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PEV Adoption Model for California Based on Heterogeneity in Single and Multi-Vehicle Households

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Executive Summary

In this paper, we build an electric vehicle adoption model using heterogeneity in first-time PEV buyer household characteristics in California between 2012-2020. Utilizing a multi-year survey of 18,921 respondents, adopters are segmented using sociodemographic, vehicle fleet, and land use characteristics through latent class analysis into eight clusters. Single-vehicle households are split between *Lower-Income Old Families, Lower-Income Young Renters, High-Income Families,* and *Mid/High-Income Young Renters*. Multi-vehicle households include *High-Income SUV Families, Middle-Income Young Renter, Mid/High-Income Old Families,* and *Mid/High-Income Rural Truck Families*. After classifying the population into these segments, we fit Bass diffusion models to create a PEV adoption forecast meeting the 100% ZEV new car sales goal by 2035. We find *Rural Truck Families*, *Lower-Income Old Families*, and *Lower-Income Young Renters*, which together represent almost half of the population, are adopting PEVs much slower than other clusters. Policymakers should consider the specific infrastructure and incentives needed to electrify these segments.

Keywords: Electric Vehicle (EV), Demand, Market, Modeling, EV Adoption

1 Introduction

Plug-in electric vehicle (PEV) adopters seem like a homogenous group at first glance. Studies show that early adopters are highly educated, higher-income homeowners with many vehicles (*1*, *2*). However, there are significant differences within adopters considering their first PEV. While several studies have examined heterogeneity in potential PEV buyers (*3*–*5*), studies are increasingly focusing on revealed heterogeneity among actual PEV owners (*6*–*9*). Yet most of these studies focus on psychographics or rely on small sample sizes.

The purpose of this study is to identify revealed heterogeneity in PEV adopters and utilize findings to build a PEV adoption model. This study is one of the first to consider revealed household fleet and land use characteristics in addition to sociodemographic characteristics when considering heterogeneity in actual PEV adopters. We cluster PEV adopters into different classes and then build a PEV adoption model centered on these classes.

This paper builds off a few studies of the heterogeneity in sociodemographics and the purchase decision for people who adopted PEVs. Hardman et al. (*8*) separate battery electric vehicle buyers into high-end and low-end buyers, finding that high-end buyers have higher incomes, more education, and are older. Lee et al. (*9*) classify early PEV adopters in California, suggesting there are five main groups of buyers: high-income families, mid/high-income old families, mid/high-income young families, middle-income renters, and Tesla owners. They found that high-income families are the largest group but their proportion of PEV adopters is shrinking. This study uses similar methods as Lee at al. (*9*) but makes several additions. First, households are clustered based on their fleet and land use characteristics as well as sociodemographics. Second, unlike these studies, characteristics about the PEV purchased are not used to segment adopters. Rather, PEV characteristics are studied empirically after clustering.

Characteristics of the other vehicles in a household's fleet influence whether PEVs meet the needs of a household. Several studies have shown that is easier for multi-vehicle households to purchase a PEV as the second vehicle in their households households (*10–12*). Studies looking at GPS data (*10*, *12*) and travel diaries (*11*) confirm that the majority of trips taken by the second-most utilized vehicle in these households can be fulfilled by PEV models currently available in the market. Similarly, vehicle body type preferences can play a role. Higgins et al. (*13*) hypothesize that vehicle body type preferences shape vehicle powertrain preferences. Among other results, they find that pickup truck buyers may be the least inclined to adopt PEVs. Mohammad et al. (*14*) also investigate heterogeneity in vehicle body type preferences but instead focus on attitudes, finding that pickup buyers have highly favorable views on the environment and PEVs despite having the lowest intentions towards purchasing PEVs. This mismatch could be due to this segment's need for a vehicle that meets their ownership and operational requirements. To the best of our knowledge no existing studies consider heterogeneity from actual consumers' *ability* to purchase a PEV up to their *actualized decision* to purchase a PEV. This study is the first to do so; specifically, by looking at revealed PEV consumer preferences on vehicle number and body type. By considering fleet characteristics in clustering, we find many households who purchase PEVs despite preferring larger vehicles or owning a limited number of vehicles. By utilizing repeated cross-sectional surveys, we can examine changes in PEV adopters from 2012-early 2020.

