Assessing the Early Impacts of the Clean Miles Standard on California Ridehailing Drivers

June 2025

Prepared for: California Air Resources Board

Assessing the Early Impacts of the Clean Miles Standard on California Ridehailing Drivers

Agreement No. 21STC013-01

Prepared by: 3 Revolutions Future Mobility Program (3RFM)

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TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
UCD-ITS-RR-24-25	N/A	N/A

4. Title and Subtitle Assessing the Early Impacts of the Clean Miles Standard on California Ridehailing Drivers	**5. Report Date** June 2025 **6. Performing Organization Code** N/A
7. Author(s) Giovanni Circella, PhD, https://orcid.org/0000-0003-1832-396X James Giller, https://orcid.org/0000-0001-5773-9592 Xiatian Iogansen, PhD, https://orcid.org/0000-0002-4851-1323 Mischa Young, PhD, https://orcid.org/0000-0001-7001-1408 Yongsung Lee, PhD, https://orcid.org/0000-0002-1980-1225 Patrick Loa, PhD, https://orcid.org/0000-0002-8606-6283	**8. Performing Organization Report No.** N/A **10. Work Unit No.** N/A
9. Performing Organization Name and Address University of California, Davis Institute of Transportation Studies 1605 Tilia Street, Suite 100 Davis, CA 95616	**11. Contract or Grant No.** 21STC013
12. Sponsoring Agency Name and Address California Air Resources Board 1001 I Street Sacramento, CA 95814	**13. Type of Report & Period Covered** Final Report (April 2022 – June 2025) **14. Sponsoring Agency Code**

15. Supplementary Notes
N/A

16. Abstract
Ridehailing services have transformed passenger transportation in California, raising concerns about their environmental impacts. In response, California enacted the Clean Miles Standard (CMS), requiring that by 2030, 90% of vehicle miles traveled (VMT) by ridehailing be completed using zero-emission vehicles (ZEVs). This study, conducted by the 3 Revolutions Future Mobility Program at the University of California, Davis in collaboration with the California Air Resources Board and the California Public Utilities Commission, investigates ridehailing drivers' current adoption of battery electric vehicles (BEVs), barriers to BEV transition, and willingness to adopt BEVs. A two-wave survey of Uber and Lyft drivers revealed substantial disparities in charger access, with lower-income and apartment-dwelling drivers facing greater challenges. Logistic regression analysis showed that the perceived availability of public chargers and familiarity with federal BEV incentives significantly increased the likelihood of BEV adoption. An integrated choice and latent variable model identified three attitudinal factors—positive EV attitudes, social norms, and perceived barriers—as key determinants of fuel type choice. Charger access had differential impacts depending on whether vehicles were obtained for ridehailing or personal use. A Heckman selection model further found that willingness to adopt a BEV was shaped by charger access, incentive awareness, prior EV experience, and the intention to add or replace vehicles for ridehailing. Policy recommendations include expanding the public charger infrastructure in high-demand areas, enhancing awareness of incentives among drivers with limited resources, and strategically locating chargers to reduce deadheading. These strategies are critical for supporting driver-level transitions to ZEVs and achieving CMS goals for a more sustainable ridehailing fleet.

17. Key Words	18. Distribution Statement
Ridehailing, Transportation Network Companies (TNCs), Clean Miles Standard (CMS), Battery Electric Vehicles (BEVs), Charging Infrastructure, Incentive Awareness	No restrictions

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	115	N/A

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

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Acknowledgements

This study was made possible with funding received by the California Air Resources Board (CARB). The authors would like to thank CARB for their support of university-based research in transportation, and especially for the funding provided in support of this project. The authors would also like to thank Joshua Cunningham, Katherine Dillon, Stephanie Seki, Samantha Serafica, and Joshua Huneycutt for providing their feedback on the design, scope, execution, and results of the study. Additionally, the authors would like to thank Rainer Lempert, Sarah Cormack-Patton, and Sara Chen for the invaluable role that they played in the recruitment of ridehailing drivers for the survey that was completed as part of this study.

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Executive Summary

The introduction of ridehailing services (also referred to as *ridesourcing*, *on-demand ride services*, and *rideshare* services) transformed the passenger transportation sector. The growing utilization of ridehailing prompted concerns about the potential for these services to worsen the environmental impacts of the transportation sector, which is already the largest source of greenhouse gas (GHG) emissions in California. To help address the environmental impacts of ridehailing services, California introduced Senate Bill 1014 (the *Clean Miles Standard* (CMS)) in 2018. Under the CMS regulations, TNCs with an annual vehicle miles traveled (VMT) exceed 5 million miles must achieve annual GHG emission and VMT targets. These targets become more stringent over time, culminating in targets of: 1) achieving GHG emissions of 0 g CO_2-eq/ PMT and 2) delivering 90% of their VMT using battery electric vehicles (BEVs) or fuel cell electric vehicles (FCEVs) by 2030 (Clean Miles Standard Requirements, 2022). Since the composition of the ridehailing fleet is determined by the vehicle ownership and fuel type choices of ridehailing drivers, the success of the CMS regulations will ultimately depend on the willingness and ability of drivers to transition to zero-emission vehicle (ZEVs).

To support ongoing efforts to reduce emissions from ridehailing services, the research team from the 3 Revolutions Future Mobility Program at the University of California, Davis (referred to hereafter as the *research team*) partnered with the California Air Resources Board (CARB) and the California Public Utilities Commission (CPUC) to assess the current status of ridehailing drivers in California. The goals of the project were to: 1) assess the current uptake of ZEVs among ridehailing drivers in California, 2) identify potential barriers to the transition from internal combustion engine vehicles (ICEVs to ZEVs), and 3) explore the willingness to use ZEVs for ridehailing work.

The research team conducted a multi-wave, web-based survey of California ridehailing drivers with the assistance of the two largest TNCs in California – Uber and Lyft. The TNCs played an invaluable role in the project by recruiting drivers to participate in the survey, which helped to ensure that the research team was able to obtain stratified random samples of California ridehailing drivers and that the samples of the two waves of the survey were sufficiently large. The first wave of the survey was conducted prior to the implementation of the CMs regulations, while the second wave of the survey was conducted during the first year of its implementation. This approach was motivated by the desire to explore changes in trends related to the uptake of battery electric vehicles, including the use of these vehicles to provide ridehailing services, availability of chargers, and familiarity with ZEV-related incentives. The questionnaires used in the two surveys were designed based on a review of existing studies, consultations with project stakeholders at the CARB, the CPUC, Uber, and Lyft, and in-depth interviews with ridehailing drivers. Both waves of the survey were comprised of three sections: 1) ridehailing driver activities, 2) vehicle ownership and costs, 3) socio-demographic characteristics.

The research team developed a stratified random sampling procedure to recruit ridehailing drivers to participate in the first and second waves of the survey. This approach was chosen due to its potential to produce a representative sample of ridehailing drivers, which can yield insights that are more generalizable to the population of California ridehailing drivers than those obtained through other approaches. The primary goal when designing the stratified random sampling procedure was to facilitate the inclusion of drivers from all regions of California, with varying levels of driving experience and weekly working hours. Consequently, strata were defined based on the region where drivers provide the plurality of their rides, the number of years that they have been active on the TNC platform, and the number of hours that they spend providing ridehailing services during an average week.

Using data from the two waves of the survey, the research team applied statistical analysis methods to investigate the uptake of BEVs among California ridehailing drivers and identify motivators and barriers to the greater adoption of BEVs. The research team began by investigating the potential barriers to the greater uptake of BEVs among ridehailing drivers using data from both waves of the survey. Specifically, the research team explored responses related to a lack of familiarity with incentives, lack of access to public and home chargers, and adverse opinions towards the use of EVs for ridehailing work. Income was positively associated with the familiarity with federal incentives; however, relatively few drivers have used these incentives. In particular, only 7.4% of respondents used these incentives (and only 12.4% of drivers from higher-income households). With regards to charger availability, 74% of wave 1 respondents perceived public chargers as available to them, with 28.5% perceiving fast chargers as available, 15.5% perceiving level 1 or 2 chargers as available, and 30% not knowing the type of charger. There was a higher rate of perceived public charger availability in wave 2 than in wave 1, with 44% of respondents perceiving that fast chargers are available, 12% perceiving level 1 or 2 chargers as available, and 29% not knowing the type of charger.

Next, the research team explored the characteristics of California ridehailing drivers and their uptake of BEVs to provide ridehailing services. The availability of home chargers appears to differ among drivers, with higher-income drivers being more likely to have access to a Level 2 or DC fast charger[1] than lower-income drivers. Among drivers who were not able to install a home charger, living in a rental property and financial constraints were the two most common reasons that were provided. Additionally, a binary logistic regression model was estimated to identify the factors influencing the decision to register at least one BEV with a TNC. Two policy-relevant variables stood out from the results of this analysis. First, perceiving that DC fast chargers are available in public areas was associated with an average increase in the probability of a driver having a BEV registered on a ridehailing platform by 13.8%. Moreover, perceiving that level 1 or 2 chargers were available in public areas was associated with an average increase of 9.5%. As expected, being very familiar with federal BEV incentives increased the probability of having at least one BEV registered with a TNC by an average of 8.9%.

The research team then turned its attention to investigating the factors influencing fuel type choices, how they differ between various segments of ridehailing drivers, and the potential impacts of increasing familiarity with incentives on the uptake of BEVs. Three latent attitudinal variables were found to influence vehicle fuel type choices – *EV attitude*, *EV subjective norm*, and *EV perceived barriers*. The EV attitude factor is characterized by the belief that using a BEV to provide ridehailing services offers the potential benefits of lower energy costs, greater profits, cost savings, and lessened environmental impacts. The EV subjective norm factor is defined by the belief that ridehailing users have positive perceptions towards BEVs and that BEVs are viewed favorably by one's peers and the ridehailing industry as a whole. Finally, the EV perceived barriers factor is characterized by the belief that BEVs are impractical to provide ridehailing services, in part due to the limited range, (purchase) cost, and potential need for mid-shift charging.

[1] Drivers who reported having a DC fast charger at home may have misidentified the type of charger, as this type is usually not found in private homes.

Additionally, perceived access to chargers also influenced fuel type choice decisions. However, its impact varies based on whether the driver obtained the vehicle with the intention of using it for ridehailing work (i.e., *ridehailing intention*) and the location of the chargers. For example, access to home chargers increased the likelihood of BEV adoption among drivers who *did not* exhibit ridehailing intention. In contrast, access to chargers in public areas was positively associated with BEV adoption among drivers who exhibited ridehailing intention. This distinction could be due to vehicles in the former category also being used for personal trips and potentially being used by other members of the household, whereas the ability to charge during a shift may be a more important consideration for drivers in the latter category. Besides, being very familiar with federal BEV incentives was positively associated with the likelihood of BEV adoption irrespective of ridehailing intention. Moreover, being somewhat familiar with these incentives was positively associated with BEV adoption among drivers who did not exhibit ridehailing intention. Although the influence of familiarity with state and local incentives was also tested, the results suggest that their effects were not statistically significant.

Finally, the research team examined the factors influencing the willingness to consider obtaining a BEV among drivers who indicated that they intend to add or replace vehicle(s) they have registered with TNCs within the next year. This analysis involved the estimation of a Heckman sample selection model, as it allows for the distinction to be made between factors that directly influence the willingness to consider obtaining a BEV and the factors that indirectly influence this outcome through their impact on the intention to add or replace vehicle(s) within the next year. The selection model offers insights into the factors influencing the intention to add or replace vehicle(s) registered with a TNC. The age of the oldest vehicle registered with a TNC and obtaining one's primary vehicle through leasing or a rental program were positively associated with the likelihood of indicating an intention to add or replace vehicle(s). Interestingly, respondents who had at least one PHEV registered with a TNC or who had experience driving a BEV in the past year showed a higher likelihood of adding or replacing their current vehicle(s) registered on the TNC platform. Moreover, the perception that BEV chargers are available in public areas was positively associated with the likelihood of expressing an intention to add or replace vehicle(s) registered with a TNC. Similarly, familiarity with federal BEV incentives was also found to increase the likelihood of expressing an intention to add or replace vehicle(s) registered with a TNC.

The outcome model sheds light on the factors influencing the willingness to consider obtaining a BEV. For example, drivers who indicated that they had access to private or reserved parking at their residence were more likely to indicate their willingness to consider obtaining a BEV. In contrast, respondents who indicated that they were unable to install a home charger were less likely to indicate their willingness to consider obtaining a BEV. Additionally, respondents who indicated that they were very familiar with or have used federal BEV incentives were more likely to indicate their willingness to consider obtaining a BEV. Finally, respondents who had at least one BEV registered with a TNC were more likely to indicate their willingness to consider obtaining a BEV.

This report concludes with three major policy recommendations. First, the perceived availability of chargers is found to influence the uptake of BEVs and the decision to use a BEV to provide ridehailing services. Consequently, initiatives aiming to improve the availability of chargers have the potential to contribute to the greater uptake of BEVs among ridehailing drivers (and ultimately, help ensure that the goals of the CMS regulations are achieved). Second, increasing the level of familiarity with federal incentives has the potential to increase the market share of BEVs among ridehailing drivers. Consequently, strategies aiming to ensure that the goals of the CMS regulations are met should include efforts to increase familiarity with federal, state, and local BEV-related incentives and address disparities in familiarity across different segments of drivers. Third, public charging infrastructure has the potential to play an important role in supporting the electrification of the ridehailing fleet. However, charging stations are not always located in areas of high ridehailing demand, and this disparity could result in drivers having to travel to a charging station while they are not transporting a passenger. This form of deadheading would contribute to greater VMT among ridehailing drivers and increase the inconvenience and potential earnings loss associated with mid-shift charging interruptions. Thus, ensuring that public chargers are available in areas where ridehailing demand is relatively high can help assuage concerns regarding mid-shift charging and the need to carefully plan driving activities when using a BEV to provide ridehailing services.

1 Introduction

The introduction of ridehailing services (also known as *ridesourcing*, *on-demand ride*, and *rideshare* services (Tirachini, 2020)) transformed the passenger transportation sector. These services, which allow customers to request and pay for rides through a smartphone application, are offered by Transportation Network Companies (TNCs) such as Uber and Lyft. The prevalence and utilization of ridehailing have grown substantially since they were first introduced in 2009. This growth has prompted concerns about the potential for these services to worsen the environmental impacts of the transportation sector, which is already the largest source of greenhouse gas (GHG) emissions in California (California Air Resources Board, 2024). In particular, ridehailing services can contribute to increases in vehicle miles traveled (VMT), which are associated with congestion and GHG emissions (Erhardt et al., 2019; Schaller, 2021; Wu & MacKenzie, 2021). Moreover, the California Air Resources Board (CARB) estimated that in 2018, the average ridehailing vehicle produced 301 grams of CO_2-equivalent emissions per passenger mile traveled (g CO_2-eq/ PMT) compared to 203 g CO_2-eq/ PMT for the average passenger vehicle (California Air Resources Board, 2019). The environmental impacts of ridehailing can be attributed to several factors, including: 1) induced travel (i.e., trips that would not have been made if ridehailing services were not available) (Loa et al., 2025), 2) the potential for ridehailing to attract demand from more sustainable modes of travel (Gehrke et al., 2019; Giller et al., 2024), and 3) deadheading (i.e., travel without a passenger in the vehicle) (Henao & Marshall, 2019).

To help mitigate the environmental impacts of ridehailing services, California introduced Senate Bill 1014 – the Clean Miles Standard (CMS) – in 2018. The implementation of the CMS regulations was a joint effort between CARB and the California Public Utilities Commission (CPUC). As part of the CMS regulations, CARB is responsible for establishing annual targets for GHG emissions and VMT corresponding to zero-emission vehicles (ZEVs), while the CPUC is responsible for implementing said targets. The established GHG emissions targets were defined with respect to the values outlined in the *2018 Base-year Emissions Inventory Report* published by CARB in 2019 and become more stringent over time (California Air Resources Board, 2022b; California Legislative Information, 2018). Under the CMS regulations, TNCs with an annual VMT that exceeds 5 million must achieve: 1) GHG emissions of 0 g CO_2-eq/ PMT and 2) deliver 90% of their VMT using battery electric vehicles (BEVs) or fuel cell electric vehicles (FCEVs) by 2030 (Clean Miles Standard Requirements, 2022). In order to achieve these targets, ridehailing fleets will need to transition from internal combustion engine vehicles (ICEVs) to ZEVs (including BEVs and FCEVs). Ridehailing platforms are a two-sided market where TNCs connect customers to drivers who use their own vehicle to provide rides (Wang & Yang, 2019), meaning that the composition of the ridehailing fleet is determined by the vehicle ownership and fuel type choices of ridehailing drivers. Consequently, the success of the CMS regulations will ultimately rest on the willingness and ability of drivers to transition to ZEVs.

To help ensure that the goals of the CMS regulations are achieved and the burden imposed on drivers is minimized, it is crucial to understand the current uptake of ZEVs, investigate the factors influencing the use of ZEVs, and identify potential barriers to transitioning from ICEVs to ZEVs. To support ongoing efforts to reduce emissions from ridehailing services, the research team from the 3 Revolutions Future Mobility Program at the University of California, Davis (referred to hereafter as the research team) partnered with the California Air Resources Board (CARB) and the California Public Utilities Commission (CPUC) to assess the current state of ridehailing drivers in California. The goals of the project were to: 1) assess the current uptake of ZEVs among ridehailing drivers in California, 2) identify potential barriers to the transition from ICEVs to ZEVs, and 3) explore the willingness to use ZEVs for ridehailing work. As part of this project, the research team conducted two surveys of ridehailing drivers in California – one before the implementation of the CMS regulations (referred to hereafter as the *first wave* of the survey) and another during the first year of implementation (referred to hereafter as the *second wave* of the survey). As part of the survey, respondents were asked to provide information on their socio-demographic characteristics, the vehicle(s) that they use to provide ridehailing services, driving behavior, attitudes towards electric vehicles (EVs), and barriers to the use of EVs for ridehailing work. The design and conduct of the two waves of the survey are detailed in Chapter 3, while the work that was completed to clean, process, and develop weights for the survey data are summarized in Chapter 4.

After providing information on how the data were collected, cleaned, and processed, Chapter 5 presents descriptive statistics pertaining to the socio-demographic characteristics of the drivers, their driving activity, familiarity with BEV-related incentives, perceived availability of chargers, and their attitudes towards the use of a BEV to provide ridehailing services. The goal of this chapter is to provide a high-level overview of the information obtained through the two waves of the survey and set the stage for the more detailed analyses that are presented in the subsequent chapters. This is followed by an analysis of barriers to the greater uptake of BEVs among respondents of the first and second waves of the survey in Chapter 6. As part of this analysis, the distributions of responses to questions related to barriers to BEV uptake are compared across different segments of drivers in California. This information offers insights into the composition of the ridehailing fleet and the factors influencing vehicle fuel type choices among California ridehailing drivers.

Chapter 7 through Chapter 9 present the results of investigations into the use of BEVs among California ridehailing drivers, the willingness to consider obtaining a BEV, and potential barriers to the greater uptake of BEVs. The results presented in these chapters aim to provide insights into the factors influencing BEV trends among California ridehailing drivers. While the survey collected information on the use of both BEVs and FCEVs, very few respondents indicated that they owned an FCEV; consequently, the analysis presented in this report focuses on the uptake of BEVs. Chapter 7 details the key findings of an exploration of the factors influencing the uptake of EVs. This analysis used data collected through the first wave of the survey to explore how the socio-demographic characteristics of California ridehailing drivers differ based on their work hours and examine the factors influencing the uptake of EVs. The results shed light on the attributes of drivers that are more likely to be using a BEV to provide ridehailing services and the factors that dissuade certain drivers from using a BEV.

This is followed by an analysis of the factors influencing vehicle fuel type choices, the results of which are presented in Chapter 8. Using data from the first wave of the survey, the factors influencing the choice of fuel type for the vehicle that is used to provide the most rides are examined. As part of this analysis, the distinction is made between drivers who did and did not obtain their vehicle with the intention of using it to provide ridehailing services. Moreover, this analysis explores how initiatives to increase the availability of chargers and familiarity with incentives pertaining to ZEV purchases and charger installation can influence the uptake of BEVs. This information can inform policies that help ensure that the goals of the CMS regulations are met. The results of an examination into the factors influencing the willingness of drivers to consider obtaining a BEV are then presented in Chapter 9. As part of this analysis, the factors influencing the intention to add or replace a vehicle that is registered with a TNC are distinguished from those influencing the willingness to consider obtaining a BEV. The results provide insights into the impacts of familiarity with incentives and perceived availability of chargers on the willingness to consider obtaining a BEV. Finally, the key findings of the projects are summarized, the policy implications of the project are discussed, and pathways for future work are outlined in Chapter 10.

2 Literature Review

2.1 Evolution of the Ridehailing Industry

Ridehailing services were first introduced in the United States in 2009 when Uber launched in San Francisco (Uber Technologies Inc., 2018). Three years later Lyft, the other major TNC in the United States, followed suit (Greiner et al., 2019). In the decade since ridehailing was first introduced, these services have become available in cities across the globe. Moreover, information provided by Uber and Lyft suggest that the utilization of these services grew substantially in the decade following their introduction (Tirachini, 2020). For example, in 2015 the CEO of Uber reported that the number of trips made in San Francisco were "increasing three-fold year by year" (Transportation Research Board, 2016). Similarly, Lyft reported that the company served 375.5 million trips in 2017, representing a 130% increase from the previous year (Kerr, 2016). This trend can also be observed in the summary of publicly available trip information from New York City produced by Schneider (2024) (see Figure 2-1). The growing prevalence and utilization of ridehailing resulted in significant effort being dedicated to understanding the benefits and negative externalities associated with these services. Overall, studies on the topic found that, while ridehailing can improve mobility and accessibility, these services can also contribute to increases in VMT (and by extension, congestion and emissions), attract demand from more sustainable modes, and induce additional travel (Brown, 2019; Erhardt et al., 2019; Giller et al., 2024; Henao & Marshall, 2019).

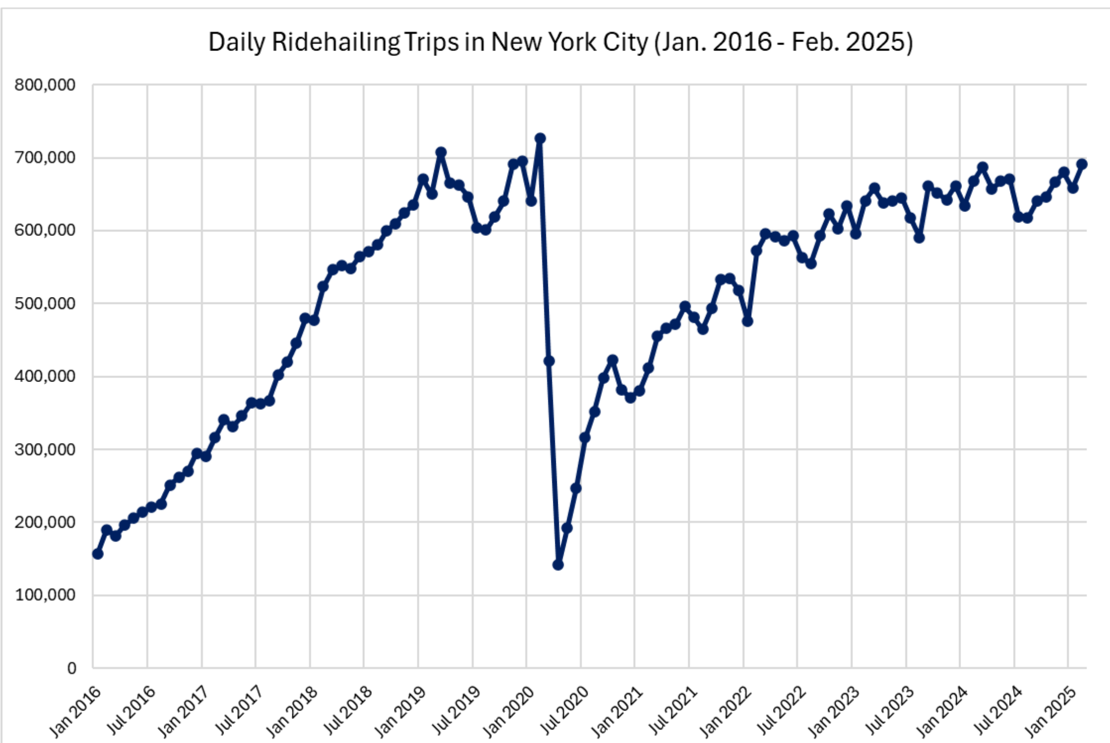

Figure 2-1 Daily ridehailing trip counts in New York City (source: Schneider (2024))

However, growth in the utilization of ridehailing services was halted by the onset of the COVID-19 pandemic in 2020. The onset of the pandemic resulted in substantial changes in travel patterns due to increases in the prevalence of remote work, the temporary closure of non-essential businesses, and the fear of infection (International Monetary Fund, 2021; Oum & Wang, 2020; Shamshiripour et al., 2020). In the midst of these disruptive impacts, the use of ridehailing services sharply declined during early stages of the COVID-19 pandemic (specifically, Spring 2020 and Summer 2020) (Loa et al., 2022; San Francisco County Transportation Authority, 2023). Trip information from New York City and Chicago (the only cities in the United States where this information is publicly available) suggests that ridehailing use has gradually rebounded since the disruptions caused by the onset of the pandemic (as shown in Figure 2-1 and Figure 2-2). The data from these cities also suggest that post-pandemic usage has approached the levels observed during the pre-pandemic period. Besides, recent reports in the media suggest that the use of ridehailing for commuting trips may be more common during the post-pandemic period than it was during the pre-pandemic period (Heinzl, 2024). Anecdotal evidence suggests that this trend is related to the greater prevalence of remote work in the post-pandemic period compared to the pre-pandemic period, resulting in fewer commuting trips being made (Levin, 2024).

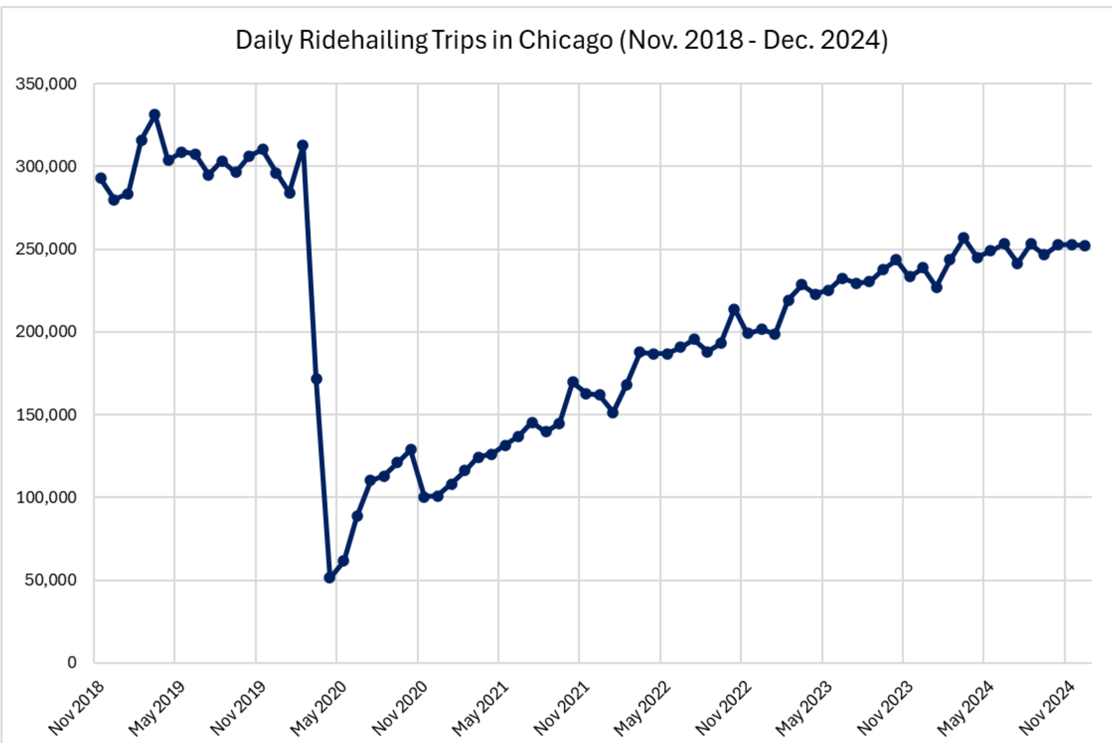

Figure 2-2 Daily ridehailing trip counts in Chicago (source: Schneider (2024))

2.2 Transportation Electrification in California

Section 237.5 of the California Public Utilities Code defines transportation electrification as "the use of electricity from external sources of electrical power ... for all or part of vehicles ... that are mobile sources of air pollution and greenhouse gases" (California Legislative Information, 2016). In 2015, transportation electrification was identified as a means of helping to achieve reductions in GHG emissions by Senate Bill 350 – the Clean Energy and Pollution Reduction Act of 2015 (California Legislative Information, 2015). In the decade that followed, several executive orders and pieces of legislation have been passed to facilitate and encourage transportation electrification among passenger vehicles. In addition to the passing of several Assembly Bills and Senate Bills pertaining to EV charging infrastructure, Governors Brown and Newsom issued Executive Orders outlining targets for zero-emission vehicles (California Public Utilities Commission, 2025). This includes Executive Order N-79-20, which establishes the target for all new passenger vehicles sold in California being zero-emission by 2035.

As part of the push toward transportation electrification, the CMS regulations were introduced through Senate Bill 1014. The bill notes that TNCs are well-positioned to help California meet its goals for reductions in GHG emissions by increasing the number of rides served by zero-emission vehicles, encouraging the use of pooled rides, and contributing to reduced congestion (California Legislative Information, 2018). The CMS regulations establish annual targets corresponding to reductions in emissions (measured in g CO_2-eq/ PMT) and the percentage of VMT corresponding to BEVs (California Air Resources Board, 2022b). TNCs with annual VMT exceeding 5 million in a given calendar year are subject to the targets outlined by the CMS regulations and are required to submit an annual compliance report to the CPUC. Under the CMS regulations, TNCs can receive credits for overcompliance, investments in bikeway and sidewalk infrastructure, and serving trips that connect to mass transit (California Air Resources Board, 2022b). Given that drivers typically use their own vehicles to provide ridehailing services, the achievement of the goals of the CMS regulations hinges on the uptake of ZEVs (particularly BEVs) among ridehailing drivers. Consequently, it is crucial to understand the attributes of ridehailing drivers in California, the factors that influence the vehicles they choose to use to provide ridehailing services, and potential barriers to the uptake of BEVs.

2.3 Factors Influencing Acceptance and Uptake of Electric Vehicles Among Ridehailing Drivers

Studies exploring the potential uptake of BEVs among ridehailing drivers tend to focus on understanding the factors influencing BEV acceptance. As expected, BEV acceptance tends to vary among different segments of ridehailing drivers. For example, in their study of ridehailing drivers in the United States, Bansal et al. (2020) noted that younger drivers, drivers who provided ridehailing services on a daily basis, drivers with a postgraduate degree, and drivers who live in a metropolitan area were more likely to indicate a preference to switch to a “fuel-efficient” vehicle. Du, Cheng, Li, & Yang (2020) also found that satisfaction with the use of BEVs to provide ridehailing services can differ based on socio-demographic characteristics in their study of ridehailing drivers in Shenzhen. Specifically, the authors noted that educational attainment, household income, and the use of vehicles provided by TNCs (e.g., through rental programs) to provide ridehailing services were associated with a greater likelihood of drivers indicating their satisfaction with BEVs. The authors also found that a perceived lack of subsidies related to both operating and charging a BEV were associated with a reduced likelihood of drivers indicating their satisfaction with BEVs.

The acceptance of BEVs among ridehailing drivers can also be influenced by their working hours, mileage, and the number of rides that they provide. For example, Du, Cheng, Li, & Yang (2020) found that drivers whose daily mileage was less than 250 km (approximately 155 miles) were more likely to express their satisfaction with the use of BEVs to provide ridehailing services. A possible explanation for this finding is that BEVs can adequately meet their travel preferences without the need to recharge. However, it is important to note that the relationship between mileage and current BEV use can be bidirectional – past adoption of BEVs could result in lower mileage, or lower mileage may have influenced the decision to start using a BEV for ridehailing work. Moreover, using driving data provided by Lyft, Taiebat et al. (2022) found that BEVs with a range of at least 250 miles are more suitable for ridehailing drivers compared to shorter-range BEVs.

The availability and adequacy of charging infrastructure also play a crucial role in the acceptance of BEVs (Du, Cheng, Li, & Xiong, 2020; Jenn, 2024; Liu et al., 2022). This could be a crucial barrier to the greater uptake of BEVs among ridehailing drivers, as mid-shift charging (i.e., charging during work hours) directly reduces their revenue. The importance of access to chargers and charging speeds were noted by Rajagopal & Yang (2020) in their study of ridehailing drivers in West Los Angeles. The authors noted that the average driver was concerned that they would run out of charge if they were using a BEV to provide ridehailing services, and that access to chargers and charging speed would be important factors if they were to consider using a BEV to provide ridehailing services. Additionally, in their survey of ridehailing drivers in the United States and Canada who drove plug-in hybrid electric vehicles (PHEVs), Sanguinetti & Kurani (2021) found that driving range was a key factor in the drivers' decision to not use a BEV. While overnight charging can reduce the need for mid-shift charging (Moniot et al., 2019; Pavlenko et al., 2019), many drivers do not have access to home charging infrastructure. This issue is especially pronounced for those who live in multi-family dwellings that lack dedicated parking spaces equipped with electrical outlets (Nicholas et al., 2020). Additionally, the lower-income communities where ridehailing drivers tend to reside often have lower public charger coverage (Hsu & Fingerman, 2021).

In addition to the acceptance of BEVs, a relatively limited number of studies have explored the factors influencing the intention to purchase a BEV. For example, Zhou et al. (2021) applied the theory of perceived value to understand the potential for perceptions of BEVs to influence the intention to purchase a BEV among ridehailing drivers in China. The results suggest that perceptions of functional value (e.g., the perceived benefits of using a product), emotional value (e.g., the experience when purchasing a product), and societal value (e.g., the social effect that results from using a product) were positively associated with the intention to purchase a BEV. In contrast, the authors found that functional risks (e.g., the risk that the functionality of BEVs may not deliver the anticipated benefits), financial risks (e.g., potential financial losses associated with using BEVs), and physical/ mental risks (e.g., the potential negative physical or mental outcomes associated with BEVs) were negatively associated with the intention to purchase a BEV. Additionally, Rye & Sintov (2024) explored how the perceptions of BEVs influence the intention to adopt a BEV among ridehailing drivers in central Los Angeles. The results of this study suggest that perceptions of both the symbolic (e.g., the implications of driving a BEV on the perceptions of a person's technological savvy or concern for the environment) and instrumental (e.g., comparisons of the fuel and maintenance costs of BEVs compared to ICEVs) attributes of BEVs were associated with a greater intention to adopt BEVs. Moreover, the results suggest that ridehailing drivers placed greater value on instrumental attributes than on symbolic attributes.

A limited number of studies have also utilized stated preference experiments to explore the factors associated with preferences for electric vehicles among ridehailing drivers. For example, the results of Waluyo et al. (2022) suggest that cost and range played a key role in the probability of motorcycle-based ridehailing drivers in Yogyakarta indicating that they would purchase an electric motorcycle. Additionally, in their survey of ridehailing drivers in Singapore, the results of Ding et al. (2025) suggest that the probability of indicating that a driver would use a BEV to provide ridehailing services is influenced by uncertainty in operating costs. Moreover, the authors also noted that drivers who were younger, those who worked more than five days per week, and those whose daily mileage exceeded 350 km (approximately 217 miles) were more likely to indicate that they would use a BEV to provide ridehailing services and more likely to be sensitive to fluctuations in the operating cost of BEVs.

Studies on the factors influencing the acceptance of and intention to adopt BEVs offer important insights into the factors that could potentially influence the uptake of BEVs among ridehailing drivers. However, studies of this nature offer insights into neither the attributes of drivers who currently use BEVs to provide ridehailing services nor the factors influencing the vehicle fuel type choices of ridehailing drivers. Moreover, to the research team's knowledge, there has yet to be a study examining the uptake of BEVs among ridehailing drivers. To support the goals of the CMS regulations, it is crucial to understand the factors influencing the use of a BEV to provide ridehailing services, including the potential impacts of financial incentives and perceived access to chargers.

2.4 Previous Surveys of Ridehailing Drivers

There are relatively few examples of surveys that have recruited ridehailing drivers. This largely stems from the challenges associated with recruiting drivers to participate in surveys, particularly when TNCs are not involved in the recruitment process. One of the more common approaches to overcome these challenges has been to conduct intercept surveys of ridehailing drivers. Overall, there are two broad categories of intercept surveys. First, there are intercept surveys that involve requesting rides through ridehailing platforms and inviting the driver to participate in the survey. Examples of this approach include the surveys conducted by Rajagopal & Yang (2020) in West Los Angeles (N = 148), Rye & Sintov (2024) in central Los Angeles (N = 136), and Brugger & Watts (2021) in Washoe County, Nevada (N = 75). Second, there are intercept surveys that involve approaching drivers at specific locations. For example, the survey conducted in Singapore (N = 152) by Ding et al. (2025) involved recruiting drivers at fuel stations and parking lots. Similarly, the surveys in Shenzhen conducted by Du, Cheng, Li, & Xiong (2020) (N = 786) and Du, Cheng, Li, & Yang (2020) (N = 769) involved recruiting drivers at locations such as charging stations, gas stations, and vehicle service centers. Additionally, the survey conducted by Waluyo et al. (2022) in Yogyakarta involved recruiting motorcycle-based ridehailing drivers in public areas. Although intercept surveys allow the researchers to ensure that all participants are ridehailing drivers, the context in which drivers are recruited tends to limit the amount of information that can be collected. Moreover, intercept surveys can be quite time- and labor-intensive, which can limit the number of responses that are collected through this approach. This limitation can preclude the resulting dataset from being used for more rigorous quantitative analyses.

