Measuring Consumer Willingness to Enroll in Battery Electric Vehicle Smart Charging Programs

Pingfan Hu
Department of Engineering Management and Systems Engineering
George Washington University
Washington DC, USA
pingfan.hu@gwu.edu

Brian Tarroja, Ph.D., P.E.
Department of Civil and Environmental Engineering
University of California, Irvine
Irvine CA, USA
bjt@apep.uci.edu

Matthew Dean, Ph.D.
Department of Civil and Environmental Engineering
University of California, Irvine
Irvine CA, USA
deanmd@uci.edu

Kate Forrest, Ph.D.
Advanced Power and Energy Program
University of California, Irvine
Irvine CA, USA
kef@apep.uci.edu

Eric Hittinger, Ph.D.
Department of Public Policy
Rochester Institute of Technology
Rochester NY, USA
eshgpt@rit.edu

Alan Jenn, Ph.D.
Institute of Transportation Studies
University of California, Davis
Davis CA, USA
ajenn@ucdavis.edu

John Paul Helveston, Ph.D.
Department of Engineering Management and Systems Engineering
George Washington University
Washington DC, USA
jph@gwu.edu

***Abstract*— As Battery Electric Vehicles (BEVs) gain popularity, managing their charging becomes crucial for grid stability. Smart charging programs can help utilities manage this demand and integrate more renewable energy by controlling when and how BEVs are charged. However, these programs require participation from BEV owners, who may be hesitant to freely provide such control. This study uses a discrete choice experiment (also called conjoint analysis) to measure BEV owners' willingness to participate in smart charging programs under various incentives and features. We examine two types of smart charging: Supplier-Managed Charging (SMC), which controls charging times, and Vehicle-to-Grid (V2G), allowing BEVs to return power to the grid. In an online survey conducted via Facebook and Instagram ads, we collected 858 valid responses, with 815 responses for SMC program choices and 414 for V2G program choices. We used mixed logit (MXL) models to quantify respondents' willingness to participate. The findings indicate a general reluctance to participate in both programs without some form of incentive, with respondents being most sensitive to recurring monetary incentives. For SMC, there is also concern about ensuring sufficient battery levels in the mornings. Simulations were conducted to predict enrollment rates based on different program features. Additional data will be collected to refine the models in the coming months.**

***Keywords* - Smart Charging, Grid Management, Consumer Preferences, Discrete Choice Experiment (DCE), Logit Models, Battery Electric Vehicle (BEV), Vehicle-to-Grid (V2G)**

I. Introduction

BEVs are a cornerstone in plans to decarbonize the U.S. energy system [1]. As a result, they are also expected to be the largest source of electricity demand in the coming decades, but the timing of that charging could be detrimental to sustainability and infrastructure longevity if left unmanaged [2]. Due to patterns in BEV owner behavior, BEV charging often coincides with peak electricity demand on regional electric grids, which can lead to increased strain on the grid and increased greenhouse gas (GHG) emissions [3]. A solution is to align BEV charging with off-peak electricity demand periods, which can alleviate these problems and help reduce the curtailment of renewable electricity sources such as wind and solar [2].

One strategy to achieve this outcome is "smart charging," an approach where BEV owners provide utilities control over charging to smooth out the electricity demand and re-align it with off-peak periods. There are two major approaches for smart charging: Supplier-Managed Charging (SMC), which monitors and controls the timing of the charging, and Vehicle-to-Grid (V2G), which enables BEVs to send power back to the grid, providing grid operators even more flexibility in load balancing. Both SMC and V2G have been found to be economically beneficial to the grid and facilitate greater use of renewable energy [4], [2].

The promise of smart charging rests on the willingness of BEV owners to give utilities control over their charging. Many are unwilling to do so freely due to privacy concerns, the potential for reduced operational capabilities (e.g. waking up with insufficient charge), and inadequate compensation [5], [6]. This research aims to quantify how different smart charging program incentives and control settings can align with BEV owner charging preferences. We address two research questions:

1. How do changes in individual smart charging program features influence the willingness of BEV owners to opt in to SMC and V2G programs?
2. Under what conditions will BEV owners be more willing to opt-in to different smart charging (considering both SMC and V2G) programs?

We address these questions using a survey-based discrete choice experiment (also called "conjoint analysis") to quantify user preferences for different smart charging programs.

The potential benefits of smart charging programs are well-documented under ideal conditions of full BEV owner adoption [7], [2]. Therefore, the success of these programs hinges on BEV owners' willingness to participate. For example, in a real-world experiment of a SMC program, a study by Bailey et al. [8] found that once financial incentives were removed, BEV owners stopped participating. It is therefore crucial to understand the conditions under which BEV owners are more likely to participate in smart charging programs. As BEV adoption and renewable energy deployment continue to grow, this information will be vital for utilities to make investment and operational decisions.

One commonly used approach to assess preferences for a variety of features is discrete choice experiments. A recent study by Wong et al. [9] examined how incentives affect the acceptance of EV smart charging among various groups using a discrete choice experiment based on the features of 14 actual BEV smart charging programs in North America from 2020 to 2022. They found that monetary incentives are important to smart charging program enrollment but diminishing returns exist. Another discrete choice experiment by Philip and Whitehead [10] conducted in Australia found guaranteed driving range can increase consumers' willingness to participate. Finally, a study by Huang et al. [11] on Dutch BEV owners revealed that willingness to particiapte in a V2G program increases if BEVs can be quickly recharged, making access to a level-2 charger essential for the program.

One limitation of these prior studies is that they all primarily sampled respondents from the general car owning public, with few actual BEV owners in the sample. The BEV ownership rate among the participants in the study of Wong et al. [9] was 19%, and in the study of Philip and Whitehead [10] it was just 1.28%, suggesting most respondents had little to no prior experience operating or charging a BEV. In contrast, in the study by Huang et al. [11], 99% of the respondents claimed to have driven a BEV, but their total sample was only 157 respondents.

Our research builds on this prior work through a discrete choice experiment aimed at a large sample of BEV users and owners (currently N = 858) in the U.S. All participants on our survey passed the checks that suggest they indeed own a BEV. We examine their willingness to participate in the SMC and V2G programs, taking into account both the financial benefits to customers and the operational flexibility that customers would have under different programs.

II. Method

A. Survey Design

We designed and fielded a nationwide discrete choice survey experiment online to quantify how different smart charging features affect BEV owners' willingness to participate in SMC and V2G programs. The survey was designed and published on formr.org, an open-source platform that leverages the R programming language to design surveys [12]. The choice task randomization and data collection were made possible thanks to the ability to use R code in the survey. A full copy of the survey text can be accessed here: https://gwu.quarto.pub/smartchargingsurvey/.

One important design requirement was to ensure that we were indeed sampling current BEV owners. To achieve this, we began the survey with a screener section where respondents were asked to select their current vehicle from a drop down list of all possible vehicles in the last 30 years. We only kept responses from those who selected a BEV model, and the survey would end if they picked a conventional car. Since there was no indication from the advertisement that it involved BEVs, we are confident that the respondents who filtered through truly owned a BEV as they were able to select their BEV model from a list of hundreds of vehicle models.

The conjoint choice questions used randomized sets of choice tasks, each containing different attributes for the programs. Respondents were asked six choice questions for SMC programs, and then an additional set of six questions for V2G. Each choice question included two smart charging options and a "not interested" option. We leverage discrete choice models to estimate the independent value that users have towards each individual smart charging program feature. We chose 5 attributes each for the SMC and the V2G programs. Their attributes are shown in Table 1 and Table 2 below.

Table 1: SMC Program Attributes

No.	Attribute	Range	Explanation
1	Enrollment Cash	\$50, \$100, \$200, \$300	One-time payment upon enrollment.
2	Monthly Cash	\$2, \$5, \$10, \$15, \$20	Recurring monthly payment.
3	Override Allowance	0, 1, 3, 5	Monthly frequency of freely override to normal.
4	Minimum Threshold	20%, 30%, 40%	SMC won't be triggered below this threshold.
5	Guaranteed Threshold	60%, 70%, 80%	SMC will give you this much of range by the morning.

Table 2: V2G Program Attributes

No.	Attribute	Range	Explanation
1	Enrollment Cash	\$50, \$100, \$200, \$300	One-time payment upon enrollment.
2	Occurrence Cash	\$2, \$5, \$10, \$15, \$20	Earning for each occurrence of V2G.
3	Monthly Occurrence	1, 2, 3, 4	Monthly occurrence of V2G.
4	Lower Bound	20%, 30%, 40%	V2G won't drain your battery below this percentage.
5	Guaranteed Threshold	60%, 70%, 80%	V2G will charge your battery back to this percentage.