This study relies on a unique dataset which allows us to demonstrate heterogeneity within adopters. We examine first-time PEV adopters and cluster them into classes, then fit Bass diffusion models to classes to model the PEV market (*15*). Both the clustering and diffusion models are calibrated on empirical data of actual adopters. Highlighting variations within PEV adoption allows policymakers to create targeted incentives and identify the unique obstacles faced by each group.

2 Methods

2.1 Data Collection

Data for this work comes from surveys conducted by the Electric Vehicle Center at the University of California, Davis. The surveys were administered between 2015 and 2020 and collected data on households in California with recent PEV purchases made between 2012 and early 2020. The California Air Resources Board recruited California Clean Vehicle Rebate (CVRP) applicants to participate in the surveys which collected data from 18,921 respondents who were both first-time adopters and had sufficient sociodemographic data for clustering. Of these respondents, 2,896 belonged to a household with a single vehicle and 16,025 belonged to a household with multiple vehicles. Table 1 summarizes the survey data characteristics and more detailed information can be found in the report prepared by Tal et al. (*16*).

Because this survey was only administered to those who applied for the CVRP, there are certain limitations with the data. There are two sources of selection bias when attempting to represent PEV adopters using this survey. First, the population of CVRP applicants may not be accurately represented by survey respondents. Second, CVRP applicants may not be representative of the population of PEV adopters. These biases may be further heightened by changing CVRP requirements over time. Starting in 2016, income caps were instituted by the program and disqualified high-income PEV buyers from receiving a rebate (*17*). Thus, high-income adopters may be underrepresented in our survey. We address these potential biases by weighting our survey by PEV sales in California. Sales information is gathered from the California Energy Commission's New ZEV Sales data which is derived from analysis of the state's DMV data.

Finally, we extend the cluster membership model to the entire population by using the 2017 National Household Travel Survey California Add-On (CA-NHTS) (*18*). This survey collected sociodemographic data and travel behavior for 26,095 households in California with appropriate weights. Weighting the survey responses, the survey finds 7.2% of Californian households have no vehicles while 31.8% are single-vehicle households and 61% are multi-vehicle households. Additional data on housing type was gathered from the 2015-2019 American Communities Survey (*19*).

Table 1: Summary of PEV survey data used for clustering

Demographics & Context	*Single-Vehicle Households*	*Multi-Vehicle Households*	*Sample Total*
Proportion of Total	15%	85%	100%
Sample Size	2,896	16,025	18,921
Income (thousands USD)*	129.5	194.1	184.1
Age	45.9	49.2	48.7
Proportion of Females**	38%	27%	28%
Education***	2.30	2.33	2.33
Household Size	1.65	2.99	2.78
Number of Drivers	1.35	2.22	2.09
Housing Type & Tenure			
Proportion in MUDs	35%	14%	17%
Proportion in Owned Detached SFH	35%	71%	65%
Proportion in Owned Attached SFH	12%	7%	7%
Proportion in Rented Detached SFH	10%	6%	6%
Proportion in Rented Attached SFH	8%	3%	4%
Land Use			
Proportion in Rural areas	17%	27%	26%
Proportion in Suburban areas	43%	53%	51%
Proportion in Urban areas	39%	20%	23%
Fleet Characteristics			
Number of Vehicles	-	2.56	2.32
Fleet Age (years)****	-	6.39	5.72
Proportion of Truck Owners	-	13%	11%
Proportion of SUV Owners	-	56%	48%

* Average income calculated by using the midpoint of income ranges
** Includes all genders except males
*** Measured on an ordinal scale from 0 = Some High School or Less, 1 = High School Graduate, 2 = College Graduate, 3 = Graduate or Professional Degree|
**** Modeled using an ordinal scale 0 = Under 2 years, 1 = 2-5 years, 2 = 5-10 years, 3 = Over 10 years
MUD = Multi-unit Dwelling, SFH = Single-Family Home

