					
	N	Pct	N	Pct	N	Pct	N	Pct	N	Pct	N	Pct	N	Pct
Too expensive to maintain	35	17%	16	17%	16	59%	4	10%	2	14%	82	19%	153	19%
Unreliable or unsafe	16	8%	4	4%	0	1%	N/A	N/A	0	0%	69	16%	90	11%
Need more seating or cargo space	23	11%	10	11%	4	16%	5	13%	3	27%	79	19%	125	16%
Want a different or newer make/model	85	41%	49	54%	6	23%	22	60%	7	54%	146	35%	315	39%
Can no longer afford vehicle	1	1%	0	0%	0	1%	4	10%	N/A	N/A	24	6%	30	4%
Other	48	23%	11	13%	N/A	N/A	3	7%	1	5%	23	5%	86	11%
Total	**209**	**100%**	**90**	**100%**	**27**	**100%**	**36**	**100%**	**13**	**100%**	**424**	**100%**	**798**	**100%**

Table A5-32. Percent of Households That Would Choose the Choice Set Vehicle If Getting Rid of Current Main Vehicle, by Race/Ethnicity

		Yes		No		Sample Total	
		N	Pct	N	Pct	N	Pct
Non-Hispanic	White	348	81%	80	19%	428	100%
Non-Hispanic	Black	131	90%	14	10%	146	100%
Non-Hispanic	Asian	64	80%	16	20%	81	100%
Non-Hispanic	Other	70	96%	3	4%	73	100%
Non-Hispanic	2+ Races	23	63%	13	37%	36	100%
Hispanic		681	84%	129	16%	809	100%
Sample Total		**1,317**	**84%**	**256**	**16%**	**1,573**	**100%**

Table A5-33. Percent of Households That Would Choose the Choice Set Vehicle If Getting Rid of Current Main Vehicle, by Urbanization Geography

	Yes		No		Sample Total	
	N	Pct	N	Pct	N	Pct
Urban	550	82%	124	18%	673	100%
Suburban	562	85%	95	15%	657	100%
Rural	189	86%	30	14%	219	100%
Sample Total	**1,300**	**84%**	**249**	**16%**	**1,549**	**100%**

Table A5-34. Percent of Households That Would Choose the Choice Set Vehicle If Getting Rid of Current Main Vehicle, by AQMD Geography

	Yes		No		Sample Total	
	N	Pct	N	Pct	N	Pct
Bay Area	152	90%	17	10%	169	100%
Sacramento Metro	38	82%	8	18%	47	100%
San Diego	115	80%	29	20%	144	100%
San Joaquin Valley	162	89%	20	11%	182	100%
South Coast	599	83%	126	17%	724	100%
Other	235	83%	48	17%	283	100%
Sample Total	**1,300**	**84%**	**249**	**16%**	**1,549**	**100%**

Table A5-35. Percent of Households That Would Send Their Current Main Vehicle to the Junkyard and Replace I t with Choice Set Vehicle, by Race/Ethnicity

		Yes		No		Sample Total	
		N	Pct	N	Pct	N	Pct
Non-Hispanic	White	289	68%	137	32%	427	100%
Non-Hispanic	Black	123	85%	21	15%	144	100%
Non-Hispanic	Asian	50	63%	30	37%	80	100%
Non-Hispanic	Other	62	84%	12	16%	75	100%
Non-Hispanic	2+ Races	21	59%	15	41%	36	100%
Hispanic		538	68%	255	32%	793	100%
Sample Total		**1,084**	**70%**	**470**	**30%**	**1,555**	**100%**

Table A5-36. Percent of Households That Would Send Their Current Main Vehicle to the Junkyard and Replace it with Choice Set Vehicle, by Urbanization Geography

	Yes		No		Sample Total	
	N	Pct	N	Pct	N	Pct
Urban	478	72%	185	28%	663	100%
Suburban	450	70%	197	30%	647	100%
Rural	135	61%	86	39%	221	100%
Sample Total	**1,064**	**69%**	**467**	**31%**	**1,531**	**100%**

Table A5-37. Percent of Households That Would Send Their Current Main Vehicle to the Junkyard and Replace It with Choice Set Vehicle, by AQMD Geography

	Yes		No		Sample Total	
	N	Pct	N	Pct	N	Pct
Bay Area	130	78%	38	23%	168	100%
Sacramento Metro	30	64%	16	36%	46	100%
San Diego	90	62%	55	38%	145	100%
San Joaquin Valley	133	73%	48	27%	181	100%
South Coast	488	69%	218	31%	706	100%
Other	193	68%	92	32%	285	100%
Sample Total	**1,064**	**69%**	**467**	**31%**	**1,531**	**100%**

Table A5-38. Lowest Amount of Money Households Would Accept to Participate in a Vehicle Scrapping Program, by Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
$250	15	4%	18	4%	15	5%	0	0%	49	4%
$500	28	8%	30	6%	29	10%	15	11%	102	8%
$750	17	5%	43	9%	8	2%	0	0%	68	5%
$1,000	55	15%	48	10%	59	19%	17	14%	179	14%
$1,500	41	11%	50	11%	29	10%	25	19%	145	11%
$2,000	37	10%	26	5%	23	7%	3	2%	88	7%
$2,500	18	5%	25	5%	12	4%	9	7%	64	5%
$3,000	52	14%	87	19%	49	16%	19	15%	208	16%
None of the above	50	13%	81	17%	37	12%	23	18%	191	15%
I would not participate	55	15%	58	12%	45	15%	16	13%	175	14%
Total	**368**	**100%**	**466**	**100%**	**306**	**100%**	**127**	**100%**	**1267**	**100%**

Table A5-39. Lowest Amount of Money Households Would Accept to Participate in a Vehicle Scrapping Program, by Race/Ethnicity