Aside from intercepting drivers, previous surveys have also tried to recruit ridehailing drivers through market research panels. For example, in their survey (N = 309) on attitudes towards pooled ridehailing services in the United States (such as UberX Share and Lyft Shared), Morris et al. (2020) recruited ridehailing drivers from the panel maintained by Qualtrics (the *Qualtrics Online Sample*). Because the panel was not exclusively comprised of ridehailing drivers, the researchers used screening questions to ensure that the survey was only completed by those who drove for Uber or Lyft in the two years prior to the survey. Similarly, Zhou et al. (2021) partnered with a "consulting company" to recruit participants for their survey of ridehailing drivers in China (N = 836). While this approach to recruitment can yield relatively large sample sizes, additional effort tends to be required to ensure the quality of the data. This typically includes the inclusion of screening questions to ensure that all participants are actually ridehailing drivers and processing the data to ensure that unrealistic or low-quality responses are not included in the final dataset. Similar considerations also apply when recruiting participants from lists of email addresses, which was the approach taken by Campbell (2022) in his surveys on ridehailing drivers in 2017 (N = 1,150), 2018 (N = 1,143), and 2019 (N = 947).

Finally, there are a limited number of examples where surveys of ridehailing drivers have been conducted in partnership with TNCs. For example, Benenson Strategy Group (BSG) partnered with Uber to conduct surveys of drivers in both 2014 (N = 601) and 2015 (N = 632) (Benenson Strategy Group (BSG), 2015; Hall & Krueger, 2018). Similarly, Sanguinetti & Kurani (2021) partnered with Uber to recruit participants for their survey (N = 780) on the experiences of drivers with BEVs. Taking this approach to recruiting participants offers the benefit of helping to ensure that all active drivers have a non-zero probability of being included in the sample. Limiting the potential for active ridehailing drivers to be excluded from the sampling frame helps to increase the extent to which the results obtained from the survey data can be generalized to the population of ridehailing drivers as a whole. However, it is also important to note that the generalizability of the results will be impacted by discrepancies between the attributes of the sample and the population of ridehailing drivers. The credibility that is gained by partnering with TNCs to recruit drivers can also have a positive impact on the response rate of the survey.

3 Data Collection

To support CARB in their evaluation of the impacts of the CMS regulations, the research team conducted a multi-wave, web-based survey of California ridehailing drivers with the assistance of the two largest TNCs in California – Uber and Lyft. The TNCs played an invaluable role in the survey by recruiting drivers to participate in the survey, which helped ensure that the research team was able to obtain stratified random samples of California ridehailing drivers and that the sample sizes of the two waves of the survey were sufficiently large. These factors improved the extent to which the results of the project can be generalized to the population of California ridehailing drivers and facilitated the use of the survey data for rigorous quantitative analyses. Moreover, it is very likely that the involvement of the TNCs in the recruitment process positively contributed to the response rates of the two waves of the survey.

The first wave of the survey was conducted prior to the implementation of the CMS regulations, while the second wave of the survey was conducted during the first year of implementation. The administration of two waves of the survey was motivated by the desire to explore changes in trends related to the uptake of battery electric vehicles, including the use of these vehicles to provide ridehailing services, availability of chargers, and familiarity with ZEV-related incentives. The surveys were implemented in the online survey platform provided by Qualtrics and drivers were invited to participate in the survey through email invitations. In both waves of the survey, the TNCs sent invitations to participate in the survey to their drivers. Additionally, drivers who completed the first wave of the survey and provided their consent to be contacted for future research were invited to participate in the second wave of the survey. This subset of drivers was invited to participate in the survey through an email sent by the research team. Regardless of how the drivers were recruited, those who completed the survey were sent an electronic gift card for the vendor of their choosing. This chapter presents key details regarding the surveys, including the design of the questionnaire, the strategy used to sample and recruit participants, the pilot test that determined the incentive that was used in the surveys, and the conduct of the surveys.

3.1 Questionnaire Design

The questionnaires used in the two surveys were designed based on a review of existing studies, consultations with project stakeholders at the CARB, the CPUC, Uber, and Lyft, and in-depth online interviews with ridehailing drivers. Drivers who participated in the in-depth interview were recruited from previous surveys conducted by the research team who both self-identified as ridehailing drivers and provided their consent to be contacted for future research projects. The interviews were conducted by members of the research team, with drivers being offered a $25 electronic gift card as an incentive to participate. As part of the interviews, drivers reviewed the survey tool and shared their issues and concerns regarding vehicle electrification.

Both waves of the survey were comprised of three sections: 1) ridehailing driver activities, 2) vehicle ownership and costs, and 3) socio-demographic characteristics. In the first section of the surveys, drivers were asked to provide information about the companies for which they provide ridehailing services, as well as the region(s) where they provided ride-hailing services, their average weekly working hours, and the average number of rides that they provided per week in the past three months. In the second wave of the survey, respondents who indicated that they stopped driving for one or more TNCs were asked to provide the reason(s) for their decision.

As part of the second section of the survey, drivers were asked to report the number of passenger vehicles that they and the members of their household had access to at the time of the survey and to provide information about the make, model, model year, and fuel type of up to three vehicles that they had registered with a TNC. In the second wave of the survey, respondents who completed the first wave of the survey were also asked to indicate whether they made any changes to the vehicle(s) that they have registered with a TNC since they completed the previous survey. Those who indicated that they added or replaced a vehicle that they had registered with a TNC were asked to indicate their reason(s) for doing so. In both waves of the survey, respondents were also asked to report their total mileage corresponding to providing ridehailing services and other activities in the past 12 months for each vehicle, indicate how they obtained each vehicle, and indicate whether they obtained each vehicle with the intention of using it to provide ridehailing services. Additionally, respondents were asked to report their annual expenditures corresponding to maintenance, refueling, and charging for each vehicle, as well as their gross fare revenue and tips.

In the second section of both waves of the survey, respondents were also asked to provide information about their perceptions of the availability of EV chargers in a variety of locations (including at their home, in public areas, and at their workplace or school). The response options for these questions included level 1 (L1), level 2 (L2), and direct current (DC) fast chargers, as well as not knowing the type of charger, and perceiving no chargers as being available at the location. The various types of chargers were described in terms of their electrical requirements and speed of charging. Respondents could make multiple selections among L1, L2, and DC fast chargers for a given location. If a driver reported perceiving no chargers as being available at their home/garage, they were asked whether they would be able to install one. Additionally, respondents were asked to indicate their level of familiarity with federal, state, and local incentives related to the purchase, leasing, or rental of ZEVs and the installation of EV chargers. As part of the second wave of the survey, respondents who indicated that they were familiar with these incentives were asked to identify where they learned about said incentives. Respondents of the second wave of the survey who indicated that they have used any of the listed incentives were also asked to indicate whether they were used to obtain any of the vehicles that they have registered with a TNC. Finally, respondents in both waves of the survey were asked to indicate their level of agreement with a series of statements pertaining to the use of BEVs to provide ridehailing services using a five-point Likert scale.

The third section of both waves of the survey included questions pertaining to the socio-demographic characteristics of the drivers. As part of this section, respondents were asked to report the year they were born and whether they were born in the United States. Additionally, respondents were asked to provide information about their gender, race and ethnicity, educational attainment, household income, and the composition of their household. Finally, respondents were asked to provide information about their residence, including their address, type of dwelling, whether they own or rent their home, and whether they have access to private or reserved parking.

3.2 Sampling Strategy

The first step in the development of the sampling strategy was to determine the target sample size for each wave of the survey. As part of this process, the research team decided to target a 3:1 ratio of Uber to Lyft drivers in the survey, due to the relative size of the driver pool of each TNC. The target sample size for the first wave of the survey was 2,000 responses (1,500 from Uber and 500 from Lyft), while the target sample size for new respondents for the second wave of the survey was 1,000 (750 from Uber and 250 from Lyft).

Next, the research team developed a stratified random sampling procedure to sample ridehailing drivers to participate in the first and second waves of the survey. This approach was chosen due to its potential to produce a representative sample of ridehailing drivers, which can yield insights that are more generalizable to the population of California ridehailing drivers than those obtained through other sampling approaches. The primary goal when designing the stratified random sampling procedure was to facilitate the inclusion of drivers from all regions of California, with varying levels of driving experience, and varying levels of weekly working hours. Consequently, strata were defined based on the region where drivers provide the plurality of their rides, the number of years that they have been active on the TNC platform, and the number of hours that they provide ridehailing services during an average week.

Analyses of ridehailing trip records in California from 2018 through 2020 indicate that ridehailing vehicles are highly concentrated around large urban centers (California Air Resources Board, 2019; San Francisco County Transportation Authority, 2023). To facilitate the recruitment of drivers from outside these areas, the state was divided into five regions: 1) Sacramento Area; 2) San Diego; 3) San Francisco Bay Area; 4) Southern California (i.e., Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura counties); and 5) rest of California (see Figure 3-1). The strata corresponding to the tenure and working hours of drivers were defined based on input from project stakeholders at Uber and Lyft. With regards to the former, three categories were defined: less than 2 years, 2 to 5.5 years, and over 5.5 years. In terms of the latter, three categories were also defined: *occasional* drivers (less than 10 hours per week), *part-time* drivers (between 10 and 25 hours per week), and *full-time* drivers (over 25 hours per week). Only weeks in which drivers were active on the TNC platform were used to calculate their average weekly hours.

Once the definitions of the strata were defined and shared with the TNCs, the sample size for each stratum was determined by multiplying the target sample size for the respective TNC with the proportion of their drivers belonging to said stratum. As part of this process, drivers who provide the plurality of their rides in Southern California were under-sampled (i.e., the sample size was divided by 2) while drivers who provide the plurality of their rides in the Sacramento Area, San Diego, and the rest of California region were over-sampled (i.e., the sample size was multiplied by 2). This decision was motivated by the desire to enable the recruitment of an adequate number of drivers from more sparsely serviced areas of the state and was made based on distributional data provided by one of the TNCs as part of the project. Following these adjustments, the TNCs identified strata where the calculated sample size was below the minimum group size (N = 20) and set the sample size for those strata to be equal to the minimum value.

Following the completion of the sample size calculations, the number of invitations that would be sent to the members of each stratum was calculated by dividing the sample size by an expected response rate. Based on information provided by the TNCs, the research team assumed a 7% response rate for full-time drivers and a 5% response rate for part-time and occasional drivers. These values were reviewed by the TNCs, with both raising the issue that their population of drivers in California was not large enough to support 45 strata. Consequently, adjustments were made to the definitions of the strata to ensure that the number of invitations that would be distributed did not exceed the number of all drivers on a TNC platform in each stratum.

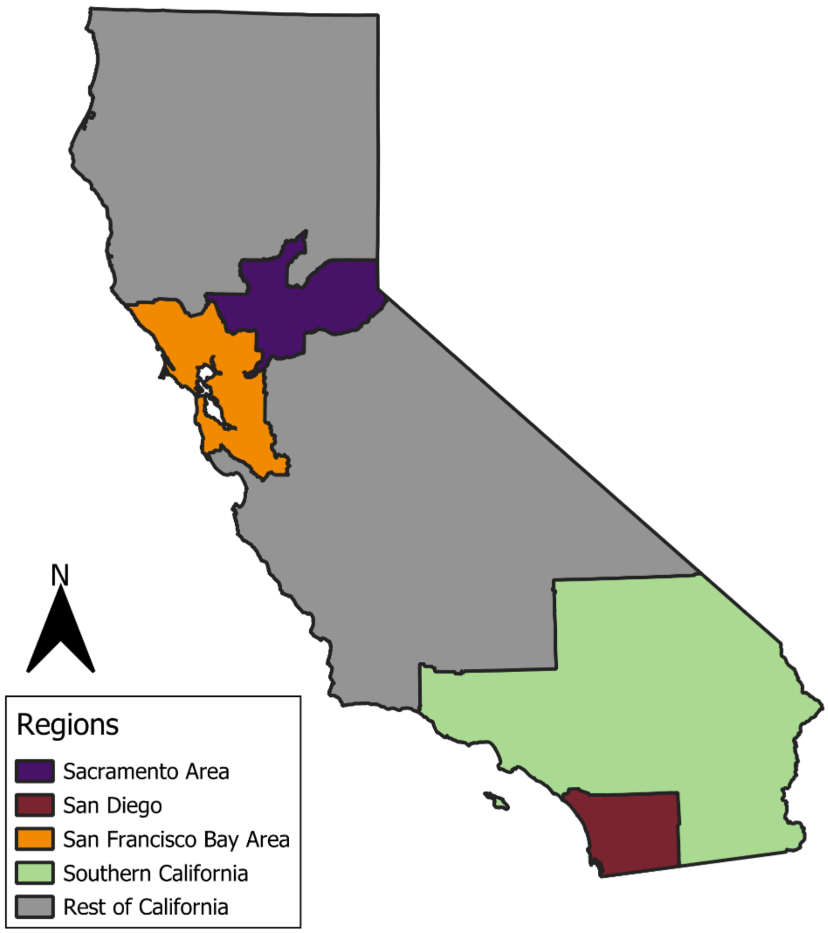

Figure 3-1 Regions used in the stratified random sampling proceure

3.3 Testing the Impacts of Incentives on Response Rates

Prior to the full deployment of the first wave of the survey, the research team conducted a pilot test to understand how response rates could be affected by the value of the electronic gift card that was offered to respondents for completing the survey. The pilot test was carried out by one of the TNCs and considered three values of electronic gift cards – $5, $8, and $10. Invitations were sent to 1,135 drivers, with approximately equal numbers of drivers being offered each incentive. In addition to the initial invitation, a reminder email was also sent to drivers. The overall response rate for the pilot test was 4.22%, and somewhat surprisingly, the highest response rate was observed among the drivers who were offered an $8 electronic gift card for completing the survey. As a result, the invitations for both the first and second waves of the survey offered drivers an $8 electronic gift card in exchange for completing the survey.

3.4 Survey Administration

Invitations to participate in the first and second waves of the survey were distributed by the TNCs. Additionally, the research team emailed invitations to drivers who completed the first wave of the survey and provided their consent to be contacted for future research. The invitation that was sent to drivers outlined the contents of the survey, emphasized that their responses would remain confidential, and that they would receive an $8 electronic gift card to a vendor of their choosing upon completion of the survey. The first wave of the survey was administered from October 2023 through June 2024, while the administration of the second wave of the survey began in March 2025. A total of 1,739 responses were received during the first wave of the survey and 463 were received during the second wave of the survey (including 215 drivers who participated in both waves). The distribution of respondents based on the wave(s) of the survey that they completed is summarized in Figure 3-2 below. At the time of writing, the second wave of the survey is still active, and the recruitment of drivers from one TNC has yet to start. Consequently, the results from the second wave of the survey that are presented in this report were derived from responses received on or before May 7, 2025.

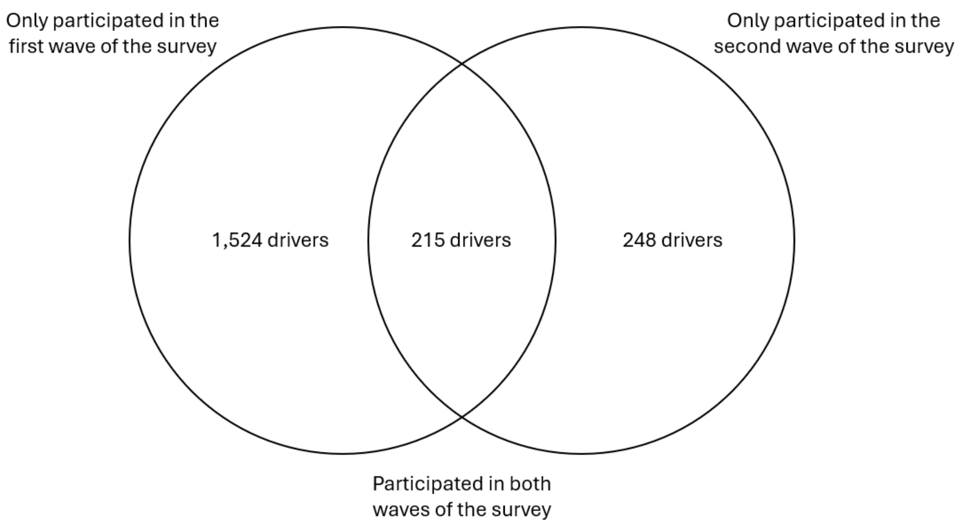

Figure 3-2 Number of completed surveys, by the wave(s) completed by each respondent

4 Data Cleaning and Processing

4.1 Data Cleaning

Before the data were analyzed, the research team took several steps to clean and process the data collected through the two waves of the survey. First, the research team reviewed responses to questions regarding: 1) working hours, 2) annual mileage, 3) fare revenue, 4) expenditures associated with providing ridehailing services, and 5) attitudes towards electric vehicles. As part of this process, flags corresponding to each set of questions were added to responses where the research team identified issues with the information provided by the respondents. Examples of such issues include reporting expenditures that exceed fare revenues, reporting working zero hours but serving at least one ride, and selecting the same response option for 10 consecutive attitudinal questions. The questions that were used to flag responses were selected based on the goals of the project. Responses with flags corresponding to at least two of these sets of questions were removed from the dataset.

Two additional criteria were applied to identify responses that were removed from the dataset. First, the research team removed responses from those who did not complete the survey. Second, the research team analyzed the time taken by each respondent to complete the survey. Responses that were completed in an unreasonably short amount of time (defined as the median completion time minus 1.5 times the median absolute deviation of completion times) were also removed from the survey. The value of this threshold was approximately 12 minutes. Following the data cleaning process, 1,357 remained from the first wave of the survey, while 386 responses (including 40 responses from respondents who stopped driving for TNCs) remained from the second wave of the survey. This includes 195 responses from drivers who completed both waves of the survey.

4.2 Weighting

The ability to make inferences about a population using data collected through a survey is influenced by the extent to which the sample represents the target population (Solon et al., 2015). Several factors can affect the representativeness of a survey sample, including sampling bias, non-response bias, response bias, and the recruitment of respondents through non-probability-based sampling methods. To address the impacts of these factors, a weighting procedure was developed and applied to improve the extent to which the data from the two waves of the survey represent the attributes of ridehailing drivers in California. More broadly, the development and application of weights were motivated by a desire to improve the representativeness of the sample. The following sections summarize the variables that were used to develop the weights, the dataset from which the target distributions were obtained, and procedure used to develop the weights.

4.2.1 Variable Selection for Weighting

The variables that were considered in the weighting procedure were informed by the sampling strategy and the goals of the survey. Three variables pertaining to the driving activities of the respondents were considered in the weighting procedure – the region where they provide the plurality of their rides, the number of years that they have been active on ridehailing platforms, and the number of hours that they spend providing ridehailing services during an average week. These variables were included in the weighting procedure because they were used in the stratified random sampling procedure. Additionally, four socio-demographic characteristics were considered in the weighting process – age, gender, racial and ethnic identity, and household income. The inclusion of these variables was motivated by the desire to understand the uptake of BEVs and potential impacts of the CMS regulations among different segments of drivers. The target distributions of the variables considered in the weighting procedure were obtained from internal data that was provided by one of the major TNCs in California. As part of this process, it was assumed that the population of drivers registered with one major TNC was not systematically different from the population of drivers registered with the other major TNC. Due to unanticipated delays in obtaining this information for the wave 2 sample, the same dataset was used to develop weights for the first and second waves of the survey.

4.2.2 Weighting Procedure

The first step of the weighting procedure was to account for the under-sampling of drivers from the Southern California region and the over-sampling of drivers from other regions. To account for differences in sampling rates across the regions, initial weights for drivers in each region were computed by dividing the population percentage of drivers who provide the plurality of their rides in a given region by the sample percentage of drivers who provide the plurality of rides in that region. Using the initial weights, the marginal distributions of variables pertaining to age, gender, racial and ethnic identity, household income, number of years on the ridehailing platform, and the average number of hours spent providing ridehailing services in the average week were computed for both the sample and in the dataset provided by the TNC. The research team then calculated the root mean square error (RMSE) for each of these six variables to quantify differences between the distributions of each variable in the two datasets.

Next, the research team applied an iterative proportional fitting (IPF) procedure to compute the final weights for the first and second wave datasets. The goal of IPF is to reduce differences between the marginal distributions of one or more target variables in the sample and the target distribution, which in this procedure were calculated using the data provided by the TNC. In a given iteration of the IPF procedure, variables were processed in descending order based on the RMSE value corresponding to each variable. The IPF procedure continued until the maximum difference between the weights produced in successive iterations was less than 0.01. Following the completion of the IPF procedure, extremely large and small weights were trimmed to reduce their impacts on the variance of estimates derived from the weighted dataset (Haziza & Beaumont, 2017). Finally, the trimmed weights were multiplied by an adjustment factor to ensure that: 1) the weighted distribution of the average number of hours spent providing ridehailing services in the average week matched that of the dataset provided by the TNC, and 2) the weighted sample size matched the unweighted sample size. The IPF procedure was implemented using the *mipfp* package written for the R programming language (Barthélemy et al., 2018). The weighting procedure applied by the research team is outlined in Figure 4-1.

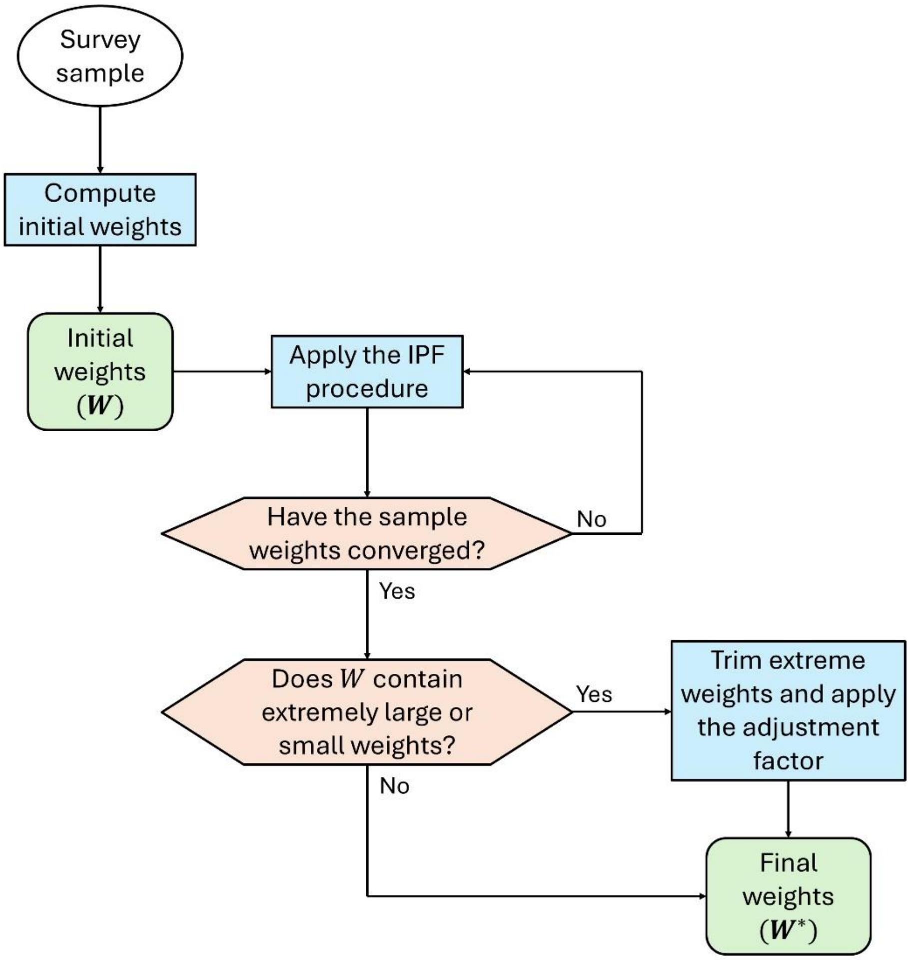

Figure 4-1 The procedure used to develop weights for the samples from the first and second waves of the survey

As shown in Table 4-1 and Table 4-2, the RMSE values corresponding to the weighted datasets tend to be lower than those corresponding to the unweighted datasets. In particular, the development of weights also resulted in lower RMSE values for most of the variables that were considered in the IPF procedure. For data collected through the first and second waves of the survey, the RMSE values corresponding to five of the six variables considered in the IPF procedure were lower in the weighted dataset compared to the unweighted dataset (as shown in Table 4-1 and Table 4-2). The only variable where the RMSE corresponding to the weighted dataset was higher than that of the unweighted dataset was gender, which had relatively low unweighted RMSE values. Overall, it appears that the development of weights helped to reduce discrepancies between the distributions of key socio-demographic and driver attributes between the samples and the dataset provided by the TNC. However, it is important to note that the data collected through the second wave of the survey contains respondents who also completed the first wave of the survey, meaning that the sample is not entirely random.

Table 4-1 Comparison of RMSE values between the unweighted and weighted datasets from the first wave of the survey

Variable	RMSE (Unweighted)	RMSE (Weighted)
Age	0.147	0.052
Gender	0.025	0.047
Racial and ethnic identity	0.132	0.059
Household income	0.144	0.085
Number of years on the ridehailing platform	0.113	0.010
Average number of hours spent providing ridehailing services per week	0.388	0.000

Table 4-2 Comparison of RMSE values between the unweighted and weighted datasets from the second wave of the survey

Variable	RMSE (Unweighted)	RMSE (Weighted)
Age	0.127	0.052
Gender	0.023	0.031
Racial and ethnic identity	0.110	0.079
Household income	0.158	0.091
Number of years on the ridehailing platform	0.192	0.084
Average number of hours spent providing ridehailing services per week	0.356	0.000

5 Sample Description and Descriptive Statistics

The data collected through the two waves of the survey were used to understand the attributes of ridehailing drivers in California, the current uptake of BEVs, and the factors that could influence the future uptake of BEVs. First, the distributions of key socio-demographic characteristics and driver attributes are presented. Second, the attributes of the vehicles that the drivers have registered with TNCs are summarized. Third, the factors influencing the decision to use specific vehicles to provide ridehailing services are explored. Fourth, the perceived availability of EV chargers and the awareness of ZEV-related incentives are examined. Finally, attitudes towards the use of BEVs to provide ridehailing services are compared between the two waves of the survey. All of the descriptive statistics presented in the chapter are based on data from the weighted datasets. However, the descriptive statistics for the second wave do not include responses from the 40 respondents who indicated that they no longer provide ridehailing services.

5.1 Attributes of Drivers

5.1.1 Socio-demographic Characteristics

The distributions of key socio-demographic characteristics of respondents from the first and second waves of the survey are compared to data from the American Community Survey (ACS) in Table 5-1. There are several differences between the socio-demographic characteristics of ridehailing drivers and the adult population of California. For example, ridehailing drivers in the sample are more likely to be between the ages of 35 and 54, male, and identify as Hispanic or Latino compared to the adult population of California. In contrast, respondents were less likely to indicate that they possessed a graduate or professional degree and more likely to indicate that they had some college experience or a bachelor's degree. Moreover, ridehailing drivers were more likely to belong to a lower-income household compared to the average adult resident of California.

As part of the survey, respondents were also asked several questions about how their work providing ridehailing services interacts with other commitments that they may have. As shown in Table 5-2, a relatively small percentage of respondents indicated that they were students, while roughly half of respondents indicated that they were employed on a full-time basis outside of ridehailing work. The household attributes of the respondents were also compared in Table 5-2. The majority of respondents from both waves of the survey indicated that they were renting their homes, which could limit their ability to install a home BEV charger. Besides, slightly less than half of the respondents reported that they lived in a stand-alone house, while slightly over one-third indicated that they lived in an apartment or condo. Finally, the majority of respondents reported that they have access to private or reserved parking at their homes.

Table 5-1 Distributions of key socio-demographic characteristics of the adult population of California, wave 1 respondents, and wave 2 respondnets

Variable	ACS	Wave 1	Wave 2
Age			
18 to 34	19%	22.0%	25.1%
35 to 54	40%	55.6%	51.1%
55 to 66	22%	18.1%	21.7%
67 and older	20%	4.3%	2.1%
Gender			
Male	50%	76.8%	84.2%
Not male	50%	23.2%	15.8%
Race and ethnicity			
White alone	60%	28.7%	30.1%
Black or African American alone	10%	8.0%	5.9%
Hispanic or Latino	19%	37.8%	33.6%
Asian or Pacific Islander alone	2%	14.3%	18.7%
Other (incl. multi-racial)	4%	11.2%	11.8%
Education			
High school or below	23%	17.3%	11.9%
Some college or technical school	16%	42.3%	34.1%
Bachelor's degree	25%	30.7%	44.3%
Graduate or professional degree	36%	9.7%	9.7%
Household income			
Less than $50,000	29%	43.1%	42.1%
$50,000 to $99,999	26%	33.9%	34.5%
$100,000 and over	47%	23.0%	23.4%
Sample size	20,958,415	1,357	346

Table 5-2 Personal and household attributes of wave 1 and wave 2 respondents

Variable	Wave 1	Wave 2
Student status		
Student	9.5%	9.6%
Not a student	90.5%	90.4%
Employment outside of ridehailing		
Full-time	51.3%	47.1%
Part-time	11.3%	14.4%
Unpaid or no other work	37.4%	38.6%
Housing tenure		
Owned	28.0%	30.0%
Rented	63.8%	58.0%
Other	8.2%	12.0%
Housing type		
Stand-alone house	46.1%	47.9%
Attached home, duplex, or townhouse	13.6%	10.8%
Apartment or condo	35.1%	36.3%
Other	5.2%	5.0%

Variable	Wave 1	Wave 2
Access to private or reserved parking at home		
Yes	68.3%	70.0%
No	31.7%	30.0%
Sample size	1,357	346

5.1.2 Driver Characteristics

Respondents of both waves of the survey were asked to complete a series of questions regarding their work as a ridehailing driver. As shown in Table 5-3, slightly over 90% of respondents indicated that they only had one vehicle registered with a TNC at the time of the respective surveys and the majority of drivers spent less than 10 hours per week on average providing ridehailing services. However, there are slight discrepancies between the attributes of respondents from the first and second waves of the survey. For example, respondents of the first wave were more likely to have stayed less than two years on a TNC platform at the time of the survey, whereas respondents of the second wave were more likely to have spent more than 5.5 years on a TNC platform.

Table 5-3 Summary of driver characteristics among wave 1 and wave 2 respondents

Variable	Wave 1	Wave 2
Number of vehicles registered with a TNC		
1	91.1%	90.7%
2	8.7%	9.1%
3	0.2%	0.1%
Driver status		
Occasional (Less than 10 hours per week)	62.6%	62.6%
Part-time (10 to 25 hours per week)	30.3%	30.3%
Full-time (More than 25 hours per week)	7.1%	7.1%
Years on TNC platform		
Less than 2 years	41.1%	30.6%
2 to 5.5 years	25.8%	30.2%
Over 5.5 years	33.1%	39.1%
Region where the plurality of rides is provided		
Sacramento Area	6.7%	15.5%
San Diego	18.1%	11.5%
San Francisco Bay Area	17.1%	15.4%
Southern California	45.4%	38.6%
Rest of California	12.8%	18.9%
Annual ridehailing mileage		
Less than 25,000 miles	84.2%	80.8%
25,000 to 49,999 miles	11.1%	15.6%
50,000 to 74,999 miles	4.2%	0.7%
75,000 to 99,999 miles	0.2%	1.6%
100,000 miles and over	0.3%	1.2%
Sample size	1,357	346

Similarly, respondents to the second wave of the survey were more likely to provide the plurality of their rides in the Sacramento Area and less likely to provide the plurality of their rides in the San Diego and San Francisco Bay Area regions. Nevertheless, respondents were most likely to indicate that they provided the plurality of their rides in Southern California, irrespective of the wave of the survey that they completed. Additionally, the majority of respondents from both waves of the survey indicated that they drove less than 25,000 in the past 12 months while providing ridehailing services. However, there is also a subset of respondents who indicated that their mileage corresponding to providing ridehailing services exceeded 100,000 miles in the past year.

To help contextualize these values, self-reported estimates of the annual mileage corresponding to each household vehicle were obtained from the 2022 iteration of the National Household Travel Survey (NHTS). Due to limitations in the publicly available version of the 2022 NHTS data, estimates of annual mileage were obtained for respondents from the pacific division, which consists of Alaska, California, Hawaii, Oregon, and Washington (Bricka et al., 2024). As shown in Figure 5-1, the estimated mileage of roughly 94.1% of vehicles in the pacific division that were included in the 2022 NHTS was less than 25,000 miles annually. Conversely, the estimated annual mileage of roughly 5.9% of vehicles exceeded 25,000 miles in the 2022 NHTS compared to between 15-20% of respondents in the data collected through the two waves of the survey. This underscores the benefits of encouraging the electrification of the ridehailing fleet, given the relatively high mileage corresponding to providing ridehailing services.

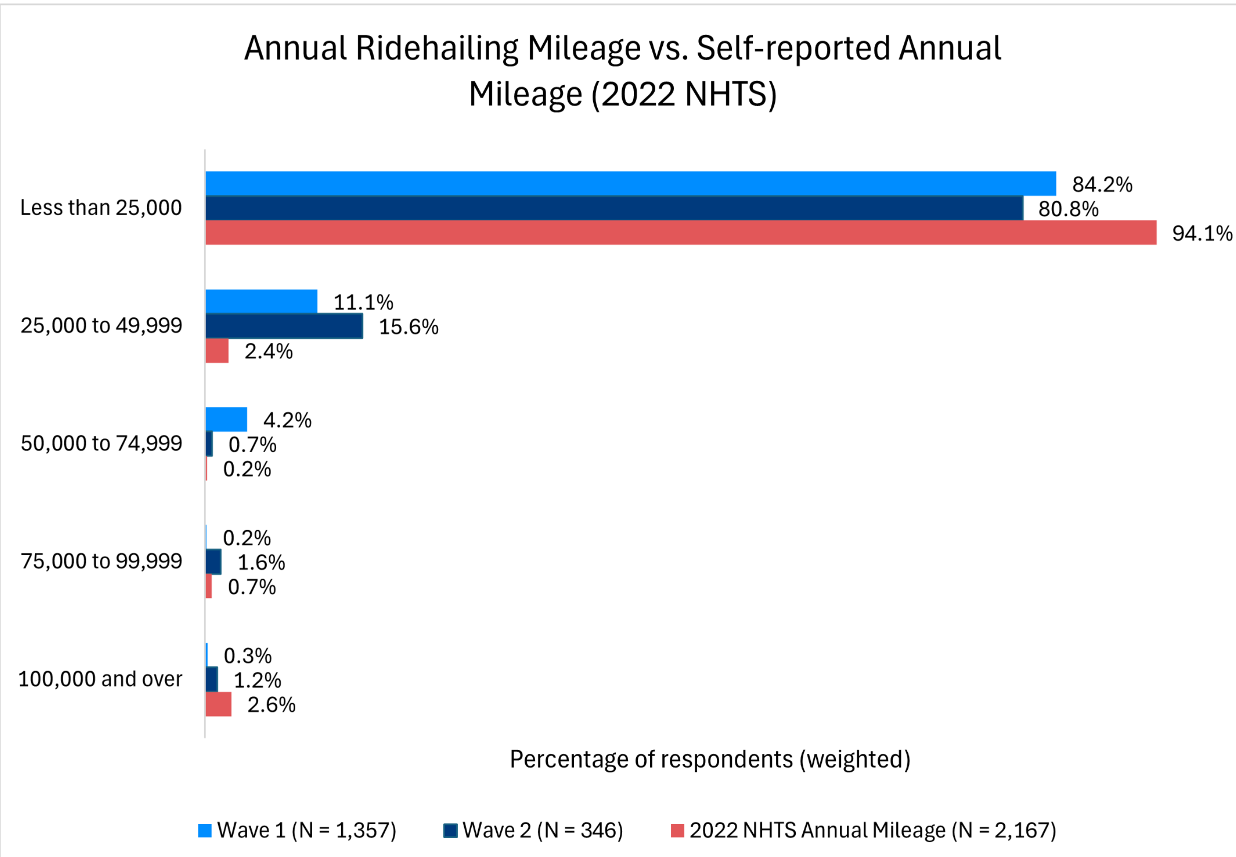

Figure 5-1 Comparison of annual ridehailing mileage and self-reported overall mileage from the 2022 NHTS

5.2 Attributes of Vehicles Registered with TNCs

This section examines responses to questions regarding the attributes of the vehicle(s) that the respondents had registered with a TNC at the time of the survey. The majority of this section will focus on each respondent's *primary vehicle*, defined as the vehicle that they used to provide the most rides. The section begins by exploring the distribution of responses among respondents from the first and second waves of the survey before exploring variations in the fuel type of the primary vehicle between different segments of drivers.

5.2.1 Sample-level Statistics

The distributions of key attributes of the primary vehicle used by respondents from the first and second wave of the survey are compared in Table 5-4. Almost two-thirds of respondents from the first and second wave of the survey indicated that their primary vehicle was powered by gasoline. In contrast, respondents from the first wave of the survey were more likely to indicate that their primary vehicle was a gasoline hybrid or plug-in hybrid, whereas respondents from the second wave of the survey were more likely to report that their primary vehicle was a battery electric vehicle. This trend is also reflected in the greater likelihood of respondents from the second wave of the survey reporting that they had at least one BEV registered with a TNC at the time of the survey.