Figure 1 shows example choice questions for the SMC questions. The V2G questions are similar and its sample can be accessed in Section B of the Appendix. In each question, the values shown were randomized according to a pre-determined experiment design, generated using the `cbcTools` R package [13].

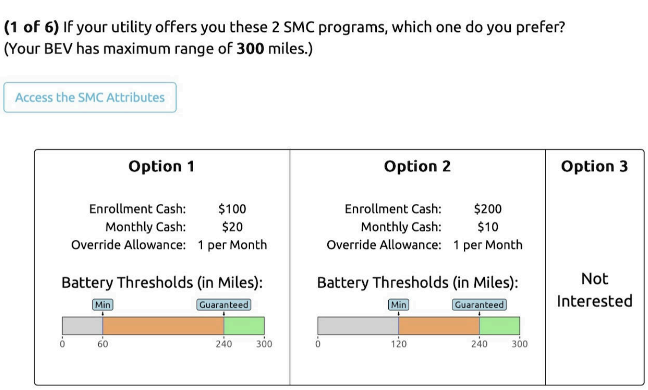

Figure 1: Sample SMC Conjoint Question

Apart from the choice questions, there were also two other sections on BEV usage and demographic questions to capture more about the BEV owners themselves. The purpose of these sections is to explore heterogeneity in preferences across the survey sample. On average, the time respondents spent on the V2G section was 50 seconds faster than that of the SMC section.

B. Data Collection

To field the survey, we posted ads on Facebook and Instagram, following ad-based survey recruitment guidelines by [14], who found that social media is an effective sampling approach for identifying difficult-to-find populations. We used general keywords associated with sustainability as well as several keywords associated with specific BEV makes and models. Participants were not paid to complete the survey; we simply targeted ads towards them and asked them to take a survey. We followed our approved IRB protocol and revealed that we were a GWU research team, but we did not reveal that the survey involved BEVs or charging in order to ensure that participants would get through our initial screener section uninformed about the motive of the survey. Respondents were simply asked to complete a survey about their vehicle ownership.

The fielding began in March 2024 and is expected to last for several months until we obtain our target goal of approximately 1,500 completed survey responses. As of July 2024, we have 858 total responses, which we use in this paper to present preliminary results. Of those, 815 completed the SMC choice questions, and 414 completed the V2G questions, which was an optional section in the second half of the survey. We include a series of plots containing all demographics of the sample in a survey result summary file that can be accessed here: https://sc.pingfanhu.com/files/survey_summary.pdf.

C. Model Specification

We construct a random utility model as the sum of weighted attributes and a random error term, as shown in Eq (1) below:

$$u_j = v_j + \varepsilon_j = \beta' x + \varepsilon_j \tag{1}$$

where β is a vector of weights, x is a matrix of attributes, and ε_j is an error term that follows Gumbel distribution. Given this form, the probability of choosing alternative j from a set of J alternatives is given by the usual logit probability function, as shown in Eq (2) below:

$$P_j = \frac{e^{v_j}}{\sum_{k=1}^{J} e^{v_k}} \tag{2}$$

The SMC program contains 6 attributes: enrollment cash, monthly cash, override, minimum threshold, guaranteed threshold, and "no choice". Based on Eq (1), the utility model for the SMC program is written as Eq (3) shown below:

$$u_j = \beta_1 x_j^{\text{enroll}} + \beta_2 x_j^{\text{monthly}} + \beta_3 x_j^{\text{override}} + \beta_4 x_j^{\text{min}} + \beta_5 x_j^{\text{guaranteed}} + \beta_6 x_j^{\text{no}} + \varepsilon_j \quad (3)$$

The V2G program also contains 6 attributes: enrollment cash, occurrence cash, monthly occurrence, lower bound, guaranteed threshold, and "no choice". Based on Eq (1), the utility model for the V2G program is written as Eq (4) shown below:

$$u_j = \beta_1 x_j^{\text{enroll}} + \beta_2 x_j^{\text{occur}} + \beta_3 x_j^{\text{monthly}} + \beta_4 x_j^{\text{lower}} + \beta_5 x_j^{\text{guaranteed}} + \beta_6 x_j^{\text{no}} + \varepsilon_j \quad (4)$$

One result of the logit model is the Independence of Irrelevant Alternatives (IIA) property, which often produces unrealistic predictions in predicted probabilities between similar alternatives. To relax this assumption and explore heterogeneity in user preferences, we estimate a mixed logit (MXL) model. The MXL model accounts for variation in preferences across individuals by allowing the coefficients to vary according to assumed distributions while relaxing the IIA assumption, allowing for more flexible substitution patterns among alternatives. We use the `logitr` R package to estimate the models [15].

To search for a better solution and avoid local minima, we used 100 multi-starts (re-starting the algorithm from different random starting points) and simulate MXL parameter distributions using 500 Sobol draws for both the SMC and V2G programs. These outcomes are later tested with extreme values in sensitivity analysis to ensure expected behavior.

III. Results

A. BEV Ownership & Demographics

The BEV ownership & demographic information are collected by single-answer choice questions and saved in Sections C and D in Appendix. According to Appendix Section C, out of the 858 responses, 78% of participants own at least two vehicles and only 22% own just one vehicle. 94% of the BEV owners regularly charge at home, and 46% report having some form of user-managed charging (UMC), such as using an app to control their charging, and 6% are enrolled in an SMC program.

According to Appendix Section D, 70% of the respondents report caring about the climate very much. We also find that our sample is highly skewed in gender, with 85% being male. However, a gender skew is also observed in BEV ownership in general, thus it is difficult to tell if this skew is a feature of our sampling approach or actually representative of the true BEV owner population. Additionally, 86% of the respondents self-identify as white, 53% are below the age of 60, and 51% report living in a two-person household.

B. Models

We initially employed multinomial logit (MNL) preference models for both SMC and V2G programs. However, to explore heterogeneity, we transitioned to mixed logit (MXL) models. The final models are presented in Section E of the Appendix.

For the SMC model, the mean utility value for "No Choice" is 5.52, suggesting that respondents on average prefer not to participate, all else being equal. For the V2G model, the utility value for "No Choice" is 5.42, again indicating that respondents on average prefer not to participate, all else being equal.

C. Sensitivity

While the estimated coefficients are difficult to directly interpret (utility can only be compared in a relative sense), they do indicate the relative strength of changes in attribute values in affecting user preferences. To make the results more interpretable, we generate sensitivity plots of user enrollment changes due to changes in each feature. Two sets of sensitivity analyses were conducted and illustrated as sensitivity plots and tornado plots, where sensitivity plots reveal single attributes and tornado plots show all five attributes together. In each simulation, we compare the percent of respondents that are predicted to opt in to the smart charging program compared to opting out (i.e. choosing the "no choice" option).

In these simulations, we chose a baseline simulation for each smart charging program against which to compare all other simulation results. For the SMC program, the baseline is defined as $50 Enrollment Cash, $5 Monthly Cash, 1 time Override, and 20%/50% battery thresholds (minimum and guaranteed states of charge). For the V2G program, the baseline is defined as $50 Enrollment Cash, $5 Occurrence (Event) Cash, 1 time Monthly Occurrence, and 20%/50% battery thresholds.

Figure 2 shows the sensitivity of each attribute in the smart charging programs. The curves form an "S" shape if expanded to a wider range, which is the expected shape for logit models. In these plots, the solid lines indicate predictions within the ranges of features included in our survey and the dashed lines indicate predictions made beyond the range of levels shown on the survey. For example, for the SMC program, the Enrollment Cash included a range from $50 to $300, but in the plot it is expanded from $0 and $1000.

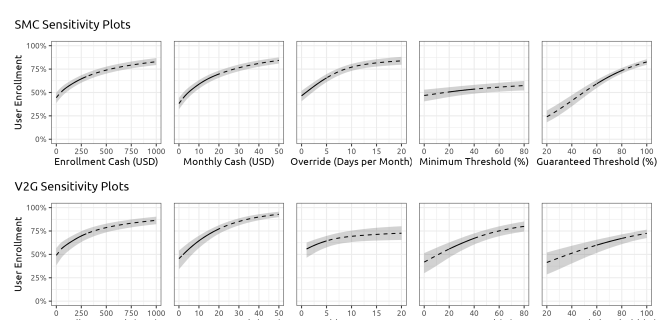

Figure 2: SMC & V2G Sensitivity Plots

The sensitivity plots reveal how sensitive the BEV owners are in each attribute. These slopes indicate the “importance” of each attribute. For instance, monetary incentives demonstrate a noticeably higher sensitivity in both smart charging programs, suggesting their importance in program enrollment.

