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ABSTRACT

Climate change and environmental problems have spurred new strategies to reduce fossil fuel consumption in transportation. Two important strategies include a rapid transition to green energy and the replacement of internal combustion vehicles with electric vehicles (EVs). However, the increasing demand for electricity by EVs, especially from time-dependent green sources of energy (e.g., solar, wind), will likely overload the grid at peak hours. Smart charging programs for EVs could defer charging to off-peak times and better match demand with supply. Yet, little is currently known about people's willingness to sign up for a program.

To understand incentive effects on smart charging program adoption, we distributed a survey (n=785) in October 2018 across the United States targeting three groups: 1) EV owners/lessees (n=151), 2) EV interested buyers/lessees (n=555), and 3) a general population (n=79). We first found that a significant portion of both EV groups would be interested in the program without any incentive, but there was a participation limit. Employing three mixed logit models, we found that monetary incentives and free charging equipment increased participation for the two EV groups, although the attributes exhibited heterogeneity. Guaranteed battery level (or rides home) increased participation for all three groups and at least one random parameter was present for all three groups. Penalties deployed to discourage participants from taking back charging control decreased participation willingness in the two EV groups, although EV interested buyers/lessees responded heterogeneously. While higher monetary incentives increased participation, the effects displayed diminishing returns.

Keywords: Smart charging, electric vehicles, demand response, incentives, behavior, vehicle-to-grid

Highlights:

- Using a survey and choice models, we tested incentives for smart charging adoption.
- Monetary incentives, free equipment, and guaranteed rides/battery spurred adoption.
- Penalties for retaking control of charging discouraged participation in a program.
- Heterogeneity was found for multiple attributes and different respondent groups.
- Some respondents would refuse to participate, even at very high incentive levels.

Introduction

Between 2020 and 2021, sales of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) more than doubled, bringing the worldwide total of BEVs and PHEVs to approximately 16 million vehicles on the road (International Energy Agency, 2022). In the United States (U.S.), approximately 325,000 PHEVs were sold in 2019 (U.S. Department of Energy, 2022), representing strong growth compared to 2017 and earlier. With increasing advances in battery technology, faster production rates of auto manufacturers, growing charging networks, and federal and state government incentives, sales of EVs (collectively BEVs and PHEVs in this paper) are expected to increase at a faster rate in the coming years. While this growth may decrease carbon emissions and help governments reach greenhouse gas (GHG) reduction goals, the growth will also coincide with several challenges for the power grid. Most notably, the increase in EVs will put additional stress on the grid, particularly in the evening when individuals generally return from work and plug in to charge. A charging peak already exists for this evening period as people home and begin using appliances that require electricity. Concurrently, the energy sector is undergoing a large transformation to renewable and green energy with a strong focus on solar and wind power. Despite the environmental benefits of this transformation, solar power is only available during daylight hours, and wind power tends to be highly variable (Ueckerdt et al., 2015). Without consistent generation, peaks in electricity consumption often coincide with an inability to produce and distribute enough renewable electricity, increasing the electricity rates of consumers and stressing the grid.

Consequently, there has been interest among researchers, utility companies, and aggregators to consider methods to reduce peak electricity usage by BEVs and PHEVs. One method is to employ "smart charging" wherein vehicle owners/lessees or a third party can control when the electric vehicle charges. A smart charging program is a type of demand response (DR) program that defers the charging of EVs when the electricity demand is lower. This process is enabled through unidirectional power flow (also called V1G) technology for vehicles, which allows BEV owners/lessees (or a third-party operator) to permit the stop and start of vehicle charging based on signals sent by the grid. Often, BEV owners/lessees are allowed to manage their preferences and charging schedules via a smartphone app. By shifting when EV charging occurs, smart charging programs can:

- Reduce the strain on the electrical grid during periods of peak demand;
- Allow utilities to forgo costly grid distribution and power generation upgrades (for extra capacity) since demand is more even;
- Reduce electricity costs for EV owners/lessees, enabled via time-of-use (TOU) electricity rate plans; and
- Bolster the effectiveness of renewable energy sources, which often produce more electricity at off-peak times.

Despite these smart charging benefits, one critical barrier is the enrollment and retainment of EV owners/lessees in a smart charging program. Electricity cost savings have not been sufficient to nudge behavior. Despite some research on smart charging programs and their potential revenue for third parties, work remains ongoing to understand how customers would respond to these programs and if they would be willing to sign up for a program. To address this gap in the literature, we developed several key research questions.

1) What is the perception and attitude of people toward smart charging programs?

2) What influences an individual to participate (or not) in a smart charging program?

To understand the implications of potential smart charging programs and answer these research questions, we distributed a survey (n=785) that was administered to most states in the U.S., targeting 1) EV owners/lessees (n=151); 2) EV interested buyers/lessees (n=555), 3) a random general population (n=79). We begin this paper by presenting the current state of literature, focusing on smart charging literature. We then provide the data and the methodology. Next, we present the descriptive statistics from the survey and results from the discrete choice analysis using a choice experiment. We close the paper with limitations and conclusions.

2) Literature Review

In this review, we first identify the early history of demand response, smart charging programs, and related vehicle-to-grid (V2G) programs, including research on opportunities for these programs. Next, we discuss research on behavioral responses to smart charging and V2G programs. We follow this with the current state of smart charging in North America and key gaps in understanding behavior and incentives.

2.1) History and Opportunities for Demand Response, Smarting Charging, and V2G

Demand response (DR) generally refers to mechanisms and signals that allow customers to change their electricity consumption. The earliest DR programs in North America – occurring before 2000 – were focused on interruptible tariffs where lower power usage from large customers was requested by utilities via paging or calling (Brown et al., 2017). Technological advances have enabled requests to occur more automatically with closer to real-time signals (Brown et al., 2017). One example of this has been V1G technology – often called smart charging. Smart charging is a type of DR program and technology that sends signals/communication in a unidirectional manner to control the charging of an EV (Noel et al., 2019). Stepping beyond V1G, one key development for EVs was the early conceptualization of vehicle-to-grid (V2G) technology, which enables bidirectional power flow and communication (Noel et al., 2019). Kempton and Letendre (1997) led this effort, identifying significant benefits to using large EV fleets as batteries including lower costs for customers, improved grid reliability, and easier integration of renewables. Further history and definitions of V2G can be found in Noel et al. (2019). Current conceptualization has also included vehicle-to-everything (V2X) which encompasses V2G, vehicle-to-home (V2H), and vehicle-to-business (V2B) (Pearre and Ribberink, 2019).

Despite increasing opportunities, some early large-scale DR programs were focused only on emergency demand. This included California's blackout reduction program that was formed following an extreme heat wave in the summer of 2006 (CPUC, 2022a). The program has evolved to include pilots for smart metering, air conditioning cycling, and plug-in vehicles (CPUC, 2022a). Early smart charging work included the design of a digital EV smart charging system (Alvarez et al., 2003), smart management for buses (Wang et al., 2005), and integration of smart charging into the electrical grid (Lopes et al., 2010). A full review of smart charging approaches can be found in Garcia-Villalobos et al. (2014). V2G pilots have generally lagged behind smart charging, but new opportunities have arisen for large V2X pilots in California (CPUC, 2022b) and the United Kingdom (Cenex, 2021).

Additional research has been conducted on how smart charging via EVs may offer revenue opportunities for operators and transaction facilitators. Research has found that smart charging could yield a loss of $300 per vehicle per year up to a profit of over $4600 depending on the context, with most studies indicating a profit in the $100 to $300 per vehicle per year range (Richardson, 2013). More recent research claims that there exists upwards of $15 billion in opportunity value for battery storage using electric vehicles in a demand response program (Coignard et al., 2018), while another study found potential cost savings of $690 million per year for grid operation costs with 5 million vehicles per year using smart charging in California (Szinai et al., 2020). Other studies of the system cost have found savings of 227 Euros per vehicle per year by using smart charging over a normal charging plan (Kiviluoma and Meibom, 2011). Pratt and Bernal (2018) found that smart charging could produce savings of upwards of over $20 per month for plug-in EV owners that were not already on time-of-use electricity plans.

Additional studies on the system cost (and potential savings) of BEVs on the electricity grid have found mixed results on the degree of the benefit, which is heavily dependent on assumptions such as the mix of electricity (Wang et al., 2011; Lyon et al., 2012). In the opposite direction (grid-to-vehicle) wherein the vehicle is used as a battery for electricity, one study found a revenue level of a maximum of 192 euros per year and an average of just 60 Euros per year for vehicles as battery storage (Jargstorf and Wickert, 2013). A further review of demand response programs with a focus on smart charging can be found in Tomić and Kempton (2007), Richardson (2013), and Niesten and Alkemade (2016). New optimization strategies for smart charging also exist to use electricity infrastructure more effectively (Frendo et al., 2020).

2.3) Participation in Smart Charging and V2G Programs

While revenue is a crucial determinant in the success of a V1G or V2G program, the vehicle owner or lessee may need some incentive or compensation to participate. While V1G and V2G programs benefit grid system optimality for grid operators, there is less of an inherent benefit to the consumer for deferring vehicle charge or slowing the speed of it, which may explain why just 31% of Canada EV owners reported they were enrolled in smart charging (Al-Obaidi, et al. 2021). The research went on to develop a model of bidirectional charging that considered user preferences and optimized profits and minimized costs for EV users (Al-Obaidi, et al. 2021). Indeed, consumers can benefit by receiving compensation from the grid operator or third party who benefits by earning higher revenue or avoiding higher generation or distribution costs. Both opportunities present an economic structure in which consumers, operators, and third-party transaction facilitators (such as automakers) can engage in an exchange that earns revenue and/or avoids opportunity costs. The broader objective is to increase the overall cost-effectiveness of charging and BEV ownership while minimizing the impact on the grid. In addition, by considering user preferences and behavior (Clairand et al., 2018), models also can be developed that reduce the cost on the aggregator (i.e., third-party) that is responsible for managing EV charging. Despite a focus on incentives, research has found other motivations for smart charging participation including: 1) improved fire safety (rather than using a wall socket); 2) faster charging; 3) interest and joy in using smart technology; and 4) flexibility that can lead to physical comfort (e.g., preheating a vehicle) (Henriksen et al., 2021).

