Accelerate Plug-in Electric Vehicles adoption via Understanding Household Adoption Decisions and Designing Sustainable Transportation Finance Policies

By

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ABSTRACT

The transportation sector has been a dominant contributor to greenhouse gas (GHG) emissions in the United States, contributing to 27% of GHG emissions in 2020 (EPA, 2022). In the last decade, vehicle electrification has rapidly taken place, especially in California. By the end of 2023, zero-emissions vehicles (ZEVs) consisted of 24% of all new car sales and accounted for around 5% of the total light-duty vehicles (LDVs) in the state (CEC, 2024). While vehicle electrification is an important strategy for reducing GHG emissions in the transportation sector, this fuel transition has implications for transportation infrastructure funding, which has traditionally been funded by motor fuel taxes. The transition from internal combustion engine vehicles (ICEVs) to ZEVs also invites research questions around the substitutions between these two technologies, especially at the household level. To explore these implications, this dissertation sets out to 1) explore the feasibility of implementing a per-mile road-usage charge (RUC) in replacement of the motor fuel taxes, 2) estimate the changes in vehicles-miles travelled (VMT) and the revenues generated from motor fuel taxes under the backdrop of vehicle electrification, and 3) quantify the effects of vehicle class and fuel type portfolios in ZEV-adopting households' vehicle replacement decisions.

In the first project, the feasibility of integrating RUC programs and tolling was explored to identify potential opportunities to reduce operating and administrative costs. Semi-structured interviews were conducted with experts from tolling programs across the U.S. to identify areas of overlap between tolling and RUC. The interview findings are leveraged to inform the criteria of a multi-criteria decision analysis (MCDA) to evaluate how well the state-level RUC pilots and programs can integrate with tolling systems. The results demonstrate that there are numerous mutual benefits of a RUC-tolling integration. Both the tolling industry and RUC implementations can benefit from the increased scale of operations and the spur of technical innovations, which would reduce administrative costs. RUC programs can also learn from the tolling industry on addressing data privacy and security issues. Lastly, an area that is highly

relevant in the rate design of RUC is ensuring equity by alleviating financial burdens on low-income populations and ensuring that unbanked and underbanked populations have access to the system.

In the second project, a time-series model is constructed to estimate state-level VMT in California from 2023 to 2030. The model is fitted on county-level sociodemographic and public roadway data, and the model specification which maximize the log-likelihood is an autoregressive integrated moving average (ARIMA) model with two lags of VMT, one-period error term and two lags of explanatory variables. The estimated VMT is leveraged to compute the gasoline excise tax revenues under three scenarios: 1) baseline scenario assuming a constant market share of ZEVs, 2) modest market growth of ZEVs, and 3) more aggressive market growth of ZEVs. The results demonstrate that under both scenarios of modest and aggressive ZEV market growths, the gap in gasoline excise tax would continue to widen between the present and 2030. By 2030, the revenue loss is expected to be around $0.23 billion. To address revenue shortfalls, re-creating the linkage between road usage and payment is a crucial policy solution. The per-mile LDV RUC rate is 3 cents/mile based on the results from this study. Future research will focus on refining the specification of the time-series regression model to explicitly estimate how the cost of driving and potential technological innovations such as autonomous vehicles affect VMT.

Finally, the last project employs a vehicle transaction model to account for vehicle portfolio preferences when households decide to replace one of their vehicles with a plug-in electric vehicle (PEV). A sample of two-vehicle and PEV-adopting Californian households' vehicle transactions from 2017 to 2020 was examined via a mixed multinomial logistic regression. The results demonstrate that there are strong complementarities among certain vehicle classes in a two-vehicle household portfolio. Namely, when adopting a PEV, households are more likely to pair a car with a large truck or a SUV than pairing a car with a car. Fuel type complementarities are also observed as households prefer to own a PEV and an ICEV rather than a PEV-PEV portfolio. Our dataset did not include plug-in electric trucks as they became available for sale in the United States in 2021. Future research should collect data on households who have adopted an electric truck and to understand the changes in preference parameters for vehicle class portfolios once the availability of plug-in electric trucks has increased. The implications of this work are two-fold: to estimate PEV-adopting households' preference parameters for vehicle portfolios and to highlight the importance of vehicle portfolio complementarities in projecting future household vehicle fleet compositions in California.

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Chapter 1. Introduction

Climate change is one of the direst challenges of the twenty-first century, bringing about rapid changes to our natural environments and an increase in the frequency and intensity of extreme climate events (IPCC, 2022). To mitigate the impacts of climate change, significant reductions of greenhouse gases (GHG) emissions are crucial. In the United States, transportation sector is the largest contributor of GHG emissions, accounting for 27% of its total GHG emissions in 2020 (EPA, 2022). Within the transportation sector, GHG emissions from light-duty vehicles (LDVs) account for 57% of all transportation-related emissions (EPA, 2022). Curbing GHG emissions from LDVs by electrifying them would yield significant climate benefits. To accomplish this, the United States have implemented a suite of policies at the federal and State level to incentivize the adoption of plug-in electric vehicles (PEVs), including both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). Most recently at the federal level, the Inflation Reduction Act of 2022 institutionalized tax credits of up to $7,500 for both new and used PEVs, for both residential and commercial uses (Congressional Research Service, 2022). In addition to the financial incentives being implemented at the federal level, some States have implemented policies to promote PEVs adoption, especially California.

To promote the adoption of PEVs, California implemented a suite of policies including two major ones: the Clean Vehicle Rebate Project (CVRP) and the Advanced Clean Cars II Regulations (ACC II), to target the demand and supply sides of zero-emissions vehicles (ZEVs), respectively (CARB, 2022). The CVRP provides rebates of up to $7,500 to consumers on purchases or leases of new and eligible ZEVs, including PEVs (CVRP, 2023). Between 2010 and 2023, the program has provided rebates to more than 493,000 PEVs, which helped lower the financial barrier of adopting them (CVRP, 2023). While the CVRP creates financial incentives to increase the demand for PEVs, the ACC II increases their supply in California. Under the ACC II, auto manufacturers are required to produce a certain number of ZEVs.

Depending on the auto manufacturer's total sales in California, the percentage of ZEVs of their total production ranges from 4.5% in 2018 to 22% by 2025, indicating an upward trend in the supply share of ZEVs (CARB, 2021). As a result of policy efforts aimed at spurring consumer adoptions and increasing ZEVs supply, California has approximately 1.5 million registered PEVs by the end of 2023, accounting for around 5% of the total LDVs in the State (CEC, 2024).

While the transition to PEVs will bring about positive environmental and climate change benefits, there are concerns around their lack of contribution to financing transportation infrastructures. Historically, transportation funding in the United States has been supported by motor fuel taxes. In 2021, the federal gasoline tax raised about $32.8 billion in revenue which accounted for about 70% of the Federal Highway Trust Fund's expenditures, creating a shortfall of approximately $14 billion (FHWA, 2021). As consumers adopt more PEVs, especially BEVs which do not consume any motor fuel, the revenues collected via the gasoline tax have been dwindling at both the federal and state levels (Jenn, 2020). To temporarily address this issue, States with increasingly high rate of PEVs adoption, such as California, introduced an annual additional registration fee of $118 on ZEVs to compensate for the fact that these vehicles do not contribute to road infrastructure funding via the traditional fuel taxes (California Department of Motor Vehicles, 2024).

The additional registration fee is often viewed as a stopgap measure, since it is indirectly linked to the amount of driving by the vehicle being taxed. In addition, an annual fee of $118 generates less revenue than the average amount of fuel taxes raised by a vehicle, which is about $280, assuming an average fuel efficiency of 25 MPG and an annual mileage of 14,000 miles (California Department of Transportation, 2022). As a result, many states have begun exploring and, in some cases, even implementing road-usage charges (RUC), also known as mileage-based user fee (MBUF). Rather than being linked to fuel consumption, these programs instead enact a fee based on the distance driven by an individual vehicle. By imposing a fee to reflect the direct cost that driving poses on infrastructures, RUC is a sustainable funding source for infrastructures. In practice, RUC possesses relatively higher administrative costs when compared to the collection of motor fuel taxes, which may create financial burdens on low-income driving populations. Furthermore, there may be distributional impacts on drivers, depending on their vehicles' fuel efficiency and their travel patterns.

Existing research has studied transportation finance and electric vehicle adoption separately. For instance, studies have been conducted on road pricing mechanisms' public acceptance (Agrawal et al., 2016, Rentziou et al., 2011, Zmud et al., 2008), acceptance by elected officials (Hensher & Bliemer, 2014), equity impacts (Hosford et al., 2021), and the interactions between land use policies and road pricing (Guo et al., 2011). They found that the following factors are important when considering road-pricing schemes to fund transportation infrastructure: concerns about privacy and data security, administrative burdens, and the equity implications of the redistribution of revenues. On the other hand, a plethora of literature has studied electric vehicle adoption, especially in the LDVs segment of the vehicle market. Hardman conducted a review on the impacts of non-financial incentives, such as special lane access (e.g. HOV/carpool lanes, bus lanes), parking incentives, charging infrastructure development, road toll fee waivers, and licensing incentives, on promoting electric vehicle adoption (2019). He found that toll or road charge fee waivers have not been as well researched as the other interventions. This further highlights the lack of research on the impacts of road pricing on EV adoption and the corresponding implications of electric vehicle adoption on transportation finance policies.

To this end, my dissertation contributes to both fields of research by explicitly quantifying the impacts of LDV electrification on transportation infrastructure funding in California. As the state's LDV fleet transitions away from gasoline, alternative funding mechanisms, such as RUC, not only need to meet the revenue requirements but should also enhance the fairness and equity of transportation infrastructure funding. This dissertation also explores ways to reduce administrative costs and streamline operations between tolling agencies and RUC programs. Lastly, I evaluated the impacts of vehicle portfolios on PEV-adopting households' vehicle replacement decisions to provide insights into PEV adoption behaviors. To accomplish these research objectives, I engaged in a three-part research agenda as part of my dissertation, which is summarized below:

- **Chapter 2: The Present and Future of Road Financing: Leveraging knowledge from the tolling industry to implement road-usage charge programs in the U.S.**
    - Synthesizing the lessons learned from the implementation of tolling systems and devising potential opportunities within these programs to collaborate with a RUC program.
    - Conducted semi-structured interviews with experts from tolling programs across the country to identify key themes related to program administration, operational challenges, data privacy, and equity concerns which are relevant to both tolling and RUC programs.
    - Built upon these key themes with findings from state-level RUC reports by conducting a multi-criteria decision analysis (MCDA) to evaluate how well the state-level RUC pilot projects can integrate with tolling systems.

- **Chapter 3: Forecasting revenues of motor fuel taxes in California: an application of time-series regression to estimate changes in vehicle miles-travelled (VMT) among light-duty vehicles (LDVs)**
    - Constructed a time-series regression model to predict future VMT at the county level in California leveraging sociodemographic and road mileage data.
    - Estimated future gasoline excise tax revenues while accounting for varying paces of LDV electrification to inform policymaking around transportation infrastructure finance mechanisms.
- **Chapter 4: Understanding the effects of vehicle portfolios on plug-in electric vehicles (PEVs)-adopting households' vehicle replacement decision: an application of vehicles transaction model**

- Employed a vehicle transaction model to account for vehicle portfolio preferences among two-vehicle households when deciding which vehicle to replace.
- Quantified households' preference parameters for vehicle class and fuel type portfolios.

The purpose of the dissertation is to provide insights into both the transitions of vehicle technology and of infrastructure funding in California, especially in identifying areas of overlap between these two transitions. Understanding how LDV electrification impacts future transportation infrastructure funding helps facilitate policymaking around the transition away from motor fuel taxes as the sole funding mechanism. At the same time, the cost of driving, as reflected by fuel prices and road-usage fees, impacts the adoption of PEVs which have implications for decarbonizing our transportation sector.

Chapter 2: The Present and Future of Road Financing: Leveraging knowledge from the tolling industry to implement road-usage charge programs in the U.S.

2.1 Introduction

Transportation funding in the United States has historically been supported by motor fuel taxes. In 2021, the federal motor fuel taxes raised about $32.8 billion in revenues which accounted for about 70% of the Federal Highway Trust Fund’s expenditures on infrastructures (FHWA, 2022). However, with the increasing uptake of alternative fuels vehicles, improved vehicle’s fuel efficiencies, and inflation, the revenues generated by the motor fuel taxes are projected to dwindle, creating shortfalls in the federal infrastructure funding (Jenn, 2020). This is not only a concern at the federal level, as many states have explored ways to address the widening gap between transportation funding availability and needs. In 2017, California passed the Road Repair and Accountability Act (Senate Bill 1) that increased the tax rates on gasoline and diesel. The Bill also introduced an annual registration fee of $108 on zero-emission vehicles to compensate for the fact that these vehicles do not contribute to road infrastructure funding via motor fuel taxes (Caltrans, 2022). While many other states have also begun to enforce registration fees on electric vehicles (EVs), this form of revenue is often viewed as a stopgap measure, since it is not linked to the amount of driving by the vehicles. In addition, an annual fee of $108 generates less revenue than the average amount raised from fuel taxes per vehicle in California, which is about $260, assuming an average fuel efficiency of 25 MPG and an annual mileage of 12,000 miles (Caltrans, 2017).

As a result, multiple states have begun exploring and, in some cases, even implementing a road-usage charge (RUC), also known as mileage-based user fee. Rather than being linked to fuel consumption, these programs instead enact a fee based on the distance driven by an individual vehicle. Many states have launched pilot programs to investigate implementation issues related to RUC, including California, Washington, Hawaii, and the Eastern Transportation Coalition (i.e., Delaware, New Jersey, North Carolina, and Pennsylvania) (National Conference of State Legislatures, 2022). Most recently, California is set to begin its second RUC pilot in June 2024, with the goal of testing multiple mileage collection options (State of California, 2024). Oregon, Utah, and Virginia launched full-fledged RUC programs where drivers can voluntarily opt-in to pay a RUC instead of motor fuel taxes. In 2022 alone, Hawaii, Massachusetts, Minnesota, Tennessee, Utah, Vermont, Virginia, and Washington considered legislatures to set up or to expand existing RUC programs. For example, Hawaii enacted Senate Bill 3183 in January 2024 to transition all vehicles in the State to the RUC program by 2033 (State Senate of Hawaii, 2024). Meanwhile, Massachusetts, Vermont, and Tennessee are considering legislatures to conduct RUC pilot programs (National Conference of State Legislatures, 2022). Additionally, the federal Inflation Investment and Jobs Act, passed at the end of 2021, directed the U.S. Department of Transportation to begin establishing a national RUC pilot. Evidently, there is substantial momentum at both the state and federal levels to replace the motor fuel taxes with a RUC system, especially as the adoption of EVs continues to grow.

One of the fundamental challenges of a RUC program is the relatively prohibitive cost of implementation compared to traditional motor fuel taxes – higher administrative and enforcement costs (Caltrans, 2017). The administration of the motor fuel taxes, less than 1% of the collected revenue, benefits from the fact that fees are collected from a small number of bulk storage terminals, which amounts to slightly more than a thousand across the entire country. Meanwhile, a RUC program would need to be assessed at a much broader scale with collection points at the individual vehicle level, numbering in the hundreds of millions across the entire country. One strategy to address issues related to high administrative costs and other implementation challenges of a RUC program is to leverage existing vehicle-level pricing programs, such as road tolling systems to gain knowledge from their implementation challenges and to learn of synergies between the programs.

In this paper, we looked specifically at road-tolling programs in the U.S., synthesizing the lessons learned from the implementation of these systems and devising potential opportunities within these programs to collaborate with a RUC program. To elicit insights from the tolling industry, we conducted nine semi-structured interviews with experts from tolling programs across the country. Following the interviews, we identified key themes related to program administration, operational challenges, data privacy, and equity concerns which are relevant to both tolling and RUC programs. We then built upon these key themes with findings from state-level RUC reports by conducting a MCDA to evaluate how well the state-level RUC pilot projects can integrate with tolling systems. Synthesizing the insights gained from the expert interviews to inform the objectives and evaluation criteria in the MCDA, we leveraged a two-pronged approach to provide policy guidance for large-scale implementations of RUC.

2.2 Background and Literature Review

Historically, the Federal Highway Act of 1921 provided federal financial assistance to states for building highways to improve nationwide connectivity to accommodate the rise of automobile usage (Kirk, 2019). Tolls were collected on many of these roads, bridges, and tunnels to help pay for their construction and maintenance. However, the Federal-Aid Highway Act, passed in 1956, halted the need to collect tolls on these public transportation infrastructures, since it legislated the Interstate highway system to be funded by motor fuel taxes revenues, which continued for a few decades (Kirk, 2017). By 1980, some of these originally constructed highways under the Federal Aid Highway Act began to wear out. The need for continued maintenance in combination with a shortage of government funds to support the infrastructure prompted the revival of the need for tolling (Kirk, 2017). Since then, tolling and motor fuel taxes have remained the primary sources of funding for the maintenance and repair of the Interstate and general highway infrastructures in the U.S.

In addition to being a revenue-generating source for transportation infrastructure funding in the U.S., tolling, when linked with time- and usage-based road pricing, can address negative externalities associated with transportation. Economists have long advocated for pricing the use of roadways as an efficient way of allocating scarce roadway capacity and tackling the negative externalities, including congestion, air and noise pollution, and road wear-and-tear (Vickrey, 1965). Examples of road pricing include distance-based tolling, cordon tolling, congestion pricing, and RUC. Until very recently, road pricing has rarely been implemented in the United States and is strongly opposed by the public and elected officials due to the nature of charging drivers a fee in addition to paying motor fuel taxes, resistance to paying more for transportation, and privacy concerns, among other things (Schade & Schlag, 2003). While road-pricing has faced public resistance in the United States, it has been implemented in other countries to externalities, such as air pollution, congestion, and noise pollution. The first application was in the form of congestion pricing adopted by Singapore in 1975 (Santos, 2005). Today, cordon tolling and congestion pricing are present in many cities worldwide, including London, Milan, Oslo, and Stockholm (Beevers & Carslaw, 2005, Börjesson & Kristoffersson, 2018, Lehe, 2019). Some of the major motivations behind these road pricing schemes included the reduction of greenhouse gases (GHG) and local air pollutants as well as congestion mitigation (Beevers & Carslaw, 2005, Deng, 2017). Beevers & Carslaw found that the London congestion charging scheme, which went into effect in 2003, has reduced particulate matter 10 (PM10) emissions by 12% in the charging zone (2005).