Table 5-4 Distribution of key attributes of respondents' primary ridehailing vehicle among wave 1 and wave 2 respondents

Variable	Wave 1	Wave 2
Fuel type of primary vehicle		
Gasoline	65.9%	65.4%
Gasoline hybrid	17.4%	16.1%
Plug-in hybrid	4.8%	2.5%
Battery electric	11.4%	15.8%
Hydrogen fuel cell	0.1%	0.2%
Other	0.5%	0.0%
At least one BEV registered with a TNC		
Yes	13.8%	15.8%
No	86.2%	84.2%
Method of obtaining primary vehicle		
Owned or financing	89.7%	89.4%
Lease	7.0%	1.3%
Rent through a TNC rental partner	2.3%	4.7%
Other	1.0%	4.6%
Primary vehicle was obtained with the intention of using it to provide ridehailing services		
Yes	36.2%	59.0%
No	63.8%	41.0%
Sample size	1,357	346

With regards to the method of obtaining the primary vehicle, the majority of respondents indicated that they owned or are financing their primary vehicle. This result suggests that BEV-related incentives that help address the relatively high upfront costs of BEVs could help increase the uptake of these vehicles among ridehailing drivers. Additionally, respondents from the first wave of the survey were more likely to indicate that they were leasing their vehicle, whereas respondents from the second wave of the survey were more likely to indicate that they were renting their primary vehicle from a TNC rental partner. Finally, respondents from the second wave of the survey were more likely to report that they obtained their primary vehicle with the intention of using it to provide ridehailing services. Ensuring that those who obtain a vehicle with the intention of using it to provide ridehailing services are aware of all available BEV-related incentives can help increase the uptake of BEVs among ridehailing drivers.

To understand how the distributions of the fuel type of the primary vehicle among respondents from the first and second waves of the survey compare to that of California, information on registered vehicles was obtained from the California Open Data Portal (California Department of Motor Vehicles, 2025). This publicly available dataset contains information on the number of registered light-duty vehicles corresponding to each fuel type for each ZIP code in California as of January 1, 2025. As shown in Figure 5-2, the primary vehicle used by respondents from the first and second wave of the survey are less likely to be gasoline vehicles and more likely to be gasoline hybrid, plug-in hybrid, and battery electric vehicles. While this trend is encouraging, the uptake of BEVs among ridehailing drivers is still well below that of gasoline-powered vehicles.

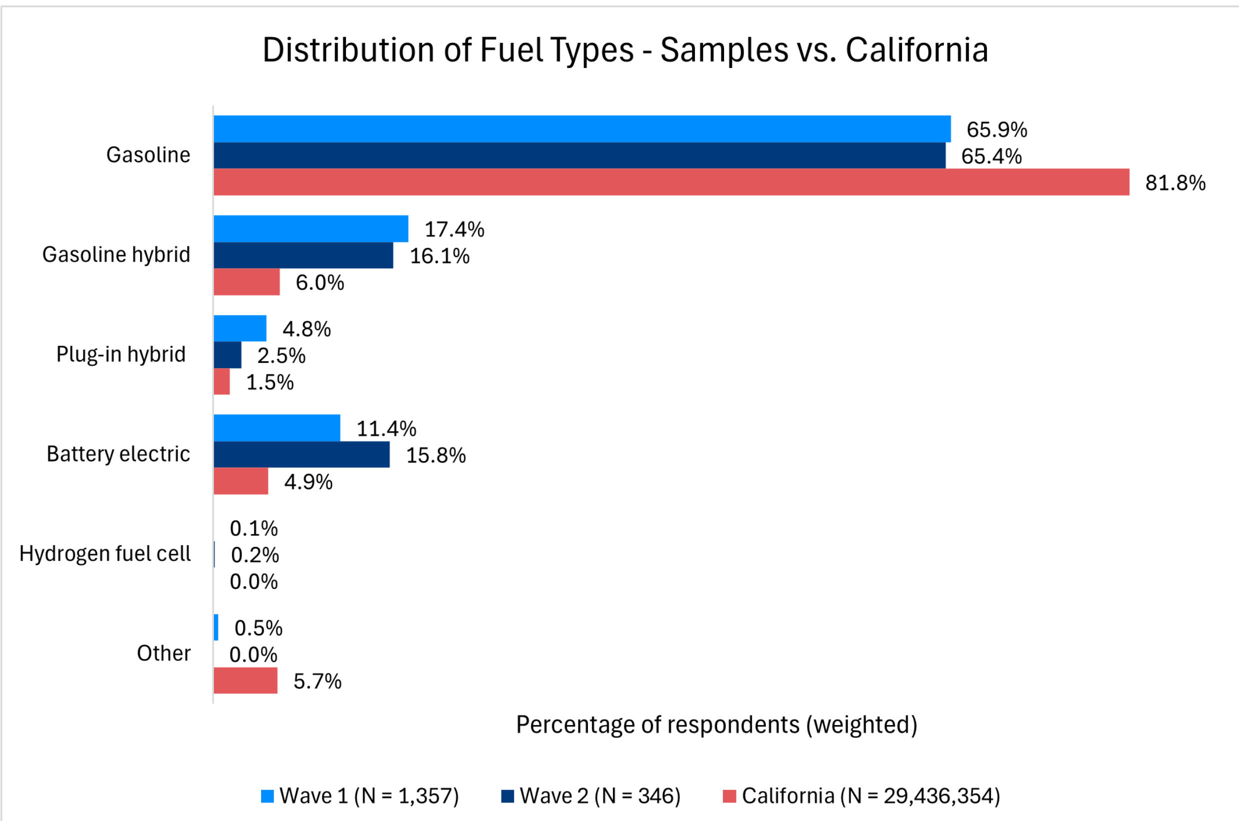

Figure 5-2 Comparison between fuel type of primary vehicle and all light-duty vehicles in California

Additionally, respondents of both waves of the survey were asked to identify up to three factors that influenced their decision to use their primary vehicle to provide ridehailing services. As shown in Table 5-5, the factors selected by the largest percentage of respondents from both waves of the survey were fuel efficiency, followed by vehicle price. This suggests that highlighting the fuel efficiency of BEVs could help influence ridehailing drivers to consider using a BEV to provide ridehailing services. However, this result also suggests that the relatively high upfront costs of BEVs could be a barrier to the uptake of these vehicles. Moreover, roughly one in seven respondents indicated that their choice of primary vehicle was influenced by the potential to become eligible to provide upgraded services for higher earnings. In light of this finding, TNCs could explore whether offering drivers greater compensation for services that utilize sustainable vehicles (such as Uber Green or Lyft Green) could persuade drivers to use BEVs to provide ridehailing services. Additionally, almost one-third of the respondents from the second wave of the survey indicated that they already had access to their primary vehicle prior to it being used to provide ridehailing services.

Table 5-5 Factors influencing the decision to use the primary vehicle to provide ridehailing services (respondents could select up to 3 options)

Factor	Wave 1	Wave 2
Fuel efficiency	48.3%	49.7%
Vehicle price	34.7%	32.5%
Size	31.1%	26.9%
Mileage on the vehicle [a]	29.6%	19.0%
Vehicle age	20.7%	13.1%
Fuel type	18.0%	19.0%
Safety rating	16.9%	9.5%
Eligibility to provide upgraded services (and receive higher earnings)	15.3%	14.7%
Desirability of the vehicle for riders	10.3%	14.4%
Interior design	8.8%	10.8%
Communication technologies	8.3%	8.2%
Driver assistance features	7.8%	7.0%
Other vehicle(s) did not meet TNC requirements [b]	NA	19.7%
Already had access to the vehicle	NA	31.8%
Other	10.5%	3.4%
Sample size	1,357	346

Notes:

[a] This response option was only displayed to respondents who indicated that they obtained their primary vehicle used (and not new); N(wave 1) = 654 and N(wave 2) = 160

[b] This response option was only displayed to respondents who indicated that they and other members of their household had access to more than one vehicle at the time of the survey; N(wave 2) = 201

NA: denotes response options that were not available to respondents of the first wave of the survey

Finally, the distribution of the ages of the primary vehicle used by respondents from the first and second waves of the survey were compared to that of light-duty vehicles registered in California using the same dataset from the California Open Data Portal (California Department of Motor Vehicles, 2025). As shown in Table 5-5, almost two-thirds of the primary vehicles used by respondents to provide ridehailing services are less than seven years old, while light-duty vehicles registered in California are much more likely to be over 10 years old. This trend is likely the result of the vehicle age restrictions that are imposed by TNCs and the relatively high mileage associated with providing ridehailing services resulting in a need to change vehicles relatively quickly compared to privately owned vehicles.

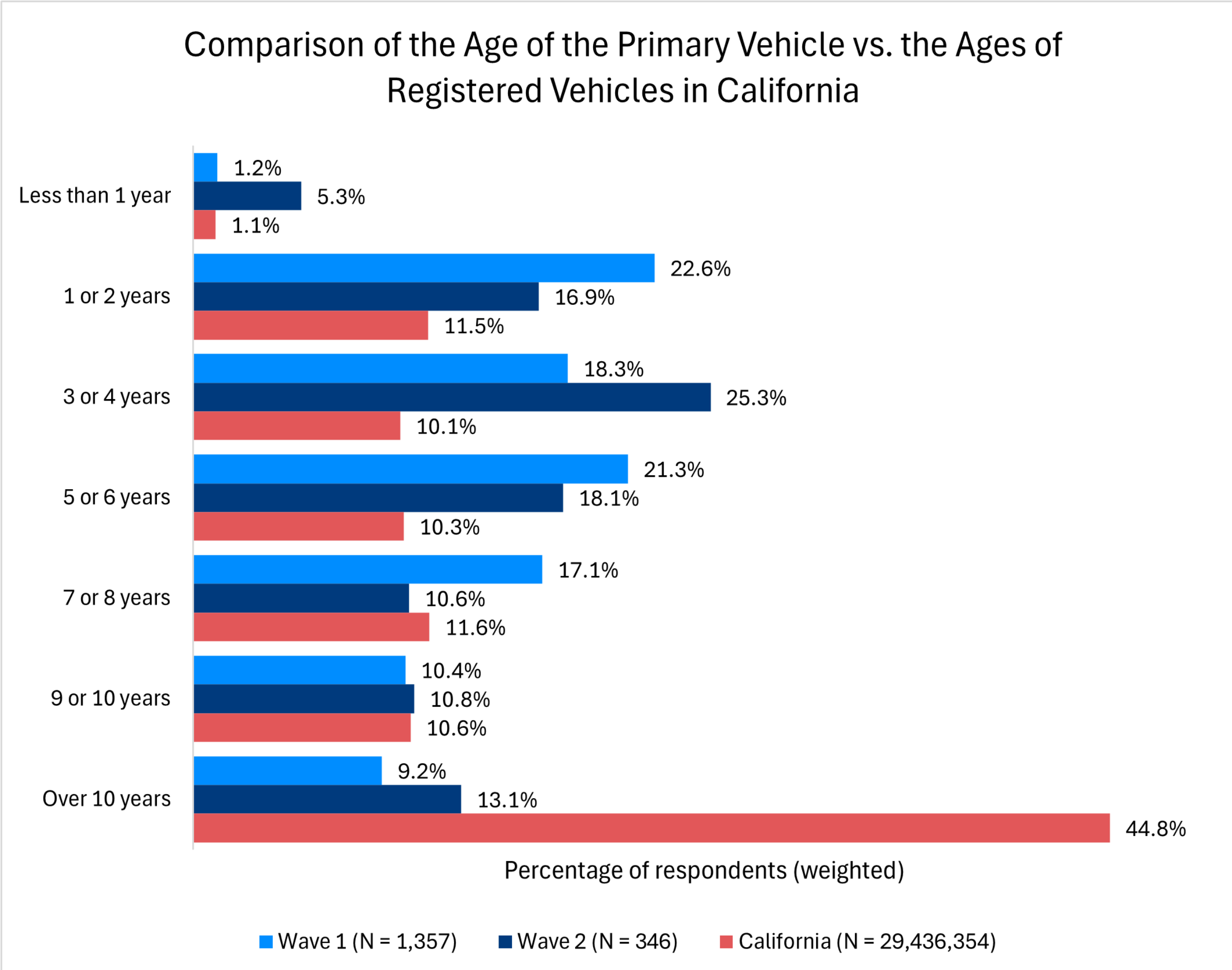

Figure 5-3 Age distribution of primary vehicles and registered light-duty vehicles in California

5.2.2 Comparison of Fuel Types Across Different Segments of Drivers

To explore variations in the fuel type of the primary vehicle, the distribution of fuel types was compared across different segments of drivers. While both waves of the survey considered six fuel types (as shown in Figure 5-2), the FCEV and “other” options were omitted from this analysis due to the small number of vehicles corresponding to these fuel types. As shown in Figure 5-4, the likelihood of a driver indicating that their primary vehicle corresponds to a given fuel type varies across income categories. For example, the likelihood of one’s primary vehicle being an ICEV decreases as household income increases. Additionally, respondents from households earning between $50,000 and $99,999 annually were most likely to indicate that their primary vehicle was a gasoline hybrid. Moreover, respondents from households earning over $100,000 annually were the most likely to indicate that they used a BEV to provide most of their rides. Interestingly, respondents from households earning less than $50,000 annually were more likely to indicate that their primary vehicle was a BEV compared to respondents from households earning between $50,000 and $99,999 annually. These trends are likely due to a confluence of factors, including differences in the upfront cost of vehicles across fuel types, access to chargers, eligibility for incentives, mileage, and the availability of ZEVs in the used vehicle market.

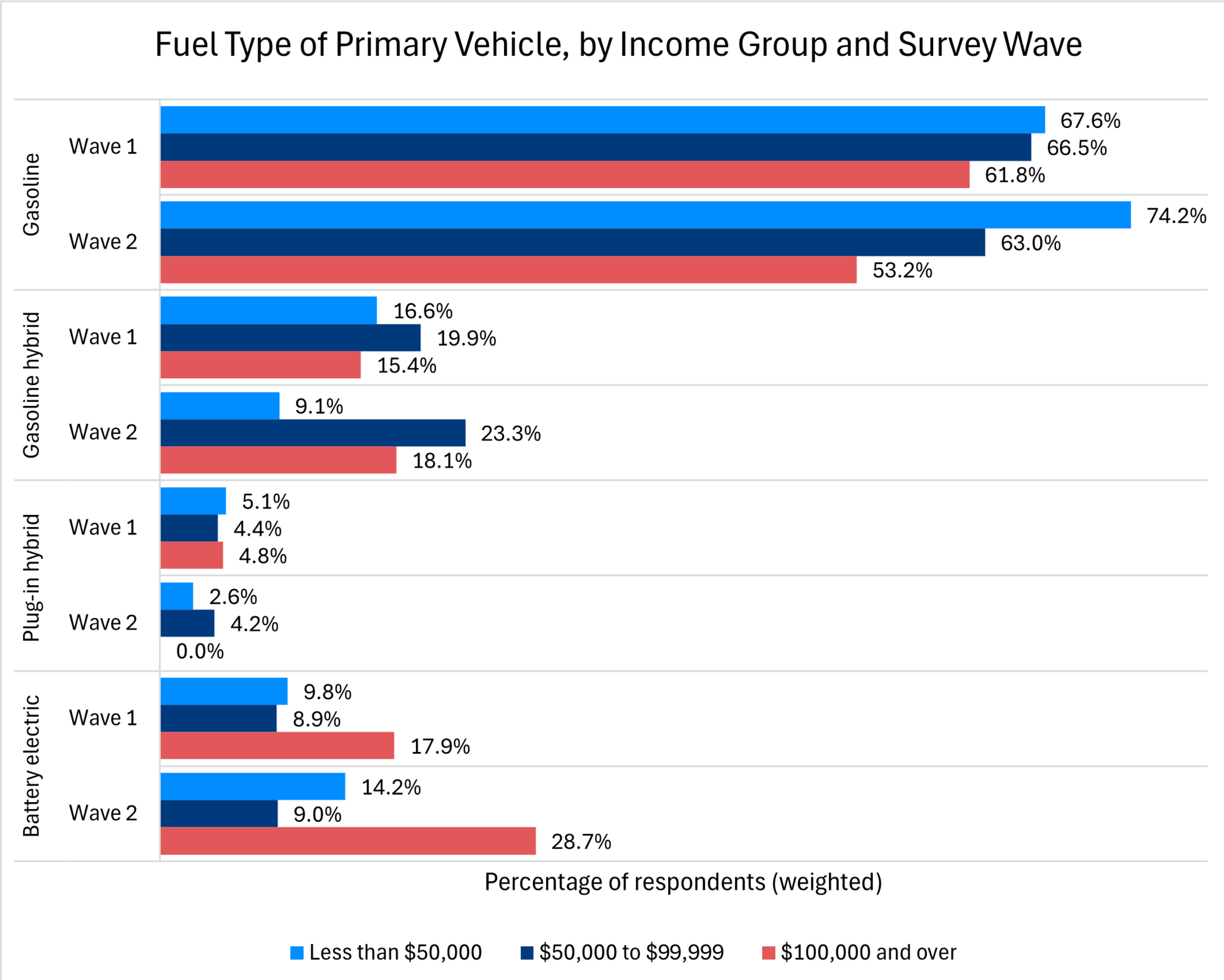

Figure 5-4 Comaprison of fuel type, by household income

A similar trend is also observed with regard to differences in the likelihood of one's primary vehicle being an ICEV based on driver status. As shown in Figure 5-5, the likelihood of a respondent indicating that their primary vehicle was an ICEV decreased as their average weekly working hours increased. Additionally, full-time drivers (i.e., those who spent more than 25 hours providing ridehailing services during the average week) were more likely to indicate that their primary vehicle was a gasoline hybrid compared to occasional drivers. Differences in the uptake of battery electric vehicles were also observed between respondents of the first and second waves of the survey. In particular, among respondents of the first wave of the survey, the likelihood of indicating that one's primary vehicle was a BEV increased as average weekly working hours increased. However, among respondents from the second wave of the survey, full-time drivers had the lowest likelihood of indicating that their primary vehicle was a BEV. Nevertheless, these trends suggest that full- and part-time drivers are more likely to be using a hybrid or battery electric vehicle as their primary vehicle. Understanding the reasons for favoring a hybrid over a battery electric vehicle can help identify barriers to the uptake of BEVs among these segments of drivers.

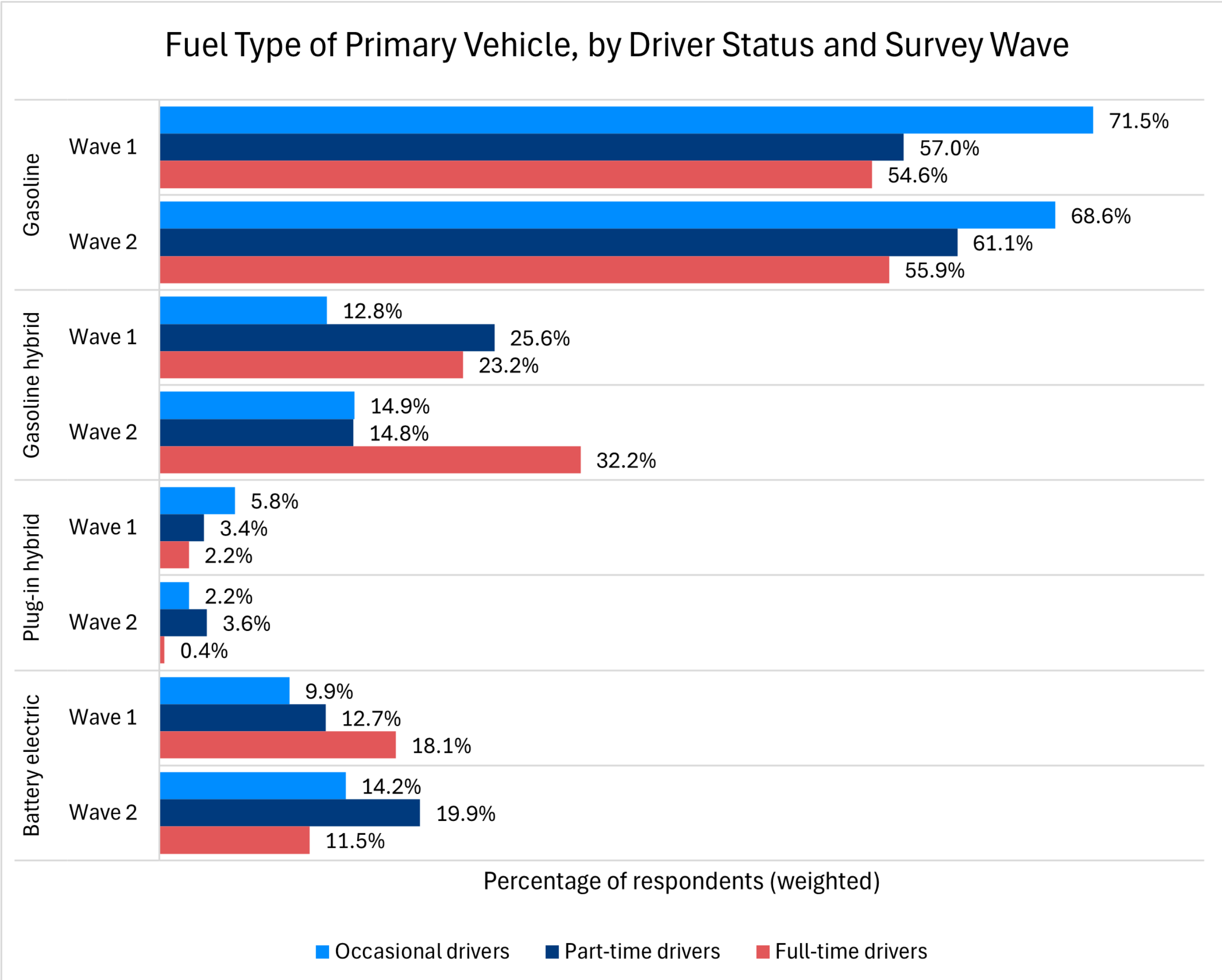

Figure 5-5 Comparison of fuel type, by driver status

Differences in the fuel type of the primary vehicle were also compared based on the annual mileage corresponding to providing ridehailing services. In contrast to the previous comparisons, the clear trend does not emerge from the information summarized in Figure 5-6. In both waves of the survey, gasoline hybrids were the second most common fuel type among higher-mileage drivers (i.e., those whose annual mileage was 50,000 miles or longer), while BEVs were the third most common fuel type. Moreover, higher-mileage drivers in the second wave of the survey were more likely to indicate that their primary vehicle was a gasoline hybrid or battery electric vehicle compared to higher-mileage drivers in the first wave of the survey. A similar discrepancy was also observed for drivers whose annual mileage was below 25,000 miles. Conversely, drivers whose annual mileage was between 25,000 and 49,999 miles were more likely to indicate that their primary vehicle was an ICEV in the second wave of the survey compared to the first wave. Understanding the factors influencing the fuel type choices could offer valuable insights into barriers to the greater uptake of BEVs among this segment of drivers.

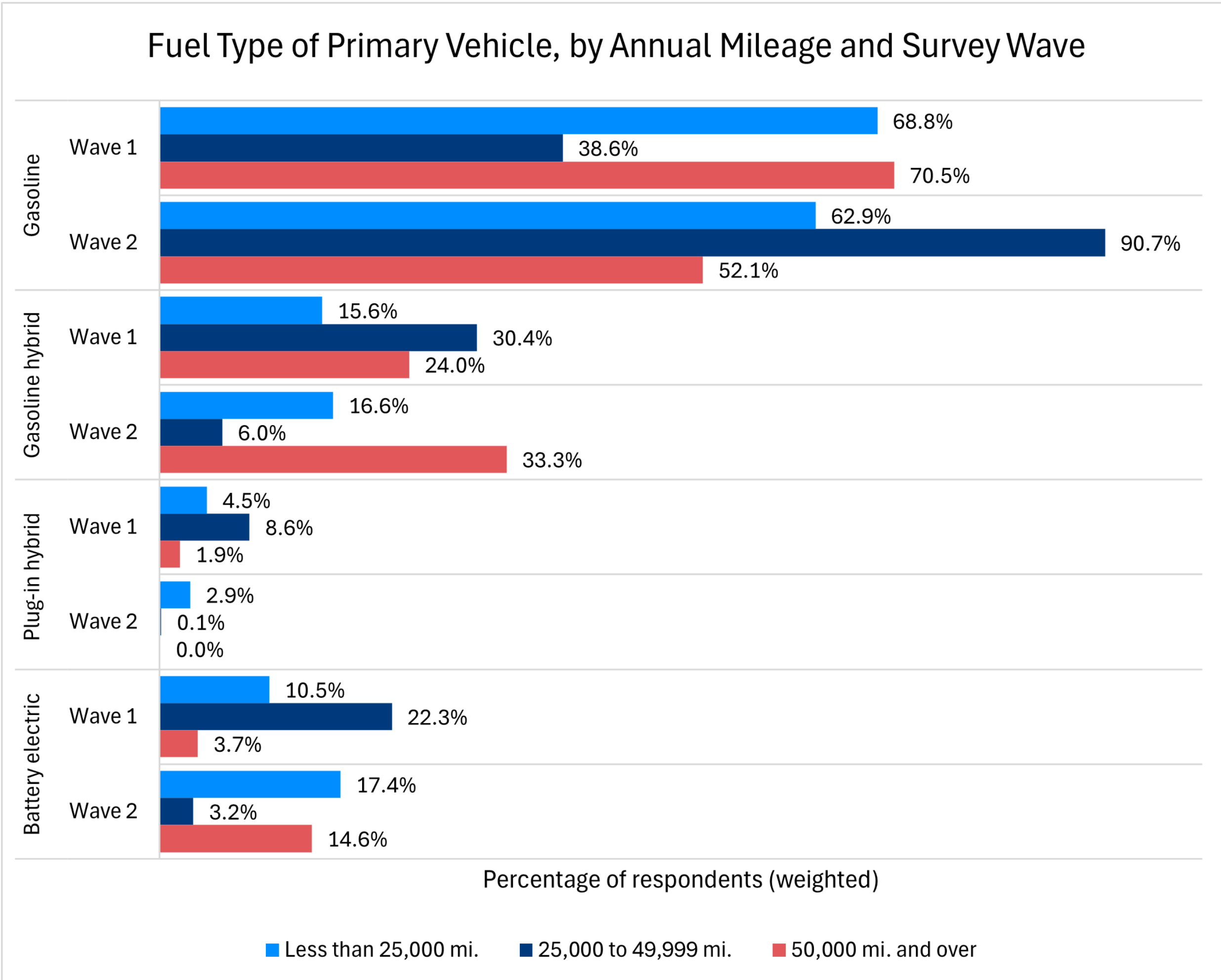

Figure 5-6 Comparison of fuel type, by annual ridehailing mileage

Finally, differences in the fuel type of the primary vehicle were examined based on whether it was obtained with or without the intention of using it to provide ridehailing services. As shown in Figure 5-7, vehicles that were obtained with the intention of being used to provide ridehailing services were less likely to be ICEVs and more likely to be gasoline hybrids. Among respondents from the first wave of the survey, vehicles obtained with the intention of using them to provide ridehailing services were less likely to be BEVs, while the opposite was observed for respondents from the second wave of the survey. Additionally, BEVs were the second most common fuel type of vehicles that were obtained with the intention of using them to provide ridehailing services among respondents from the second wave of the survey.

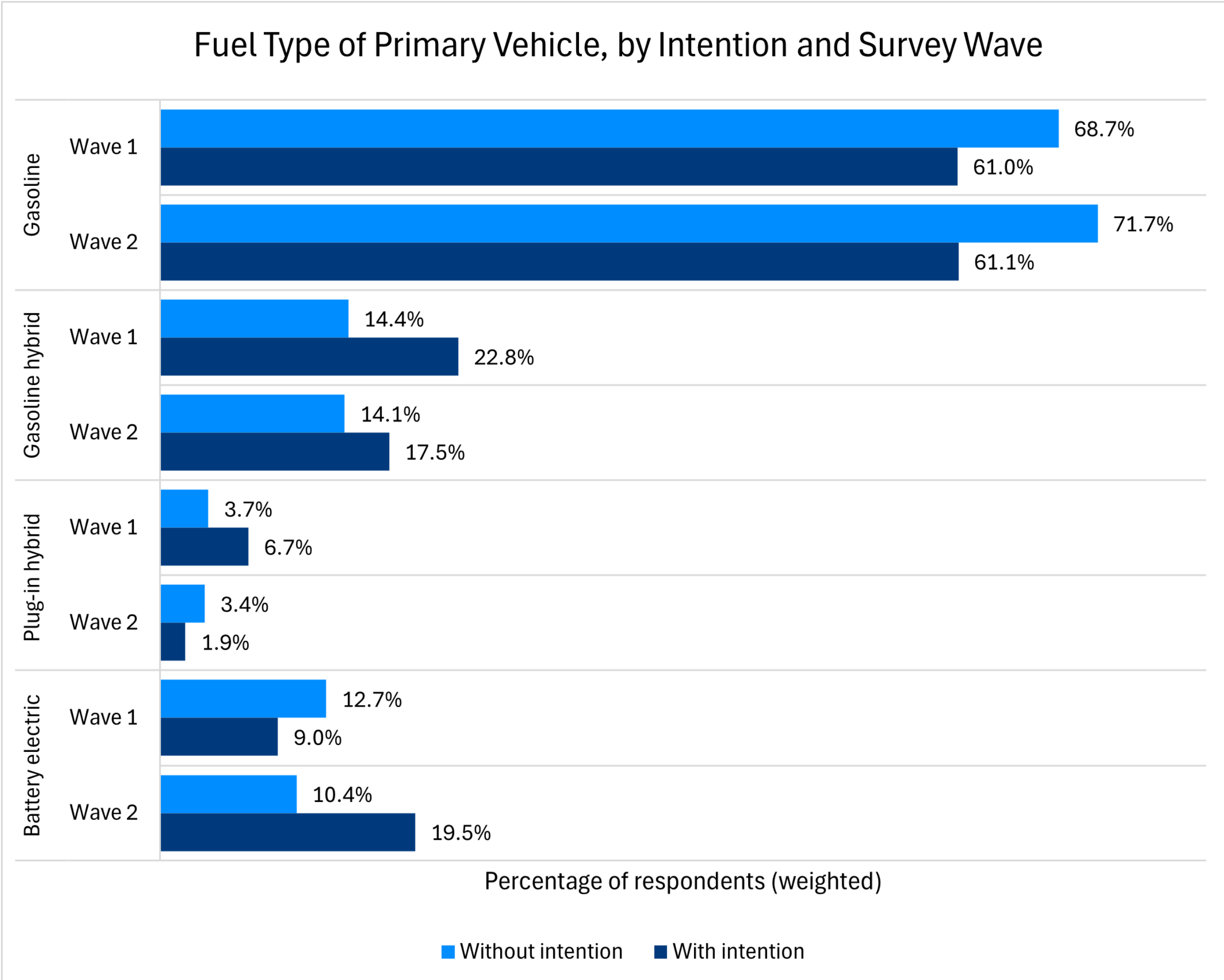

Figure 5-7 Comparison of fuel type, by whether the vehicle was obtained with the intention of using it to provide ridehailing services

5.3 Familiarity with Incentives and Perceived Availability of Chargers

5.3.1 Familiarity with Federal, State, and Local Incentive Programs

In both waves of the surveys, respondents were asked to indicate their level of familiarity with a variety of federal, state, and local incentives related to the purchase, leasing, or rental of ZEVs and the installation of EV chargers. Familiarity was measured using a four-point scale, with response options ranging from *not at all familiar* to *I have used this incentive*. As shown in Figure 5-8, most respondents were not at all familiar with federal incentives and very few have used these incentives themselves. The only exception was the new electric vehicle tax credit, as over 50% of respondents indicated that they were at least somewhat familiar with this incentive. Additionally, this incentive was used by the largest percentage of respondents (4.4% of wave 1 respondents and 5.5% of wave 2 respondents). As outlined in Figure 5-9, the level of familiarity with state and local incentives was also fairly low. Moreover, the level of familiarity with state and local incentives was generally lower than the level of familiarity with federal incentives. Given their potential to help address the financial barriers associated with obtaining a BEV and the installation of charging infrastructure, improving familiarity with federal, state, and local incentives will be crucial to help ensure that the goals of the CMS regulations are achieved.

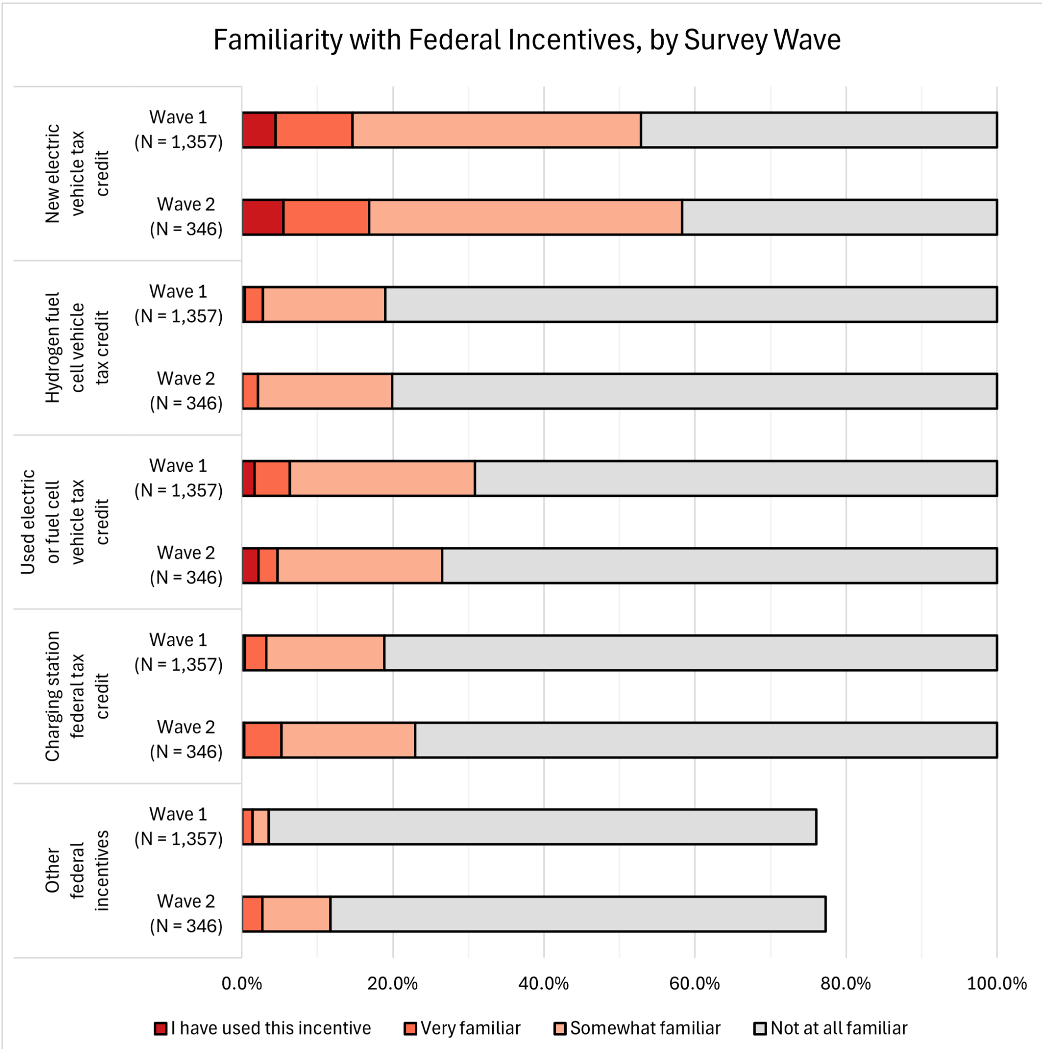

Figure 5-8 Level of familiarity with federal incentives, by survey wave
(Note: missing responses were omitted from the figure)

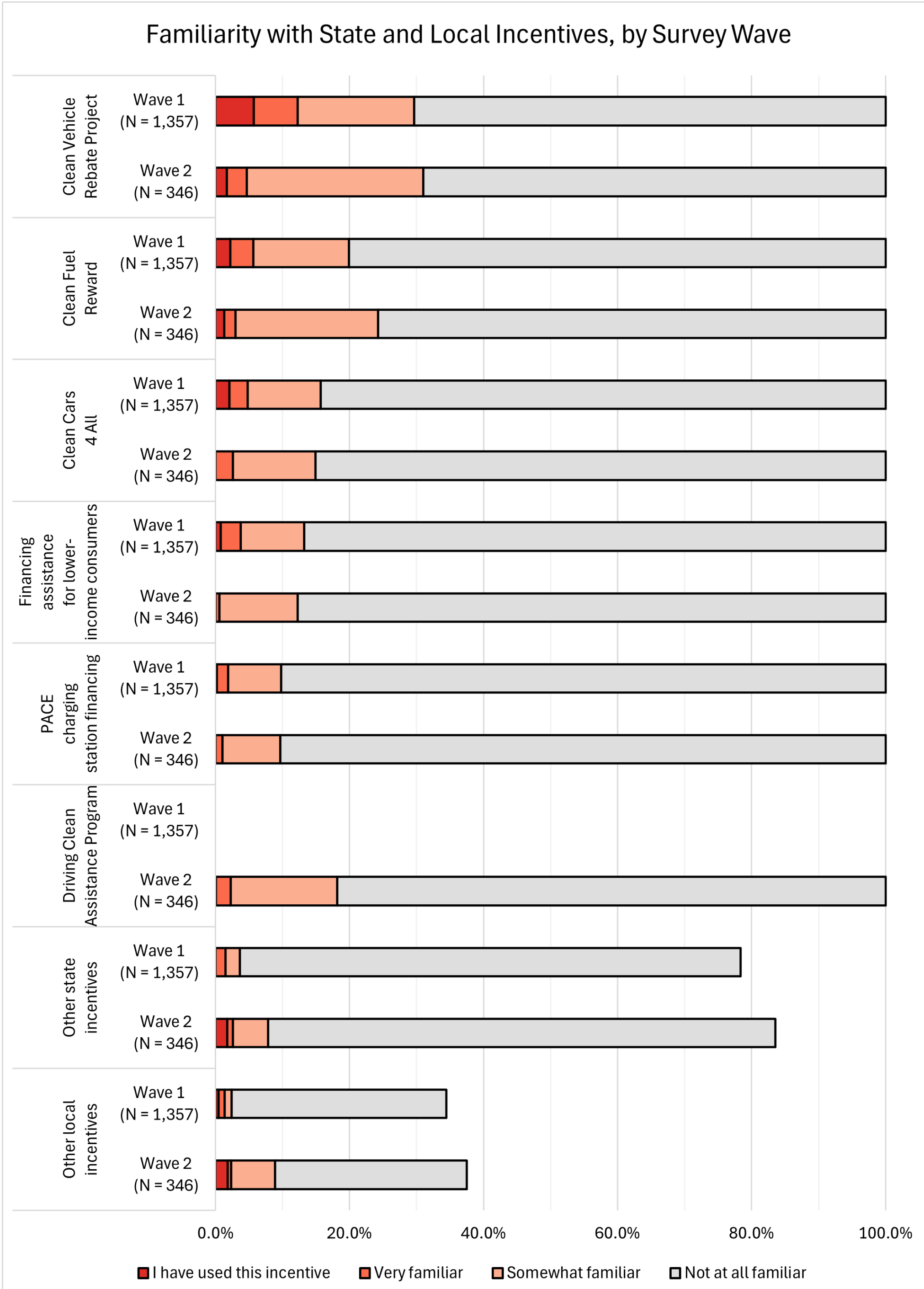

Figure 5-9 Level of familiarity with state and local incentives, by survey wave
(Note: missing responses were omitted from the figure, and the *driving clean assistance program* response option was not included in the first wave of the survey)

As part of the second wave of the survey, respondents who reported being at least somewhat familiar with an incentive were asked to indicate the method(s) through which they learned about the incentive. As outlined in Table 5-6, the most common method of learning about incentives was through social media or newsletters, followed by information provided by TNCs. Consequently, efforts to improve ridehailing drivers' familiarity with federal and state incentives could include identifying the social media pages or newsletters that are popular among drivers. Additionally, approximately one-fifth of respondents who were familiar with a federal incentive indicated that they learned about the incentive from a car dealership or retailer, while only one-tenth of those who were familiar with state incentives indicated the same. This discrepancy could be due to differences in the nature of federal and state incentives. However, it also highlights the potential role of car dealerships and vehicle retailers in improving familiarity with state incentives. More broadly, the results also suggest that efforts to increase familiarity with federal and state incentives will require a multi-faceted approach, given the absence of a single method through which the majority of respondents learned about these incentives.