We use tornado plots to compare the differences across each attribute. All attributes are ranked in descending order based on their sensitivity in terms of changes in enrollment. For SMC (Figure 3), a vertical line at user enrollment being 0.51 separates the 5 bars as orange and blue. Guaranteed Threshold, as the most sensitive attribute, is placed on the top. With other 4 attributes staying at baseline, user enrollment increases from 42% at a 40% guaranteed threshold to about 74% at an 80% guaranteed threshold. The same logic is true for the rest attributes. The V2G tornado plot (Figure 4) can be interpreted in the same way, with baseline indicated at Section III.C.

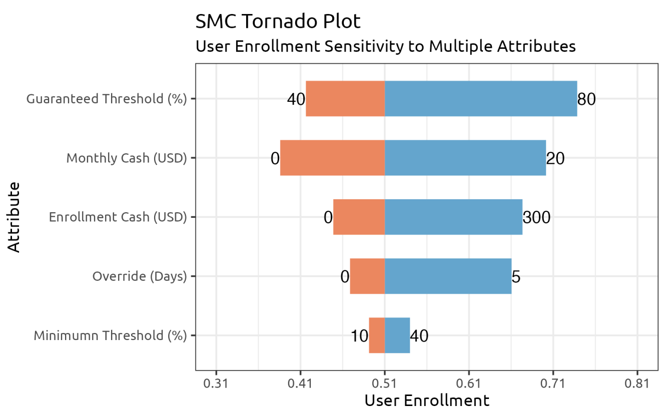

Figure 3: SMC Tornado Plot

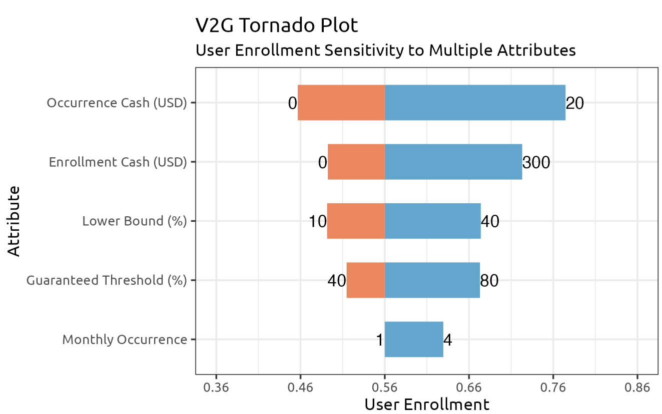

Figure 4: V2G Tornado Plot

D. Simulations

The ultimate goal of this study is to understand which “combination” of smart charging program features for both SMC and V2G that lead to higher overall enrollment. To assess this, we run a series of simulations comparing specific smart charging programs against the no choice option. The simulation results illustrated in Figure 5 and Figure 6 reveal the results.

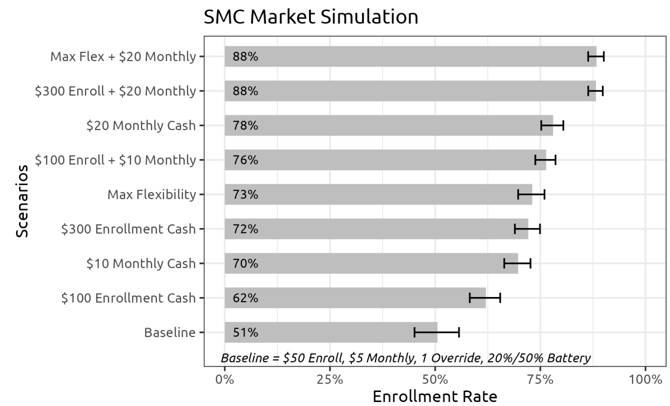

Figure 5: SMC Market Simulation

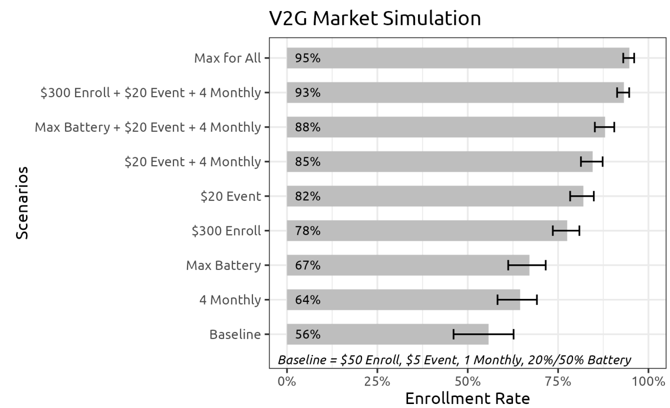

Figure 6: V2G Market Simulation

IV. Discussion

Through a discrete choice experiment with real BEV owners, we have gained new insights into their willingness to participate in smart charging. According to sensitivity analyses, the most influential attributes of SMC are Monthly Cash and Guaranteed Threshold, as shown in Figure 3. It is reasonable that the recurring Monthly Cash is more important than a one-time Enrollment Cash. This is consistent with real-world trials where researchers found that the overall participation rate in a trial SMC program fell once the recurring payment was reduced or removed [8]. Range anxiety is also a major concern for BEV users [16], which aligns with the importance of the Guaranteed Threshold of battery. In contrast, the minimum threshold is the least important, suggesting that users are willing to allow smart charging to begin at low battery levels.

Likewise, as shown in Figure 4, the most influential attributes for V2G are Occurrence Cash and Enrollment Cash. Unlike SMC, which can occur at any time, V2G discharge events are less common and provide opportunities to earn money on a case-by-case basis. Another interesting finding is that although only 74% of respondents chose to answer the V2G section of our survey, those who did participate showed a higher overall baseline participation rate compared to SMC.

As shown in Figure 5, the SMC simulation shows enrollment rate of 78% by providing $20 Monthly Cash, based on which, providing a $300 Enrollment Cash gives 10% more resulting in 88% of enrollment. Since adding max flexibility provides the same 88% enrollment as adding $300, we can have a reasonable judgement that sacrificing $300 as Enrollment Cash efficiently hedges the necessity of providing flexibility.

The V2G simulation, shown in Figure 6, shows a straightforward connection between the incentives and willingness to participate. Here, a full course of monetary combination (Enrollment Cash, Occurrence Cash, and monthly occurrence) results in enrollment rate of 93%, which is close to the best attributes results of 95%. For BEV users, since V2G trades usability with income, they are highly sensitive to monetary returns. A conclusion for the V2G program is that the success of V2G highly depends on the budget from the utility suppliers.

Since the study is still in progress, the limitations are mainly in the amount of data, which in its current state limits a more fine-grained comparison of preferences across different subgroups in the population. Future work will also integrate consumer preference models into grid simulations to estimate the benefit-cost trade-off of different smart charging programs from the perspective of utilities.

V. Conclusion

This study explores the willingness of BEV owners to enroll in various smart charging programs. The purpose of smart charging is to have utilities control BEV charging to align with grid stability and achieve lower emissions and higher use of renewable energy sources. We consider two forms of smart charging: SMC in which utilities control charging timing and duration, and V2G in which bidirectional charging can occur to serve the grid. We use a discrete choice survey experiment to measure the preferences of BEV owners to enroll in these programs. While we plan to recruit 1,500 respondents, we present results for our current 858 to date. The responses revealed demographic information regarding BEV usage. We used the choice data results to estimate mixed logit (MXL) models and conducted sensitivity analyses based on the models of both programs. We found that guaranteed driving ranges during smart charging events and continued payments are the two important features of smart charging. Based on the sensitivity results, we conducted market simulations and revealed trade-offs between these important features. With more data, we will be able to provide more information about preferences for different subgroups of interest.

