UC DAVIS
Electric Vehicle Research Center
Institute of Transportation Studies

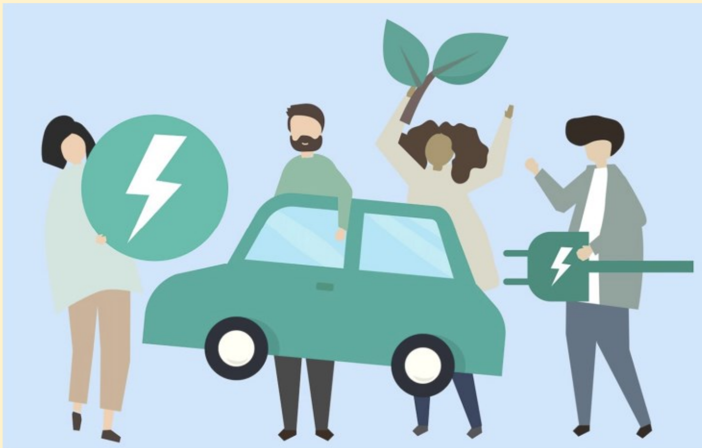
Appendices 1-4

Appendix 1: Listening session materials 2
Appendix 2: Survey statistical analysis 15
Appendix 3: Exploring secondary data... 27
Appendix 4: Code for multivariate analysis 49

Appendix 1: Listening session materials

Education slides

Electric Vehicles



Self-Help ENTERPRISES

TransForm
Our communities. Our transportation. Our future.

THE GREENLINING INSTITUTE

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CALIFORNIA AIR RESOURCES BOARD

1

Zero Emission Vehicles (ZEVs)

Battery Electric Vehicle (BEV)

- Only runs on electricity
- Bigger battery, more range (distance)

Plug-in Hybrid Electric Vehicle (PHEV)

- Can switch between electric and gas power
- Less electric range than a BEV

Fuel Cell Electric Vehicle (FCEV)

- Runs on hydrogen
- The battery is fueled by the hydrogen

2

2

What's happening in California?

- All new cars sold after 2035 must be ZEVs
- Aim to reduce impacts of climate change and air pollution
- There have been 1.3 million EVs sold

3

3

Battery Electric Vehicle (BEV)

2013 Nissan Leaf

- Price: from **$6,500** (Used)
- Driving distance: 75 miles

2023 Chevrolet Bolt

- Price: from **$26,500** (New)
- Range: 259 miles

4

4

Plug-in Hybrid Electric Vehicle (PHEV)

2013 Toyota Prius Plug-in

- Price: from **$10,000** (Used)
- Range: 11 electric miles (540 total miles

2023 Kia Niro Plug-in Hybrid

- Price: from **$33,900** (New)
- Range: 33 electric miles (510 total miles)

5

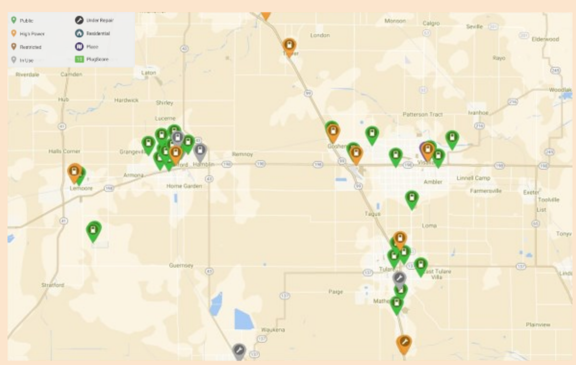
5

EV Charging Stations [Visalia]

Home

Work

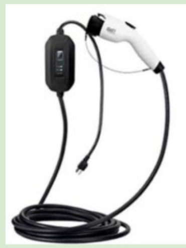
Public



6

6

Charging Levels



Time from Empty to Full BEV	Level 1	Level 2	Level 3
	10-40 hours	4-10 hours	20 min- 1 hour

7

7

Incentives

- Depending on income level and car type can get money for buying an EV
- Can get these federal, state, and local credits for EVs up to:
    - **$12,000** (Used)
    - **$20,000** (New)

8

8

Finances

- Can get up to **$2,000** for Home EV charging or to spend on public charging
- Can have carpool lane access and half price bridge tolls
- Fuel Price to drive 25 miles:
  - **$2-2.50** EVs
  - **$3-5** Gas Cars

9

9

Other ways to use an EV

EV Carshare
Around $4 per hour

e-bikes
About 15 cents per minute

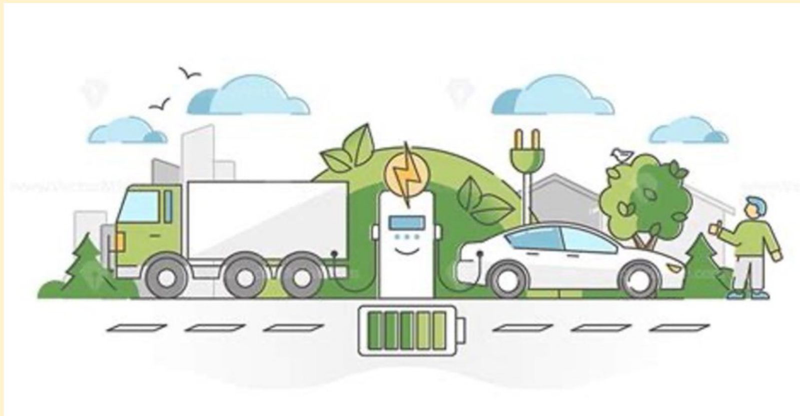
E-bike incentive programs coming

e-scooters
About 15 cents per minute

10

10

Thank You! Any Questions?



11

Resources

Governor Newsom’s Zero Emission by 2035 Executive Order (link)
California’s Electric Vehicle Market Oct 2022 Quick Facts (link)
Autotrader Vehicle Price Tool (link)
PlugShare EV Station Locator Website (link)
EV Charging Speeds (link)
Fuel Economy (link)

Incentives
Enter your zip code on this page to learn about incentives that may apply to you.
US Department of Energy Federal Tax Credit for new(link) used (link) cars- **up to $7,500 for new EVs and up to $4,000 for used EV**
California Clean Vehicle Rebate Project (CVRP) (link)- **between $1,500 and $4,500 for a new EV**
Clean Vehicle Assistance Program(CVAP) (link)- **up to $5,000 for a new or used EV**
Clean Cars for all (CC4A) (link)- **up to $5,000- 9,500 when you scrap an older car and buy an EV**

12

12

Listening Session Protocol

Before starting

- Provide, fill out name tags
- Fill out consent forms
- Distribute one-page survey

Introduction

Good afternoon and thank you for joining us today. My name is XX from YY and I will be facilitating this listening session today. This is a study funded by the California Air Resources Board and led by researchers from UC Davis. Our purpose today is to learn more about your experiences and thoughts about transportation in the [Bay Area/LA] and what officials can do to help create a greener transportation system while also making it easier for you, your friends, your family, and your neighbors to get around. [*Introduce other research team members present.*]

We are here for the next 90 minutes or so to learn from you. Your input is necessary as we provide recommendations to the state that will determine its strategy for emissions from vehicles while prioritizing equity for already-burdened communities. We will ask you some questions about how you use transportation—whether that's driving, taking transit, or walking and biking—what challenges you face in getting around, and what you see for the future of transportation. We'll also give you some information about new transportation technologies and how you think they might impact you.

We'll facilitate this conversation using a topic guide. That means we have a set of questions for you that we want to ask, but this is an open discussion and you should feel free to bring up issues that are relevant to our conversation today. There are no right or wrong answers to any questions we ask today. Everyone's knowledge and opinions matter; we encourage you to speak up when you have something you'd like to say and to make space for everyone to contribute. We ask that you speak one at a time so that we can accurately record what the group says. [*Verify that recording is OK.*] We'll have an incentive to thank you for your participation once we are done. [*Modify for virtual focus groups.*]

Do you have any questions before we begin? OK, let's get started!

Part I: Travel experiences, barriers, and needs

Experiences

1. [*If in person*] How did you get to this place today? Why did you choose that mode of transportation? [*If virtual*] Did you go anywhere outside your home today? How did you get there? Why did you choose that mode of transportation?
    a. *Potential prompts: Car/transit availability, perceptions of safety for non-motorized modes, relative costs of other modes*
2. How do you usually get around for your trips, like work, shopping, medical appointments, or religious services? Why do you choose those modes of transportation?
    a. *Potential prompts: Car/transit availability, perceptions of safety for non-motorized modes, relative costs of other modes*
3. Are there other transportation options available to you that you don't usually use (carpooling, transit, walking, cycling, scooters, etc.)? Why might you choose your main mode of transportation over other options?
    a. *Potential prompts: Driving is easier, car/transit availability, perceptions of safety for non-motorized modes, relative costs of other modes*

Barriers and solutions

4. What do you like about transportation in your area (whether that's driving, taking transit, walking, or biking)? What do you dislike?
    a. *Potential prompts: Availability, frequency (of transit), safety/security, cost, connected network*
5. Was there anywhere you wanted to go today or recently because of a transportation issue? What was the circumstance? What did you do?
6. What improvements to transportation in your area would you like to see?
7. Car use questions
    a. How often do you use a car to get around?
    b. Do you always have a car available when you need it? What do you do in the cases when you don't?
    c. What do you think about the costs of driving a car? Have you had to make tradeoffs in your household budget to afford the costs of driving or owning a car? In other words, do you find yourself having to cut out other things from your budget to make sure you have your transportation needs covered?

Part II: Electric Vehicles

8. Who has heard of zero-emission vehicles (or ZEVs) before? What do you know about them? How do you think they work?
    a. *Prompts: Electric cars, alternative fuel vehicles, e-bikes, e-scooters*
9. Do you feel that these kinds of vehicles (ZEVs) are for you? (In other words, would they help you get around? Do they have the features that you need to meet your transportation needs?)

[Presentation about ZEVs: key facts and features, overall costs and compared to ICE, also mention carsharing, etc.]

10. Now that you know a few more details about ZEVs, do you think they would help meet your transportation needs?
    a. Private vs shared ownership
    b. Charging availability (at home, at work, public, available when you need it?)
    c. Cost (purchase cost, individual ownership, shared ownership, operating costs esp. vs gas)
    d. Used vs. new
    e. Reliability (range fears)
    f. First-/last-mile connections to transit (e-scooters, shared e-bikes, personal e-bikes)
    g. Micromobility in general
11. What would make you feel more comfortable about adopting a ZEV as your main source of transportation?
    a. *Potential prompts: Incentives, infrastructure, outreach and education, non-ownership models*

Part III: Conclusions

12. What are some changes you would like to see to make it easier for you to get around? What are the most important things that transportation planners and decision makers should address?
    a. *Potential prompts: Changes to transportation services (availability of car sharing, more transit service), investment in infrastructure, denser development*
13. Is there anything we didn't discuss today that you feel is important for us and state decision makers to know about transportation for you and in your communities?

Summary statistics from listening session survey

Table 1: Demographic and house households characteristics, note not all participants completed the surveys (n=66)

Question group	Response	Count
Race or ethnicity	Black/African American	6
	White/Caucasian	13
	Asian	2
	Hispanic or Latino/Latina/Latinx	40
	American Indian or Alaska Native	5
	Middle Eastern/North Africa	1
	Other, unspecified	2
	Other, "Mexican"	1
Household income	Less than $10,000	12
	$10,000 - $24,999	12
	$25,000 - $49,999	13
	$50,000 - $74,999	10
	$75,000 - $99,999	5
	$100,000 or more	5
Credit and Debit Card Access	Credit Card	31
	Debit Card	49
Smartphone Access	No	4
	Yes	61
Household vehicles	0	8
	1	25
	2	17
	3	10
	4 or more	2
Mode use on day of session	Transit	21
	Drove	28
	Got a ride	19
	Walked	18
	Biked	7
	Uber or Lyft	4
	Taxi	4
	Other, please specify	1
Alternative fuel vehicle ownership	Hybrid	8
	Electric vehicle	4
	Other, unspecified	2
	Other, biofuel	1
Total responses		66

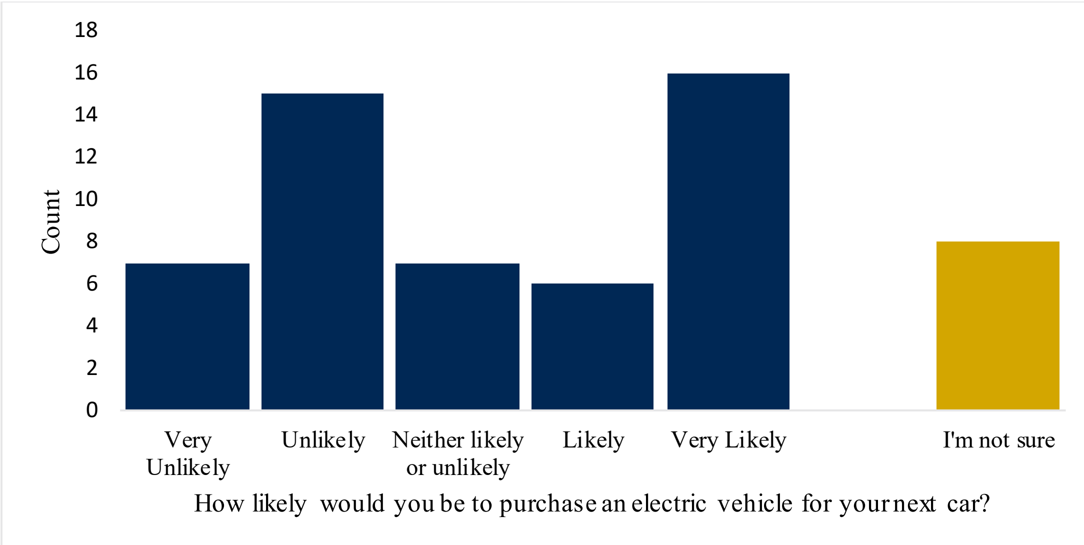


Figure 1: Participant likelihood to purchase an electric vehicle for their next car (n=59).

Table 2: Sentiment analysis for codes by instrument of change area.