Recently, several research papers have investigated customer acceptance of V2G programs and the incentives needed to induce program participation. However, most research studies have only considered cost savings on monthly electricity bills as opposed to lump sum or yearly compensation. One study (Bailey and Axsen, 2015) attempted to gauge the openness to V2G of potential plug-in BEV buyers. Around 60% of the potential EV buyers were open to V2G without any incentives, while the most effective programs offered 20% savings on electricity bills. With 20% electricity bill savings and a guaranteed minimum charge of 100%, the program enrollment rose to 72%. Using the same survey among a population of current BEV owners, researchers found that BEV owners need more than twice as much financial compensation to enroll in controlled charging programs than potential early mainstream users (Axsen et al, 2016). Parsons et al. (2014) administered a web-based stated preference survey of randomly selected U.S. respondents (n=3029). Respondents completed a choice experiment to determine their willingness-to-pay for EVs with no V2G capability, which was used to develop a latent class random utility model to analyze respondent choices of V2G-EVs and their contract terms. The researchers simulated several contracts (varying in the minimum number of plug-in hours and minimum guaranteed driving range) and estimated the payment (as annual cash-back) that respondents would require to sign the contracts. Through this modeling, the researchers found that individuals would require $2,000 to $8,000 per year to enroll in a V2G program (Parsons et al., 2014).

Separately, Daina et al. (2017) claimed that the current appraisal of smart charging relies on simplistic and theoretical representations of driver charging and travel behavior, which is not policy sensitive and lacks strong empirical foundations. They offered a charging behavioral model, developed from a random utility model for joint EV driver activity travel scheduling and charging choices. Empirical versions of the model using data from two discrete choice experiments revealed the value placed by individuals on the main attributes of the charging choices. The main attributes of the charging choices included: 1) the amount of battery available after charging (E), 2) effective charging time (ECT), and 3) charging cost (CC). They found that 80-90% of drivers have a positive marginal utility for E, and 60% of drivers have a positive marginal utility for ECT if charging levels do not induce schedule delays. Latinopoulos et al. (2017) assessed the effectiveness of dynamic pricing by examining how EV drivers responded to uncertain future prices when charging their vehicles away from home. The authors designed a survey to observe the stated preferences of respondents for hypothetical charging services. The survey included two stated preference exercises: 1) a charging game to understand driver preference for charging attributes and 2) a booking game to see how drivers make their charging choices when provided with additional information regarding uncertain travel choices. Latinopoulos et al. (2017) presented a risky-choice framework where expected utility (EUT) and non-expected utility theory (non-EUT) specifications were compared to evaluate booking behavior during dynamic pricing and attitudes toward risk. The results suggested that most tend to opt for the safe option over the risky one, but there are specific demographic groups, such as young and educated individuals, who are more likely to do the opposite.

Monetary incentives offered by the government to buy EVs have been successful to some degree. However, in the case of smart charging, studies have found the opposite case. Results from Schmalfuβ et al. (2015) indicated that monetary compensation was not a primary motivation to participate in smart charging. On the contrary, the authors found that users were instead strongly motivated by the feeling of ‘doing something good’ and contributing to society (Schmalfuβ et al., 2015). Similarly, Will and Schuller (2016) found that contribution to grid stability and integration of renewable energy sources were influential factors in the acceptance of smart charging, underlining the impact of communicating the benefits of smart charging to potential users. Huber and Weinhardt (2018) explored this idea by suggesting a feedback nudge that encourages users to provide more temporal charging flexibility. The authors suggested providing information on carbon dioxide saving potentials as the feedback nudge, which can be incorporated into a smart charging algorithm. Asensio and Delmas (2016) expanded upon this idea with their results that suggested that providing feedback about energy consumption in a health-based frame was particularly effective in encouraging the desired behavioral response.

Spencer et al. (2021) evaluated non-monetary incentives in which participants were incentivized with increasingly valuable sweepstakes opportunities as group participation increased. Participants were encouraged to increase their number of plug-ins throughout a two-week period, without any restriction on the time of the day that they should be charging. Zhang et al. (2018) also proposed a real-time system that used a non-monetary concept of prioritization to incentivize EV users to engage in the smart charging schedule. Users were rewarded with high or low priority depending on their charging behavior, and those with high priority had increased flexibility with their charging schedules and increased the amount of energy that they can receive. Zhang et al. (2018) conducted numerical simulations and experiments to verify the effectiveness of this non-monetary system and found that the local solar consumption rate would increase by 37% as a result. While the experimental results have shown this non-monetary incentive alone produces the desired effect, the authors also suggested an optional cryptocurrency mechanism that could be included to further increase the effectiveness of the overall system.

At the same time, an overarching theme in the literature was the potential for consumer distrust of the electric utilities or third party that would determine vehicle charging (Sovacool et al., 2017) along with the social dimensions of V2G (Sovacool et al., 2018). Baily and Axsen (2015) found that while respondents to a survey thought that V2G should be deployed, 24% of respondents were concerned about an invasion of privacy and 39% were worried about a loss of control. Survey respondents have also been known to be very sensitive to any perceived restrictions, and they have tended to place a high value on flexibility in their driving lifestyle (Parsons et al., 2014). Therefore, respondents will likely need higher incentives for charging programs that do not guarantee full levels of charge. In related research, Delmonte et al. (2020) determined that a charging program conducted by a supplier (or third-party) was less preferred than a charging program managed by the individual user, due to a perceived potential loss of control. This has implications beyond incentives: having control, especially in ensuring the vehicle is fully charged, affects smart charging participation (Delmonte et al. 2020).

Given this recent V2G literature, researchers are concerned that the revenue opportunities may not be high enough to absorb the costs of incentivizing vehicle owners and lessees to join smart charging programs (Richardson, 2013; Mallette and Venkataramanan, 2013). One of the largest challenges for smart charging is merely encouraging vehicle owners and lessees to opt into the smart charging program. Some research has suggested that a "set and forget" strategy is more effective in engaging with consumers in a smart metering scheme than strategies that require manual input (U.S. Department of Energy, 2015).

2.4) Current Smarting Charging Programs and Pilots

We also reviewed current smart charging programs and pilots in North America to better understand the type, delivery, and value of different incentives. This helps anchor the research to current trends for smart charging. Recently, utilities, auto manufacturers, and transaction facilitators have begun setting various incentives for smart charging programs. For example, Con Edison has built incentive packages for smart charging with electric vehicles where participants are able to earn money per month along with a $150 signup bonus to enable Con Edison to control when the BEV charges (Con Edison, 2022). Table 1 presents a list of many of these smart charging programs across North America, including some specific values and incentives. In addition to these smart charging programs, many of the same providers and other providers offer time-of-use (TOU) pricing specifically for EV. Customers can opt for the BEV rate plan, which encourages late-night charging of BEVs by decreasing the price of electricity during off-peak hours. For example, San Diego Gas and Electric (SDG&E) offers three different TOU plans for EVs, all of which enable customers to save money by shifting their charging away from peak times to super saving periods (SDG&E). Southern California Edison offers a Charge Ready Program, which provides multi-family housing, public sector, and commercial properties assistance in obtaining charging infrastructure and installation (SCE, 2022). While the program does not currently operate a smart charging program, businesses can choose different TOU rate plans (SCE, 2022).

Table 1: List of Selected Smart Charging Pilots and Programs in North America*

Provider	Program Name	Location	Description	Status	Source
Con Edison	SmartCharge New York	New York, USA	Customers can earn $150 for signing up and additional money for charging at specific times or locations.	Program	Con Edison (2022)
Dominion Energy	Smart Charging Infrastructure Pilot Program	Virginia, USA	Customers can receive a rebate for charging equipment that enables smart charging technology and data collection.	Pilot	Dominion Energy (2020)
DTE Energy	DTE Smart Charge	Michigan, USA	In partnership with Ford and Chevrolet, DTE offered a $100 incentive for participating in a one-year pilot.	Pilot	DTE Energy (2021)
ENMAX	Charge Up	Calgary, Canada	EV owners may opt-in to a pilot that assesses their charging behavior.	Pilot	ENMAX (2022)
GA Power	SmartCharge Georgia	Georgia, USA	Participants can earn up to $85 per year by allowing smart charging for their EV.	Program	SmartCharge Rewards (2022b)
NB Power	SmartCharge New Brunswick	New Brunswick, Canada	Participants are rewarded $25 for signing up and are paid out various rewards each month.	Program	SmartCharge Rewards (2022d)
Nova Scotia Power	Electric Vehicle Smart Charging Program	Nova Scotia, Canada	EV owners can apply to have an EV smart charger installed in their home.	Pilot	Nova Scotia Power (2022)
Pacific Gas & Electric and BMW	ChargeForward**	California, USA	BMW EV owners living in PG&E service areas in California can opt-in to a smart charging program that shifts vehicle charging in exchange for incentives to the customer.	Program	BMW Group (2021)
Portland General Electric	SmartCharge PGE	Oregon, USA	Participants can earn between $100 and $800 during the course of the smart charging program.	Pilot	SmartCharge Rewards (2022e)
Sacramento Municipal Utility	Workplace Fleet Charging Case Study	California, USA	Sacramento Municipal Utility EVs were managed on a smart charging system, identifying	Pilot	Enel X (2022b)

			potential for EV fleet management.		
Shell	Shell RechargePlus	California, USA	Shell gas station owners may participate in a smart charging program that helps decrease overall electricity costs.	Program	Shell (2022)
Tennessee Valley Authority	SmartCharge Nashville	Tennessee, USA	EV owners can receive cash bonuses and other incentives for participating in the program.	Program	SmartCharge Rewards (2022c)
Toronto Hydro	EV Smart Charging Pilot Program	Toronto, Canada	EV owners can receive a free EV charger for their home for participating in a smart charging pilot.	Pilot	Plug 'N Drive (2022)
Xcel Energy	Charging Perks	Colorado, USA	Customers can receive up to $300 for participating in a pilot, alongside BMW, Ford, General Motors, and Honda.	Pilot	Xcel Energy (2021)

*This information was updated to early 2022. This list contains only selected smart charging programs. Elements of programs will likely change over time, and the source links will also likely change with information.