	Non-Hispanic										Hispanic		Total	
	White		Black		Asian		Other		2+ Races					
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
$250	9	3%	13	14%	1	2%	1	1%	1	4%	23	3%	49	4%
$500	39	10%	6	6%	6	11%	3	6%	1	3%	47	7%	102	8%
$750	23	6%	2	2%	3	6%	1	2%	3	13%	36	5%	68	5%
$1,000	51	14%	19	19%	10	18%	6	11%	3	15%	90	14%	179	14%
$1,500	43	11%	14	14%	1	1%	0	0%	2	9%	85	13%	145	11%
$2,000	20	5%	10	10%	1	3%	5	8%	2	10%	50	8%	88	7%
$2,500	27	7%	7	8%	1	2%	5	8%	0	0%	24	4%	64	5%
$3,000	55	15%	17	18%	5	10%	14	26%	0	2%	115	17%	208	16%
None of the above	40	11%	3	3%	10	19%	18	34%	8	38%	111	17%	191	15%
I would not participate	67	18%	6	6%	15	28%	2	5%	1	6%	82	12%	175	14%
Total	**374**	**100%**	**98**	**100%**	**54**	**100%**	**55**	**100%**	**22**	**100%**	**664**	**100%**	**1267**	**100%**

Table A5-40. Lowest Amount of Money Households Would Accept to Participate in a Vehicle Scrapping Program, by Urbanization Geography

	Urban		Suburban		Rural		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
$250	19	4%	23	4%	7	3%	49	4%
$500	29	6%	50	9%	20	11%	99	8%
$750	24	5%	34	6%	4	2%	62	5%
$1,000	74	14%	82	15%	18	9%	174	14%
$1,500	49	9%	62	12%	33	17%	144	12%
$2,000	37	7%	35	7%	13	7%	85	7%
$2,500	17	3%	34	6%	11	6%	62	5%
$3,000	96	19%	87	16%	23	12%	206	17%
None of the above	88	17%	65	12%	36	19%	190	15%
I would not participate	82	16%	65	12%	28	14%	175	14%
Total	**515**	**100%**	**536**	**100%**	**193**	**100%**	**1245**	**100%**

Table A5-41. Lowest Amount of Money Households Would Accept to Participate in a Vehicle Scrapping Program, by AQMD Geography

	Bay Area		Sacramento Metro		San Diego		San Joaquin Valley		South Coast		Other		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
$250	2	2%	0	1%	5	5%	20	14%	17	3%	4	1%	49	4%
$500	2	2%	4	13%	13	12%	12	8%	46	8%	21	8%	99	8%
$750	12	10%	0	0%	2	2%	11	7%	31	5%	7	3%	62	5%
$1,000	29	25%	1	4%	15	14%	16	11%	79	14%	33	13%	174	14%
$1,500	5	4%	1	4%	8	7%	29	20%	76	13%	24	9%	144	12%
$2,000	3	2%	2	5%	12	11%	11	7%	42	7%	17	7%	85	7%
$2,500	7	6%	4	13%	6	6%	3	2%	29	5%	13	5%	62	5%
$3,000	16	14%	5	17%	16	14%	9	6%	105	18%	55	21%	206	17%
None of the above	9	7%	2	6%	17	15%	17	12%	104	18%	41	16%	190	15%
I would not participate	31	27%	12	38%	15	14%	17	12%	57	10%	43	17%	175	14%
Total	**118**	**100%**	**31**	**100%**	**109**	**100%**	**144**	**100%**	**588**	**100%**	**256**	**100%**	**1245**	**100%**

6. Comparison of Main Vehicle With Other Household Vehicles in Terms of Age, Odometer Reading, and Fuel Economy

Table A5-42. Comparison of Main Vehicle Age With Other Household Vehicles, by Income

Age	Main Vehicle		Additional Vehicles		Fleet	
	N.	Mean	N.	Mean	N.	Mean
<$25K	467	2006.5	237	2007.1	704	2006.7
$25K-$50K	587	2006.7	521	2006.8	1,108	2006.8
$50K-$75K	364	2008.9	579	2007.0	943	2007.7
>$75K	138	2010.2	286	2006.4	423	2007.6
Total	**1,556**	**2007.5**	**1,622**	**2006.8**	**3,178**	**2007.1**

Table A5-43. Comparison of Main Vehicle Mileage With Other Household Vehicles, by Income

ODO	Main Vehicle		Additional Vehicles		Fleet	
	N.	Mean	N.	Mean	N.	Mean
<$25K	442	90,229	209	74,406	651	85,220
$25K-$50K	566	90,049	484	90,290	1,049	90,212
$50K-$75K	344	91,230	518	94,530	862	93,215
>$75K	125	77,865	255	95,944	380	89,997
Total	**1,477**	**89,345**	**1,467**	**90,503**	**2,943**	**89,966**

Chapter 6 Appendix

This appendix contains tables produced to address the research questions in Chapter 6 that were not included in the chapter. Additional tables in support of ARB's analysis plan are included below as well. For reference, the appendix will list the tables in the order they are discussed in the chapter, which is based on the guiding research questions. We then list the tables requested by ARB's analysis plan (if they are not already included or addressed by the guiding research questions for Chapter 6).

The research questions guiding this chapter are as follows:

1. Do surveyed households face additional barriers in getting vehicle repairs, the price of fuel, or obtaining insurance or credit status? If so, what socioeconomic and geographic factors are associated with these challenges?
2. How often do surveyed households use alternatives to driving their personal vehicle? How often would they consider alternative modes if they were made as convenient and affordable as using a personal vehicle?

All tables requested by ARB's analysis plan can be found in Chapter 6 or in the tables below.

1. Additional Barriers to Vehicle Access: Fuel, Insurance, Repairs, and Credit

Table A6-1. Mean Weekly Mileage, by Race/Ethnicity

		N.	Mean
Non-Hispanic	White	423	136
	Black	142	114
	Asian	82	121
	Other	74	147
	2+ Races	34	156
Hispanic		780	136
Total		**1,535**	**134**

Table A6-2. Mean Weekly Mileage, by Urbanization Geography

	N.	Mean
Urban	642	110
Suburban	656	155
Rural	214	143
Total	**1,512**	**134**

Table A6-3. Mean Weekly Mileage,by AQMD Geography

	N.	Mean
Bay Area	160	106
Sacramento Metro	47	154
San Diego	132	131
San Joaquin Valley	174	120
South Coast	706	124
Other	292	182
Total	**1,512**	**134**

Table A6-4. Low-Cost Automobile Insurance Program Awareness, by Income

	Aware		Not Aware		Total
	N	Pct	N	Pct	N
<$25K	122	26%	347	74%	469
$25K-$50K	136	23%	458	77%	593
$50K-$75K	94	26%	264	74%	358
>$75K	41	30%	98	70%	140
Total	**393**	**25%**	**1,167**	**75%**	**1,560**