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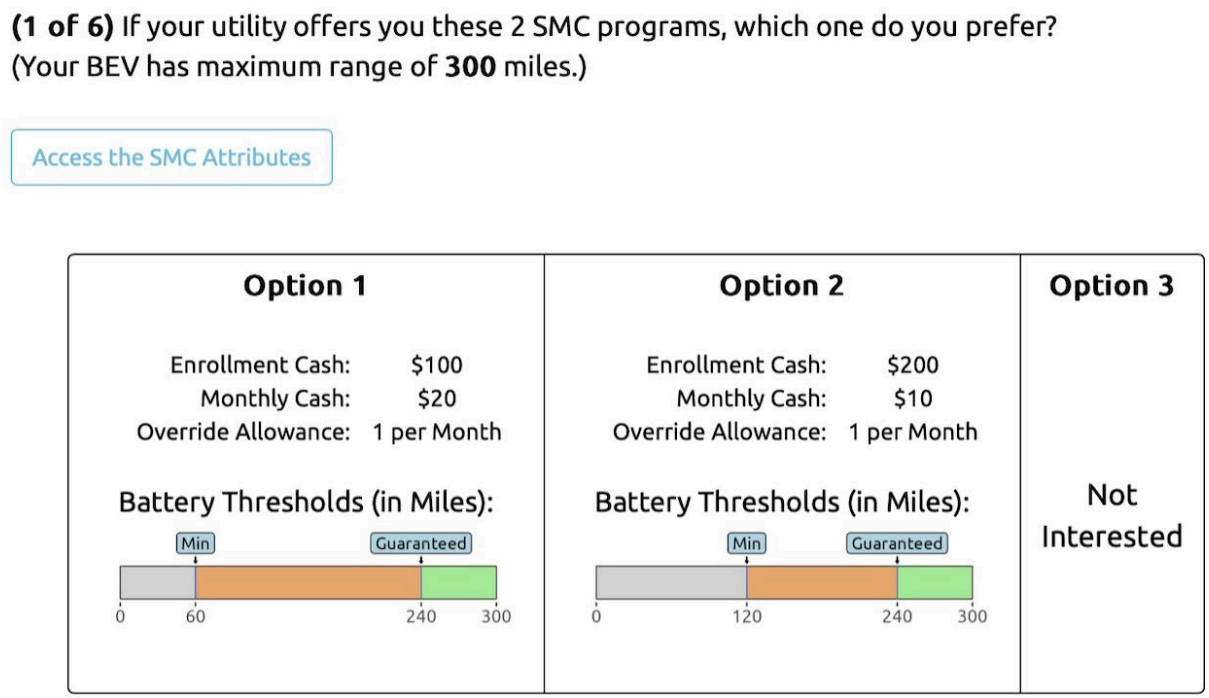
Appendix

A. SMC Programs

Appendix Table 1: **SMC Program Attributes**

No.	Attribute	Range	Explanation
1	Enrollment Cash	$50, $100, $200, $300	One-time payment upon enrollment.
2	Monthly Cash	$2, $5, $10, $15, $20	Recurring monthly payment.
3	Override Allowance	0, 1, 3, 5	Monthly frequency of freely override to normal.
4	Minimum Threshold	20%, 30%, 40%	SMC won't be triggered below this threshold.
5	Guaranteed Threshold	60%, 70%, 80%	SMC will give you this much of range by the morning.

We chose 5 attributes each for the SMC programs. Ranges were chosen based on prior survey work and conversations with electric power companies.



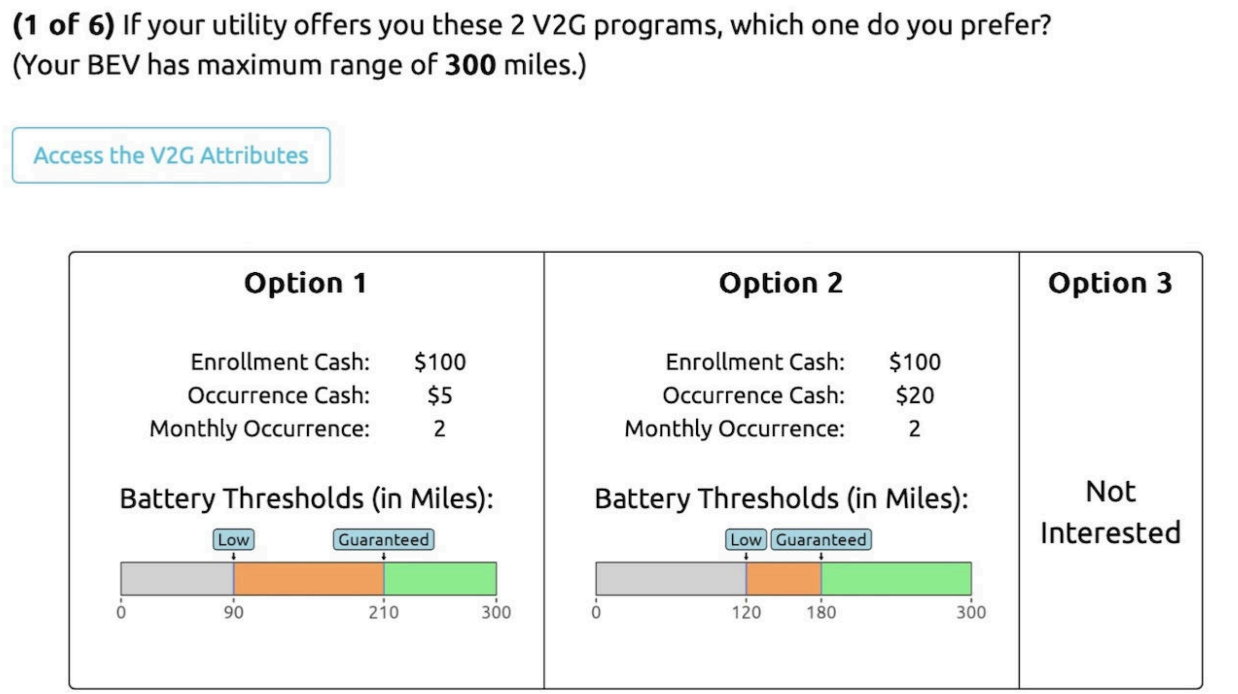
Appendix Figure 1: **Sample SMC Conjoint Question** - *Option 1, for example, provides $100 upon enrollment, $20 per month, and an override allowance of once per month, along with a designated battery threshold. Each respondent would be asked 6 randomized choice questions.*

B. V2G Programs

Appendix Table 2: **V2G Program Attributes**

No.	Attribute	Range	Explanation
1	Enrollment Cash	$50, $100, $200, $300	One-time payment upon enrollment.
2	Occurrence Cash	$2, $5, $10, $15, $20	Earning for each occurrence of V2G.
3	Monthly Occurrence	1, 2, 3, 4	Monthly occurrence of V2G.
4	Lower Bound	20%, 30%, 40%	V2G won't drain your battery below this percentage.
5	Guaranteed Threshold	60%, 70%, 80%	V2G will charge your battery back to this percentage.

We chose 5 attributes each for the V2G programs. Ranges were chosen based on prior survey work and conversations with electric power companies.



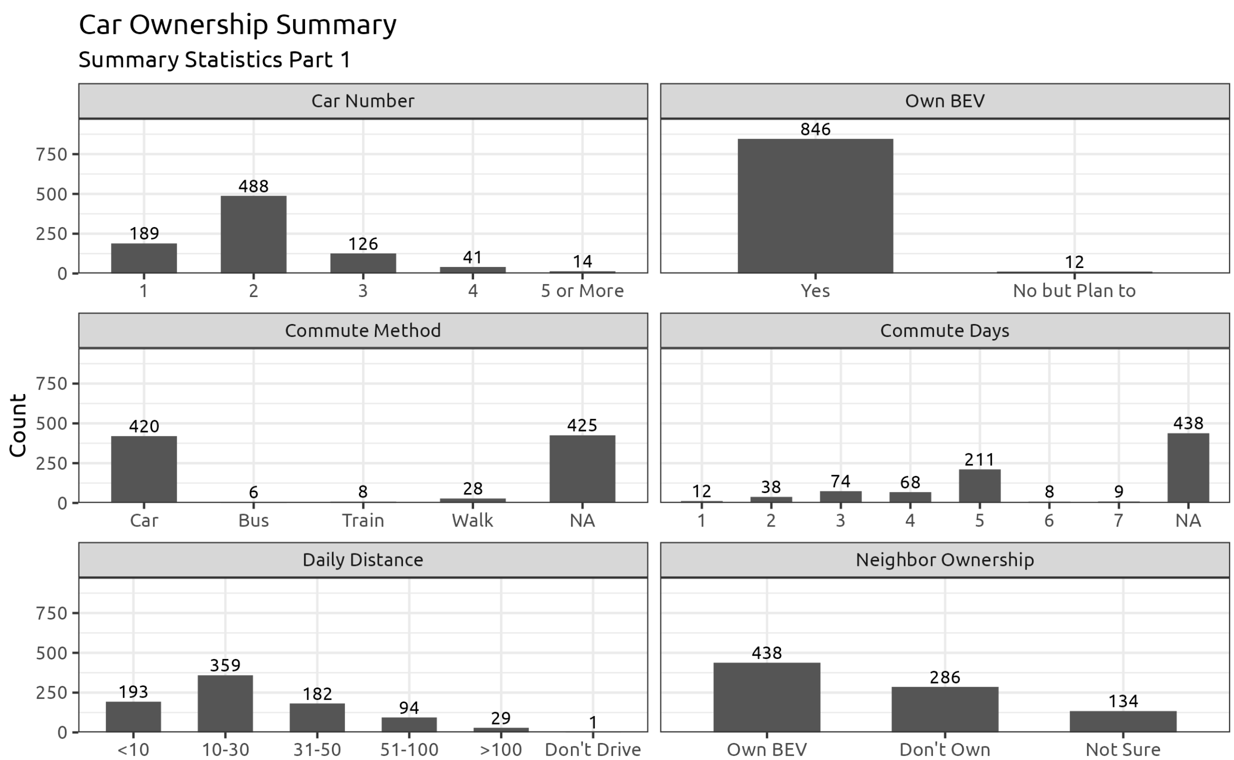
Appendix Figure 2: **Sample V2G Conjoint Question** - *See descriptions in **Appendix Figure** 1, with the exception of a twice-monthly V2G event instead of an override allowance, which is a feature of SMC.*