2.2 Data Analysis

This study clusters PEV adopters using household fleet and land use characteristics in addition to sociodemographic data. First, we group survey respondents by number of vehicles into single- and multi-vehicle households. Second, we cluster these adopters using sociodemographic, land use, and fleet characteristics. Because there has been a limited variety of PEV body types available and the survey is a convenience sample of PEV buyers, additional fleet characteristics are restricted to multi-vehicle households. In our study, latent class clustering is preferable to Euclidean distance-based clustering methods (like K-means and Hierarchical clustering) for two main reasons. First, it can handle different variable scales including ordinal, nominal, and count scales. Second, it can incorporate probability distributions of the variables when clustering.

To account for selection biases in the survey data, we weight our survey and cluster membership by PEV sales in California. This step ensures that survey respondents are more representative of the population of PEV adopters. Survey respondents are given weights based on the annual sales of the PEV make and powertrain (either battery-electric or plug-in hybrid) they purchased. We aggregate sales to this level because there is not enough data to weight by model or location as well.

Finally, we translate PEV adopter clusters to the general population. We create a representative population using the CA-NHTS with missing variables imputed from the ACS. Then we follow the method developed by Lee et al. (*9*) to fit Bass models to the adoption pattern in line with adopted state policy goals. S-shaped adoption patterns such as Bass models are appropriate to use for California zero-emission vehicle (ZEV) adoption because the state has a 100% ZEV target for new car sales by 2035. As ZEVs, specifically the commercially available subset of PEVs, take over the new car market, they will subsequently filter into the used car market, ensuring full adoption. Bass is chosen because of the simplicity of the model which relies on only two parameters, p which characterizes earlier adoption and q for later adoption.

2.2.1 Latent Class Clustering

Household income, respondent age, gender & education, number of drivers, household size, housing type & tenure, and land use classification are used in the cluster analysis. For individual-level variables (age, gender, & education), information of the survey respondent/main driver of the PEV is used. The land use variable was adapted from Salon et al. (*20*) and simplified the five original categories to three, rural, suburban, and urban, by grouping the two lowest- and two highest-density categories. Additional household fleet characteristics are examined for multi-vehicle households: number of vehicles, average fleet age, presence of trucks, presence of SUVs/vans.

A latent class analysis model without covariates is summarized by the equation below, where x is a single nominal latent variable with K categories, y_{it} is the response variable i for individual t, and T is the total number of individuals. In this analysis, y_{it} is a household's sociodemographic or fleet characteristics and x is the class membership of sociodemographic groups. The conditional probability density for y_{it} given condition of the membership x is $f(y_{it}|x)$.

$$f(y_i) = \sum_{x=1}^{K} P(x) \prod_{t=1}^{T} (y_{it}|x) \tag{1}$$

2.2.2 Bass Diffusion

We use the model developed by Bass (*15*), which describes the diffusion of innovations, to model the future PEV market. This model of product uptake, summarized in Equation 2, is an S-shaped curve that forecasts adoption trajectories. The function $F(t)$ is the cumulative fraction of households that have adopted the new technology by time t (Equation 2). The rate of adoption depends on two parameters: p and q. A key attribute of the Bass model is that it is symmetric about its inflection point t^*, the mean year of adoption (Equation 3). Using the method developed by Lee et al. (*9*), we estimate Bass models for each cluster obtained from the latent class analysis. We fit the Bass curves on cumulative cluster sales data, testing a range of years for $t = 0$ and selecting the best-fit model for each cluster.

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}} \tag{2}$$

$$t^* = \frac{\ln q - \ln p}{p + q} \tag{3}$$

Parameter p represents adoption due to media channels while q accounts for interpersonal communication channels. At the inception of diffusion, p governs new adoptions, but as time progresses, it is dwarfed by adoptions governed by the rate q.