Motivated by the potential societal benefits realized by road pricing schemes, researchers have conducted both quantitative and qualitative analysis on them. Some examples of quantitative analysis include cost-benefit analysis conducted by Anas and West & Börjesson to evaluate the benefits of congestion pricing in the Greater Los Angeles region and Gothenburg, respectively (2020, 2020). They both found congestion pricing scheme to be socially beneficial at reducing congestion and generating revenues that can be recycled to the public. Similarly, Casady et al. applied a benefit-cost analysis to investigate toll managed lanes on seven projects in the U.S. and found that two out of seven projects yield positive benefits (2020). Odeck and Eliasson & Mattson employed regression-based analysis to estimate operational costs of tolling systems and the distributional impacts of congestion pricing, respectively (2019, 2006). They found that the increasing volume of vehicles using the tolling facility reduces operational costs, demonstrating the existence of economy of scales.

Meanwhile, a plethora of qualitative analysis has been conducted, such as public acceptance study (Agrawal et al., 2016, Rentziou et al., 2011, Zmud et al., 2008), acceptance by elected officials (Hensher & Bliemer, 2014), equity impacts analysis (Hosford et al., 2021), and the interactions between land use policies and road pricing (Guo et al., 2011). The studies found several factors are important when considering road-pricing schemes to fund transportation infrastructure, including concerns about privacy and data security, the administrative burdens, and the equity implications of the redistribution of congestion pricing revenues. While existing literature revealed some of the salient concerns of road pricing, these studies considered standalone cordon tolling or congestion tolling projects. Moreover, these studies focused on the impacts of road pricing programs on addressing environmental pollution, congestion, and equity concerns, and not on the administrative, technical, or operational challenges of implementing these systems.

Since one of the fundamental challenges of a RUC program is the relatively excessive cost of implementation compared to traditional motor fuel taxes, some state agencies and metropolitan planning organizations (MPOs) have conducted pilot studies to explore these challenges. In the wave of states testing and adopting RUC programs, it is important to thoroughly investigate the overlaps between existing tolling systems and RUC to understand the impacts that these programs can have on each other. To accomplish this goal, we focused on detailing the lessons learned from the semi-structured interviews to inform key topics in RUC-tolling integration. These topics include technology, operations, administration, and equity implications. The paper proceeds as follows: Section 3 covers the methodology on qualitative semi-structured interviews and MCDA. Section 4 presents the results from interview analysis and the MCDA. Section 5 discusses the results and highlights important findings, and Section 6 concludes.

2.3 Methodology

We used a two-pronged analysis approach, where we began with conducting semi-structured interviews and identifying themes from our interviews. The second piece of our analysis leveraged the thematic findings from the interviews to inform the evaluation criteria for the MCDA. This approach allowed us to integrate the learnings from our expert interviews with findings from state-level RUC programs, which led us to craft well-informed and timely policy recommendations to RUC program practitioners.

2.3.1 Interview Approach

Over the period of July to October 2022, our team conducted nine semi-structured interviews with tolling industry experts across the United States. Semi-structured interviews are conversations where the interviewers set an agenda for topics of discussion, but they allow the interviewees a free range of response. It is often used in social science research to elicit perspectives and insights from the interviewees (Zeigler-Hill & Shackelford, 2020). Like Hardman et al.'s work on understanding the barriers to fuel-cell vehicles adoption, this project investigated a new area of transportation finance, the integration of tolling and RUC (2017). Therefore, we elected to conduct semi-structured interviews to gain in-depth knowledge from our experts. To conduct the interviews, we first designed a set of questions which was informed by our literature review on road pricing programs. The topics covered in the questions included system operations, finances, data collection and handling, and technology.

Our recruitment strategy of interviewees was based on contacts suggested by our funding agency: the California Department of Transportation (Caltrans), therefore we had a convenient sample of respondents, which was biased towards tolling experts from California. The interviewees were identified as experts in the tolling industry, since they have on average ten years of experience working in the industry, and they represent a body of knowledge that spans across the tolling industry, including development/deployment, technology, pricing and payment, policy, and administration. The interviewees were contacted via email, inviting them to a 45 to 60-minute interview. Most of the interviewed experts have worked in states that have implemented RUC programs or conducted RUC demonstrations, which makes them the ideal candidates for eliciting opinions on RUC-tolling integration. We also heard from experts who operate tolling systems in states that have not yet held a RUC demonstration, such as Ohio and Texas. Even though these states have not implemented a RUC, the tolling experts are very well-aware and educated about the potential opportunities for collaboration between tolling and RUC, which makes them good candidates for the interview as well. Table 1 below summarizes the interviewees' organization, organization type, whether they are from the private or public sector, the geographic area of representation, and the date of the interview.

The interviews were conducted by a pair of researchers. At the beginning of each interview, the primary interviewer asked the interviewees about their background, roles, and responsibilities in their agencies. Then, the primary interviewer proceeded to ask a predefined set of questions. During the interview, the research team would follow-up with questions when they identified points raised by the interviewees that would benefit from more elaboration. All interviews were conducted via the online conference platform: Zoom, and most interviews lasted between 45 minutes to an hour. After we finished conducting the interviews, the research team transcribed them and reviewed the transcripts for accuracy. We then applied thematic coding on the transcripts, where we identified key themes that emerged from the interviews and grouped responses according to the key themes. In doing so, we deconstructed the transcripts into the following key themes: technology, operations, data, revenue leakage, equity, interoperability, and rate design. Once the key themes were formed, we collected data on interviewees' sentiments and positions around these key themes. The results from the interviews are presented in Section 4.

Table 1. Organizations represented by the interviewed tolling industry experts.

Organization	Organization Type	Private or Public?	System Geographical Coverage	Date of Interview
International Bridges, Tunnel and Turnpike Association (IBTTA)	Industry association	Private	N/A	July 15, 2022

The Transportation Corridor Agencies (TCA)	Tolling agency	Public	Orange County, CA	July 20, 2022
AECOM	Consulting	Private	N/A	July 22, 2022
WSP USA	Consulting	Private	N/A	July 22, 2022
Metropolitan Transportation Commission (MTC)	Tolling agency	Public	San Francisco Bay Area, CA	July 29, 2022
San Diego Association of Governments (SANDAG)	Tolling agency	Public	San Diego, CA	August 5, 2022
Los Angeles County Metropolitan Transportation Authority (LA Metro)	Tolling agency	Public	Los Angeles, CA	August 25, 2022
The Ohio Turnpike	Tolling agency	Public	Northern Ohio	October 14, 2022
North Texas Tollway Authority (NTTA)	Tolling agency	Private	Dallas-Fort Worth Area, TX	October 28, 2022

2.3.2 Multi-criteria Decision Analysis

MCDA is an evaluation technique from the discipline of operations research, and it has been developed for the past four decades with the goal of evaluating decisions that include multiple and often conflicting criteria (Stein, 2013). Criteria may include financial, technical, and social factors that influence the decision-making process. Evaluations of these criteria may be based on historical data or preference rankings by experts (Stein, 2013). Because of its ability to accommodate multiple criteria in its evaluation, MCDA is often employed by governmental agencies to evaluate alternatives in their decision-making process. By assessing how each alternative performs on the established criteria, MCDA helps decisionmakers establish preferences among different alternatives (*Multi-Criteria Analysis*, 2009). The process for designing a MCDA is as follows: identifying the objectives, identifying options for achieving the objectives, identifying criteria that can be evaluated to compare the options, analyzing the criteria in the context of evaluating the options, and arriving at a decision (*Multi-Criteria Analysis*, 2009). MCDA helps decisionmakers recognize the trade-offs among the alternatives; a crucial step in the exploratory stage of implementing RUC programs and tolling-RUC integration when policymakers from different states may learn from each other and tailor RUC implementations to fit their state's transportation funding needs.

To operationalize a MCDA in the context of RUC-tolling integration, we identified the objective as evaluating how well the state-level RUC pilot projects conducted to date can integrate with tolling systems. Then to identify the options for achieving the objective, we reviewed reports from states that have either implemented a full-scale RUC program or have conducted RUC pilot programs. These states include California, Colorado, the Eastern Transportation Coalition, Hawaii, Minnesota, Oregon, Utah, and Washington. By comparing the objectives from these reports to the key topic areas identified from our interviews with experts from the tolling industry, we constructed a value tree that reflects the shared objectives in a RUC-tolling integration. These objectives are revenue generation, equity, technology feasibility, public acceptance, and autonomy. After identifying the objectives of state-level RUC programs, we selected specific and measurable evaluation criteria for each value branch. These criteria were selected via identifying the commonly mentioned themes by our interviewees and identifying the overlaps between them and state-level RUC reports. For instance, equity was a key theme mentioned by all interviewees and was highlighted in all state-level RUC programs that we reviewed. Understanding that this is an important area of consideration in both tolling and RUC, we identified the specific metrics used by tolling agencies to ensure equity, which are affordability and inclusiveness/accessibility. To translate these findings to evaluation criteria for RUC, we measured how affordable a RUC program is and how accessible and inclusive it is. For instance, we scored “5” on “accessibility/inclusiveness”, if the program is open to all drivers with additional mechanisms to improve accessibility for populations with different needs (e.g., technology barrier, language barrier). A score of “3” or below on accessibility/inclusiveness indicated that the RUC program is only open to selected drivers.

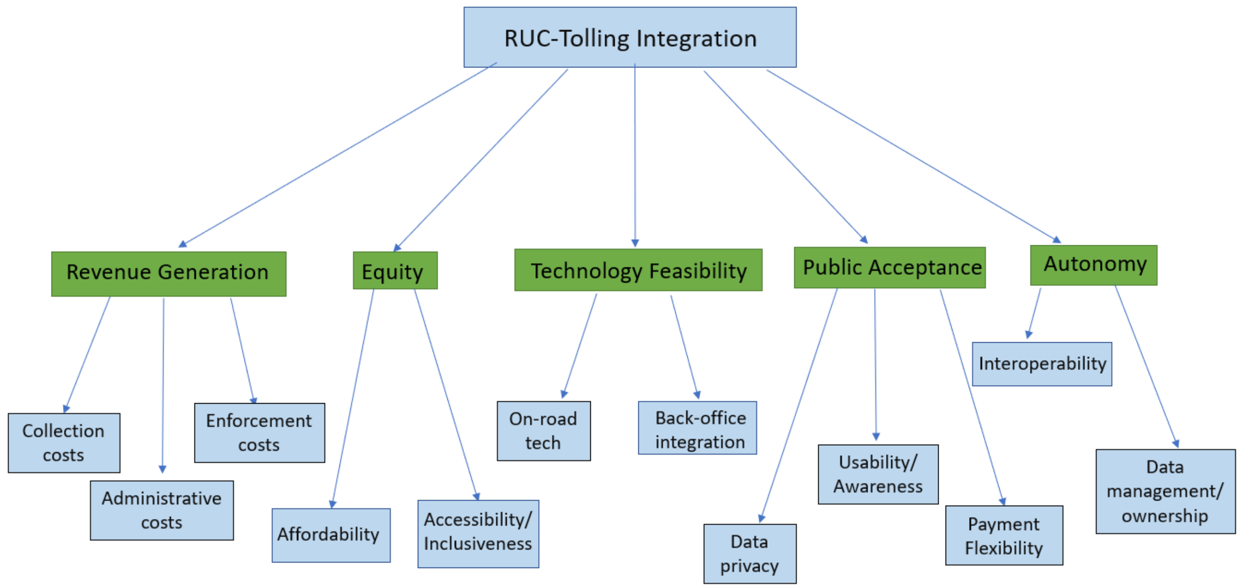

Figure 1. Value tree in the RUC-tolling integration context emphasizes the objectives that the integration is trying to achieve, including but not limited to revenue generation, equity, technology feasibility, public acceptance, and autonomy.

In evaluating a complex decision that involves multiple objectives, some of these criteria are quantitative in nature, such as collection costs, administrative costs, and enforcement costs, while others are qualitative like usability, payment flexibility, interoperability, etc. Keeping this in mind, we collected data on each of these criteria from the RUC reports for each of the abovementioned states and organized them in a performance matrix. The main purpose of a performance matrix is to present each alternative against the evaluation criteria to describe each alternative's performance on the criteria. For this project, the evaluated alternatives are the states that have conducted a RUC pilot or have an operational RUC program, including California, Colorado, Eastern Transportation Coalition, Hawaii, Minnesota, Oregon, Utah, and Washington. Our interviewed experts have experience working on tolling in California, North Carolina, Oregon, and Utah, representing about 40% of the states evaluated in the MCDA. By evaluating how well each state has performed on these criteria, we gained insights on how prepared each state is in terms of integrating their RUC program with tolling systems. Table 2 below presents the rubric of our evaluation which provides additional details on the ratings.

Table 2. Evaluation Rubric for each Criterion

	Evaluation Rubric					
Criteria	n/a	1	2	3	4	5
Collection costs	No mentioning of collection costs	Some mentions of collection costs in conjunction with administrative cost	Some mentions of collection costs but no quantitative estimates or indication of future research	Indicated an increase in collection costs and future investigation is needed	Provided specific actions to take for reducing collection costs	Provided estimates for collection costs
Administrative costs	No mentioning of administrative costs	Vague mentions of administrative costs, no examples or estimates provided	Some mentions of administrative costs but no quantitative estimates or indication of future research	Indicated an increase in administrative costs and future investigation is needed	Provided specific actions to take for reducing administrative costs	Provided estimates for administrative costs
Enforcement costs	No mentioning of enforcement costs	Vague mentions of enforcement costs, no examples or estimates provided	Some mentions of enforcement costs but no quantitative estimates or indication of future research	Indicated an increase in enforcement costs and future investigation is needed	Provided specific actions to take for reducing enforcement costs	Provided estimates for enforcement costs
Affordability	No mentioning of affordability	Vague mentions of financial impacts of RUC	Only interested in state-level financial impacts of RUC, but not distributional impacts	Interested in analyzing the distributional impacts of RUC along the margins of household income, locale, driving patterns	Evaluated the financial impacts of RUC on different populations along the margins of household income, locale, driving patterns	Devised action plans to address distributional impacts of RUC on populations along the margins of household income, locale, driving patterns
Accessibility/ Inclusiveness	No mentioning of accessibility or inclusiveness	Vague mentions of accessibility or inclusiveness	RUC program is only open to selected drivers	RUC program is open to selected drivers with the objective of improving inclusiveness in the future	RUC program is open to all drivers with the goal to improve accessibility for populations with special needs (e.g., language, technology barrier)	RUC program is open to all drivers with additional mechanisms to improve accessibility for populations with different needs (e.g., technology

	Evaluation Rubric					
Criteria	n/a	1	2	3	4	5
						barrier, language barrier)
On-road tech	No mentioning of on-road technology	Vague mentions of on-road technology	Focused on one mileage reporting option only	Focused on one mileage reporting options with the goal of expanding	Focused on three to four mileage reporting options	Offered a variety of mileage reporting options, including manual and automated options
Back-office integration	No mentioning of back-office integration	Vague mentions of back-office integration	Lack of integration between on-road technology and data processing	Some integration between on-road technology and data processing, but not smooth	Leveraged account manager to provide data collection, processing, and invoices.	Leveraged account manager to provide data collection, processing, and invoices. Consider inter-agency data-sharing
Data privacy	No mentioning of data privacy	Vague mentioning of data privacy	Lack of standards or protocols to protect personally identifiable information (PII)	Lack of State laws to protect PII	Devise data privacy laws to protect PII	Statutorily protected data privacy laws applied to RUC programs
Usability/ Awareness	No mentioning of usability/ awareness	Vague mentioning of usability/ awareness	Only RUC participants were educated on and exposed to RUC	Both RUC participants and the public were exposed to and educated on RUC	Only RUC participants were educated on and exposed to RUC and had a positive experience	Both RUC participants and the public were exposed to and educated on RUC and had a positive experience
Payment flexibility	No mentioning of payment flexibility	Vague mentioning of payment flexibility	Simulated invoices but not payment methods	Offered prepaid wallet as a payment option or flexibility in payment frequency	Offered prepaid wallet as a payment option and flexibility in payment frequency	Offered more payment options, especially accounting for unbanked or underbanked populations

	Evaluation Rubric					
Criteria	n/a	1	2	3	4	5
Interoperability	No mentioning of interoperabilit y	Vague mention of interoperability	Interoperability was not assessed	Interoperability was not assessed but indicated as a future research area	Assessed interoperability with other States	Assessed interoperabilit y with other States and tolling agencies
Data management/ Ownership	No mentioning of data-sharing	Vague mention of data-sharing	Capable of sharing data between one governmental agency and account managers	Capable of sharing data between State agencies and account managers	Capable of sharing data across agencies within one State and account managers	Capable of sharing data across different State agencies and account managers

2.4 Results

The results of the MCDA present the evaluations of existing RUC programs and pilots based on the key characteristics synthesized from our expert interviews and evaluation criteria identified in Figure 1. Table 3 **Table *3***provided the evaluation of eight RUC programs with '5' indicating the state has well-accounted for the characteristics in their RUC program design to integrate with tolling while '1' indicating that the characteristic was considered but not adequately. 'N/A' indicates that there was no data regarding the characteristic in the report we evaluated.

Table 3. Evaluation of each State's RUC program or pilot against the criteria identified in the value tree above.

	Revenue Generation			**Equity**		**Technology Feasibility**		**Public Acceptance**			**Autonomy**	
	Collec-tion Cost	**Admin-trative Costs**	**Enforce-ment Costs**	**Afforda-bility**	**Accessi-bility**	**On-road Tech**	**Back-office integra-tion**	**Data Privacy**	**Usa-bility**	**Payment Flexibility**	**Inter-opera-bility**	**Data manage-ment**
CA	3	5	4	3	3	5	4	5	5	3	4	4
CO	3	3	4	3	4	4	5	4	5	3	3	3
TETC *	4	4	4	5	4	4	5	4	5	2	5	5
HI	4	4	3	4	4	5	4	5	5	3	2	2

MN	3	3	3	3	2	3	5	4	4	2	4	3
OR	3	4	4	4	4	3	5	4	4	3	4	4
UT	4	4	4	4	3	4	4	5	5	4	3	4
WA	4	5	4	3	4	5	5	4	4	3	4	5

*The Eastern Transportation Coalition

2.4.1 Revenue Generation

To assess the revenue generation capacity of each State's RUC pilot or program, the following criteria are evaluated: collection costs, administrative costs, and enforcement costs. Keeping in mind that most of the RUC implementations to date have been demonstration projects, there are limited capacities in generating revenue from RUC. Therefore, most state-level RUC reports either provide quantitative estimates on costs or qualitative descriptions on how to reduce these costs. In terms of administrative costs, all the states agreed that administrative costs of RUC would be much greater than those of the existing motor fuel taxes. This is largely due to the increase in the number of collection points, as explicitly mentioned in the Minnesota RUC report. In contrast to the low administrative costs of collecting motor fuel taxes, which is about 0.5% of revenues, the administrative costs of RUC ranges from 7% to 12%. For instance, Washington estimated that the administrative costs of a RUC were about 7% and 12% for the manual odometer reporting option and the electronic odometer reading device, respectively (2020). California also provided a similar range of estimates on the administrative costs of RUC, ranging from 5% to 10% (2017). The higher end of the estimate reflects the high upfront costs in collecting a small percentage of the state's driving population. As RUC programs transition to replace motor fuel taxes for all drivers, the administrative costs would decrease to the lower end of approximately 5% of total revenue.