Node	Positive Sentiments	Neutral Sentiments	Negative Sentiments
Physical Capability	**13**	**18**	**20**
Cost	**8**	**16**	**20**
Charger cost	0	5	0
Charger costs vary	1	7	0
Charger incentives	3	1	0
EV affordability	2	1	5
EVs are expensive	1	1	9
Support from power companies	0	0	4
Used vehicle incentives	1	1	2
Availability	**5**	**2**	**0**
More EV manufacturers	5	2	0
Psychological Capability	**5**	**16**	**14**
Familiarity	**2**	**7**	**0**
Tesla	2	7	0
Knowledge	**2**	**7**	**8**
More information about EVs	0	5	3
EV repairs	0	1	5
More informational meetings	2	2	0
Preparation	**1**	**2**	**6**
Additional Planning	1	2	6
Physical Opportunity	**12**	**14**	**41**
Community Accessibility	**3**	**5**	**1**
Solar-powered charging	3	5	1
Infrastructure	**3**	**5**	**23**
Infrastructure Issues	3	5	23
Living Situation	**6**	**4**	**17**
Apartments	3	0	11
Homeowners	3	4	6
Social Opportunity	**0**	**0**	**0**
Automatic Motivation	**3**	**5**	**14**
Unfamiliarity	**0**	**3**	**13**
Talking Car	0	1	3
EVs are too new	0	2	10
Interest	**3**	**2**	**1**

Interest	3	2	1
Reflective Motivation	**19**	**19**	**53**
Vs. Gas	**4**	**3**	**10**
EVs cheaper than gas	4	0	0
Gas refuels faster	0	0	4
EV maintenance	0	3	6
Environment	**7**	**2**	**11**
Grey area environmentally	0	1	3
EVs important for the planet	7	1	0
EV battery materials	0	0	8
Mobility	**3**	**5**	**8**
No longer trips	2	1	5
Older EVs	0	1	3
Short EV trips	1	3	0
Novel Aspects of EVs	**5**	**1**	**0**
Powering a house	5	1	0
Reliability	**0**	**4**	**3**
Battery lifespan	0	4	3
Safety	**0**	**3**	**12**
EV Safety	0	3	12
Time	**0**	**1**	**9**
EV charging too long	0	1	5
Can’t rush with EVs	0	0	4
TOTAL	**52**	**72**	**128**
GRAND TOTAL		**252**	

Appendix 2: Survey statistical analysis

Table 1. Descriptive statistics of model parameters for the vehicle ownership model

	Model parameters	mean	std	min	max	Observations
Household Parameters	HH_Size	2.54	1.43	1	10	1644
	HH_Income ($)	122049.4	120408.2	5000	500000	1644
	PP/HH_income	0.29	0.64	0	11.51	1644
	Additional_vehicles	0.81	1.11	0	5	1644
	Children	0.21	0.54	0	3	1644
	Number_Drivers	1.87	0.89	0	4	1644
Household Indicator Variables	Home_Own (ref. category)	0.42	0.37	0	1	1123
	Home_Rent	0.32	0.47	0	1	521
	Education_College_graduate (ref. category)	0.30	0.39	0	1	753
	Education_Grade 8 or less	0.02	0.12	0	1	26
	Education_High School Graduate or GED	0.22	0.41	0	1	361
	Education_Masters, Doctorate, or Professional Degree	0.31	0.46	0	1	504
	Tract_Type_LI only (ref. category)	0.24	0.31	0	1	830
	Tract_Type_DAC and Low Income	0.18	0.39	0	1	304
	Tract_Type_DAC only	0.1	0.3	0	1	167
	Tract_Type_Tribal: Full Tract	0.09	0.28	0	1	142
	Tract_Type_Tribal: Partial Tract	0.12	0.33	0	1	201
	Gender_Male (ref. category)	0.43	0.49	0	1	826
	Gender_Decline to state	0.01	0.12	0	1	24
	Gender_Female	0.47	0.5	0	1	777
	Gender_Genderqueer/non-binary	0.01	0.09	0	1	13
	Gender_Other	0	0.03	0	1	2
	Gender_TransMale/Transman	0	0.03	0	1	2
	Purchase_purchase_new (ref. category)	0.43	0.46	0	1	879
	Purchase_Leased New	0.04	0.2	0	1	70
	Purchase_Leased Used	0.01	0.11	0	1	20
	Purchase_Purchased Used	0.41	0.49	0	1	675
	House_Type_Detached house (ref. category)	0.33	0.40	0	1	957
	House_Type_Apartment or condo	0.26	0.44	0	1	426
	House_Type_Attached house (townhouse, duplex, triplex)	0.09	0.29	0	1	150
	House_Type_Mobile home	0.04	0.19	0	1	65
	House_Type_Other	0.01	0.11	0	1	22
	House_Type_Prefer not to say	0.01	0.12	0	1	24
	Race_White Caucasian (ref. category)	0.37	0.32	0	1	982
	Race_AmericanIndian/AlaskaNative	0.02	0.13	0	1	29
	Race_Asian	0.13	0.33	0	1	211
	Race_Black/AfricanAmerican	0.04	0.2	0	1	71
	Race_Hispanic/Latino/Latina/Latinx	0.2	0.4	0	1	325
	Race_MiddleEastern/NorthAfrican	0.01	0.1	0	1	16
	Race_NativeHawaiian/OtherPacificIslander	0.01	0.08	0	1	10
	Employment_type_Employed ful-time (ref. category)	0.41	0.38	0	1	755
	Employment_type_Employed part-time	0.1	0.31	0	1	172

	Employment_type_Full-time student	0.03	0.16	0	1	46
	Employment_type_Part-time student	0.01	0.1	0	1	15
	Employment_type_Retired	0.3	0.46	0	1	492
	Employment_type_Seasonal work	0.01	0.08	0	1	10
	Employment_type_Self-employed	0.07	0.25	0	1	111
	Employment_type_Unemployed	0.03	0.16	0	1	43
	Powertrain_PEV (ref. category)	0.21	0.43	0	1	374
	Powertrain_ICEV	0.77	0.42	0	1	1270
Built Environment Parameters	Gross residential density (HU/acre) (D1A)	5.51	8.47	0	163.29	1644
	Jobs per household (D2A_JPHH)	4.5	11.24	0.06	228.08	1644
	Total road network density (D3A) (mile/sq.mile)	19.15	9.18	0.18	55.75	1644
	Distance from the population-weighted centroid to nearest transit stop (meters) D4A	336.91	245.19	0	1134.59	1644

Table 3: Crosstabulations and chi-square test results comparing analysis of charging access at home by different demographics.

Do you own or rent your home?					
		Level 1	Level 2	No charging	Total
Other/Prefer not to say	Count	45	14	89	
	Row %	30.41	9.46	60.14	148
Own	Count	682	79	393	
	Row %	59.1	6.85	34.06	1154
Rent	Count	114	20	375	
	Row %	22.4	3.93	73.67	509
Total		841	113	857	1811
N		DF	-LogLike	RSquare (U)	
1811		4	124.1696	0.0776	
Test		ChiSquare	Prob>ChiSq		
Likelihood Ratio		248.339	<.0001*		
Pearson		241.616	<.0001*		
Home type					
		Level 1	Level 2	No charging	Total
Apartment or condo	Count	80	16	326	
	Row %	18.96	3.79	77.25	422
Attached house (townhouse, duplex, triplex)	Count	81	12	64	
	Row %	51.59	7.64	40.76	157
Detached house/single family home	Count	623	78	394	
	Row %	56.89	7.12	35.98	1095
Mobile home	Count	35	4	27	
	Row %	53.03	6.06	40.91	66
Other/Prefer not to say	Count	22	3	46	
	Row %	30.99	4.23	64.79	71
Total		841	113	857	1811
N		DF	-LogLike	RSquare (U)	
1811		8	115.4231	0.0721	
Test		ChiSquare	Prob>ChiSq		
Likelihood Ratio		230.846	<.0001*		
Pearson		222.177	<.0001*		
Age					
		Level 1	Level 2	No charging	Total
18 or younger	Count	7	2	15	
	Row %	29.17	8.33	62.5	24
19 to 29	Count	43	7	106	
	Row %	27.56	4.49	67.95	156
30 to 39	Count	88	13	175	
	Row %	31.88	4.71	63.41	276
40 to 49	Count	107	16	152	
	Row %	38.91	5.82	55.27	275
50 to 59	Count	134	22	112	
	Row %	50	8.21	41.79	268
60 to 69	Count	224	26	147	
	Row %	56.42	6.55	37.03	397
70 to 79	Count	165	22	92	
	Row %	59.14	7.89	32.97	279
80 or older	Count	53	2	22	
	Row %	68.83	2.6	28.57	77
Total		821	110	821	1752
N		DF	-LogLike	RSquare (U)	
1752		14	63.70038	0.0411	
Test		ChiSquare	Prob>ChiSq		

Likelihood Ratio		127.401	<.0001*		
Pearson		125.688	<.0001*		
Gender					
		Level 1	Level 2	No charging	Total
	Count	333	47	463	
Female	Row %	39.5	5.58	54.92	843
	Count	471	58	341	
Male	Row %	54.14	6.67	39.2	870
	Count	24	7	30	
Other	Row %	39.34	11.48	49.18	61
Total		828	112	834	1774
N		DF	-LogLike	RSquare (U)	
1774		4	23.05351	0.0147	
Test		ChiSquare	Prob>ChiSq		
Likelihood Ratio		46.107	<.0001*		
Pearson		46.441	<.0001*		
Census tract community type					
		Level 1	Level 2	No charging	Total
	Count	98	21	183	
DAC and Low Income	Row %	32.45	6.95	60.6	302
	Count	96	10	91	
DAC only	Row %	48.73	5.08	46.19	197
	Count	217	33	240	
Low Income only	Row %	44.29	6.73	48.98	490
	Count	193	26	205	
None	Row %	45.52	6.13	48.35	424
	Count	94	11	58	
Tribal: Full Tract	Row %	57.67	6.75	35.58	163
	Count	143	12	80	
Tribal: Partial Tract	Row %	60.85	5.11	34.04	235
Total		841	113	857	1811
N		DF	-LogLike	RSquare (U)	
1811		10	27.91957	0.0175	
Test		ChiSquare	Prob>ChiSq		
Likelihood Ratio		55.839	<.0001*		
Pearson		55.059	<.0001*		
Household income					
		Level 1	Level 2	No charging	Total
	Count	140	25	91	
>200,000	Row %	54.69	9.77	35.55	256
	Count	313	42	430	
<100,000	Row %	39.87	5.35	54.78	785
	Count	265	35	195	
100,000-200,000	Row %	53.54	7.07	39.39	495
	Count	123	11	141	
Prefer not to say	Row %	44.73	4	51.27	275
Total		841	113	857	1811
N		DF	-LogLike	RSquare (U)	
1811		6	24.89459	0.0156	
Test		ChiSquare	Prob>ChiSq		
Likelihood Ratio		49.789	<.0001*		
Pearson		49.637	<.0001*		
Highest level of education					
		Level 1	Level 2	No charging	Total
	Count	5	3	20	
Grade 8 or less	Row %	17.86	10.71	71.43	28
High School Graduate or GED	Count	154	21	200	375

	Row %	41.07	5.6	53.33	
College Graduate	Count	375	48	357	
	Row %	48.08	6.15	45.77	780
Masters, Doctorate, or Professional Degree	Count	290	40	234	
	Row %	51.42	7.09	41.49	564
Total		824	112	811	1747
N		DF	-LogLike	RSquare (U)	
1747		6	11.81639	0.0076	
Test		ChiSquare	Prob>ChiSq		
Likelihood Ratio		23.633	0.0006*		
Pearson		22.697	0.0009*		
Number of vehicles in the household					
		Level 1	Level 2	No charging	Total
1 or less	Count	241	27	331	
	Row %	40.23	4.51	55.26	599
2	Count	354	51	305	
	Row %	49.86	7.18	42.96	710
3	Count	140	21	120	
	Row %	49.82	7.47	42.7	281
4	Count	68	8	66	
	Row %	47.89	5.63	46.48	142
5 or more	Count	38	6	35	
	Row %	48.1	7.59	44.3	79
Total		841	113	857	1811
Likelihood Ratio		24.839	0.0017*		
Pearson		24.724	0.0017*		
Census tract type					
		Level 1	Level 2	No charging	Total
Rural	Count	159	16	118	
	Row %	54.27	5.46	40.27	293
Urban	Count	682	97	739	
	Row %	44.93	6.39	48.68	1518
Total		841	113	857	1811
1811		2	4.300933	0.0027	
Test		ChiSquare	Prob>ChiSq		
Likelihood Ratio		8.602	0.0136*		
Pearson		8.622	0.0134*		

Table 4: Survey attitudinal statements and survey responses.

Statement	Strongly Disagree		Disagree		Neither Agree or Disagree		Agree		Strongly Agree	
	n	%	n	%	n	%	n	%	n	%
I like the idea of walking as a means of travel for me.	150	7%	331	16%	537	25%	751	35%	356	17%
Learning how to use new technologies is often frustrating for me.	469	22%	781	37%	456	21%	342	16%	77	4%
My commute is a useful transition between home and work (or school).	184	9%	237	11%	904	43%	612	29%	188	9%
I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.	153	7%	245	12%	352	17%	815	38%	560	26%
I'm too busy to have as much leisure time as I'd like.	181	9%	566	27%	590	28%	576	27%	212	10%
I usually go for the basic ("no-frills") option rather than paying more money for extras.	79	4%	452	21%	604	28%	760	36%	230	11%
I prefer to do one thing at a time.	77	4%	452	21%	674	32%	755	36%	167	8%
Cost or convenience takes priority over environmental impacts (e.g. pollution) when I make my daily choices.	148	7%	570	27%	648	30%	568	27%	191	9%
Family/friends play a big role in how I schedule my time.	86	4%	208	10%	425	20%	950	45%	456	21%
I prefer to live in a spacious home, even if it's farther from public transportation or many places I go to.	189	9%	524	25%	581	27%	586	28%	245	12%
Having to wait is an annoying waste of time.	55	3%	261	12%	604	28%	849	40%	356	17%
I generally enjoy the act of traveling itself.	53	2%	187	9%	412	19%	981	46%	492	23%
I consider myself to be a sociable person.	47	2%	189	9%	450	21%	1078	51%	361	17%
I definitely want to own a car.	67	3%	69	3%	244	11%	756	36%	989	47%
The importance of exercise is overrated.	972	46%	805	38%	223	10%	87	4%	38	2%

Table 5: BEV statements factor loadings from the exploratory factor analysis.

Survey question	Battery quality	Awareness and knowledge	Charging and range
"I am aware of the different electric vehicle incentives available to me"	0.00	**0.59**	0.07
"There are enough places to charge battery electric vehicles"	0.08	0.05	**0.54**
"Electric vehicle batteries degrade too fast"	**0.52**	0.00	0.17
"I know enough about battery electric vehicles to decide about getting one"	0.05	**0.75**	0.01
"Battery electric vehicles are easier to maintain than gasoline vehicles"	**0.49**	0.27	0.25
"Battery electric vehicles are more damaging to the environment than gasoline vehicles"	**0.74**	-0.03	0.06
"Gasoline vehicles are safer than battery electric vehicles"	**0.66**	0.03	0.13
"Battery electric vehicles travel far enough before needing to be charged"	0.28	0.03	**0.66**

Tucker-Lewis index: 0.984 RMSEA: 0.034

Exploratory Analysis of Latent Classes

We examine differences in averages across the groups identified using LCA using a one way analysis of variance test (ANOVA) with the “aov” function in base R, where the independent variable is categorical and the dependent variable is continuous. The null hypothesis for each test is there is no difference between the groups and equality between means of the dependent variables across groups.

We examine association between latent classes and several variables using chi-square tests with the “chisq.test” function in base R, where both variables are categorical. The null hypothesis for each test is there is no association between the two variables. Both tests are rejected if the p-value, or the probability of observing test results as extreme as the observed results when the null hypothesis is true, is greater than 0.05.

Analysis of class characteristics- ANOVA and Chi-Square Test

The results the statistical tests as part of our exploratory analysis are shown in **Table 6**. All variables are significant at the 0.05 significance level or below. For ANOVA tests, this indicates that we reject the null hypothesis that there is no different in the variables tested across classes. For chi-square tests, this indicates that we reject the null hypothesis that there is no association between the categorical variable and the classes.

Demographic differences

“Active” classes consisting of the largest proportion of older respondents. Conversely, the “Unengaged” and “Passive” classes have the largest proportion of individuals that are 40 years of age or younger. Three classes are predominantly made up of individuals that identify as Male, while the “Unengaged” and “Passive Supporters” classes consist of a higher proportion of individuals that identify as non-male. The classes are predominantly comprised of individuals that identify as White, but the “Supporter” classes have sizable proportions of individuals that identify as Asian and the “Unengaged” class has the largest proportion of individuals that identify as Hispanic/Latinx or African American.

“Active Supporters” has the largest proportion of individuals that have obtained a college degree or more while the “Unengaged” class has the largest proportion of individuals that are high school graduates or less. The “Unengaged” class also has the highest proportion of individuals that have a household income of less than $50,000, while half of the “Active Supporters” class earn up to $149,999. Both “Resister” classes contain the largest proportion of respondents that are retired. “Passive Supporters” consists of the largest proportion of students while the “Active Supporters” comprise the largest proportion of individuals who work full time and the “Passive Supporters” have the largest proportion of students.

Home ownership is highest among “Active Supporters” and lowest among the “Unengaged”. The “Unengaged” and “Passive Supporters” have larger proportions of individuals living in apartments or condos, while the both “Active” support and resister classes have the highest proportion of individuals living in single family or detached housing. Across all classes, majority of the individuals drive and have 1 or 2 household cars. The “Unengaged” and “Supporter” classes have the highest share of careless households, and the “Active Resister” class has the highest proportion of households with 3 or more vehicles. The "Unengaged" and "Resister" classes have the largest share of 1 or more vehicles in use.