**An original pilot had been offered for PG&E and BMW customers in Northern California (BMW 2020).

Alongside the increase of smart charging programs, companies are beginning to offer smart charging software, program management, and smart equipment. For example, SmartCharge Rewards (formally FleetCarma) has developed a platform for utilities and other stakeholders to operate their smart charging pilots/programs (SmartCharge Rewards, 2022a). The company has 18 current or past partnerships in the United States and five in Canada (SmartCharge Rewards, 2022a). Other companies offer similar smart charging platforms (GreenFlux, 2022), while ChargePoint has opted to continue focusing on infrastructure, but ensuring that new charging stations are smart charging compatible and enabled (ChargePoint, 2022). Hilo, a private company that specializes in smart home technology in Quebec, is currently operating a smart charging pilot with incentives for smart home purchases (Hilo, 2022). Other companies, such as Enel X (formally eMotorwerks), are selling EV charging equipment that is compatible with smart charging for home use (Enel X, 2022a). Enel X also partnered with the Sacramento Municipal Utility District on a fleet charging project that was enabled through smart charging technology (Enel X, 2022b). In addition to more readily available V1G technology, V2G technology could also expand functions to handle changes in demand and supply of electricity. According to a Smart Electric Power Alliance survey of utility companies (n=48), just nine utilities were piloting V2G technologies (Blair et al., 2021). The number of utilities piloting this technology will likely grow, similar to the rapid increase in smart charging pilots and programs in the last few years.

2.5) Key Gaps

Despite the interest in offering incentives to defer charging through a smart charging program, only some work has been conducted in either research or practice to determine an optimal strategy for incentives or the factors that may influence consumer behavior in this context. Most research has focused on pricing or incentives in a dynamic way once people have signed up for the program. Despite some behavioral work related to smart charging programs, it remains unclear what incentives (monetary or otherwise) are needed to influence smart charging participation in the first place. A stronger behavioral understanding of smart charging program adoption could improve and guide many of the above programs in Table 1, while also encouraging sign-ups to enable more dynamic pricing and nudging in the midst of the program. In addition, as seen with the current smart charging programs, nearly all programs focus on a monetary incentive. This is paid as a sign-up bonus and/or as a reward throughout the program. While the effectiveness of these programs is not currently known, the types, delivery, and value of the incentives are insightful for how operators are testing and planning to introduce smart charging to consumers and increase sign-ups.

Consequently, this research analyzes how different incentives and smart charging benefits could nudge consumers into participating in a smart charging program, including potential bundles of incentives that include yearly monetary incentives, guaranteed ride/charge, and free charging equipment. We also introduce a penalty variable that could be applied if there was excessive opt-out during the program. This paper differs from most other literature by: 1) focusing on program adoption (i.e., opting into a program); 2) inquiring directly with consumers about their current behavior, preferences, and intentions; and 3) developing different bundles of incentives for signing up. In particular, this work builds off of Bailey and Axsen (2015) and related behavioral studies with data from the U.S., alternative incentives, and more recent data across EV owners/lessees, EV interested buyers/lessees, and a general population.

3) Data

We distributed a survey to individuals with varying levels of EV experience (n=785) in October 2018 through a recruitment process with the help of Qualtrics, a survey management company. Qualtrics includes an option to request panels of individuals based on specific criteria. For the survey, three different respondent-type panels were created, with the intent to collect about 1,000 responses: 1) EV owners/lessees (n=200); 2) EV interested buyers/lessees (n=700); and 3) a general population (n=100) to reflect the diversity of gender, race, education, and income of the general U.S. population. We note that our focus in this research was on EV owners/lessees and EV interested buyers/lessees as they would be current or near-term adopters of smart charging. The EV interested buyers/lessees group was particularly targeted in the research since an operator of a smart charging program (such as an original equipment manufacturer [OEM]) could pair the program sign-up with the point-of-sale of an EV. The general population was included in the data collection as a point of reference and comparison to the other two EV groups. These reasons account for the large difference in responses among the three groups. Respondents were split into these three categories based on their answer to the question: “Are you interested in purchasing or leasing a battery electric vehicle (BEV) or a plug-in hybrid electric vehicle (PHEV)?”

- **EV Owners/Lessees:** Answered “Currently an owner/lessee.”
- **EV Interested Buyers/Lessees:** Answered “Actively shopping for this kind of vehicle,” “Plan to research it for my next purchase/lease,” or “Open to learning more about it.”
- **General Population:** Chose any answer to the purchase/lease question (respondents sampled to reflect US Census data (2010) across age, gender, and income characteristics).

The survey was distributed in 30 specified states and the District of Columbia based on four factors at the time of distribution in 2018: 1) states in the Multi-State ZEV Task Force, 2) states with more than 1 BEV per 1,000 residents, 3) states with over 5,000 BEV units sold per year, *or* 4) states of current Honda Fit EV owners/lessees (Multi-State ZEV Task Force, 2018; Ayre, 2017; Shahan, 2017). While California and New York remain the dominant EV markets in the U.S., we were also interested in assessing the charging and incentive preferences of individuals across the U.S. in markets primed for EV sales growth. For this reason, we focused on a variety of criteria to better capture states with these market conditions. The first criterion factors in states that must (or are committed to) sell a certain number (or percentage) of EVs in the coming years based on state policy. The second criterion was chosen to account for smaller states that may have fewer total sales but have a relatively high adoption per capita (i.e., Nevada, Utah, Hawaii, New Hampshire, and Washington, D.C.). The third criterion captured larger states with a high number of sales, although they may be isolated to major cities in the state (e.g., North Carolina, Ohio, Pennsylvania, Virginia, Texas, and Illinois). Finally, Honda (the funder of the project) was interested in assessing the charging and incentive preferences of individuals across the U.S. in states where they intend to sell vehicles. Unique states to this criterion included South Carolina, Alabama, Mississippi, and Maine.

Data cleaning was executed through a review of responses and completed surveys. Only completed surveys from Qualtrics were retained in the dataset. Demographic and location questions were deployed at the beginning of the survey to screen potential respondents to ensure representation reflective of the general population. All respondents had to be 18 or older. Responses were reviewed for misspellings and updated accordingly (e.g., state/city names). Data were otherwise retained as created by the respondents. After data cleaning, the total complete responses for each panel were as follows: 1) n=151 for EV owners/lessees, 2) n=555 for EV interested buyers/lessees, 3) and n=79 for general population respondents.

4) Methodology

The research methodology using the survey data from study includes: 1) descriptive statistics of survey results, and 2) a discrete choice analysis of the decision to take part in a smart charging incentive program. Descriptive statistics were gathered based on key questions posed to participants in the survey. Questions asked for the likelihood to purchase an EV, current travel behavior, charging behavior (for EV owners/lessees), perceptions of a potential smart charging program, and demographic characteristics. Along with these descriptive statistics, a series of questions were asked that identified the likelihood that people would participate in a smart charging program. Across the questions, the value of a monetary incentive ranged from $0 to $1000 per year.

We next developed three discrete choice models to determine the factors that influence the willingness to participate in smart charging programs. Discrete choice analysis is a modeling technique that uses variables of the decision-maker or a set of alternatives to predict an individual's or household's choice. The majority of discrete choice models employ utility maximization as the decision rule. A decision-maker will consider all the variables and characteristics and choose the most attractive alternative that "maximizes" their utility or satisfaction. Utility maximization has been the primary decision rule in discrete choice analysis, largely because it has statistical properties that produce relatively simple, accurate, and tractable solutions (Ben-Akiva and Lerman, 1985). Ben-Akiva and Lerman (1985) contains the framework for calculating utility, employing maximum likelihood estimation, estimating the coefficients of the covariates, and determining the choice probabilities (additional information can also be found in Washington et al., 2010).

Through a choice experiment, survey respondents were introduced to an incentive program with four attributes, as shown in Table 2. These attributes were based on a number of factors. First, monetary incentives are a key mechanism for current smart charging programs. Past literature has also considered the effect of some monetary benefit (e.g., Bailey and Axsen, 2015; Parsons et al., 2014; Schmalfuβ et al., 2015), although the results have been mixed. Internal discussions between the project funder (i.e., Honda) and local utilities in California were influential in determining the attribute levels. Honda determined that any incentives beyond $400 would not be feasible from an economic standpoint. Moreover, most monetary incentives appeared to range from $50 to $300 from our review of current programs.

Penalties have yet to be studied in the literature, but they can be a vital part of a smart charging program. Without a penalty, EV users could participate at a very minimum level, which would render the smart charging program ineffective. Through discussions between Honda and the local utilities, there was significant concern that people could take the monetary incentive but still choose to forgo long-term participation. By asking respondents upfront if they would choose a program with a penalty, the experiment helped make the program more realistic from an operator's perspective.

Free EV charging equipment (whether Level 1 or Level 2) was mentioned in several smart charging programs. This prompted the team to consider if the equipment could shift program uptake, especially since it could be seen as a "signing bonus." Moreover, it would help address the upfront costs of home charging. The team, including Honda, was interested to see if this free equipment might induce a response from respondents.

Finally, an internal survey of Honda EV users found that a major concern was not receiving a sufficient charge to travel during the day. Indeed, they found that the stopping and starting of charging from a program would be too risky. By guaranteeing a minimum charge start of providing rides (or reimbursements) for stranded motorists, the incentive could reduce EV owner/lessee anxiety with signing up for the program. It also would be a relatively inexpensive incentive for Honda if its program was effective. While a minimum guaranteed charge was studied in Bailey and Axsen (2015), we note that these last three program attributes have not been generally studied in the literature. However, they were deemed important from the perspective of an OEM or a utility. Importantly, the attributes could also be used at the time of sign-ups. This is key since smart charging programs will likely remain opt-in programs (as seen with the various pilots in the literature review). We recognize that the attributes and associated levels have limitations, which are discussed in the Limitations section near the end of the paper.