Given the limitation of data availability around cost estimates, our interview findings can shed light on some aspects of the potential revenue-generating capacity of a RUC-tolling integration by drawing on lessons learned from the tolling industry. When moving to an open-road and all-electronic tolling system, where vehicles do not need to stop to pay tolls, agencies are concerned about leakage in toll collections. One form of leakage occurs when violators refuse to pay their invoices; these uncollectible invoices account for about 8% of total transactions on the NTTA system. One of the interviewed experts expressed that even though tolling agencies can work with the Department of Motor Vehicles (DMV) to put holds on vehicle registrations, they do not have direct authority over the vehicle owners to make them pay their tolls. Especially in the case when vehicles are sold or the registrations are transferred from the violators to someone else, tolling agencies lose the authority to pursue the uncollected tolls. The remaining 6% of leakage are associated with unidentifiable vehicles, which can take the form of vehicle owners intentionally disguising their license plates. In total, both forms of leakage account for approximately 14% of total transactions on the NTTA tolling system, which could amount to a loss of revenue in the order of millions of dollars annually.

To mitigate the impact of leakage on revenue, the interviewed experts encourage their users to adopt radio frequency identification (RFID) transponders, because these established accounts are usually backed by credit cards. According to the interviews, the leakage rate of RFID transponder transactions is less than 1%. In applying this insight to RUC implementations, the interviewed tolling experts recommend a “pay now” model, where users should be charged a certain amount of money based on their expected usage of the road. A true-up can be conducted on a monthly, quarterly, or annual basis to ensure that users are being fairly charged for their use of the roads, and that the charge would not create an undue financial burden for them. While the interviewed experts believe that this approach would reduce leakage, it would pose equity concerns as low-income populations might be financially burdened by such a model. Considering these lessons learned from tolling systems about revenue leakage, most state-level RUC pilots and programs have proposed several solutions that are tailored to the state’s existing program. For instance, Hawaii conducts inspections of vehicles as part of their annual registration (2022). Integrating RUC into the annual vehicle inspection would streamline the mileage data collection process which would reduce administrative and collection costs. Similarly, California has expressed interest in integrating manual RUC mileage reporting with smog checks which are required annually for vehicles that are more than eight model-years old (2017). On the other hand, Minnesota has approached this issue differently by leveraging in-vehicle telematics to directly capture and report mileage driven by vehicles to RUC agencies (2022). The integration between tolling and in-vehicle telematics is also an area of interest that many states would like to explore. Collaboration with automakers on this front could potentially reduce the cost barrier to accessing these data and help build a secure system for auto manufacturers to share these data with tolling and RUC agencies. Lastly, given the characteristics and existing infrastructures, each state should have the autonomy to design and to implement a RUC program that not only minimizes costs but also works well for their residents.

2.4.2 Equity

The equity considerations from each state's RUC program are evaluated by the affordability and inclusiveness of the programs. In this context, inclusiveness is defined as how well the program accommodates drivers of different socioeconomic backgrounds, travel behaviors, and vehicle classifications. For instance, one major concern brought up by many of the RUC reports is whether the implementation of RUC would disproportionately and negatively impact rural drivers who tend to travel longer distances to access required services. This concern was addressed by many states' RUC programs via recruiting participants from a wide range of geographies and evaluating the difference between their RUC payments and their motor fuel taxes payments. For instance, California RUC pilot recruited a total of about 5,100 participants from both rural/ agricultural and urban/suburban communities and from different income levels, ethnicities, genders, and age groups (2017). Similarly, the RUC pilot program conducted by the Eastern Transportation Coalition across Delaware, New Jersey, North Carolina, and Pennsylvania also recruited about 380 participants from both rural and urban geographies (2022). By evaluating the financial impacts of the RUC program on rural drivers, the Eastern Transportation Coalition found that rural drivers are likely to pay less under RUC because they tend to drive less fuel-efficient vehicles which amounts to higher motor fuel taxes payments. The estimated range of difference in annual payment between RUC and gasoline tax is about $18 for rural drivers (2022).

Another area of equity consideration is considering the affordability of RUC for different segments of the driving population, especially in the context of RUC where alternatives to not using the roads may not exist for some population or would significantly reduce their mobility and quality of life. For instance, as mentioned by one of the interviewees, low-income populations may not be able to afford paying upfront for their annual expected road use, which is in the hundreds of dollars, if they drive around 12,000 miles each year and the RUC rate is about 2¢/mile. When designing a RUC program where the alternatives to driving on public roads may be limited, it is important to consider the financial impacts on different income groups and devise assistance programs that equitably address these impacts. According to the interviews, one potential solution to this would be to implement a flexible payment frequency as part of RUC enrollment, so drivers can decide whether a monthly, quarterly, or biannually payment frequency would reduce their financial burden.

Researchers have also investigated the adoption of an income-based RUC rate, where lower-income drivers would pay a lower per-mile fee than higher-income drivers. This may help address the regressivity of RUC by lowering the financial burden on lower-income drivers (Speroni et al., 2022). Thus far, the conversations around the rate-setting of RUC have been centered on ensuring fairness and equality, as demonstrated by states like Utah and Hawaii waiving the enhanced registration fee on EVs and devising a cap of RUC at the average annual gasoline tax payment, respectively (2021, 2022). In a similar vein, all the other states have emphasized the need to devise a refund mechanism for the gasoline taxes that drivers paid while our transportation funding transitions from motor fuel taxes to RUC. While these considerations are important for designing a fair transportation funding mechanism, they do not address the disproportional impacts that RUC may pose on drivers of different income levels. These equity challenges need to be addressed via careful rate-setting to minimize the regressivity of RUC.

Another aspect of equity that arose in the interviews is ensuring that the technology of an all-electronic tolling system does not hinder the unbanked and underbanked populations from accessing the system. While the tolling industry is moving towards the model of RFID transponder and established accounts backed by credit cards, there still needs to be other ways for the unbanked and underbanked populations to pay their tolls. Some tolling agencies currently allow their facility users to pay tolls with cash at physical locations across their service area. In addition, LA Metro allows users of their toll roads to pay via a prepaid card which they can also use to pay for transit services. Furthermore, NTTA partners with a cell phone carrier to allow the transfer of tolls to users' monthly phone bills. These alternative payment methods are key to addressing the technology burden that all-electronic tolling may place on unbanked or underbanked populations, because it ensures that they have access to the tolling system while reducing potential leakages from toll evasions. Offering multiple payment options and consolidating the utility services that users need to pay into one channel would be important to the implementation of RUC.

2.4.3 Technology feasibility: on-road technology

To evaluate how feasible the technology integration is between RUC and tolling, we focused on the on-road technology and the back-office integration. Many states offer a variety of on-road technologies for participants and enrollees to choose from. All the states, except for Minnesota, offered multiple mileage-reporting options to their RUC participants, including GPS-enabled onboard diagnostic device (OBD), non-GPS-enabled OBD, smartphone-based apps, manual odometer image captures, and in-vehicle telematics. An OBD is a plug-in device which allows drivers to view diagnostic data regarding their vehicle, such as the powertrain, emission control systems, and speed. GPS-enabled OBD allows vehicles to be tracked in real-time in terms of their location. Smartphone-based apps leverages GPS technology to track the location and miles driven of vehicles. Manual odometer image capture involves the drivers taking a picture of their odometer and submitting it. Offering a plethora of technological options not only allow the states and the account managers to evaluate out different on-road technologies, but it also provides participants with options that best suit their travel needs. Specifically, manual odometer image capture is a high-privacy option which provides RUC participants with an additional level of privacy.

California and Washington offered the highest number of mileage reporting options, with California offering six options and Washington offering five options. From its 2018 RUC pilot, Washington found that about 56% of its 2,000 participants chose either the GPS-enabled or non-GPS-enabled OBD options, while about 30% chose the manual odometer image capture option, with the remaining 14% choosing the smartphone-based apps (2020). On the contrary, about 60% of Hawaii's RUC pilot participants selected the manual odometer image capture option, while 30% and 10% opted for GPS-enabled and non-GPS-enabled OBD options, respectively (2022). This difference in preferences for on-road technology emphasizes the geographical differences and the need to tailor to each state's residents and its existing processes that bring the most familiarity to both the RUC enrollees and the staff. By offering a variety of reporting options, the states learned the reporting options that work best for their RUC participants.

Ideally, one of the capabilities of RUC on-road technology is to distinguish whether the miles were driven inside or outside a state's boundary because only miles driven inside a state should be subject to that state's RUC. From the RUC pilots and programs, Colorado and Oregon learned that GPS-enabled OBD can effectively distinguish in-state and out-of-state miles driven by a vehicle (2017, 2021). In addition to the advantage of distinguishing between in-state and out-of-state miles driven, GPS-based OBD can also integrate with tolling systems to collect tolls by leveraging the RFID technology. All the tolling agencies that we interviewed are moving towards an open-road tolling system with all-electronic tolling technologies because of the increase in efficiency and accuracy of toll collections. To do so, they rely on all-electronic tolling technologies, which include RFID-reading technology, such as gantries and sensors that are implemented at certain checkpoints in the systems and along the road. The RFID-reading technology can sense vehicles accessing the tolling systems via the RFID transponder that is in the vehicle. As an application to RUC, the Eastern Transportation Coalition conducted a tolling-RUC integration pilot on passenger vehicles in 2021 by recruiting about two hundred existing tolling customers in Virginia (2022). From the pilot, they learned that GPS-enabled OBD is successful at collecting tolls when the tolling systems are in the following configurations: single-directional toll plazas that are at least eight feet from other traffic flows or toll plazas and cumulative tolls collected as vehicle passes under gantry. This result demonstrated that it is technologically feasible to integrate RUC and tolling using existing on-road technologies.

On the other hand, the nation-wide truck pilot project conducted by the Eastern Transportation Coalition from 2020 to 2021 implemented the use of in-vehicle telematics to track mileage driven (2022). The in-vehicle telematics on heavy-duty trucks require professional installation which prevents any potential odometer fraud and provides accurate mileage data. Vehicles' miles driven on tolling systems are captured by tolling agencies which would help reduce the need to implement a different set of technology for RUC implementation. However, if the vehicles do not drive on tolled roads or do not have RFID-transmitting technology, then additional technology solutions would need to be implemented to capture these miles for RUC, such as camera captures of license plates. Furthermore, there currently exists a barrier for tolling agencies to leverage in-vehicle telematics because they are proprietary to the auto manufacturers. Future directions on tolling-RUC integration should consider leveraging both in-vehicle telematics and GPS-enabled OBD to evaluate more complex tolling configurations and business rules and to reduce technology redundancy.

2.4.4 Technology feasibility: back-office integration

Besides on-road technology to collect mileage data, back-office operation of RUC programs is also crucial in processing transactions, consolidating invoices, and providing customer services to the participants. The back-office handles transactions by either directly matching the associated RFID to existing accounts or reviewing the license plates captured and working with the DMV to identify the vehicle owners. From our interview with the Ohio Turnpike and the NTTA, their annual operational costs of the back-office are about $3 and $35 million dollars, respectively. The operational costs of the Ohio Turnpike back-office included staff salaries, which consisted of approximately 50% of the costs. Software systems maintenance consisted of approximately 34% of the annual operational costs of the Ohio Turnpike. Given that the Ohio Turnpike manages approximately 440,000 accounts, this translates to approximately $6.8 per active account of annual operating costs. As the scale of the tolling system increases, the per-account operational cost decreases. The NTTA manages 11 million active accounts, which yields a per-account operational costs of $3.2. Because of the similarities in the requirements and capabilities between a tolling system's back-office and that of the RUC program, the Eastern Transportation Coalition, Oregon, and Washington have expressed interest in integrating the back-office operations between tolling and RUC. Like the tolling agencies, the RUC program's back-offices are operated by third-party account managers who interface with RUC participants to collect their data, to process their transactions and invoices, and to answer any customer service-related questions.

An essential component to back-office integration in RUC, whether it is with tolling agencies or with other governmental agencies, is creating technical infrastructures for data-sharing. With the implementation of RUC, the interviewed experts agreed that there exists an opportunity to ensure that business rules and processes are in place for implementation agencies to obtain accurate data from the DMV efficiently. Furthermore, building a flexible and secure database among the implementing agencies of RUC would boost the cost-efficiency and security of the program. For instance, Utah is developing and testing secure data linkages between its operational RUC program and the DMV by leveraging the existing technical expertise of its third-party account managers (2021). Hawaii is pursuing a similar integration on the data-sharing front between its RUC program and its DMV (2022). State-level interests and efforts in investigating the technological feasibility of different on-road technologies and back-office integration would help reduce costs and administrative burdens of future RUC implementations.

2.4.5 Public Acceptance

Public acceptance of a RUC program hinges on multiple aspects, including but not limited to data privacy, usability of the system, and flexibility of payments. While payment flexibility is emphasized by tolling agencies, especially in providing means for unbanked and underbanked populations to pay tolls, the RUC programs and pilots assessed were voluntary and only simulated payments. Due to the lack of concrete financial transactions, states have mostly addressed payment flexibility around the payment frequency. For instance, Hawaii found that about 52% of their 39,600 survey participants prefer quarterly or monthly RUC payments instead of an annual payment (2022). Utah supported the idea of providing flexibility in payment frequency, stating that a statewide implementation of RUC would entail an annual lump sum payment to reduce administrative costs associated with more frequent payments (2021). On the front of payment methods, California, Colorado, Minnesota, and Utah assessed the method of a prepaid wallet, managed by the third-party account managers. From reading the reports, it is unclear whether unbanked or underbanked populations could access the prepaid wallet method. This remains an area of concern which needs to be addressed as states expand their RUC programs.

Another key component to boosting public acceptance of a RUC program is ensuring data privacy. To accomplish this, states have focused their efforts on these two fronts: distancing the state governments from handling PII and ensuring the highest security standards and management procedures of PII. Besides Hawaii, all the other states have considered the heavy involvement of a third-party account manager as part of their future RUC implementation. As identified by Colorado's RUC pilot participants, there was a considerable amount of concern on providing their PII to governmental agencies (2017). To address this, many States including California, Colorado, the Eastern Transportation Coalition, Minnesota, Oregon, and Utah have explicitly expressed that only aggregated and anonymized data would be shared with their state agencies. By placing the responsibility of collecting and managing PII on the third-party account managers, the States need to enact and enforce the most stringent data privacy laws for the RUC program. Learning from the tolling industry, the back office of the tolling agencies is PCI-compliant which means that they adhere to the Payment Card Industry (PCI) Data Security Standards regarding the handling of credit card information. The standards mandate that the agencies do not store credit card information directly, instead, they use tokenization to access a secure database, which prevents sensitive PII from being transmitted in its original format. According to the interviewed experts, tolling agencies are required by state laws, such as the case in California, to purge the data within 30 days when it is no longer needed. When applying to RUC implementation, California has stated that the data collected from the RUC program would be protected pursuant to the statutorily mandated privacy provisions in SB 1077 (2017). Coupling high standards of data management and data security with the stringent and statutorily mandated data privacy provisions, the States can provide the necessary peace-of-mind to RUC participants.

On the usability and awareness front, we evaluated the efforts that the states have taken to educate the public about RUC via surveys and focus groups. In addition to conducting RUC pilots, education, and outreach efforts on RUC to the public are essential to promoting the public's acceptance of this new transportation funding mechanism. Through an extensive outreach program, Hawaii surveyed about 49,500 residents, and about 80% of residents indicated that they had a high level of initial understanding of motor fuel taxes as a source of transportation funding (2022). In contrast, Colorado surveyed about 500 participants in 2016, prior to the start of the RUC pilot project, and found that about 70% of survey participants are unfamiliar with transportation funding sources (2017). Similarly, the Eastern Transportation Coalition also found that out of its 2,000 survey participants across Delaware, New Jersey, North Carolina, and Pennsylvania, about 70% of them are not familiar with RUC (2022). The differences in the initial public awareness of RUC across states further highlight the importance of educational and outreach efforts on RUC. Except for Hawaii, the residents from other states were not familiar with RUC or motor fuel taxes as means to fund transportation infrastructure. Despite that, most of the RUC pilot participants became aware of RUC and are supportive of it replacing the motor fuel taxes. Specifically, 83% of California's RUC pilot participants were satisfied with the pilot (2017). Similarly, the Eastern Transportation Coalition found that over 90% of passenger vehicle pilot participants were satisfied with the program (2022). This further demonstrates the effectiveness of conducting RUC pilot projects to educate the public on transportation infrastructure funding.

2.4.6 Autonomy

As demonstrated in the evaluations of the above criteria, geographical differences largely influence how states may approach RUC implementation. Through conducting pilot projects, each state learned which technology options, reporting options, and administration of RUC are best suited for their residents. Recognizing that RUC implementation would not be "one-size-fits-all" and that states should have the autonomy to design and to implement their RUC programs, we evaluated how prepared they are in collaborating with other states to process interstate travel and how robust their operations and technologies are in facilitating interstate and inter-agency data transfer, sharing, and management to allow RUC implementation and enforcement. Drawing from lessons learned from tolling agencies, we defined interoperability in the context of RUC implementation as the ability for multiple RUC programs to exchange data on transactions and vehicles to accurately recuperate the payments from their users.