Attitudes

Across all classes, responses were generally positive when it came to being sociable, liking travel, and family and friends influencing one's schedule, and generally negative when it came to finding new tech frustrating, exercise being overrated, and hating waiting. Opinions were split across the five answer choices when it came to busyness, preference for spacious homes, doing one thing at a time, prioritizing cost over environment, and finding one's commute a useful transition. The "Passive" classes more heavily preferred basic options compared to other classes that had split responses, while the "Support" classes liked walking compared to the other classes that had split responses. The "Active Resisters" strongly favored wanting to own a car compared to the other classes who were also in favor but less strongly. This class also preferred a spacious home while other classes were split, and was split when it came to mixed neighborhoods while other classes were more in favor.

Built Environment

Population density tends to be highest among the "Unengaged" and "Passive Supporters", followed by "Active Supporters" and "Passive Resisters", and "Active Resisters". "Active Resisters" have the highest proportion of individuals that live in census tracts that were categorized as Rural while the "Supporters" has the highest proportion of individuals that live in urban census tracts.

On average, charging appears to be more readily available for the "Supporter" classes followed by the "Unengaged" and "Resisters" classes. In particular, the "Supporter" classes have access to between 2.2 and 3.7 level 1 and level 2 chargers available within the three drive times. The "Unengaged" and "Passive Resisters" classes have access to between 1 and 3.3 level 1 and level 2 chargers, while the "Active Resisters" have access to around 1.1 to 1.3 chargers. The "Supporter" classes have access to about 0.6 to 1.1 DC fast chargers available within the three drive times, while the "Unengaged" and "Passive Resisters" generally have access to between 0.3 to 0.8 chargers. The "Passive Resister" cluster have access to the fewest number of DC fast chargers, ranging between 0.1 to 0.4. Though these could be related to exogenous factors that we will control for in the forthcoming logistic regression model.

Table 6: ANOVA and Chi-Square test details and results comparing demographic, attitudinal, and built environment characteristics of latent classes.

Category	Variable	Test	χ^2(Chi-Square) or F (ANOVA)	P	Levels Combined
Demographics	Age	Chi-square	64.47	***	"<29" – "18 or younger" & "18–29" "80 or older" – "Decline to state" & "80 or older"

Category	Variable	Test	χ^2(Chi-Square) or F (ANOVA)	P	Levels Combined
	Gender	Chi-square	102.66	***	"Other" – Not "Male" or "Female"
	Race	Chi-square	109.12	***	"Other" – "AA", "AI/AN", "ME/NA", "NH/PI", "Multi-Racial", "Prefer not to say", &"Other"
	Education	Chi-square	103.89	***	"HS or less" – "Grade 8 or less", "HS Grad", "Prefer not to say"
	Income	Chi-square	198.29	***	
	Work	Chi-square	57.47	***	"Other" – "Seasonal work", "Self employed", "Student" & "Doesn't work for pay"
	Home Ownership	Chi-square	76.10	***	"Other" – Not "Own" or "Rent"
	Home Type	Chi-square	74.65	***	"Other" –"Other", "Prefer not to say"
	Driving	Chi-square	22.32	***	
	Vehicles in House	Chi-square	87.11	***	
	Vehicles in Use	Chi-square	35.11	***	"3 or more" – 3, 4, 5 or more
	Household Size	Chi-square	58.82	***	"6 or more" – 6, 7, 8, 9, 10 or more
Attitudes	want to own car	Chi-square	109.93	***	
	too busy for leisure	Chi-square	91.81	***	
	sociable	Chi-square	47.52	***	"Disagree" – "Disagree" &"Strongly Disagree"
	prefer spacious home	Chi-square	209.58	***	
	prefer basic options	Chi-square	104.66	***	
	one thing at a time	Chi-square	90.80	***	
	new tech frustrating	Chi-square	138.03	***	
	like walking	Chi-square	105.74	***	
	like travel	Chi-square	60.59	***	"Disagree" – "Disagree" &"Strongly Disagree"
	like mixed neighborhood	Chi-square	216.05	***	
	hate waiting	Chi-square	69.02	***	"Disagree" – "Disagree" &"Strongly Disagree"
	fam/friends influence schedule	Chi-square	79.51	***	
	exercise overrated	Chi-square	113.06	***	"Agree" – "Agree" &"Strongly Agree"

Category	Variable	Test	χ^2(Chi-Square) or F (ANOVA)	P	Levels Combined
	cost priority over env	Chi-square	251.3	***	
	commute useful transition	Chi-square	71.08	***	
Built Environment	2010 People per Square km	ANOVA	3.91	***	
	Urban/Rural	Chi-square	50.77	***	
	AddLevel5/Square km	ANOVA	6.54	***	
	AddLevel10/Square km	ANOVA	11.4	***	
	AddLevel15/Square km	ANOVA	12.35	***	
	AddDCFC5/Square km	ANOVA	3.23	***	
	AddDCFC10/Square km	ANOVA	9.47	***	
	AddDCFC15/Square km	ANOVA	11.62	***	

Statistical significance: 0 '***' 0.001 '**' 0.01 '*' 0.05.

Table 7: Fit metrics for various latent class models. The AIC and BIC do not improve significantly when increasing the clusters to more than 5. Moreover, the entropy score of 0.81 is above the 0.8 threshold, indicating a good model fit.

	LL	AIC	BIC	Npar	df	Entropy	Smallest Class Proportion
1 Cluster	-35318.32	70728.64	70989.07	46	2097	NaN	1.0000000
2 Cluster	-33706.15	67598.30	68124.82	93	2032	0.76	0.42
3 Cluster	-32525.99	65331.97	66124.59	140	1985	0.82	0.23
4 Cluster	-32072.24	64518.49	65577.19	187	1938	0.79	0.13
5 Cluster	**-31729.37**	**63926.75**	**65251.54**	**234**	**1891**	**0.81**	**0.08**
6 Cluster	-31562.12	63926.75	65277.13	281	1844	0.89	0.078
7 Cluster	-31395.85	63447.70	65304.69	328	1797	0.87	0.077

Appendix 3: Exploring secondary data

The data presented here will be used when analyzing the survey data and were also used to inform our decision to choose a stratified random sample rather than only a random sample of all priority populations. We consider differences in transportation and infrastructure across communities in California including disadvantaged communities (DACs), low income only communities, communities which are both disadvantaged and low income, tribal communities, and communities which are none of these referred to as "none". This is done using census data, data on vehicle registrations, rebates distribution, rebate approved dealerships, and electric vehicle (EV) charging. Our results indicate that vehicle and EV ownership is highest among none priority census tracts followed by DAC only, Low Income only, Tribal, and DAC and Low Income. DAC and Tribal communities tend to have most access to chargers and vehicles per household but much lower rates of EVs, rebates, and transportation access when compared to non-DAC and non-Tribal communities.

Data and Methods

Secondary data includes the following sources:

- CalEnvironScreen 4.0 ("CalEnviroScreen 4.0 Results," n.d.)
- Department of Energy, Alternative Fuels Data Center, EV Charging Infrastructure Data ("Alternative Fuels Data Center," n.d.)
- DMV Vehicle Registration data from 2020
- U.S. Department of Transportation's ETC (Equitable Transportation Community) Explorer ("ETC Explorer | US Department of Transportation," n.d.)
- Clean Vehicle Rebate data ("CVRP Rebate Statistics," n.d.)
- American Community Survey Census data ("Census Bureau Data," n.d.)

Version 4.0 of CalEnviroScreen, released in October 2021. This data is used to identify each census tract in California into one of five groups: disadvantaged communities (DAC only), low income communities (Low Income only), low income and disadvantaged communities (DAC and Low Income), Tribal communities, and communities that are not one of these priority populations. DAC only communities are defined as those that suffer most from factors related to environment, health, and economics. Low Income only communities are defined as those that have household incomes at or below 80% of the median income in California or below a level set by the Department of Housing and Community Development's State Income Limits. DAC and Low Income communities are communities that meet both criterion. None are communities that meet neither criterion. Tribal communities are those classified as fully or partially tribal and represent areas of land federally recognized as American Indian Reservation or off-reservation trust land. Data on land area, population, household size, income, home ownership, home type, number of vehicles, education, employment, and other demographics are obtained from the 2020 American Census Survey (ACS).

The Department of Energy, Alternative Fuels Data Center, provides data and other tools related to vehicles, transportation, and fuel in the United States, and was used to identify the number of chargers in each census tract, including the type of chargers (level 1, level 2, or DCFC).

DMV vehicle registration data was used to obtain information about the number of vehicles and electric vehicles registered in each census tract in California, according to the 2020 census definition. The DMV data we currently have access to represented vehicle registrations in the year 2020.

Data regarding transportation accessibility was obtained from the U.S. Department of Transportation's ETC (Equitable Transportation Community) Explorer dashboard. This dashboard includes data on five categories: transportation insecurity, climate and disaster risk burden, environmental burden, health vulnerability, and social vulnerability. We select two variables from the data to include in our dataset: transportation access sub-component score and transportation insecurity component score. The transportation access sub-component score uses indicators that include automobile prevalence, average commute time, average walking and driving times to places of interest, and access to jobs and transit which are normalized, summed, and normalized again. A higher transportation access sub-component score indicates that there is greater transportation access burden while a lower score indicates lower burden. The transportation insecurity component score uses indicators that include those used for the transportation access sub-component score as well as average cost of transportation, and traffic fatalities which are normalized, summed, and normalized again.

The California Air Resources Board is the agency leading the climate change programs in California and offers a rebate of up to $7,500 under the Clean Vehicle Rebate Program (CVRP). The CVRP is a rebate program that offers between $1,000 and $7,500 to go towards the purchase or lease of a new ZEV in an effort to support clean vehicle adoption in California. This rebate was only given to those leasing or purchasing vehicles from approved dealerships. As of September 2023, the CVRP is no longer offering rebates due to low funds. The CVRP rebate statistics dashboards was used to access data containing information on each rebate that was given out from 2010 to 2023. Because census tract identifications were changed in 2020 and all of the data used is according to 2020 census tract definitions, any observations for census tracts before 2020 had to be updated. This was done by comparing 2010 and 2020 census tracts geographically to see what percentage of the 2010 census tracts overlapped with the 2020 census tracts. The 2010 census tract was converted to the 2020 census tract with which it overlapped the most. Once the census tract information was updated, observations were grouped by census tract to provide a count of rebates for each tract.

As mentioned earlier, CVRP is a rebate program that offers up to $7,500 to go towards the purchase or lease of a new ZEV in an effort to support clean vehicle adoption in California. The Clean Vehicle Assistance Project (CVAP) is a collaboration between the Beneficial State Foundation and the California Air Resources Board that offers up to $7,500 in rebates for California residents living in a disadvantaged community (as defined by CalEnviroScreen) and meeting a certain income requirement. As of June 2023, the CVAP is no longer offering rebates due to low funds. Data on CVRP and CVAP approved dealerships was obtained through a mapping tool created by JC Sanchez of the Institute of Transportation Services EV Research Center at the University of California, Davis. This data consisted of the longitude and latitude of each dealership, which was used to identify the census tract ID for where the dealership was located. The number of dealerships in each census tract was determined by obtaining the frequency of each census tract ID.

Several new variables were created using the data. People Per 10 Square Miles is defined as the total population divided by land area and then multiplied by 10. Rebates Per 1000 Households is defined as total rebates divided by households, and then multiplied by 1000. Vehicle Per Capita is defined as the total vehicles divided by population. Vehicle Per Household is defined as the total vehicles divided by households. EV Per 10 Individuals is defined as the total EVs divided by population and then multiplied by 10. EV Per Capita is defined as the total EVs divided by population. EV Per Household is defined as the total EVs divided by households. Total Chargers is defined as the sum of Level 1 Chargers, Level 2 Chargers, and DC Fast Chargers. Charger per 1000 Vehicles is defined as total chargers divided by total vehicles, and then multiplied by 1000. Charger Per 1000 Individuals is defined as the total chargers divided by population. Charger Per 1000 Households is defined as the total chargers divided by households, and then multiplied by 1000. Charger Per Square Mile is defined as total chargers divided by land area. Dealership Per Square Mile is defined as total dealerships divided by land area. Dealership Per 1000 Households is defined as total dealerships divided by households, and then multiplied by 1000.

Census tracts with more than 2 vehicles per capita were excluded from the data. Many of these 32 census tracts had lower populations and higher vehicle ownership, likely representing non-residential areas. Census tracts with more than 5 vehicles per household were also excluded. Of these 23 census tracts, 11 belong to DAC and Low Income communities, 5 belong to Low Income only communities, and 7 belong to None. Finally, census tracts with more than 300 chargers per 1000 vehicles were excluded. These 2 census tracts also represented non-residential areas; Stanford University and Golden Gate Park. Any census tracts with missing data were also excluded. The final data set contains 8,989 census tracts with 58 variables. The largest number of Census tracts are classified are None priority tracts, followed by Low Income only, then DAC and Low Income, DAC only, and finally Tribal (Figure 2).

Because CalEnviroScreen 4.0 still uses 2010 census tracts and all other data was classified according to the 2020 census tract definitions, the CalEnviroScreen data was updated in order to be joined with all of the other data. This was done by comparing 2010 and 2020 census tracts geographically to see what percentage of the 2010 census tracts overlapped with the 2020 census tracts. Next, it was determined what percentage of each 2020 census tract was classified as DAC, Low Income only, DAC and Low Income, None, or Tribal. The final classification of each 2020 census tract was made by determining which percentage was largest. For example, if a 2020 census tract was comprised of two 2010 census tracts, with the first being Low Income only and representing 90% of the area and the second being DAC only and representing 10% of the area, the 2020 census tract would be classified as Low Income only.

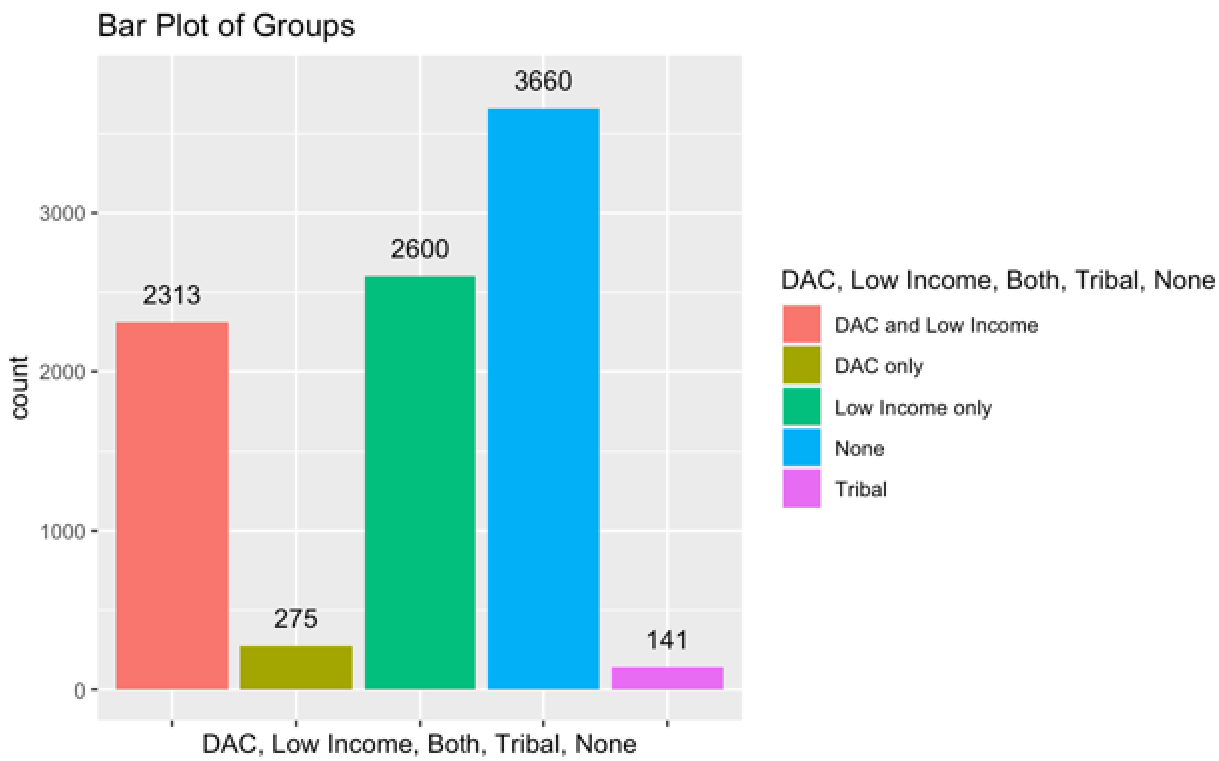


Figure 2: Bar plot detailing the number of census tracts that fall in each group category: DAC and Low Income, DAC only, Low Income only, None, and Tribal. A significantly low number of census tracts are classified as being DAC only compared to the four other categories.