3 Results

3.1 Latent Class Model

We estimate two sets of latent class cluster models with 1-8 cluster assumptions (LatentGold version 5.0, 2016), one for single-vehicle and one for multi-vehicle households. Four-cluster models were chosen for further analysis for both groups based on the marginal improvement of model fit measures (BIC, AIC, AIC-3). These models were the best at capturing the heterogeneity among PEV adopters and model fit measures did not significantly improve after four clusters. Tables 2 and 3 summarize the resulting four-cluster models for each group.

Table 2: Characteristics of four-cluster model for single-vehicle households

Variables	*Clusters*				
	Lower-Income Old Families	*Lower-Income Young Renters*	*High-Income Families*	*Mid/High-Income Young Renters*	**Single-Vehicle Households**
Proportion of Total	27.1%	26.2%	24.8%	21.9%	100.0%
Cluster Size	784	758	719	635	2,896
Income (thousands USD)*	86.0	74.9	191.6	172.7	129.5
Age	61.3	35.4	47.9	37.1	45.9
Proportion of Females**	52%	41%	30%	24%	38%
Education***	2.22	2.11	2.46	2.44	2.30
Household Size	1.42	1.54	1.98	1.70	1.65
Number of Drivers	1.23	1.27	1.49	1.43	1.35
Housing Type & Tenure					
Proportion in MUDs	22%	47%	0%	76%	35%
Proportion in Owned Detached SFH	55%	9%	72%	0%	35%
Proportion in Owned Attached SFH	16%	7%	20%	3%	12%
Proportion in Rented Detached SFH	4%	21%	6%	8%	10%
Proportion in Rented Attached SFH	2%	16%	2%	13%	8%
Land Use					
Proportion in Rural	25%	15%	21%	7%	17%
Proportion in Suburban	51%	44%	45%	31%	43%
Proportion in Urban	24%	41%	34%	62%	39%

* Average income calculated by using the midpoint of income ranges
** Includes all genders except males
*** Measured on an ordinal scale from 0 = Some High School or Less, 1 = High School Graduate, 2 = College Graduate, 3 = Graduate or Professional Degree|
MUD = Multi-unit Dwelling, SFH = Single-Family Home

Table 3: Characteristics of four-cluster model for multi-vehicle households

Variables	*Clusters*				
	High-Income SUV Families	*Middle-Income Young Renters*	*Mid/High-Income Old Families*	*Mid/High-Income Rural Truck Families*	**Multi-Vehicle Households**
Proportion of Total	41.6%	22.3%	20.0%	16.1%	100.0%
Cluster Size	6,671	3,569	3,200	2,585	16,025
Income (thousands USD)*	237.6	149.7	164.0	174.8	194.1
Age	46.2	37.4	67.8	50.4	49.2
Proportion of Females**	22%	33%	21%	37%	27%
Education***	2.48	2.24	2.38	2.01	2.33
Household Size	3.44	2.79	2.17	3.12	2.99
Number of Drivers	2.30	2.09	2.05	2.41	2.22
Housing Type & Tenure					
Proportion in MUDs	8%	32%	12%	7%	14%
Proportion in Owned Detached SFH	82%	28%	80%	88%	71%
Proportion in Owned Attached SFH	4%	15%	6%	1%	7%
Proportion in Rented Detached SFH	4%	14%	1%	4%	6%
Proportion in Rented Attached SFH	1%	11%	1%	0%	3%
Land Use					
Proportion in Rural	25%	17%	30%	43%	27%
Proportion in Suburban	57%	48%	53%	47%	53%
Proportion in Urban	17%	35%	17%	10%	20%
Additional Fleet Characteristics					
Number of Vehicles	2.55	2.25	2.46	3.11	2.56
Fleet Age (years) ****	5.75	5.32	6.93	8.84	6.39
Proportion of Truck Owners	0%	7%	13%	54%	13%
Proportion of SUV Owners	77%	35%	41%	48%	56%