Table A6-5. Low-Cost Automobile Insurance Program Awareness, by Race/Ethnicity

		Aware		Not Aware		Total
		N	Pct	N	Pct	N
Non-Hispanic	White	79	19%	345	81%	425
	Black	32	23%	110	77%	142
	Asian	22	27%	60	73%	82
	Other	18	23%	58	77%	76
	2+ Races	12	35%	22	65%	34
Hispanic		230	29%	571	71%	802
Total		**393**	**25%**	**1,167**	**75%**	**1,560**

Table A6-6. Low-Cost Automobile Insurance Program Awareness, by Urban Geography

	Aware		Not Aware		Total
	N	Pct	N	Pct	N
Urban	190	29%	472	71%	662
Suburban	156	24%	503	76%	659
Rural	44	20%	172	80%	216
Total	**390**	**25%**	**1,147**	**75%**	**1,537**

Table A6-7. Low-Cost Automobile Insurance Program Awareness, by AQMD Geography

	Aware		Not Aware		Total
	N	Pct	N	Pct	N
Bay Area	47	28%	119	72%	166
Sacramento Metro	21	45%	26	55%	47
San Diego	21	15%	118	85%	138
San Joaquin Valley	44	25%	132	75%	176
South Coast	183	26%	533	74%	715
Other	75	25%	219	75%	294
Total	**390**	**25%**	**1,147**	**75%**	**1,537**

Table A6-8. Low-Cost Automobile Insurance Program Participation, by Race/Ethnicity

		Yes		No		Total
		N	Pct	N	Pct	N
Non-Hispanic	White	8	11%	71	89%	79
	Black	7	22%	25	78%	32
	Asian	6	25%	17	75%	22
	Other	2	14%	15	86%	18
	2+ Races	7	63%	4	37%	12
Hispanic		44	19%	186	81%	230
Total		**75**	**19%**	**318**	**81%**	**393**

Table A6-9. Low-Cost Automobile Insurance Program Participation, by Urban Geography

	Yes		No		Total
	N	Pct	N	Pct	N
Urban	35	18%	155	82%	190
Suburban	30	19%	126	81%	156
Rural	10	22%	35	78%	44
Total	**74**	**19%**	**316**	**81%**	**390**

Table A6-10. Low-Cost Automobile Insurance Program Participation, by AQMD Geography

	Yes		No		Total
	N	Pct	N	Pct	N
Bay Area	9	19%	38	81%	47
Sacramento Metro	1	3%	20	97%	21
San Diego	4	21%	16	79%	21
San Joaquin Valley	5	11%	39	89%	44
South Coast	44	24%	139	76%	183
Other	12	16%	63	84%	75
Total	**74**	**19%**	**316**	**81%**	**390**

Table A6-11. Mean Repair Cost, by When Last Repaired and Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
<= 6 Months	139	$511	136	$712	78	$879	24	$513	377	$660
<= 1 Year	58	$1,339	94	$605	60	$668	23	$618	236	$804
<= 3 Years	61	$746	67	$851	27	$1,153	17	$1,196	172	$896
Total	**258**	**$753**	**296**	**$709**	**166**	**$848**	**65**	**$731**	**785**	**$755**

Table A6-12. Mean Repair Cost, by When Last Repaired and Race/Ethnicity

	Non-Hispanic										Hispanic		Total	
	White		Black		Asian		Other		2+ Races					
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
<= 6 Months	95	$709	26	$361	34	$953	13	$782	8	$464	203	$625	377	$660
<= 1 Year	48	$599	35	$714	10	$736	18	$1,125	5	$473	120	$883	236	$804
<= 3 Years	48	$1,078	27	$490	6	$484	9	$1,552	0	$799	82	$876	172	$896
Total	**191**	**$774**	**87**	**$542**	**49**	**$856**	**40**	**$1,116**	**13**	**$469**	**405**	**$752**	**785**	**$755**

Table A6-13. Mean Repair Cost, by When Last Repaired and Body Type

	Small Vehicle		Medium Vehicle		Large Vehicle		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean
<= 6 Months	128	$516	162	$726	78	$758	369	$660
<= 1 Year	117	$975	62	$575	56	$698	235	$804
<= 3 Years	59	$1,020	62	$810	49	$835	171	$890
Total	**305**	**$791**	**286**	**$712**	**184**	**$760**	**775**	**$754**

Table A6-14. Limited Mobility From Vehicle Repairs, by Income

	No		Yes		Total
	N	Pct	N	Pct	N
<$25K	184	59%	128	41%	313
$25K-$50K	247	66%	129	34%	376
$50K-$75K	141	73%	51	27%	192
>$75K	50	65%	27	35%	78
Total	**623**	**65%**	**336**	**35%**	**959**

Table A6-15. Limited Mobility From Vehicle Repairs, by Race/Ethnicity

		No		Yes		Total
		N	Pct	N	Pct	N
Non-Hispanic	White	173	73%	65	27%	238
	Black	61	61%	38	39%	99
	Asian	38	71%	16	29%	54
	Other	39	70%	17	30%	57
	2+ Races	9	64%	5	36%	14
Hispanic		302	61%	195	39%	497
Total		**623**	**65%**	**336**	**35%**	**959**

Table A6-16. Destination a Vehicle Repair Prevented Households From Traveling To

	Total	
	N.	Pct.
Work	178	29%
Education	69	11%
Healthcare	76	12%
Social	62	10%
Shopping	103	17%
Errands	132	21%
Total	**620**	**100%**

Table A6-17. Destination a Vehicle Repair Prevented Respondents From Getting To, by Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Work	65	26%	62	29%	31	34%	20	34%	178	29%
Education	28	11%	27	13%	13	14%	1	1%	69	11%
Healthcare	36	14%	20	10%	15	17%	4	6%	76	12%
Social	23	9%	17	8%	9	10%	12	20%	62	10%
Shopping	51	20%	40	19%	5	6%	7	11%	103	17%
Errands	51	20%	46	22%	18	19%	17	28%	132	21%
Total	**255**	**100%**	**213**	**100%**	**92**	**100%**	**60**	**100%**	**620**	**100%**

Table A6-18. Destination a Vehicle Repair Prevented Respondents From Getting To, by Race/Ethnicity