ANOVA Testing

We examine differences in averages across the five groups (DAC and Low Income, DAC only, Low Income only, Tribal, and None) using a one way analysis of variance test (ANOVA) with the "aov" function in base R, where the independent variable is categorical and the dependent variable is continuous. A test is conducted to check for differences in means of the dependent variable across the independent variable groups. When conducting an ANOVA test, the following assumptions are made: independence between groups, equal variances, and normality. The data obtained for this study was collected for all census tracts in California so independence can be assumed. Since the sample sizes are fairly large, it is expected that violations of the equal variance normality assumptions are okay.

The null hypothesis for each test is there is no difference between the groups and equality between means of the dependent variables across groups. The alternative hypothesis is that there does exist a difference between the groups and there is not equality between means of the dependent variables across groups. The test statistic F denotes the variance due to random chance. In other words, it signifies whether the difference in means across groups is significant or not by looking at the ratio of mean sum of squares between the groups and the mean square errors. The null hypothesis is rejected if the p-value, or the probability of observing test results as extreme as the observed results when the null hypothesis is true, is greater than 0.05. Hence, a larger F indicates significance or that there does exist a difference between the groups and there is not equality between means of the dependent variables across groups.

Demographics
The average number of people per 10 square miles is highest in DAC and Low Income communities at 125,595.93 people, followed by Low Income only communities at 104,608.65 people, None priority communities at 58,913.65 people, DAC only at 46,019.46 people, and Tribal at 6,165.73 (Figure 3). Across all census tracts the average number of people per 10 square miles is around 88,067. An ANOVA test with a null hypothesis that the average number of people per 10 square miles is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 9).

The average median income is highest in None priority communities, followed by DAC only communities, Low Income only communities, Tribal communities, and finally DAC only and Low Income communities. (Figure 4) An ANOVA test with a null hypothesis that the average median income is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 9). This is in line with what is expected according to the definitions of the Low Income and DAC groups.

The average rate of home ownership is highest in Tribal communities at 73.12%, followed by None priority communities at 68.4%, DAC only communities at 64.86%, Low Income only communities at 48.85%, and finally DAC only and Low Income communities at 39.46% (Figure 5). Across all census tracts the average rate of home ownership is around 55.26%. An ANOVA test with a null hypothesis that the average rate of home ownership is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 9).

The average employment/population ratio is highest in None priority communities at 60.57%, followed by DAC and Low Income communities at 59.9%, DAC only communities at 59.08%, Low Income only communities at 58.62%, and finally Tribal communities at 48.6% (Figure 6). Across all census tracts the average employment/population ratio is around 58.84%. An ANOVA test with a null hypothesis that the average employment/population ratio is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 9).

The average median age in years is highest in Tribal communities at 45 years, followed by None priority communities at 41 years, Low Income only communities at 37 years, DAC only communities at 34 years, and finally DAC and Low Income communities at 33 years (Figure 7). Across all census tracts the average median age in years is around 38 years. An ANOVA test with a null hypothesis that the average median age in years is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 9).

The average percentage of people 25 years of age and over that have obtained a Bachelor's degree or higher is highest in None priority communities at 49.6%, followed by Low Income only communities at 30.7%, DAC only communities at 22.2%, Tribal communities at 24.04%, and finally DAC and Low Income communities at 16.27% (Figure 8). Across all census tracts the average percentage of people 25 years of age and over that have obtained a Bachelor's degree or higher is around 34.38%. An ANOVA test with a null hypothesis that the average percentage of people 25 years of age and over that have obtained a Bachelor's degree or higher is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 9).

DAC and Low Income, DAC only communities, Low Income only communities, None priority communities and Tribal communities all appear to be dominated by single family homes, with DAC only communities having the highest proportion, followed by None priority communities, Tribal communities, DAC and Low Income communities, and finally Low Income only communities. DAC and Low Income and Low Income only communities have the highest rates of multi unit dwellings, while Tribal communities have the highest rate of mobile home or other home types (Figure 9).

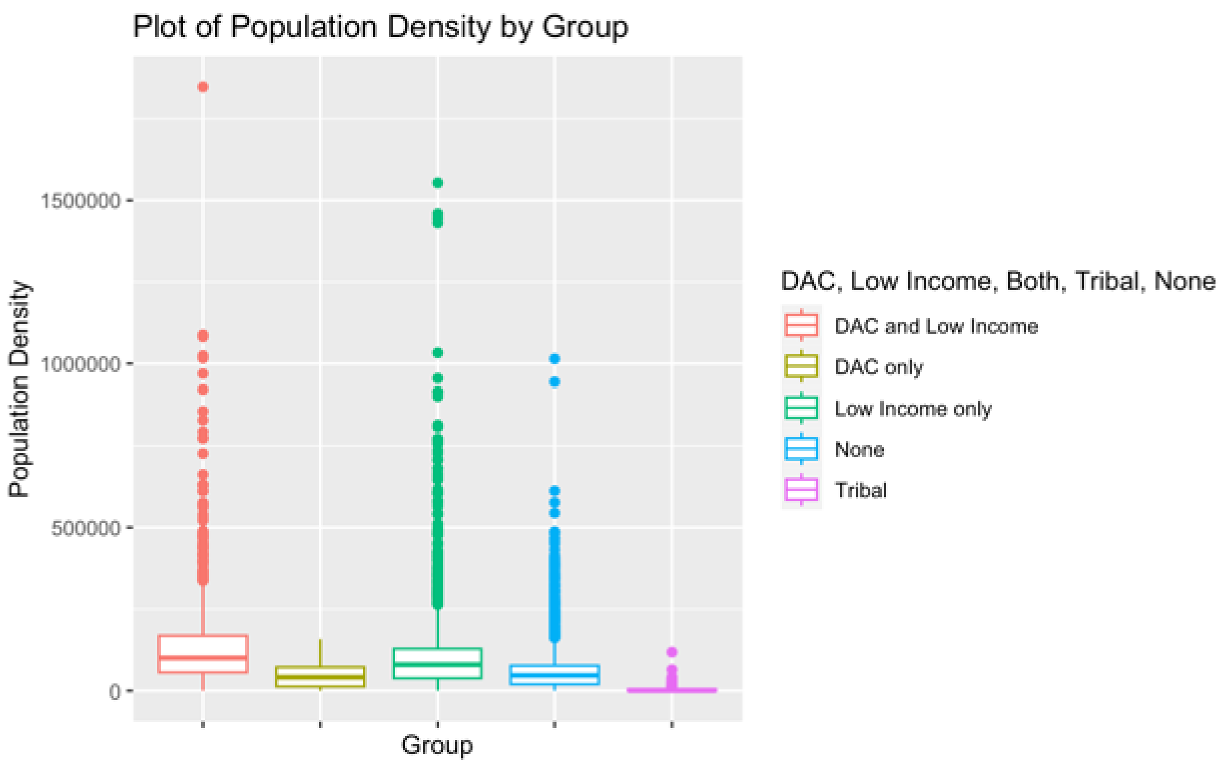


Figure 3: Boxplots of population density by group.

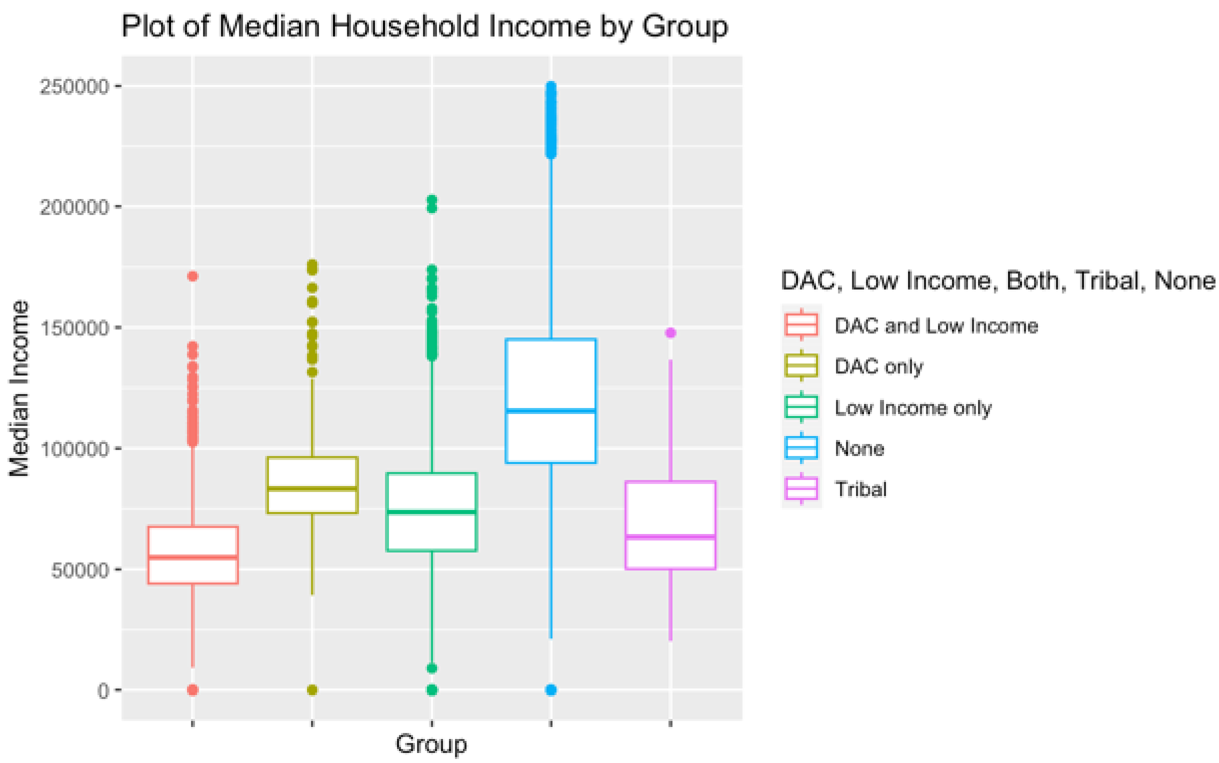


Figure 4: Boxplots of median income by group.

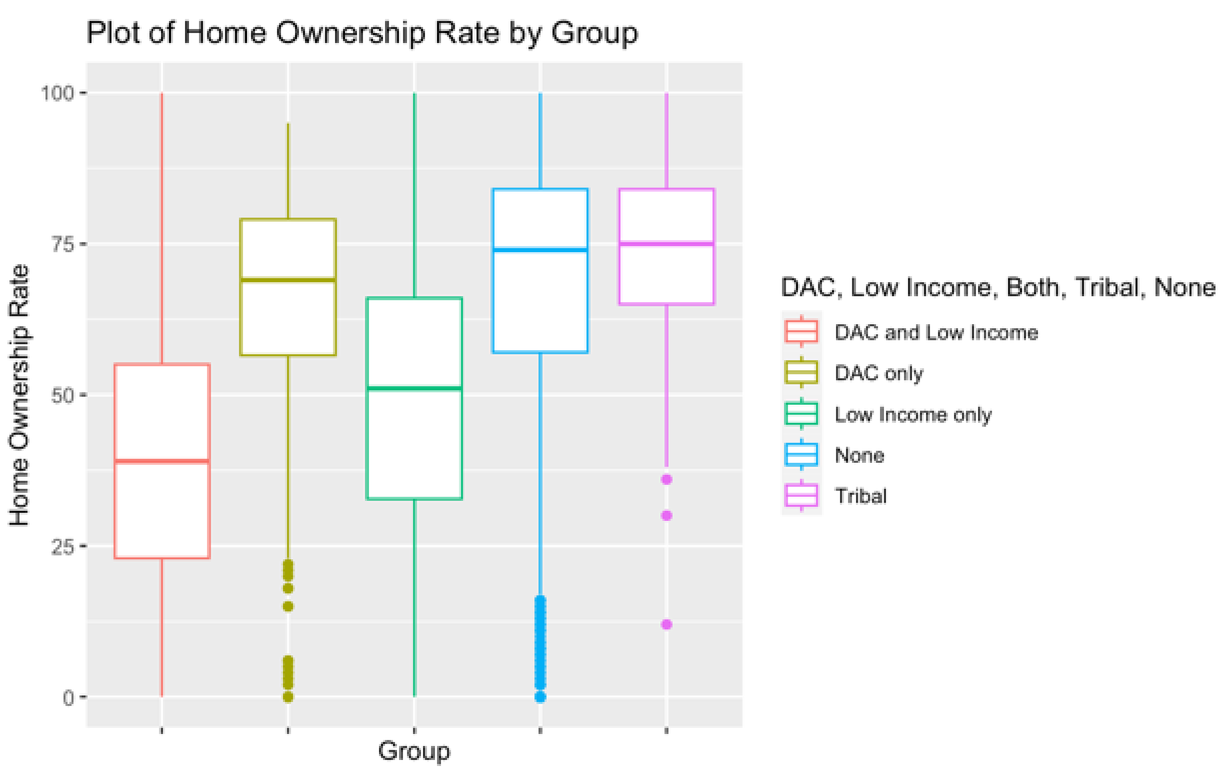


Figure 5: Boxplots of home ownership rate by group.

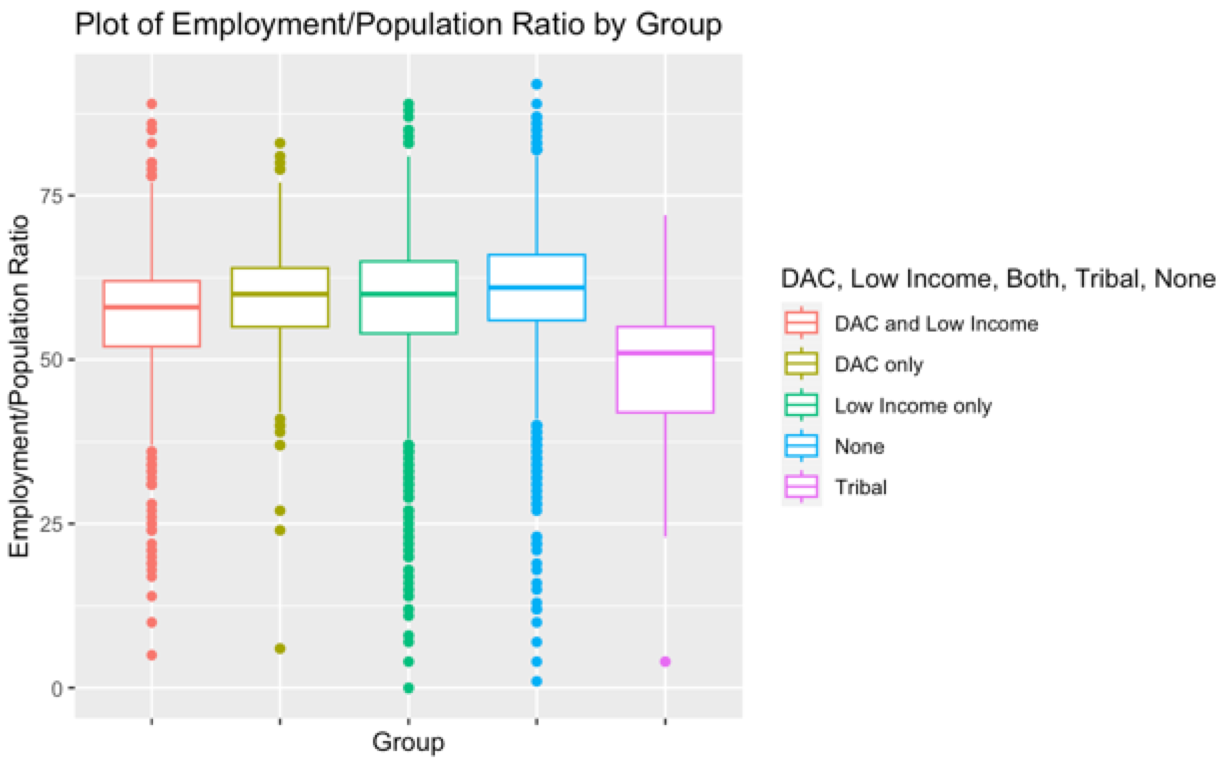


Figure 6: Boxplots of employment/population ratio by census tract type.