* Average income calculated by using the midpoint of income ranges
** Includes all genders except males
*** Measured on an ordinal scale from 0 = Some High School or Less, 1 = High School Graduate, 2 = College Graduate, 3 = Graduate or Professional Degree|
**** Modeled using an ordinal scale 0 = Under 2 years, 1 = 2-5 years, 2 = 5-10 years, 3 = Over 10 years
MUD = Multi-unit Dwelling, SFH = Single-Family Home

All four single-vehicle household clusters are similarly sized, and some diverge significantly from the archetypal PEV early adopter who is high-income, male, highly-educated, and owns a detached home. Notably, two of the four clusters are lower-income groups and have a higher proportion of female adopters. Two clusters have very high proportions of renters and MUD occupants. We use “lower-income” to indicate that a cluster has an average income much lower than the survey average and the survey respondent/main driver of the PEV is used for individual-level variables like gender. Vehicle fleet characteristics are not included in the single-vehicle model because all households had a single PEV and an overwhelming majority were PEV sedans.

The first cluster (27.1%) is composed of lower-income, older homeowners. We refer to this cluster as *Lower-Income Old Families*. This cluster has the highest proportion of females, with less than half of the main PEV users in the households identifying as men. The second cluster (26.2%) also includes lower-income families but differs on several other factors. Households in this cluster are younger, more rent their homes, and more live in urban areas. About 41% are female. We refer to this cluster as *Lower-Income Young Renters.*

Unlike the first two clusters, the third cluster (24.8%) comprises higher-income households. A higher proportion identify as male, highly educated, and own their homes. This cluster most resembles the average PEV adopter, and we refer to this cluster as *High-Income Families*. Households in the final cluster (21.9%) have mid/high incomes, are younger, more urban, and more often in MUDs. They are similarly educated and even more male than the third cluster. Thus, we call this group *Mid/High-Income Young Urban Renters.*

All four clusters have small household sizes and few drivers in the household. Descriptive statistics for each cluster in the single-vehicle latent class model is shown in Table 2.

Unlike the single-vehicle clusters, the multi-vehicle clusters are uneven with one large cluster and three similarly sized smaller clusters. Compared to the single-vehicle clusters, these households have higher incomes, a higher proportion are male, have larger household sizes, and have more drivers. Descriptive statistics for each cluster in the multi-vehicle latent class model are shown in Table 3.

The first cluster is the largest (41.6%) and is composed of very high-income and middle-aged households. They are highly educated, suburban homeowners with large household sizes. These families have high rates of SUV ownership, own 2-3 vehicles, and tend to own newer vehicles. We refer to this group as *High-Income SUV Families.* The second cluster (22.3%) comprises younger, middle-income households. They have the lowest incomes of multi-vehicle PEV households and have smaller household fleets. More live in urban areas and more rent their homes or live in MUDs. As such, we term this group *Middle-Income Young Renters.*

The third cluster (20.0%) is composed of mid/high-income, older families with smaller households and high rates of home ownership. They have similar fleet sizes to households in the first cluster but tend to have slightly older vehicles. We refer to this group as *Mid/High-Income Old Families.* The final cluster (16.1%) consists of mid/high-income households mostly living in rural areas. These families have the highest rates of detached home ownership of any cluster. They have also have the largest household fleets with many older vehicles and high rates of truck ownership. Thus, we call this group *Mid/High-Income Rural Truck Families.*

3.2 Cluster Classification in the General Population

Next, we examine how the Californian population is distributed among these clusters. Applying the latent class scoring formulas to a representative sample of households from the CA-NHTS, we assign households in the state to clusters and calculate the total population of each cluster. Separate models are used for single- and multi-vehicle households, and we do not consider households moving between the groups. While we know that a single cluster may not represent every type of household, such as older families in MUDs, we can calculate the probability with which a household belongs to each cluster and calculated weighted totals. Table 4 summarizes some variable means across the eight clusters in the PEV sample as compared to the overall population. We see that same-cluster averages between the population and PEV sample are similar for most variables except income and housing type, likely because PEV adopters are disproportionately high-income homeowners. However, inter-cluster relationships or differences between different clusters are similar between the two samples.