	Non-Hispanic										Hispanic		Total	
	White		Black		Asian		Other		2+ Races					
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Work	32	27%	14	15%	10	50%	15	38%	3	24%	104	31%	178	29%
Education	14	11%	6	6%	2	8%	5	12%	1	12%	41	12%	69	11%
Healthcare	8	6%	21	22%	1	7%	7	18%	3	26%	37	11%	76	12%
Social	14	12%	10	10%	1	4%	1	3%	0	3%	36	11%	62	10%
Shopping	20	17%	21	22%	2	11%	3	9%	2	16%	55	16%	103	17%
Errands	31	26%	23	24%	4	20%	7	19%	2	18%	64	19%	132	21%
Total	**120**	**100%**	**94**	**100%**	**20**	**100%**	**38**	**100%**	**10**	**100%**	**336**	**100%**	**620**	**100%**

Table A6-19. Mode of Getting to Work During Vehicle Repair, by Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Did not go to work	9	9%	22	24%	5	11%	8	18%	43	16%
Drove another HH vehicle	15	16%	8	8%	6	13%	5	11%	34	12%
Got a ride with family/friends	30	30%	21	23%	17	39%	14	32%	81	29%
Used public transit	23	23%	13	14%	9	19%	7	16%	51	18%
Borrowed a car from outside HH	3	3%	7	7%	1	1%	0	0%	10	4%
Carpooled	7	7%	1	1%	2	5%	7	16%	17	6%
Used ride-sharing	7	7%	9	9%	4	10%	0	1%	21	8%
Walked and/or biked	4	5%	10	11%	0	1%	0	0%	14	5%
Other	0	0%	3	3%	0	1%	3	6%	6	2%
Total	**98**	**100%**	**91**	**100%**	**44**	**100%**	**43**	**100%**	**277**	**100%**

Table A6-20. Mode of Getting to Work During Vehicle Repair, by Race/Ethnicity

	Non-Hispanic										Hispanic		Total	
	White		Black		Asian		Other		2+ Races					
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Did not go to work	9	13%	2	12%	0	3%	10	37%	1	36%	20	14%	43	16%
Drove another HH vehicle	7	9%	2	10%	0	4%	1	3%	0	5%	24	16%	34	12%
Got a ride with family/friends	19	26%	5	22%	7	66%	4	14%	1	43%	46	32%	81	29%
Used public transit	12	17%	7	36%	2	16%	1	5%	0	2%	28	20%	51	18%
Borrowed a car from outside HH	2	3%	0	0%	1	5%	3	10%	0	0%	5	3%	10	4%
Carpooled	12	17%	0	0%	0	1%	1	5%	0	4%	3	2%	17	6%
Used ride-sharing	5	7%	1	5%	1	7%	3	11%	0	9%	11	8%	21	8%
Walked and/or biked	3	4%	3	14%	0	0%	3	13%	0	1%	5	4%	14	5%
Other	3	5%	0	0%	0	0%	0	0%	0	0%	2	2%	6	2%
Total	**72**	**100%**	**21**	**100%**	**11**	**100%**	**26**	**100%**	**3**	**100%**	**144**	**100%**	**277**	**100%**

Table A6-21. Credit Card Ownership, by Income

	Yes		No		Total
	N	Pct	N	Pct	N
<$25K	295	59%	205	41%	499
$25K-$50K	435	73%	162	27%	597
$50K-$75K	279	76%	87	24%	366
>$75K	106	76%	34	24%	140
Total	**1,115**	**70%**	**487**	**30%**	**1,602**

Table A6-22. Credit Card Ownership, by Race/Ethnicity

		Yes N	Yes Pct	No N	No Pct	Total N
Non-Hispanic	White	316	73%	118	27%	434
	Black	80	54%	68	46%	148
	Asian	69	84%	13	16%	82
	Other	55	73%	21	27%	76
	2+ Races	23	64%	13	36%	36
Hispanic		572	69%	254	31%	826
Total		**1,115**	**70%**	**487**	**30%**	**1,602**

Table A6-23. Credit Card Ownership, by Urban Geography

	Yes N	Yes Pct	No N	No Pct	Total N
Urban	471	69%	209	31%	680
Suburban	477	71%	193	29%	670
Rural	157	68%	72	32%	229
Total	**1,104**	**70%**	**474**	**30%**	**1,578**

Table A6-24. Credit Card Ownership, by AQMD Geography

	Yes N	Yes Pct	No N	No Pct	Total N
Bay Area	139	82%	31	18%	170
Sacramento Metro	36	76%	11	24%	48
San Diego	92	63%	54	37%	147
San Joaquin Valley	121	65%	65	35%	187
South Coast	497	68%	233	32%	730
Other	220	74%	79	26%	298
Total	**1,104**	**70%**	**474**	**30%**	**1,578**

Table A6-25. Credit Self-Assessment by Race/Ethnicity

	Non-Hispanic										Hispanic		Total	
	White		Black		Asian		Other		2+ Races					
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Excellent	141	32%	16	11%	23	28%	30	40%	8	22%	169	21%	387	24%
Good	129	30%	41	28%	41	50%	13	18%	9	26%	292	36%	527	33%
Fair	83	19%	66	45%	11	14%	14	18%	6	18%	190	23%	370	23%
Poor	47	11%	19	13%	0	0%	2	3%	11	32%	108	13%	189	12%
Unknown	10	2%	1	1%	6	7%	10	13%	1	1%	22	3%	49	3%
No history	24	6%	4	3%	1	1%	6	8%	0	0%	38	5%	73	5%
Total	**434**	**100%**	**147**	**100%**	**82**	**100%**	**76**	**100%**	**36**	**100%**	**820**	**100%**	**1,595**	**100%**

Table A6-26. Credit Self-Assessment, by Urban Geography

	Urban		Suburban		Rural		Total
	N.	Pct.	N.	Pct.	N.	Pct.	N.
Excellent	170	44%	153	40%	62	16%	385
Good	217	42%	229	44%	77	15%	523
Fair	168	46%	145	40%	51	14%	364
Poor	71	39%	82	45%	31	17%	184
Unknown	26	52%	17	34%	7	14%	49
No credit history	26	40%	38	58%	1	2%	65
Total	**679**	**43%**	**663**	**42%**	**229**	**15%**	**1,571**