C. Survey Summary of BEV Ownership

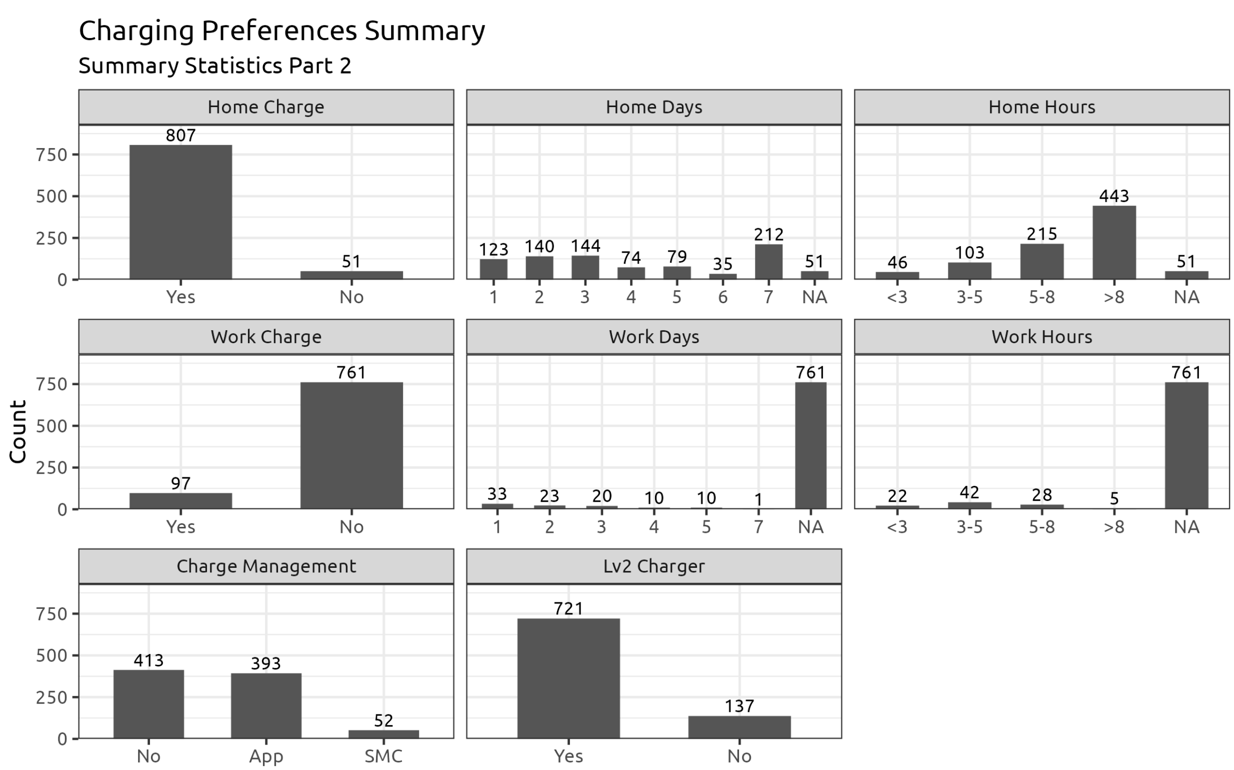
Appendix Table 3: **Summary of Vehicles**

Category	Value	Count	Percentage
Car Number	1	189	22%
	2	488	57%
	3	126	15%
	4	41	5%
	5 or More	14	2%
Daily Distance	<10	193	22%
	10-30	359	42%
	31-50	182	21%
	51-100	94	11%
	>100	29	3%
	Don't Drive	1	0%
Neighbor Ownership	Own BEV	438	51%
	Don't Own	286	33%
	Not Sure	134	16%
Charge Management	App	393	46%
	SMC	52	6%
	No	413	48%
Lv2 Charger	No	137	16%
	Yes	721	84%
Tesla Ownership	No	593	69%
	Yes	265	31%
V2G Interest	No	226	26%
	Yes	632	74%
Pay for V2G Charger	Willing to	364	42%
	Don't Want	250	29%
	Already Have	18	2%
	NA	226	26%

1. *N = 858.*
2. *This is only a part of the electric vehicles information. For full results please refer to the BEV summary plots below.*



Appendix Figure 3: **Car Ownership Summary**



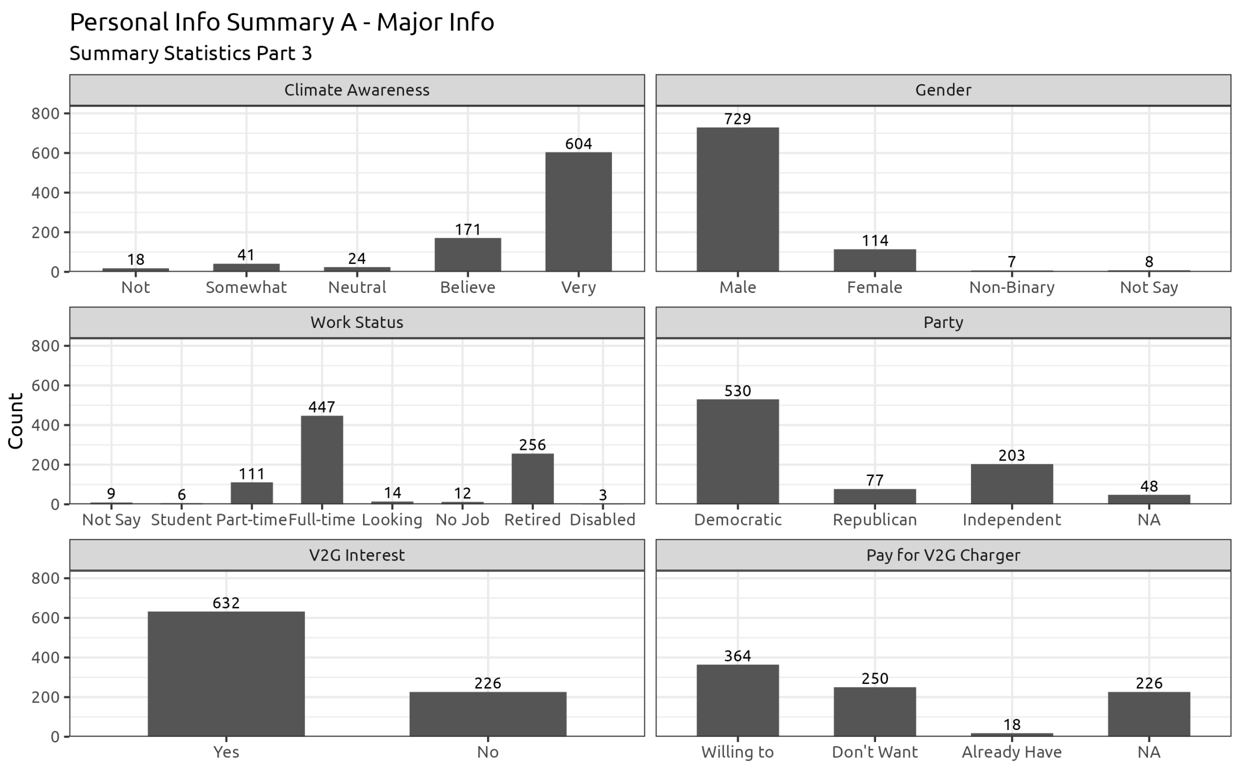
Appendix Figure 4: **Charging Preferences Summary**