The largest groups are the fourth and second multi-vehicle clusters, *Mid/High-Income Rural Truck Families* (20.5%) and *Middle-Income Young Renters* (16.6%), and the first single-vehicle cluster, *Lower-Income Old Families* (14.3%). All three of these groups currently make up a small portion of PEV buyers, 13.7%, 18.9%, and 4.1% respectively, but have the largest total market potential (Table 4).

Table 4: Market size m of clusters in the general population along with cluster variable averages in the general population (Pop) and in current PEV adopters (PEV)

			Income (1,000s)		*Rural Percent*		*MUD Percemt*	
Cluster Name	m	*%*	*Pop*	*PEV*	*Pop*	*PEV*	*Pop*	*PEV*
Single-Vehicle								
Lower-Income Old Families	1,840,737	14%	$47	$86	27%	25%	38%	22%
Lower-Income Young Renters	1,592,762	12%	$42	$75	17%	15%	61%	47%
High-Income Families	243,488	2%	$160	$192	16%	21%	1%	0%
Mid/High-Income Young Renters	406,220	3%	$154	$173	4%	7%	89%	76%
Multi-Vehicle								
High-Income SUV Families	1,486,974	12%	$155	$238	25%	25%	13%	8%
Middle-Income Young Renters	2,134,446	17%	$84	$150	19%	17%	51%	32%
Mid/High-Income Old Families	1,584,099	12%	$95	$164	29%	30%	17%	12%
Mid/High-Income Rural Truck Families	2,637,109	20%	$96	$175	46%	43%	14%	7%

3.3 Bass Diffusion Models

We weight the survey and class membership model by sales in California then fit Bass diffusion curves to each cluster to demonstrate the growth of the PEV market. California regulation will ensure all new vehicles sold in the state will be zero-emission by 2035. All households will need to adopt PEVs between 2045-2055 as the last ICE vehicles sold will only stay on the road for another 1-2 decades after 2035 (*21*). To model the PEV market, we fit Bass curves to historical adoption data along with a synthetic 100% adoption year in this range. Fig. 1. demonstrates the Bass adoption curves choosing the most conservative fitted Bass model for each cluster while Table 5 summarizes the resulting Bass parameters.

Table 5: Bass parameters for all eight clusters including t^*, the year of peak adoptions

Cluster Name	p	q	t^*
Single-Vehicle			
Lower-Income Old Families	0.00115	0.290	2033
Lower-Income Young Renters	0.00118	0.303	2032
High-Income Families	0.00302	0.257	2028
Mid/High-Income Young Renters	0.00155	0.339	2028
Multi-Vehicle			
High-Income SUV Families	0.00654	0.195	2028
Middle-Income Young Renters	0.00222	0.251	2031
Mid/High-Income Old Families	0.00174	0.231	2031
Mid/High-Income Rural Truck Families	0.00122	0.262	2032