Table A6-27. Credit Self-Assessment, by AQMD Geography

	Bay Area		Sacramento		San Diego		SJV		South Coast		Other		Total
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.
Excellent	45	12%	19	5%	38	10%	37	10%	168	44%	78	20%	385
Good	71	14%	18	3%	38	7%	42	8%	244	47%	111	21%	523
Fair	42	12%	7	2%	38	10%	42	11%	173	47%	63	17%	364
Poor	3	1%	2	1%	17	9%	47	25%	92	50%	24	13%	184
Unknown	4	8%	0	0%	7	15%	3	6%	17	35%	18	36%	49
No credit history	6	8%	2	3%	8	12%	9	14%	35	54%	5	8%	65
Total	**170**	**11%**	**48**	**3%**	**147**	**9%**	**180**	**11%**	**729**	**46%**	**298**	**19%**	**1,571**

Table A6-28. Last Time You Checked Your Credit Score, by Urban Geography

	Urban		Suburban		Rural		Total
	N.	Pct.	N.	Pct.	N.	Pct.	N.
<= 1 Month	189	39%	229	47%	68	14%	487
<= 3 Months	107	36%	152	51%	40	13%	299
<= 1 Year	75	42%	76	43%	27	15%	177
1 or More Years	104	57%	49	27%	31	17%	184
I can't remember	102	52%	70	36%	23	12%	195
Total	**576**	**43%**	**575**	**43%**	**190**	**14%**	**1,342**

Table A6-29. Last Time You Checked Your Credit Score, by AQMD Geography

	Bay Area		Sacramento		San Diego		SJV		South Coast		Other		Total
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.
<= 1 Month	41	8%	19	4%	39	8%	58	12%	218	45%	112	23%	487
<= 3 Months	42	14%	13	4%	19	6%	39	13%	126	42%	60	20%	299
<= 1 Year	22	12%	1	1%	18	10%	13	7%	93	52%	31	17%	177
1 or More Years	24	13%	3	2%	16	9%	17	9%	106	58%	17	9%	184
I can't remember	24	12%	8	4%	22	11%	25	13%	90	46%	26	13%	195
Total	**153**	**11%**	**44**	**3%**	**114**	**8%**	**152**	**11%**	**633**	**47%**	**245**	**18%**	**1,342**

Table A6-30. Last Time You Checked Your Credit Score, by Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.
<= 1 Month	138	28%	191	39%	117	24%	48	10%	494
<= 3 Months	74	25%	115	38%	81	27%	31	10%	301
<= 1 Year	48	27%	83	46%	33	19%	15	8%	179
1 or More Years	70	37%	42	22%	48	26%	28	15%	187
I can't remember	87	43%	71	35%	35	17%	9	5%	202
Total	**416**	**31%**	**502**	**37%**	**315**	**23%**	**131**	**10%**	**1,363**

Table A6-31. Last Time You Checked Your Credit Score, by Race/Ethnicity

	Non-Hispanic													
	White		Black		Asian		Other		2+ Races		Hispanic		Total
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.
<= 1 Month	143	29%	59	12%	18	4%	24	5%	9	2%	242	49%	494
<= 3 Months	53	18%	43	14%	22	7%	9	3%	7	2%	167	56%	301
<= 1 Year	55	31%	13	7%	16	9%	8	5%	8	5%	79	44%	179
1 or More Years	53	28%	12	7%	3	2%	13	7%	8	4%	99	53%	187
I can't remember	47	24%	13	6%	12	6%	10	5%	2	1%	118	59%	202
Total	**352**	**26%**	**140**	**10%**	**72**	**5%**	**63**	**5%**	**33**	**2%**	**704**	**52%**	**1,363**

Table A6-32. Mean Interest Rate, by Credit Self-Assessment and Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Excellent	22	3.4%	56	7.5%	48	4.0%	39	8.2%	165	6.1%
Good	44	4.4%	100	6.2%	115	5.1%	29	4.6%	288	5.3%
Fair	74	4.4%	81	11.1%	39	13.4%	9	6.4%	203	8.9%
Poor	23	9.1%	25	11.6%	19	8.9%	12	11.2%	78	10.2%
Unknown	3	2.7%	4	8.0%	6	4.0%	N/A	N/A	13	4.9%
No credit history	7	2.2%	7	3.2%	3	10.9%	5	1.0%	22	3.3%
Total	**172**	**4.8%**	**273**	**8.4%**	**229**	**6.6%**	**94**	**6.9%**	**769**	**6.8%**

Table A6-33. Mean Interest Rate, by Credit Self-Assessment and Race/Ethnicity

	Non-Hispanic													
	White		Black		Asian		Other		2+ Races		Hispanic		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
Excellent	53	5.7%	9	2.2%	9	3.4%	6	4.0%	3	5.0%	85	7.2%	165	6.1%
Good	54	5.6%	25	4.8%	23	5.2%	9	4.2%	4	7.2%	172	5.3%	288	5.3%
Fair	36	13.4%	42	6.5%	4	5.7%	10	7.2%	2	8.3%	108	8.6%	203	8.9%
Poor	21	10.5%	6	11.0%	N/A	N/A	N/A	N/A	8	1.2%	43	11.6%	78	10.2%
Unknown	2	2.9%	1	9.4%	6	4.0%	N/A	N/A	1	6.3%	3	6.5%	13	4.9%
None	6	1.2%	N/A	N/A	0	5.0%	N/A	N/A	N/A	N/A	16	4.0%	22	3.3%
Total	**172**	**7.7%**	**84**	**6.0%**	**44**	**4.7%**	**25**	**5.3%**	**19**	**4.3%**	**427**	**7.1%**	**769**	**6.8%**

Table A6-34. Mean Interest Rate by Length of Automobile Loan for Current Vehicle

	Interest Rate N.	Interest Rate Mean
1 Year	16	3.1%
2 Years	49	7.0%
3 Years	133	7.5%
4 Years	112	6.0%
5+ Years	462	7.0%
Total	**772**	**6.8%**

2. Reliance on Alternative Travel Modes

Table A6-35. Transit Stop Near Both Home and Workplace, by Income

	No		Yes		Total	
	N.	Pct.	N.	Pct.	N.	Pct.
<$25K	472	94%	28	6%	500	100%
$25K-$50K	553	92%	46	8%	598	100%
$50K-$75K	330	90%	35	10%	366	100%
>$75K	125	90%	14	10%	140	100%
Total	**1481**	**92%**	**123**	**8%**	**1604**	**100%**