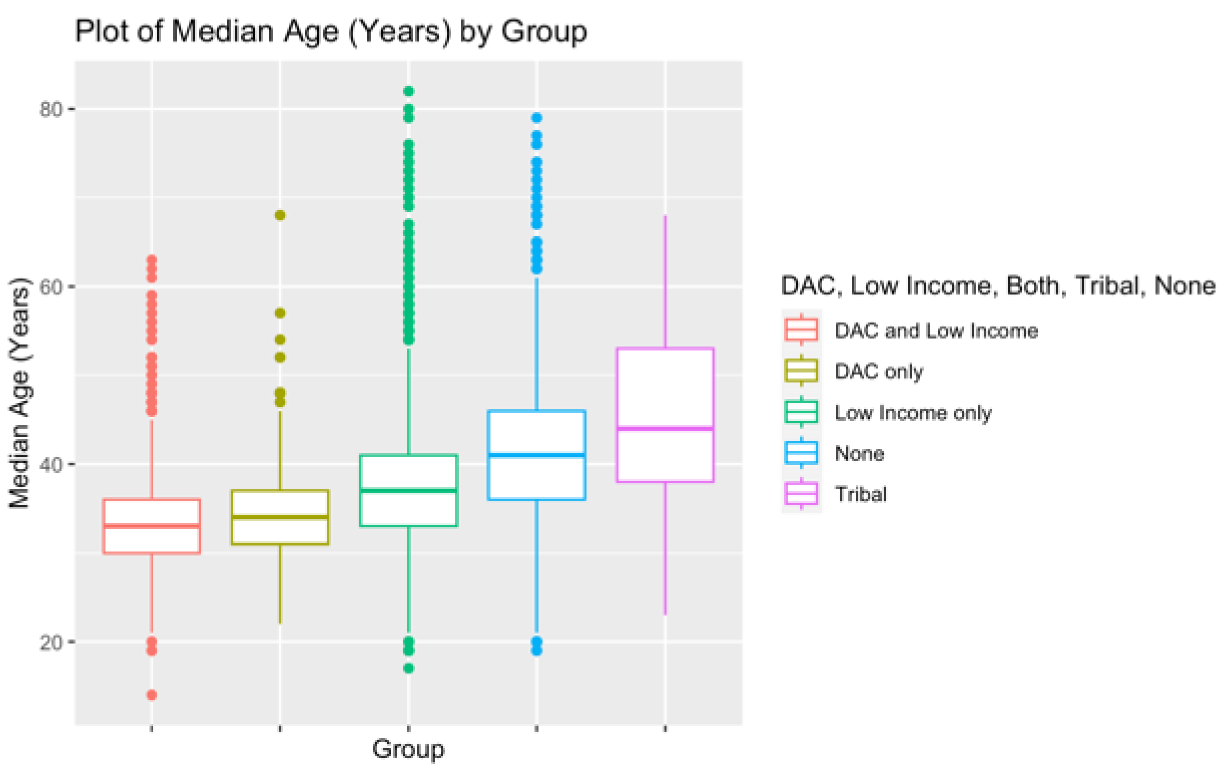


Figure 7: Boxplots of median age in years by census tract type.

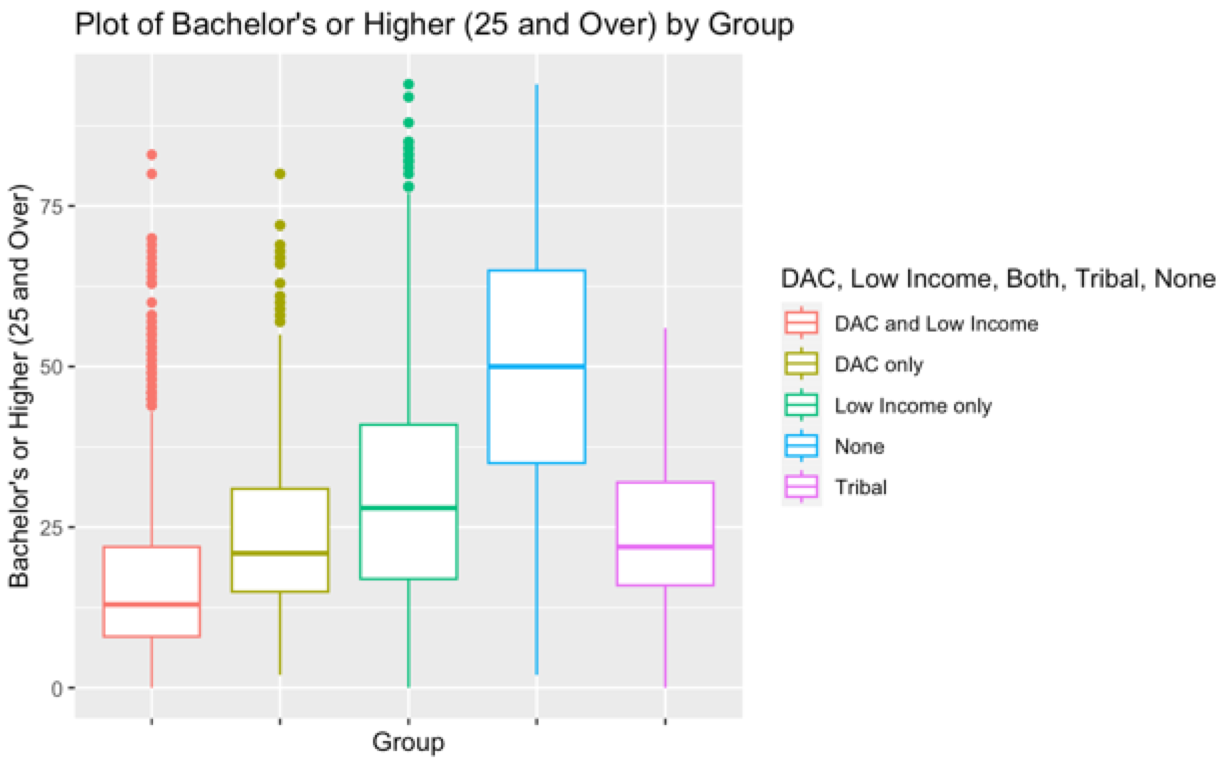


Figure 8: Boxplots of Bachelor's or higher (25 and over) by census tract type.

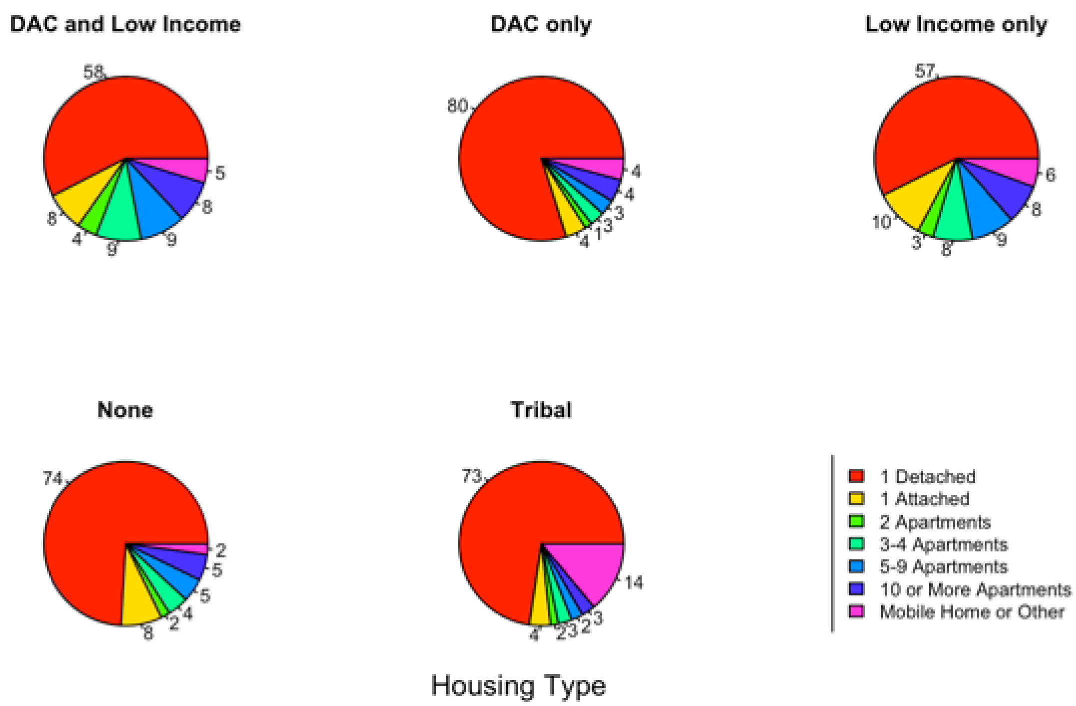


Figure 9: Pie charts of housing type by census tract type.

Transportation Access

A higher transportation access sub-component score indicates that there is greater transportation access burden while a lower score indicates lower burden. The average transportation access sub-component score percentage is highest in Tribal communities at 86.64%, followed by DAC only communities at 65.38%, None priority communities at 56.96%, Low Income only at 48.45%, and finally DAC and Low Income at 36.38%. Across all census tracts the average transportation access sub-component score percentage is around 49.93% (Figure 10). An ANOVA test with a null hypothesis that the average transportation access sub-component score percentage is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 9).

A higher transportation insecurity component score indicates that there is greater transportation access burden while a lower score indicates lower burden. The average transportation insecurity component score percentage is highest in Tribal communities at 87.73%, followed by DAC only communities at 66.02%, None priority communities at 56.07%, Low Income only at 48.3%, and finally DAC and Low Income at 37.62%. Across all census tracts the average transportation insecurity component score percentage is around 49.87% (Figure 11). An ANOVA test with a null hypothesis that the average transportation insecurity component score percentage is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 9).

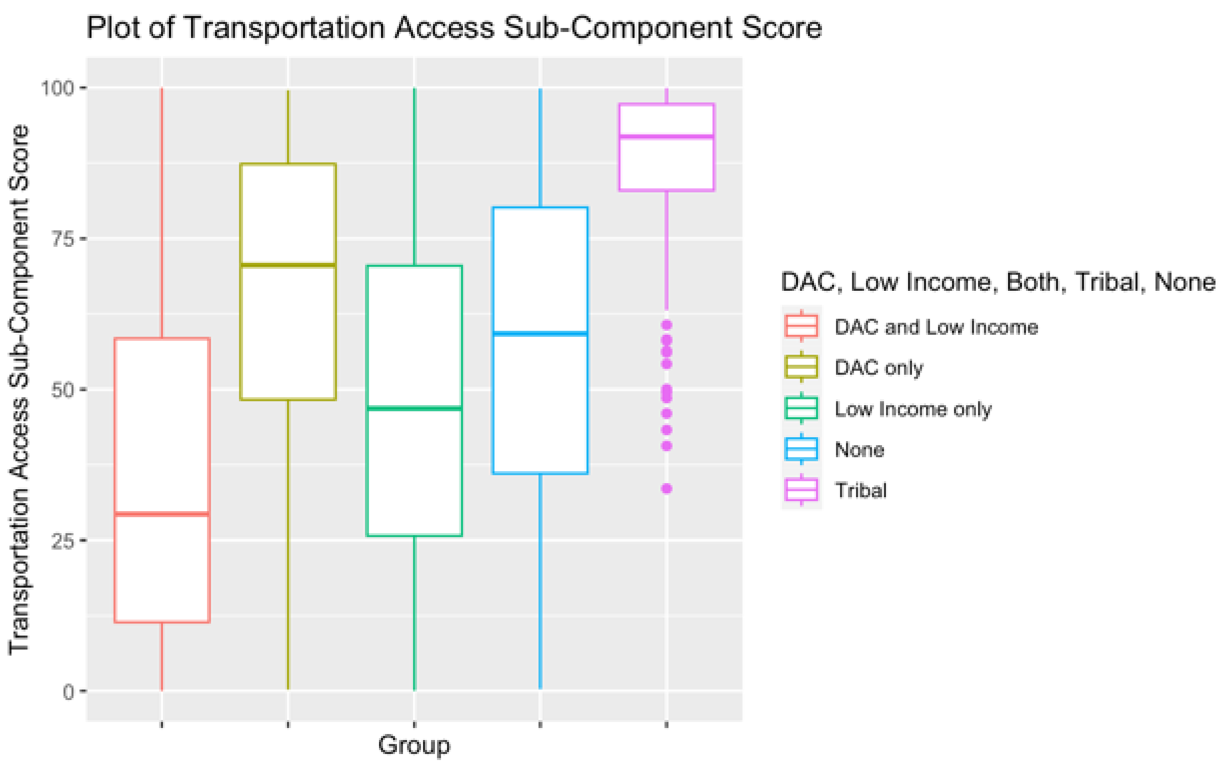


Figure 10: Boxplots of transportation access sub-component score by census tract type.

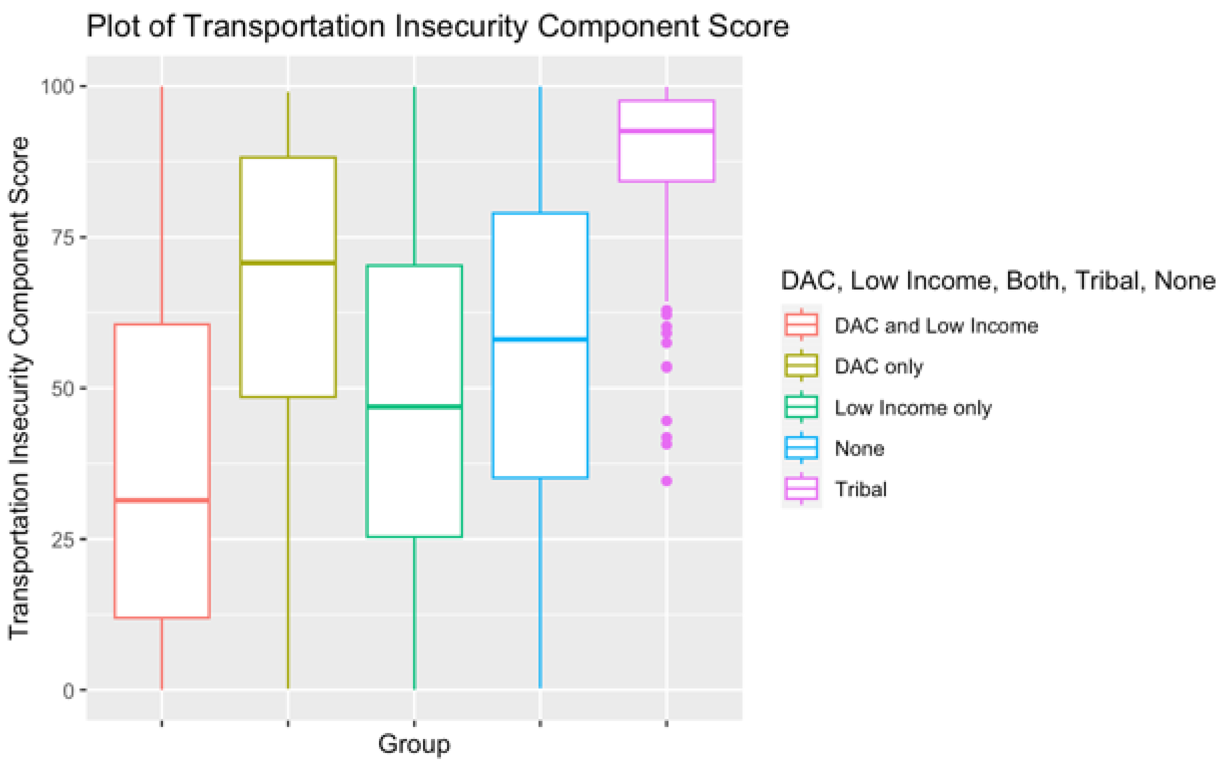


Figure 11: Boxplots of transportation insecurity component score by census tract type.