As demonstrated by the RUC interoperability pilot between Oregon and Washington, a financial clearinghouse or interoperability hub model would be best suited for RUC (2021, 2020). Under this model, each state can have different technologies and back-offices, but they coordinate interstate travel such that the drivers would pay for their RUC payments to their home state only. This model was evaluated between two pairs of Western States: Oregon-Washington and California-Oregon by leveraging GPS-enabled OBD. The drivers only got billed by their home state agency, which reduces the burden on drivers to pay multiple agencies. While the technologies of interoperability hubs are feasible, one of the challenges that Washington expressed was the administrative burden in determining the amount and the location of fuel that each vehicle purchased to process refunds of motor fuel taxes paid (2020). Additionally, California found that it was difficult to process refund requests for interstate travel for drivers who did not use GPS-enabled OBD, since it required more supporting evidence to demonstrate their inter- vs. intra-state travel (2017). Refunds for motor fuel taxes paid would occur during the transitional period from motor fuel taxes to RUC, especially those who voluntarily opt into the RUC program. As RUC implementation became more widespread, processing refund would be less administratively burdensome.

Given the multi-state nature of the Eastern Transportation Coalition, their passenger vehicle pilot project recruited participants from Delaware, New Jersey, North Carolina, and Pennsylvania from 2020 to 2021. The RUC system for these 383 participants across four states was uniform in design and implementation, which mimics another form of interoperability as observed in some of the interviewed tolling agencies (2022). In this form of interoperability, multiple states agree to synchronize their on-road technologies and send transactions to one back-office for processing. Under this model, RUC participants across different states would not notice any difference in reporting mileage, submitting payments, and accessing customer service. While this approach of interoperability would require a high degree of coordination and standardization of on-road technologies and back-office operations, it may be a desirable option for the Eastern states since they are closer to each other in proximity and intestate travel is more common. For instance, about 10% of all 1.4 million miles traveled during the RUC pilot project was outside of Delaware, New Jersey, North Carolina, and Pennsylvania, which highlighted the importance of adopting interoperability hubs to capture these transactions (2022).

Another dimension of interoperability is the ability to transfer data and settle transactions among agencies. Besides Hawaii, which is an island state with an existing annual vehicle inspection program currently administered by the Hawaii Department of Transportation, other states would require data-sharing among governmental agencies or among governmental agencies and account managers. In most of the evaluated RUC programs, the data is collected and managed by account managers. If a RUC program has multiple account managers, like the case in California, then there needs to be a central repository to accept the data collected from all the account managers (2017). This database infrastructure can serve as the backbone for building an interoperability hub, where mileage data collected from each state can be uploaded to a secure data repository, and any interstate travel would be determined and accounted for before invoicing the drivers through the system of their home state. Many interviewed experts expressed that there exists an opportunity to leverage the existing account management and customer service expertise from tolling agencies to manage the administration and collection of RUC payments. For instance, the account holders in the NTTA tolling system covered about 70% of the registered vehicles in the Dallas-Fort Worth Area and surrounding metroplex, which span across 26 counties. The geographical reach of existing tolling systems coupled with their expertise in account management should be leveraged by RUC implementation to consolidate the back-office operations to reduce administrative costs.

2.5 Discussion

From the interviews and MCDA, we observed that there are many parallels between the transition to all-electronic and open-road tolling and the transition from motor fuel taxes to RUC. While as an industry, tolling agencies share some common practices and standards, different agencies have tailored their technology and operation to meet the needs of their users. This is also reflected in the state-level RUC programs, where each state has tailored their program to best serve its transportation funding needs. Despite the geographical differences, the key to designing a successful RUC is to have clear objectives and mechanisms for achieving these objectives, while allowing for enough flexibility to manage differences among participants. These differences can be participants' sociodemographic, geographies, and vehicle fuel efficiencies, which have implications on the financial impacts of RUC. In addition, the administration of RUC needs to ensure that unbanked and underbanked populations are not excluded. The tolling industry has successfully implemented alternative ways besides credit cards for unbanked and underbanked populations to pay their tolls. Tolling agencies have not had to grapple too much with the equity issue of devising different toll rates for populations of different income levels. This is in part due to populations can find alternatives to not accessing tolled roads. However, in the context of RUC, where all roads are priced, the alternative to not using them is not readily available or may largely impact mobility. Prioritizing equity considerations along all this dimension would ensure that mitigations for these impacts are in place when RUC is being implemented at-scale.

Another key takeaway from our research is managing revenue leakage in the transition from a "pay now" to a "pay later" model when moving from motor fuel taxes to RUC. This transition is currently taking place in the tolling industry for its move to an open-road and all-electronic system. The potential revenue leakage of a "pay later" model may largely compromise the efficiency gains from a more technology-centric and less manual system if safeguards are not implemented to reduce the incentives and means for toll or RUC evasions. Some potential safeguards mentioned in the interviews include partnering with the DMV to streamline the process of data request and account matching, so the accuracy of transactions matching to accounts increases. Another area of exploration is leveraging in-vehicle telematics to directly communicate with existing tolling technology to track mileage. RUC implementation can also leverage such an opportunity to reduce the manual labor required in tabulating vehicles miles traveled while reducing chances of evasion or alteration. Lastly, there is a large potential to consolidate back-office account management between RUC and tolling. Instead of creating a brand-new customer service center, RUC implementation should consider leveraging the existing staffing and system infrastructures of the tolling industry. Furthermore, distance-based tolling such as express lanes already has the capability to track in-lane miles driven by vehicles, so there exists an additional opportunity to leverage existing tolling technology to track vehicles miles driven.

2.5.1 Policy Recommendations

Based on the above discussion of findings from our MCDA and semi-structured interviews, we provide the following policy recommendations for stakeholders associated with implementing a RUC program.

Table 4. Summary of policy recommendations for the relevant stakeholders: state agencies, auto manufacturers, and third-party account managers.

Stakeholders	Objective	Recommendations
State agencies	Revenue generation	1) Create a payment system where RUC participants pay a certain amount at the beginning of the payment period to avoid revenue shortfalls. True ups can happen on a quarterly or annual basis.
	Equity	2) Implement a flexible payment frequency, so RUC participants can decide whether a monthly, quarterly, or biannual payment is appropriate for their financial situation.
		3) Offer multiple RUC payment options to reduce the technology burden on unbanked or underbanked populations.
	Technology: on-road	4) Explore both in-vehicle telematics and GPS-enabled OBD to evaluate feasibility of capturing transactions.
	Technology: back-office	5) Cohesive integration with the state's Department of Motor Vehicles to obtain vehicle data efficiently
	Public acceptance	6) Statutory protection of personally identifiable information
Auto manufacturers	Technology: on-road	7) Reduce cost barriers for accessing in-vehicle telematics data for mileage reporting
Third-party account managers	Technology: back-office	8) Build a flexible and secure database to exchange and to transfer pertinent information among the implementing agencies and customers
	Public acceptance	9) Ensure the highest standards of data management and security
	Autonomy	10) Leverage the existing account management and customer service expertise from tolling agencies to manage the administration and collection of RUC payments

2.6 Acknowledgements

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Chapter 3. Forecasting revenues of motor fuel taxes in California: an application of time-series regression to estimate changes in vehicle miles-travelled (VMT) among light-duty vehicles (LDVs)

3.1 Introduction

Motor fuel taxes have been the major funding source for transportation infrastructures in the United States for the past century. In 2021, the federal motor fuel taxes raised about $32.8 billion in revenues which accounted for about 70% of the Federal Highway Trust Fund's expenditures on infrastructures (FHWA, 2022). Light-duty vehicles (LDVs) contribute primarily to the gasoline taxes, while medium- and heavy-duty vehicles contribute to diesel taxes. In California, the state gasoline excise taxes raised about $7.4 billion in 2023, which is about 50% of spendings on transportation programs, including programs to maintain state, county, and local roads (LOA, 2023). Between 1923 to 1983, the state gasoline tax rate has been raised gradually from 2 cents/gallon to 9 cents/gallon (LOA, 2023). Post 1980s, the gradual pace of increase of gasoline excise tax rate can no longer keep pace with revenue requirements for road maintenance. The tax rate doubled to 18 cents/gallon in the 1990s, and it effectively doubled again to 35 cents/gallon in 2010 (LOA, 2023). Even though the rapid increase in the gasoline excise tax rate was an attempt to keep up with the revenue requirements to maintain state roadways, inflation and the improvements in vehicle efficiency outpaced gasoline excise tax increases. Faced with a challenging reality to fund its transportation infrastructures, California passed the Senate Bill 1 in 2017 which increased the gasoline excise tax rate to 47 cents/gallon and indexed it to inflation starting in 2020 (LOA, 2023). While this significant raise in the gasoline excise tax rate temporarily relieves the pressure of maintaining our transportation infrastructures, it also raises many concerns including the affordability of gasoline, the appropriateness of using gasoline consumption as a proxy for road usage, and the sustainability of revenues raised by the gasoline excise tax as California electrifies its LDV fleet.

In the recent decades, relying on motor fuel taxes to fund transportation infrastructures in the U.S. has not been sustainable. Some of the major issues include the lack of revenue generating capacity, economic efficiency, and regressivity of the taxes. The lack of revenue generation by motor fuel taxes has been studied by Dumortier et al., where they compared the revenue-generating capacity among three policy options: indexing the motor fuel taxes to inflation, imposing sales taxes on the motor fuels, and replacing motor fuel taxes with a road-usage charge (RUC) (2017). Their study found that without indexing the motor fuel taxes to inflation, the revenues generated would decrease by 46% from 2015 to 2040 (Dumortier et al., 2017). This trend is mitigated when indexing motor fuel taxes to inflation, where the decrease in revenues is estimated to be between 3% and 16%. Based on their simulation results, Dumortier et al. found that RUC is the only funding mechanism that is sustainable in the long run (2017). This further highlights that California's current approach to indexing motor fuel taxes to inflation is only a stop-gap measure and that RUC is necessary to generate sustainable funding for transportation infrastructures.

Even though the lack of revenue-generating capacity of motor fuel taxes presents a challenge for transportation infrastructure funding, the transition away from motor fuel taxes has been delayed due to considerations of alternative policy options' performance around economic efficiency and equity. The current underpayment in motor fuel taxes results in underinvestment in transportation, which has widespread impacts on the quality and reliability of transportation infrastructures (Zhao et al., 2015). This indicates that motor fuel taxes are not economically efficient at funding transportation infrastructures. Furthermore, Zhao et al. also found that motor fuel taxes are highly regressive because they incur much higher burdens on lower-income groups (2015). On the front of regressivity, the magnitude of impacts has been quantified by Steinsland et al. and Glaeser et al. (2018, 2023). Steinsland et al. evaluated the distributional impacts of implementing a RUC vs. raising the motor fuel taxes in Oslo, Norway, and they found that increasing fuel taxes would create a bigger financial burden on lower-income groups (2018). More specifically, the lowest-income group would be made seven times worse than the highest-income group, severely worsening the regressivity of motor fuel taxes (Steinsland et al., 2018). Similarly, Glaeser et al. investigated the distributional impacts of motor fuel taxes in the United States, and they found that the lower six income deciles pay less under a RUC than gasoline tax, while the higher four deciles pay more under a RUC than gasoline tax (2023). These two sets of results indicate that RUC has the potential to improve regressivity of transportation infrastructure funding policy instrument.

Another important factor in the transition away from motor fuel taxes is the increasing adoption of zero-emissions vehicles (ZEVs), namely electric vehicles (EVs) which do not run on motor fuels. Jenn et al., Jia et al., and Davis & Sallee evaluated the impacts of EVs on motor fuel taxes revenues (2015, 2019, and forthcoming). Jenn et al. estimated that the revenue loss under a less aggressive EV adoption growth would result in approximately $200 million from 2015 to 2025 (2015). Under a more aggressive EV adoption growth scenario, the loss in total revenue is in the order of $900 million by 2025 (Jenn et al., 2015). Davis & Sallee applied a utility-maximizing microeconomic model to estimate the foregone motor fuel taxes revenues across the United States. They found that exempting EVs from paying motor fuel taxes translates to an approximate forgone revenue of $249 million in 2017. As the projected EV adoption accelerates, the impacts on foregone gasoline taxes revenue are expected to increase to $6 billion by 2030, if there are no stop-gap measures that charge EVs for their impacts on the roads (Davis & Sallee, forthcoming). As EVs become more widely adopted, many states began implementing an additional flat annual registration fee to capture some of the revenue losses from EV's lack of consumption of motor fuels. For instance, beginning in July 2020, California began charging an annual Road Improvement Fee of $118 for each ZEV model year 2020 or newer (DMV, 2024). To illustrate this gap in revenues generated by an annual flat fee leveraged on ZEVs, Jia et al. quantified the required annual flat fee on ZEVs to meet the revenue requirements in Virginia in 2016. They found that the annual flat fee leveraged on ZEVs in replacing the moto fuel taxes payment would need to increase to $218 (Jia et al., 2019). As the fuel types of our vehicle fleet diversify, motor fuel taxes become an increasingly obsolete proxy for road usage. This broken linkage between vehicle miles travelled (VMT) and payment for road usage emphasizes the urgency to seek replacement for the motor fuel taxes, one which re-establishes the linkage between VMT and road usage payments.

To address the sustainability of revenues raised by the gasoline excise tax in California and to understand the impacts of LDV electrification on transportation infrastructure revenues, it is essential to estimate and to forecast VMT by LDVs. To this end, our paper focuses on answering this research question by constructing a time-series regression model to predict future VMT at the county level in California. Increasing the data granularity can improve the estimates of our parameters and provide more robustness in policy analysis at both county and state levels. For the purpose of this study, our VMT results are aggregated to the state level to answer policy-relevant questions regarding future gasoline excise tax revenues while accounting for varying paces of LDV electrification. The implications of our work are two-fold: to apply time-series regression modeling techniques to forecast VMT and to provide recommendations on rate structures for alternative funding mechanism, such as RUC. The paper is organized as follows: Section 2 presents existing literature on VMT estimation techniques and applications. Section 3 details the method of our analysis, Section 4 presents the results, and Section 5 discusses our findings.

3.2 Literature Review

Existing literature has extensively investigated methods for forecasting VMT, with the earlier literature focused on testing and identifying modeling techniques. The two main categories of VMT forecast techniques are travel-demand-based models and regression-based models. Travel-demand-based models treat LDV VMT as an induced demand due to personal activities. One of the advantages of these models is their ability to capture how households respond to travel demand management policies, such as transit improvements and telecommuting incentives (Shiftan & Suhrbier, 2002). By changing the inputs of the models in terms of sociodemographic variables, land-use patterns, and transportation networks, Shiftan and Suhrbier simulated changes in LDV trip generations and the resulting VMT (2002). Later work has leveraged travel-demand-based models to forecast VMT, including Erhardt et al.'s work on estimating changes in per-capita VMT in the San Francisco Bay Area under different planning scenarios which vary in land-use patterns, employment, and population (2011). In addition, Shabanpour et al. integrated an activity-based travel demand model with a dynamic traffic assignment model to estimate the VMT and air quality impacts in the Chicago metropolitan area under different congestion management scenarios (2018).

On the other hand, there is a plethora of existing literature on leveraging regression-based models to forecast VMT. For instance, Liu et al. tested multiple model specifications, including ordinary least-squares (OLS), cross-sectional time-series OLS, and two-stage least-squares by using sociodemographic data to forecast county- and state-level VMT in Pennsylvania (2006). The authors concluded that regression models provide a consistent framework for forecasting state-level VMT when the required sociodemographic and road mileage data is available (Liu et al., 2006). A more recent study by Rentziou et al. applied a random coefficient panel data model to estimate the total passenger VMT in the U.S. (2011). The random coefficients model specification allowed the estimated coefficients to vary over time and across states, as well as to capture the random disturbances at the state level and in each year (Rentziou et al., 2011). One major contribution from this study was estimating the elasticity of VMT with respect to fuel tax. Additionally, Rentziou et al. found that an increase in the percentage of alternative fuels vehicles would result in an increase in VMT (2011). These studies demonstrated that quantitative modeling of VMT is the backbone for forecasting VMT growth. To build on existing studies, our work contributes to regression-based forecasting techniques by applying time-series regression techniques to better incorporate the impacts of past VMT on future growth.

Governmental agencies have also adopted regression-based VMT forecasts, including the Volpe Center in the U.S. Department of Transportation, which has been developing national and state-level VMT forecasting models. Their model employed an autoregressive distributed lag specification which captures the long-run impacts of both VMT and the explanatory variables, such as population, economic activity, and cost of driving (FHWA 2022 & Cohen et al., 2021). The primary objective of the model is to provide thirty-year forecast of VMT at the national and state- level for light-duty, medium-duty, and heavy-duty vehicles. Policymakers leverage the VMT estimates as inputs to design scenarios of plausible economic, demographic, and technological changes to capture a range of potential policy impacts (Cohen et al., 2021). While the VMT forecast model developed by the Volpe Center serves as an important tool in policy analysis, one of the disadvantages of this model is the lack of granularity in the input data. Namely, the model is constructed using either national or state-level sociodemographic data, which limits the number of observations per year. By increasing the granularity of input data to county-level, the input data captures more variability within the state which helps our model provide more stable and reliable state-level VMT forecasts.

In terms of constructing more granular VMT estimation models, Mahmud et al. built a heteroskedastic log-linear regression model to estimate VMT in St. Louis by leveraging past VMT, sociodemographic, and roadway data (2023). The geographic granularity of the collected data is at the census block-group level, which allowed them to precisely estimate VMT for a given city (Mahmud et al., 2023). While the granularity of a VMT estimation model hinges on the data availability of the VMT and the explanatory variables, gaining access to more granular data can expand VMT estimation models' ability to answer policy-relevant questions at the state and regional levels. Similarly, Langer et al. employed a log-linear regression to build a short-run demand model of VMT on a sample of Ohio drivers (2017). They applied the model to quantify the economic efficiency of implementing a revenue-neutral RUC vs. motor fuel taxes and found that a RUC would yield positive social welfare because of reductions in air pollutions and congestions (Langer et al., 2017). Both of these studies demonstrate the importance of increasing data granularity in regression-based models to answer policy-relevant questions related to VMT at the regional and state level.

Lastly, Williams et al. conducted a literature review and synthesis on the existing methods of VMT estimation (Williams et al., 2016). They found that time-series regression model which considers sociodemographic and road data have not been widely applied to forecast statewide VMT. The plethora of literature to date on VMT estimation and forecast has served as a scholarly foundation to inform our methods of analysis. The contribution of our work is uniquely situated in constructing a state-level time-series regression-based model to forecast VMT in California by leveraging county-level sociodemographic and roadway data. Furthermore, we apply the VMT model to estimate impacts of LDV electrification on transportation infrastructure revenues, which is a novel application of VMT estimation model to provide quantitative understandings on transportation infrastructure funding.