Table A6-36. Transit Stop Near Both Home and Workplace, by Race/Ethnicity

		No		Yes		Total	
		N.	Pct.	N.	Pct.	N.	Pct.
Non-Hispanic	White	406	94%	28	6%	434	100%
Non-Hispanic	Black	130	88%	18	12%	148	100%
Non-Hispanic	Asian	73	88%	10	12%	82	100%
Non-Hispanic	Other	70	92%	6	8%	76	100%
Non-Hispanic	2+ Races	32	89%	4	11%	36	100%
Hispanic		770	93%	58	7%	828	100%
Total		**1,481**	**92%**	**123**	**8%**	**1604**	**100%**

Table A6-37. Transit Stop Near Home, Workplace or Both, by Urbanization Geography

	Near Home		Near Workplace		Near Home & Workplace		Total
	N. (YES)	Pct.	N. (YES)	Pct.	N. (YES)	Pct.	N. (ALL)
Urban	507	75%	84	12%	45	7%	680
Suburban	466	69%	92	14%	60	9%	671
Rural	124	54%	21	9%	18	8%	229
Total	**1097**	**69%**	**197**	**12%**	**123**	**8%**	**1581**

Table A6-38. Transit Stop Near Home, Workplace or Both, by AQMD Geography

	Near Home		Near Workplace		Near Home & Workplace		Total
	N. (YES)	Pct.	N. (YES)	Pct.	N. (YES)	Pct.	N. (ALL)
Bay Area	120	71%	22	13%	17	10%	170
Sacramento	29	61%	6	14%	2	4%	48
San Diego	115	78%	24	16%	15	10%	147
SJV	113	61%	14	8%	12	6%	187
South Coast	540	74%	108	15%	60	8%	732
Other	180	60%	22	7%	19	6%	298
Total	**1097**	**69%**	**197**	**12%**	**170**	**11%**	**1581**

Table A6-39. If Transit Rides Were Free, How Often Would You Use I t to Get to the Following Destinations? By Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Work	215	18%	218	20%	192	20%	67	16%	692	19%
School	159	13%	128	12%	135	14%	63	15%	485	13%
Taking Children to School/ Daycare/Activities	129	11%	145	13%	165	17%	75	17%	514	14%
Shopping/Errands/Fitness	284	24%	240	22%	189	19%	81	19%	794	21%
Healthcare	179	15%	155	14%	133	14%	67	15%	534	14%
Entertainment/Social	225	19%	215	20%	162	17%	80	19%	682	18%
Total	**1191**	**100%**	**1102**	**100%**	**974**	**100%**	**433**	**100%**	**3700**	**100%**

Table A6-40. Secondary Reason Respondents Prefer to Own/Keep Vehicle Regardless of Alternative Travel Modes, by Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Ownership is an investment	27	10%	37	10%	31	15%	5	8%	100	11%
Ownership provides a safety net	79	29%	76	20%	36	17%	4	7%	195	21%
Ownership is valued by family/friends	22	8%	50	13%	14	6%	16	27%	102	11%
Alternative modes are more expensive	31	11%	63	17%	34	16%	8	14%	137	15%
Alternative modes are not as useful for my travel needs	56	21%	56	15%	42	20%	18	30%	171	19%
I enjoy driving	49	18%	74	19%	39	18%	1	1%	162	18%
Other	9	3%	25	7%	17	8%	8	13%	59	6%
Total	**272**	**100%**	**380**	**100%**	**213**	**100%**	**60**	**100%**	**926**	**100%**

Table A6-41. Primary and Secondary Reasons (Combined Responses) Respondents Prefer to Own/Keep Vehicle Regardless of Alternative Travel Modes, by Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Ownership is an Investment	89	16%	90	12%	59	14%	13	11%	252	14%
Ownership provides a safety net	139	25%	146	19%	109	26%	17	14%	411	22%
Ownership is valued by family/friends	32	6%	77	10%	27	6%	21	17%	157	8%
Alternative modes are more expensive	47	9%	74	10%	35	8%	9	7%	165	9%
Alternative modes are not as useful for my travel needs	89	16%	142	19%	70	16%	20	17%	321	17%
I enjoy driving	132	24%	181	24%	86	20%	26	22%	425	23%
Other	17	3%	52	7%	40	9%	15	12%	122	7%
Total	**545**	**100%**	**763**	**100%**	**427**	**100%**	**120**	**100%**	**1,854**	**100%**

Chapter 7 Appendix

This appendix contains tables produced to address the research questions in Chapter 7 that were not included in the chapter. Additional tables in support of ARB's analysis plan are included below as well. For reference, the appendix will list the tables in the order they are discussed in the chapter, which is based on the guiding research questions. We then list the tables requested by ARB's analysis plan (if they are not already included or addressed by the guiding research questions for Chapter 7).

The research questions guiding this chapter are as follows:

1. Are surveyed households aware of PEVs, state incentives for PEVs, and nearby high-occupancy vehicle (HOV) lanes?
2. Do these households have long distance, weekly, and commute travel patterns which would make home PEV charging difficult?
3. Do households live in residences which can easily accommodate PEV charging infrastructure or would facilitating such access require additional support?

All tables requested by ARB's analysis plan can be found in Chapter 7 or in the tables below.

1. Awareness of PEVs, PEV Incentives, and HOV Lane Access

Table A7-1. Percent of Respondents Who Have Seen PEVs, by Percent of Income to the Federal Poverty Line

	At or below 225% FPL		Above 225% FPL		Total	
	N.	Pct	N.	Pct	N.	Pct
Yes	811	74%	439	87%	1,250	78%
No	279	26%	68	13%	347	22%
Total	**1,090**	**100%**	**507**	**100%**	**1,597**	**100%**

Table A7-2. Percent of Respondents Who Have Seen PEVs, by Race/Ethnicity

	Non-Hispanic													
	White		Black		Asian		Other		2+ Races		Hispanic		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Yes	365	85%	110	74%	66	80%	64	84%	27	75%	618	75%	1,250	78%
No	64	15%	38	26%	17	20%	12	16%	9	25%	208	25%	347	22%
Total	**429**	**100%**	**148**	**100%**	**82**	**100%**	**76**	**100%**	**36**	**100%**	**826**	**100%**	**1,597**	**100%**