Table 5-6 Method(s) through which drivers learned about incentives

Method	Federal Incentives	State Incentives
Social media or newsletters	43.1%	39.1%
TNCs	31.1%	26.2%
Car dealership or vehicle retailer	21.5%	9.8%
Government agencies	19.2%	14.6%
Other drivers (e.g., word of mouth, driver groups)	10.2%	13.9%
Driver information programs	9.3%	6.4%
Accountants, tax software, or finance companies	2.2%	1.6%
Other	11.8%	12.9%
Sample size	244	156

Note:

Respondents were allowed to select multiple response options

5.3.2 Perceived Availability of Electric Vehicle Chargers, by Location

To explore the potential for perceived access to chargers to influence BEV uptake, respondents in both waves of the survey were asked to indicate the types of chargers that they perceived were available to them in several locations. Respondents were provided with five response options per location (none, unknown type, level 1, level 2, and DC fast charger) and asked to provide information regarding four locations – at their home (garage/ driveway), at the home (residential parking lot), in their neighborhood, and in public areas. Two key changes were made to this question between the first and second waves of the survey. First, visual examples of a level 1, level 2, and DC fast charger were provided to respondents of the second wave of the survey. Second, *unknown type* was not treated as an exclusive response option in the second wave of the survey.

As shown in Figure 5-10, respondents from both waves of the survey were more likely to indicate that chargers were not available at their home than they were to indicate that chargers were not available in their neighborhood or in public areas. Compared to wave 1 respondents, wave 2 respondents were more likely to indicate that level 1 and 2 chargers were available at their homes and where they live, and less likely to indicate that they had access to a DC fast charger or a charger of an unknown type. This difference could be the result of respondents more accurately identifying the type of charger that they perceived as available. Similarly, wave 2 respondents were less likely to indicate that BEV chargers were not available in their neighborhood and public areas compared to wave 1 respondents, and more likely to indicate that level 1, level 2, and DC fast chargers were available.

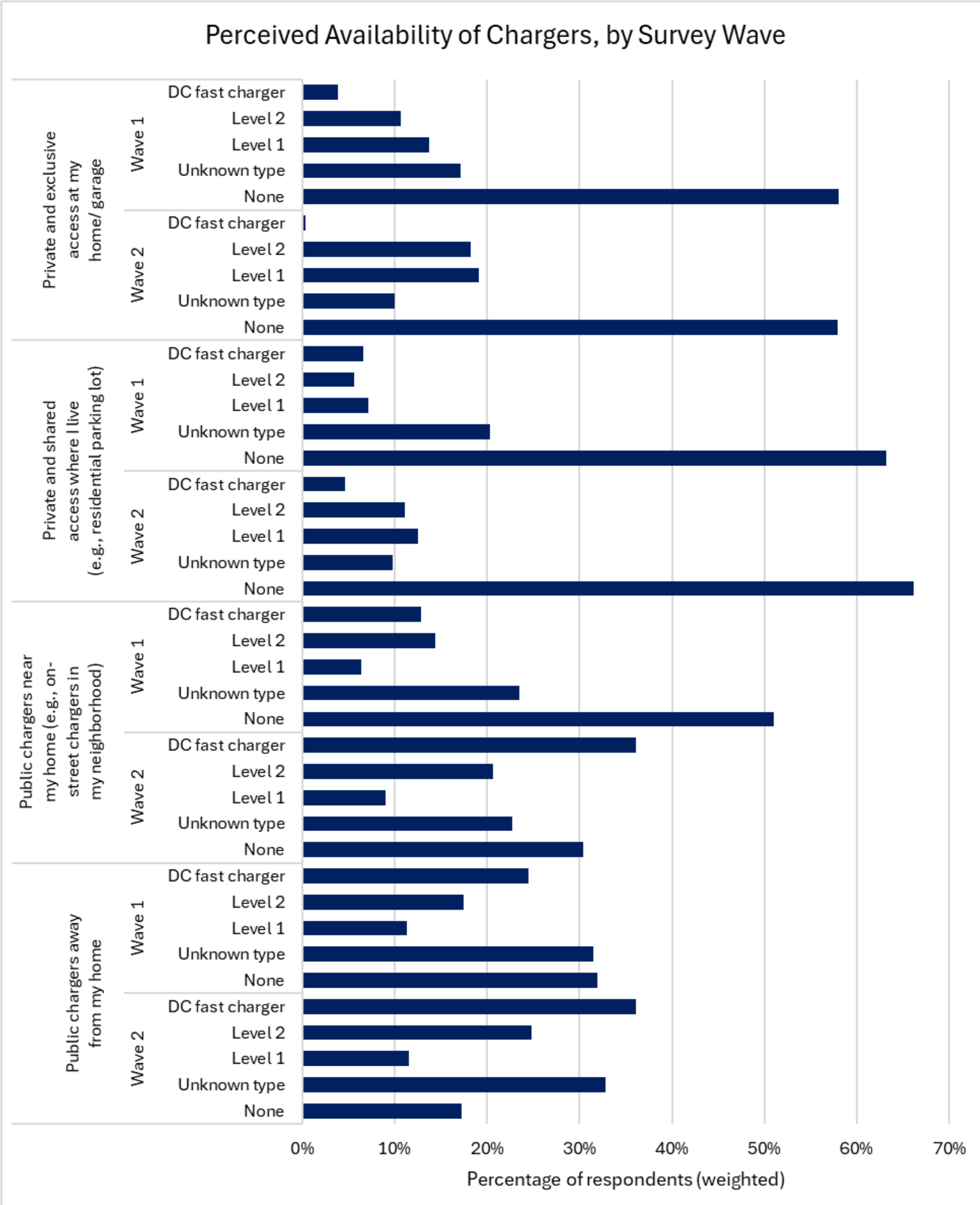

Figure 5-10 Perceived access to chargers, by charger level and survey wave
(Note: respondents were allowed to select multiple response options)

5.4 Attitudes Towards the Use of Battery Electric Vehicles to Provide Ridehailing Services

In both waves of the survey, respondents were asked to complete a series of attitudinal questions to gain insights into their perceptions towards the use of BEVs to provide ridehailing services. As part of these questions, respondents were asked to indicate their level of agreement with a series of statements using a five-point ordinal scale, with the response options ranging from *strongly disagree* to *strongly agree*. These statements fell into one of four broad categories – barriers to BEV uptake, ease of using a BEV, perceived benefits of BEV use, and perceived social norms regarding BEVs. The responses to these statements offer insights into the perceptions of BEVs among California ridehailing drivers and can be used to examine how latent attitudinal factors can affect the uptake of BEVs and the vehicle fuel type choices of ridehailing drivers. Overall, the weighted distributions of responses to the attitudinal questions are relatively consistent between the first and second waves of the survey.

The distribution of responses to statements regarding perceived barriers to BEV uptake are summarized in Table 5-7. Notably, over 50% of respondents from both waves of the survey agreed that the cost of a BEV to provide ridehailing services was too high. Additionally, almost 40% of respondents expressed the belief that the driving range of BEVs was insufficient for their needs as a ridehailing driver. However, 31.7% of respondents from the second wave of the survey indicated their disagreement with this statement, up from 23.4% of respondents from the first wave. Similarly, wave 2 respondents were less likely to agree and more likely to disagree that the need for charging makes BEVs impractical for ridehailing drivers compared to respondents from wave 1. However, over 60% of respondents from both waves of the survey agreed that using a BEV to provide ridehailing services would require them to carefully plan their driving activities.

The responses to statements regarding the perceived ease of using a BEV to provide ridehailing services are presented in Table 5-8. Overall, the responses to these statements suggest that drivers tend to believe that it would be easy for them to learn how to drive a BEV and to become skillful at driving a BEV to provide ridehailing services. Conversely, approximately 40% of respondents from both waves of the survey disagreed that charging facilities for ridehailing drivers who use BEVs were sufficient. Somewhat promisingly, respondents from the second wave of the survey were more likely to agree that charging facilities were sufficient, that it was easy to charge a BEV, and that maintenance facilities for BEVs were sufficient.

As shown in Table 5-9, respondents from both waves of the survey tended to agree that using a BEV to provide ridehailing services offered potential benefits. For example, 54.3% of respondents from the first wave of the survey and 60.9% of respondents from the second wave agreed that using a BEV to provide ridehailing services would be beneficial to the environment. Additionally, roughly 50% of respondents agreed that driving a BEV would eventually result in cost savings. Besides, respondents from the second wave of the survey were more likely to agree that driving a BEV could produce greater profits and lower energy costs. Conversely, respondents from the second wave of the survey were less likely to agree that they would be able to drive for any TNC that they want using a BEV. Finally, respondents from the second wave of the survey were more likely to both agree and disagree with each statement compared to respondents from the first wave of the survey. However, less than or about a quarter of the respondents indicated their disagreement with the statements pertaining to the perceived benefits of using BEVs to provide ridehailing services.

Finally, the responses to statements regarding the respondents' perceptions of social norms regarding BEVs are summarized in Table 5-10. Among the four categories of statements that were presented to the respondents, this set of statements had the largest percentage of respondents who indicated that they neither agreed nor disagreed. Interestingly, over one-third of respondents disagreed that people who are important to them think that they should use a BEV to provide ridehailing services, while less than 20% expressed their agreement with this statement. Additionally, roughly one quarter of respondents expressed their belief that riders tend to favor BEVs and that they are more satisfied with BEVs. Besides, respondents from the second wave of the survey were less likely to express their agreement that they know ridehailing drivers who are considering BEVs and that BEVs are viewed favorably within the ridehailing industry. Although these trends are somewhat discouraging, they could be due to changes in the perception of certain BEV manufacturers or differences in the respondents that were included in the respective samples.

Table 5-7 Comparison of responses to statements regarding perceived barriers to BEV uptake

Statement	Survey Wave	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
The price of an electric vehicle for rideshare work is too high.	Wave 1	4.6%	5.9%	34.8%	28.8%	25.9%
	Wave 2	3.4%	8.5%	31.3%	33.6%	23.2%
The driving range of electric vehicles is too short for my rideshare work.	Wave 1	12.1%	11.3%	38.6%	23.8%	14.2%
	Wave 2	6.7%	25.0%	27.8%	13.5%	27.0%
The need for charging makes electric vehicles very unpractical for rideshare work.	Wave 1	6.5%	13.8%	32.8%	31.9%	15.0%
	Wave 2	9.7%	18.8%	31.5%	21.0%	18.9%
Using an electric vehicle would require careful planning of my activities as a rideshare driver.	Wave 1	5.7%	4.8%	26.9%	34.2%	28.4%
	Wave 2	1.3%	6.0%	27.6%	34.0%	31.1%

Table 5-8 Comparison of responses to statements regarding the perceived ease of using a BEV

Statement	Survey Wave	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
The charging facilities for electric rideshare vehicles are sufficient.	Wave 1	17.6%	24.4%	37.6%	17.4%	2.9%
	Wave 2	19.6%	19.7%	34.5%	23.8%	2.4%
It is easy to charge an electric rideshare vehicle.	Wave 1	10.5%	16.9%	40.7%	24.6%	7.3%
	Wave 2	11.4%	17.6%	32.8%	30.0%	8.2%
Learning how to drive an electric vehicle for my rideshare work would be easy for me.	Wave 1	8.0%	3.8%	26.0%	32.0%	30.3%
	Wave 2	0.9%	8.1%	26.4%	33.4%	31.2%
Maintenance facilities for electric rideshare vehicles are sufficient.	Wave 1	10.5%	15.3%	50.4%	18.8%	5.0%
	Wave 2	15.9%	14.8%	41.6%	18.9%	8.7%
It would be easy for me to become skillful at driving an electric vehicle for my rideshare work.	Wave 1	6.1%	3.5%	28.5%	35.3%	26.6%
	Wave 2	4.9%	6.7%	27.3%	35.7%	25.3%

Table 5-9 Comparison of responses to statements regarding the perceived benefits of BEVs

Statement	Survey Wave	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
Driving an electric vehicle for rideshare work would be beneficial to the environment in the long term.	Wave 1	8.9%	6.2%	30.6%	30.8%	23.4%
	Wave 2	10.8%	5.7%	22.6%	36.3%	24.6%
I would increase my profits by driving an electric vehicle for my rideshare work.	Wave 1	9.9%	8.8%	41.1%	22.6%	17.6%
	Wave 2	13.0%	13.3%	26.2%	33.4%	14.0%
I could drive for any rideshare service that I want with an electric vehicle.	Wave 1	3.8%	4.6%	35.4%	35.8%	20.5%
	Wave 2	4.5%	9.4%	33.5%	38.6%	14.0%
It is advantageous to drive an electric vehicle for rideshare work because of the low energy cost.	Wave 1	9.9%	7.7%	36.9%	30.7%	14.9%
	Wave 2	12.5%	9.4%	32.0%	33.5%	12.6%
Driving an electric vehicle for rideshare work would eventually result in cost savings.	Wave 1	7.9%	6.2%	36.0%	32.0%	18.0%
	Wave 2	10.6%	7.0%	29.7%	33.9%	18.8%

Table 5-10 Comparison of responses to statements regarding perceived social norms regarding BEVs

Statement	Survey Wave	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
Some people who are important to me think I should have an electric vehicle for my rideshare work.	Wave 1	16.4%	18.8%	46.8%	13.7%	4.3%
	Wave 2	18.6%	17.1%	50.7%	8.8%	4.7%
More riders favor electric rideshare vehicles.	Wave 1	10.0%	7.2%	53.9%	20.1%	8.9%
	Wave 2	11.8%	12.3%	47.3%	22.7%	5.8%
I know rideshare drivers who are considering electric vehicles.	Wave 1	11.2%	14.0%	41.7%	26.7%	6.4%
	Wave 2	20.1%	13.9%	39.5%	22.2%	4.4%
Electric vehicles are viewed favorably in the rideshare industry.	Wave 1	8.3%	5.3%	40.6%	28.5%	17.4%
	Wave 2	11.5%	7.7%	39.2%	31.6%	10.0%
Riders are more satisfied with electric rideshare vehicles.	Wave 1	7.6%	7.3%	56.1%	17.6%	11.4%
	Wave 2	7.4%	9.2%	59.5%	16.5%	7.3%

6 Evolution of Barriers to Greater Uptake of Battery Electric Vehicles

6.1 Introduction

Previous studies have identified several concerns that ridehailing drivers have about using BEVs and potential barriers to the greater uptake of BEVs among ridehailing drivers. These include insufficient charging facilities and electric driving range (Du, Cheng, Li, & Xiong, 2020; Rajagopal & Yang, 2020; Sanguinetti & Kurani, 2021), drivers perceiving a lack of subsidies (Du, Cheng, Li, & Yang, 2020), and drivers lacking information about EVs and awareness of financial incentives (Rajagopal & Yang, 2020). For some drivers, the barriers to obtaining a BEV are great enough that they may choose to leave the ridehailing industry if regulation requires the electrification of TNC fleets. A study of ridehailing drivers in Shenzhen, China—where the city government implemented a policy to achieve a complete transition of ridehailing to EVs by 2020— found that drivers with lesser acceptance of EVs for ridehailing were more willing to leave the industry, whereas those with greater acceptance of EVs were less likely to leave the industry (Du, Cheng, Li, & Yang, 2020). The study also found that the use of a personal vehicle for ridehailing work (relative to renting a vehicle from a TNC or rental company), a lack of subsidies, insufficient electric driving range, and a long charging duration were associated with a greater willingness to leave the industry.

Barriers to obtaining a BEV for ridehailing work can be experienced differently by drivers based on their personal characteristics and circumstances. It has been suggested that drivers with a lower level of formal education and lesser acceptance of EVs may be forced to continue working in the ridehailing industry due to difficulties in finding another job (Du, Cheng, Li, & Yang, 2020). Drivers with relatively low daily mileage and access to a home charger may not perceive a shortage of public chargers as a barrier to using a BEV for their ridehailing work, whereas insufficient public charging infrastructure could make it difficult for high-mileage drivers and those without a home charger to charge in the middle of their shift. High-mileage drivers who rely on public fast chargers may also incur higher charging costs than those who can charge at home. While Taiebat et al. (2022) found BEVs to be competitive with ICEVs in terms of total cost, they suggest that the high upfront cost of BEVs may be a barrier to drivers with low incomes or other financial difficulties. There may also be differences in the barriers faced by drivers in obtaining a BEV that are associated with their age, gender, ethnicity, or racial identity due to systematic inequities.

This chapter investigates the potential barriers to the greater uptake of BEVs among ridehailing drivers and compares the experiences of these barriers between the two survey waves and different segments of ridehailing drivers. The barriers include a lack of familiarity with incentives, lack of access to public and home chargers, and adverse opinions toward EVs. Because full-time and low-income drivers are of primary concern in the electrification of TNC fleets as the drivers who generate the most miles and face the highest financial burdens, drivers are segmented by their weekly working hours and household income.

6.2 Data and Methods

Variables were created to represent drivers' highest level of familiarity with federal and state incentives. For each driver, their self-reported highest level of familiarity (not at all, somewhat, or very familiar) and whether they have used any of the pre-defined incentives in each group was evaluated. Additional variables were created to represent drivers' perceptions of the highest level of both public and private home chargers available to them. Public chargers included those on-street close to the driver's home and in other public areas with the following four levels: no public chargers; charger(s) of unknown type; L1 or L2 charger(s); and DC fast charger(s). Because DC fast chargers are not generally suitable for home installation, the private home charger variable had the following four levels: no home charger(s); charger(s) of unknown type; L1 charger(s); and L2 or DC fast charger(s). The following subset of the attitudinal statements listed in Section 5.4 were also selected for analysis as they reflect drivers' opinions about several potential barriers to obtaining an EV for ridehailing work. The first four statements reflect drivers' opinions about the costs associated with driving an EV for ridehailing work, while statements 5 – 8 reflect their opinions about vehicles' electric driving range and the practicalities of charging. The last statement reflects drivers' opinions about the variety of EVs available to suit the requirements for different ridehailing services, e.g., extra-large or luxury vehicles, etc.

1. The price of an electric vehicle for rideshare work is too high
2. It is advantageous to drive an electric vehicle for rideshare work because of the low energy cost
3. Driving an electric vehicle for rideshare work would eventually result in cost savings
4. I would increase my profits by driving an electric vehicle for my rideshare work
5. The driving range of electric vehicles is too short for my rideshare work
6. The charging facilities for electric rideshare vehicles are sufficient
7. The need for charging makes electric vehicles very unpractical for rideshare work
8. Using an electric vehicle would require careful planning of my activities as a rideshare driver
9. Maintenance facilities for electric rideshare vehicles are sufficient
10. I could drive for any rideshare service that I want with an electric vehicle.

The variables described above were cross tabulated with variables measuring drivers' annual household income levels (less than \$50,000, \$50,000 – \$99,999, and \$100,000 or more) and average weekly ridehailing working hours (occasional, part-time, and full-time). Drivers' access to shared chargers where they live was also compared across income and working hour groups for those with and without a private home charger. Separate comparisons were made for respondents to the first (N = 1,357) and second (N = 346) survey waves. Additionally, for the longitudinal sample of drivers who responded to both waves of the survey (N = 195), changes in their responses to several variables between waves were visualized using Sankey diagrams.

The descriptive analyses presented in this chapter were conducted using unweighted data. The limitations of the weighting process as applied to the second wave of data, which are outlined in Section 10.4, may be exacerbated by further segmentation of the sample. Moreover, weights are not necessary to compare the responses from the longitudinal sample between survey waves.

6.3 Results

6.3.1 Changes in Familiarity with Federal and State Incentive Programs

Figure 6-1 and Figure 6-2 show the differences in the highest level of familiarity with federal incentives across household income categories for respondents to the first and second wave of the survey, respectively. Drivers from moderate- and high-income households tend to be more likely to be at least somewhat familiar with federal incentives than drivers from low-income households. Before the implementation of the CMS, as captured by the first wave data in Figure 6-1, there was a clear pattern of drivers' familiarity and usage of federal incentives increasing with household income. Still, there was relatively low utilization of federal incentives, with only 7.4% of all respondents indicating that they have used an incentive including 12.4% of drivers from high-income households —the largest group share. Among respondents to the second wave, one year into the CMS program, the rate of unfamiliarity with federal incentives is much lower across low- and moderate-income groups. The level of familiarity with federal incentives among moderate-income drivers is similar to high-income drivers in the second wave and there in not as clear a pattern of familiarity increasing with household income. Some 11% of all wave 2 respondents indicated that they have used a federal incentive with higher-income drivers still being more likely to have used an incentive than those with lower household incomes. One caveat to these comparisons is that the data underlying both Figure 6-1 and Figure 6-2 include responses from the longitudinal sample. As such, the observed increase in familiarity with federal incentives may partially reflect this group's strong interest and motivation—likely higher than that of the TNC driver population in California.

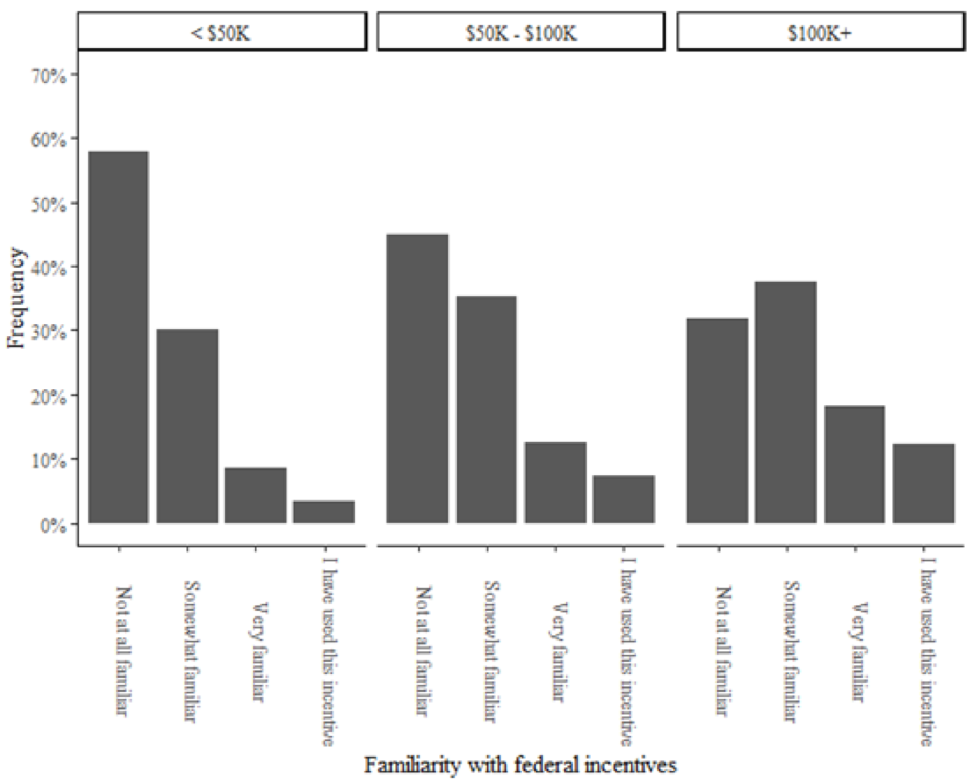

Figure 6-1 Highest level of familiarity with federal incentives among wave 1 respondents by household income (N = 1,357)

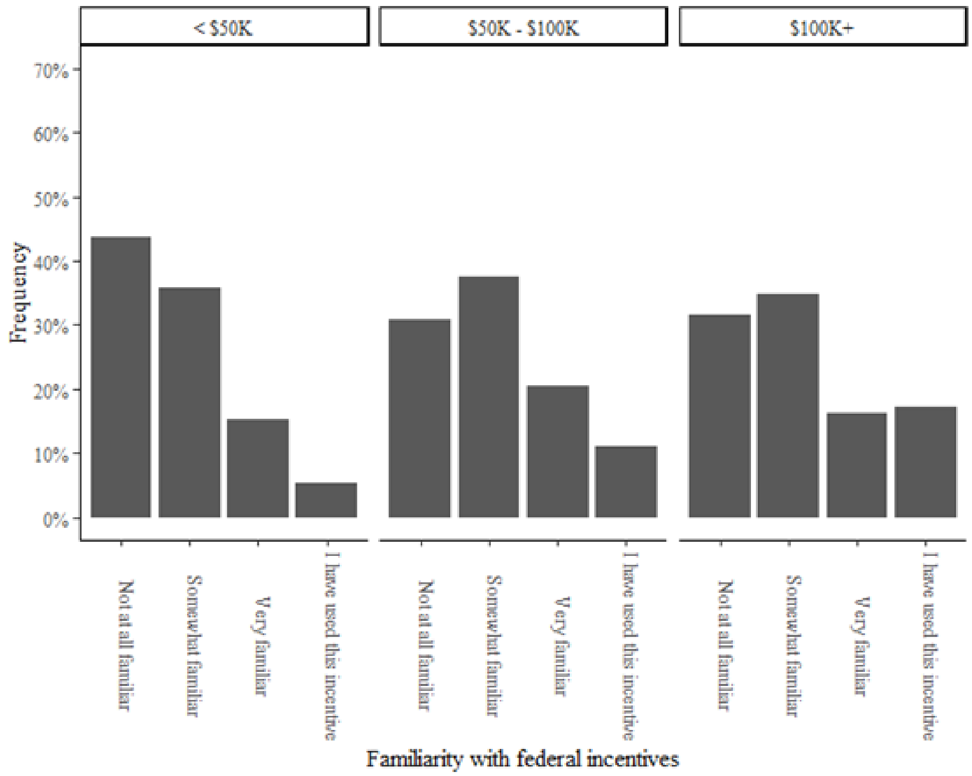

Figure 6-2 Highest level of familiarity with federal incentives among wave 2 respondents by household income (N = 346)

Figure 6-3 and Figure 6-4 show the differences in the highest level of familiarity with state incentives across household income categories for respondents to the first and second wave of the survey, respectively. It is more likely for respondents to be unfamiliar with state incentives than federal incentives across all income groups in both survey waves. There is also not a clear association between household income and familiarity with state incentives as the distributions for each income group are relatively similar. As with federal incentives, more low- and moderate-income drivers seem to be at least somewhat familiar with state incentives one year into the CMS program; however, the usage level did not change between waves with just 5.8% of respondents in both waves saying that they have used a state incentive.

Turning to the relationship between average weekly ridehailing working hours and familiarity with incentives, Figure 6-5 and Figure 6-6 show the differences in the highest level of familiarity with federal incentives between occasional, part-time, and full-time drivers for waves 1 and 2, respectively. In wave 1, the different groups of drivers reported similar levels of familiarity with federal incentives. Among wave 2 respondents, part-time and full-time drivers were more likely to be very familiar with or to have used federal incentives than occasional drivers. As shown for state incentives in Figure 6-7 and Figure 6-8, there is not a clear association between average weekly ridehailing working hours and familiarity in either survey wave.

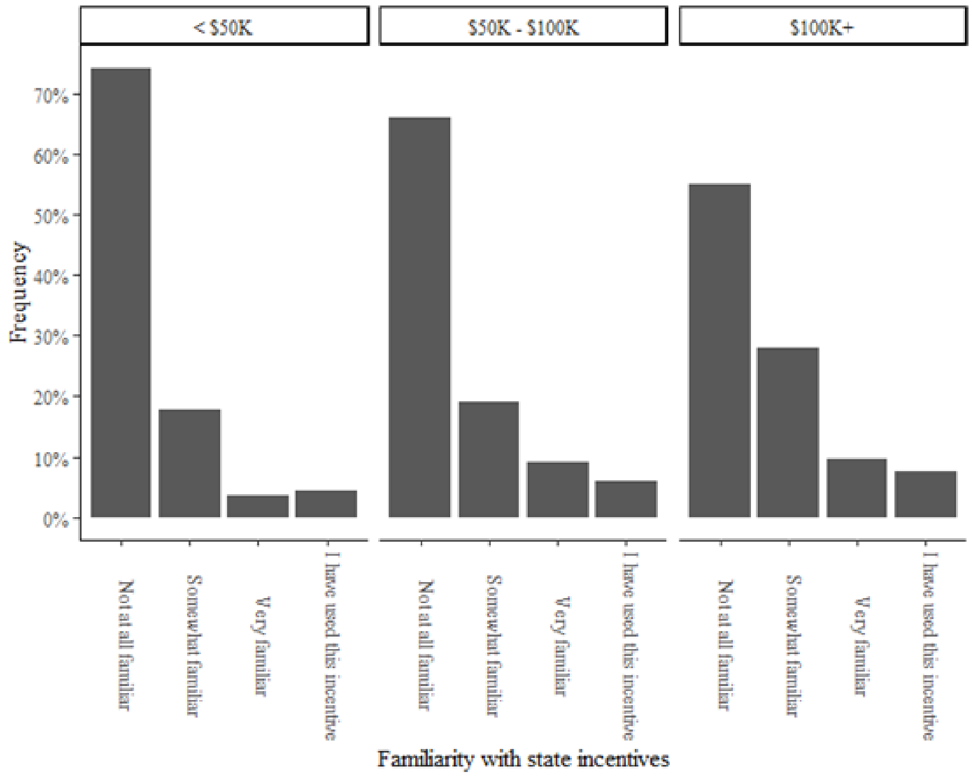

Figure 6-3 Highest level of familiarity with state incentives among wave 1 respondents by household income (N = 1,357)

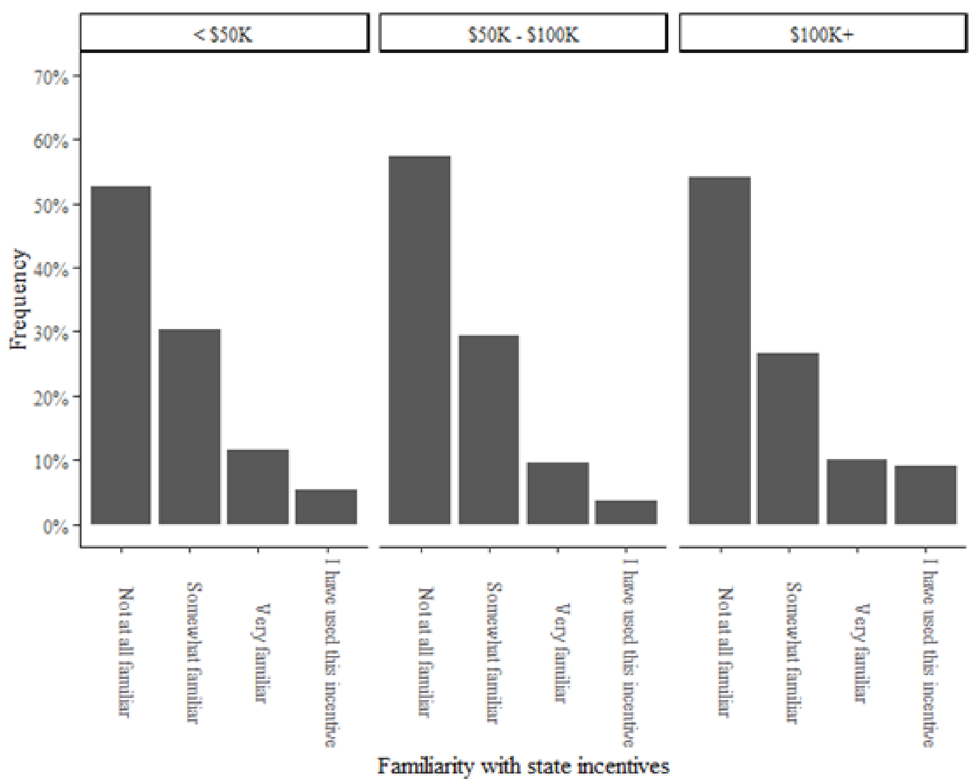

Figure 6-4 Highest level of familiarity with state incentives among wave 2 respondents by household income (N = 346)

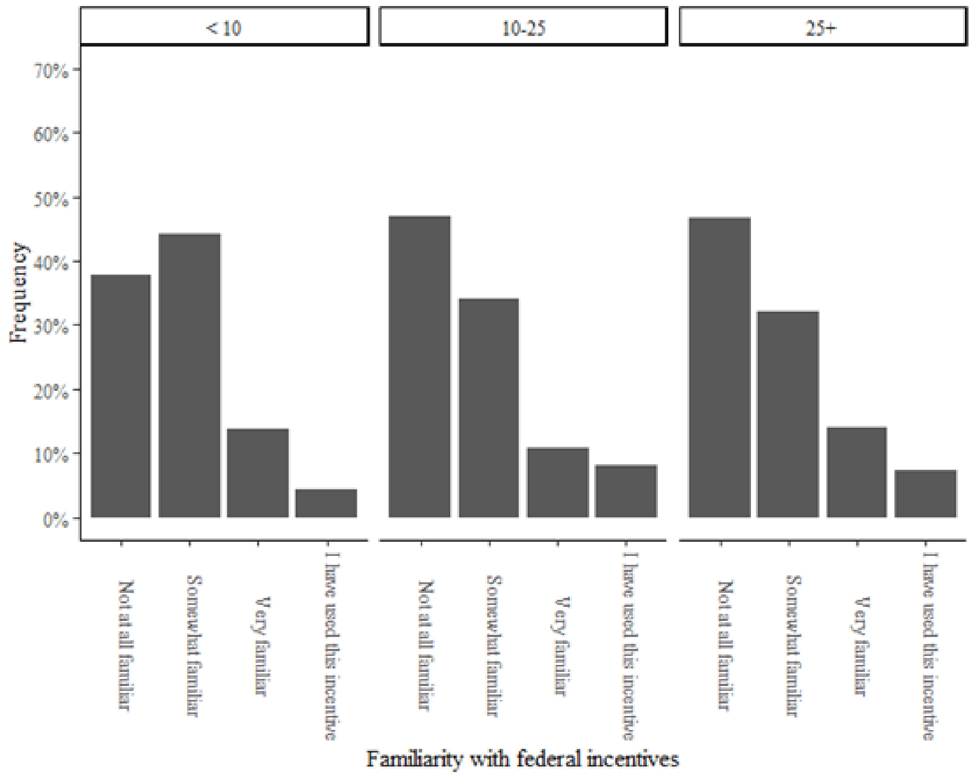

Figure 6-5 Highest level of familiarity with federal incentives among wave 1 respondents by average weekly ridehailing working hours (N = 1,357)