3.3 Methodology

The main sources of data for this project consist of county-level VMT data obtained from California Air Resources Board's Emissions Factors Model (EMFAC), sociodemographic data from American Community Survey (ACS), and public road mileage data from the California Department of Transportation (Caltrans). EMFAC2021 leverages a dynamic machine-learning model to search a large pool of relevant socioeconomic variables and to optimize the parameter selection based on the model's ability to predict historical VMT data (CARB, 2021). The county-level VMT data is reported on https://arb.ca.gov/emfac/project-analysis. We filtered for VMT associated with LDVs, including light-duty passenger vehicles and light-duty trucks which correspond to Class 1 and 2 vehicles per Federal Highway Administration's classification.

The relevant sociodemographic data from the Volpe Center's LDV forecast model included total population, number of households, number of households with children, total employment, and median income (Cohen et al., 2021). Informed by the explanatory variables selected by the Volpe Center for their time-series VMT estimation model, we selected the following explanatory variables for our model specifications. **Error! Reference source not found.** below shows the summary statistics of the included county-level explanatory variables. We collected the county-level data on these variables from the ACS 1-year estimates. For counties with low populations, 1-year estimates were unavailable for the following variables: number of households, number of households with children, total employment, and median income. Therefore, we obtained the 5-year estimates for the study period: 2010 to 2022. We then employed linear interpolations to obtain the estimates of these variables for years between 2010-2015, and 2015-2020. For the years 2021 and 2022, we extrapolated linearly to estimate these variables. Lastly, we obtained the annual county-level public road mileage data from Caltrans' Highway Performance Monitoring System's Public Road Data (Caltrans, 2022). Public roads include city, county, state highway, and federal highways.

Table 5. Summary statistics of variables in our model including population, household composition, employment, income, and road mileage data

Explanatory variables	Min.	Max.	Avg.	Std. deviation
Total population	1,047	10,105,708	665,481	1,438,201
Total number of households	225	2,217,649	152,532	319,714
Number of households with children	173	1,187,690	76,734	159,186
Total employment	406	5,037,815	309,745	687,028
Median income ($)	33,219	15,839	65,166	21,069
Total public roads (thousands miles)	220	23,143	3,062	3,460

To estimate the VMT changes among LDVs in California, it is essential to first determine the relationships between factors influencing the induced travel demand and the outcome variable of interest: VMT. According to the Volpe Center, factors which influence LDV VMT are mainly sociodemographic factors (Cohen et al., 2021). Specifically, the factors which demonstrated statistical significance in explaining the changes in VMT are population, household composition, economic activity indicators such as employment, and cost of driving (Cohen et al., 2021). One of the biggest contributions of our work is overcoming the lack of data granularity in the existing models of VMT estimation by conducting our analysis at the county-level. Increasing the sample size of our data allows us to have more confidence in the predictive power of our models. We also performed both in-sample and out-of-sample validation procedures to demonstrate model fit and selection, which will be detailed later in this section.

3.3.1 Model specification: Autoregressive integrated moving average model (ARIMA)

The specification of ARIMA model is a logarithmic specification of the dependent and independent variables. The lags of the dependent variable: annual VMT at county i and at time t (Y_{it}) and the matrix of lags of explanatory variables ($\mathbf{X}_{it}$) are included in the model. The matrix of explanatory variables includes total population, total number of households, number of households with children, total employment, median income, and public road miles at the county level from 2010 to 2022. The advantage of including the lags of explanatory variables is to capture the potential long-run effects of sociodemographic and road infrastructure on VMT. Furthermore, ARIMA models provide a flexible structure to include the lagged error terms ($\varepsilon_{i,t-n}$) from previous periods which are known as the moving averages. One of the key assumptions of employing ARIMA model specifications is that the time-series data must be stationary, meaning that it has no trend and that the autocorrelation is constant over time. We leveraged the Augmented Dickey-Fuller test on the county-level time-series VMT data to test for stationarity; the results demonstrated that the time-series of VMT is stationary. We also controlled for the effect of Year 2020 on VMT via a dummy variable due to the global COVID-19 pandemic significantly reducing travel.

In selecting the number of lags of VMT and explanatory variables that best fit our data, we employed a stepwise testing procedure which computes the Bayesian information criterion (BIC), Akaike information criterion (AIC) and log-likelihood for each model specification. By varying the number of lags of the explanatory variables in each iteration, we determined the number of lags of VMT that minimizes BIC. After performing the stepwise testing procedures on ARIMA model specifications, we learned that ARIMA with two lags of VMT, one-period error term and two lags of explanatory variables maximize the log-likelihood while minimizes AIC and BIC. We then computed mean squared errors

(MSE) for this specification. The data on BIC, AIC, and the log-likelihood of the models tested are detailed in the Appendix. The specification of the ARIMA model is demonstrated in Equation 1 below.

$$\ln(Y_{it}) = \alpha + \beta_1 \ln(Y_{i,t-1}) + \beta_2 \ln(Y_{i,t-2}) + \boldsymbol{\delta}_1 \ln(\mathbf{X}_{i,t-1}) + \boldsymbol{\delta}_2 \ln(\mathbf{X}_{i,t-2}) + 2020\, dummy + \varepsilon_{i,t-1} \tag{1}$$

3.3.2 Baseline projections of VMT

One of the objectives of our work is to forecast VMT at the county-level to 2030 by leveraging the estimated ARIMA model parameters. To do so, we first generated forecasts for the explanatory variables from 2023 to 2030. We fitted both linear and exponential growth models to the explanatory variables at the county level to identify the trend from 2010 to 2022. We then compared the ratio between residual sum-of-squares (RSS) and total sum-of-squares (TSS) between the linear and the exponential models to determine which model best fits the explanatory variables by minimizing the ratios. The lower the ratio, the better the model fits our data. The results from this step are presented in the Appendix.

We identified that the exponential model is the best fit for all the explanatory variables except for the total number of households. Based on these results, we generated forecasts on the explanatory variables from 2023 to 2030. Once we completed generating the forecasts on the explanatory variables, we applied the estimated coefficients of the explanatory variables from the ARIMA model to generate the VMT forecast for each county from 2023 to 2030. We constructed the 95% confidence intervals of the VMT estimates by bootstrapping the estimated errors of the model to account for the variability in the residuals.

3.4 Results

The results of the statewide VMT forecast from 2023 to 2030 are presented below in **Error! Reference source not found.**Table 6 and in Figure 2. As demonstrated by the figure, we observed a drop in the estimated VMT from 2022 to 2023 and a slow upward trend starting in 2023. While the point estimates of VMT from 2023 to 2030 are below the linearly extrapolated VMT from historical data (2010 to 2022), the 95% confidence intervals encompass the linearly extrapolated VMT from historical data. The estimated statewide VMT has a direct implication on future motor fuel taxes revenue in California.

Table 6. Estimated statewide LDV annual VMT (in billions of miles)

	2023	**2024**	**2025**	**2026**	**2027**	**2028**	**2029**	**2030**
Point estimate	328.17	334.38	342.32	346.65	351.05	355.53	360.07	364.67
High 95%-tile	474.13	485.63	496.67	505.17	515.08	522.75	529.42	537.17
Low 5%-tile	207.59	211.17	215.94	218.10	219.72	222.58	225.41	229.09
EMFAC	379.85	384.11	386.61	388.16	390.41	392.59	394.68	396.70
Linear extrapolation	374.56	380.81	387.06	393.31	399.56	405.81	412.06	418.31

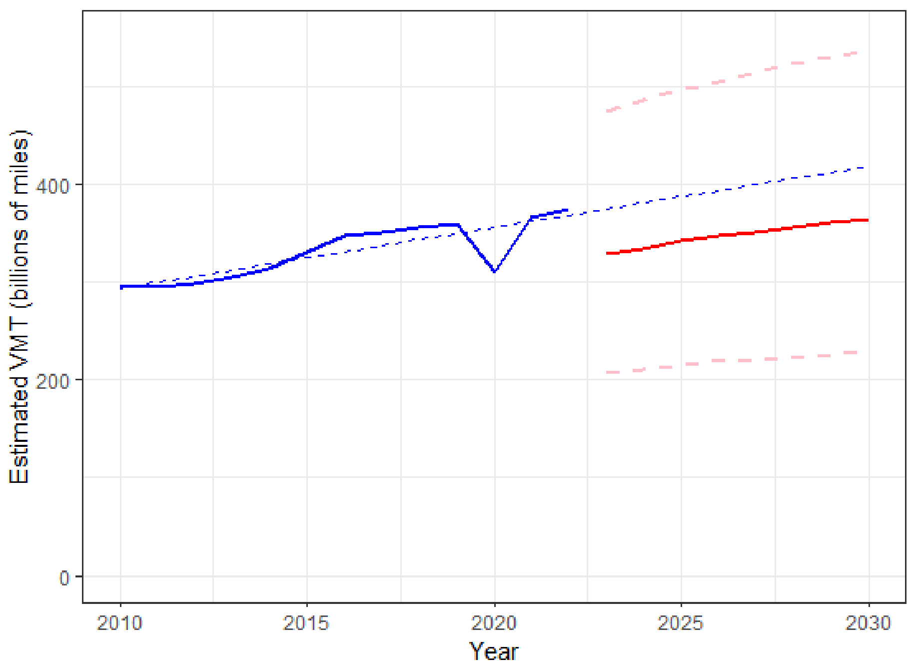

Figure 2. Historical (Year 2010 to Year 2022) and forecast statewide VMT (Year 2023 to Year 2030). Point estimates of VMT from the AIRMA model are slightly below the linearly extrapolated VMT from historical data. The 95% confidence interval contains the linearly extrapolated VMT.

3.4.1 Revenue impacts under different LDV electrification scenarios

After we forecasted the VMT, we constructed two scenarios to capture the varying levels of LDV electrification in California and their impacts on gasoline taxes revenues, including both excise and sales taxes. The first scenario follows the market share of ZEVs in California and assumes a linear increase in the market share from the present to 2030. This corresponds to approximately 5.2% of ZEV market share in 2023 and an annual growth rate of 37%, which is estimated from historical ZEV market share data from 2011 to 2023 (CEC, 2024). The second scenario assumes a more aggressive adoption of ZEVs by increasing their market share by 30% from the market share of the first scenario. While ZEVs do not contribute to gasoline taxes, they are currently subject to an annual Road Improvement Fee of $118, if the model year of the ZEVs is 2020 or later. In our analysis, we assumed that all ZEVs adopted post 2023 are subject to this fee, which is going to offset their lack of contributions to the motor fuel taxes.

In Table 7 below, we present the results of the estimated statewide gasoline taxes revenues under three scenarios: 1) Baseline scenario of assuming the market share of ZEVs stay at 5.2% and contributes to statewide gasoline taxes revenue via paying the Road Improvement Fee, 2) Scenario 1 of ZEV growth by including the revenues generated by the Road Improvement Fee, and 3) Scenario 2 of a more aggressive adoption of ZEVs and its impact on gasoline taxes revenues. The revenues are computed at the average LDV fleet efficiency of 25 MPG, the gasoline excise tax rate of $0.60/gallon, and an average sales tax rate of 3.8% of average retail gasoline prices. The average gasoline prices are obtained from the Energy Information Agency's Annual Energy Outlook and presented in the Appendix (AEO, 2023). Based on the results, we learned that as the pace of LDV electrification increases, the gasoline tax revenues are projected to decrease relative to the baseline scenario. The magnitude of the gap between the baseline and the two electrification scenarios are expected to widen over time as ZEVs market share increases. By 2030, the gap widens to $0.10 and $0.23 billion between the baseline and Scenario 1 and 2, respectively. The revenue gap from Scenario 1 and 2 represents approximately 1% and 2.2% of the estimated gasoline excise tax revenues in 2030, respectively. See Figure 3 below for the magnitude of gasoline excise tax revenues under the three scenarios. The negative revenue gaps between Scenario 1 and the baseline scenario are resulting from the linearly extrapolated market share of ZEVs for Year 2024 to 2026 to be lower than 5.2%, the market share of ZEVs in 2023. Post 2026, both scenarios project widening revenue gaps due to the increasing pace of LDV electrification.

Table 7. Estimated statewide LDV gasoline taxes revenue (in billions of $) under three scenarios.

Scenarios		**2023**	**2024**	**2025**	**2026**	**2027**	**2028**	**2029**	**2030**
Baseline	**Point estimate**	9.76	9.79	9.89	9.98	10.09	10.22	10.36	10.50
	High 95%-tile	14.03	14.13	14.26	14.46	14.72	14.94	15.14	15.37
	Low 5%-tile	6.23	6.25	6.30	6.35	6.39	6.47	6.56	6.67
	EMFAC	11.27	11.22	11.14	11.16	11.21	11.27	11.34	11.40
Scenario 1	**Point estimate**	9.75	9.84	9.91	9.99	10.07	10.18	10.29	10.40
	High 95%-tile	14.01	14.22	14.31	14.47	14.69	14.86	15.02	15.20
	Low 5%-tile	6.23	6.27	6.32	6.35	6.38	6.45	6.53	6.63
	EMFAC	11.26	11.28	11.17	11.16	11.18	11.22	11.26	11.29
Scenario 2	**Point estimate**	9.75	9.76	9.82	9.89	9.97	10.06	10.17	10.27
	High 95%-tile	14.01	14.08	14.16	14.30	14.50	14.66	14.80	14.97
	Low 5%-tile	6.23	6.23	6.28	6.31	6.34	6.41	6.48	6.58
	EMFAC	11.26	11.18	11.07	11.04	11.06	11.08	11.11	11.14

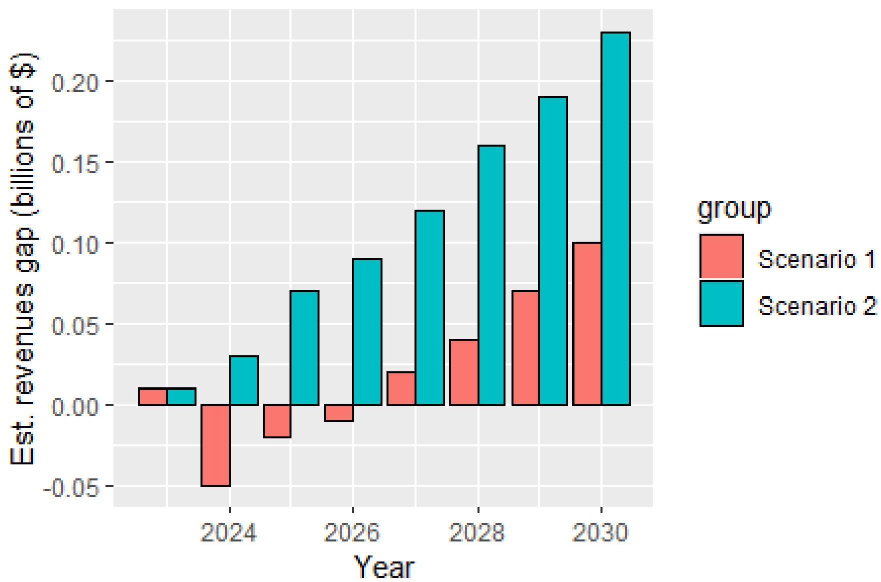

Figure 3. The estimated revenue gaps between the two LDV electrification scenarios and the baseline scenario.

3.5 Discussion

One of the contributions of this paper is to construct a state-level VMT prediction model that leverages county-level sociodemographic and public road data to forecast both county-level and state-level VMT. By improving the input data granularity, our work contributes to refining the geographic granularity of VMT prediction models. Obtaining the point estimates and confidence intervals of VMT provides practical applications for evaluating transportation policies, such as estimating future motor fuel taxes revenues. Based on our model results, we expect to see a steady increase in VMT at a level that is lower than the linearly extrapolated forecast for VMT between the present and 2030. This could be potentially due to the short-term effect of a gradual rebound in VMT post the COVID-19 pandemic that is being captured in the autoregressive terms of the model: VMT_{t-2} and VMT_{t-1}. When comparing the point estimates of VMT from our model to EMFAC, which is a dynamic machine-learning model predicting VMT using historical VMT and socioeconomic data, our model underpredicts VMT by 8% to 14%.

While recognizing the potential underprediction of our model, we constructed the 95%-confidence intervals around the VMT forecasts to understand the variability of our estimates. The standard deviation of the VMT forecasts increase over time as the model is calibrated to include two autoregressive terms and two lags of explanatory variables. Another interesting point to note is that probability distribution is right skewed, because on average, the standard deviation of the VMT forecasts above the point estimate is greater than that below the point estimate. This indicates that the point estimates of VMT, which represent the mode of the right skewed distribution, are smaller than the estimated averages of VMT. In other words, because of the positive skewedness of the distribution, the estimated averages of VMT are larger than the point estimates, which makes them closer to the estimates of EMFAC model results and the linear extrapolation of historical VMT.

In terms of understanding the implications of the gasoline excise taxes revenues, it is important to contextualize the results in terms of transportation infrastructure fundings in California. According to the California Legislative Analyst's Office, gasoline excise taxes are expected to raise approximately $7.4 billion in 2023-2024 fiscal year, which constitutes approximately 50% of spendings on transportation programs, including programs to maintain state, county, and local roads (2023). Out of the $7.4-billion revenue, $3.9 billion is deposited into the State Highway Account (SHA) to pay for state highway maintenance, rehabilitation, and related administration. Meanwhile, $2.4 billion is directed to counties and cities for the maintenance of their roads. The rest of the $1.1 billion is deposited into the Road Maintenance and Rehabilitation Account (RMRA), which is established following the passage of Senate Bill 1 (LOA, 2023). Out of the $1.1 billion in RMRA, approximately $0.4 billion is used for funding active transportation projects, such as walking and biking facilities. The rest of the $0.7 billion is earmarked for state-level highway maintenance, rehabilitation and administration.