D. Survey Summary of Demographics

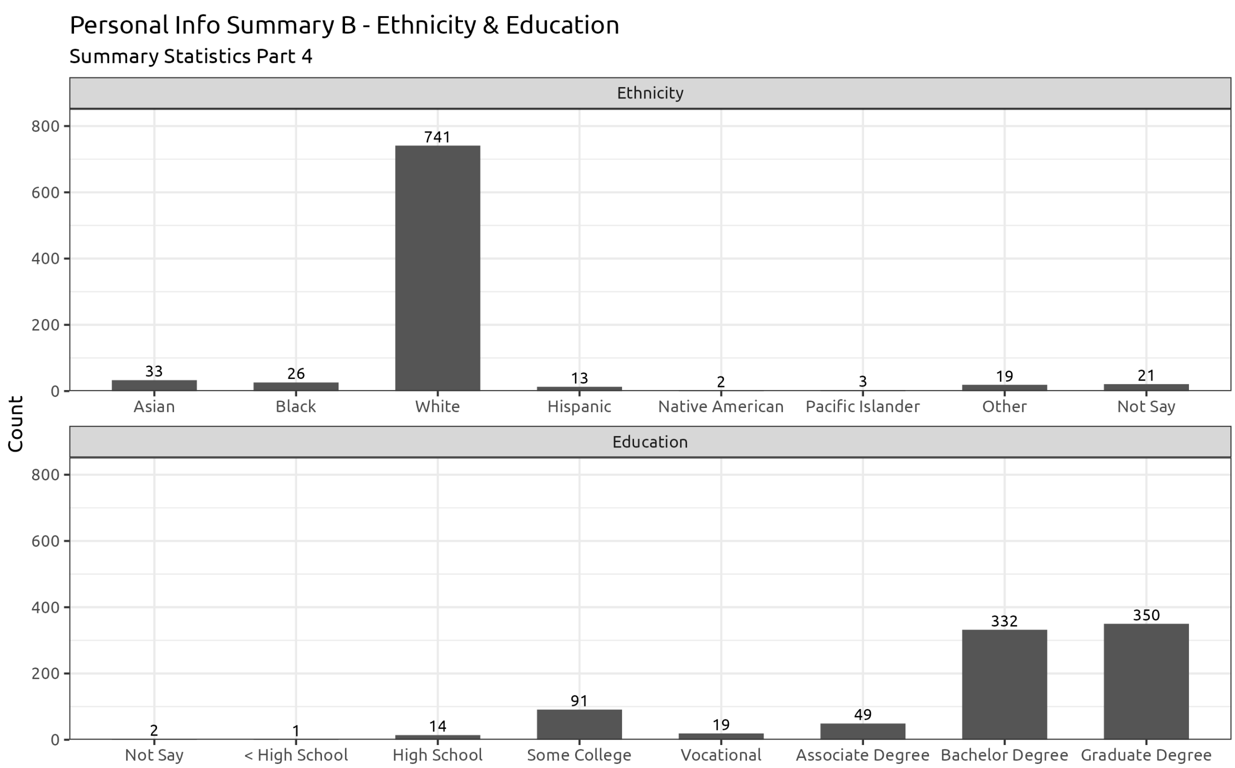
Appendix Table 4: Summary of Demographics

Category	Value	Count	Percentage
Gender	Male	729	85%
	Female	114	13%
	Non-Binary	7	1%
	Not Say	8	1%
Age Group	<=30	13	2%
	31-40	66	8%
	41-50	144	17%
	51-60	235	27%
	61-70	263	31%
	>70	128	15%
	NA	9	1%
Party	NA	48	6%
	Democratic	530	62%
	Republican	77	9%
	Independent	203	24%
Climate Awareness	Not	18	2%
	Somewhat	41	5%
	Neutral	24	3%
	Believe	171	20%
	Very	604	70%
Work Status	Not Say	9	1%
	Student	6	1%
	Part-time	111	13%
	Full-time	447	52%
	Looking	14	2%
	No Job	12	1%
	Retired	256	30%
	Disabled	3	0%
Household Size	Not Say	8	1%
	1	79	9%
	2	445	52%
	3	148	17%
	4	128	15%
	>4	50	6%
House Ownership	Not Say	9	1%
	Own	800	93%
	Rent	49	6%

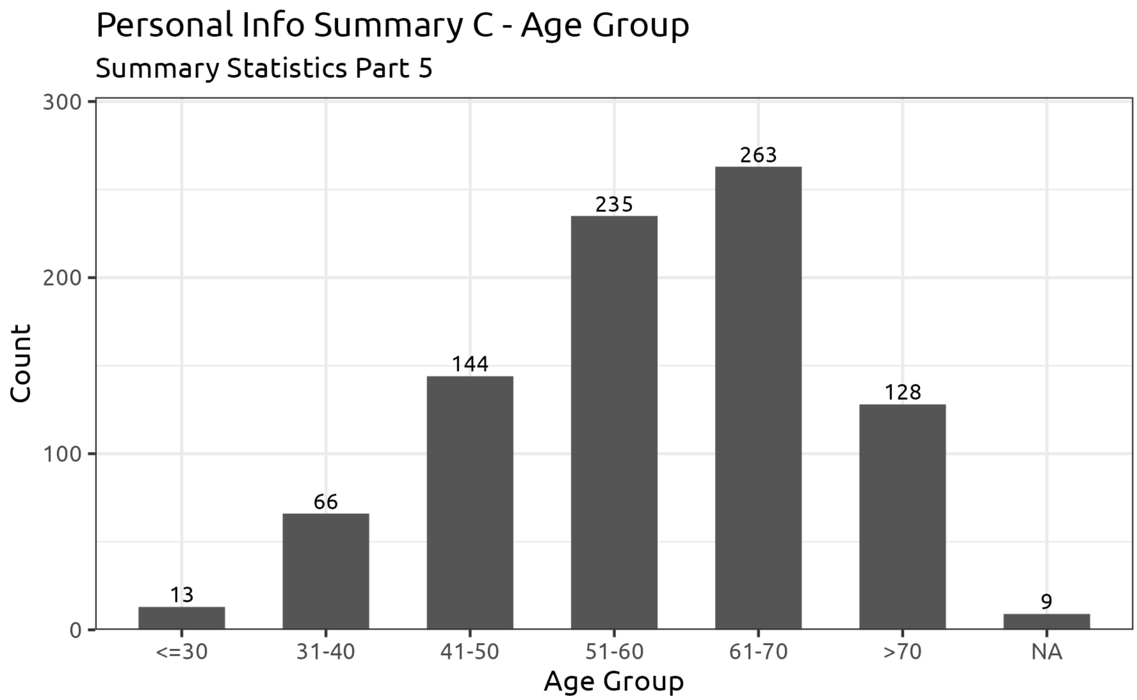
1. *N = 858.*
2. *This is only a part of the demographics information. For full results please refer to the BEV ownership plots below.*