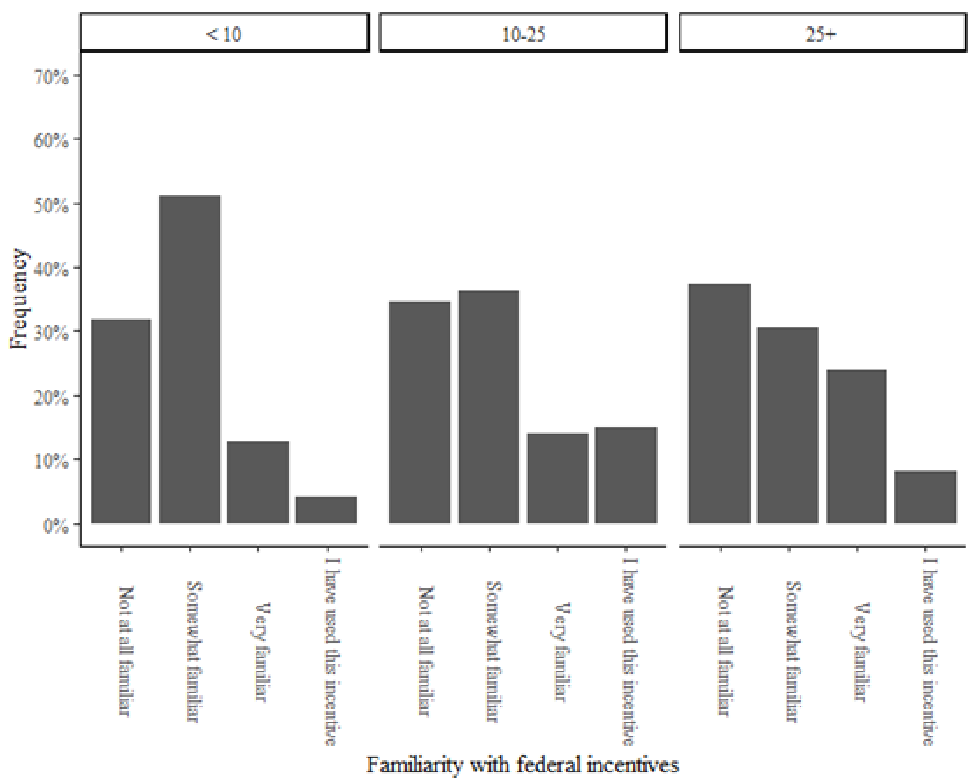

Figure 6-6 Highest level of familiarity with federal incentives among wave 2 respondents by average weekly ridehailing working hours (N = 346)

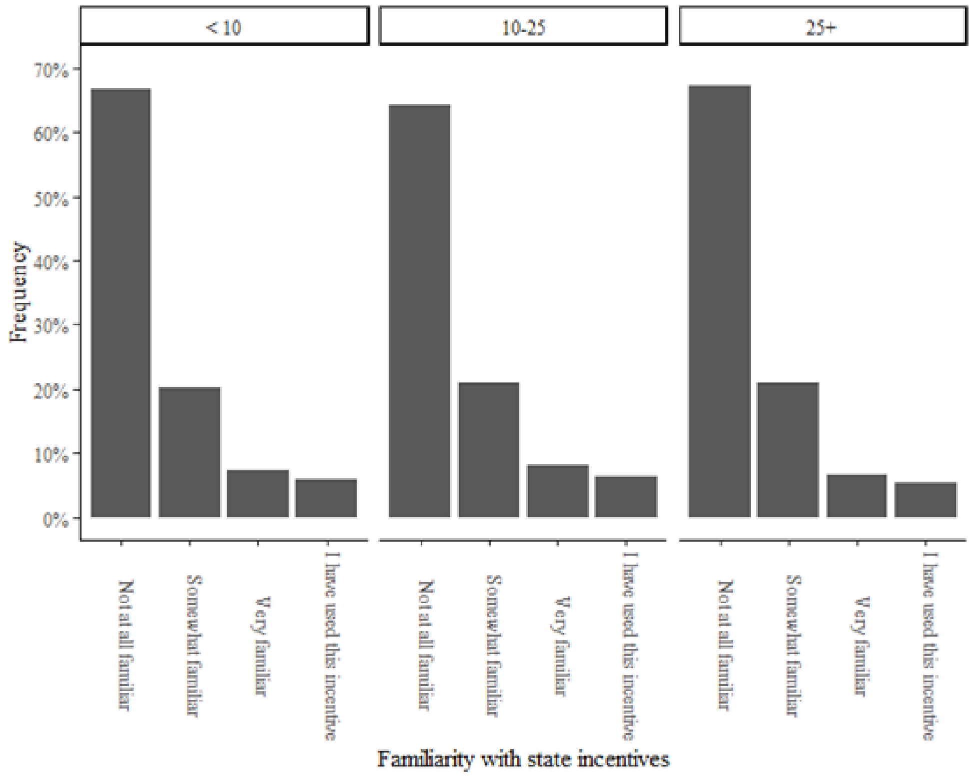

Figure 6-7 Highest level of familiarity with state incentives among wave 1 respondents by average weekly ridehailing working hours (N = 1,357)

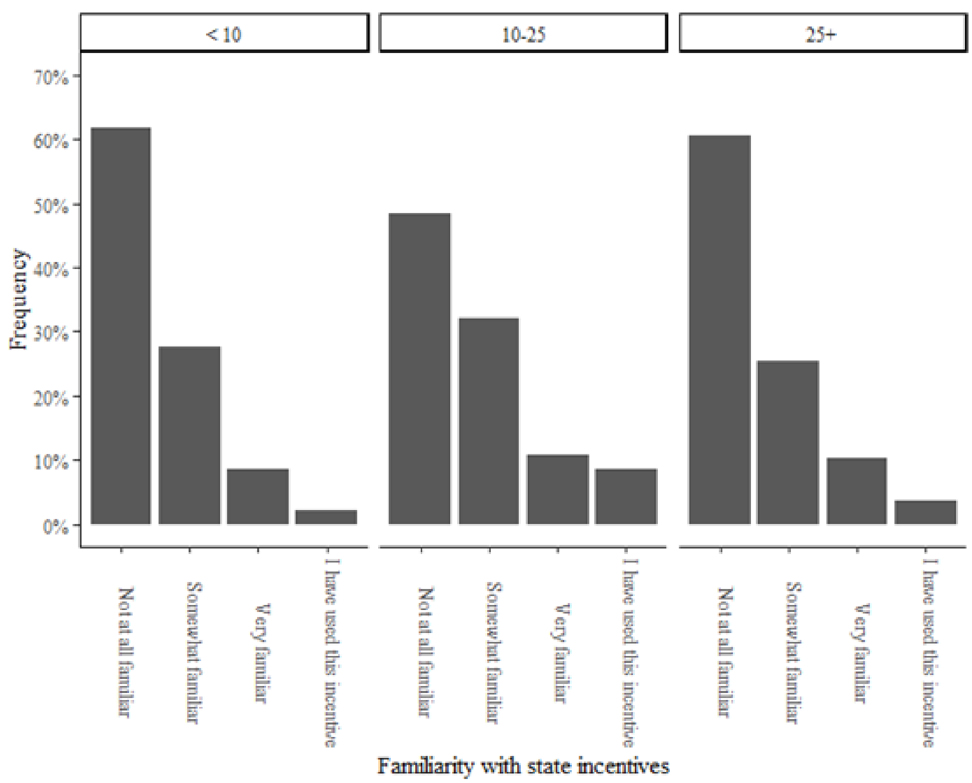

Figure 6-8 Highest level of familiarity with state incentives among wave 2 respondents by average weekly ridehailing working hours (N = 346)

Figure 6-9 and Figure 6-10 show the changes in reported familiarity between the first and second survey waves among the respondents in the longitudinal sample for the Federal New EV Tax Credit and Clean Fuel Reward, respectively. According to Figure 6-9, approximately 4% of respondents changed their response between survey waves to indicate that they used the Federal New EV Tax Credit. Figure 6-10 shows that the level of familiarity with and use of the Clean Fuel Reward among members of the longitudinal sample did not change significantly between survey waves. However, these figures highlight the difficulty of accurately tracking familiarity and use of incentives based on self-reporting, as there are counterintuitive flows of responses from higher to lower levels of the familiarity scale, such as from "Very familiar" in wave 1 to "Not at all familiar" in wave 2. It is not clear what proportion of such changes in self-reported familiarity represent respondent error or genuine loss of familiarity with the incentive.

Figure 6-9 Sankey diagram of the changes in familiarity with the Federal New EV Tax Credit incentive between survey waves among longitudinal respondents (N = 195)

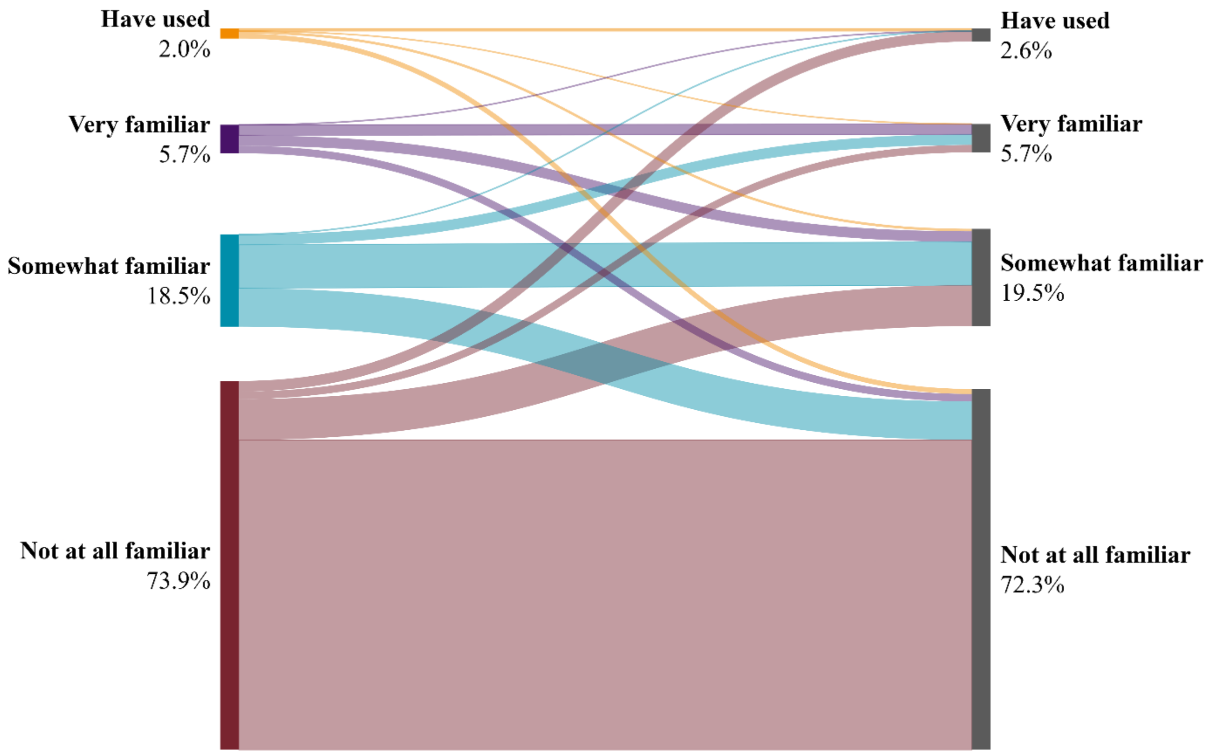

Figure 6-10 Sankey diagram of the changes in familiarity with the state Clean Fuel Reward incentive between survey waves among longitudinal respondents (N = 195)

6.3.2 Changes in the Perceived Availability of Electric Vehicle Chargers

In the first survey wave, before the implementation of the CMS, 74% of respondents perceived public chargers as available to them, with 28.5% perceiving fast chargers as available, 15.5% perceiving level 1 or 2 chargers as available, and 30% not knowing the type of charger. Figure 6-11 shows that the percentage of wave 1 drivers in each income group who perceived public chargers as available is similar, with only a slight increase in the number of drivers from high-income households perceiving fast chargers as available relative to the low- and moderate-income groups. According to Figure 6-12, more moderate- and high-income respondents to wave 2 perceived public chargers as available than low-income respondents. Overall, there was a higher frequency of perceived public charger availability in wave 2 than in wave 1, with 44% of respondents perceiving fast chargers as available, 12% perceiving level 1 or 2 chargers as available, and 29% not knowing the type of charger. Figure 6-13 and Figure 6-14 show that there is not a clear association between average weekly ridehailing working hours and the perception of public charger availability in either survey wave. Among longitudinal respondents, Figure 6-15 shows the large increase in the frequency of perceiving fast public chargers as available, from about 34% in wave 1 to 52% a year later in wave 2. The number of longitudinal respondents perceiving no public chargers as available also fell from 15% to 8%.

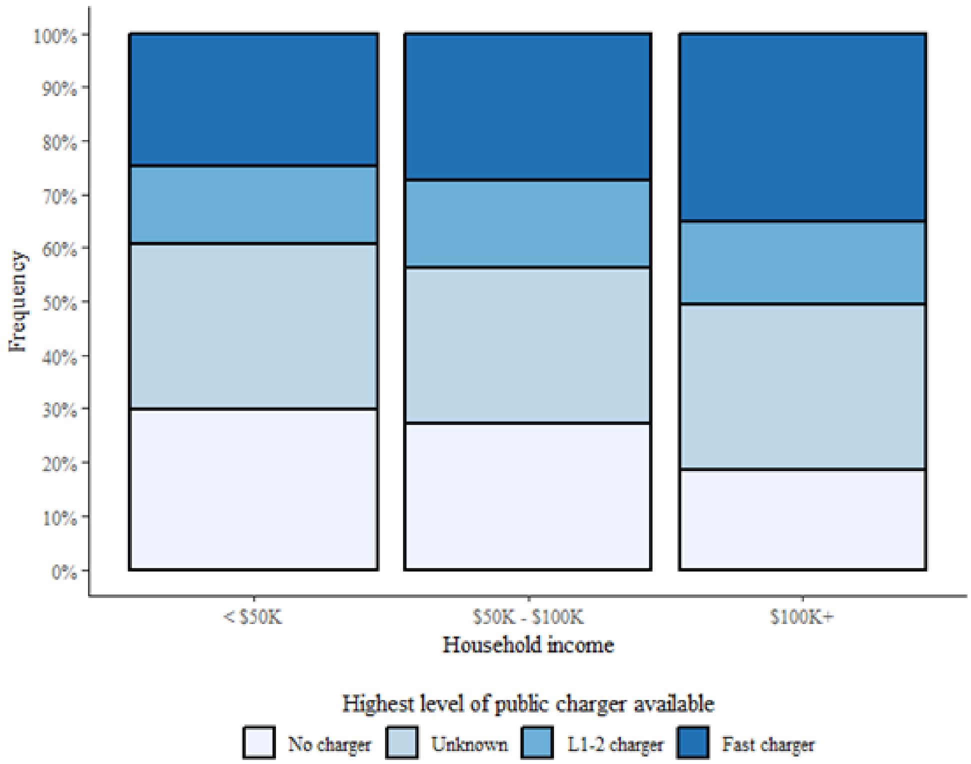

Figure 6-11 Highest level of public charger available among wave 1 respondents by household income (N = 1,357)

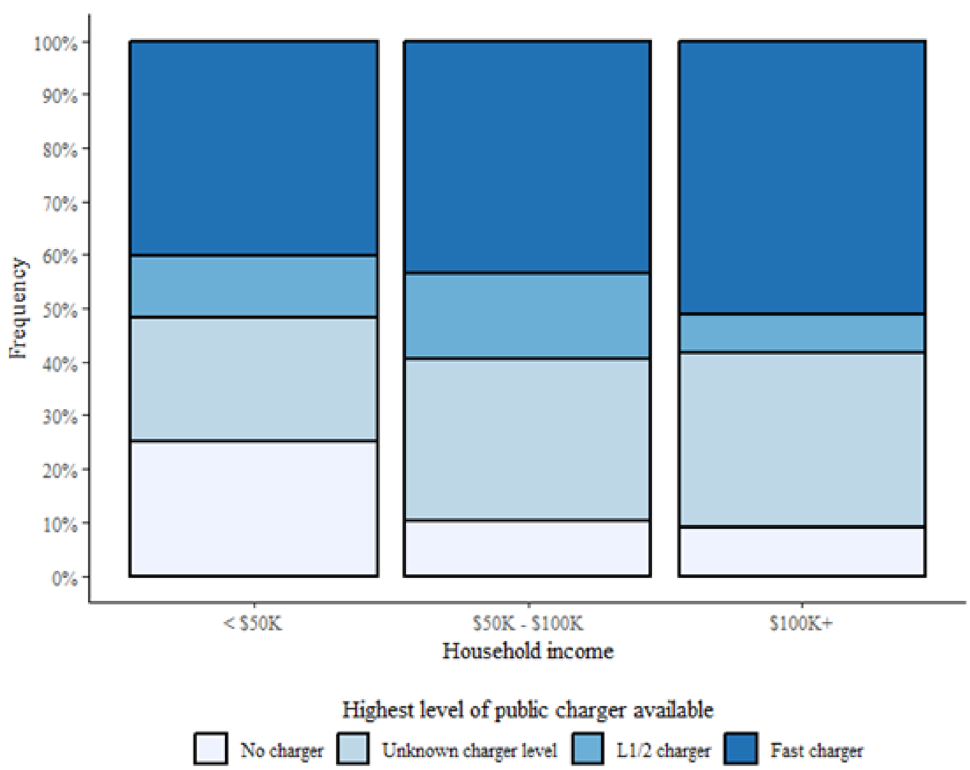

Figure 6-12 Highest level of public charger available among wave 2 respondents by household income (N = 346)

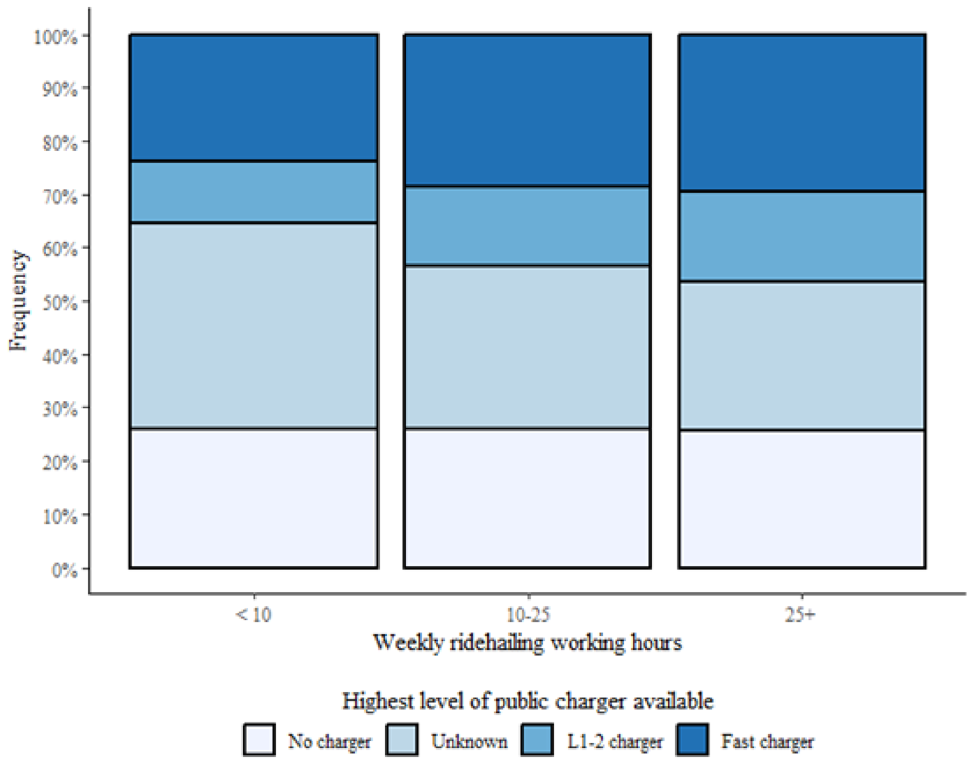

Figure 6-13 Highest level of public charger available among wave 1 respondents by average weekly ridehailing working hours (N = 1,357)

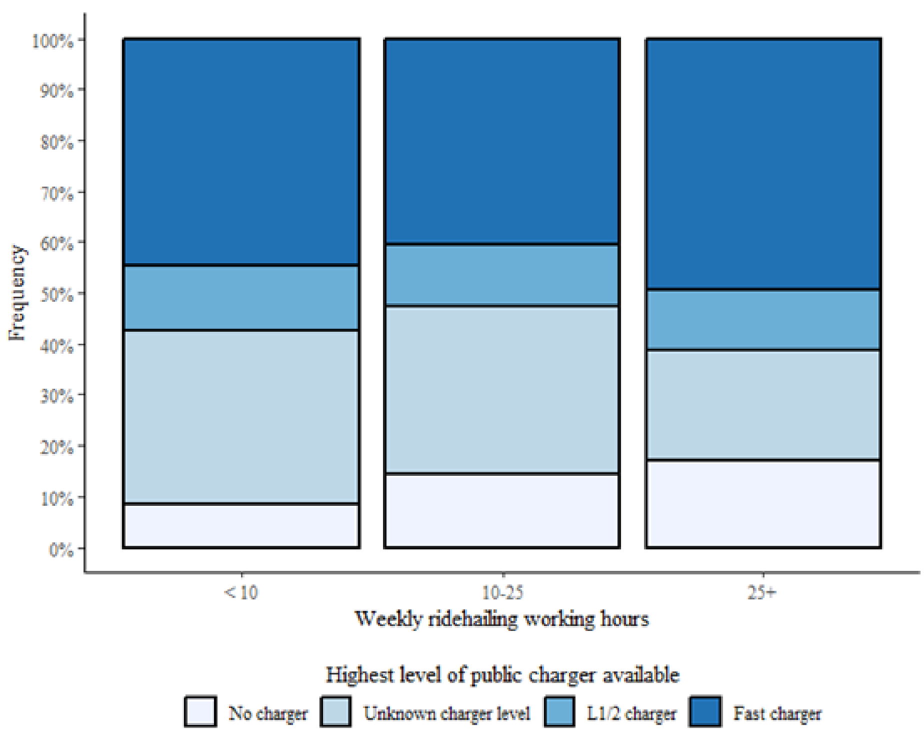

Figure 6-14 Highest level of public charger available among wave 2 respondents by average weekly ridehailing working hours (N = 346)

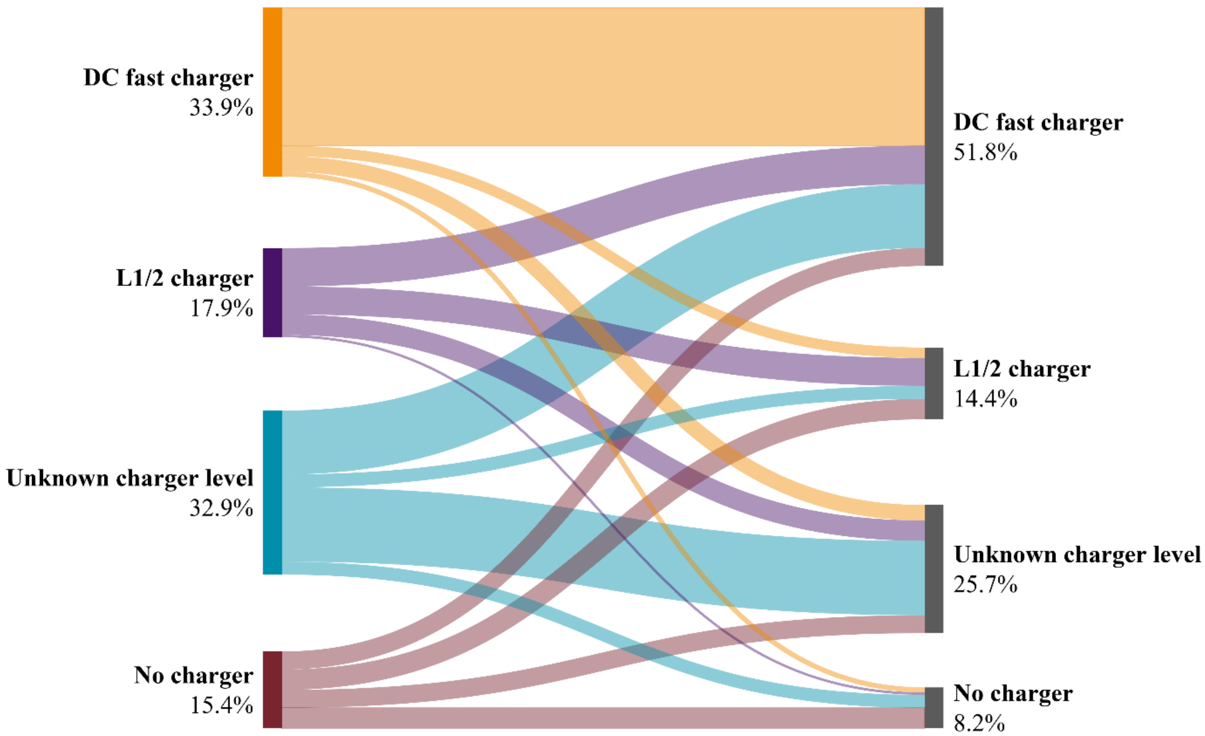

Figure 6-15 Sankey diagram of the changes in perceived highest level of public charger available between survey waves among longitudinal respondents (N = 195)

In terms of home chargers, in wave 1, roughly 18% of respondents perceived that a level 2 charger or fast charger was available to them, while 13% indicated that a level 1 charger was available. Additionally, 55% of respondents reported that no chargers were available to them, while the remaining 14% did not know the type of home charger that was available to them. As shown in Figure 6-16, the availability of home chargers appears to differ across income groups among respondents to the first survey wave. In particular, drivers from higher-income households were more likely to indicate that a level 2 charger or DC fast charger was available to them. In contrast, drivers from lower-income households were more likely to indicate that no home charger was available to them. Among drivers who indicated that chargers were not available, 50% reported that they would not be able to install a charger at their home, while another 25% were unsure about their ability to install a charger. Figure 6-17 shows the highest level of home charger perceived as available to respondents to the second wave of the survey, by household income. Unlike with public chargers, the pattern of perceived home charger availability is essentially the same as in wave 1.

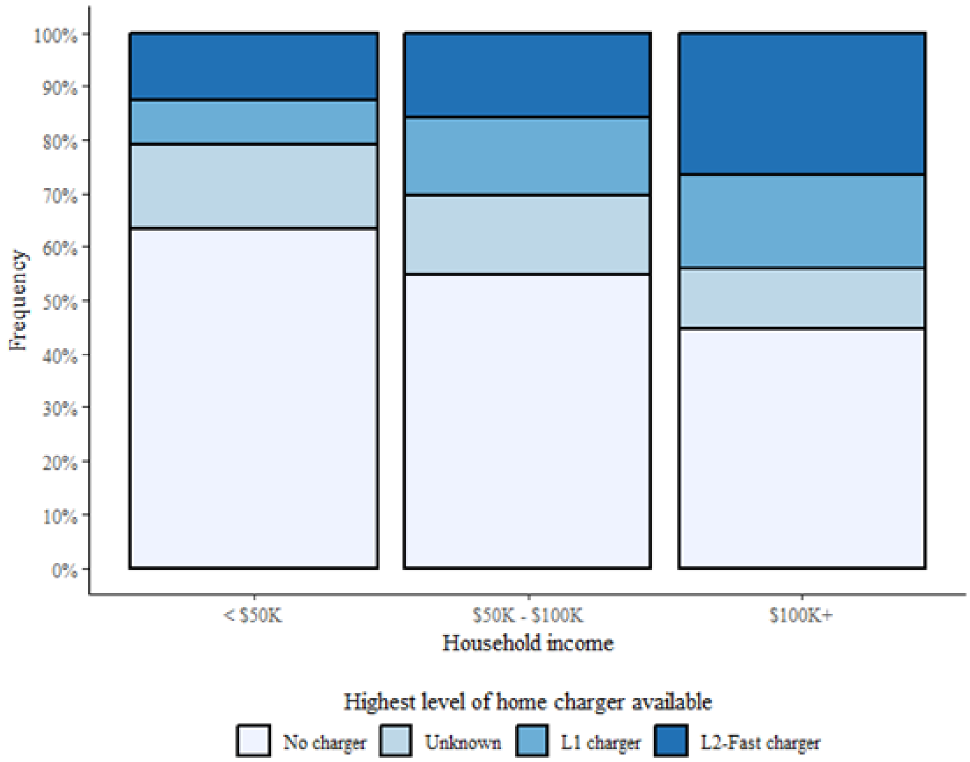

Figure 6-16 Highest level of home charger available among wave 1 respondents by household income (N = 1,357)

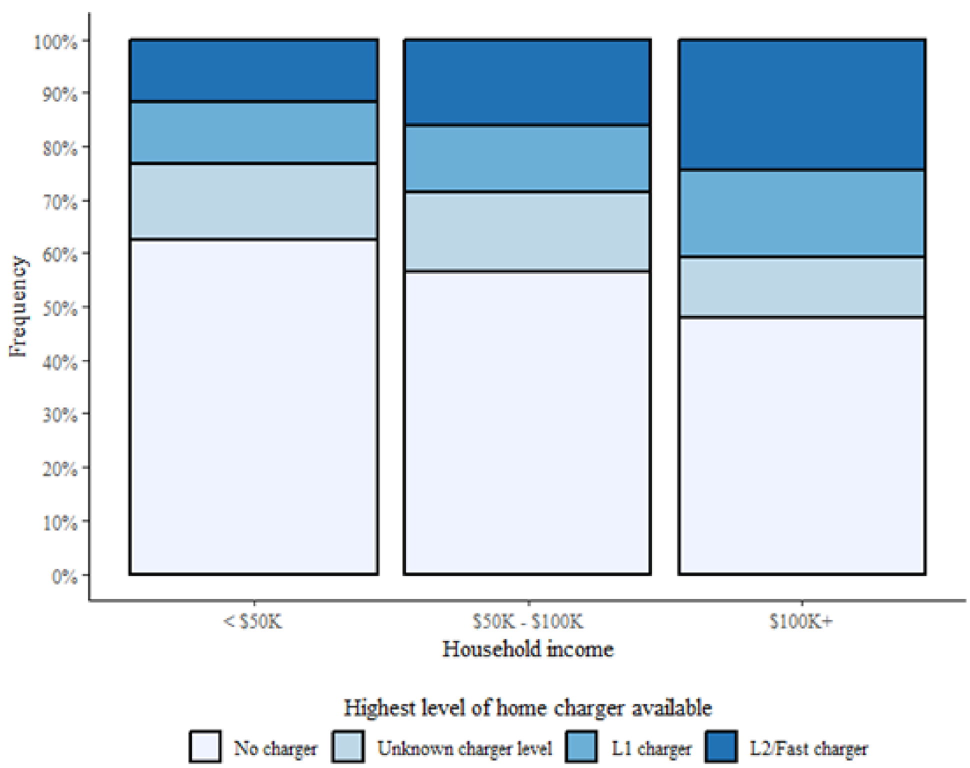

Figure 6-17 Highest level of home charger available among wave 2 respondents by household income (N = 346)

As shown in Figure 6-18, the stated ability to install a home charger varies based on housing type, with wave 1 respondents living in a stand-alone house being the most likely to be able to install a home charger, and those living in an apartment or in other conditions (e.g., mobile home) being the least likely. Additionally, the most commonly reported barrier to being able to install a home charger was living in a rented property, followed by financial constraints. When segmenting respondents by weekly working hours, Figure 6-19 and Figure 6-20 show no clear association between working hours and home charger availability in either survey wave. One apparent difference between wave 2 and wave 1 is that fewer occasional drivers in wave 2 did not know the type of home charger available to them than drivers in wave 1. Finally, Figure 6-21 shows changes in the perceived highest level of home charger available to longitudinal respondents between the two survey waves. Unlike with public chargers, perceived access to home chargers remained consistent from wave 1 to wave 2.

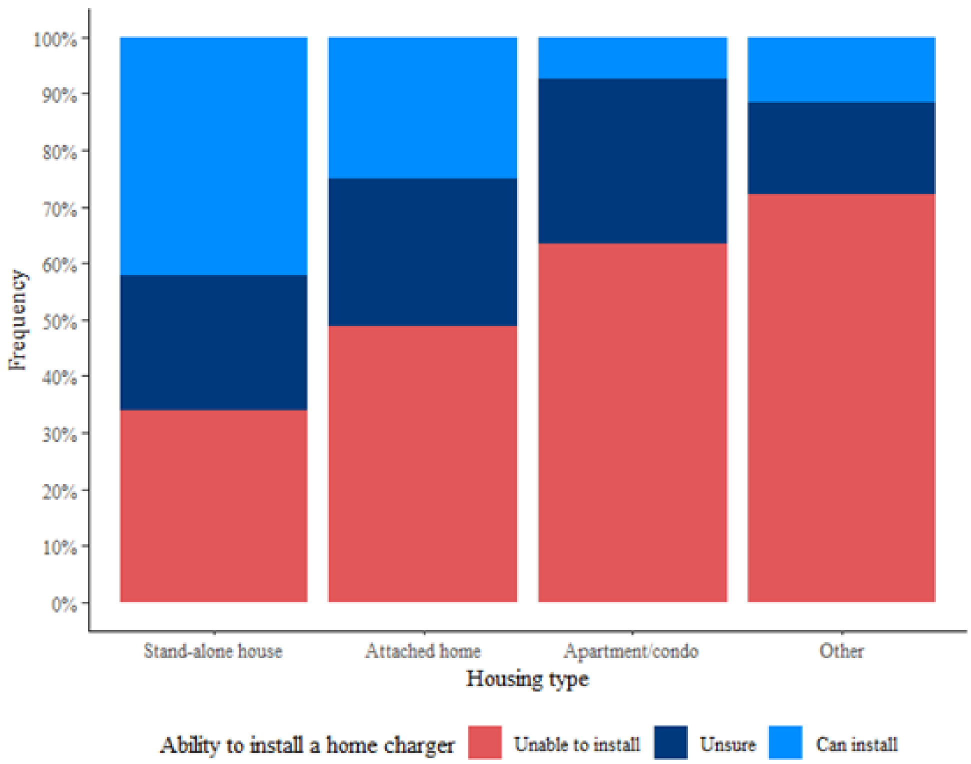

Figure 6-18 Ability to install a home charger among wave 1 respondents, by housing type (N = 787)

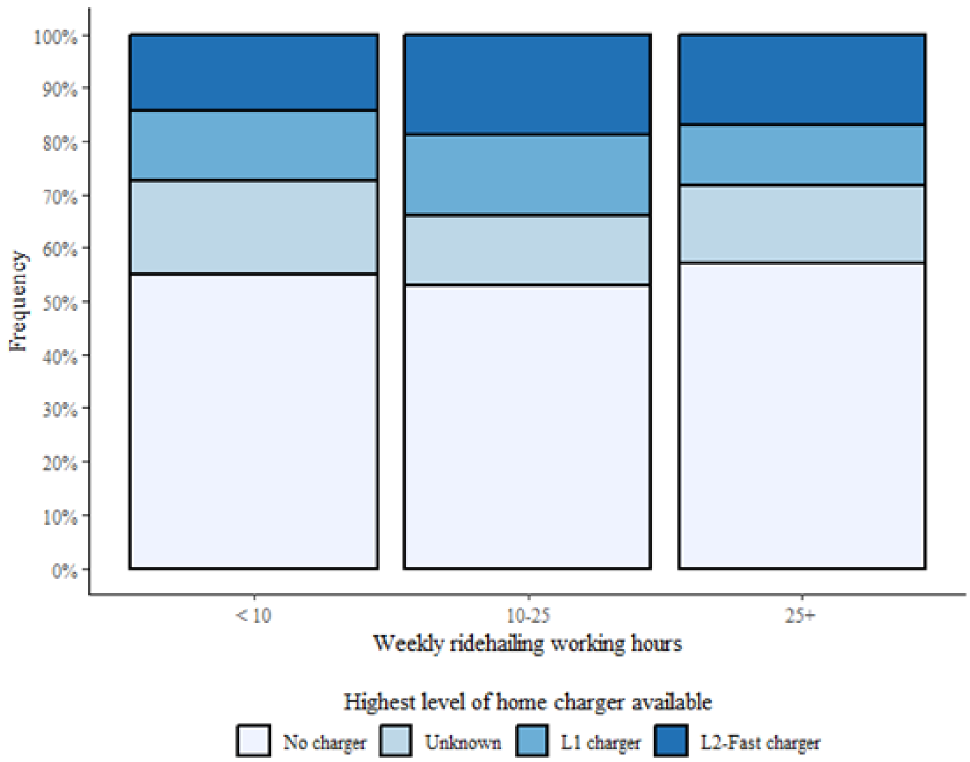

Figure 6-19 Highest level of home charger available among wave 1 respondents by average weekly ridehailing working hours (N = 1,357)

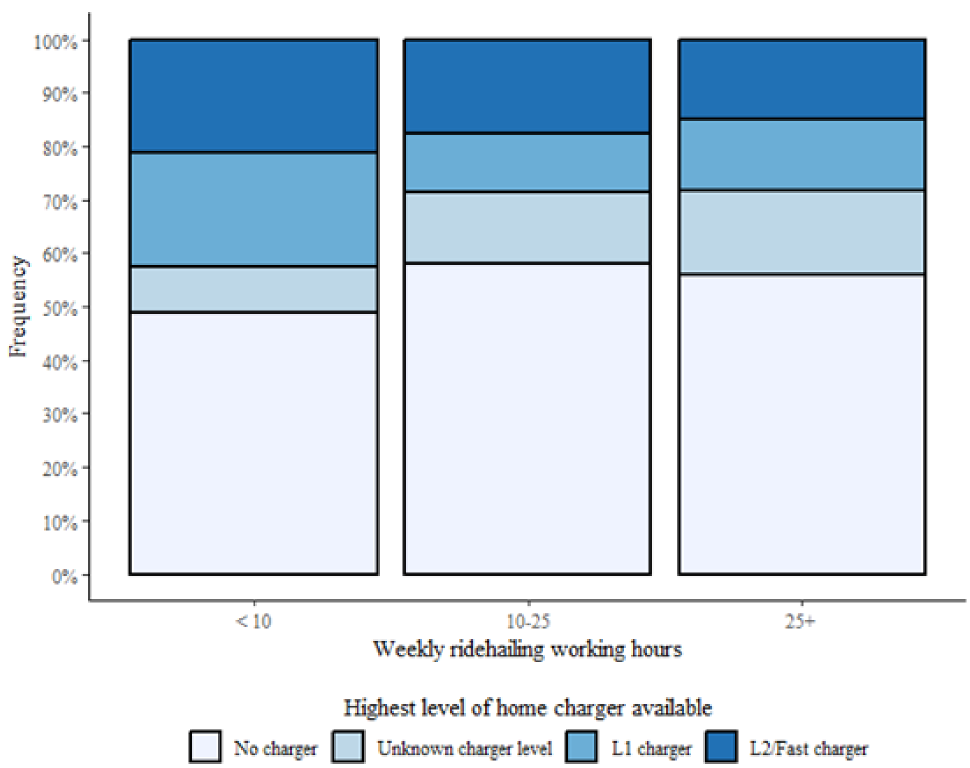

Figure 6-20 Highest level of home charger available among wave 2 respondents by average weekly ridehailing working hours (N = 346)

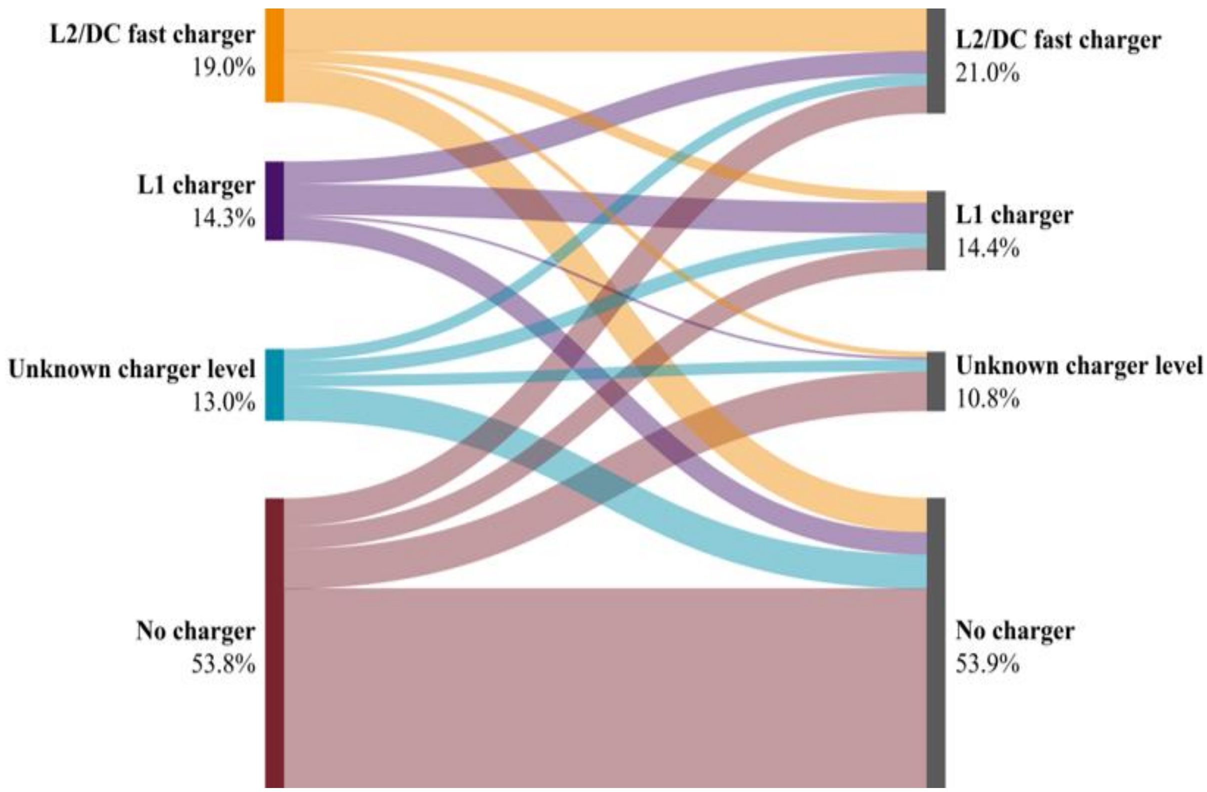

Figure 6-21 Sankey diagram of the changes in perceived highest level of home charger available between survey waves among longitudinal respondents (N = 195)

6.3.3 Changes in Attitudes Towards Electric Vehicles

Survey respondents in both waves were also asked to indicate their level of agreement with several statements regarding the use of EVs to provide ridehailing services. As shown in Figure 6-22 through Figure 6-25, the distributions of responses to these questions can vary based on the household income and average weekly working hours of the respondents, and between survey waves. While drivers across income groups in both survey waves mostly agreed that the price of an EV for ridehailing work is too high, as shown in Figure 6-22, low-income drivers in Figure 6-23 were less likely to strongly disagree, and more likely to agree with the idea that driving an EV for ridehailing would eventually result in cost savings in wave 2 than in wave 1. In accordance with the previous results about the perceived availability of public chargers, Figure 6-24 shows that part-time and full-time drivers in wave 2 were more likely to agree that charging facilities for EVs are sufficient for ridehailing work than in wave 1. This is also the case among respondents in the longitudinal sample, with the percentage in agreement with the statement increasing from 15.8% in wave 1 to 32.4% in wave 2, and the percentage in disagreement falling from 52.4% in wave 1 to 34.3% in wave 2. Interestingly, occasional drivers in wave 2 were more likely to agree that using an EV as a ridehailing driver would require careful planning than occasional drivers in wave 1. The need to maintain battery charge might make it more complicated for occasional drivers to fit ridehailing into their schedule with an EV, whereas they may log into the TNC platform and start providing rides at almost any time with a gas car.