Based on our estimates under Scenario 1, the combination of future gasoline excise tax revenue and Road Improvement Fee generate $10.40 billion by 2030. While this is on par with revenues generated in the baseline scenario, there still exists a gap of approximately $0.10 and $0.23 billion between Scenario 1 and 2 and the baseline scenario in 2030, respectively. Furthermore, this gap is expected to widen if the market share of ZEVs increases faster than Scenario 2 which highlights the importance of transitioning away from motor fuel taxes to per-mile-based usage fee to fund infrastructures. Also, one of the limitations of our model is assuming that ZEVs are like-for-like substitutes for ICEVs in terms of their VMT. In reality, ZEVs may be driven more or less than ICEVs depending on the price of charging, convenience of charging, and range of vehicles. These mechanisms can affect how much ZEVs are being driven which have an impact on our estimated revenue. Future research aims to expand the specification of our ARIMA model to include the cost of driving and potential technological innovation such as autonomous vehicle as explanatory variables to obtain the estimated parameters to inform our scenario designs on LDV electrification and automation.

Lastly, while California has relied on the gasoline tax to generate funding for its transportation system since 1923, this funding mechanism has become increasingly unsustainable in the face of inflation, improvements of fuel efficiency, and vehicle electrification (LOA 2023). The amount of gasoline purchased is no longer an appropriate proxy for how much people drive and their associated impacts on the roadways. The decoupling of motor fuel taxes and transportation infrastructure funding will require alternative funding mechanisms which directly price the impacts of driving on our roadways, such as a RUC. Assuming a revenue-neutral RUC design with the baseline scenario, the estimated per-mile rate is 3 cents/mile in 2024. This rate is on par with the California Road Charge Technical Advisory Committee recommended rate of 2.5 cents/mile for LDVs as part of the statewide RUC pilot under Senate Bill 339, which will take place later this year (CTC 2023).

3.6 Acknowledgements

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Chapter 4: Understanding the effects of vehicle portfolios on plug-in electric vehicles (PEVs)-adopting households' vehicle replacement decision: an application of vehicles transaction model

4.1 Introduction

In combating climate change, many governments around the world, including California, have set ambitious targets to electrify its transportation sector. In November 2022, California lawmakers passed the Advanced Clean Cars II Regulations (ACC II) which mandates that the sales of all new light-duty vehicles be zero-emissions by 2035 (CARB, 2022). This regulation would dramatically increase the supply of PEVs over the next decade and provide more choices to Californians in terms of vehicle makes and models. PEVs are defined as either battery electric vehicles (BEVs) or plug-in hybrid electric vehicles (PHEVs), and they are considered technological alternatives to ICEVs. Environmental benefits of PEVs manifest in the reduction of tailpipe greenhouse gasses (GHG) emissions and local criteria air pollutants during vehicles' drive cycles. Currently, PEVs sales constitute about 14% of the state's new light-duty vehicle sales, which is a small percentage compared to the target of 100% by 2035 (CEC, 2023). A dramatic uptake of PEVs at the household level is expected over the next decade to reach the State's mandated target.

According to the 2017 National Household Travel Survey California Add-on, 37% of California households own two vehicles. On average, California households keep their vehicle for about 11 years, which implies that over the next decade, it is likely that two-vehicle California households would face the decision to replace one or more of their vehicles with PEVs (FHWA, 2017). On the other hand, given the policy directive from the ACC II, auto manufacturers have also pledged to increase their production of PEVs, offering a larger variety of PEVs in terms of vehicle classes, such as compact, subcompact, sports-utility vehicles (SUVs), trucks etc. (Consumer Reports, 2023). This research aims to understand how PEV-adopting households choose among different vehicle makes and models and to quantify their preferences for vehicle portfolios.

In this paper, we contribute to the literature on PEVs adoption, while addressing an important research gap in the existing literature: the lack of explicit consideration of the households' vehicle portfolios in their adoption decisions. We empirically estimated the effects of household vehicle portfolios on PEV-adopting households' vehicle replacement decision in our mixed multinomial logistic regression models. The quantification of households' preference parameters of vehicle portfolios serves as a unique contribution to the existing literature on PEV adoption. Furthermore, our work is well-situated to project future household vehicle fleet compositions in jurisdictions that have mandated the phase-out of ICEVs. By understanding how households value certain portfolios of vehicle attributes (e.g., fuel type and vehicle class), we can more accurately predict future fleet compositions under these policy mandates.

4.2 Literature Review

Existing literature on PEV adoption has investigated consumers' purchase intentions to identify factors which influence their decisions. Using PEV registration data as a proxy for the number of PEVs purchased in a community, Canepa et al. investigated PEV adoption in disadvantaged communities versus non-disadvantaged communities in California (2019). Similarly, Wee et al. analyzed differences in PEV registrations among different zip code areas in Hawaii, and they found that income and college education are positively correlated with increasing levels of PEV adoption across the zip code areas (2020). Both abovementioned work leveraged actual PEV registration data and spatial heterogeneity in household sociodemographic to quantify factors which influence households' PEV adoption. However, they treated PEV adoption as a stand-alone decision at the household level, unrelated to other vehicles which existed in the current household fleet. We address this research gap by explicitly evaluating the impacts of household vehicle fleets in their vehicle replacement decision-making, conditional on the households adopting a PEV.

Motivated by the desire to better forecast vehicle demands, the literature on modeling household vehicle choices began to develop in the late 1970s (Berkovec, 1985). Researchers have studied the topic of household vehicle choices extensively by leveraging the techniques of discrete choice modeling. The advantage of discrete choice modeling techniques lies in its ability to represent each household as a decision-making unit, which eliminates the reliance of assuming a representative consumer in an aggregate model that is built upon macroeconomic and time-series data. Besides assuming a representative consumer, aggregate demand models introduce simultaneity issues when estimating vehicle demand using both aggregate quantity and price data. Due to these shortcomings of the aggregate modeling techniques, discrete choice modeling has been widely adopted to study household vehicle choices and is applied to forecast vehicle demand. The results from a discrete choice model demonstrate the probability that a household would choose a certain vehicle out of all the available alternatives because the chosen alternative maximizes the utility to the household (Berkowitz et al., 1987).

Early literature on this subject focused on two main categories of modeling: households' vehicle holdings (Manski & Sherman, 1980, Hensher & Le Plastrier, 1985, Berkowitz et al., 1987) and households' vehicle transactions (Hocherman et al., 1983, McCarthy, 1985). Vehicle holding models describe household-level vehicle portfolios as discrete choices made by households with heterogeneous preferences (Manski & Sherman, 1980). This modeling technique cleverly captures two major components of household vehicle decisions: the purchase of new vehicles and the scrappage or sales of the replaced vehicle(s). By modeling both components explicitly, household-level vehicle holdings models address the endogeneity between new vehicle sales and used vehicles scrappage, which is an improvement from aggregate models of vehicle demand. On the other hand, vehicle transaction models explain households' specific vehicle transactions by leveraging data on their past vehicle transactions and sociodemographic variables (Hocherman et al., 1983). Methodologically, vehicle transaction models incorporate attributes of the purchased and replaced vehicles and households' sociodemographic data in logistic regression models to explicitly evaluate the influences of these factors on the vehicle transaction decisions (Hocherman et al., 1983). When comparing household-level vehicle holdings and vehicle transactions models, vehicle transactions models are well-suited for scenario analysis and forecasting policy of changes in the vehicle market because they thoroughly account for past vehicle attributes and household sociodemographic data.

Researchers applied disaggregated vehicle transaction model to understand the demand for alternative fuels vehicles because of its ability to forecast household vehicle stocks under different policy scenarios. Bunch et al. conducted a stated preference choice survey in southern California and leveraged logistic regression techniques on the survey data to estimate the demand for alternative fuels vehicles, including electric vehicles (1993). They included PEV-specific attributes, such as range, in the model to reflect one of the major distinctions between PEVs and ICEVs. From their work, Bunch et al. found that applying discrete choice modeling techniques to stated preference data on households' choices of alternative fuels vehicles provided statistically significant and economically reasonable results. Building upon Bunch et al. 's work, Brownstone et al. constructed a vehicle transaction model that leveraged both revealed preferences and stated preferences data on household vehicle choices and portfolios (1996). Specifically, the model estimated stated preference data on alternative fuels vehicles while conditioning on the revealed preference data of the households' current vehicle portfolios (Brownstone et al., 1996). To operationalize this, attributes of the replaced, the held, and the chosen vehicles all entered the model. For instance, net capital costs of the vehicle portfolio were computed by subtracting the depreciated market value of the replaced vehicle from the purchase price of the chosen vehicle (Brownstone et al., 1996). In doing so, they cleverly incorporated the influence that the households' current vehicle portfolio has on their choices of the desired vehicle.

Since the seminal work on applying discrete choice modeling techniques to describe household vehicle holdings and transactions, a plethora of research has been conducted to advance the techniques of logistic regressions to capture more accurately the impacts of household sociodemographic variables on vehicle choices. For instance, Fatmi and Habib assessed the lead and lagged effects of life-cycle events on household vehicle ownership by developing a panel-based latent segment logit model to account for repeated vehicle transaction decisions over the surveyed lifetime of the households and to capture unobserved heterogeneity among the sampled households (2016). In another example, hypothesizing that first-time and transient (purchased a vehicle before) households may behave differently in terms of vehicle purchase decisions, Khan and Habib separately identified the effects of sociodemographic data and life events on first-time and transient owners via developing a panel random parameter accelerated hazard-based model to capture the expected duration of time between a household's decision to own zero vehicle to owning one vehicle (2021). Additionally, in evaluating the factors that influence household's decision on certain vehicle classes, they applied a mixed multinomial logit model to capture heterogeneity among households' preferences (Khan & Habib, 2021). All these methodological advancements were made to better understand how heterogeneity in preferences among households affect their vehicle choices.

Besides refining the methodology of logistic regressions to explain households' vehicle choices, an important area of research in household vehicle choice modeling lies in data collection. As described in Bunch et al.'s study on estimating the demand for alternative fuels vehicles, they leveraged surveys to collect data on the participants' stated preferences of vehicles (1993). Surveys are extremely important tools for collecting the required data for building vehicle choice models. Musti and Kockelman surveyed approximately 600 households in Austin, Texas to collect data on current, past vehicle holdings and use, and the intended future holdings (2011). In addition, survey respondents participated in a choice experiment where they selected one of the twelve vehicles that they are likely to acquire based on the body types, fuel economy, and purchase price (Musti & Kockelman, 2011). Similarly, Jensen et al. leveraged stated preference data on respondents' attitudes on vehicle attributes and charging infrastructures to investigate Danish households' preferences towards substituting ICEVs with PEVs of different vehicle classes (2021). Abovementioned research leveraged stated preference data collected via surveys to quantify households' preferences for certain vehicle attributes. While stated preference data is valuable, revealed preference data where vehicle transactions actually took place can enhance our understanding of households' preferences towards PEVs.

In the Economics literature, a recent study by Xing et al. investigated the emissions impacts of PEV adoption by estimating a random coefficients discrete choice model of new vehicle demand to identify the vehicles that PEVs are more likely to replace (2021). By using survey data on households' chosen PEV, replaced vehicle, and their second-choice vehicle if they did not choose a PEV, the authors leveraged the preference heterogeneity among households' second-choice vehicles to more precisely estimate the random coefficients (Xing et al., 2021). In terms of substitutions between PEVs and ICEVs, Xing et al. found that about 80% of PEVs replaced fuel-efficient vehicles with an average fuel economy of 27 MPG (2021). This result not only has implications for emissions reductions, but it also urges more research on how multi-car households choose PEV in consideration of the complementarity of their vehicles. Most recently, Davis published a paper on the importance of understanding PEV adoption in multi-vehicle households, which further emphasized the need for more quantitative research on this topic (2023).

To this end, we identified the research gap which our work intends to address: modeling the impacts of vehicle portfolios on two-vehicle households' decisions to replace one of their vehicles, conditional on their adopting a PEV. To our knowledge, two pieces of research have attempted to address part of the question of evaluating portfolio effects at the household fleet level as it relates to PEV adoption. Archsmith et al. evaluated how California households' choice of ICEV is influenced by the fuel economy of the replaced and the kept vehicle(s) by explicitly modeling vehicle portfolio effects at the household level (2020). While Archsmith et al. accounted for household vehicle portfolio effects on vehicle adoption, the study was solely focused on ICEVs. A working paper by Johansen and Munk-Nielson aims to achieve a similar objective to ours by investigating fuel type portfolio complementarities among Norwegian households via revealed preference data. Their work leverages discrete-continuous choice modeling techniques to account for both vehicle purchase choice and vehicle usage in order to quantify the portfolio effects on vehicle fuel type portfolios (Johansen & Munk-Nielsen, forthcoming). Johansen and Munk-Nielson leveraged vehicle registration data in Norway from 2005 to 2017 to study more than one million households, which would allow them to produce generalizable results on Norwegian households' vehicle portfolio complementarities. From their study, Johansen and Munk-Nielson found strong evidence on fuel type complementarity between PEV and ICEV. For some households, PEVs and ICEVs are "strict Hicksian complements", which means that owning a PEV would almost imply owning an ICEV. The results from their working paper are largely supported by the results from our work, which will be discussed in detail in the Results section.

4.3 Data

The main data source for this project is from the proprietary UC Davis PEVs Study, where the Electric Vehicles Research Center has surveyed approximately 10,500 PEV adopters in California from 2017 to 2020. The survey was distributed to applicants of the California Vehicle Rebate Project (CVRP), which means that the sampled households either purchased or leased a new PEV, since only new PEVs were eligible for the rebate during the study period. Furthermore, the CVRP implemented a MSRP cap of $60,000 on trucks, minivans, and SUVs, and a $45,000-cap on sedans, which took effect in February 2022 (Center for Sustainable Energy, 2023). This means that some luxury PEVs would not qualify for the rebate, such as Tesla Model 3, Tesla Model Y, and Tesla Model X. However, since our sample was collected before 2022, we observed households who adopted a wide range of PEVs, including the ones that have become ineligible due to the MSRP cap. In addition to the MSRP cap, the CVRP also implemented requirements on income eligibility. After February 2022, households were ineligible for the rebate if their household income was above $135,000 for single-filers or $200,000 for joint filers (Center for Sustainable Energy, 2023). We adjusted the net capital costs of the sampled households' vehicle fleet based on the appropriate rebates that they received per the make-and-model of the PEV.

For our study, we focused on two-vehicle households from the dataset who replaced one of their vehicles with a PEV from 2017 to 2020, because these households constituted approximately 60% of all surveyed households. For our study period, there were 6,080 two-vehicle households in the sample. After cleaning the data, the sample has 4,079 two-vehicle households. From the survey dataset, we identified these households' vehicle portfolio, including the vehicle that they chose to replace the PEV with and the vehicle that they kept. From there, we collected data on vehicle attributes of the replaced, the kept, and the chosen vehicle for each household at the model year-make-and-model level (i.e., 2019 Honda Civic). In addition to the survey data, the main sources of vehicle attributes data came from the Fuel Economy Data on www.fueleconomy.gov and the DataOne VIN Decoder, which is an industry-leading software for providing vehicle-level attributes data. Table 8 and Table 9 below show the summary of the household demographics and vehicle attributes, respectively. From the households' demographics, we can see that these sampled households tend to be higher income, educated, and property-owning households.

Table 8. Summary of household demographics from the 4,079 two-vehicle households in the UC Davis PEVs study

Demographics Variables	Value

Number of households with annual household income below $50,000	77
Number of households with annual household income from $50,000 to $149,999	1,543
Number of households with annual household income from $150,000 to $199,999	1,023
Number of households with annual household income at or above $200,000	1,436
Number of households own a home	3,437
Number of households rent a home	642
Number of households highest level of education is high school diploma	55
Number of households highest level of education is a Bachelor’s degree or higher	4,024

Table 9. Vehicle attributes summary statistics and data sources

Vehicle Attributes	**Replaced vehicle**				**Kept vehicle**				**Chosen vehicle**				**Data Sources**
	Min	Max	Avg.	Std. dev.	Min	Max	Avg.	Std. dev.	Min	Max	Avg.	Std. dev.	
MSRP (1000’s $)	10.1	121	31	12	8.6	447	35	16	27	102	45	16	DataOne VIN Decoder
Fuel efficiency (MPG/MPGe)	11	130	40	29.98	10	140	34	26.58	25	136	98	35.53	fueleconomy.gov
Vehicle age (years)	0	34	8	5.46	0	54	6	5.64	0	4	0.1	0.31	UC Davis PEVs Study
Vehicle class	Vehicle class			Count	Vehicle class			Count	Vehicle class			Count	fueleconomy.gov
	Cars			3044	Cars			1725	Cars			3056	
	SUV			877	SUV			1805	SUV			925	
	Trucks			70	Trucks			262	Trucks			0	
	Minivan			88	Minivan			287	Minivan			98	
Fuel type	Fuel type			Count	Fuel type			Count	Fuel type			Count	fueleconomy.gov
	BEV			565	BEV			383	BEV			2918	
	PHEV			383	PHEV			237	PHEV			1161	
	ICEV			3131	ICEV			3459	ICEV			0	

After collecting the data, we conducted the following steps to process the data in order to obtain the variables of interest. First, from the fuel efficiency data, we computed the per mile operating costs for all vehicles. For BEVs, the operating cost (¢/mile) was computed by multiplying household electricity rates (¢/kWh) and the fuel economy of PEVs (kWh/mile). The households’ electricity rates were collected from the websites of their corresponding utilities companies which the households provided in the survey.

There were about 13 unique utilities companies in the sample, and the electricity rates range from 12¢/kWh to 44¢/kWh (See Figure 4 below). For ICEVs, the operating cost was computed by multiplying the average annual gasoline prices in California for 2017, 2018, 2019, and 2020 ($/gallon) by the inverse of the ICEV's fuel economy ratings (gallons/mile). If the household purchased the vehicle in 2019, then the average California gasoline price of 2019 was used to compute the vehicle's operating costs. The gasoline price data was collected from the U.S. Energy Information Administration's historical database on average annual gasoline prices for each State (See Table 10 below). For PHEVs, we computed both the operating costs for the gasoline and electricity components by leveraging the utility factor of the PHEVs to determine the portion of the vehicle driving on electricity vs. gasoline. The utility factors data was collected from fueleconomy.gov.