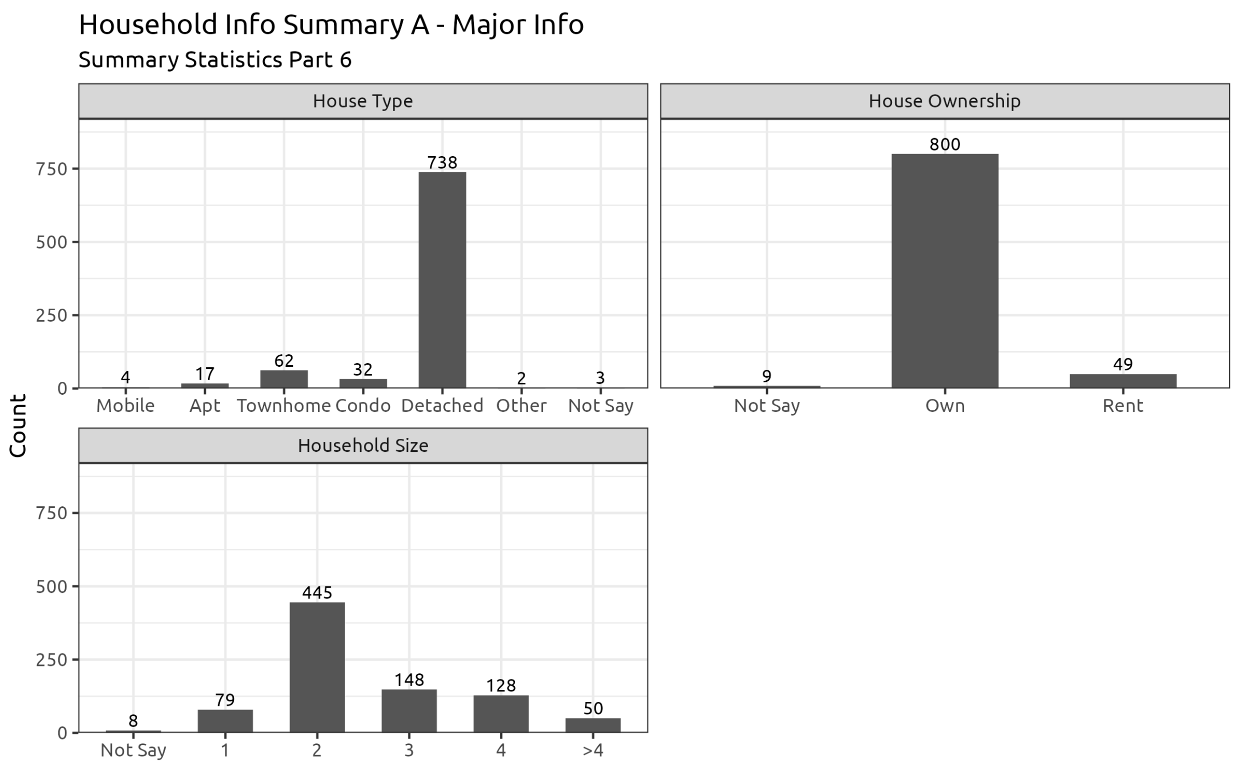
Appendix Figure 5: **Personal Info Summary A - Major Info**



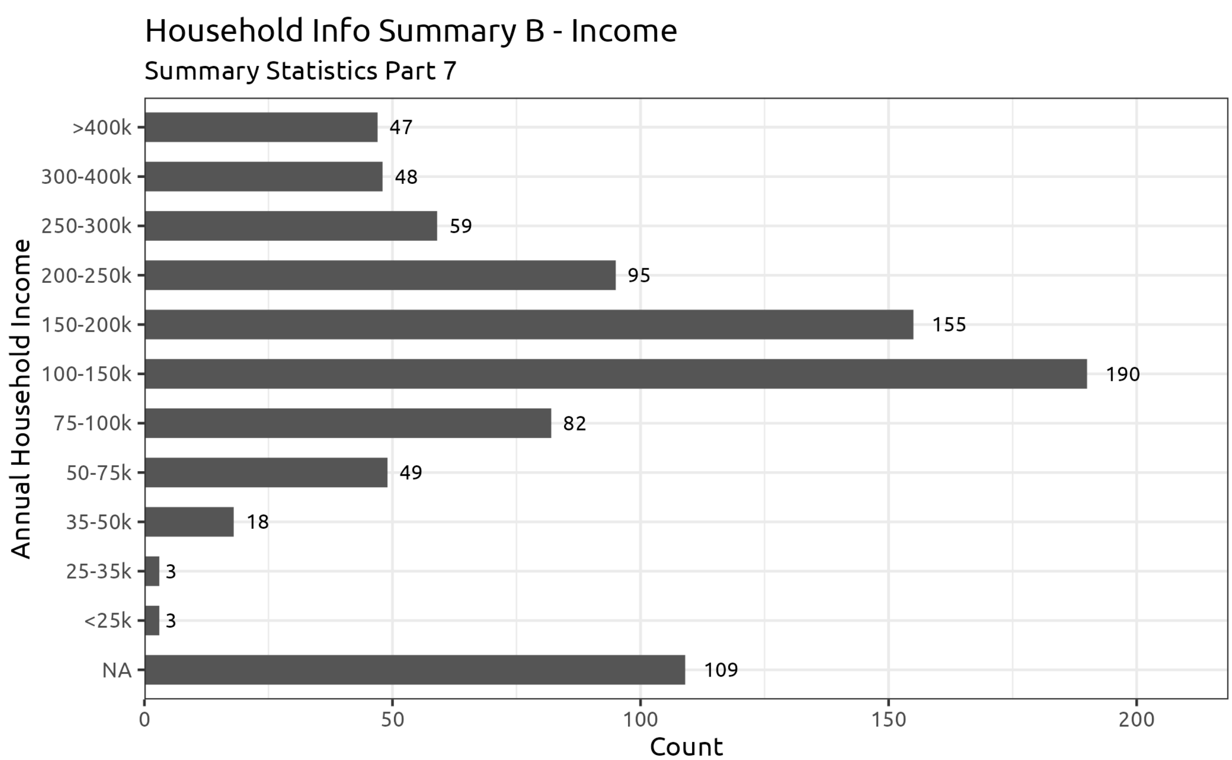
Appendix Figure 6: **Personal Info Summary B - Ethnicity & Education**



Appendix Figure 7: **Personal Info Summary C - Age Group**



Appendix Figure 8: **Household Info Summary A - Major Info**



Appendix Figure 9: **Household Info Summary B - Income**

E. MXL Model Coefficients of Smart Charging Programs

Appendix Table 5: **SMC Model Coefficients**

Attribute	Coefficient	Distribution	Type	Estimate	Std Error
Enrollment Cash	β_1	*log-normal*	μ	0.0043	0.1173
			σ	1.3187	0.1149
Monthly Cash	β_2	*log-normal*	μ	0.1045	0.0827
			σ	1.2127	0.0991
Override Allowance	β_3	*normal*	μ	0.3259	0.0224
			σ	0.2755	0.0305
Minimum Threshold	β_4	*normal*	μ	0.0135	0.0044
			σ	0.0449	0.0055
Guaranteed Threshold	β_5	*normal*	μ	0.0715	0.0046
			σ	0.0257	0.0032
No Choice	β_6	*normal*	μ	5.5186	0.3964
			σ	1.5755	0.2552

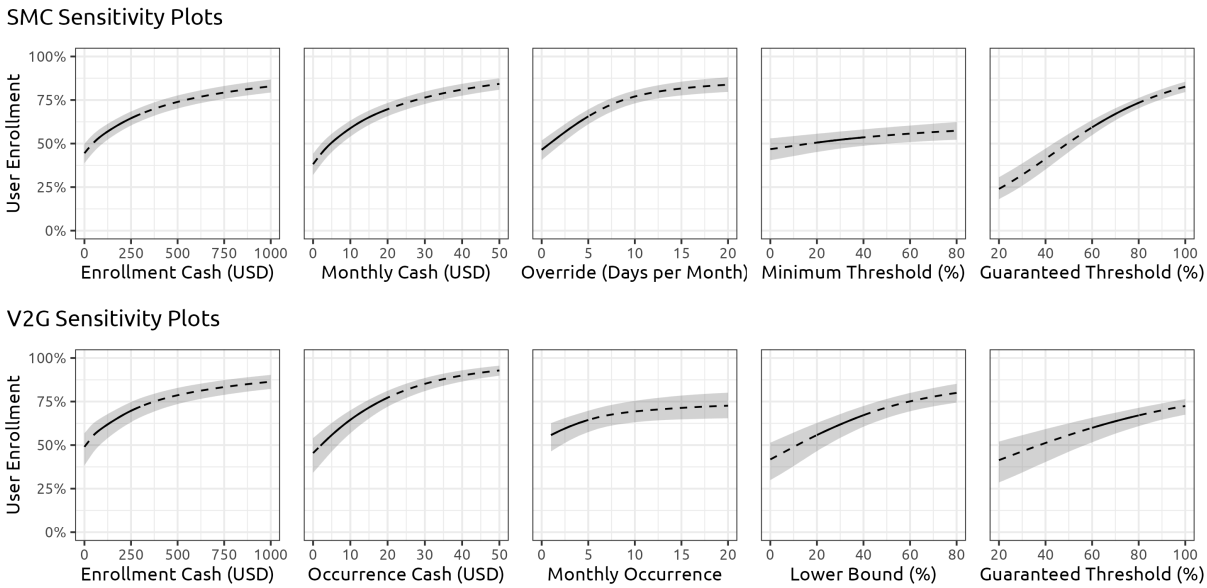
1. *This model shows the utility of each attribute with 1 unit of increment of its value. For example, monthly cash has a coefficient of 0.1045, meaning with $1 more of monthly cash, the customer utility will increase by 0.1045.*
2. *MXL models require an assumed random parameter distribution for each random feature. We use log-normal for monetary attributes and normal for the rests.*