Table A7-3. Percent of Respondents Who Have Seen PEVs, by Urbanization Geography

	Urban		Suburban		Rural		Total	
	N.	Pct	N.	Pct	N.	Pct	N.	Pct
Yes	498	74%	556	83%	176	78%	1,230	78%
No	179	26%	116	17%	49	22%	343	22%
Total	677	100%	671	100%	225	100%	1,573	100%

Table A7-4. Percent of Respondents Who Have Seen PEVs, by AQMD Geography

	Bay Area		Sacramento		San Diego		SJV		South Coast		Other		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Yes	134	79%	34	73%	109	75%	130	70%	586	80%	237	80%	1,230	78%
No	36	21%	13	27%	36	25%	56	30%	144	20%	58	20%	343	22%
Total	**170**	**100%**	**48**	**100%**	**145**	**100%**	**186**	**100%**	**730**	**100%**	**295**	**100%**	**1,573**	**100%**

Table A7-5. PEV Incentives Awareness, by Household Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Pct	N.	Pct	N.	Pct	N.	Pct	N.	Pct
Yes	170	34%	240	40%	116	32%	62	45%	587	37%
No	329	66%	355	60%	250	68%	78	55%	1,011	63%
Total	**499**	**100%**	**595**	**100%**	**366**	**100%**	**140**	**100%**	**1,599**	**100%**

Table A7-6. PEV Incentives Awareness, by Urbanization Geography

	Urban		Suburban		Rural		Total	
	N.	Pct	N.	Pct	N.	Pct	N.	Pct
Yes	239	35%	244	37%	90	39%	572	36%
No	442	65%	424	63%	138	61%	1,003	64%
Total	**680**	**100%**	**668**	**100%**	**227**	**100%**	**1,575**	**100%**

Table A7-7. HOV Lanes Near You That You Could Use for Your Daily Commute, by Income

	Yes		No		Total	
	N.	Pct.	N.	Pct.	N.	Pct.
<$25K	253	51%	239	49%	492	100%
$25K-$50K	267	46%	319	54%	585	100%
$50K-$75K	188	53%	166	47%	354	100%
>$75K	57	42%	80	58%	136	100%
Total	**765**	**49%**	**803**	**51%**	**1,568**	**100%**

Table A7-8. HOV Lanes Near You That You Could Use for Your Daily Commute, by Urbanization Geography

	Yes		No		Total	
	N.	Pct.	N.	Pct.	N.	Pct.
Urban	368	55%	297	45%	665	100%
Suburban	321	49%	336	51%	657	100%
Rural	71	32%	152	68%	223	100%
Total	**760**	**49%**	**785**	**51%**	**1,544**	**100%**

Table A7-9. HOV Lanes Near You That You Could Use for Weekend Trips, by Income

	Yes		No		Total	
	N.	Pct.	N.	Pct.	N.	Pct.
<$25K	283	58%	203	42%	486	100%
$25K-$50K	365	62%	223	38%	588	100%
$50K-$75K	250	74%	90	27%	341	100%
>$75K	98	74%	35	26%	133	100%
Total	**997**	**64%**	**551**	**36%**	**1,548**	**100%**

Table A7-10. HOV Lanes Near You That You Could Use for Weekend Trips, by Race/Ethnicity

		Yes		No		Total	
		N.	Pct.	N.	Pct.	N.	Pct.
Non-Hispanic	White	246	57%	186	43%	432	100%
	Black	85	61%	54	39%	139	100%
	Asian	54	66%	28	34%	82	100%
	Other	49	64%	27	36%	76	100%
	2+ Races	30	84%	6	16%	36	100%
Hispanic		533	68%	251	32%	784	100%
Total		**997**	**64%**	**551**	**36%**	**1,548**	**100%**

Table A7-11. HOV Lanes Near You That You Could Use for Weekend Trips, by Urbanization Geography

	Yes		No		Total	
	N.	Pct.	N.	Pct.	N.	Pct.
Urban	457	69%	202	31%	659	100%
Suburban	419	65%	221	35%	640	100%
Rural	113	50%	114	50%	227	100%
Total	**988**	**65%**	**537**	**35%**	**1,526**	**100%**

Table A7-12. HOV Lanes Near You That You Could Use for Weekend Trips, by AQMD Geography

	Yes		No		Total	
	N.	Pct.	N.	Pct.	N.	Pct.
Bay Area	95	56%	75	44%	170	100%
Sacramento Metro	26	55%	21	45%	47	100%
San Diego	92	65%	50	35%	142	100%
San Joaquin Valley	92	51%	89	49%	181	100%
South Coast	520	75%	174	25%	693	100%
Other	164	56%	128	44%	292	100%
Total	**988**	**65%**	**537**	**35%**	**1,526**	**100%**

2. Travel Patterns and Related Vehicle Needs

Table A7-13. Frequency of Trips Longer Than 100 Miles

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Weekly	39	8%	34	6%	22	6%	10	7%	104	7%
Monthly	137	29%	143	24%	107	29%	43	31%	430	27%
Yearly	156	33%	225	38%	151	41%	39	28%	570	36%
Rarely/Never	137	29%	193	32%	85	23%	46	33%	461	29%
Total	**470**	**100%**	**594**	**100%**	**364**	**100%**	**137**	**100%**	**1,565**	**100%**

Table A7-14. Frequency of Trips Longer Than 100 Miles, by Race/Ethnicity

	Non-Hispanic										Hispanic		Total	
	White		Black		Asian		Other		2+ Races					
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Weekly	18	4%	14	10%	20	25%	2	2%	6	19%	44	5%	104	7%
Monthly	99	23%	42	30%	29	35%	31	41%	4	11%	225	28%	430	27%
Yearly	189	45%	30	21%	17	21%	28	36%	13	40%	292	36%	570	36%
Rarely/Never	120	28%	56	39%	16	20%	15	20%	10	30%	244	30%	461	29%
Total	**425**	**100%**	**142**	**100%**	**82**	**100%**	**76**	**100%**	**34**	**100%**	**806**	**100%**	**1,565**	**100%**