PEV rebate distribution, PEV Ownership, and vehicle ownership
The average number of rebates per 1000 households is highest in None priority communities at 57.35, followed by Low Income only communities at 27.29, DAC only communities at 20, DAC and Low Income communities at 14.22, and finally Tribal communities at 13.65 (Figure 12). Across all census tracts the average number of rebates per 1000 households is around 35.73 rebates. An ANOVA test with a null hypothesis that the average number of rebates per 1000 households is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 9).

The average number of vehicles per capita is highest in Tribal communities at 0.72, followed by None priority communities at 0.69, then DAC only communities at 0.67, Low Income only at 0.61, and finally DAC and Low Income at 0.56. Across all census tracts the average number of vehicles per capita is around 0.63 vehicles (Figure 14). An ANOVA test with a null hypothesis that the average number of vehicles per capita is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 9).

The average number of vehicles per household is highest in DAC only communities at 2.3, followed by None priority communities at 1.95, DAC and Low Income communities at 1.93, Tribal communities at 1.92, and finally Low Income only communities at 1.81 (Figure 15). Across all census tracts the average number of vehicles per household is around 1.6 vehicles. An ANOVA test with a null hypothesis that the average number of vehicles per household is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 9).

The average number of EVs per 1000 individuals is highest in None priority communities at 25.25, followed by Low Income only communities at 9.98 DAC only communities at 9.57, Tribal communities at 7.87, and finally DAC and Low Income at 4.84 (Figure 16). Across all census tracts the average number of EVs per 10 individuals is around 14.83 vehicles. An ANOVA test with a null hypothesis that the average number of EVs per 10 individuals is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 9).

The average number of EVs per 1000 households is highest in None priority communities at 69.54, followed by DAC only communities at 29.56, Low Income only communities at 27.37, Tribal communities at 20.2, and finally DAC and Low Income at 15.12 (Figure 17). Across all census tracts the average number of EVs per 1000 households is around 41.35 vehicles. An ANOVA test with a null hypothesis that the average number of EVs per 1000 households is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 9).

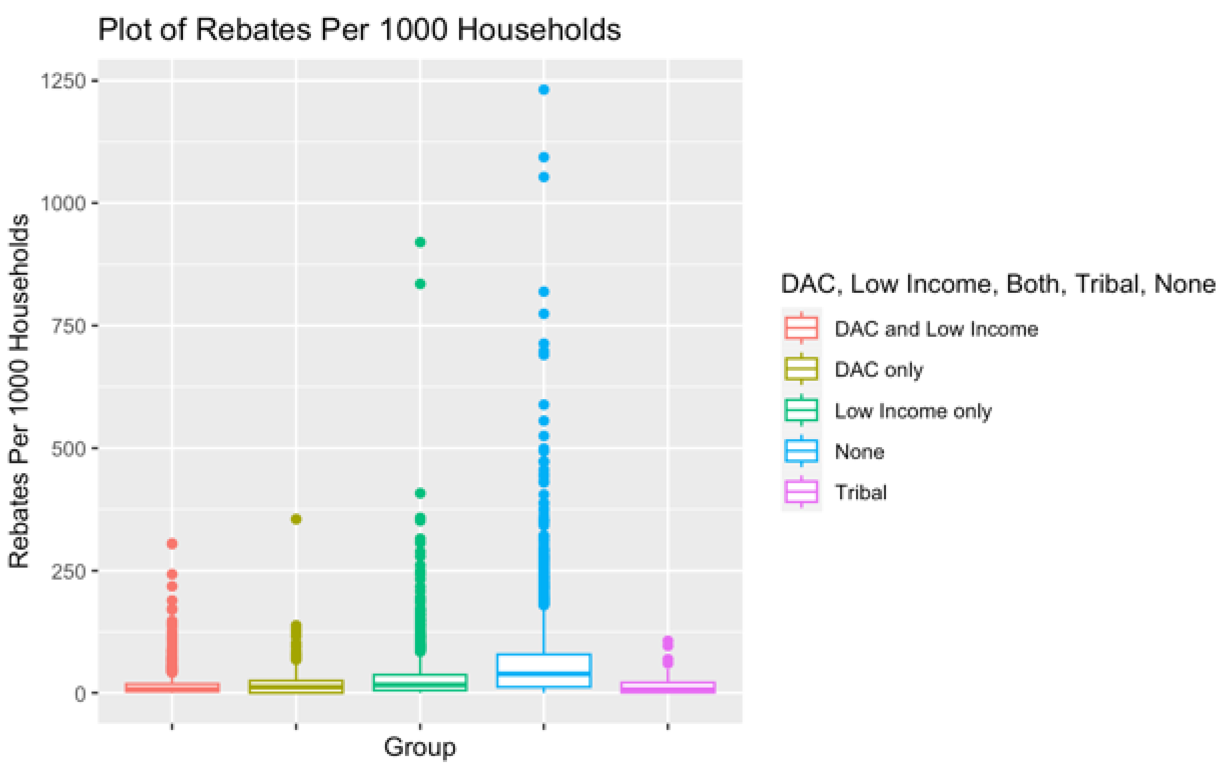


Figure 12: Boxplot of rebates per 1000 households by census tract type.

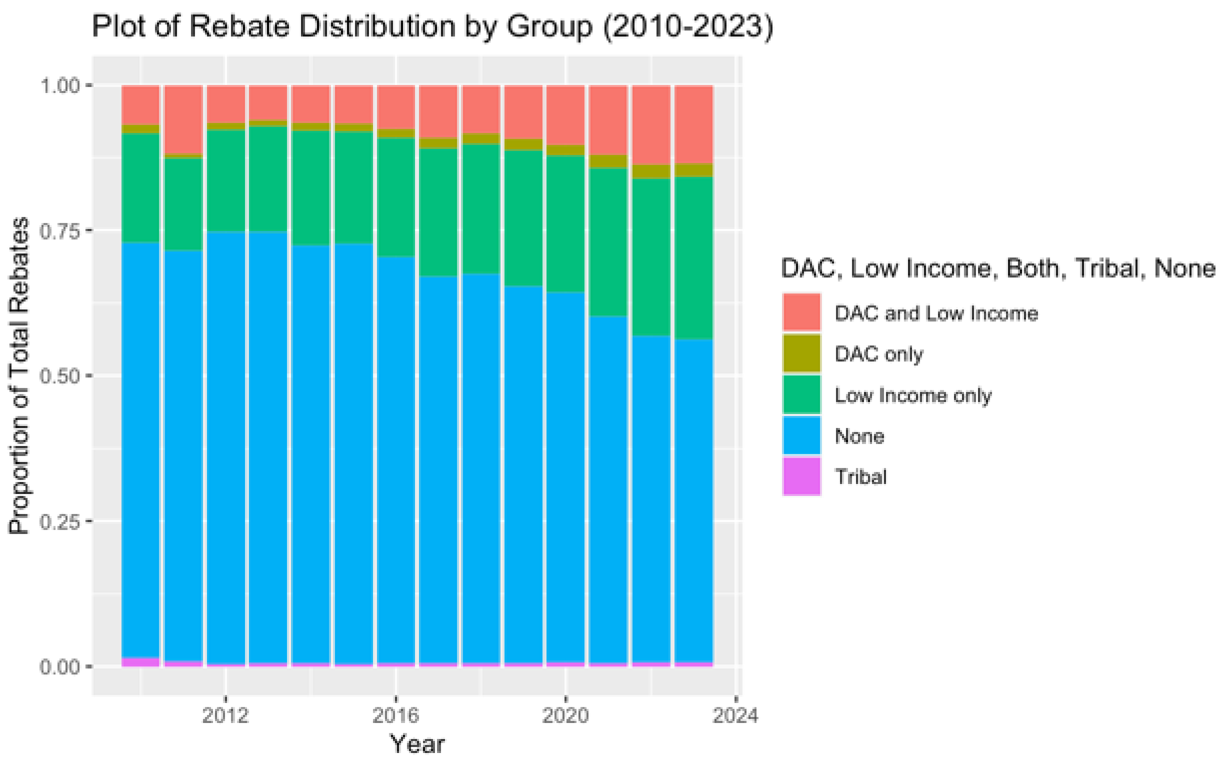


Figure 13: Proportion of rebates by year by census tract type

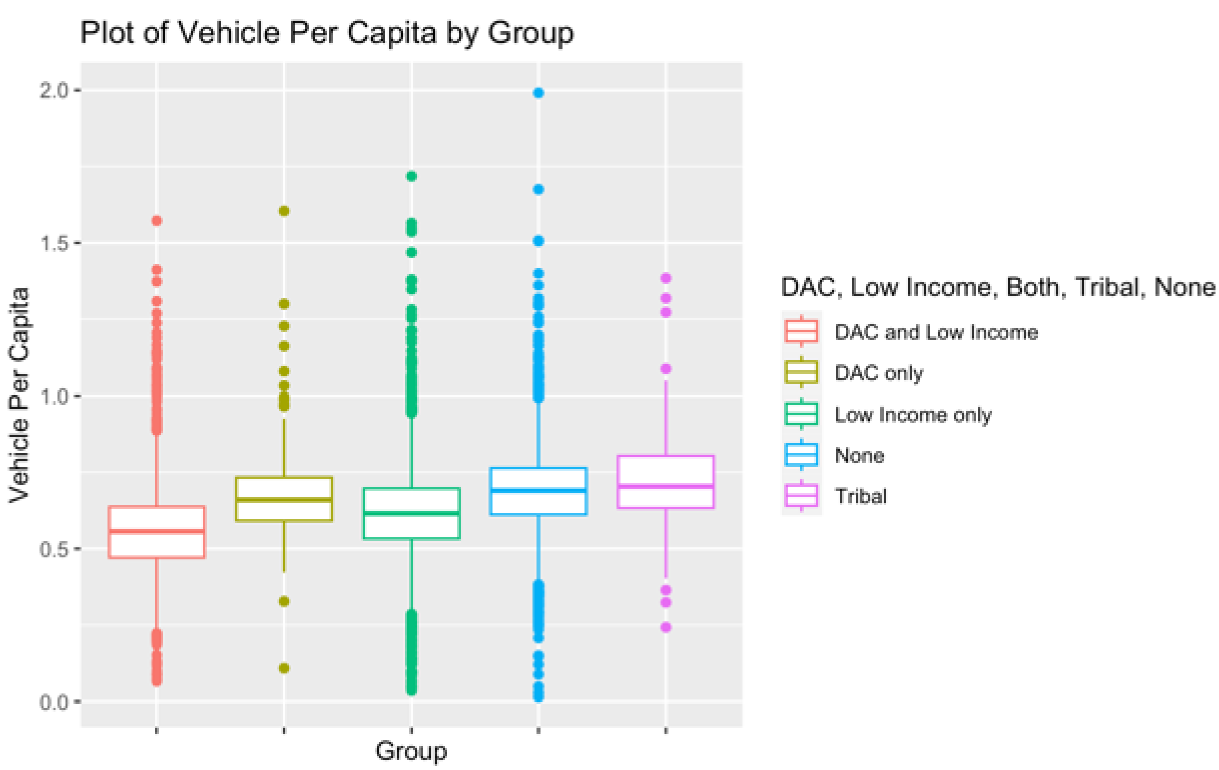


Figure 14: Boxplots of vehicle per capita by census tract type.

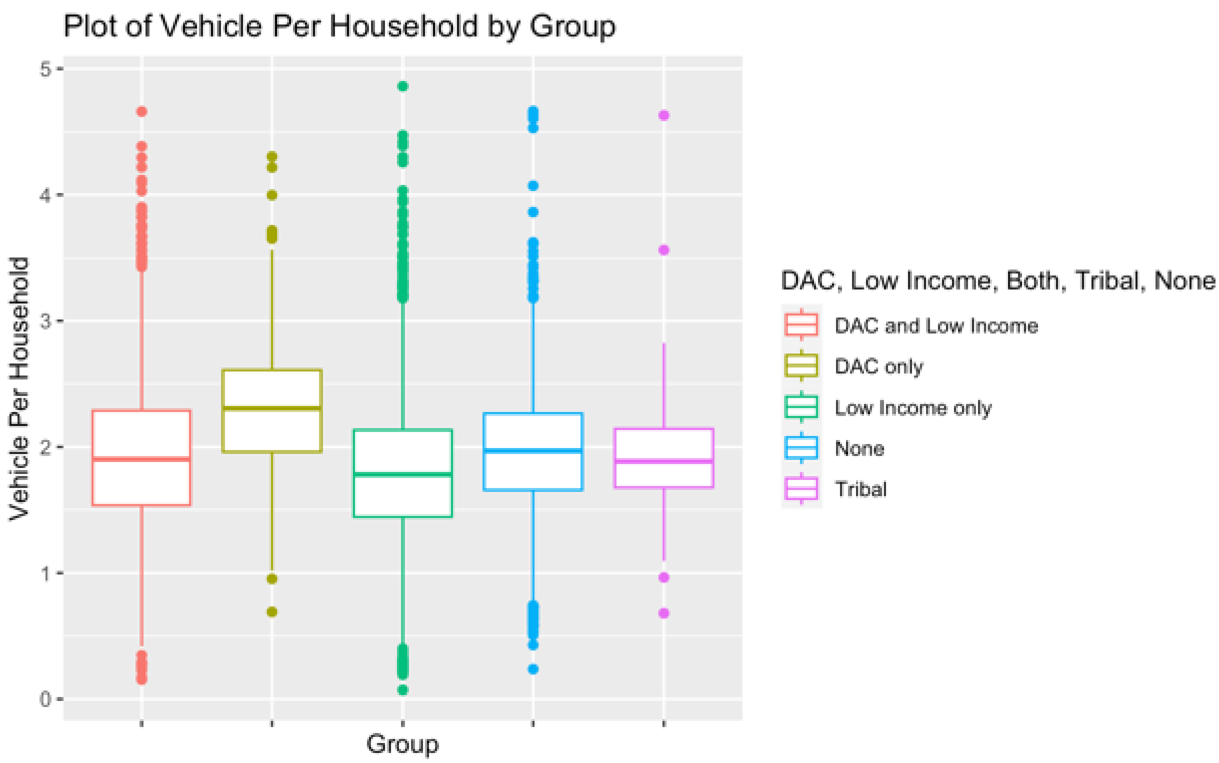


Figure 15: Boxplots of vehicle per household by census tract type.