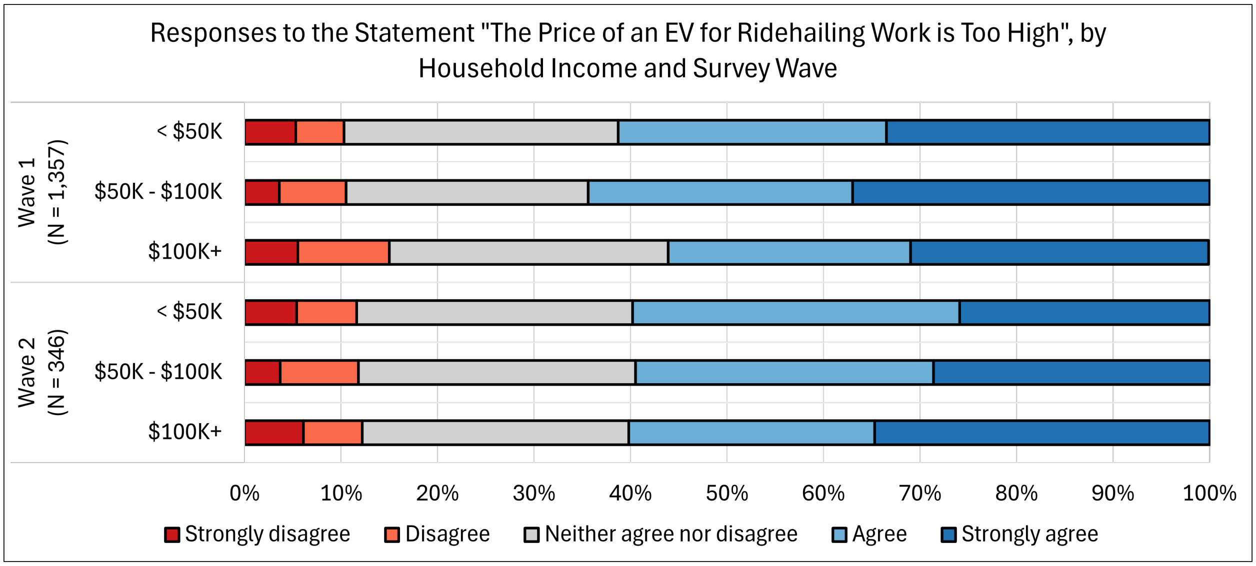

Figure 6-22 Level of agreement with the price of an EV for ridehailing being too high, by household income and survey wave

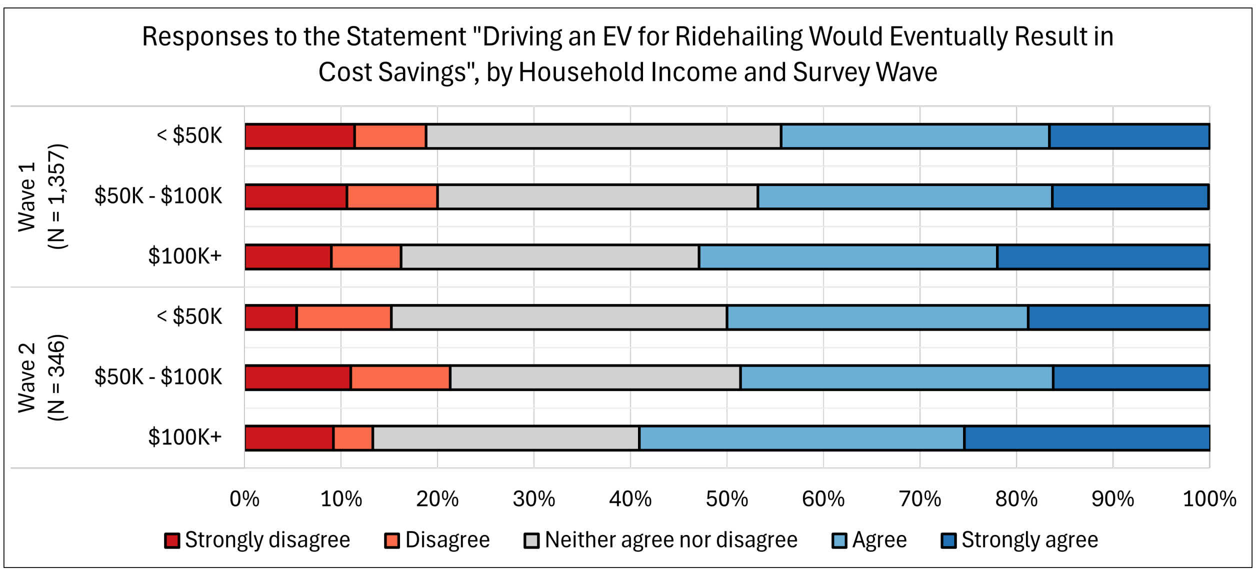

Figure 6-23 Level of agreement with the the use of an EV for ridehailing eventually resulting in cost savings, by household income and survey wave

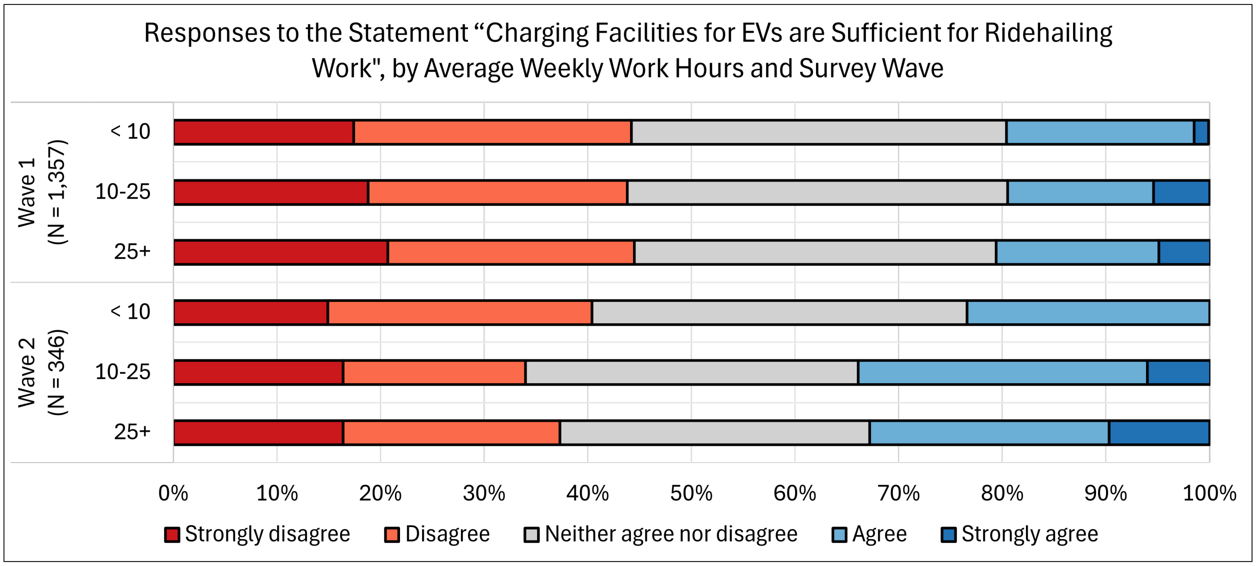

Figure 6-24 Level of agreement with charging facilities being sufficient for ridehailing work, by average weekly ridehailing working hours and survey wave

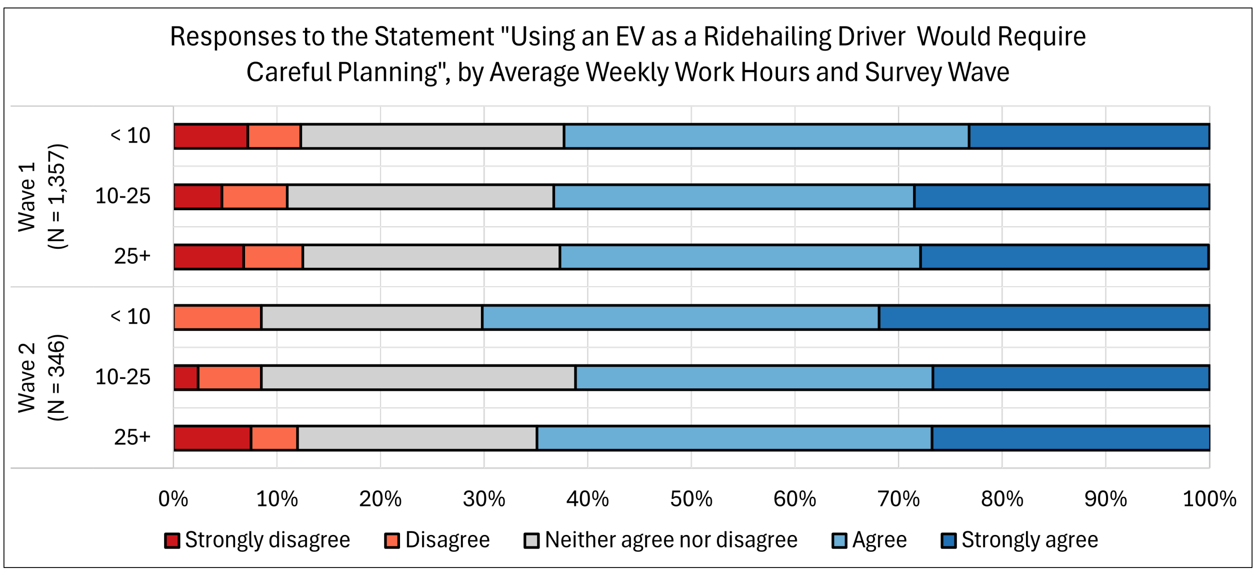

Figure 6-25 Level of agreement with using an EV as a ridehailing driver requiring careful planning, by average weekly ridehailing working hours and survey wave

7 Exploring the Factors Influencing the Uptake of Battery Electric Vehicles

7.1 Introduction

As the usage and prevalence of ridehailing grew in the 2010s, concerns were raised about the potential climate impacts of these services. Studies have reported that ridehailing services could have negative environmental impacts due to travel induced by the availability of these services, the tendency for these services to attract demand from more sustainable modes of travel, and the distance driven by ridehailing vehicles while not serving passengers (i.e., deadheading) (Clewlow & Mishra, 2017; Gehrke et al., 2019; Henao & Marshall, 2019; Tirachini, 2020). Several strategies for addressing the environmental impacts of ridehailing have been proposed, including encouraging the use of pooled ridehailing, implementing initiatives to reduce deadheading, and the electrification of the ridehailing fleet. As part of its efforts to address GHG emissions from the transportation sector, California has prioritized policies related to transportation electrification (California Air Resources Board, 2022a).

Promoting the electrification of the ridehailing fleet can contribute to GHG emission reductions, given the relatively high emissions per passenger mile of ridehailing vehicles compared to privately owned passenger vehicles. In particular, the *2018 Base-year Emissions Inventory Report* published by CARB noted that the emissions associated with the average ridehailing vehicle 301 g CO_2-eq/ PMT, whereas that of the average passenger vehicle in California was 203 g CO_2-eq/ PMT. Given that ridehailing drivers typically use their own vehicles to provide ridehailing services, the extent to which the benefits of vehicle electrification are achieved will be dictated by their willingness and ability to adopt BEVs. Moreover, the challenges faced by ridehailing drivers related to the adoption of BEVs could differ from those faced by the general population. For example, the decision to adopt a BEV could be influenced by the need to minimize costs and maximize fare revenues or concerns about the need to spend time charging the vehicle (that could otherwise be spent serving passengers). Consequently, understanding the characteristics of ridehailing drivers and the factors influencing their uptake of BEVs is crucial to inform the development of electrification efforts and supportive policies.

This chapter presents the results of an exploration of the characteristics of California ridehailing drivers and their uptake of BEVs to provide ridehailing services. Specifically, two research questions are addressed in this chapter: 1) How do the attributes of ridehailing drivers differ based on their average weekly working hours? 2) What factors influence the likelihood of using a BEV to provide ridehailing services? The findings presented in this chapter shed light on how the socio-demographic characteristics of California ridehailing drivers vary based on the amount of time they spend providing ridehailing services. Additionally, the results provide what could be the first empirical insights into the determinants of *observed* BEV uptake among ridehailing drivers.

7.2 Data and Methods

Descriptive analysis and binary logistic regression were applied to analyze data collected through the first wave of the survey. Prior to the data being analyzed, several new variables were defined. First, new variables capturing the highest level of BEV charger available to the respondents at home (specifically, their garage, driveway, or residential parking lot) and in public areas (including in their neighborhood and other public areas) were defined. Next, variables capturing the highest level of familiarity with federal and state BEV incentives were defined. Finally, a binary variable related to the uptake of BEVs was defined based on whether a given driver had at least one BEV registered with a TNC. The value of this variable was equal to 1 if they indicated that they had at least one BEV registered with a TNC at the time of the survey and 0 otherwise.

The factors influencing BEV uptake among ridehailing drivers were examined using a binary logistic regression model. Let P_i be the probability of individual i having at least one BEV registered with a TNC. The logged odds of individual i having at least one BEV registered with a TNC (L_i) is defined as (Pampel, 2020):

$$L_i = \ln\left(\frac{P_i}{1 - P_i}\right) \tag{7.1}$$

The logged odds can be modeled as a function of observed variables (such as socio-demographic characteristics, perceived charger availability, and familiarity with EV incentives):

$$L_i = \beta_0 + \boldsymbol{\beta}'\boldsymbol{x_i} \tag{7.2}$$

Where:

β_0 is the intercept of the regression equation

$\boldsymbol{\beta}$ is a vector of coefficients capturing the effects of the explanatory variables on L_i

$\boldsymbol{x_i}$ is a vector of explanatory variables corresponding to individual i

Combining Equation 7.1 and Equation 7.2, the probability of individual i having at least one BEV registered with a TNC is defined as:

$$P_i = \frac{\exp(\beta_0 + \boldsymbol{\beta}'\boldsymbol{x_i})}{1 + \exp(\beta_0 + \boldsymbol{\beta}'\boldsymbol{x_i})} \tag{7.3}$$

The binary logistic regression model was estimated using the *survey* package written for the R programming language (Lumley et al., 2024). Based on the final specification of the model, a marginal effects analysis was executed using the *margins* package written for the R programming language (Leeper et al., 2024). The model was estimated using the unweighted dataset.

7.3 Results

7.3.1 Characteristics of Ridehailing Drivers

The distributions of key socio-demographic characteristics of respondents from the first wave of the survey are presented in Table 7-1. The demographics of the sample skewed towards individuals between the ages of 35 and 54, males, those born outside of the United States, and individuals from lower-income households. Moreover, those who identified as Hispanic or Latino represent the largest ethnic group in the sample (37%). Additionally, the majority of respondents indicated that they possess either a college or bachelor's degree, while almost 50% of the respondents reported that they were employed on a full-time basis outside of providing ridehailing services. Besides, the majority of respondents indicated that they were renting their current residence.

In addition to descriptive analysis, rank tests were applied to examine whether differences in the shares of socio-demographic segments across three driver groups (defined by average weekly working hours) were statistically significant. The results of these tests suggest that differences based on age, race and ethnicity, household income, employment outside of ridehailing, and housing tenure were statistically significant at the 5% significance level. As shown in Table 7-1, full-time and part-time drivers include a higher proportion of individuals aged 18 to 34 compared to occasional drivers, while occasional drivers are more likely to be between the ages of 35 and 66. Additionally, roughly 50% of full- and part-time drivers identify as Hispanic or Latino, whereas occasional drivers are twice as likely to identify as White alone compared to the other two driver groups. Notably, full- and part-time drivers are much more likely to belong to lower-income households compared to occasional drivers. Given the relatively high costs of BEVs and home charging equipment, this suggests that financial support may be necessary to encourage full-time drivers to transition to BEVs. Finally, full- and part-time drivers were more likely to report that they were renting their homes compared to occasional drivers. Consequently, full-time drivers could be less likely to be able to install a BEV charger at their homes.

Table 7-1 Distributions of the socio-demographic characteristics of the wave 1 sample (N = 1,357)

Variable	Category	Full Sample	Occasional Driver [a]	Part-time Driver [b]	Full-time Driver [c]	Non-BEV Driver	BEV Driver [d]
Sample size	N/A	1,357	138	575	644	1,140	217
BEV driver status	BEV driver	15%	13%	14%	18%	0%	100%
	Non-BEV driver	85%	87%	86%	82%	100%	0%
Age group	18 to 34	22%	15%	33%	33%	22%	22%
	35 to 54	58%	60%	48%	48%	55%	60%
	55 to 66	18%	21%	12%	15%	18%	18%
	67 and older	3%	3%	7%	4%	5%	1%
Gender	Male	81%	74%	80%	85%	75%	87%
	Not male [e]	19%	26%	20%	15%	25%	13%
Place of birth	U.S. state or territory	62%	70%	63%	58%	69%	55%
	Other non-U.S. state or territory	38%	30%	37%	42%	31%	45%
Race and ethnicity	White alone	28%	36%	18%	15%	29%	27%
	Black or African American alone	7%	9%	6%	7%	8%	6%
	Hispanic or Latino [f]	37%	29%	51%	57%	38%	36%
	Asian alone	18%	14%	17%	11%	13%	22%
	Other (incl. multi-racial)	11%	12%	9%	11%	12%	9%
Education	High school or below	13%	15%	21%	21%	19%	6%
	Some college or technical school	42%	44%	38%	50%	43%	41%
	Bachelor's degree	36%	31%	33%	22%	29%	43%
	Graduate or professional degree	10%	11%	8%	7%	10%	9%
Household income	Less than $50,000	42%	33%	59%	70%	45%	36%
	$50,000 to $99,999	34%	36%	34%	24%	35%	32%
	$100,000 and over	28%	32%	9%	5%	21%	32%
Employment outside of ridehailing	Full-time	48%	62%	39%	12%	53%	43%
	Part-time	15%	9%	15%	12%	10%	19%
	Self-employed	15%	13%	17%	22%	15%	15%
	Unpaid or no other work	23%	16%	29%	55%	22%	23%

Variable	Category	Full Sample	Occasional Driver [a]	Part-time Driver [b]	Full-time Driver [c]	Non-BEV Driver	BEV Driver
Housing tenure	Owned	32%	33%	21%	16%	26%	38%
	Rented	59%	59%	71%	78%	66%	52%
	Provided by someone else	8%	8%	7%	6%	7%	9%
	Other	1%	0%	1%	0%	1%	1%
Housing type	Stand-alone house	45%	49%	43%	36%	47%	43%
	Attached home, duplex, or townhouse	17%	15%	11%	14%	12%	22%
	Apartment or condo	35%	32%	41%	43%	36%	35%
	Other	4%	4%	6%	7%	5%	1%
Access to private or reserved parking at home	Yes	70%	69%	68%	61%	68%	72%
	No	30%	31%	32%	39%	32%	28%

Notes:

[a] *Occasional drivers* are those who work less than 10 hours per week

[b] *Part-time drivers* are those who work between 10 and 25 hours per week

[c] *Full-time drivers* are those who work more than 25 hours per week

[d] *BEV drivers* are those who have at least one BEV registered with a TNC

[e] The *not male* category corresponds to those who selected “woman” or “prefer to self-describe”

[f] Respondent selected Hispanic or Latino alone or in combination with any other racial or ethnic group

N/A = not applicable

Percentages are based on weighted data and may not add up to 100% due to rounding

7.3.2 Binary Logistic Regression Model

The final specification of the binary logistic regression model is presented in Table 7-2. Responses from those who indicated that they have used a federal, state, or local BEV-related incentive were omitted from the dataset used to estimate the model, due to the possibility that their use of an incentive directly relates to their use of a BEV to provide ridehailing services. During the model estimation process, variables pertaining to socio-demographic characteristics, perceived access to chargers, familiarity with BEV-related incentives, and driver characteristics were tested. A backwards stepwise approach was used to develop the final specification of the model, where variables were removed one by one until only variables with statistically significant parameters remained. Moreover, the variance inflation factors were calculated to ensure that excessive multicollinearity was not present among the variables included in the final specification of the model. The Cox-Snell pseudo-R^2 of the model was 0.202, which is indicative of a reasonable goodness-of-fit.

Drivers over the age of 66, those who identified as being part of "other" racial or ethnic groups (including those who identified as being multi-racial), and who have been providing ridehailing services for between 2 and 5.5 years were less likely to have at least one BEV registered with a TNC. Conversely, being a full-time driver, perceiving that DC fast chargers are available in public areas, perceiving that level 2 or DC fast chargers are available at home, and being very familiar with federal BEV-related incentives were all positively associated with the likelihood of having at least one BEV registered with a TNC. The impact of being a full-time driver on BEV uptake echoes the findings of Du, Cheng, Li, & Yang (2020), who examined the determinants of BEV acceptance among ridehailing drivers in China. This association is likely due to BEVs being more cost-efficient than conventional vehicles when usage is high (Weldon et al., 2018). The specification of the binary logistic regression model is also consistent with the findings of previous studies regarding the impacts of access to chargers and financial incentives on attitudes and perceptions towards BEVs among ridehailing drivers (Du, Cheng, Li, & Xiong, 2020; Du, Cheng, Li, & Yang, 2020; Rajagopal & Yang, 2020).

Marginal effects analysis was applied to quantify the impact of each variable included in the final specification of the model on the likelihood of a driver having at least one BEV registered with a TNC. The average marginal effect of each variable, along with the corresponding 95% confidence interval, are presented in Table 7-3. Being over the age of 66 and belonging to the "other" racial and ethnic group both reduced the probability of having at least one BEV registered with a TNC by 13% on average. Additionally, being a full-time driver increased the probability of having at least one BEV registered with a TNC by an average of 6%, while having provided ridehailing services for between 2 and 5.5 years was associated with an average decrease of 8.2%. Importantly, the perceived availability of chargers in public areas increased the probability of having at least one BEV registered with a TNC. Specifically, perceiving that DC fast chargers are available in public areas was associated with an average increase of 13.8%, while perceiving that level 1 or 2 chargers were available in public areas was associated with an average increase of 9.5%. As expected, being very familiar with federal BEV incentives increased the probability of having at least one BEV registered with a TNC by an average of 8.9%.

Table 7-2 Final estimates of the binary logistic regression model

Variable	Estimate	t-stat.	p-value
Intercept	-4.786	-4.379	0.000***
Age (reference: 35 to 54)			
18 to 34	0.665	1.039	0.299
55 to 66	0.188	0.278	0.781
67 and older	-2.530	-3.026	0.003***
Gender (reference: male)			
Not male	-1.090	-1.674	0.094*
Race and ethnicity (reference: Hispanic or Latino)			
Asian alone	0.625	0.732	0.464
Black or African American alone	1.095	1.125	0.261
White alone	0.096	0.129	0.897
Other (incl. multi-racial)	-2.503	-2.874	0.004**
Driver status (reference: occasional or part-time)			
Full-time driver	1.103	2.484	0.013**
Years on TNC platform (reference: less than 2 years)			
2 to 5.5 years	-1.523	-2.081	0.038**
Over 5.5 years	-0.886	-1.502	0.133
Housing tenure (reference: not owned)			
Owned	1.227	1.748	0.081*
Housing type (reference: single-family house)			
Apartment, condo, or other	0.924	1.905	0.057*
Public charger availability (reference: none or unknown charger type)			
Level 1	1.760	1.951	0.051*
Level 2 or DC fast charger	2.558	3.178	0.002***
Home charger availability (reference: none or unknown charger type)			
Level 1	-0.170	-0.176	0.86
Level 2 or DC fast charger	1.480	1.976	0.048**
Familiarity with federal BEV incentives (reference: not at all or somewhat familiar)			
Very familiar	1.650	3.050	0.002***
Goodness-of-fit statistics			
Number of observations		1,229	
Cox-Snell pseudo-R^2		0.202	

Notes:

Significance levels: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table 7-3 Average marginal effect of each variable in the binary logistic regression model

Variable	Average Marginal Effect	p-value	95% CI
Age (reference: 35 to 54)			
18 to 34	0.036	0.294	[-0.02, 0.11]
55 to 66	0.010	0.779	[-0.06, 0.08]
67 and older	-0.137	0.009***	[-0.27, -0.06]
Gender (reference: male)			
Not male	-0.059	0.129	[-0.15, 0.00]
Race and ethnicity (reference: Hispanic or Latino)			
Asian alone	0.034	0.460	[-0.05, 0.13]
Black or African American alone	0.059	0.275	[-0.03, 0.18]
White alone	0.005	0.897	[-0.07, 0.09]
Other (incl. multi-racial)	-0.135	0.007***	[-0.26, -0.07]
Driver status (reference: occasional or part-time)			
Full-time driver	0.060	0.005***	[0.03, 0.11]
Years on TNC platform (reference: less than 2 years)			
2 to 5.5 years	-0.082	0.037**	[-0.18, -0.02]
Over 5.5 years	-0.048	0.132	[-0.12, 0.00]
Housing tenure (reference: not owned)			
Owned	0.066	0.072*	[0.01, 0.15]
Housing type (reference: house)			
Apartment, condo, or other	0.050	0.045**	[0.01, 0.11]
Public charger availability (reference: none or unknown charger type)			
Level 1	0.095	0.047**	[0.02, 0.21]
Level 2 or DC fast charger	0.138	0.001***	[0.09, 0.25]
Home charger availability (reference: none or unknown charger type)			
Level 1	-0.009	0.859	[-0.11, 0.09]
Level 2 or DC fast charger	0.080	0.060*	[0.01, 0.18]
Familiarity with federal BEV incentives (reference: not at all or somewhat familiar)			
Very familiar	0.089	0.001***	[0.05, 0.16]

Notes:

Significance levels: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

8 Examining the Determinants of Fuel Type Choices

8.1 Introduction

Transportation electrification has been identified as a crucial component of addressing the emissions associated with passenger transportation. Given their relatively high mileage, vehicles that are used to provide ridehailing services are a promising candidate for electrification efforts. Although substantial effort has been dedicated to understanding the adoption of zero-emission vehicles among the general population and taxi fleets (Hagman & Langbroek, 2019; Iogansen et al., 2023; Kinsella et al., 2023; Mandev et al., 2022), limited research has focused on the factors influencing the uptake of these vehicles among ridehailing drivers. However, studies have noted that encouraging ridehailing drivers to shift from internal combustion engine vehicles (ICEVs) to ZEVs (and particularly BEVs) has the potential to produce environmental, public health, and economic benefits (Hunt & McKearnan, 2020; Jenn, 2020; Sprei, 2018; Yu et al., 2017). Hall et al. (2021) also note that such a shift could contribute to the acceleration of BEV adoption among the general population by increasing public awareness and exposure to these vehicles. Although BEVs offer the potential for reduced fuel and maintenance costs, driving range, relatively high upfront costs, and a lack of access to charging infrastructure can serve as barriers to the adoption of these vehicles (Moniot et al., 2019; Rajagopal & Yang, 2020; Weiss et al., 2019).

Despite the potential benefits, relatively little is known about the factors influencing the adoption of BEVs among ridehailing drivers or the barriers to the greater adoption of BEVs. Additionally, while there are numerous federal, state, and local incentives that aim to encourage BEV adoption, the awareness, utilization, and impacts of these incentives among ridehailing drivers remain unclear. More broadly, there is a dearth of studies examining the factors influencing vehicle fuel type choices among ridehailing drivers and how these factors could vary across different segments of drivers. In particular, the determinants of fuel type choices could differ based on whether the vehicle was obtained with the intention of using it to provide ridehailing services. Similarly, the impacts of incentives on fuel type choices could differ based on whether the vehicle registered on the TNC platform was obtained with the intention of using it to provide ridehailing services.

This chapter presents the results of an investigation into the factors influencing fuel type choices, differences in the determinants of fuel type choices among various segments of ridehailing drivers, and the potential impacts of increasing familiarity with incentives on the uptake of BEVs. Three research questions are addressed in this chapter: 1) What factors influence the decision to obtain a vehicle with the intention of using it to provide ridehailing services (referred to hereafter as *ridehailing intention*)? 2) What are the determinants of vehicle fuel type choices and how do they differ among those who do and do not exhibit ridehailing intention? 3) How can incentives and the availability of BEV chargers contribute to the greater uptake of BEVs among ridehailing drivers? The findings presented in this chapter offer insights into the factors influencing fuel type choices among ridehailing drivers and the extent to which key policy levers can contribute to the greater uptake of BEVs. This information can inform initiatives to accelerate the transition from ICEVs to BEVs among ridehailing drivers.

8.2 Data and Methods

The analysis presented in this chapter used data collected through the first wave of the survey. Similar to the analysis presented in Chapter 7, variables pertaining to the highest level of charger that was perceived as being available in a given location and variables capturing the highest level of familiarity with federal and state BEV-related incentives were defined prior to the analysis. The data from the first wave of the survey was supplemented with information from two additional datasets to facilitate a more comprehensive examination of the determinants of fuel type choices. First, information on population density and employment density at one's residential neighborhood were obtained from the *Smart Location Database* that is maintained by the U.S. Environmental Protection Agency (see Chapman et al. (2021) for more information). The continuous density measures were converted into categorical variables with three levels based on the distributions of these measures in California – low (33rd percentile value and below), medium (between the 34th to 66th percentile values), and high (67th percentile value and above). Second, information regarding the percentage of registered vehicles that are BEVs in a given ZIP code was obtained from the U.S Department of Energy (U.S. Department of Energy, 2024). The inclusion of this information in the analysis facilitates the exploration of the so-called *EV neighborhood effect*, which refers to the potential for perceptions towards BEVs to be influenced by one's neighbors.

An integrated choice and latent variable (ICLV) model was estimated to examine the factors influencing vehicle fuel type choices. As shown in Figure 8-1, the ICLV model consists of two components – the latent variable model (which is comprised of a structural and a measurement model) and a choice model (Abou-Zeid & Ben-Akiva, 2014; Ben-Akiva et al., 2002).