Table A7-15. Frequency of Trips Longer Than 100 Miles, by AQMD Geography

	Bay Area		Sacramento		San Diego		SJV		South Coast		Other		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Weekly	15	9%	0	1%	5	3%	5	3%	54	8%	26	9%	104	7%
Monthly	30	18%	17	36%	48	35%	36	20%	209	29%	86	29%	425	28%
Yearly	78	47%	20	43%	58	42%	62	35%	228	32%	120	41%	567	37%
Rarely/Never	44	26%	10	20%	28	20%	74	42%	226	31%	65	22%	446	29%
Total	**166**	**100%**	**48**	**100%**	**139**	**100%**	**176**	**100%**	**717**	**100%**	**297**	**100%**	**1,541**	**100%**

Table A7-16. Mean Commute Distance (Miles), by Income

	N.	Mean
<$25K	352	19
$25K-$50K	393	19
$50K-$75K	288	29
>$75K	122	22
Total	**1,155**	**22**

Table A7-17. Mean Commute Distance (Miles), by Race/Ethnicity

		N.	Mean
Non-Hispanic	White	245	22
	Black	115	27
	Asian	58	24
	Other	62	28
	2+ Races	31	30
Hispanic		645	20
Total		**1,155**	**22**

Table A7-18. Mean Commute Distance (Miles), by Urbanization Geography

	N.	Mean
Urban	504	20
Suburban	486	22
Rural	146	26
Total	**1,135**	**22**

Table A7-19. Typical Workday Commute Pattern

I commute to:	N.	Pct.
Same primary work location each workday	909	75%
Different work site or location each workday	165	14%
Multiple work sites or locations each workday	131	11%
Total	**1,205**	**100%**

Table A7-20. Typical Workday Commute Pattern, by Income

	<$25,000		$25K-$50K		$50K-$75K		>$75,000		Total	
	N.	Mean	N.	Mean	N.	Mean	N.	Mean	N.	Mean
Same location each day	254	69%	315	79%	246	81%	93	71%	909	75%
Different location each day	75	20%	35	9%	38	13%	17	12%	165	14%
Multiple locations in a day	39	11%	50	13%	19	6%	23	17%	131	11%
Total	**368**	**100%**	**401**	**100%**	**304**	**100%**	**133**	**100%**	**1,205**	**100%**

Table A7-21. Typical Workday Commute Pattern, by Race/Ethnicity

	Non-Hispanic										Hispanic		Total	
	White		Black		Asian		Other		2+ Races					
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Same location each day	206	81%	72	62%	48	81%	38	59%	24	77%	521	76%	909	75%
Different location each day	29	11%	30	26%	10	17%	14	21%	1	2%	81	12%	165	14%
Multiple locations in a day	18	7%	13	12%	1	2%	12	19%	7	22%	80	12%	131	11%
Total	**252**	**100%**	**115**	**100%**	**59**	**100%**	**65**	**100%**	**31**	**100%**	**682**	**100%**	**1,205**	**100%**

Table A7-22. Typical Workday Commute Pattern, by Urbanization Geography

	Urban		Suburban		Rural		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Same location each day	388	72%	384	77%	117	78%	889	75%
Different location each day	86	16%	66	13%	12	8%	164	14%
Multiple locations in a day	62	12%	48	10%	20	13%	131	11%
Total	**536**	**100%**	**498**	**100%**	**150**	**100%**	**1,184**	**100%**

Table A7-23. Typical Workday Commute Pattern, by AQMD Geography

	Bay Area		Sacramento		San Diego		SJV		South Coast		Other		Total	
	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.	N.	Pct.
Same location each day	110	88%	32	75%	77	69%	86	67%	426	75%	158	76%	889	75%
Different location each day	7	6%	5	12%	21	19%	27	21%	65	12%	39	19%	164	14%
Multiple locations in a day	7	6%	6	13%	14	13%	16	12%	76	13%	12	6%	131	11%
Total	**125**	**100%**	**43**	**100%**	**112**	**100%**	**128**	**100%**	**567**	**100%**	**209**	**100%**	**1,184**	**100%**

3. Built Environment Factors Affecting PEV Charging Potential

Table A7-24. Presence of Electrical Outlet Within 100 Feet of Parked Car, by Housing Type

	Yes		No		Unsure		Total	
	N.	Pct	N.	Pct	N.	Pct	N.	Pct
Single Family Detached	151	44%	171	50%	21	6%	342	100%
Single Family Attached	40	35%	68	59%	7	6%	115	100%
Multi-Unit Dwellings	93	32%	156	54%	38	13%	287	100%
Mobile Home	3	14%	18	79%	2	7%	23	100%
Boat, RV, Van, etc.	1	59%	0.3	21%	0.3	20%	2	100%
Total	**288**	**37%**	**414**	**54%**	**68**	**9%**	**770**	**100%**

Table A7-25. Presence of Electrical Outlet Within 25 Feet of Parked Car, by Housing Tenure

	Yes		No		Unsure		Total	
	N.	Pct	N.	Pct	N.	Pct	N.	Pct
Own	436	65%	202	30%	33	5%	671	100%
Rent	335	40%	440	52%	69	8%	844	100%
Occupied without payment of rent	21	45%	12.3	26%	13.9	29%	48	100%
Total	**793**	**51%**	**654**	**42%**	**116**	**7%**	**1,563**	**100%**

Table A7-26. Presence of Electrical Outlet Within 100 Feet of Parked Car, by Housing Tenure

	Yes		No		Unsure		Total	
	N.	Pct	N.	Pct	N.	Pct	N.	Pct
Own	120	51%	100	43%	15	6%	235	100%
Rent	164	32%	298	59%	46	9%	508	100%
Occupied without payment of rent	3	13%	15.7	60%	7.1	27%	26	100%
Total	**288**	**37%**	**414**	**54%**	**68**	**9%**	**770**	**100%**

Table A7-27. Presence of Electrical Outlet Within 100 Feet of Where Vehicle Is Typically Parked

	Yes		No		Unsure		Total	
	N.	Pct	N.	Pct	N.	Pct	N.	Pct.
Private garage	24	37%	35	55%	5	8%	65	100%
Carport	52	37%	80	56%	9	7%	141	100%
Driveway	109	49%	94	42%	18	8%	221	100%
Multi-car garage	13	42%	9	31%	8	27%	30	100%
Parking lot	36	34%	60	57%	9	9%	105	100%
Street	54	26%	136	66%	17	8%	207	100%
Total	**288**	**37%**	**414**	**54%**	**68**	**9%**	**770**	**100%**

UCLA Luskin Center for Innovation

https://innovation.luskin.ucla.edu