Respondents were asked, based on the attributes, if they would participate in the charging program ("Yes") or not participate in the charging program ("No") (hence a binary choice). Each respondent was first presented with a sample scenario in which the incentive was set at $150 and all other attributes as "yes." This was built into the survey to prepare the respondent for the next eight experiments. In each of the eight experiments and for each respondent, a program was randomly generated using the four attributes. In all, the number of total experiments (i.e., the sample size for our models) for EV owners/lessees (n=1,118), EV interested buyers/lessees (n=4,369), and the general population (n=622) was sufficiently large for model estimation. The data were used to develop three mixed logit models (using procedures from Train, 2009): one for EV interested buyers/lessees, one for EV owners/lessees and one for the general population. A mixed logit was chosen to account for the multiple experiments that each person performed in the survey.

Based on recommendations from Ben-Akiva and Lerman (1985), we chose covariates based on statistical significance, behavioral importance, and correct a priori coefficient sign. We opted for a more efficient model by retaining only a few insignificant variables. We also conducted a sample enumeration that used the coefficients from the models to inform forecasts of different incentive values (i.e., \$100, \$200, \$300). The sample enumeration gives the probability that the aggregated sample would choose the program under each incentive value. This predictive work can be useful for establishing a set price and other attributes for a future smart charging incentive program. We also present marginal effects for the dummy variables and an average point elasticity by program type for the monetary incentives.

Table 2: Stated Preference Attributes for Choice Experiment

Incentive Program Attribute	**Levels**
Incentive Per Year	\$0, \$50, \$100, \$150, \$200, \$250, \$300
Potential to Receive a Penalty, Based on Lack of Program Participation or Excessive Opt-Outs	Yes or No
Free level 1 (120V) and Level 2 (240V) Charging Equipment	Yes or No
Guaranteed Battery Level; Uber/Lyft/Taxi Ride Reimbursement if Battery Level is Not Met	Yes or No

5) Results

In this section, we provide key results from the survey of EV owners/lessees, EV interested buyers/lessees, and a general population. We discuss the characteristics of each group, responses to varying monetary incentives, and modeling results from a choice experiment using multiple types of incentives and benefits.

5.1) Statistics of Survey Respondents

Characteristics of survey respondents across the three groups (EV owners/lessees, EV interested, and the general population are provided in Table 3. For the three categories, gender was evenly split between male and female, and most respondents were white (between 71% and 75%). However, EV owners/lessees tended to be younger on average, have higher levels of educational attainment, and skewed toward higher income levels. Despite these differences, the racial composition of EV owners/lessees was similar to the EV interested group and the general population.

We note that these characteristics do not automatically align with other research on EV owners/lessees. Compared to a large sample of California EV owner/lessees (Tal et al., 2020), our sample skews more female and lower in income. A similar result was found based on a small sample of EV owners in Virginia (Jia and Chen, 2021) and an older sample from California (California Center for Sustainable Energy, 2013). Our sample also skews more white than recent results for BEV and PHEV sales in California, although the income distribution is similar (Muehlegger and Rapson, 2018). Compared to a survey of EV drivers in the United Kingdom (Latinopoulos et al., 2017), our survey skews more female and higher in education. These differences in comparison to these other studies likely reflect the different population that was sampled for this research (i.e., 30 states plus D.C.).

EV interested buyers/lessees mostly reflected the demographic characteristics of the general population. Interestingly, the income levels of the EV interested group and the general population were similar, suggesting that EVs are now within the price range of more Americans. The general population sample mostly mirrors the U.S. population, though there are some differences in race/ethnicity and education. Across the full sample (n=785), a surprising number of respondents were actively shopping for an EV (10%), planning to research EVs for future purchases (32%), or were open to learning more about EVs (35%). Of the full sample, 19% were current EV owners/lessees (targeted panel) and just 4% were *not* interested in EV ownership/leasing. We also provide a comparison of the demographics against that of the U.S. population using 2020 American Community Survey (ACS) 5-Year Estimates (ACS, 2022) in Table 3.

Table 3: Characteristics of Survey Respondents

Gender	**EV owners/lessees(n=151)**	**EV interested (n=555)**	**General population (n=79)**	**U.S. population [See notes]**
Female	48%	51%	52%	50.8%
Male	52%	49%	48%	49.2%
Race and Ethnicity	**EV owners/lessees (n=151)**	**EV interested (n=555)**	**General population (n=79)**	**U.S. population**
American Indian or Alaska Native	0%	1%	3%	1.8%
Asian	6%	6%	10%	6.8%
Black or African American	13%	8%	8%	14.2%
Caucasian/White	71%	74%	75%	75.1%
Hispanic or Latino	5%	6%	4%	(18.2%)
Native Hawaiian or Pacific Islander	5%	5%	0%	0.4%
Other/Mixed	0%	1%	1%	10.3%
Age	**EV owners/lessees (n=151)**	**EV interested (n=555)**	**General population (n=79)**	**U.S. population**
18-24	12%	13%	14%	12.0%
25-34	29%	11%	10%	18.0%
35-44	14%	14%	15%	16.3%
45-54	9%	14%	19%	16.4%

55-64	16%	19%	20%	16.6%
65-74	15%	22%	13%	12.1%
75-85	4%	6%	8%	6.0%
85 or older	1%	1%	1%	2.6%

Highest Level of Education	**EV owners/lessees (n=151)**	**EV interested (n=555)**	**General population (n=79)**	**U.S. population**
Less than high school	1%	1%	3%	10.7%
High school graduate (or equivalent)	7%	14%	13%	26.3%
Some college or associate's degree	23%	30%	39%	28.1%
Bachelor's degree	37%	27%	28%	21.2%
Graduate or professional degree	32%	27%	18%	13.8%

Annual Household Income	**EV owners/lessees (n=151)**	**EV interested (n=555)**	**General population (n=79)**	**U.S. population**
Less than $10,000	5%	5%	6%	5.8%
$10,000-$14,999	1%	4%	4%	4.1%
$15,000-$24,999	3%	8%	8%	8.5%
$25,000-$34,999	3%	10%	10%	8.6%
$35,000-$49,999	6%	11%	13%	12%
$50,000-$74,999	14%	19%	16%	17.2%
$75,000-$99,999	15%	14%	14%	12.8%
$100,000-$124,999	13%	8%	6%	15.6%
$125,000-$149,999	13%	6%	8%	
$150,000-$174,999	5%	4%	4%	7.1%
$175,000-$199,999	5%	1%	3%	
More than $200,000	10%	3%	9%	8.3%
No answer	7%	7%	0%	0%

Electricity Program at Home	**EV owners/lessees (n=151)**	**EV interested (n=555)**	**General population (n=79)**
Fixed-rate	38%	38%	33%
Variable-rate	24%	18%	22%
Tiered-rate	11%	8%	14%
Time-of-use (TOU)	7%	10%	9%
Demand response	6%	3%	0%
EV-specific plan	5%	1%	0%
Other	2%	1%	1%
I don't know	6%	21%	22%

Notes: U.S. population educational attainment is for the population 25 years and over.
U.S. population race statistics reported as a single race only.
Hispanic/Latino is considered ethnicity in the ACS but was streamlined in our survey.
Age is calculated as a percentage of the U.S. population 18 and over

ACS does not include a prefer not to answer for the income question.
May not equal 100% due to rounding or multi-choice answer.

Respondents were asked to provide the top five attributes of a vehicle that they would consider during the purchasing/leasing process. Across the three groups, battery range (over half of all respondents) followed by price/cost of ownership were the most important attributes of an EV (as indicated in Table 4). Expected maintenance costs were also an important consideration for buying/leasing an EV for all groups. Separately, EV owners/lessees noted the importance of handling/maneuverability (i.e., performance), while the EV interested group and the general population considered the location and availability of charging stations.

For just EV owners/lessees, we asked several questions related to their travel and charging behavior (Table 5). EV owners/lessees tended to be new (66% receiving their vehicle from 2016-2018) and have a BEV (69%). A significant number of EV owners/lessees still experienced range anxiety at least once a month (64%), even though 55% did not have a failed trip due to insufficient charge across an entire year. For charging, 44% of respondents charged every day, with 55% always charging at home and 53% always charging at work/school. Public charging was generally lower, with just 21% always charging in that context. Approximately 71% of EV owners always (33%) or most times (38%) charge their EVs as soon as they arrive home. While the drivers could cause significant peak demand on the grid, these individuals could also be amenable to shifting the time of charge via smart charging, especially if smart charging systems are readily available and/or if they receive an incentive. Approximately 84% of respondents would "always" or "most of the time" plug in immediately at work/school. Since these charging decisions may cause significant peaks during the middle of the day, smart charging could be effective in spreading out demand.