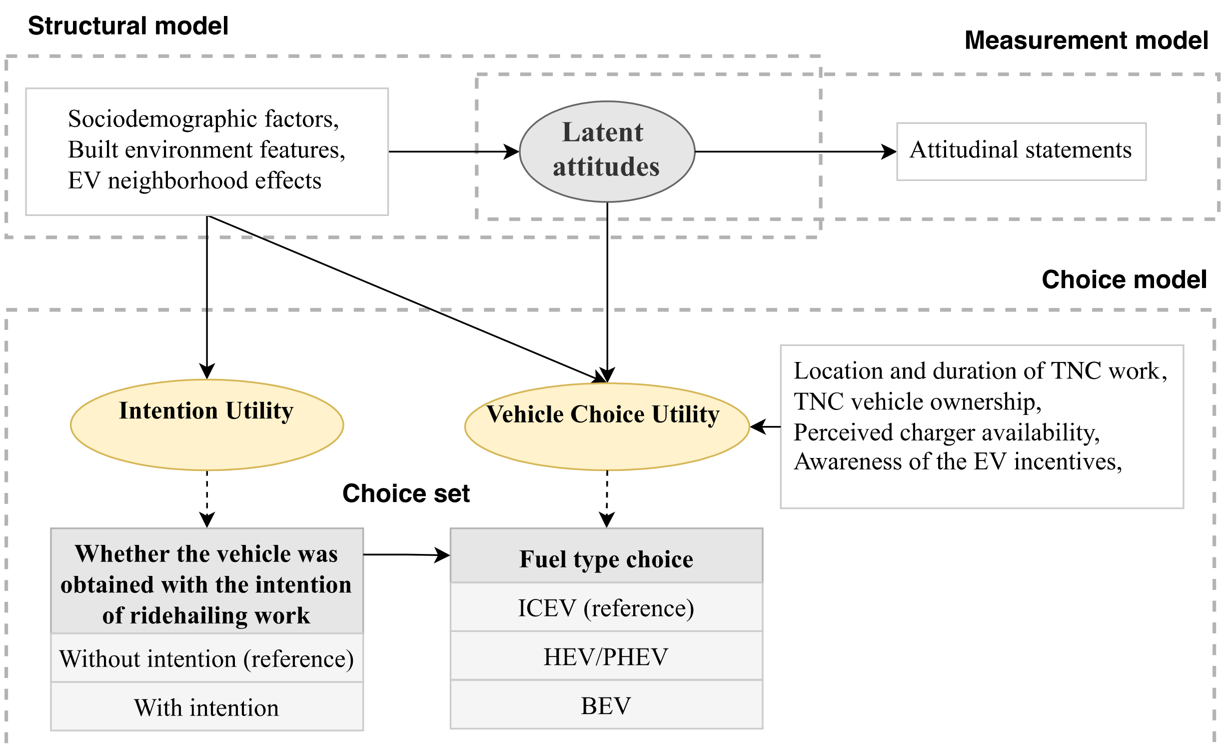

Figure 8-1 Overview of the ICLV model estimated as part of this analysis

The structure of the ICLV model facilitates an examination into the influence of observable attributes on the latent attitudes of drivers and the impacts of said attitudes on vehicle fuel type choices. Within the modelling framework, responses to attitudinal questions (also referred to as *indicator variables*) are assumed to be a manifestation of latent attitudes. The measurement model component of the ICLV model captures the relationship between the indicator variables ($\boldsymbol{l_i}$) and the latent attitudinal variables ($\boldsymbol{x_i^*}$) for individual i (Vij & Walker, 2016):

$$\boldsymbol{l_i} = \boldsymbol{D}'\boldsymbol{x_i^*} + \boldsymbol{\eta_i} \tag{8.1}$$

Where:

$\boldsymbol{D}$ is a matrix of factor loadings that capture the relationships between the indicators and latent variables

$\boldsymbol{\eta_i}$ is a vector of random error terms that are normally distributed with a mean of 0

The other component of the latent variable model – the structural model – captures the influence of observable attributes ($\boldsymbol{s_i}$) on the values of latent attitudinal variables for individual i (Vij & Walker, 2016):

$$\boldsymbol{x_i^*} = \boldsymbol{A}'\boldsymbol{s_i} + \boldsymbol{\nu_i} \tag{8.2}$$

Where:

$\boldsymbol{A}$ is a matrix of parameters that capture the influence of the observable attributes on the latent variables

$\boldsymbol{\nu_i}$ is a vector capturing measurement errors that are normally distributed with a mean of 0

The choice model component of the ICLV model consists of two components – a binary logit model corresponding to whether the vehicle was acquired with the intention of using it to provide ridehailing services and two multinomial logit (MNL) models corresponding to the fuel type of the vehicle. Let r_i be a binary variable denoting whether individual i does ($r_i = 1$) or does not ($r_i = 0$) exhibit ridehailing intention. The utility derived by individual i obtaining their vehicle with the intention of using it to provide ridehailing services is defined as:

$$U_i^{r_i} = \begin{cases} \boldsymbol{\beta}^{\boldsymbol{r_i}\prime}\boldsymbol{s_i^{r_i}} + \varepsilon_i^{r_i} & for\ r_i = 1 \\ 0 + \varepsilon_i^{r_i} & for\ r_i = 0 \end{cases} \tag{8.3}$$

Where:

$\boldsymbol{\beta}^{\boldsymbol{r_i}}$ is a vector of parameters that capture the influence of the observable attributes on the utility derived from exhibiting ridehailing intention r_i

$\boldsymbol{s_i^{r_i}}$ is a vector of observable attributes corresponding to individual i that influences the utility they derive from exhibiting ridehailing intention

$\varepsilon_i^{r_i}$ are the unobserved (i.e., random) components of the utility associated with exhibiting ridehailing intention; these terms are independent and identically distributed and follow the Gumbel distribution

The two MNL models are conditional on whether individual i does or does not exhibit ridehailing intention. The utility obtained by individual i obtaining fuel type j given that they exhibit ridehailing intention r_i is defined as:

$$U_{ij|r_i}^{f} = \boldsymbol{\beta}_{j|r_i}^{f}{}'\boldsymbol{s}_i^{f} + \boldsymbol{\Gamma}_{j|r_i}^{f}{}'\boldsymbol{x}_i^{*} + \varepsilon_{j|r_i}^{f} \tag{8.4}$$

Where:

$\boldsymbol{\beta}_{j|r_i}^{f}$ is a vector of parameters that capture the influence of the observable attributes on the utility derived from choosing fuel type j, given that they exhibit ridehailing intention r_i

$\boldsymbol{s}_i^{f}$ is a vector of observable attributes corresponding to individual i that influence the utility they obtain by choosing fuel type j

$\boldsymbol{\Gamma}_{j|r_i}^{f}$ is a vector of parameters that capture the influence of the latent attitudinal variables on the utility derived from choosing fuel type j, given that they exhibit ridehailing intention r_i

$\boldsymbol{x}_i^{*}$ is a vector of latent attitudinal variables corresponding to individual i that influence the utility they obtain by choosing fuel type j

$\varepsilon_{j|r_i}^{f}$ are the unobserved (i.e., random) components of the utility associated with exhibiting ridehailing intention; these terms are independent and identically distributed and follow the Gumbel distribution

The probability of individual i exhibiting ridehailing intention r_i and choosing fuel type j is defined as:

$$P_i(r_i, j) = P_i(r_i) * P_i(j|r_i) \tag{8.5}$$

Where:

$P_i(r_i)$ is probability of individual i exhibiting ridehailing intention r_i

$P_i(j|r_i)$ is the conditional probability of individual i choosing fuel type j, given that they exhibit ridehailing intention r_i

In the choice model, not exhibiting ridehailing intention $(r_i = 0)$ and choosing an ICEV were defined as the reference outcomes for the binary logit and MNL models, respectively. The ICLV model was estimated using the *Apollo* package written for the R programming language (Hess & Palma, 2019). Using the final specification of the ICLV model, average treatment effects were calculated to examine the impacts of improvements in charger availability and familiarity with federal incentives on the uptake of BEVs among ridehailing drivers.

8.3 Results

8.3.1 Number and Fuel Types of Household and Ridehailing Vehicles

Respondents of the first wave of the survey were asked to provide information about the number of vehicles that they or anyone in their household had access to at the time of the survey. Next, drivers were asked to provide details about up to three vehicles that they had registered with a TNC, starting with the vehicle they used to provide the most rides. In total, the 1,099 respondents considered in this analysis provided information about 1,218 vehicles. As outlined in Figure 8-2, approximate equal proportions (40%) of respondents indicated that their household had access to 1 and 2 vehicles. In contrast, almost 90% of respondents indicated that they had one vehicle registered with a TNC.

The ten most common fuel type combinations of vehicles that respondents had registered with a TNC are summarized in Table 8-1. The three most common combinations correspond to a single ICEV being registered with a TNC, followed by a single hybrid electric vehicle (HEV) and BEV. In terms of the registration of multiple vehicles, the most common fuel type combination was the registration of two ICEVs, followed by an ICEV and a BEV, two BEVs, and one PHEV and one BEV.

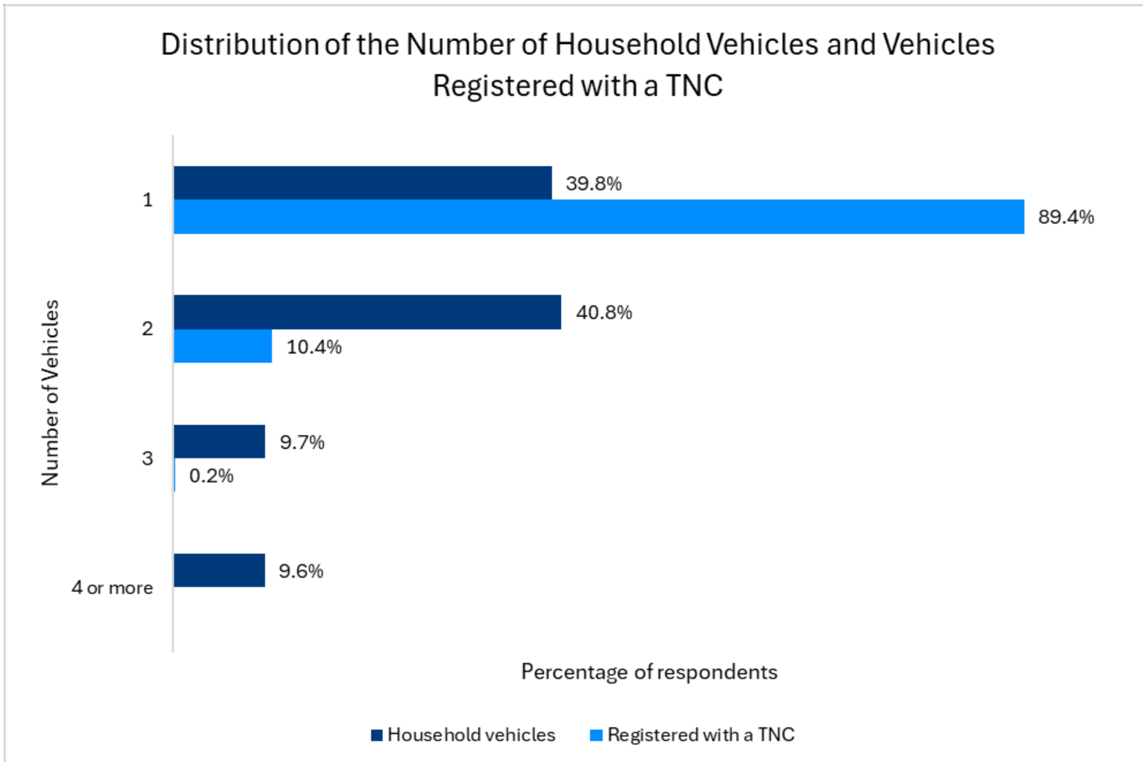

Figure 8-2 Comparison of household vehicles and vehicles registered with a TNC (N = 1,099)

Table 8-1 Ten most common fuel type combinations for vehicles used to provide ridehailing services. The fuel type of the vehicle used to provide the most rides is listed first (N = 1,099)

Rank	Fuel Type Combination	Percentage
1	ICEV	58.2%
2	HEV	15.3%
3	BEV	12.1%
4	ICEV, ICEV	3.9%
5	PHEV	3.8%
6	ICEV, BEV	1.8%
7	BEV, BEV	1.1%
8	PHEV, BEV	1.1%
9	BEV, ICEV	0.8%
10	ICEV, HEV	0.5%

Notes:

ICEV: internal combustion engine vehicle
HEV: hybrid electric vehicle
BEV: battery electric vehicle
PHEV: plug-in hybrid electric vehicle

8.3.2 Factors Influencing Fuel Type Choices

To gain insights into the motivations for using vehicles of a given fuel type to provide ridehailing services, drivers were asked several questions regarding their fuel type choices. First, respondents were asked to identify up to three reasons why they chose to use each of their registered vehicles to provide ridehailing services. As shown in Figure 8-3, the reasons for using a given vehicle differ based on the fuel type of said vehicle.

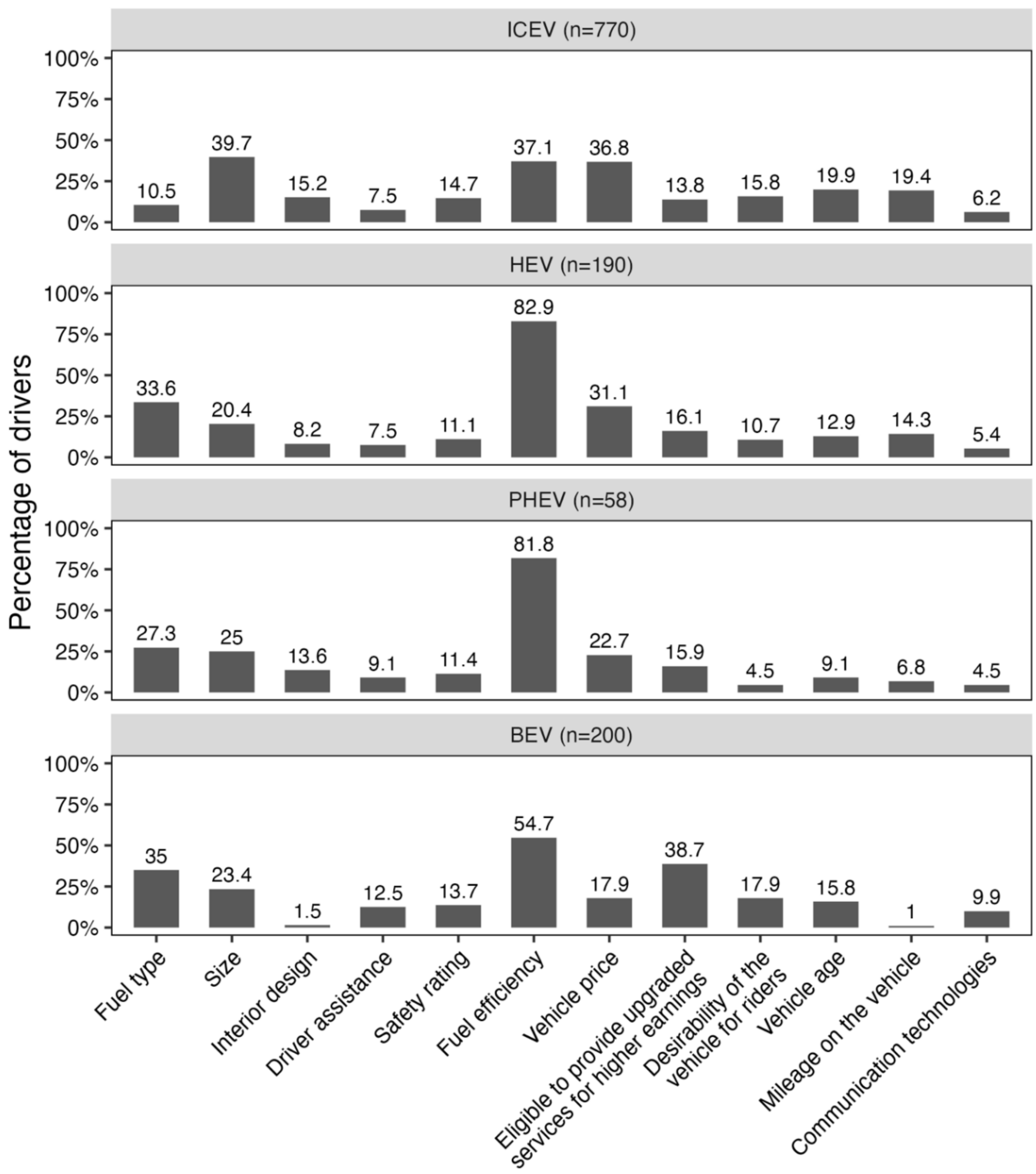

Figure 8-3 Reason(s) for using a given vehicle to provide ridehailing services (N = 1,218)

For example, over 50% of respondents selected fuel efficiency one of the reasons they used HEVs, PHEVs, and BEVs to provide ridehailing services. In contrast, size, fuel efficiency, and price were the most common reasons for using an ICEV, although these reasons were only selected by approximately 40% of ICEV drivers. With regards to BEVs, the potential eligibility to provide upgraded services (such as Uber Comfort Electric or Lyft Green) and fuel type were also among more common reasons for using these vehicles to provide ridehailing services.

Additionally, respondents who indicated that they had an EV (either a BEV or PHEV) registered with a TNC were asked to identify up to three reasons for choosing to use these vehicles to provide ridehailing services. As outlined in Figure 8-4, the desire to save money on fuel was the most commonly cited reason for using an EV, followed by the desire to save money on maintenance and potential access to cheaper or priority parking. These results are consistent with the findings of Sanguinetti & Kurani (2021), who explored motivations for using EVs to provide ridehailing services in the United States and Canada. Roughly one-quarter of respondents also cited environmental concerns and the potential to receive incentives from TNCs as reasons why they chose to use an EV.

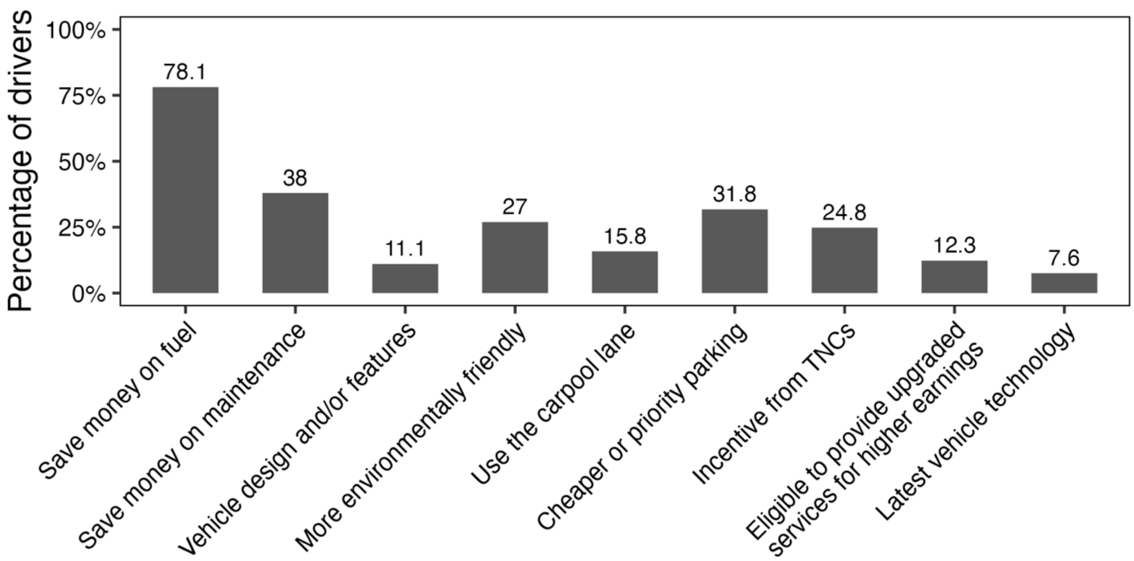

Figure 8-4 Reason(s) for using a BEV or PHEV to provide ridehailing services (N = 233)

Furthermore, respondents who indicated that they had at least one PHEV and no BEVs registered with a TNC were asked to select up to three reasons for using a PHEV rather than a BEV. As shown in Figure 8-5, the most common response selected by drivers was related to range anxiety, followed by wanting to avoid mid-shift charging and insufficient access to chargers where they drive. Finally, respondents did not use a PHEV or BEV to provide ridehailing services despite their households having access to such vehicles were asked to select up to three reasons(s) for this decision. As shown in Figure 8-6, the overwhelming majority of respondents indicated that the PHEV or BEV was used by another member of the household.

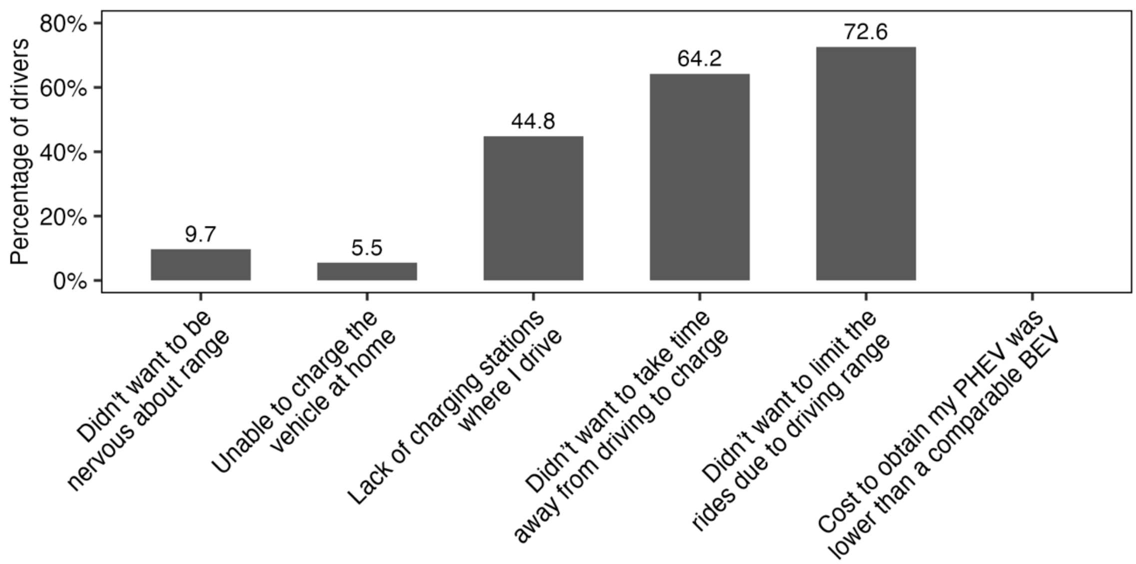

Figure 8-5 Reason(s) for using a PHEV to provide ridehailing services rather than a BEV (N = 45)

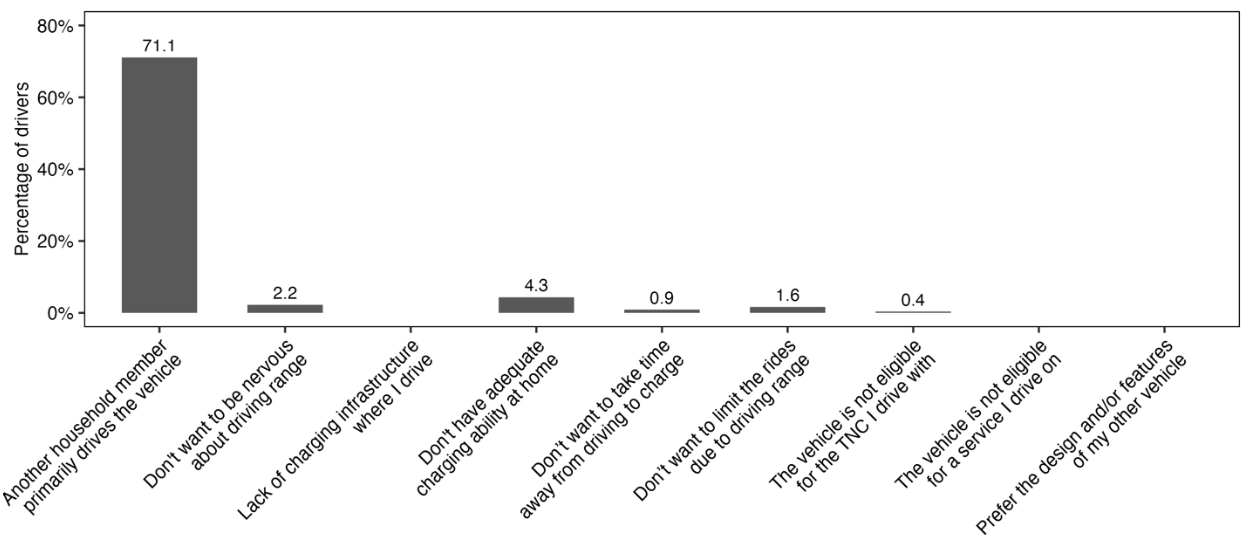

Figure 8-6 Reason(s) for not using a PHEV or BEV to provide ridehailing services despite having access to these vehicles (N = 22)

8.3.3 ICLV Model

Given that almost 90% of respondents indicated that they had a single vehicle registered with a TNC, the ICLV model estimated as part of this analysis focused on the fuel type of the vehicle that was used to provide the most rides. Additionally, HEVs and PHEVs were grouped together in this analysis due to the relatively low proportion of PHEVs in the dataset and their similarity to HEVs. The distribution of the fuel type of these vehicles, broken down by whether it was obtained with or without the intention of using it to provide ridehailing services, is presented in Figure 8-7. The results of the chi-squared test suggest that the differences in the distributions of fuel type between vehicles that were and were not obtained with the intention of being used to provide ridehailing services are statistically significant at the 1% significance level.

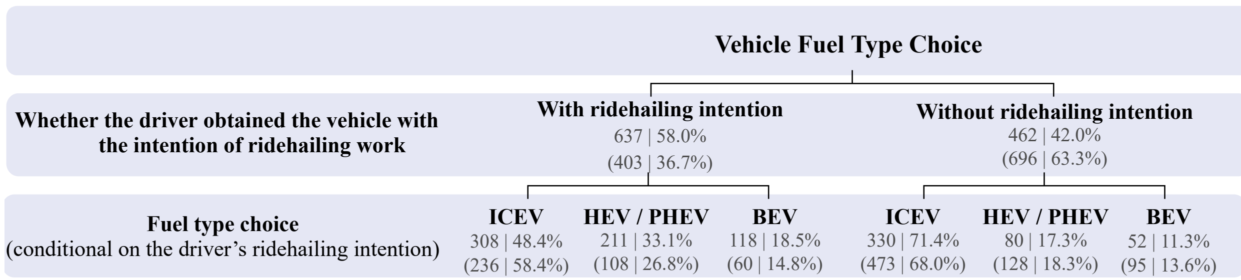

Figure 8-7 Distribution of fuel types, by ridehailing intention (N = 1,099)

As part of the model estimation process, numerous variables pertaining to socio-demographic characteristics, perceived access to chargers, familiarity with federal and state incentives, driver characteristics, population density, employment density, and the EV neighborhood effect were tested. Given that the survey did not ask drivers whether they used a federal, state, or local incentive to obtain the vehicle(s) they have registered with a TNC, drivers who indicated that they have used one of these incentives were omitted from the dataset that was used to estimate the ICLV model. The omission of these respondents addresses the potential for the use of incentives to be a strong predictor of BEV adoption by removing this confounding factor from the analysis. The decision of whether to retain a variable in the final specification of the ICLV model was determined based on the sign and significance of the corresponding parameters, as well as the findings of previous studies. The final estimates of the individual components of the ICLV model are presented and discussed in the following subsection.

8.3.3.1 Latent Variable Model

As part of the first wave of the survey respondents were asked to complete a series of questions indicating their level of agreement with a series of statements related to the use of BEVs to provide ridehailing services. Responses to these questions were collected using a five-point Likert scale, with the response options ranging from *strongly disagree* to *strongly agree*. The statements were determined based on the latent constructs that were developed as part of the *Theory of Planned Behavior* (Ajzen, 1991; Haustein & Jensen, 2018; Mohamed et al., 2016; Zhou et al., 2021). Using the responses to these questions (i.e., the indicator variables), confirmatory factor analysis (CFA) was applied to identify and evaluate the relationships between the indicator variables and the latent attitudinal factors. The results of the CFA (Tucker-Lewis Index = 0.90, Comparative Fit Index = 0.91, Standardized Root Mean Squared Residual = 0.06) satisfied established standards for goodness-of-fit measures, suggesting that the constructs identified by the Extended Theory of Planned Behavior were supported by the survey responses (Hu & Bentler, 1999).

Three latent attitudinal factors were found to have a statistically significant impact on vehicle fuel type choices – *EV attitude*, *EV subjective norm*, and *EV perceived barriers*. The final specification of the measurement model is presented in Table 8-2. The EV attitude factor is characterized by the belief that using a BEV to provide ridehailing services offers the potential benefits of lower energy costs, greater profits, cost savings, and lessened environmental impacts. The EV subjective norm factor is defined by the belief that ridehailing users have positive perceptions towards BEVs and that BEVs are viewed favorably by one's peers and the ridehailing industry as a whole. Finally, the EV perceived barriers factor is characterized by the belief that BEVs are impractical to provide ridehailing services, in part due to the limited range, (purchase) cost, and potential need for mid-shift charging.

Table 8-2 Final estimates of the measurement model component of the ICLV framework (N=989)

Latent Attitudinal Factor	Indicator	Estimate	t-stat.	p-value
EV attitude	Driving an electric vehicle for rideshare work would be beneficial to the environment in the long term.	0.75	14.32	<0.001***
	It is advantageous to drive an electric vehicle for rideshare work because of the low energy cost.	0.75	15.98	<0.001***
	I would increase my profits by driving an electric vehicle for my rideshare work.	0.74	15.02	<0.001***
	Driving an electric vehicle for rideshare work would eventually result in cost savings.	0.70	12.44	<0.001***
EV subjective norm	Riders are more satisfied with electric rideshare vehicles.	0.93	20.31	<0.001***
	More riders favor electric rideshare vehicles.	0.91	20.87	<0.001***
	Electric vehicles are viewed favorably in the rideshare industry.	0.83	18.71	<0.001***
	Some people who are important to me think I should have an electric vehicle for my rideshare work.	0.71	15.78	<0.001***
	I know rideshare drivers who are considering electric vehicles.	0.55	11.44	<0.001***
EV perceived barriers	The need for charging makes electric vehicles very unpractical for rideshare work.	0.75	14.34	<0.001***
	The driving range of electric vehicles is too short for my rideshare work.	0.78	14.18	<0.001***
	Using an electric vehicle would require careful planning of my activities as a rideshare driver.	0.52	10.55	<0.001***
	The price of an electric vehicle for rideshare work is too high.	0.43	8.48	<0.001***

Notes:

Significance levels: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

The final specification of the structural model, which offers insights into the impacts of observable variables on latent attitudinal factors, is presented in Table 8-3. Younger adults, those who live in a stand-alone house, and those who live in areas with greater population density tend to display more positive attitudes towards BEVs. This is consistent with the results of prior studies, which have noted that younger adults tend to be more environmentally conscious (Iogansen et al., 2023), residents of single-family homes tend to benefit more from access to home charging infrastructure

(Horesh et al., 2023), and that access to public chargers tends to be greater in areas with greater population density (Zou et al., 2020). Similarly, younger adults also tend to exhibit greater subjective norms, suggesting that they are more likely to believe that the use of BEVs to provide ridehailing services is viewed favorably. Additionally, living in a ZIP code with a higher percentage of registered vehicles that are BEVs was also positively associated with greater levels of the EV subjective norm factor, providing evidence of the so-called EV neighborhood effect. Finally, identifying as non-Hispanic White was found to be associated with greater likelihood of perceiving barriers to the use of BEVs to provide ridehailing services. This finding could stem from differences in the impacts of the relatively high upfront costs associated with BEV ownership across different socio-demographic groups. Conversely, living in an area with greater employment density was negatively associated with the perceptions of barriers to the use of BEVs to provide ridehailing services, possibly due to greater access to chargers in these locations.

Table 8-3 Final estimates of the structural model component of the ICLV framework (N=989)

	EV Attitude			EV Subjective Norm			EV Perceived Barriers		
Variable	**Estimate**	**t-stat.**	**p-value**	**Estimate**	**t-stat.**	**p-value**	**Estimate**	**t-stat.**	**p-value**
Age (reference: 18 to 34)									
35 to 54	-0.31	-3.18	0.002***	-0.28	-3.38	0.001***			
55 and older	-0.34	-3.08	0.002***	-0.28	-3.29	0.001***			
Race and ethnicity (reference: White alone)									
Non-Hispanic, other race(s)							0.07	0.65	0.516
Hispanic or Latino							0.17	1.57	0.117
Housing type (reference: multi-family house or apartment)									
Stand-alone house	0.22	2.04	0.042**						
EV share within residential ZIP code				3.90	2.77	0.006***			
Population density (reference: low or medium)									
High	0.26	2.38	0.017**						
Employment density (reference: low or medium)									
High							-0.28	-3.46	0.001***

Notes:

Significance levels: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

8.3.3.2 Choice Model

The choice model component of the ICLV model is comprised of an *intention model* and intention-specific *fuel type choice models*. The former is used to examine the factors influencing whether a given vehicle was acquired with the intention of using it to provide ridehailing services, while the latter is used to understand the determinants of fuel type choices and how they differ based on ridehailing intention. The final specification of the intention model is presented in Table 8-4, while the final specifications of the fuel type choice models are presented in Table 8-5. The results of the intention model suggest that older drivers, those who are not employed outside of ridehailing, those who do not own their home, and those who do not live in a stand-alone house were more likely to exhibit ridehailing intention.

Table 8-4 Final estimates of the intention model component of the choice model (reference: without ridehailing intention) (N=989)

Variable	Estimate	t-stat.	p-value
Age (reference: 18 to 34)			
35 to 54	0.80	5.75	<0.001***
55 and older	1.08	6.97	<0.001***
Employment outside of ridehailing (reference: unpaid or no other work)			
Full-time	-0.02	-0.16	0.873
Part-time	-0.76	-4.81	<0.001***
Housing tenure (reference: rented or provided by someone else)			
Owned	-0.46	-2.83	0.005***
Housing type (reference: multi-family house or apartment)			
Stand-alone house	-0.25	-1.81	0.071*
Goodness-of-fit statistics			
Number of observations		989	
LL(null model)		-685.52	
LL(final model)		-640.42	

Notes:

Significance levels: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

N(with ridehailing intention) = 576 and N(without ridehailing intention) = 413

The intention-specific fuel type choice models offer insights into the factors influencing vehicle fuel type choices among ridehailing drivers based on whether they exhibit ridehailing intention. With regards to latent attitudinal factors, EV attitude is positively associated with the probability of drivers who exhibit ridehailing intention choosing a BEV and negatively associated with the probability of these drivers choosing a PHEV or HEV. This could suggest that this segment of drivers view BEVs as more environmentally friendly and cost-effective compared to HEVs (which rely on gasoline) or PHEVs (which may require planning when allocating electric and gas mileage) (Zhou et al., 2021). Additionally, EV subjective norm was positively associated with the likelihood of PHEV or HEV adoption among drivers who exhibit ridehailing intention and BEV adoption irrespective of ridehailing intention. As expected, the EV perceived barriers factor was negatively associated with BEV adoption regardless of ridehailing intention, echoing the results of prior studies (Kaplan et al., 2016). Overall, these results suggest that perceptions of value and risk can influence vehicle fuel type choices among ridehailing drivers (Wood & Scheer, 1996).

Table 8-5 Final specification of the intention-specific fuel type choice models component of the choice model (N=989)

	With Ridehailing Intention (reference: ICEV)						Without Ridehailing Intention (reference: ICEV)					
	HEV/ PHEV			BEV			HEV/PHEV			BEV		
Variable	**Estimate**	**t-stat.**	**p-value**	**Estimate**	**t-stat.**	**p-value**	**Estimate**	**t-stat.**	**p-value**	**Estimate**	**t-stat.**	**p-value**
Intercept							-1.99	-5.97	<0.001***	-7.00	-7.63	<0.001***
Latent attitudinal factors												
EV attitude	-0.42	-2.98	0.003***	0.58	3.16	0.002***						
EV subjective norm	0.50	3.18	0.002***	1.02	3.95	<0.001***				0.51	1.68	0.093*
EV perceived barriers				-0.79	-3.46	0.001***				-1.17	-3.16	0.002***
Age (reference: 18 to 34)												
35 to 54	-0.80	-5.06	<0.001***	-2.53	-6.66	<0.001***						
55 and older	-0.56	-3.26	0.001***	-2.75	-6.90	<0.001***						
Race and ethnicity (White alone)												
Non-Hispanic, other race(s)				-1.25	-3.05	0.002***						
Hispanic or Latino				-1.15	-2.95	0.003***						
Student status (reference: non-student)												
Student										1.89	2.47	0.014**
BEV share within residential ZIP code							6.62	2.33	0.002***			
Method of obtaining vehicle (reference: ownership)												
Lease or rent through TNC rental program				2.65	6.44	<0.001***						
Home charger availability (reference: none)												
Level 1	0.68	2.23	0.026**							2.52	3.00	0.003***
Level 2	0.34	1.28	0.201							3.04	3.91	<0.001***
Available, but do not know the level)	0.28	1.05	0.294									

	With Ridehailing Intention						Without Ridehailing Intention					
	HEV/ PHEV			BEV			HEV/ PHEV			BEV		
Variable	**Estimate**	**t-stat.**	**p-value**	**Estimate**	**t-stat.**	**p-value**	**Estimate**	**t-stat.**	**p-value**	**Estimate**	**t-stat.**	**p-value**
Public charger availability (reference: none)												
Level 1 or level 2				-0.40	-0.74	0.459						
DC fast charger				1.10	3.28	0.001***						
Available, but do not know the level)				-2.23	-3.18	0.002***						
Familiarity with federal BEV incentives (reference: not at all familiar)												
Somewhat familiar				0.08	0.21	0.834				1.87	2.64	0.008***
Very familiar				1.13	2.47	0.014**				2.55	1.87	0.062**
Goodness-of-fit statistics												
Number of observations	576						413					
LL (null model)	-453.73						-632.80					
LL(final model)	-246.67						-477.48					

Notes:

Significance levels: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

With ridehailing intention: N(ICEV) = 301, N(HEV/PHEV) = 198, N(BEV) = 77

Without ridehailing intention: N(ICEV) = 320, N(HEV/PHEV) = 67, N(BEV) = 26

An interesting result derived from the ICLV model is that the impacts of socio-demographic characteristics on vehicle fuel type choices largely manifest themselves through the latent attitudinal factors. Among drivers that exhibit ridehailing intention, younger drivers and drivers who identify as White were more likely to adopt BEVs. This is consistent with previous studies, which have found that younger drivers tend to be more inclined to adopt ZEVs and that White drivers tend to be more likely to adopt BEVs (Chen et al., 2020). Among drivers who do not exhibit ridehailing intention, those who are also students were more likely to adopt BEVs, while living in an area with a greater share of registered vehicles being BEVs was associated with a greater likelihood of adopting PHEVs or HEVs. The latter also indirectly influences the likelihood of drivers who do not exhibit ridehailing intention adopting BEVs, through its influence on the EV subjective norm latent attitudinal factor. Notably, obtaining one's vehicle through a TNC rental program increased the probability of adopting BEVs among drivers who exhibit ridehailing intention despite these programs offering both ICEVs and EVs.

Perceived access to chargers was also found to influence vehicle fuel type choices among ridehailing drivers. However, the impacts of perceived access differed based on whether the vehicle was obtained with the intention of using it to provide ridehailing services and the location of the chargers. For example, access to home chargers was found to have a positive and statistically significant impact on the likelihood of BEV adoption among drivers who did *not* exhibit ridehailing intention. In contrast, access to chargers in public areas has a positive and statistically significant impact on the likelihood of BEV adoption among drivers who exhibited ridehailing intention. This distinction could be due to vehicles in the former category also being used for personal trips and potentially being used by other members of the household, whereas the ability to charge during a shift may be a more important consideration for vehicles in the latter category. Moreover, this result could arise from the positive impact of renting one's home on the likelihood of exhibiting ridehailing intention (see Table 8-4).

Familiarity with federal BEV incentives was also found to influence vehicle fuel type choices. In particular, being very familiar with federal BEV incentives was positively associated with the likelihood of BEV adoption irrespective of ridehailing intention. Additionally, being somewhat familiar with these incentives was positively associated with BEV adoption among drivers who did not exhibit ridehailing intention. Although the influence of familiarity with state and local incentives was also tested, the results suggest that the effects were not statistically significant.