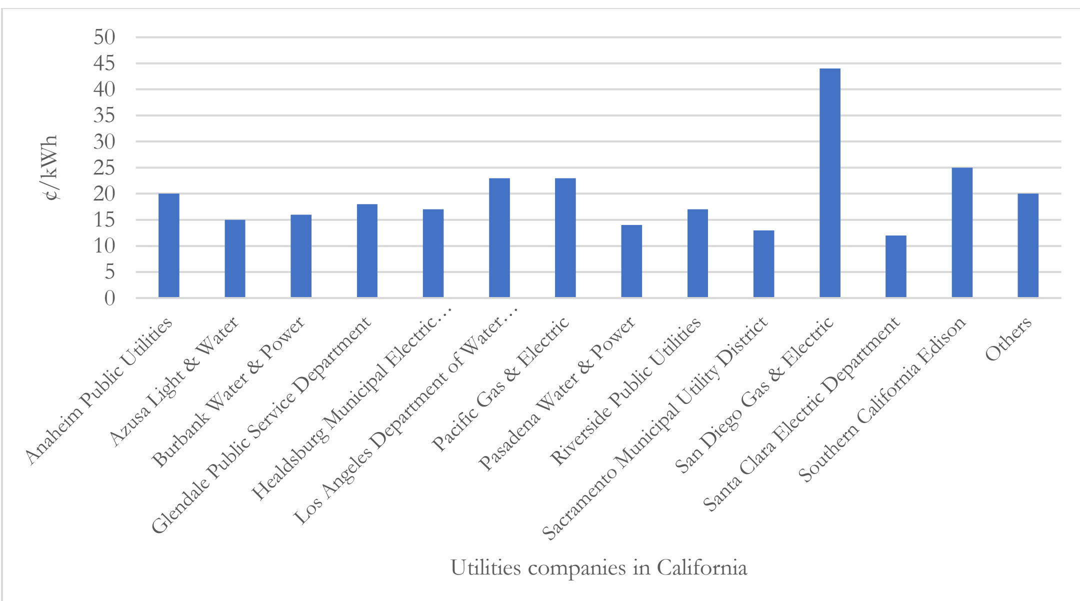

Figure 4. Average retail electricity rate across multiple utilities companies in California in 2022. San Diego Gas and Electric company has the highest residential electricity rate at 44¢/kWh. Meanwhile, most of the utilities companies average around 20¢/kWh.

Table 10. Average annual gasoline price in California from 2017 to 2020

Year	Price ($/gallon)
2017	3.08

2018	3.55
2019	3.68
2020	3.13

In addition to the vehicle attributes, we constructed the following binary variables to capture the households' vehicle portfolios. Firstly, we identified the vehicle class of the two vehicles, then we constructed binary variables to explicitly represent all the chosen portfolios. To reduce the number of portfolios represented for computational reasons, we consolidated some vehicle classes into one category which resulted in four major categories: car, SUV, truck, and minivan. In addition, we constructed binary variables to reflect fuel type portfolios. Figure 5 below demonstrates the distribution of household vehicle class portfolios, and Figure 6 shows the distribution of household fuel type portfolios. Lastly, we constructed interaction variables that may influence households' PEV adoption decisions based on their socioeconomic data (Brownstone et al., 1996). Such variables include the interactions between household tenancy and education level and their adoption of BEVs vs. PHEVs. We also separately identified the effect of households' previous ownership of a luxury vehicle on their likelihood of adopting a BEV vs. a PHEV.

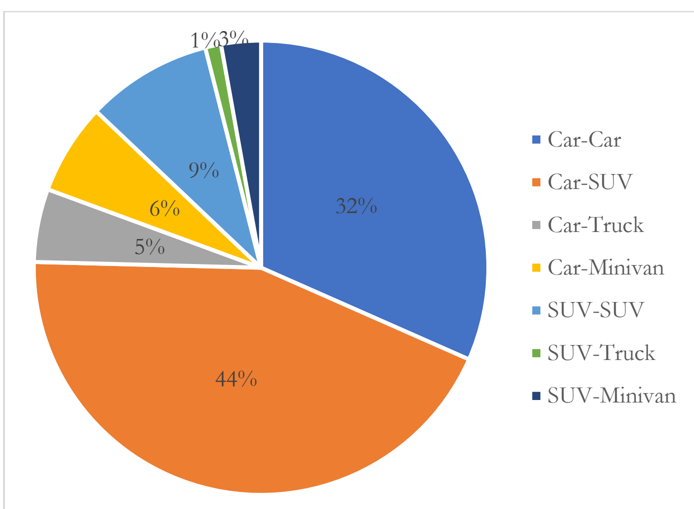

Figure 5. Distribution of vehicle class portfolios among the sampled households. The most popular vehicle portfolio among PEV-adopting and two-vehicle households in the sample was "Car-SUV", followed by "Car-Car".

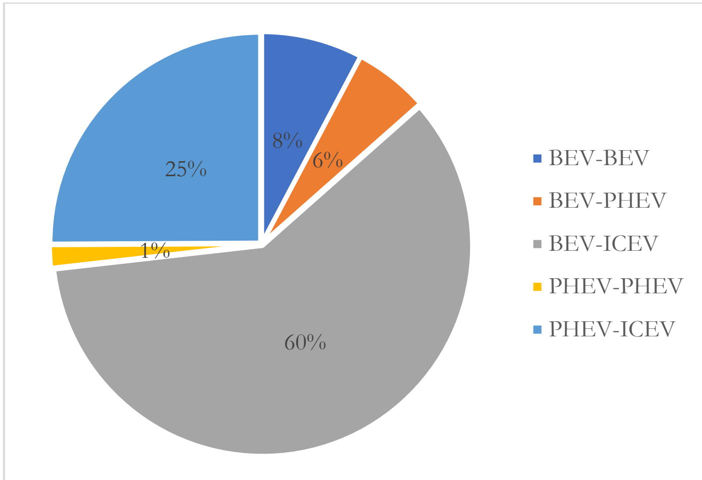

Figure 6. Distribution of fuel type portfolios among the sampled households. The most popular vehicle fuel type portfolio is "BEV-ICEV", followed by "PHEV-ICEV".

4.4 Method

In choice theories, a choice is viewed as an outcome of a sequential decision-making process that includes the following steps: 1) definition of the choice problem, 2) generation of alternatives, and 3) evaluation of the alternatives (Ben-Akiva & Lerman, 1985). To operationalize this process, it is important to capture these steps in the models and to reflect them as closely to reality as possible. In terms of defining the choice problem, identifying the level of decision making and the choice set are crucial components in the first and second steps, respectively. In our case, we modeled vehicle replacement choice conditional on households adopting a PEV. In terms of evaluating the choice alternatives, we center our analysis on random utility theory in the field of microeconomics. According to random utility theory, individuals choose the alternative from a choice set (C_n) that maximizes their utility. However, the utilities that individuals gain from their choices are unobservable to the researchers due to potentially unobservable attributes of the alternatives, unobservable taste variations among individuals, and measurement errors. Therefore, the utilities are treated as random variables and are specified in the model as the probability of alternative i being chosen is equal to the probability that the utility of alternative i, U_i

, is greater than or equal to the utilities of all other alternatives in the choice set (Ben-Akiva & Lerman, 1985).

$$P(i|C_n) = \Pr\left[U_i \geq U_j, all\ j \in C_n\right] \quad (2)$$

This approach allows modelers to derive the probability of each alternative being chosen by the individual by assuming a joint probability distribution for the set of random utilities. The specification of the utility function is broken down into two components: the deterministic (S_i) and the random components (z_i). The deterministic component of the utility function is specified by the vector of attributes of the alternative (V_i). In our model, we included attributes of the household vehicle portfolios, such as capital costs, operating costs, fuel type portfolios, and the vehicle class portfolios. Household sociodemographic variables were also included, such as tenancy, income, and level of education, to account for taste variations among households. The deterministic component of the utility function in our model are linear in parameters. On the other hand, the random component of the model refers to the error terms of the utility functions' specification. We assume that the error terms are independently and identically Gumbel distributed (Ben-Akiva & Lerman, 1985).

$$U_i = V(z_i, S_i) + \varepsilon(z_i, S_i) = V_i + \varepsilon_i \quad (3)$$

Gumbel distribution of the error terms have desirable properties when applied to a multinomial logit model. Namely, based on the property: the difference between two independently Gumbel distributed error terms is logistically distributed, which helps derive the multinomial logit (Ben-Akiva & Lerman, 1985). The estimated multinomial logits have many useful applications in microeconomics. Specifically, we derive the income choice elasticities of PEV adoption for these sampled households. In terms of model estimation, maximum likelihood estimation is applied to solve for the parameters of the modeled attributes in order to maximize the probabilistic random utility functions (Ben-Akiva & Lerman, 1985). We apply the same estimation method to our model specifications.

4.4.1 Multinomial Logit Model

Our first model specification was a multinomial logit model to estimate the households' likelihood of replacing one of their vehicles, conditional on their choosing one of the 40 PEV make-and-models in our dataset. The observed array of PEVs represented approximately 57% of all available PEV make-and-models during the study period in the United States (U.S. Department of Energy, 2023). It is important to note that we created multiple choices for the same PEV make-and-models which underwent generational changes during the study period. For instance, Nissan LEAF underwent a generational change with different vehicle attributes from 2018 to 2019. We captured this by separately creating two choices for "2017 and 2018 Nissan LEAF" and "2019 and 2020 Nissan LEAF". After identifying PEV make-and-models, we multiplied the 40 unique make-and-models of PEVs by two and incorporated 80 choice alternatives in the model in order to capture the hypothetical situation of the two-vehicle households replacing the vehicle that they decided to keep. The specification of the utility function followed closely from Brownstone et al.'s paper (1996). We defined net capital cost as the difference between the chosen PEV's MSRP and the depreciated market value of the replaced vehicle. Similarly, net operating cost is the difference between per-mile operating costs of the chosen PEV and that of the replaced vehicle.

In the model specification below, we separately identify the characteristics of the chosen PEV and the replaced vehicle. 'i' indexes the chosen PEV, and 'j' indicates the replaced vehicle. F_{ij} is the fuel type portfolio associated with buying vehicle *i* and replacing vehicle *j*. C_{ij} denotes the vehicle class portfolio of choosing vehicle *i* and replacing vehicle *j*. D_l represents demographic variables including college education dummy and home-ownership dummy variables. BEV_i and $PHEV_i$ are dummy variables representing BEV and PHEV, respectively. L_j indicates whether the replaced vehicle is a luxury vehicle.

$$V_{ijl} = \alpha_i + \sum_{f \in F} \beta_f \, \mathbb{1}\{F_{ij} = f\} + \sum_{c \in C} \gamma_c \, \mathbb{1}\{C_{ij} = c\} + \lambda D_l BEV_i + \theta L_j BEV_i + \mu L_j PHEV_i + \beta_{ncc} \, NCC_{i-j} + \beta_{noc} \, NOC_{i-j} \tag{4}$$

Because our choice space accounted for the hypothetical situation where households could have decided to replace the vehicle that they kept, the net capital cost is a proxy for the asset value of vehicles to the household. To illustrate this point, households faced the decision to replace either their Vehicle A or Vehicle B, with Vehicle A being the newer and more valuable vehicle (i.e., higher market value at the time of transaction). If they decide to replace Vehicle A, they face a smaller net capital cost. However, that also means that in the hypothetical situation where they replaced Vehicle B, their net capital cost would be greater. Our specification captures this tradeoff that households make when they decide which vehicle to replace vs. which to keep.

To quantify the impact of vehicle portfolios on vehicle replacement choice, we explicitly included vehicle class and fuel type portfolios in the model specification. The model included home ownership and college education binary variables to control for their impacts on households' likelihood of adopting BEVs, since we observed that the sampled households tend to own homes and have higher-education degrees. In addition, we included binary variables to indicate whether the households replaced a luxury vehicle with a PEV and its effect on their likelihood to adopt BEV and PHEV, respectively. The determination of whether a vehicle is luxury or not is based on its make. For instance, BMW, Mercedes-Benz, Jaguar, and Lexus etc. are considered luxury vehicles. Including sociodemographic variables and luxury vehicles' influence on PEV adoption can separately identify these variables' influences on vehicle replacement decision, while simultaneously preserving the dynamics that the net capital cost and net operating cost variables intend to capture.

4.4.2 Multinomial Logit Model with Income Elasticities of Choice

In the second model specification, we evaluated how household income affects households' choice of PEV make-and-model, since household income is one of the important factors in influencing

PEV adoption. We interacted household income with net capital costs and net operating costs. The specification of the income interaction follows from Axhausen et al.'s paper, where the interaction terms were continuous rather than segmented levels (2008). The advantage of estimating a continuous interaction is the increased flexibility of our specification by avoiding having to assume segmentations by income levels. For instance, the income interaction terms in our second model specification took the following exponential form, where λ^{inc} represents the income sensitivity of the variables of interest (e.g., net capital costs and net operating costs) to changes in household income. This specification allows us to estimate the sampled households' income elasticities of choice, at the average household income level.

$$V_{ijl} = \alpha_i + \cdots + \beta_{ncc} \left(\frac{inc_n}{\overline{inc}}\right)^{\lambda_{ncc}^{inc}} NCC_{i-j} + \beta_{noc} \left(\frac{inc_n}{\overline{inc}}\right)^{\lambda_{noc}^{inc}} NOC_{i-j} \tag{5}$$

4.4.3 Mixed Multinomial Logit Model

To capture inter-household heterogeneity, we employed a mixed multinomial logit model which allows the estimated coefficients on net capital costs and net operating costs to have a distribution among the sampled households. We specify the random taste variation among households to have a lognormal distribution because of its desirable property of being non-negative. Each household's estimated coefficients on net capital costs (β_{ncc_n}) and net operating costs (β_{noc_n}) are therefore different from the population mean by some unobserved amount. Since there is no closed-form solution to the estimation of the random coefficients, Monte Carlo simulations are employed to approximate the value of random coefficients (Ben-Akiva & Lerman, 1985). Furthermore, this approach was proposed by Brownstone et al. in their work to implement a mixed multinomial logit model on both revealed and stated preference data on alternative fuels vehicles adoption (2000).

$$V_{ijl} = \alpha_i + \cdots + e^{(\overline{\beta}_{ncc}+\sigma_{ncc})} NCC_{i,-j} + e^{(\overline{\beta}_{noc}+\sigma_{noc})} NOC_{i,-j} \tag{6}$$

4.5 Results

In this section, we present the estimated parameters from six model specifications. The first three specifications in Table 11 demonstrate the estimated parameters from the multinomial logit model, followed by the multinomial logit model with income elasticities, and then the mixed multinomial logit model. The common parameters among these specifications are vehicle class portfolios, fuel type portfolios, interaction terms of household education and tenancy with BEV adoption, and interaction terms of previous ownership of luxury vehicles with BEV adoption. The model specification with income elasticities of choice added two more parameters: income elasticities of choice with respect to net capital cost and that with respect to net operating cost. Lastly, results from the mixed multinomial logit model presented the estimated means and standard deviations of the parameters of net capital cost and net operating costs. The latter three specifications estimated the naïve model without accounting for portfolio complementarities at the fuel type and vehicle class levels.

Table 11. Estimated coefficients of vehicle class portfolios, fuel type portfolios, and household sociodemographic variables on household choice of PEV make-and-models.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Portfolio: car-car	NA	NA	NA	NA	NA	NA
Portfolio: car-SUV	0.68 (11.22) ***	0.68 (11.24) ***	1.38 (9.99) ***	NA	NA	NA
Portfolio: car-truck	1.83 (9.67) ***	1.82 (9.64) ***	2.98 (7.65) ***	NA	NA	NA
Portfolio: car-minivan	1.82 (10.29) ***	1.82 (10.32) ***	3.07 (6.88) ***	NA	NA	NA
Portfolio: SUV-SUV	2.53 (13.83) ***	2.53 (13.85) ***	1.91 (7.87) ***	NA	NA	NA
Portfolio: SUV-truck	3.30 (10.03) ***	3.30 (10.03) ***	4.16 (5.03) ***	NA	NA	NA
Portfolio: SUV-minivan	2.94 (15.29) ***	2.95 (15.29) ***	2.69 (7.12) ***	NA	NA	NA
Portfolio: minivan-truck	4.72 (3.27) ***	4.72 (3.27) ***	3.70 (2.52) **	NA	NA	NA
Portfolio: minivan-minivan	0.72 (0.77)	0.71 (0.78)	-82.1 (-1.31)	NA	NA	NA
Portfolio: BEV-BEV	NA	NA	NA	NA	NA	NA

Portfolio: BEV-PHEV	0.64 (4.03) ***	0.65 (4.05) ***	0.56 (2.02) *	NA	NA	NA
Portfolio: BEV-ICEV	2.08 (16.65) ***	2.09 (16.65) ***	3.12 (8.82) ***	NA	NA	NA
Portfolio: PHEV-PHEV	0.49 (1.81) *	0.51 (1.86) *	0.43 (0.78)	NA	NA	NA
Portfolio: PHEV-ICEV	2.37 (9.97) ***	2.37 (9.93) ***	2.93 (4.68) ***	NA	NA	NA
Net capital cost	0.10 (22.81) ***	0.10 (22.66) ***	NA	0.08 (25.1) ***	0.08 (24.9) ***	NA
Net capital cost mean [standard deviation]	NA	NA	-8.93 [1.21]	NA	NA	-9.63 [0.77]
Income elasticity wrt. net capital cost	NA	0.12 (1.53)	NA	NA	0.15 (1.74)	NA
Net operating cost	0.94 (1.08)	0.89 (1.00)	NA	0.12 (17.3) ***	0.12 (16.7) ***	NA
Net operating cost mean [standard deviation]	NA	NA	-9.86 [8.16]	NA	NA	-9.39 [0.01]
Income elasticity wrt. net operating cost	NA	0.08 (0.08)	NA	NA	0.09 (0.72)	NA
Home ownership on BEV adoption	6.19 (5.89) ***	6.18 (5.89) ***	6.13 (5.24) ***	8.71 (8.55) ***	8.73 (8.39) ***	8.68 (8.34) ***
College education on BEV adoption	6.25 (5.96) ***	6.25 (5.96) ***	6.21 (5.34) ***	8.94 (8.54) ***	8.91 (8.76) ***	8.91 (8.71) ***
Replaced a luxury vehicle on BEV adoption	0.51 (5.37) ***	0.51 (5.42) ***	0.38 (2.92) ***	0.65 (7.96) ***	0.66 (8.00) ***	0.32 (3.89) ***
Replaced a luxury vehicle on PHEV adoption	0.23 (1.55)	0.24 (1.62)	0.20 (0.98)	0.46 (3.40) ***	0.47 (3.45) ***	0.15 (1.05)
Alternative Specific Constants	X	X	X	X	X	X
			Model Statistics			
AIC	19469.92	19470.15	19798.10	20642.61	20642.37	21015.13
BIC	19829.80	19842.66	20170.60	20926.71	20939.11	21311.87
Rho-squared	0.46	0.46	0.45	0.43	0.43	0.41

Note 1: Robust t-test statistics are included in “()”; standard deviations of random parameter are reported in “[]”.
Note 2: “*” indicates 5% significance level, “**” indicates 1% significance level, and “***” indicates 0.5% significance level.