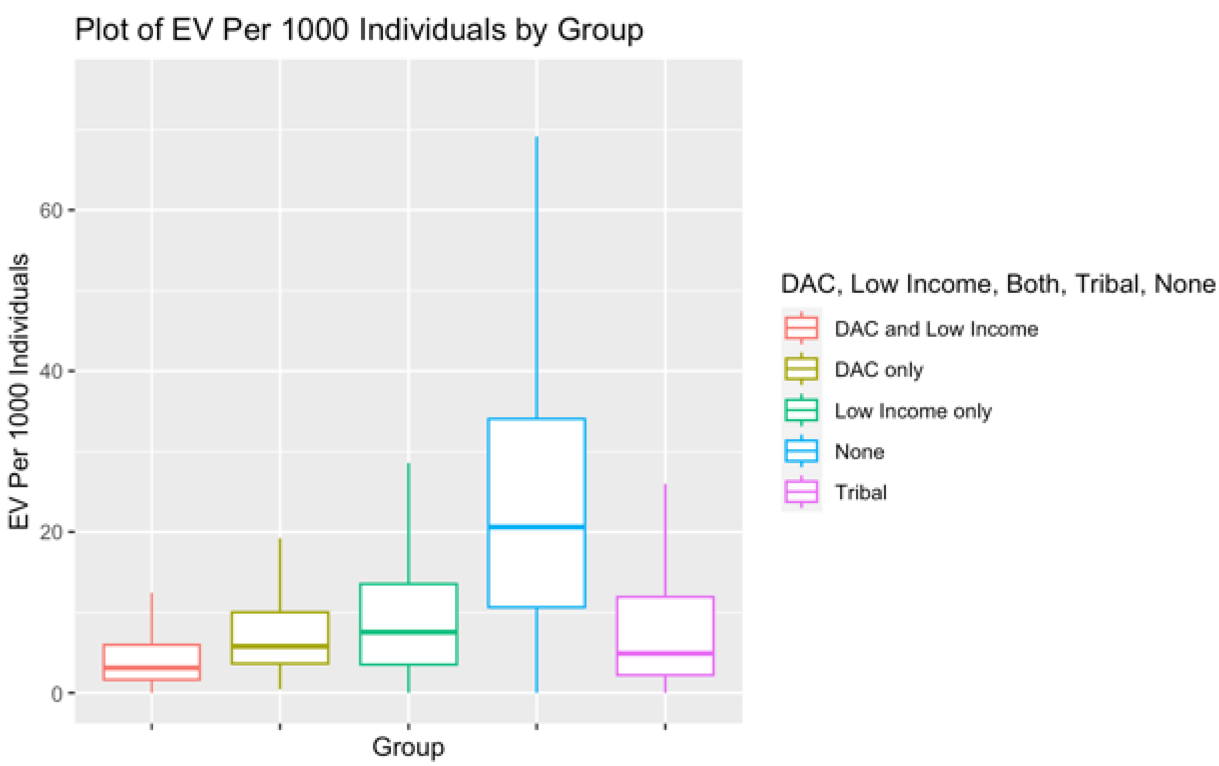


Figure 16: Boxplots of EV per 1000 individuals by census tract type.

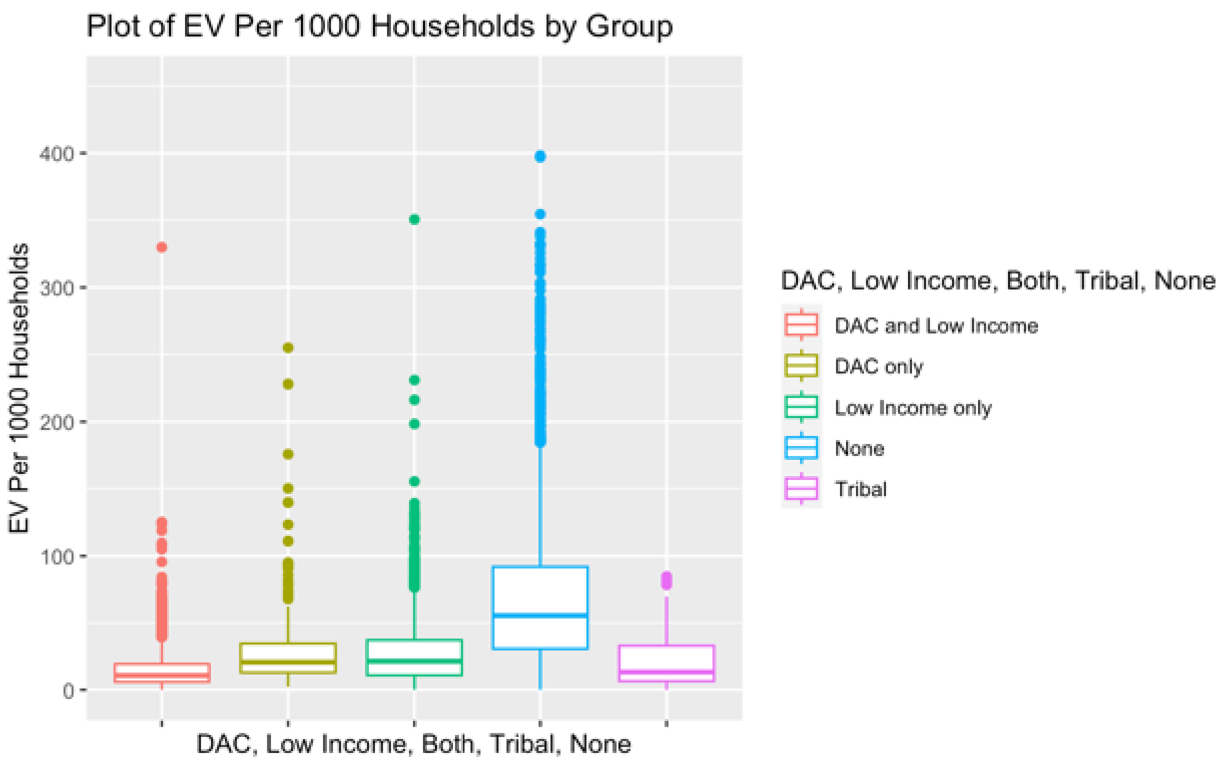


Figure 17: Boxplots of EV per 1000 households by group.

Charging Infrastructure and Dealerships

The average number of chargers per 1000 individuals is highest in Tribal communities at 1.98, followed by DAC only communities at 1.77, None priority communities at 1.15, Low Income only at 1.04, and finally DAC and Low Income at 0.86. Across all census tracts the average number of chargers per 1000 individuals is around 1.07 chargers. An ANOVA test with a null hypothesis that the average number of chargers per 1000 individuals is the same for different groups is rejected at the 5% significance level in favour of the alternative hypothesis that there does exist some difference (Table 8).

The average number of chargers per 1000 households is highest in Tribal communities at 5.37, followed by DAC only communities at 4.44, None priority communities at 3.05, Low Income only at 2.79, and finally DAC and Low Income at 2.53. Across all census tracts the average number of chargers per 1000 households is around 3 chargers. An ANOVA test with a null hypothesis that the average number of chargers per 1000 households is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 8).

The average number of chargers per 1000 vehicles is highest in DAC only communities at 3.02, followed by Tribal at 2.62, then None priority communities at 1.72, Low Income only at 1.71, and finally DAC and Low Income at 1.64. Across all census tracts the average number of chargers per 1000 vehicles is around 1.78 chargers. An ANOVA test with a null hypothesis that the average number of chargers per 1000 vehicles is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 8).

The average number of chargers per square mile is highest in DAC only communities at 8.33, followed by DAC and Low Income at 7.51, followed by Low Income only at 6.84, None priority communities at 5.93, and finally Tribal at 0.917. Across all census tracts the average number of chargers per square mile is around 6.6 chargers. An ANOVA test with a null hypothesis that the average number of chargers per square mile is the same for different groups fails to be rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 8).

The average number of L1 and L2 chargers per 1000 households is highest in DAC only communities at 3.7, followed by Tribal communities at 3.3, None priority communities at 2.36, Low Income only communities at 2.18, and finally DAC and Low Income communities at 1.83. Across all census tracts the average number of L1 and L2 chargers per 1000 households is around 2.23 chargers. An ANOVA test with a null hypothesis that the average number of L1 and L2 chargers per 1000 households is the same for different groups fails to be rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 8).

The average number of DC fast chargers per 1000 households is highest in Tribal communities at 2.06, followed by DAC only communities at 0.73, DAC and Low Income communities at 0.697, None priority communities at 0.69, and finally Low Income only communities at 0.6. Across all census tracts the average number of DC fast chargers per 1000 households is around 0.69 chargers. An ANOVA test with a null hypothesis that the average number of DC fast chargers per 1000 households is the same for different groups is rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 8).

Table 8: Mean, standard deviation (in parentheses), and ANOVA test results for charging infrastructure.

Dependent Variables	DAC and Low Income	DAC Only	Low Income Only	None	Tribal	F	P Value
Chargers Per 1000 Individuals	0.85 (3.68)	1.78 (9.03)	1.04 (5.18)	1.15 (4.12)	1.98 (4.68)	4.679	***
Charger Per 1000 Households	2.53 (11.37)	4.44 (24)	2.79 (14.92)	3.06 (12.47)	5.37 (13.82)	2.669	*
Charger Per 1000 Vehicles	1.64 (8.19)	3.02 (18.94)	1.72 (7.83)	1.72 (5.9)	2.62 (5.83)	2.416	*
Charger Per Square Mile	7.52 (39.56)	8.33 (55.15)	6.84 (39.23)	5.93 (25.75)	0.92 (3.98)	1.876	0.112
L1 and L2 Chargers Per 1000 Households	1.84 (9.32)	3.7 (23.16)	2.19 (13.71)	2.37 (11.1)	3.3 (9.67)	2.060	0.0833

Dependent Variables	DAC and Low Income	DAC Only	Low Income Only	None	Tribal	F	P Value
DC Fast Chargers Per 1000 Households	0.7 (4.54)	0.73 (2.5)	0.6 (3.38)	0.69 (3.59)	2.07 (9.21)	4.673	***

Statistical significance: 0 '***' 0.001 '**' 0.01 '*' 0.05.

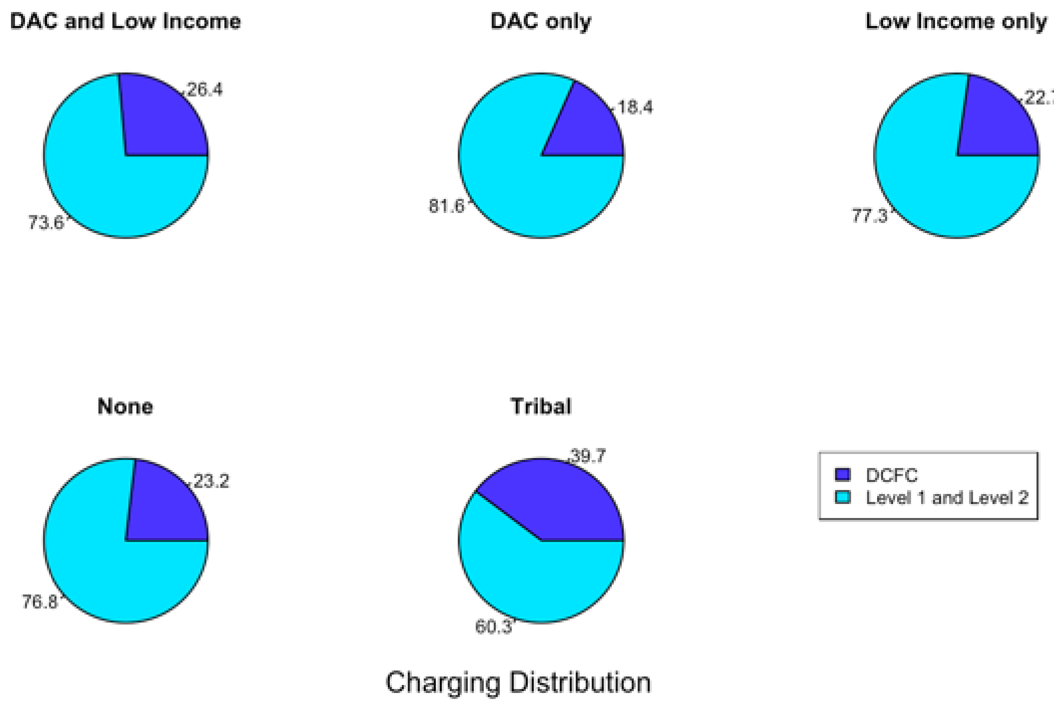


Figure 18: Pie charts of charger type by group.

The average number of dealerships per square mile is highest in Low Income only communities at 0.05, followed by DAC and Low Income at 0.04, followed None priority communities at 0.02, Tribal communities at 0.015, and finally DAC only communities at 0.01. Across all census tracts the average number of dealerships per square mile is around 0.04. An ANOVA test with a null hypothesis that the average number of dealerships per square mile is the same for different groups fails to be rejected at the 5% significance level in favor of the alternative hypothesis that there does exist some difference (Table 9).

Summary and Discussion

There are multiple significant differences in demographics, transportation access, vehicle ownership, EV ownership, infrastructure access and rebate distribution among the census tract types relevant to this project. Based on there being differences between each census tract type we decided to use a stratified sample with the aim of being able to detect differences in survey responses by census tract type. An only random sample would result in a sample size of households in DAC only and tribal communities insufficient to detect statistically significant differences. Communities that are classified as DAC and Low Income or Low Income only have greater population densities, around double that of None priority communities and around 16 times that of Tribal communities. These communities also have a greater incidence of multi-unit housing reflecting the higher density of these tracts. Home ownership is also lower with less than 50% of households in DAC and Low Income or Low Income only communities owning homes. The higher population densities of these tracts may signify that more of these tracts are in urban areas. DAC only communities and Tribal communities have lower population densities which may indicate that these communities are more suburban, small towns, or rural areas. This may explain why single-family homes are more common in these areas. While Tribal communities have a median income of less than $80,000, DAC only communities have a median income greater than $80,000, which makes sense as DAC only communities are not necessarily low income. This indicates that though DAC only communities are areas impacted by environmental burdens, financial burden may not be as big of an issue as it is for Low Income only communities. The higher median income also appears to justify the higher levels of home ownership in DAC only communities as groups with higher median incomes are more likely to make larger investments. It is interesting, however, that tribal communities have the highest rates of home ownership while also having the lowest employment/population ratio and a lower median income. The trend observed for education appears to almost exactly mirror the trend for median income across census tract types.

Tribal communities have the greatest transportation burden with the highest transportation access sub-component score and transportation insecurity component score, followed by DAC only communities. This may be due to these areas being more rural which increases drive times resulting in higher costs of transportation. Being more rural may mean that there are fewer public transportation options which also increases the burden and cost of providing and paying for one's own transportation. Interestingly, DAC and Low Income communities and Low Income only communities appear to face less transportation insecurity according to this measure. This may be because these tracts are in a higher population dense and urban areas with better transit access.

For rebate distribution None priority communities have received a significantly higher number of rebates when compared to all other tracts. Low Income only and DAC only communities receive a similar number of rebates at around 20 to 27 rebates per 1000 households. DAC and Low Income and Tribal communities also receive a similar number of rebates at around 13 rebates per 1000 households. The large disparity between rebates received by None priority communities and the other communities may reflect the fact that early adopters of PEVs tend to be more affluent, white men. Hence, they received a larger proportion of rebates early on in the transition to PEVs. When observing the distribution of rebates by year, there appears to be a clear trend where None priority communities have a decreasing share of rebates while Low Income only communities and DAC and Low Income communities have an increasing share. However, DAC only and Tribal communities rebate shares do not appear to be increasing (Figure 13). This coincides with the observation that these areas have fewer CVRP and CVAP registered dealerships per 1000 households when compared to other communities.

For vehicle ownership we see all vehicle and PEV ownership tends to be most commonly found among the None priority communities, followed by DAC communities, Low Income only communities, Tribal communities, and finally DAC and Low Income communities. Tribal communities may have a higher number of vehicles per capita because they live in lower density areas that may be small towns or rural where there is a greater need for vehicles. DAC communities and non-DAC communities have a similar average vehicle miles traveled (VMT) per household (Canepa et al., 2019b) which indicates that both groups are equally car-dependent, but DAC only and Tribal communities appear to rely on more vehicles per household and hence are likely to spend more on transportation. Moreover, due to these areas being more rural, public transportation options and availability are limited. According to the Consumer Expenditure Survey, the average Californian spent $2,298.24 on gasoline, other fuel, and motor oil in 2019-20 ("U.S. Bureau of Labor Statistics," n.d.). Greater use of EVs in these communities could potentially lower overall transportation costs.