Table 4: Most Important EV Attributes

EV Owners (n=151)	
Battery range	55%
Price/cost of ownership	36%
Handling/maneuverability	32%
Available financing or leasing terms	31%
Expected maintenance costs	28%
EV Interested (n=555)	
Battery range	65%
Price/cost of ownership	53%
Expected maintenance costs	43%
Location and availability of charging stations	37%
Speed of battery charging; Home electricity bills	24%
General Population (n=79)	
Battery range	58%
Price/cost of ownership	39%
Location and availability of charging stations	38%

Expected maintenance costs	37%
Cargo capacity/usefulness	25%

Table 5: Characteristics of EV Owners/Lessees

Year Became EV Owners/Lessees (n=142)	
Before 2010	4%
2010-2012	10%
2013-2015	20%
2016-2018	66%
BEV/PHEV Ownership/Leasing (n=150)	
I own/lease a BEV	69%
I own/lease a PHEV	24%
I own/lease both a BEV and PHEV	7%
Times Experiencing Range Anxiety Per Month (n=111)	
None	36%
1 to 5	53%
More than 5	11%
Commutes Per Month without Full Charge (n=118)	
None	25%
1 to 5	47%
More than 5	28%
Failed Trips Per Year Due to Insufficient Charge (n=110)	
None	55%
1 to 5	34%
More than 5	11%
Charging Frequency (n=151)	
Everyday	44%
2 to 3 times per week	35%
Once a week	15%
Less than once a week	7%
Charge at Home (n=151)	
Always	55%
Most of the time	30%
About half the time	9%
Sometimes	4%
Never	1%
Charge as Soon as Arrive at Home (n=151)	
Always	33%
Most of the time	38%
About half the time	14%
Sometimes	12%
Never	3%

Charge at Public Station (n=149)	
Always	21%
Most of the time	22%
About half the time	13%
Sometimes	24%
Never	20%
Charge at Work/School (n=75)	
Always	53%
Most of the time	28%
About half the time	7%
Sometimes	11%
Never	1%
Charge as Soon as Arrive at Work/School (n=74)	
Always	57%
Most of the time	27%
About half the time	9%
Sometimes	4%
Never	3%

5.2) Monetary Incentives for DR and Smart Charging Participation

In the survey, respondents were asked to choose the likelihood that they would participate in a DR program as the incentive offered per year increased from $0 to $1000 per year. The full text of the scenario is included in the Appendix.

As seen in Figure 1, the results indicate that as the incentive amount offered per year increased, the more likely a person wanted to participate in a DR program (in this case smart charging). The incentive programs gained the most participation from all three groups of people at levels higher than $300 per year (Figure 1-3). EV owners/lessees and EV interested buyers/lessees were more likely to consider participation in a DR program than the general population across all incentive values. Moreover, around 50% of respondents for both EV owners/lessees and EV interested buyers/lessees would definitely participate in a DR program if they were provided $1000 per year. Interestingly, 26% of EV owners/lessees would be willing to participate, even without an incentive. Participants may be sufficiently interested in saving money on electricity and/or spreading out electricity demand to not need an incentive per year. They may also have strong environmental positions or want to provide help to society, as noted in Schmalfuβ et al. (2015) and Will and Schuller (2016). However, participation in this zero-cost incentive drops to 14% for EV interested buyers/lessees and 13% for the general population.

We also note that the general population was not as motivated by incentives compared to the two EV groups. Even at $1000 per year, 38% of the general population stated that they would "definitely not" participate in a DR program. Across all three groups, when we combined the probability of those who would "definitely" or "probably" participate, we found that there are diminishing returns for each dollar given per year. For example, both $750 and $1000 per year influenced 63-64% of EV owners to definitely or probably participate. This is only a small increase from the 58% of EV owners at $500 per year. Overall, the implications of these results are that incentives help increase participation, but there is a limit to their effectiveness. At the same time, some people may participate without an incentive, offering a pathway to spread out some demand without costs beyond the program administration.

Figure 1: EV Owners/Lessees – Participation in DR Incentive Program

Please select how likely you would be to participate in the demand response program for each of the following incentive levels. (N = 151)

	Definitely	Probably	Maybe	Probably Not	Definitely Not
$0/year	26%	19%	18%	15%	22%
$50/year	23%	17%	24%	17%	20%
$100/year	25%	25%	22%	11%	18%
$150/year	26%	25%	21%	11%	17%
$200/year	26%	29%	19%	11%	15%
$250/year	26%	29%	20%	11%	14%
$300/year	33%	24%	17%	14%	12%
$400/year	32%	21%	22%	13%	12%
$500/year	42%	16%	17%	13%	12%
$750/year	44%	19%	15%	9%	13%
$1000/year	50%	14%	17%	7%	13%

Figure 2: EV Interested Buyers/Lessees - Participation in DR Incentive Program

Please select how likely you would be to participate in the demand response program for each of the following incentive levels. (N = 555)

	Definitely	Probably	Maybe	Probably Not	Definitely Not
$0/year	14%	11%	23%	17%	35%
$50/year	11%	16%	26%	20%	27%
$100/year	11%	19%	31%	19%	20%
$150/year	11%	23%	32%	16%	18%
$200/year	15%	27%	27%	16%	15%
$250/year	19%	27%	24%	14%	16%
$300/year	27%	25%	19%	12%	17%
$400/year	34%	21%	15%	11%	18%
$500/year	45%	15%	13%	10%	17%
$750/year	48%	13%	10%	11%	18%
$1000/year	54%	12%	9%	8%	17%

Figure 3: General Population - Participation in DR Incentive Program

Please select how likely you would be to participate in the demand response program for each of the following incentive levels. (N = 79)

	Definitely	Probably	Maybe	Probably Not	Definitely Not
$0/year	13%	8%	22%	11%	47%
$50/year	9%	14%	24%	13%	41%
$100/year	9%	15%	25%	13%	38%
$150/year	11%	13%	25%	16%	34%
$200/year	13%	19%	19%	16%	33%
$250/year	13%	16%	16%	22%	33%
$300/year	18%	11%	15%	19%	37%
$400/year	20%	13%	14%	15%	38%
$500/year	25%	10%	14%	14%	37%
$750/year	32%	5%	16%	11%	35%
$1000/year	33%	10%	10%	9%	38%

5.3) Factors Influencing Smart Charging Program Participation

Next, we developed a choice experiment and three mixed logit models to assess the factors that would influence an individual to participate in a smart charging program. Table 6 presents the model for EV interested buyers/lessees, Table 7 presents the model for EV owners/lessees, and Table 8 presents the model for the general population.

Table 6: Estimation Results of Mixed Logit Model for EV Interested Buyers/Lessees

Variable	Estim. Coef.	Std. Err.	p-value	
Program Preference	-0.930	0.224	0.000	***
Incentive Program Attributes				
Monetary Incentive	0.004	0.001	0.000	***
Std. Dev. of Monetary Incentive	0.009	0.001	0.000	***
Penalty for Nonparticipation	-0.471	0.131	0.000	***
Std. Dev. of Penalty for Nonparticipation	1.878	0.167	0.000	***
Free EV Supply Equipment (EVSE)	1.549	0.120	0.000	***
Std. Dev. of Free EVSE	1.297	0.158	0.000	***
Guaranteed Battery Level or Ride	1.188	0.118	0.000	***
Std. Dev. of Guaranteed Battery Level or Ride	1.307	0.160	0.000	***
Demographics				
Young (Under 35)	0.343	0.171	0.044	*
Female	-0.415	0.147	0.005	**

Black or African American†	0.671	0.283	0.018	*
Hispanic or Latino†	-0.592	0.295	0.045	*
Do Not Own Smartphone	-0.523	0.235	0.026	*
Household Characteristics				
No Children in Household	-1.325	0.172	0.000	***
Tiered Electricity Program	-0.698	0.312	0.025	*
Sole Transportation Decision-Maker	0.673	0.147	0.000	***
Living in Southeast U.S.	-0.476	0.178	0.008	**
Number of Observations	4,369			
Goodness of Fit	0.201			
Adjusted Goodness of Fit	0.195			
Log-Likelihood	-2,420.6			
LL-Null	-3,028.4			
AIC	4,877.2			
BIC	4,992.1			
Halton Draws	1000			

Significance Level *95% **99% ***99.9%
† Base: White, Asian, Other, Prefer not to Answer

5.3.1) EV Interested Buyers/Lessees Model Results

For the model specified with the EV interested buyers/lessees, the alternative specific constant (ASC) – referred to in the table as “program preference” – was negative and significant, indicating a preference against participating in a smart charging incentive program as described in our choice experiment, all else equal. Each of the coefficients for incentive program attributes was significant, indicating each attribute influenced the respondents’ decisions to participate or not. The coefficient signs met our expectations: the monetary incentive, free Electric Vehicle Supply Equipment (EVSE), and guaranteed charge level or ride home attributes were positive, indicating that these attributes increased willingness to participate in the program. The coefficient for the penalty program was negative, indicating that members of the EV interested buyers/lessees population were less inclined to join a smart charging program in which they may be penalized (in this case, lose up to the full amount of the monetary incentive given for participating in the program) for not relinquishing control of their vehicle.

However, these coefficients require additional nuance based on the mixed logit results. The standard deviation for all four coefficients of the program was significant, indicating heterogeneity in the population that can be determined based on the normal distribution. For some respondents (67%), an increase in the amount of the monetary incentive ($50) also increases their likelihood of choosing the smart charging program. However, there is a substantial part of the population (33%) where each additional $50 decreases their likelihood. A clear explanation for this heterogeneity is not immediately available, although there are some people who would not participate in a program even if they were given a substantial monetary incentive (as seen in Figure 2). A penalty for nonparticipation produced a negative program selection for approximately 60% of respondents. However, it was a positive factor for 40%. Again, the reasoning is not immediately clear, although these respondents may view penalties as necessary for nudging behavior toward the common good (i.e., approving penalties for other people). Both free charging equipment and guaranteed battery level or ride home induced very strong positive responses to choosing a program for most people (88% and 82%).

The EV interested buyers/lessees model included multiple demographic variables including: age, gender, and race or ethnicity along with smartphone access. The model indicates that younger individuals (less than 35 years old) were more likely to participate in the program (positive and significant). The coefficient for females was significant and negative, indicating a lower willingness to participate in a program. The coefficient for Black or African American individuals interested in owning an EV was positive and significant. However, the coefficient for Hispanic or Latino was negative. This indicates that compared to White, Asians, other, and prefer not to answer respondents, Black or African American individuals were most likely to be willing to participate in a smart charging program while Hispanic and Latino individuals were less willing. Those who do not own a smartphone were less willing to participate in a smart charging program.