One of the key contributions of this paper is the explicit quantification of portfolio effects within the household vehicle fleets, at both the fuel type and vehicle class levels. This is an important contribution because it provides novel insights into how PEV-adopting households consider vehicle complementarities in their household vehicle fleets. To that end, the estimated parameters from the mixed multinomial logit model on the vehicle class portfolios revealed quantitative insights on households' preferences for them. For instance, the reference level for the vehicle class portfolios was "car-car", and relative to this portfolio, we observed that the estimated coefficients for the other vehicle class portfolios, except for "minivan-minivan", are positive and statistically significant. Furthermore, we observed that the estimated coefficients of portfolios of the same vehicle class (e.g., SUV-SUV, minivan-minivan) are less preferred to portfolios of different vehicle classes (e.g., car-truck, car-minivan, SUV-truck, and SUV-minivan, minivan-truck). This set of results not only implied that households prefer to hold a fleet of different vehicle classes, but they also prefer holding onto larger vehicles. Since there were no plug-in electric trucks in our sample, we observed that households value holding onto their internal combustion engine trucks in complement to their PEV. To that point, we observed that the estimated coefficients of "car-truck" and "SUV-truck" in Specification (3) are 2.98 and 4.16, respectively. This further indicates that the sampled households highly prefer holding onto their internal combustion engine trucks, which has implications for future household fleet compositions in California. On the other hand, the increasing availability of plug-in electric trucks may impact household preferences which we discuss in detail later in the paper.

The results on the fuel type portfolios are aligned with our expectations and findings from Johansen and Munk-Nielson's forthcoming paper, where relative to the reference portfolio of "BEV-BEV", households preferred other portfolios with at least one car that is partly or fully fueled by gasoline or diesel. For instance, the estimated coefficient of the "BEV-ICEV" portfolio from the mixed multinomial logit model is the highest at 3.12, relative to the reference fuel type portfolio: "BEV-BEV". Following the "BEV-ICEV" portfolio, the "PHEV-ICEV" portfolio is the second most preferred with an estimated coefficient of 2.93. Both results are consistent with our expectations and other literature on PEV adoption, where to mitigate potential range anxiety around driving BEVs, households prefer to complement their BEVs with a PHEV or an ICEV (Johansen & Munk-Nielsen, forthcoming). This trend is also consistent with the summary statistics of fuel type portfolios, where about 60% and 25% of sampled households own "BEV-ICEV" or "PHEV-ICEV" portfolios, respectively.

When interpreting the estimated coefficients of net capital cost, we first discuss the interpretations of the estimated coefficients from the first and second model specifications. Both models yielded an estimated coefficient of 0.10, which means that households are more likely to replace a vehicle that results in a large gap between the value of the chosen PEV and the replacement vehicle. In other words, households which adopt a PEV are more likely to replace their lower-value and older vehicles. Furthermore, the fact that the average annual household income of the sampled household is $181,000 indicates that this sample is skewed towards high-income households who are likely to own a valuable portfolio of vehicles. From the estimation of the second model, we found that the households' income elasticity with respect to net capital cost of their fleet has a positive value of 0.12, but not statistically significant at 5%. This lack of statistical significance may be due to the sample being heavily skewed towards high-income households, and therefore there is a lack in variation among the sample in their income sensitivity to changes in the value of their vehicle fleets.

Interpreting the estimates of the mean and standard deviation of net capital costs from the mixed multinomial logit model requires transformations such that the estimated mean is given by: $E[\beta_{ncc}] = e^{\left(\bar{\beta}_{ncc}+\frac{1}{2}\sigma_{ncc}^2\right)}$. The estimated mean of net capital costs is 0.28, which means that households are even more likely to replace their lower-value vehicle. The magnitude of this estimated coefficient on net capital costs is approximately 3 times greater than that from the first and two model specifications. By incorporating random variations among the sampled households' preferences for the value of their vehicle fleet, the estimated impact of this variable on households' likelihood of replacing an older and less-value vehicle increases. This indicates that when we account for the fact that individual households may have different preferences for the value of their vehicle fleet, we observe that they are much more likely to have a vehicle fleet of a higher value. When it comes to the net operating cost, the sign of the estimated coefficients across the first two model specifications is positive but not statistically significant at the 5%

level. Given that the estimated coefficients on net operating costs are not statistically different from zero, we deduce that the operating costs of their vehicle portfolios do not influence the sampled high-income households' vehicle replacement decision.

Other results of interest include the effects that education level and home ownership have on households' likelihood of adopting a BEV vs. a PHEV. As demonstrated by the estimated coefficients across all three specifications, households with college-level or higher education and households who own a home are more likely to adopt a BEV. This is consistent with findings from literature on BEV adoption (Hardman et al., 2016, Tal et al., 2013). Homeownership is a significant determining factor in households' decision to adopt a BEV or not, since the ability to charge their BEV at home heavily influences the convenience factor of owning a BEV (Scorrano et al., 2020, Higgins et al., 2017). Lastly, we also included the effects of households' replacing a luxury vehicle on their adoption decision of BEVs and PHEVs. According to the results from the mixed multinomial logit model, households that replaced a luxury vehicle are 0.38 units more likely to adopt a BEV compared to those who did not replace a luxury vehicle. This finding is consistent with existing literature on the influence of luxury vehicle ownership and BEV adoption (Mohamed et al., 2018 & Nazari et al., 2023) On the other hand, this effect was not statistically significant for households who adopted a PHEV. This set of results indicated that the sampled households view BEVs similarly to luxury vehicles, and therefore are more likely to replace luxury vehicles with BEVs.

We also tested the influence of incorporating the fuel type and vehicle class portfolios on the performance of the first three model specifications by estimating three additional "naïve" model specifications without the portfolios. Specification 4-6 demonstrate the results from these models. For model specifications 4 & 5, some of the results are non-intuitive. For instance, the estimated coefficients for net operating cost are positive and statistically significant, which is counterintuitive to the finding that PEV-adopting households are more likely to replace a fuel-efficient vehicle with a PEV. The estimated coefficients on the effects of households' replacing a luxury vehicle on their likelihood of choosing a

PHEV in Specification 4 & 5 are positive and statistically significant, which are different from the results from Specification 1 & 2. When comparing the AIC and BIC between Specification 3 and 6, the naïve model underperforms by approximately 6%. By estimating the models without vehicle class and fuel type portfolios, we demonstrate the importance of incorporating them to produce intuitive estimated coefficients. Furthermore, the model performance also improved by incorporating the portfolios.

Lastly, we performed a counterfactual analysis by varying the vehicle class of the kept vehicle in the household portfolio to compute the changes in probabilities of the households replacing the vehicle that they decided to replace (i.e., Vehicle A). For instance, if a household holds a "car-car" portfolio, we simulated their changing the vehicle portfolio to "car-SUV" to compute the changes in probability of the household replacing one vehicle versus the other in their portfolio. We repeated this step for all possible vehicle class portfolios in the data set. Figure 7 below shows the results of the counterfactual analysis. The column is faceted to represent the vehicle that the households decided to replace (i.e., Vehicle A), and the row is faceted to represent the PEV that the household chose. There is no PEV truck in our data, which is why the "truck" option is missing in the row of the figure. The combination of the faceted row and column represents the vehicle class portfolio that the households own. As demonstrated, households which initially have a portfolio of "car-car" are more likely to replace Vehicle A when they decide to keep a larger vehicle (e.g., SUV, minivan and truck) in their portfolio. For households that have chosen to keep a larger vehicle with their car (e.g., car-SUV, car-minivan, and car-truck), they are less likely to replace Vehicle A if they decided to keep a smaller vehicle. For households which own a minivan as part of their portfolio, the probability of their replacing Vehicle A is close to unchanged among different counterfactual vehicle portfolio choices. Such results also apply to households which own a SUV, except for households which own a portfolio of "SUV-car". For these households, they are less likely to replace Vehicle A if they decided to keep a SUV instead of a car. This set of results indicates that Vehicle A is more likely to be a smaller and potentially more fuel-efficient vehicle, which is consistent with Xing et al.'s finding (2021).

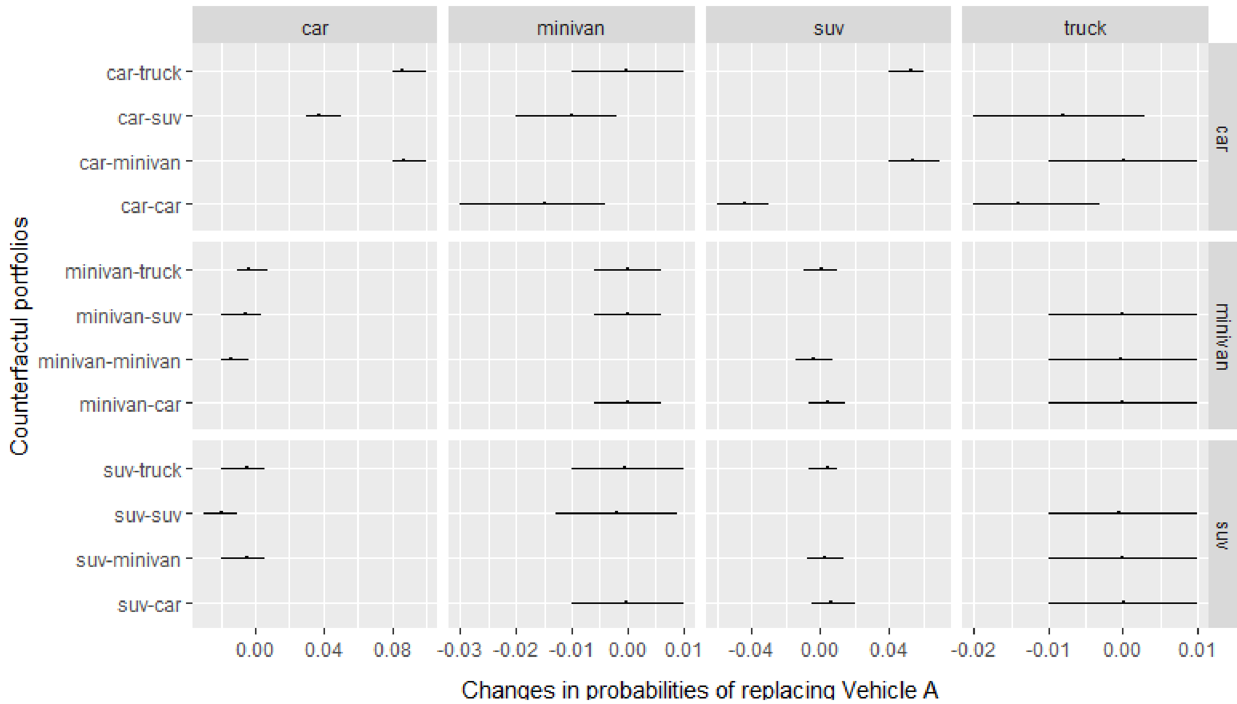

Figure 7. Changes in probabilities of households replacing the vehicle that they decided to replace (i.e., Vehicle A) as they choose to keep vehicles of different vehicle class.

4.6 Discussion

Overall, the results from our analysis demonstrate the importance of accounting for the effects of vehicle portfolios when understanding how PEV-adopting households choose which vehicle to replace. As demonstrated by our results, portfolio complementarity at both the vehicle class and fuel type levels are important factors that households consider. Namely, we found that the sampled households prefer pairing a car with a larger vehicle, such as a minivan or a truck. This demonstrates the fact that vehicles from different classes serve different purposes in a household, and therefore, they complement each other. Furthermore, it is important to note that there was no make-and-model of plug-in electric trucks available during the study period. The portfolio complementarity that we observed among “car-truck”, “SUV-truck”, and “minivan-truck” reflects the sampled households’ preferences for pairing a PEV with an internal combustion engine truck. The fact that the sampled households highly value pairing an internal combustion engine truck with their PEV signals that trucks may be a difficult vehicle segment to electrify.

As of 2021, plug-in electric trucks became available for sales in the United States. Future research should collect data on households who have adopted an electric truck and to understand the changes in preference parameters for vehicle class portfolios once the availability of plug-in electric trucks has increased.

On the front of methodological contributions, we accurately reflected the decision facing each sampled household when they replaced one of their vehicles with a PEV by leveraging a vehicle transaction model. Specifically, we modeled both the observed and the hypothetical replacements of a vehicle by a PEV among two-vehicle households. Furthermore, by explicitly quantifying the impacts that vehicle class and fuel type portfolios have on their decisions, our results addressed this knowledge gap and contributed to the growing literature on the quantitative understanding of PEV adoption. Even though our sample reflected higher-income and college-educated households in California which compromised its representativeness, the application of a multinomial logistic regression model to understand the effects of portfolio complementarities in PEV-adopting households revealed useful insights. Future work should consider expanding the sample size by surveying both PEV-adopting and non-PEV-adopting households to understand the differences in preferences between these two groups of households. A more representative sample would improve the generalizability of our results.

In terms of policy implications, our results provide practical considerations for California's transportation electrification policies. As the state pushes towards electrifying its transportation sector to achieve its GHG reduction goals, it is important to consider how households' preferences for certain vehicle portfolios affect which vehicle they choose to electrify. Our results revealed that most of the sampled households chose a PEV from the "car" vehicle class and paired it with a larger vehicle (e.g., SUV, truck, minivan). This implies that two-vehicle households may prefer to electrify their car first, while holding onto a larger and more carbon-intensive ICEV. This trend would largely compromise the State's goal of reducing GHG emissions, and it warrants careful designs of market-based instruments to shift consumers' preferences for which vehicle in their household fleet to electrify. A potential solution would be the design of financial incentives to lower the MSRP of electric trucks. As demonstrated by our work, accounting for how households value their vehicle fleet when making decisions on their PEV not only provides additional scholarly insights into their behaviors, but it is also an important area of consideration for policymaking.

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Chapter 5: Conclusion

The objective of this dissertation is to reveal and to understand the implications of light-duty vehicle electrification on transportation infrastructure funding and on household vehicle portfolio choices. By leveraging both qualitative and quantitative methods, this dissertation accomplishes this objective and synthesizes the following major conclusions:

1) **To pursue a sustainable and fair transportation funding system, the transition away from motor fuel taxes to a usage-based system is crucial.**

While there are uncertainties around implementing a new transportation revenue-generating policy, there are mutual learnings between RUC and existing vehicle-level and usage-based pricing schemes, namely tolling. From interviewing tolling industry experts across the country and synthesizing lessons learned from their industry, we addressed the research question of how well-prepared each state is at integrating their RUC system with tolling. Furthermore, we also provided insights on the mutual benefits that can be accomplished under a RUC-tolling integration. Working collaboratively with each other, both the tolling industry and RUC programs can benefit from the increased scale of operations and the spur of technical innovations, especially on the in-vehicle telematics front, which would largely reduce administrative costs. In addition to the improved technical capabilities, it is also important to strengthen relationships among transportation agencies, namely the DMV, the tolling administrators, and the RUC implementation programs to ensure smooth data-sharing, transaction settlements, and enforcements of toll and RUC payments.

2) **In searching for a replacement of motor fuel taxes to fund our transportation infrastructures, it is important to quantify the revenues in the context of LDVs electrification.**

To that end, our paper contributes to this goal by first constructing a time-series regression model to estimate future light-duty VMT in California. By building a state-level VMT forecast leveraging county-level data, we applied the results to answer policy-relevant questions around the future of transportation infrastructure funding in California. Specifically, we identified that LDV vehicle electrification is expected to impact gasoline excise tax revenues negatively, creating a gap of up to half a billion dollars per year by 2030, even after accounting for the revenues from Road Improvement Fee. This further highlights the importance of tying road usage directly to its funding mechanism by levying a per-mileage fee, such as the RUC. From our analysis, the estimated revenue-neutral RUC rate for LDVs is 3 cents/mile. While our current analysis assumed that ZEVs are driven the same amount as ICEVs do, we look to refine it by explicitly considering the impact of cost of driving on VMT to better understand the substitutions between ZEVs and ICEVs.

3) **PEV-adopting and two-vehicle households tend to replace their lower-value and older vehicle, while holding onto a fuel-intensive vehicle.**

Our vehicle transaction model captured the decision facing each sampled household when they replaced one of their vehicles with a PEV. By explicitly quantifying the impacts that vehicle class and fuel type portfolios have on their decisions, we found that portfolio complementarity at both the vehicle class and fuel type levels are important factors that households consider. Namely, the sampled households prefer pairing a car with a larger vehicle, such as a minivan or a truck. This demonstrates the fact that vehicles from different classes serve different purposes in a household, and therefore, they complement each other. In terms of policy implications, our results provide practical considerations for California's transportation electrification policies. As the state pushes towards electrifying its transportation sector to achieve its GHG reduction goals, it is important to consider how households' preferences for certain vehicle portfolios affect which vehicle they choose to electrify. Our results revealed that most of the sampled households chose a PEV from the "car" vehicle class and paired it with a larger vehicle (e.g., SUV, truck, minivan). This implies that two-vehicle households may prefer to electrify their car first, while holding onto a larger and more carbon-intensive ICEV. This trend would largely compromise the State's goal of reducing GHG emissions, and it warrants careful designs of market-based instruments to shift consumers' preferences for which vehicle in their household fleet to electrify.

As the pace of electrification accelerates among LDVs, it encourages the establishment of a usage-based pricing mechanism to ensure the solvency, fairness, and equity of transportation infrastructure funding in the United States. In the past decade, individual states have taken the initiative to test the administrative and technological aspects of RUC, but more remains to be done on the policymaking front to legislate the transition away from motor fuel taxes to RUC. Furthermore, a nationwide RUC pilot is beneficial and timely for learning about implementing interstate RUC programs. On the front of PEV adoption, obtaining and modeling household-level vehicle transactions can reveal insightful information regarding household preferences and adoption behaviors. Future research can build upon this modeling framework to quantify household preferences for various vehicle attributes and household characteristics, including but not limited to vehicle charging availability, charging patterns, and travel behaviors. Results from such studies will help generate forecasts of PEV adoption rates and market shares which are grounded in observed behaviors. Such forecasts can have broader implications for designing socially beneficial and economically efficient transportation decarbonization policies.

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