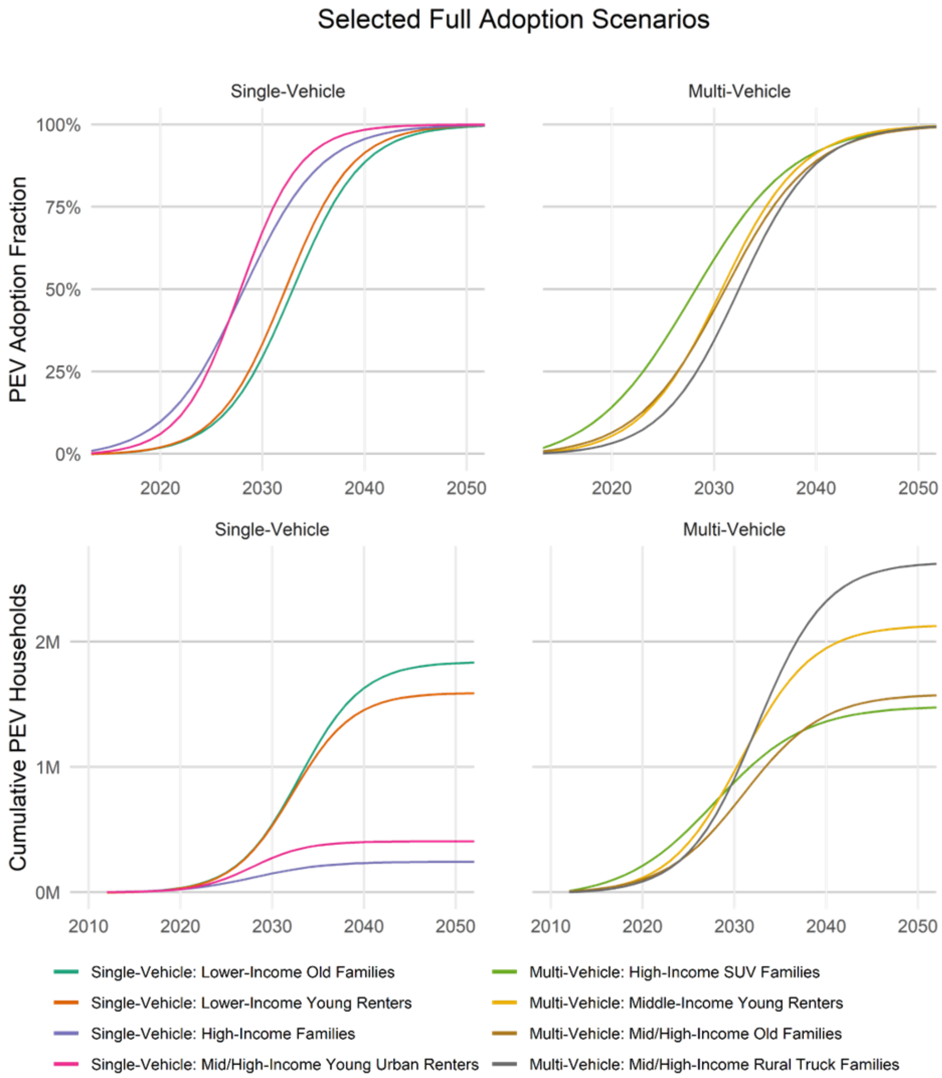

Figure 1: Bass models for PEV adoption for eight clusters in the general population

The results show that three clusters accounting for 47% of the population take the longest to electrify: *Lower-Income Young Renters*, *Lower-Income Old Families*, and *Mid/High-Income Rural Truck Families*. In contrast, the three smallest clusters accounting for 17% of the population are the quickest: *High-Income Families*, *Mid/High-Income Young Renters*, and *High-Income SUV Families*.

4 Discussion

We use repeated cross-sectional surveys of PEV owners in California to examine the heterogeneity in PEV adopters. Using latent class analysis, we cluster current households who acquired their first PEV into eight clusters: four single-vehicle and four multi-vehicle groups. This analysis is unique in that we examine single-vehicle households separately from multi-vehicle ones and we examine sociodemographic, land use, *and* fleet information.

By clustering adopters, we see many groups of PEV owners who diverge significantly from typical wealthy, suburban, home-owning early adopters. We find multiple clusters that are lower-income, urban, rural, or prefer larger vehicles like SUVs and trucks – all of which defy conventional wisdom on early PEV adopters. While classes derived from PEV adopters do not perfectly describe every Californian household, they provide a useful starting point for exploring the state's transition to a full PEV fleet. After classifying the Californian population into these eight PEV clusters, we find that the resulting population clusters have much lower incomes than the PEV clusters, but relative differences between income, age, housing type, and land use are preserved between clusters. Adoption can be categorized into the three following groups.

4.1 Population segments with lagging adoption

Significant segments of the population are adopting PEVs much slower than others through new vehicle sales alone. *Mid/High-Income Rural Truck Families*, *Lower-Income Old Families,* and *Lower-Income Young Renters,* who make up 47% of California's population, have the slowest adoption trajectories. This poses a huge equity issue as the first are more likely to live in rural areas that can most benefit from PEVs (*22*), and the last two groups are more likely to be lower-income.