The model also included several household characteristics. The negative coefficient for individuals who do not live with children was also significant. This was surprising, as we expected that parents would be less likely to participate due to the need for flexible, reliable transportation. Perhaps individuals with children may have multiple vehicles available, and thus have an extra vehicle if sufficient charging was not achieved for their EV. The model indicated that individuals with tiered electricity plans were less likely to participate in a smart charging program. In a tiered electricity plan, an individual's payment rate increases as they surpass "tiers" of energy usage. An interpretation of the model results is that individuals may be wary of losing charging control if they wish to stay within a certain allocation of energy usage. In the survey, respondents were asked whether they were the sole decision-maker for transportation decisions in their household. The model indicates that those who said they were the sole decision-maker were more likely to participate in a program than individuals who make joint transportation decisions with other household members. Finally, the model included a variable for the geographic region. The coefficient for the Southeastern U.S. (compared against all other regions) was negative and significant, indicating that EV interested buyers/lessees from the Southeast were less likely to participate than EV interested buyers/lessees from other regions. The southeast region included the states of Florida, Georgia, South Carolina, North Carolina, Louisiana, Alabama, and Mississippi.

5.3.2) EV Owners/Lessees Model Results

The model estimated with the EV owners/lessees population (Table 7) had a negative and significant coefficient for program preference, suggesting a natural inclination against participating in a smart charging program, all else equal. Similar to the EV interested buyers/lessees model, all the program attributes were significant, and the directionalities of the coefficients were the same for both models. Focusing on the random parameters, we again found that monetary incentives produced heterogeneity in the population with 75% being positively affected and 25% negatively affected. The program variables of free equipment and guaranteed battery level/ride also produced heterogeneity.

We found several demographic and household variables that were significant. Individuals who make the sole transportation decisions in their household were more likely to participate. Again, households with no children were less likely to participate, which may be related to the number of available vehicles. All other demographic and household variables were insignificant, indicating the strong effect of program characteristics on the EV owner/lessee group. Several EV-experience variables also were tested with the EV owners model. Individuals who "always" or "most of the time" plug in immediately when arriving at home were more likely to participate in a smart charging program. With a charging system readily available, these individuals might prefer a "set and forget" style program that automatically charges their vehicle. Interestingly, those who had to choose a gasoline vehicle when they had insufficient range, and those who experienced insufficient battery at the commute start were both more likely to participate. One hypothesis is that these owners may believe that a smart charging program could have reduced their negative experiences with insufficient charging.

Table 7: Estimation Results of Mixed Logit Model for EV Owners/Lessees

Variable	Estim. Coef.	Std. Err.	p-value	
Program Preference	-0.7327	0.398	0.065	
Incentive Program Attributes				
Monetary Incentive	0.008	0.002	0.000	***
Std. Dev. of Monetary Incentive	0.012	0.001	0.000	***
Penalty for Nonparticipation	-0.576	0.194	0.003	**
Free EV Supply Equipment (EVSE)	1.256	0.301	0.000	***
Std. Dev. of Free EVSE	1.827	0.350	0.000	***
Guaranteed Battery Level or Ride	0.634	0.226	0.005	**
Std. Dev. Guaranteed Battery Level or Ride	0.769	0.327	0.019	*
Household Characteristics				
No Children in Household	-1.630	0.319	0.000	***
Sole Transportation Decision-Maker	1.373	0.291	0.000	***
Electric Vehicle Experiences				
Always or Most Times Plug in Immediately at Home	0.687	0.315	0.029	*
Chose a Gasoline Car if Insufficient Range (at least once per year)	1.143	0.407	0.005	**
Experienced Insufficient Battery at Commute Start (at least once per year)	0.995	0.390	0.011	*
Number of Observations	1,188			
Goodness of Fit	0.339			
Adjusted Goodness of Fit	0.324			
Log-Likelihood	-543.9			
LL-Null	-823.5			
AIC	1,113.8			
BIC	1,179.9			
Halton Draws	1000			

Significance Level *95% **99% ***99.9%

5.3.3) General Population Model Results

Finally, we built a model using experimental results from the general population (Table 8). Program preference, unlike for the other two groups of respondents, was insignificant. Program-related attributes, such as monetary incentives and receiving a penalty, were insignificant and removed from the model. While free charging equipment was also insignificant, we found a significant standard deviation. This indicates that there is substantial heterogeneity in the population, such that 63% were positively affected by equipment and 37% are negatively impacted. Given that the population is general, the respondents may not have understood what free charging equipment would mean for them as an incentive. Guaranteed battery level or ride was also insignificant, but the value of the random effect was significant. In this case, 66% of participants were positively influenced by this attribute, while 34% were negatively influenced. A potential explanation is that the attribute may signal that the program operator would potentially leave the motorist stranded and cause inconvenience multiple times.

For demographic and household variables, we found that younger adults were more likely to participate in a program, while women were less likely. Households without children were also less likely to participate. For this population, we also found that those with a variable rate electricity program were more likely to participate in a smart charging program. We hypothesize that people with this plan would welcome a smart charging program to better address the high costs that might arise from varying electricity rates.

Table 8: Estimation Results of Mixed Logit Model for General Population

Variable	**Estim. Coef.**	**Std. Err.**	**p-value**	
Program Preference	0.048	0.274	0.861	
Incentive Program Attributes				
Free EV Supply Equipment (EVSE)	0.562	0.442	0.204	
Std. Dev. of Free EVSE	1.735	0.451	0.000	***
Guaranteed Battery Level or Ride	0.833	0.468	0.075	
Std. Dev. of Guaranteed Battery Level or Ride	1.955	0.404	0.000	***
Demographics				
Young (Under 35)	0.937	0.255	0.000	***
Female	-2.089	0.289	0.000	***
Household Characteristics				
No Children in Household	-1.594	0.254	0.000	***
Variable Rate Electricity Program	1.256	0.270	0.000	***
Number of Observations	622			
Goodness of Fit	0.320			
Adjusted Goodness of Fit	0.300			
Log-Likelihood	-293.0			
LL-Null	-431.1			
AIC	604.0			
BIC	643.9			
Halton Draws	1000			

Significance Level *95% **99% ***99.9%

5.3.4) Sample Enumeration and Incentive Testing

Using the three discrete choice models developed for EV owners/lessees and EV interested buyers/lessees, we extend our discussion by conducting sample enumeration. We used the coefficients found in the three models for the program attributes and demographic variables. We then altered the program attributes to see how they impacted the probability that individuals would choose the smart charging program. For example, we set a "full program" where the third-party would issue penalties for resuming control, provide free charging equipment, and guarantee rides home or adequate charge. We then changed the monetary incentive value from $0 to $500 to see how it would impact the likelihood to participate. This process provides the opportunity to plan out different programs with shifting attributes. We note that sample enumeration assumes that the demographic variables remain fixed and that the coefficients of the program attributes allow us to estimate the new probabilities. Since we developed mixed logit models, we conducted our sample enumeration by drawing 300 values based on the mean and standard deviation for the random parameters for each experiment. These values were used to calculate the probabilities for choosing the program or not choosing it. The probabilities were averaged across all 300 draws for each experiment. Consequently, this is a rough estimate of program participation. As a general tool, the sample enumeration helps highlight if significant changes in incentives can push individuals to participate in a smart charging program.

For EV owners/lessees (Figure 4) willingness to participate in a smart charging program is considerably high. For a program with a penalty for gaining control but no monetary incentive, equipment, or guaranteed ride/charge, approximately 28.1% of EV owners/lessees would still participate in the program. This indicates that a substantial number of EV owners/lessees could be convinced to participate with minimal cost to the third-party, especially if the program was developed as an opt-out program. For the same program at $500 per year, the participation rate climbs to 63.6%. We find that 37.2% of EV owners/lessees would participate with no incentive or equipment, but with guaranteed charge and a penalty. This number jumps to 67.2% for a value of $500 per year. The best program for EV owners/lessees would be one in which no penalty is assessed when the individual retakes control of charging. In this program, participants would still receive equipment and guaranteed rides/charge. For a $500 incentive, 75.8% of EV owners/lessees would participate in the program. For all tested programs, the results also indicate that there are strong diminishing returns with a rising monetary incentive value. For several program options, the probability difference between $300 per year and $500 per year is small.

Compared to EV owners/lessees, we find that EV interested buyers/lessees are less likely to participate in a smart charging program (Figure 5), particularly for the least attractive scenarios. Without equipment or guaranteed ride/charge but with a penalty for opt-out, only 18.5% would participate in a program at $0. When the monetary incentive increases to $500, the probability rises to 46.8%. EV interested buyers/lessees also place a higher value on guaranteed ride/charge than EV owners/lessees, which can be seen by the coefficients and the sample enumeration results. EV interested buyers/lessees gain nearly twice as much utility with a program with guaranteed ride/charge than EV owners/lessees. Consequently, we find that the difference between a full program and a program without a guaranteed ride/charge is 15.3% for no monetary incentive. This difference diminishes with higher monetary incentives (i.e., a difference of 7.9% for a $500 incentive). With no penalty and all other incentives, about 70.2% of participants would be willing to be part of a smart charging program (ceiling of adoption).