Appendix Table 6: **V2G Model Coefficients**

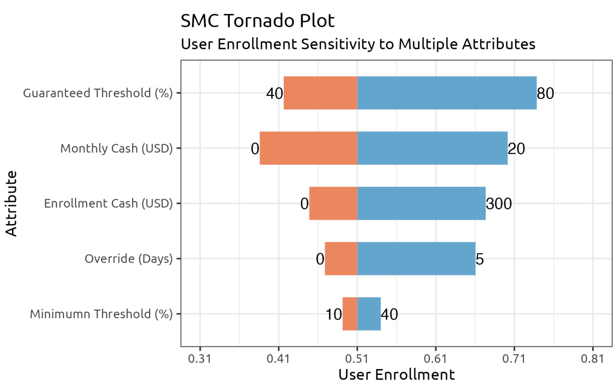
Attribute	Coefficient	Distribution	Type	Estimate	Std Error
Enrollment Cash	β_1	*log-normal*	μ	0.0065	0.1397
			σ	1.3575	0.1326
Occurrence Cash	β_2	*log-normal*	μ	0.1732	0.0774
			σ	0.6890	0.0943
Monthly Occurrence	β_3	*normal*	μ	0.3122	0.0549
			σ	0.5045	0.0803
Lower Bound	β_4	*normal*	μ	0.0748	0.0076
			σ	0.0564	0.0092
Guaranteed Threshold	β_5	*normal*	μ	0.0488	0.0066
			σ	0.0340	0.0067
No Choice	β_6	*normal*	μ	5.4156	0.6699
			σ	3.0122	0.5083

See descriptions in ***Appendix Table*** *5.*

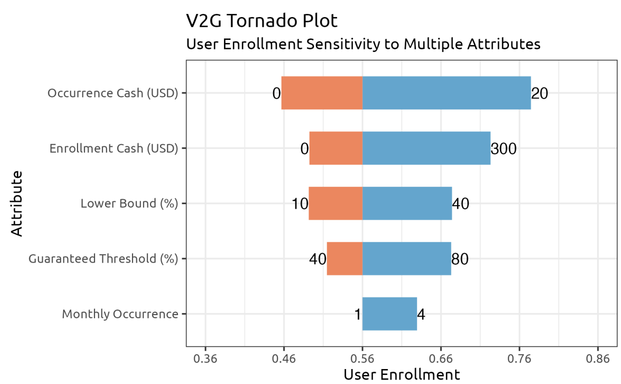
F. Sensitivity Analysis



Appendix Figure 10: Sensitivity Plots

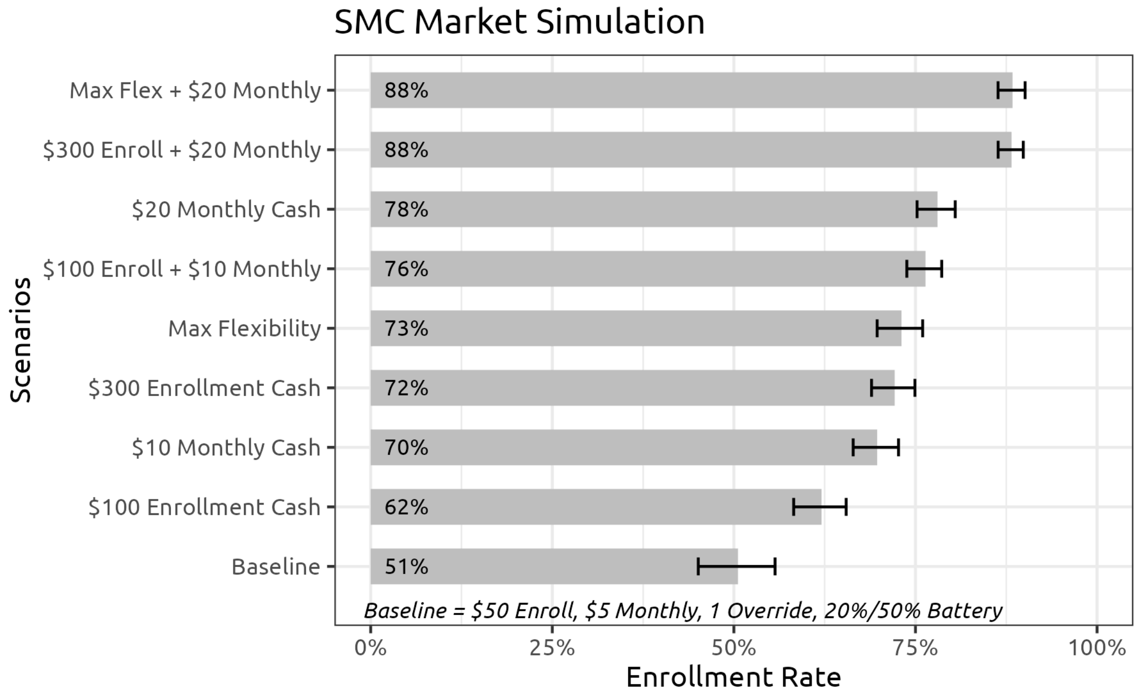


Appendix Figure 11: SMC Tornado Plot

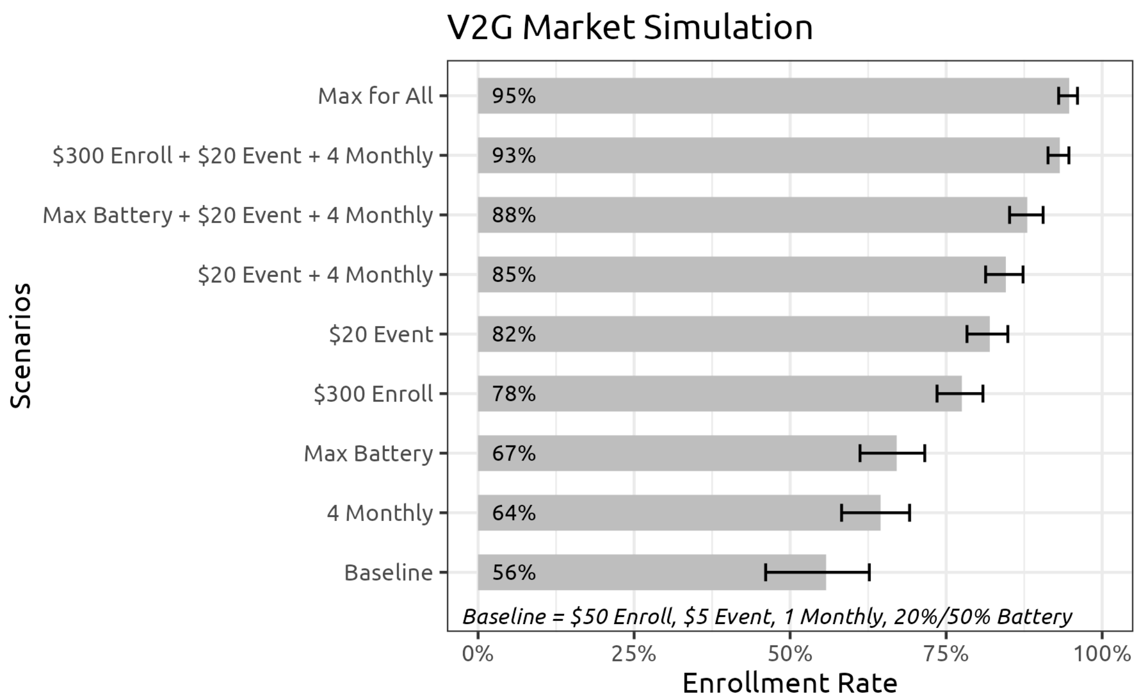


Appendix Figure 12: **V2G Tornado Plot**

G. Market Simulation



Appendix Figure 13: **SMC Market Simulation**



Appendix Figure 14: **V2G Market Simulation**