Families in the *Mid/High-Income Rural Truck Families* cluster are an interesting case of lagging adoption. Home ownership rates are high, indicating these families can charge a PEV at home, even if they are unwilling or unable to install dedicated Level 2 chargers (*23*). These households also own additional ICE vehicles, which should make it easier for them to adopt PEVs (*10–12*). However, these families have the highest and second-highest rates for truck and SUV ownership, demonstrating a strong revealed preference for larger vehicle body types yet unavailable on the PEV market at the time of the survey.

Lower-Income Old Families have moderate rates of home ownership, but unlike the previous cluster, have much lower incomes and no backup ICE vehicles. For them, higher upfront costs and quickly changing technology and policy landscapes may pose larger obstacles to PEV adoption.

The *Lower-Income Young Renters* cluster is comprised of renter or apartment-dwelling younger families in mostly urban or suburban areas with lower incomes and single vehicles. These households may have many barriers to purchasing a PEV including initial purchase cost and lack of access to low-cost charging options near home. While most current PEV owners can charge vehicles at low cost at home, MUD residents (renters) have a 9-17% (24-48%) of being able to charge even a single PEV at home (*23*). Lack of convenient and affordable charging options is a huge equity issue for these families and can threaten their adoption trajectory.

Lagging clusters will need specifically tailored solutions to boost PEV adoption. The *Mid/High-Income Rural Truck Families* cluster may require more available PEV body types, PEV education campaigns, or targeted marketing to increase adoption. In contrast, *Lower-Income Old Families* may need targeted and/or simplified rebate programs or more low-cost or used PEVs available on the market. *Lower-Income Young Renters* may need both of these in addition to programs that increase their access to affordable work or home charging.

4.2 Population segments with PEV adoption momentum

Two multi-vehicle clusters making 29% of the population have moderate adoption rates: *Middle-Income Young Renters*, and *Mid/High-Income Old Families*. While they may be electrifying slower than policymakers wish, PEV adoption among these households has strong momentum.

Like the previous renter cluster, the *Middle-Income Young Renters* cluster is comprised of renter or apartment-dwelling younger families in mostly urban or suburban areas, but they have higher incomes and more vehicles. While initial purchase cost may be a barrier to some of these families, they are sure to face other barriers to PEV ownership such as access to affordable home charging.

The multi-vehicle *Mid/High-Income Old Families* cluster is composed of moderately wealthy older families with high rates of homeownership. These families are rapidly adopting PEVs and will mostly be able to charge at home. However, they may face obstacles once they move past their first PEV and have trouble installing multiple chargers or charging multiple vehicles at home. These households could benefit from simplified charger installation processes.

4.3 Population segments leading PEV adoption

The final clusters account for 17% of the population and are adopting PEVs much quicker than others: *High-Income SUV Families,* and single-vehicle *Mid/High-Income Young Renters*, and *High-Income Families*. These households are either wealthy suburban homeowners or wealthy urban apartment-dwellers who are rapidly adopting PEVs. Many of these families will purchase additional PEVs in the coming decade and grapple with charging multiple vehicles at home. They need minimal incentive or assistance in purchasing their first PEV or charger. Indeed, subsidies for these families may not incentivize further adoption but just finance decisions that would have already been made, failing to shift behavior. These families can, however, benefit from easier home charger installations and assistance installing multiple chargers.

5 Conclusion

Higher-income suburban families have made up the bulk of PEV adopters thus far, but as PEV diffusion progresses, fewer first-time adopters will look like these families. To reach 100% adoption goals more adopters will need to be lower income, have only one household vehicle, live in MUDs, or live in rural areas. It is important to forecast PEV adoption in such granularity to predict where PEV charging will be needed, what kind will be needed, and what stresses will come with new, high levels of adoption.

By clustering adopters, we can compare how PEVs are diffusing among different types of households. Examining adoption at the cluster-level allows us to see where electrification is occurring slowest and determine what unique challenges families face. This analysis can help to inform policymakers who needs additional support to adopt electric vehicles and help the state achieve its decarbonization targets.

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