Figure 4: Sample Enumeration - Incentive Curves for Different Smart Charging Programs Assuming Constant Demographics - EV Owners/Lessees

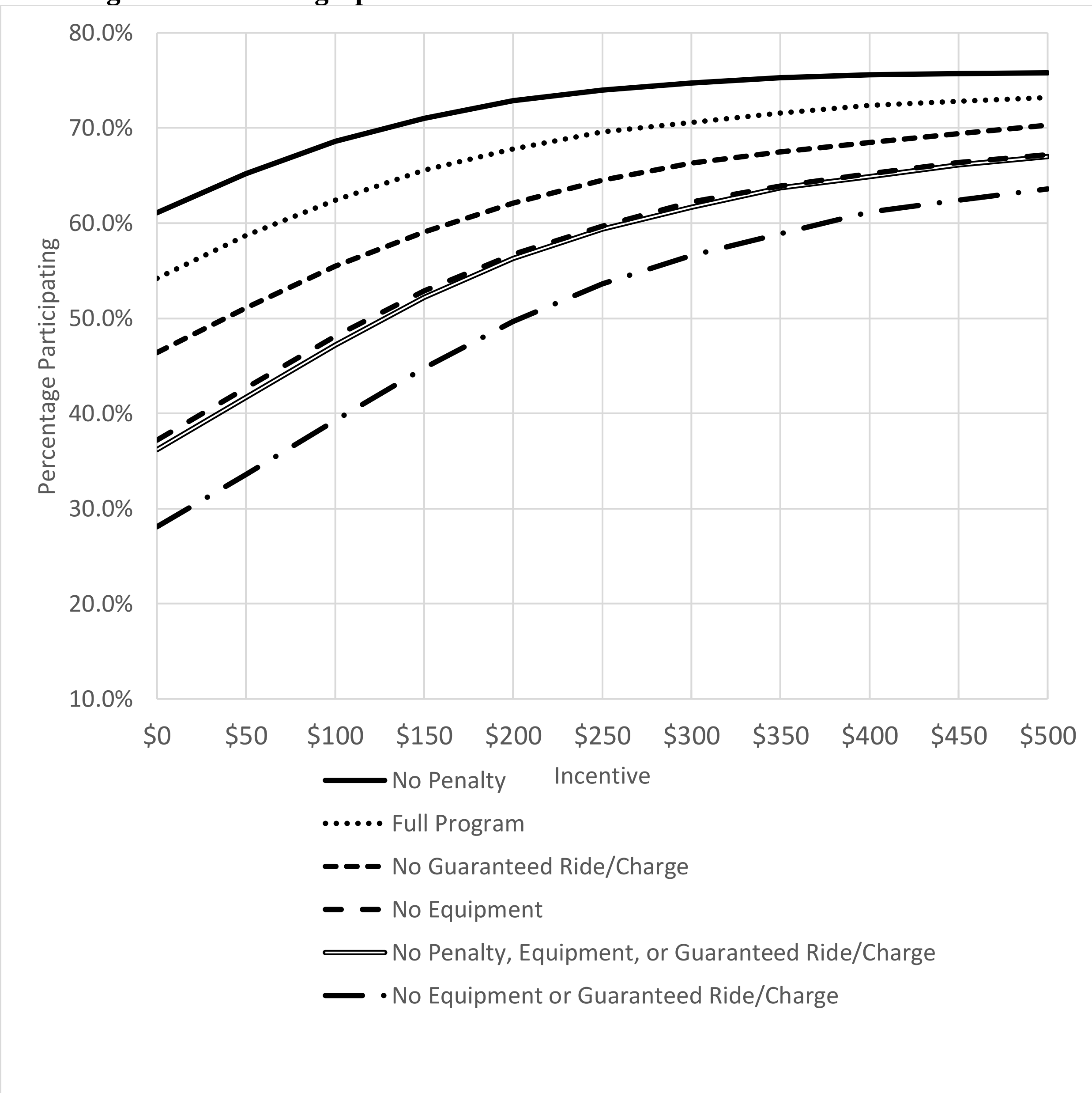
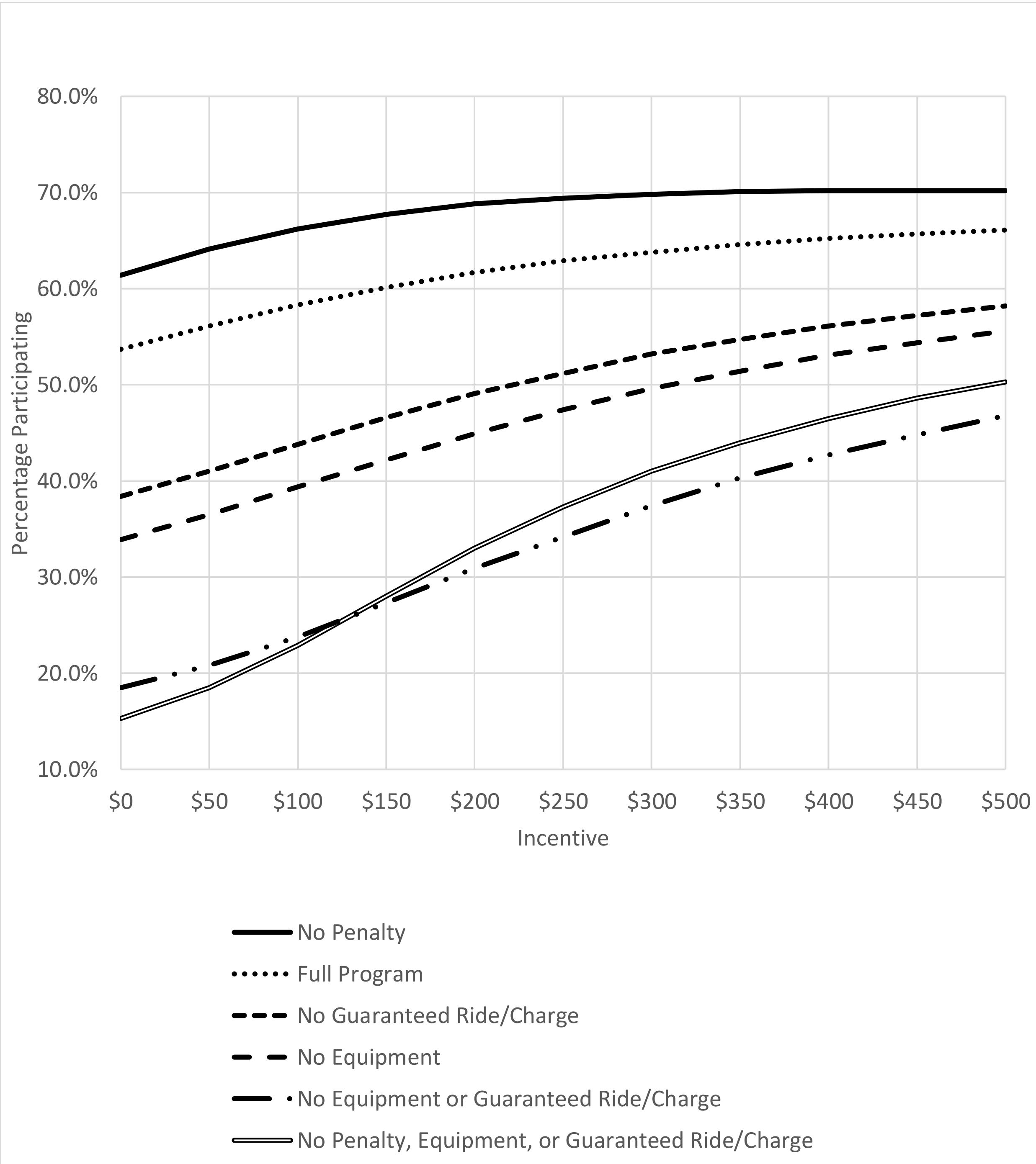


Figure 5: Sample Enumeration - Incentive Curves for Different Smart Charging Programs Assuming Constant Demographics - EV Interested Buyers/Lessees



We also conducted a sample enumeration for the general population. Since monetary incentives were not a significant variable in the mixed logit model, we were unable to conduct the enumeration across changing values. However, we were able to test four different program types based on the variables in the model: equipment and ride/charge. We found that 21.0% of the general population would choose a program if there were no equipment and no guaranteed ride/charge. A program with just a guaranteed ride/charge increased the probability to 37.6%, while a program with just free equipment increased the probability to 33.5%. The program with both incentives increased participation to 45.8%, nearly doubled the probability compared to a program with no incentives.

Through sample enumeration, we find several interesting results:

- A significant portion of EV owners/lessees (but a smaller portion of EV interested buyers/lessees) would be willing to participate in a smart charging program without any monetary incentive, equipment, or guaranteed ride/charge.
- Monetary incentives do increase willingness to participate but the impacts differ based on what other incentives are being provided.
- Monetary incentives produce diminishing returns, meaning that each additional $1 spent would yield decreasing marginal participation in the program.
- An ideal monetary incentive value to achieve optimal participation is not apparent, especially given different combinations of smart charging program attributes and the limitation that operators need to be revenue neutral or profitable.
- A ceiling exists on participation rates (assuming a maximum of $500 incentive) at 74.4% for EV owners/lessees, 68.4% for EV interested buyers/lessees, and 45.8% for the general population.

5.3.5) Marginal Effects and Elasticities

We also included an analysis of the marginal effects of all dummy variables in the three models (Table 9) and the average point elasticities of the monetary incentives by program type (Table 10). The average point elasticities across a program were calculated by averaging all point elasticities for a 1% increase in each monetary incentive value in our experiment except for $0 ($50 to $500 increments of $50). While we recognize that the point elasticities are non-linear, the averages were taken given the very small non-linear effects and for easier interpretation in Table 10.

The marginal effects (i.e., the change in probability of choosing a program given the unit change of a given variable) produced several interesting results. First, free EVSE and guaranteed battery level/ride produced relatively high increases in probability compared to other variables, although the effect was most pronounced for the EV interested buyers/lessees group. While penalties decreased the probability of choosing the program for the EV owner/lessees and EV interested buyer/lessees groups, the effect easily could be offset by the positive influence of other program characteristics. No children in the household produced a strong decrease in program selection probability for all three groups. Women in the general population reacted the most negatively compared to the other two groups. As a common theme, the demographic characteristics did produce some movement in the probabilities across all groups, which indicates that they cannot be ignored when designing a smart charging program.

The elasticities (i.e., the change in probability of choosing a program given the 1% change of monetary incentives) displayed some influence of monetary incentives in program selection. For example, in the worst-case program for the consumer (penalty, no equipment, no guaranteed battery/ride), a 1% increase in monetary incentive translated to a .14% increase in the probability of selecting the program. This program and others show that monetary incentives matter for program selection, but this is only to a small degree.