The trend that we see with charging infrastructure is that charging access on per household or people level tends to be higher among Tribal communities, then DAC communities, followed by None priority communities, Low Income only communities, and finally DAC and Low Income communities. While charging access on a per area basis is lower in Tribal communities than all other community types, None priority communities tend to have fewer DC fast chargers which may reflect the fact that these areas tend to be more urban and inner city with a higher rates of home ownership, where they are able to install L1 and L2 chargers. Low Income only and DAC and Low-Income communities also have higher rates people living in multi-unit dwellings, which makes it more difficult to access charges and may be the reason for lower levels of charging access (Figure 9). In regards to CVRP and CVAP registered dealerships, there is an extremely low occurrence across groups, but they occur at about the same level when observing dealerships per 1000 households.

DAC only and Tribal communities are less dense census tracts with greater access to charging and vehicles per household, but have fewer EVs compared to non-DAC communities. Low Income only and DAC and Low Income census tracts have lower levels of vehicle and EV ownership as well as charging access. But they are more densely populated which may suggests that these areas are more urban with greater access to public transportation. There may also be a lack of homes charging infrastructure as Low Income only and DAC and Low Income communities tend to have a lower proportion of single family homes where they are able to install home chargers.

Future Work

We plan to use CalEnvironScreen 4.0, Department of Energy, Alternative Fuels Data Center, EV Charging Infrastructure Data, DMV Vehicle Registration data, U.S. Department of Transportation's ETC (Equitable Transportation Community) Explorer, Clean Vehicle Rebate data, and Census data when we analyze our questionnaire survey data. The data is relevant for all research questions since we will consider differences in awareness, perceptions, and consideration between census tract types, while built environment variables are relevant for *RQ3 "How does the built environment impact ZEV viability (including house type, home charging access and the potential for home charging, public charging access, etc.) in underserved communities?".* In addition, we will continue to explore the secondary data with the aim of identifying communities based on their need, readiness, and current adoption for PEVs. This will include identifying communities based on their *need* for single occupant vehicle travel and therefore PEVs (e.g. those with low transit access), communities based on their *readiness* for PEVs (e.g. access to infrastructure, home charging access), and communities based on *current adoption* of PEVs. While not an aim of this project this research may help identify communities who need the most assistance in adopting PEVs, something not possible with currently available mapping tools.

Supplemental tables and figures

Table 9: Mean, standard deviation(in parentheses), and ANOVA test results.

Dependent Variables	DAC and Low Income	DAC Only	Low Income Only	None	Tribal	F	P Value
Population Density	125595.9 (116581)	46019.5 (37359)	104608.7 (121709)	58913.7 (64649.2)	6165.7 (14111)	223.3	***
Median Income	57099.1 (19014)	87517.7 (24258.6)	75168.66 (25455.1)	124670.7 (42473.5)	69378.87 (26974)	1802	***
Home Ownership Rate	39.46 (21.5)	64.86 (19.92)	48.85 (22.58)	68.39 (20.34)	73.12 (14.45)	769.3	***
Employment /Population Ratio	56.92 (8.49)	59.09 (9.06)	58.62 (10.36)	60.58 (9.02)	48.6 (10.42)	99.22	***
Median Age	33.36 (5.55)	34.73 (5.66)	37.64 (8.15)	41.37 (7.38)	45.12 (9.48)	491.9	***
Bachelor's or Higher (25 and Over)	16.27 (11.95)	24.23 (14.52)	30.7 (17.32)	49.6 (19.24)	24.05 (12.12)	1488	***
Transportation Access Sub-Component Score	36.38 (28.3)	65.38 (25.63)	48.45 (27.48)	56.96 (26.54)	86.64 (14.69)	294.9	***
Transportation Insecurity Component Score	37.62 (29.03)	66.02 (25.59)	48.3 (27.57)	56.07 (26.44)	87.73 (13.84)	258.0	***
Rebates Per 1000 Households	14.23 (20.36)	20 (31.68)	27.3 (41.69)	57.35 (74.7)	13.66 (18.04)	265.8	***
Vehicle Per Capita	0.56 (0.14)	0.67 (0.14)	0.62 (0.16)	0.69 (0.14)	0.72 (0.17)	300.9	***
Vehicle Per Household	1.93 (0.6)	2.3 (0.55)	1.81 (0.6)	1.95 (0.49)	1.92 (0.48)	59.47	***

Dependent Variables	DAC and Low Income	DAC Only	Low Income Only	None	Tribal	F	P Value
EV Per 1000 Individuals	4.85 (5.56)	9.58 (11.4)	9.99 (9.2)	25.26 (21.2)	7.87 (8.03)	797.8	***
EV 1000 Per Households	15.13 (15.42)	29.56 (30.96)	27.37 (23.45)	69.54 (60.22)	20.21 (18.93)	737.4	***
Dealership Per Sq Mile	0.04 (0.48)	0.01 (0.11)	0.05 (0.6)	0.02 (0.27)	0.01 (0.11)	2.195	0.0669
Dealership Per 1000 Households	0.02 (0.15)	0.02 (0.13)	0.02 (0.17)	0.01 (0.12)	0.01 (0.1)	0.800	0.525

Statistical significance: 0 '***' 0.001 '**' 0.01 '*' 0.05.

Table 10: Mean of percentage of households with household income $200,000 or more.

Group	Avg % of Households with $200,000 or more
DAC and Low Income	4.158668
DAC only	9.610909
Low Income only	9.236923
None	23.992076
Tribal	8.141844

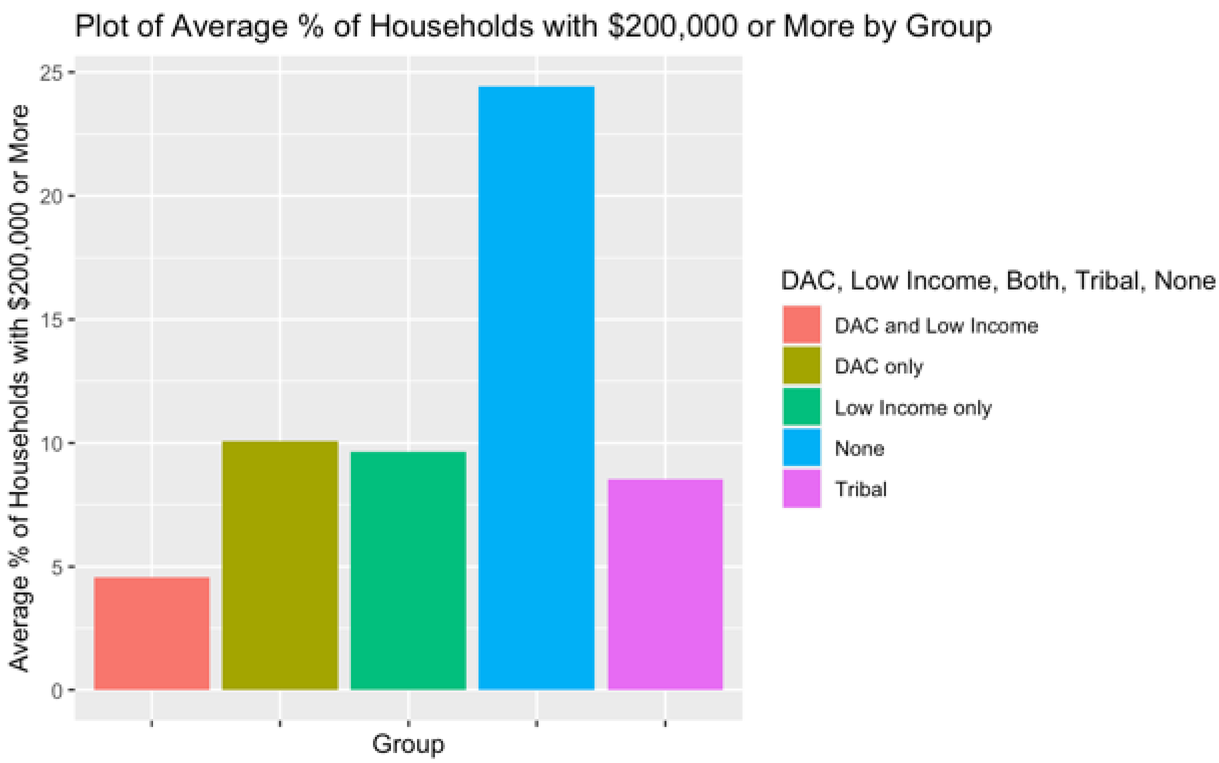


Figure 19: Bar plot of average percentage of households with $200,000 or more by group.

Appendix 4: Code for multivariate analysis

Code for Latent Class Analysis

```
# Install all necessary packages
library(poLCA)
library(foreign)
library(nnet)

# Set seed for reproduceable data
set.seed(1)

# Define function where inputs are variables used to build latent classes
f1 = as.formula(cbind(MakeModelDummy1, HomeCharge, BEVTravel,GasSafer, BEVworse,
BEVeasier, KnowBEVs, EnoughChargers, BatteryDegrades, Incentives, ConsiderBEV,
SupportLaw)~1)

# Produce model with 5 latent classes
LCA <- poLCA(f1, data=data, nclass = 5)

# Assign predicted latent class to each data observation
data$LCA = LCA$predclass

# Relevel LCA variable to set "Active "Supporters" as reference category
data$LCA = relevel(factor(data$LCA), ref = "Active Supporters")

# Fit a multinomial logistic regression model where LCA is dependent variable
m = multinom(LCA ~ `Vehicles per
driver`+Used1+RaceComb1+AgeComb1+Income2+GenderComb1+EducationComb1+OwnCo
mb1+env2+car2+mix2+tech2+busy2+social+wait2+exercise2+`2010 People per Sq
km`+`AddDCFC5/Square km`+UR+`2010 EV per 1000 Households`+`Highest Home
Charging`, data=data)

# Calculate McFadden's R squared to measure model goodness of fit
mcFadden = pscl::pR2(m)[4]
```

Variable	
MakeModelDummy1	Knowledge (Refer to Table 3)
HomeCharge	Home charge (Refer to Table 3)
BEVTravel	Range (Refer to Table 3)
GasSafer	Safety (Refer to Table 3)
BEVworse	Environmental impact (Refer to Table 3)
BEVeasier	Maintenance (Refer to Table 3)
KnowBEVs	Knowledge (Refer to Table 3)
EnoughChargers	Enough chargers (Refer to Table 3)
BatteryDegrades	Battery degradation (Refer to Table 3)
Incentives	Incentive awareness (Refer to Table 3)

ConsiderBEV	BEV consideration (Refer to Table 3)
SupportLaw	ZEV policy support (Refer to Table 3)
`Vehicles per driver`	Vehicles per driver (Refer to Table 4)
Used1	New car buyer (Refer to Table 4)
RaceComb1	Race (Refer to Table 4)
AgeComb1	Age (Refer to Table 4)
Income2	Income (Refer to Table 4)
GenderComb1	Gender (Refer to Table 4)
EducationComb1	Education (Refer to Table 4)
OwnComb1	Home Ownership (Refer to Table 4)
env2	Anti-environment (Refer to Table 4)
car2	Pro-car (Refer to Table 4)
mix2	Pro-mixed land use (Refer to Table 4)
tech2	Anti-tech (Refer to Table 4)
busy2	Pro-too busy (Refer to Table 4)
social	Pro-social (Refer to Table 4)
wait2	Anti-waiting (Refer to Table 4)
exercise2	Anti-exercise (Refer to Table 4)
2010 People per Sq km	2010 People per Square km (Refer to Table 4)
AddDCFC5/Square km	DCFC within 5 mins of residence (Refer to Table 4)
UR	Urban vs. rural (Refer to Table 4)
2010 EV per 1000 Households	2010 PEVs per 1000 Households (Refer to Table 4)
Highest Home Charging	Highest Home Charging Accessibility (Refer to Table 4)

Code for BEV assessments factor analysis

```
DAC_assess <- subset(vignette_survey_exp_data, select = c("incentive_aware_assess","enough_charging_assess","degrade_too_fast_assess","enough_knowledge_assess","maintenance_assess","envs_more_damage_assess","gas_safer_assess","range_assess"))
fa_assess<- fa(DACassess, nfactors = 3, rotate ="varimax")
```

Key:
DAC_assess: data subset with the assessment variables
fa_assess: named object; exploratory factor analysis results
fa: exploratory factor analysis function, from R package "psych"
nfactors: specified number of factors
rotate: "varimax" , or orthogonal rotation of data

Variable key:

<table>
<tr><th>Variable</th><th>Description</th></tr>
<tr><td>incentive_aware_assess</td><td rowspan="8">Continuous: Strongly Agree (1) to Strongly Agree (5)</td></tr>
<tr><td>enough_charging_assess</td></tr>
<tr><td>degrade_too_fast_assess</td></tr>
<tr><td>enough_knowledge_assess</td></tr>
<tr><td>maintenance_assess</td></tr>
<tr><td>envs_more_damage_assess</td></tr>
<tr><td>gas_safer_assess</td></tr>
<tr><td>range_assess</td></tr>
</table>

Code for Vignette Survey Experiment Analysis

beta_regression <- betareg(dep_var~ incentive_factor + charging_factor + CC4AxFast + battery_factor + age_factor + male_dummy + college_dummy + income_factor + vehicles_per_driver + newcarbuyer_dummy + evs_per_capita + urban_dummy + charging_and_range + knowledge_aware + battery_quality + home_charge_assess + tech_savvy + work_oriented + pro_exercise + family_friends_oriented + materialistic + non_car_alts + pro_car + commute_benefit + pro_travel + pro_suburban + modern_urbanite + pro_environmental + polychronic + waiting_tolerant + sociable , data = vignette_survey_exp_data)

Key:
beta_regression: named object, beta regression results
Betareg: beta regression function, from R package “betareg”

Variable key:

Category	Variable	Description
Dependent variable	dep_var	dependent variable; BEV purchase consideration likelihood between 0 and 1
Policy interventions	incentive_factor	factor with 3 levels: no info (reference reduced CC4A CC4A
	charging_factor	factor with 6 levels: public level 2 (reference: 0) public fast (1) home (2) work (3) home and work (4) home and fast (5)
	CC4AxFast	incentive factor = CC4A & charging factor = Fast
	battery_factor	factor with three levels no info (reference: 0) warranty (1) rebate (2)
Socio-demographics	age_factor	factor with 4 levels younger than 30 (reference: 0) 30 to 49 50 to 69 70 and older
	male_dummy	male (1) vs non male (0)

	college_dummy	college (1) vs non-college (0)
	income_factor	factor with five levels: less than $50,000 (1) $50,000 to $99,999 (2) $100,000 to $149,000 (3) $150,000 and over (reference: 0) prefer not to answer (4)
	vehicles_per_driver	number of vehicles per driver
	newcarbuyer_dummy	new car buyer vs (1) used car buyer (0)
	evs_per_capita	number of PEVs per 1,000 households
	urban_dummy	urban (1) vs rural (0)
	charging_and_range	charging and range factor score
	knowledge_aware	knowledge and awareness factor score
	battery_quality	battery quality factor score
	home_charge_assess	home charge assessment raw variable Strongly Disagree (-2) to Strongly Agree (5)
	tech-savvy	Continuous: Strongly Disagree (1) - Strongly Agree (5)
	work_oriented	
	pro_exercise	
	family_friends_oriented	
	materialistic	
	non_car alts	
	pro_car	
	commute_benefit	
	travel_liking	
	pro_suburban	
	modern_urbanite	
	pro_environmental	
	polychronic	
	waiting_tolerant	
	sociable	

Code for Marginal effects of policy interventions:

```
incentive_marg_eff <- effect("incentive_factor", beta_regression )
charging_marg_eff <- effect("charging_factor", beta_regression )
battery_marg_eff <- effect("battery_factor", beta_regression )
```

Key:
incentive_marg_eff, charging_marg_eff, battery_marg_eff: named objects, marginal effect values
“incentive_factor”, “charging_factor”, “battery_factor”: name of factor variables in model
effect: marginal effect function from package R package “effects”