8.3.4 Average Treatment Effects

Although the ICLV model offers insights into the factors influencing vehicle fuel type choices, the parameter estimates do not provide an indication of the relative impacts of the corresponding variable, especially between two driver segments (i.e., those with and without ridehailing intention). Understanding the magnitude of these impacts can help inform policies aiming to ensure that the goals of the CMS regulations are achieved. To gain insights into the impact of the explanatory variables on the uptake of BEVs, average treatment effects (ATEs) were calculated. In this analysis, ATEs corresponding to changes in the availability of chargers and familiarity with federal BEV incentives were calculated, as these variables are directly related to potential policy interventions. Four different intervention scenarios (I1 through I4) were tested by applying the ICLV model to predict the probability of each fuel type being chosen by each driver under the given intervention scenario. The ATE corresponding to the given scenario was then calculated by subtracting the average predicted probability of choosing the BEV alternative in the baseline scenario (I0) from that of the intervention scenario. The levels of intervention considered in this analysis are summarized in Table 8-6, while the policy interventions that were tested are outlined in Table 8-7.

The impacts of increasing access to chargers at home and in public areas and the impacts of improving familiarity with federal BEV incentives are presented in Figure 8-8. As expected, increasing access to chargers and familiarity with federal BEV incentives results in an increase in the market share of BEVs among the respective segments of drivers. Notably, in response to the policy interventions, the market share of PHEVs/ HEVs declines to a lesser extent than that of ICEVs. Additionally, it is important to note that the impact depends on the nature of the interventions and whether the driver exhibits ridehailing intention. With regards to increasing access to charging infrastructure, improving access to public chargers has a greater percentage point impact on the market share of BEVs among drivers who exhibit ridehailing intention than improving access to home chargers among drivers who do not exhibit ridehailing intention. Similarly, improving familiarity with federal BEV incentives has a greater impact on drivers who exhibit ridehailing intention (+10.0 percentage points) than on drivers who do not exhibit ridehailing intention (+3.3 percentage points).

Table 8-6 Levels of policy interventions applied in the average treatment effects analysis

Level of Intervention	Action [a]
Weak intervention (I1)	Transition 25% of drivers
Medium intervention (I2)	Transition 50% of drivers
Strong intervention (I3)	Transition 75% of drivers
Full intervention (I4)	Transition 100% of drivers

Notes:

[a] For I1, I2, and I3, the average treatment effect was calculated based on 500 random draws of X% of drivers from a given driver group

Table 8-7 Policy interventions tested as part of the average treatment effects analysis

Intervention Objectives [a]	Intervention Recipients [a]	Baseline Conditions (I0)	Intervention Methods [c]
Improve the availability of public chargers	Drivers who exhibit ridehailing intention (N = 576)	None: 26.3% Level 1 or level 2: 10.7% DC fast charger: 25.8% Available but unknown level [b]: 37.1%	Transition X% of drivers who indicated “none” or “level 1 or level 2” to “DC fast charger”
Improve the availability of home chargers	Drivers who do not exhibit ridehailing intention (N = 413)	None: 54.9% Level 1: 11.4% Level 2: 15.2% Available but unknown level [b]: 18.4%	Transition X% of drivers who indicated “none” or “level 1” to “level 2”
Increase familiarity with federal incentives	Drivers who exhibit ridehailing intention (N = 576)	Not at all familiar: 45.4% Somewhat familiar: 44.8% Very familiar: 9.8%	Transition X% of drivers who indicated “not at all familiar” or “somewhat familiar” to “very familiar”
Increase familiarity with federal incentives	Drivers who do not exhibit ridehailing intention (N = 413)	Not at all familiar: 44.1% Somewhat familiar: 43.7% Very familiar: 12.3%	Transition X% of drivers who indicated “not at all familiar” or “somewhat familiar” to “very familiar”

Notes:

[a] Intervention objectives and recipients were selected based on variables that had positive and statistically significant impacts on BEV adoption in the ICLV model

[b] Due to a lack of information, drivers who selected the “available unknown level” option with regards to the perceived availability of chargers were not considered when applying policy interventions

[c] Refer to Table 8-6 for the level of intervention

	Improving the availability of public chargers ("None" / "L1/L2" to "DCFC")			**Improving the availability of home chargers** ("None" / " L1" to "L2")		
	Drivers **with** the ridehailing intention			Drivers **without** the ridehailing intention		
	ICEV	HEV/PHEV	BEV	ICEV	HEV/PHEV	BEV
I0 (No intervention): original market share in %	*48.4*	*33.1*	*18.5*	*71.4*	*17.3*	*11.3*
I1 (Transition 25 of drivers): p.p. change	-0.8	-0.6	1.5	-0.8	-0.2	1.0
I2 (Transition 50 of drivers): p.p. change	-1.6	-1.3	2.9	-1.7	-0.4	2.1
I3 (Transition 75 of drivers): p.p. change	-2.5	-1.9	4.3	-2.5	-0.6	3.1
I4 (Transition 100 of drivers): p.p. change	-3.3	-2.5	5.7	-3.3	-0.7	4.0

	Increasing familiarity with federal incentives ("Not familiar" / "Somewhat familiar" to "Very familiar")					
	Drivers **with** the ridehailing intention			Drivers **without** the ridehailing intention		
	ICEV	HEV/PHEV	BEV	ICEV	HEV/PHEV	BEV
I0 (No intervention): original market share in %	*48.4*	*33.1*	*18.5*	*71.4*	*17.3*	*11.3*
I1 (Transition 25 of drivers): p.p. change	-1.4	-1.1	2.5	-0.6	-0.1	0.7
I2 (Transition 50 of drivers): p.p. change	-2.7	-2.1	4.9	-1.4	-0.3	1.7
I3 (Transition 75 of drivers): p.p. change	-4.2	-3.2	7.4	-2.0	-0.4	2.5
I4 (Transition 100 of drivers): p.p. change	-5.7	-4.3	10.0	-2.7	-0.6	3.3

Figure 8-8 Average treatment effects corresponding to changes in access to chargers and awareness of federal BEV incentives

9 Factors Influencing the Willingness to Consider Obtaining a Battery Electric Vehicle

9.1 Introduction

To help encourage the electrification of the ridehailing fleet, it is important to understand both the factors influencing the adoption of BEVs and the willingness to consider adopting a BEV. Theoretical frameworks of human behavior have noted that consideration is an important component of the decision-making process. For example, random utility theory assumes that individuals choose their preferred alternative from a set of options that they are considering (i.e., their consideration set) (Bierlaire et al., 2010). Correspondingly, this assumption implies that an individual will not choose an option that they have not considered or that they do not regard as a suitable option. Similarly, the Theory of Planned Behavior assumes that observed behaviors are a direct result of the intention to engage in said behavior (Ajzen, 1991). Consequently, understanding the factors that influence the willingness to consider obtaining a BEV and the willingness to consider using a BEV to provide ridehailing services are crucial components of ensuring that the goals of the CMS regulations are achieved.

Studies report the factors influencing BEV acceptance and the intention to purchase a BEV among ridehailing drivers, relatively little is known about the factors influencing the willingness to consider obtaining a BEV. When examining the outcomes of decision-making processes, deterministic criteria are often applied to identify the options that are and are not included in the consideration set (Ortúzar & Willumsen, 2011). However, this approach may be insufficient due to a lack of available information or the inherent subjectivity of these criteria. Given that ridehailing drivers typically use their own vehicles to provide ridehailing services, the willingness to consider obtaining a BEV is likely to differ based on socio-demographic characteristics and driver attributes. Moreover, the perceived availability of chargers and familiarity with BEV-related incentives could also influence the willingness to consider obtaining a BEV among ridehailing drivers.

This chapter presents the results of an investigation into the factors influencing the willingness to consider obtaining a BEV among drivers who indicated that they intend to add or replace vehicle(s) they have registered with TNCs within the next year. As part of this analysis, a Heckman sample selection model is estimated to understand the factors influencing the intention to add or replace vehicle(s) and the factors influencing the willingness to consider obtaining a BEV. The use of the Heckman sample selection model allows for the distinction to be made between factors that directly influence the willingness to consider obtaining a BEV and the factors that indirectly influence this outcome through their impacts on the intention to add or replace vehicle(s) within the next year. Two research questions are addressed in this chapter: 1) What factors influence the willingness to consider obtaining a BEV among ridehailing drivers? 2) Can familiarity with BEV-related incentives and the perceived availability of chargers influence this willingness? The results of this analysis offer insights into the factors that influence the willingness to consider a BEV among ridehailing drivers. This information can inform efforts aiming to improve the willingness of ridehailing drivers to obtain a BEV, which will contribute to efforts to electrify the ridehailing fleet in California.

9.2 Data and Methods

In this chapter, data collected through the first wave of the survey is analyzed. Similar to the analysis presented in Chapter 7 and Chapter 8, variables pertaining to the highest level of charger that was perceived as available in a variety of locations and the highest level of awareness with federal and state BEV-related incentives were defined. Several additional variables were also defined to support the goals of the analysis presented in this chapter. First, a binary variable corresponding to whether each respondent anticipated continuing to work as a ridehailing driver for at least the next year was defined. Next, a variable corresponding to the age of the oldest vehicle that each driver has registered with a TNC was defined. This was followed by the definition of a binary variable corresponding to whether the vehicle that is used to provide the most rides was leased or rented through a TNC rental partner. Moreover, a binary variable capturing whether each respondent currently had a BEV registered with a TNC was defined. To explore the potential for experience with EVs on the willingness to consider obtaining a BEV, a binary variable corresponding to whether each respondent had a PHEV registered with a TNC or indicated that they drove a BEV at least once in the past 12 months.

Finally, two binary variables were defined based on the respondents' intentions to add or replace vehicle(s) that they have registered with a TNC and their willingness to consider obtaining a BEV. The value of the former was defined to be equal to 1 if they indicated that they intended to add or replace one or more of the vehicles that they had registered with a TNC within the next year, and 0 otherwise. The value of the latter was defined to be equal to 1 if the respondent indicated that they would probably or definitely consider obtaining a BEV and 0 otherwise. As part of the survey, only respondents who indicated that they intended to add or replace vehicle(s) were asked about their willingness to consider obtaining a BEV.

Descriptive analysis was applied to explore how the willingness to consider obtaining a BEV varies among different segments of drivers. Additionally, a Heckman sample selection model was estimated to jointly analyze the factors influencing the intention to add/ replace vehicle(s) registered with a TNC and the willingness to consider obtaining a BEV. The Heckman sample selection model consists of two components – the selection model and the outcome model. Let z_i be a binary variable whose value is equal to 1 if individual i indicates their intention to add or replace a vehicle they have registered with a TNC in the next year, and 0 otherwise. In the selection model, z_i is assumed to be a manifestation of a continuous latent variable (denoted as z_i^*) that is modeled as a function of observable variables (Greene, 2012):

$$z_i^* = \mathbf{\Gamma}'\boldsymbol{x_i} + u_i \tag{9.1}$$

Where:

$\boldsymbol{x_i}$ is a vector of observable variables corresponding to individual i

$\mathbf{\Gamma}$ is a vector of parameters that capture the influence of observable variables on z_i^*

u_i is a random error term corresponding to z_i^*

The probability of individual i indicating their intention to add or replace vehicle(s) that they have registered with a TNC is defined as:

$$P(z_i = 1) = \Phi(\mathbf{\Gamma}'\boldsymbol{x_i}) \tag{9.2}$$

Where:

Φ is the standard normal distribution

Similarly, let y_i be a binary variable whose value is equal to 1 if individual i indicated their willingness to consider obtaining a BEV, and 0 otherwise. In the outcome model, y_i is assumed to be a manifestation of a continuous latent variable (denoted as y_i^*) that is modeled as a function of observable variables:

$$y_i^* = \boldsymbol{\beta}' \boldsymbol{s_i} + \varepsilon_i \tag{9.3}$$

Where:

$\boldsymbol{s_i}$ is a vector of observable variables corresponding to individual i

$\boldsymbol{\beta}$ is a vector of parameters that capture the influence of observable variables on y_i^*

ε_i is a random error term corresponding to y_i^*

The probability of individual i being willing to consider obtaining a BEV is given by:

$$P(y_i = 1|z_i) = \begin{cases} \Phi(\boldsymbol{\beta}' \boldsymbol{s_i}) & if\ z_i = 1 \\ 0 & if\ z_i = 0 \end{cases} \tag{9.4}$$

In the Heckman selection model, the error terms u_i and ε_i are assumed to follow the bivariate normal distribution, with mean values of 0, variances of 1, and a correlation denoted by ρ (Galimard et al., 2018):

$$\begin{bmatrix} u_i \\ \varepsilon_i \end{bmatrix} = \Phi_2 \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right) \tag{9.5}$$

Where:

Φ_2 is the bivariate normal distribution

The unconditional probability of observing outcomes $z_i = Z$ and $y_i = Y$ is defined as:

$$P(z_i = Z, y_i = Y) = \begin{cases} 1 - \Phi(z_i = 1) & if\ Z = 0 \\ \Phi_2(-\boldsymbol{\beta}' \boldsymbol{s_i}, \boldsymbol{\Gamma}' \boldsymbol{x_i}, -\rho) & if\ Z = 1\ and\ Y = 0 \\ \Phi_2(\boldsymbol{\beta}' \boldsymbol{s_i}, \boldsymbol{\Gamma}' \boldsymbol{x_i}, \rho) & if\ Z\ = 1\ and\ Y = 1 \end{cases} \tag{9.6}$$

The Heckman sample selection model was estimated using the *sampleSelection* package written for the R programming language (Toomet & Henningsen, 2008).

9.3 Results

9.3.1 Differences in Willingness to Consider Battery Electric Vehicles by Driver Group

As shown in Figure 9-1, approximately 17.3% of respondents indicated that they would add or replace vehicle(s) that they had registered with a TNC within the next year. Among this subset of respondents, almost two-thirds indicated that they would be willing to consider a BEV, while over 50% would be willing to consider a gasoline hybrid or gasoline vehicle (see Figure 9-2). This is an encouraging result, as it suggests that drivers are likely to consider BEVs when they are considering obtaining a vehicle to provide ridehailing services. Additionally, variations in the willingness to consider obtaining a BEV were examined across different segments of drivers.

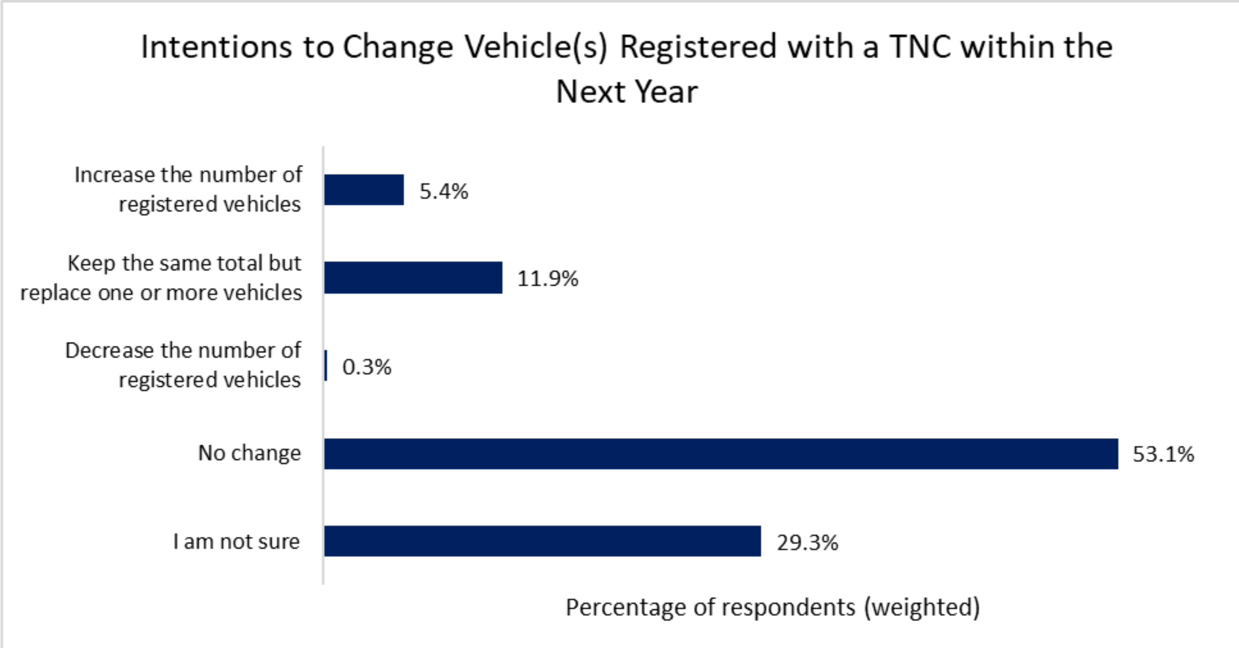

Figure 9-1 Intended changes to vehicle(s) registered with a TNC in the next year (N = 1,357)

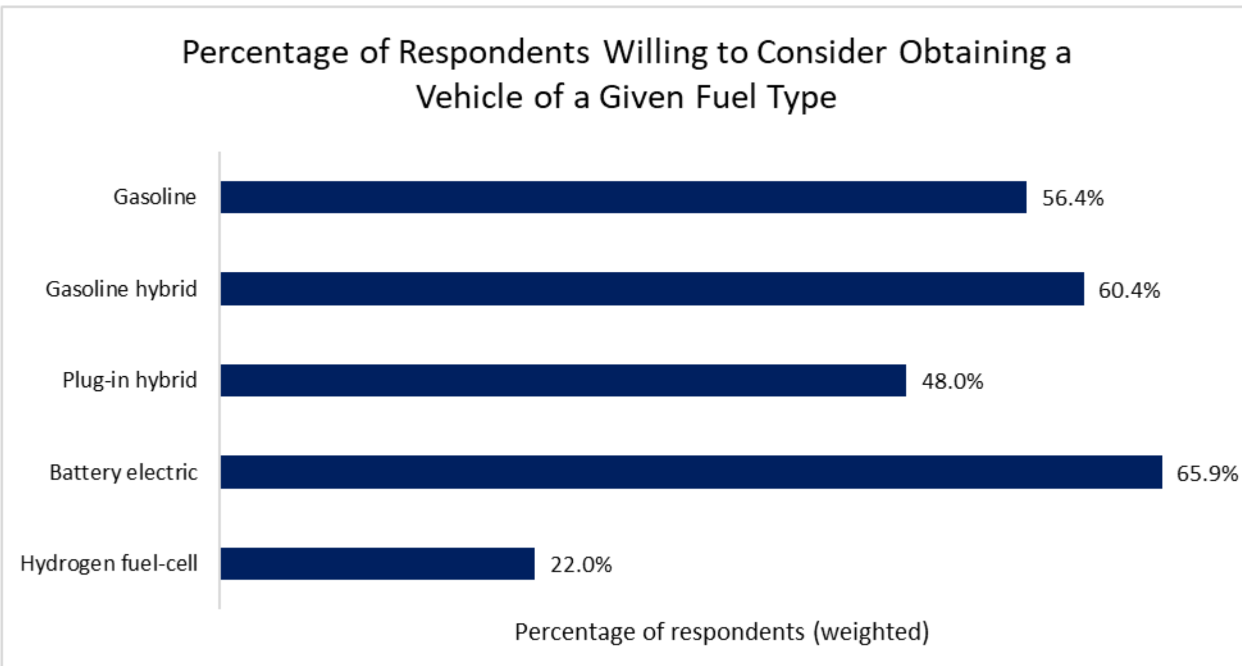

Figure 9-2 Willingness to consider obtaining a vehicle, by fuel type (N = 248)

As shown in Table 9-1, the willingness to consider a BEV differs based on income, driver attributes, and annual ridehailing mileage. For example, drivers from households earning between $50,000 and $99,999 annually had the highest likelihood of indicating that they were willing to consider obtaining a BEV. This could stem from the relative cost of a BEV compared to ICEVs and the potential cost savings offered by BEVs. With regards to driver status, the probability of being willing to consider obtaining a BEV decreases as the number of average weekly working hours increases. This trend could be related to the potential need to engage in mid-shift charging increasing as the number of hours spent providing ridehailing services increases. Additionally, drivers who have spent between 2 and 5.5 years on a TNC platform were least likely to indicate their willingness to consider obtaining a BEV. Notably, drivers with lower annual ridehailing mileage were more likely to indicate their willingness to consider obtaining a BEV than drivers with greater mileage. Similar to the trends observed with regards to driver status, this finding could reflect the relationship between mileage and the potential need to engage in mid-shift charging. Finally, drivers who used an ICEV to provide the majority of their rides were less likely to indicate a willingness to consider obtaining a BEV compared to drivers who used a PHEV, HEV, and BEV. This may reflect the potential for experience with using EVs to provide ridehailing services (or the lack thereof) to influence the willingness to consider obtaining a BEV.

Table 9-1 Willingness to consider obtaining a BEV, by driver segment (N = 248)

Variable	Category (Group Size)	Percentage of respondents (weighted)
Household income	Less than $50,000 (N = 85)	55.2%
	$50,000 to $99,999 (N = 109)	80.0%
	$100,000 and over (N = 54)	62.7%
Driver status	Occasional (N = 22)	77.2%
	Part-time (N = 71)	52.5%
	Full-time (N = 155)	48.5%
Years on TNC platform	Less than 2 years (N = 66)	68.7%
	2 to 5.5 years (N = 62)	57.9%
	Over 5.5 years (N = 120)	69.7%
Annual ridehailing mileage	Less than 25,000 mi. (N = 133)	66.4%
	25,000 to 49,999 mi. (N = 64)	73.9%
	50,000 to 74,999 mi. (N = 38)	55.5%
	75,000 to 99,999 mi. (N = 7)	37.5%
	100,000 mi. and over (N = 6)	33.3%
Fuel type of primary vehicle	Gasoline (N = 151)	62.3%
	Gasoline hybrid (N = 56)	65.4%
	Plug-in hybrid (N = 10)	94.0%
	Battery electric (N = 27)	76.8%
	Other (N = 4)	95.7%

9.3.2 Heckman Sample Selection Model

The final specification of the Heckman sample selection model is summarized in Table 9-2. During the model estimation process, variables related to socio-demographic characteristics, driver attributes, familiarity with BEV incentives, and perceived access to chargers were tested. The decision of whether to retain a variable in the final model was made based on the sign and statistical significance of the corresponding parameter.

The specification of the selection component of the Heckman sample selection model offers insights into the factors influencing the intention to add or replace vehicle(s). Respondents who did not identify as White were more likely to indicate their intention to add or replace vehicle(s) they had registered with a TNC, as were those who planned to continue to provide ridehailing services for at least the next year. In contrast, those who owned their home were less likely to indicate an intention to add or replace vehicle(s).

Table 9-2 Final estimates of the Heckman sample selection model

Variable	Estimate	t-stat.	p-value
Selection Model			
Intercept	-1.811	-12.253	<0.001***
Race and ethnicity (reference: White alone)			
Non-White	0.229	2.714	0.007***
Plans to continue working as a ridehailing driver (reference: less than one year)			
At least one year	0.139	1.685	0.092*
Housing tenure (rented or provided by someone else)			
Owned	-0.219	-2.484	0.013**
Age of oldest vehicle (yrs.)	0.067	5.893	<0.001***
Method of obtaining primary vehicle (reference: owned, borrowed, or other)			
Lease or rent through TNC rental program	0.293	2.247	0.025**
Experience using a PHEV to provide ridehailing services or driving an EV in the past year (reference: no)			
Yes	0.230	2.532	0.011**
Public charger availability (reference: none)			
Level 1 or level 2	0.299	2.841	0.005***
DC fast charger	0.324	3.336	<0.001***
Familiarity with federal BEV incentives (reference: not at all familiar or have used)			
Somewhat or very familiar	0.171	2.062	0.039**
Outcome Model			
Intercept	0.539	1.704	0.089*
Access to private or reserved parking at home (reference: no)			
Yes	0.412	2.756	0.006***
Ability to install a home BEV charger (reference: able to install)			
Unable to install	-0.297	-1.934	0.053*
Familiarity with federal BEV incentives (reference: not at all familiar)			
Somewhat familiar	0.218	1.287	0.198
Very familiar or have used	0.394	1.868	0.062*
At least one BEV currently registered with a TNC (reference: no)			
Yes	0.551	2.694	0.007***
Error term (ρ)	-0.774	-5.437	<0.001***
Goodness-of-fit statistics			
Number of observations		1,357	
LL(final model)		-756.11	
Akaike Information Criterion (AIC)		1,546.23	
Bayesian Information Criterion (BIC)		1,634.85	

Notes:

Significance levels: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Additionally, the age of the oldest vehicle registered with a TNC and obtaining one's primary vehicle through leasing or a rental program were positively associated with the likelihood of indicating an intention to add or replace vehicle(s) registered with a TNC. The former could reflect concerns about the mileage accumulated by vehicles that are used to provide ridehailing services, the better fuel efficiency of newer vehicles, or the vehicle age limits that tend to be imposed by TNCs. The latter result could stem from the relative flexibility to change vehicles that is offered by leasing and rental agreements. Interestingly, respondents who had at least one PHEV registered with a TNC or who had experience driving a BEV in the past year showed a higher likelihood of adding or replacing their current vehicle(s) registered on the TNC platform. Moreover, the perception that BEV chargers are available in public areas was positively associated with the likelihood of expressing an intention to add or replace vehicle(s) registered with a TNC. This may suggest that drivers regard the availability of chargers as a sign that charging infrastructure has reached a point where it can support their adoption of a BEV. Similarly, familiarity with federal BEV incentives was also found to increase the likelihood of expressing an intention to add or replace vehicle(s) registered with a TNC. This result could be a reflection of drivers who are planning to add or replace vehicle(s) researching available incentives.

The specification of the outcome model component of the Heckman sample selection model sheds light on the factors influencing the willingness to consider obtaining a BEV. For example, drivers who indicated that they had access to private or reserved parking at their residence were more likely to indicate their willingness to consider obtaining a BEV. This could be due to the impact of having access to private or reserved parking on the ability to install a home BEV charger. In contrast, respondents who indicated that they were unable to install a home charger were less likely to indicate their willingness to consider obtaining a BEV. Additionally, respondents who indicated that they were very familiar with or have used federal BEV incentives were more likely to indicate their willingness to consider obtaining a BEV. This likely stems from the tendency for those who have used or familiarized themselves with BEV incentives being open to the idea of using a BEV to provide ridehailing services. Finally, respondents who had at least one BEV registered with a TNC were more likely to indicate their willingness to consider obtaining a BEV. This is likely due to the experience that these drivers already have with using a BEV to provide ridehailing services. Moreover, this result could suggest that this subset of drivers believe that BEVs are capable of being used to provide ridehailing services.

10 Policy Brief: Conclusions and Key Findings

The Clean Miles Standard (CMS) regulations were implemented with the goal of addressing the environmental impacts of ridehailing services. Given that the composition of the ridehailing fleet is determined by the vehicle ownership and fuel type choices of ridehailing drivers, the success of the CMs regulations will ultimately depend on the willingness and ability of drivers to transition from internal combustion engine vehicles (ICEVs) to zero-emission vehicles (ZEVs). To support ongoing efforts to address the environmental impacts of ridehailing services, the research team partnered with the California Air Resources Board (CARB) and the California Public Utilities Commission (CPUC) to assess the current uptake of ZEVs among California ridehailing drivers and identify potential barriers to the transition from ICEVs to ZEVs. As part of this project, the research team conducted a multi-wave web-based survey of California ridehailing drivers with the assistance of the two largest transportation network companies (TNCs) in California – Uber and Lyft. Stratified random sampling was used to recruit drivers to participate in the two waves of the survey, with Uber and Lyft distributing survey invitations to their drivers.

Statistical analysis methods were used to investigate the uptake of battery electric vehicles (BEVs) among California ridehailing drivers and explore both motivators and barriers to the greater adoption of BEVs. The results of descriptive analysis suggest that there are disparities in perceived access to chargers, the ability to install home chargers, and familiarity with ZEV-related incentives across different segments of ridehailing drivers – key policy levers that can be used to increase BEV adoption. Additionally, statistical and econometric models were used to understand the factors influencing BEV adoption, fuel type choices, and the willingness to consider obtaining a BEV. For example, perceived access to chargers in public areas and familiarity with federal BEV-related incentives were both found to increase the probability of a driver having at least one BEV registered with a TNC. Similarly, having access to a home charger increased the likelihood of using a BEV among drivers who *did not* obtain their vehicle with the intention of using it to provide ridehailing services, whereas having access to chargers in public areas had a similar effect among those who *did* obtain their vehicle with this intention. Familiarity with federal incentives also increased the likelihood of using a BEV irrespective of intention. Moreover, attitudes and perceptions towards the use of BEVs to provide ridehailing services were also found to influence fuel type choices. Finally, the inability to install a home charger reduced the probability of a driver being willing to consider a BEV for their next vehicle, while familiarity with federal BEV-related incentives had the opposite effect.

10.1 Perceptions of Charger Availability Influence the Uptake of Battery Electric Vehicles

The results presented in this report demonstrate the potential for the perceived availability of chargers to influence the uptake of BEVs and the decision to use a BEV to provide ridehailing services. Consequently, initiatives aiming to improve the availability of chargers have the potential to contribute to the greater uptake of BEVs among ridehailing drivers (and ultimately, help ensure that the goals of the CMS regulations are achieved). However, it is important that these initiatives do not treat ridehailing drivers as a monolith, as the efficacy of these initiatives is influenced by a variety of factors. For example, as demonstrated in Section 6.3.2, the ability to install a home charger differs based on where a driver lives and whether they own or rent their home.

Consequently, initiatives that focus solely on addressing barriers to the installation of home chargers are unlikely to have an impact on those who are unable to install a home charger. Similarly, the results presented in Section 8.3.3 suggest that the availability of home and public chargers affect the fuel type choice decisions of different segments of drivers. As a result, initiatives aiming to improve perceived charger access should not focus solely on improving access to public chargers either.

In summation, initiatives aiming to improve access to chargers among ridehailing drivers should address access to both home and public chargers. As demonstrated by the results presented in Section 7.3.2, perceived access to level 2 or DC fast chargers in public areas and at home were both positively associated with the uptake of BEVs among ridehailing drivers. Additionally, these initiatives should include consultations with ridehailing drivers in order to gain insights into which approach is more effective: increasing access to public chargers in the areas where they live or the areas where they complete the majority of their rides. The insights gained through these consultations can help inform decisions about where to install charging stations in public areas. Finally, these initiatives should also aim to reduce disparities in charger access among different segments of drivers.

Efforts to make information regarding the locations of public chargers more easily accessible could also contribute to the greater uptake of BEVs among ridehailing drivers. The potential benefits of initiatives aiming to increase the number of available chargers are unlikely to be fully realized unless drivers are aware of where these chargers are located. Moreover, having access to information regarding the locations of chargers could help assuage range anxiety and support ridehailing drivers who wish to carefully plan their driving activities. One example of such an effort would be the development of a smartphone application that aggregates information on the locations of all public charging stations in a given area, irrespective of the entity responsible for maintaining the stations. The incorporation of this information into TNC platforms could also help improve perceptions regarding the availability of chargers in public areas. A web page containing the locations of all available public chargers within a given area could also have a similar impact, although it would likely be less convenient for drivers to use a web page to access this information while they are active on a TNC platform compared to a smartphone application.

10.2 Improving Familiarity with Incentives Will be Crucial to Achieve the Goals of the CMS Regulations

The provision of incentives is a key policy lever that can be used to help address financial barriers to obtaining a BEV and installing the associated charging infrastructure. However, the efficacy of any incentive is limited by the level of familiarity with the incentive. Simply put, an incentive cannot have its intended impact if its intended users are not aware that it exists. The results presented in this report suggest that familiarity with federal incentives was positively associated with the uptake of BEVs, the likelihood of using a BEV to provide ridehailing services, and the willingness to consider obtaining a BEV. However, as discussed in Section 5.3.1, the respondents' level of familiarity with federal, state, and local incentives was quite low. Moreover, the results presented in Section 6 suggest that familiarity with incentives tends to be lower among respondents from lower-income households.

As demonstrated in the results presented in Section 8.3.4, increasing the level of familiarity with federal incentives has the potential to increase the market share of BEVs among ridehailing driver.

Consequently, strategies aiming to ensure that the goals of the CMS regulations are met should include efforts to increase familiarity with federal, state, and local BEV-related incentives and address disparities in familiarity across different segments of drivers. Based on the results presented in Section 5.3.1, there does not appear to be a single method through which the majority of respondents learned about federal or state incentives. Consequently, efforts to increase drivers' familiarity with incentives would likely require a multi-faceted approach where information is disseminated through a variety of channels. As part of these efforts, government agencies should work with TNCs to gain a deeper understanding of how and where drivers learn about federal, state, and local BEV-related incentives. Government agencies should also identify and collaborate with organizations that are working to assist ridehailing drivers with the transition from ICEVs to BEVs to learn from their experiences and identify additional barriers to the greater uptake of BEVs.

Notably, the analysis that was completed as part of this report suggests that familiarity with state and local incentives did not have a statistically significant impact on BEV uptake or the decision to use a BEV to provide ridehailing services. Further work is required to understand the reasons for the differences between the impacts of federal vs. state and local incentives. Possible explanations for these differences could include the relatively lower levels of familiarity with state and local incentives compared to federal incentives, potential differences in how information regarding these incentives is disseminated, differences in the eligibility criteria for these incentives, or differences in the nature of the incentives themselves. Moving forward, the state of California could design its BEV-related incentives to complement federal incentives or alternatively it could design incentives to reinforce the strengths of existing federal incentives. Nevertheless, it will be crucial to ensure that drivers are aware of all available federal, state, and local incentives, particularly drivers from lower- and moderate-income households who these incentives are meant to support.

10.3 Installing Chargers in Areas with Higher Ridehailing Demand Could Help Address Concerns About Mid-shift Charging

Public charging infrastructure has the potential to play an important role in supporting the electrification of the ridehailing fleet. As discussed in Section 5.3.2 over 50% of respondents indicated that they do not have access to a home charger, meaning that they would need to rely on public chargers if they were to use a BEV to provide ridehailing services. However, charging stations are not always located in areas of high ridehailing demand. For example, Khan et al. (2022) noted that the availability of BEV chargers in New York City was positively associated with the presence of highways in a given ZIP code while population density did not influence availability. This relationship between population density and charger availability could adversely impact the uptake of BEVs among ridehailing drivers, given that the generation of ridehailing trips tend to be greater in areas where population density is higher (Ghaffar et al., 2020; H. Yu & Peng, 2019). In particular, this disparity could result in drivers having to travel to a charging station while they are not transporting a passenger. This form of deadheading would contribute to greater VMT among ridehailing drivers and increase the inconvenience and potential earnings loss associated with mid-shift charging interruptions.

To help reduce the potential for charging-related deadheading, government agencies should work with TNCs to understand drivers' preferences for where and when they prefer to charge their vehicles. These consultations with drivers can help determine whether resources should be invested in improving the availability of public chargers in the areas where the drivers live or the areas where they tend to serve rides. Examples of the former could include strategically locating charging stations in areas where the majority of residents are renters or where the majority of residences are multi-family homes. Examples of the latter could include offering discounted rates for ridehailing drivers or establishing exclusive charging stations for ridehailing vehicles. Ensuring that public chargers are available in areas where ridehailing demand is relatively high can help assuage concerns regarding mid-shift charging and the need to carefully plan driving activities when using a BEV to provide ridehailing services. While these interventions may not have a direct impact on the uptake of BEVs, they can help address barriers that may be preventing drivers from considering the use of a BEV.

10.4 Limitations

While the results of this project offer new insights into the current uptake of BEVs among California ridehailing drivers, the potential barriers to the greater uptake of BEVs, and the willingness to use BEVs to provide ridehailing services, there are several key limitations. First, the project relied on self-reported information from the survey respondents, which introduces the potential for recall errors to affect the reliability of the results. Moreover, the information provided by the respondents represents a snapshot of their characteristics at the time of the respective surveys. However, this information may not be fully reflective of their characteristics when they first registered their vehicle with a TNC. This discrepancy could affect the results derived from the binary logistic regression model presented in Section 7.3.2 and the ICLV model presented in Section 8.3.3.

Another key limitation relates to the process that was used to develop weights for the responses obtained through the two waves of the survey. For example, although both major TNCs in California invited drivers to participate in the first wave of the survey, only one TNC provided information on the distributions of the variables that were used in the weighting process. Consequently, the research team had to make the assumption that the distributions of these variables did not differ significantly between the two TNCs. Second, at the time of writing, the research team has been unable to obtain a similar dataset corresponding to drivers who were sampled for the second wave of the survey. As a result, the research team developed weights for respondents from the second wave of the survey using the data provided by the TNC following the completion of the first wave of the survey. This limitation could result in the weighted sample from the second wave of the survey representing the population of California ridehailing drivers to a lesser extent than the weighted sample from the first wave of the survey. Finally, the weighted dataset from the second wave of the survey included responses from respondents who also completed the first wave of the survey. This could adversely affect the extent to which the results derived from the weighted sample from the second wave of the survey can be representative of the population of California ridehailing drivers.

The final limitation is that the second wave of the survey was conducted one year after the first wave was completed. While this still facilitates an examination of changes in trends in the uptake of BEVs, attitudes towards the use of BEVs to provide ridehailing services, and barriers to greater BEV uptake, the time between the two waves of the survey may be too short to fully capture changes in perception and vehicle ownership. Obtaining an automobile tends to involve a multi-year commitment, particularly if it is purchased or financed. Consequently, while the information collected through the second wave of the survey provides early insights into the perception and uptake of BEVs following the implementation of the CMS regulations, additional work will be needed to more comprehensively understand the impacts of the regulations on BEV uptake among ridehailing drivers. Moreover, the second wave of the survey was conducted before the implementation of the Drivers Assistance Program by the CPUC, which could contribute to greater BEV uptake and reduced disparities in familiarity with incentives.

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