Table 9: Marginal Effects for Dummy Variables across Mixed Logit Models

EV Owners/Lessees	**X=1**	**X=0**	**Marginal effect**
Penalty for Nonparticipation	56.0%	62.1%	-6.1%
Free EV Supply Equipment (EVSE)	65.5%	53.2%	12.3%
Guaranteed Battery Level or Ride	62.5%	55.8%	6.7%
No Children in Household	48.9%	70.5%	-21.6%
Sole Transportation Decision-Maker	65.8%	51.7%	14.1%
Always or Most Times Plug in Immediately at Home	61.3%	53.9%	7.4%
Chose a Gasoline Car if Insufficient Range (at least once per year)	62.1%	49.3%	12.8%
Experienced Insufficient Battery at Commute Start (at least once per year)	61.3%	50.3%	11.0%
EV Interested Buyers/Lessees	**X=1**	**X=0**	**Marginal effect**
Penalty for Nonparticipation	45.1%	49.9%	-4.8%
Free EV Supply Equipment (EVSE)	57.1%	37.5%	19.6%
Guaranteed Battery Level or Ride	55.1%	40.1%	15.0%
Young (Under 35)	50.6%	46.5%	4.1%
Female	45.0%	50.0%	-5.0%
Black or African-American	55.0%	46.8%	8.2%
Hispanic or Latino	40.9%	47.9%	-7.0%
Do Not Own Smartphone	42.0%	48.2%	-6.2%
No Children in Household	43.3%	59.7%	-16.4%
Tiered Electricity Program	39.9%	48.1%	-8.2%
Sole Transportation Decision-Maker	51.9%	43.7%	8.2%
Living in Southeast U.S.	43.2%	48.8%	-5.6%
General Population	**X=1**	**X=0**	**Marginal effect**
Free EV Supply Equipment (EVSE)	39.3%	28.8%	10.5%
Guaranteed Battery Level or Ride	41.7%	27.2%	14.5%
Young (Under 35)	43.4%	31.1%	12.3%
Female	21.8%	47.9%	-26.1%
No Children in Household	29.1%	50.5%	-21.4%
Variable Rate Electricity Program	47.2%	30.7%	16.5%

Table 10: Averaged Point Elasticities for Monetary Incentives

	Penalty for Nonparticipation	Free EV Supply Equipment (EVSE)	Guaranteed Battery Level or Ride	Average of Point Elasticities Across Monetary Incentives from \$50 to \$500 in \$50 increments	
				EV Owners/Lessees	EV Interested Buyers/Lessees
Program 1	Yes	Yes	Yes	0.08%	0.01%
Program 2	Yes	Yes	No	0.13%	0.12%
Program 3	Yes	No	No	0.14%	0.14%
Program 4	No	Yes	Yes	0.09%	0.01%
Program 5	No	No	No	0.12%	0.17%
Program 6	Yes	No	Yes	0.09%	0.13%

5) Limitations

This research contains a number of limitations, first related to the survey. The survey exhibited some bias as it was distributed solely online. The EV owners/lessees and EV interested buyer/lessee groups may not necessarily reflect populations in certain parts of the U.S. In this case, the demographic characteristics of these surveyed groups may not represent all EV owners/lessees or EV interested buyers/lessees. There also were some cases where participants did not answer all eight discrete choice experiments. While there is no indication that participants were responding in an irrational or untrustworthy way, leaving these participants in the study may cause some bias in results. However, as noted in Lancsar and Louviere (2006), the deletion of these types of responses could instead cause a different sample selection bias and reduce statistical efficiency. We note that Qualtrics, the survey provider, has mechanisms in place to detect fraudulent responses. To test the influence of respondents with missing answers, we built a parallel series of models but removed any respondent that did not answer all eight of the discrete choice experiments. This removed 54 respondents from the EV interested buyer/lessee group, 12 respondents from the EV owner/lessee group, and four respondents from the general population group. We found remarkable consistency in the models such that only a single variable in one model became insignificant and no variable signs changed. We decided to retain the models with the full data (as originally developed) given this minimal discrepancy.

Regarding methodology, the three mixed logit models do not consider the risk perceptions of the respondents, in particular perceptions related to range anxiety, security, privacy, or relative control (some of which are noted in Delmonte et al., 2020). This presents a clear limitation that was caused by the need to have a short survey to retain respondents. In addition, the survey was more focused on monetary incentives and included additional questions on EV purchase behavior that were not specifically relevant to the research in this paper. We recommend future surveys should focus more on risk perceptions.

In our choice experiments, we did not vary some of the other attributes of a possible smart charging program. Indeed, different assumed values for equipment and alternative incentive structures (e.g., receiving a high rebate upfront in exchange for smart charging for the life of the vehicle or lease) may lead to different behavioral responses. For example, a $2,000 upfront rebate may be more effective in program uptake than $200 incentives per year for ten years. Research has generally shown that as the delay of a reward increases over time, people will choose lower values of an immediate reward (Green et al., 1994). If we gave respondents the option of $100 per year for five years or $400 immediately, more people would likely choose the $400 based on the research. This also can be conceptualized by the ideas of net present value and time value of money, which together lead to the conclusion that money today is worth more than money tomorrow (Gallo, 2014). Similarly, changing the penalty structure could lead to different behavioral responses, especially if the penalty value was altered. For example, a $1 fine per opted-out session versus a complete $200 after reaching a pre-determined threshold of opted-out sessions would yield different responses. We also note the description of the guaranteed charge level or ride is somewhat limited. This is because a guaranteed battery level would have to be tied to the EV users' equipment and the amount of time that they need to charge to meet their travel needs. The wording and the specifics of the incentive should be amended in future work to better account for this limitation. Another limitation is that individuals may have different preferences on giving up charging depending on the time of day (evening more likely, during work less likely). Individuals may also not want to give up charging for certain trip purposes, especially if the battery may be low. However, these different programmatic aspects are not generally relevant for smart charging *program adoption*. Time of day and trip purpose could be considered by operators for *program retention and satisfaction*. Future work should include a preference question to determine the periods of the day or trip purposes that would be acceptable in a smart charging program.

Currently, infrastructure remains a key barrier to EV adoption. While smart charging is not directly affected by this barrier, a lack of infrastructure could produce fewer participants for smart charging programs overall. It also would remove a relatively easy mechanism to implement smart charging. This is especially important for geographic regions with limited public charging infrastructure and for customers who live in apartments, condos, and townhomes (which have been traditionally slow to build EV charging infrastructure). Infrastructure-oriented questions, including opportunities to access a dedicated network of chargers or save money on certain charging networks, may affect willingness to participate in a smart charging program. Widely available infrastructure on a dedicated charging network could be a major perk for customers. This could also allow for more user control in a smart charging program. Finally, we note that results presented in this research, especially related to charging behavior, may have changed significantly during and following the COVID-19 pandemic. With the requirement of work-from-home policies to reduce COVID-19 spread, travel behavior and patterns have also likely shifted. Indeed, charging behavior may be less tied to the typical morning and evening commute patterns (i.e., pre-pandemic). A new iteration of research studies on this topic within this altered work landscape is necessary.

6) Conclusions

In this paper, we investigated the willingness of EV owners/lessees, EV interested buyers/lessees, and a general population to participate in a smart charging program. These programs can help shift demand from EVs to off-peak hours, improve the matching of supply and demand, reduce future grid costs, and enable more renewable energy usage. Employing a survey distributed across most of the U.S., we determined that both monetary and non-monetary incentives are generally effective in shifting willingness to participate in a smart charging program. We found that respondents, especially EV owners/lessees and EV interested buyers/lessees, were largely receptive to smart charging programs. When just considering monetary incentives, an incentive of $300 to $400 per year is sufficient for the majority of EV owners/lessees or EV interested buyers/lessees to definitely or probably participate in smart charging.

Through discrete choice modeling, we found that the willingness of the three groups to sign-up and participate in a smart charging program was significantly impacted by the attributes of the program. Monetary incentives and guaranteed battery level or ride were particularly impactful for EV owner/lessees and EV interested buyers/lessees in increasing participation. Free charging equipment increased participation across all groups. Meanwhile, penalties for non-participation or excessive opted-out sessions decreased willingness for the two EV groups. These statistically significant results come with a very important caveat. Mixed logit models revealed that heterogeneity of these attributes exists across all three samples. The implications are that some people may actually experience an opposite influence depending on the standard deviation of the attribute coefficient. Described in another way, not all people in the sample will react the same to the program attributes. This adds a layer of complexity to smart charging program design.

To add more complexity, demographic variables had differing effects on willingness, indicating that the manager of a program may want to advertise the program to specific groups. Young adults (under 35) were more likely to participate across two groups of people (interested EV buyers/lessees and general population). However, households without children were less likely to participate across all three groups. Sole transportation decision-makers were more willing to participate for the two EV groups, while women in the EV interested buyer/lessee group and the general population group were less willing. Each of the models also had unique variables, indicating some differences among EV owners/lessees, EV interested buyers/lessees, and the general population. When conducting the sample enumeration, we found diminishing returns for each invested $50 per year for both EV groups. Moreover, participation rates differ among combinations of different incentives, which indicates that program attributes need to be thoughtfully considered to increase sign-ups. Marginal effects analysis displayed the relative strength of program characteristics compared to most demographic variables. In addition, elasticities for the monetary incentives displayed a positive although relatively small effect (i.e., inelastic) on the likelihood to select a smart charging program.

The results, both discrete choice and sample enumeration, indicate that a third-party operator would have to make tradeoffs in developing a smart charging program. While equipment would be expensive to provide by a third party, it might encourage EV interested buyers/lessees to use smart charging, as Level 2 charging installation at home can cost around $2,000 (Kurczewski, 2022). Guaranteed rides/charges would increase willingness to participate, but the coordination of rides and recharging might be challenging. For example, a third party would need a mechanism to reimburse drivers for their ride (which can be taken via public transit, ridesourcing/ridehailing, etc.), operate a fleet of mobile charging vehicles, or contract with a towing or roadside assistance service. Alternatively, a guaranteed battery level that is too high might render a smart charging program ineffective since there is no temporal opportunity to shift charging. Monetary incentives would be an easy mechanism to calculate costs, but they have a limited impact on willingness due to diminishing returns and inelastic effects. Finally, penalties decrease willingness to participate, but they may be necessary for the third party to maintain consistency and profits in a smart charging program. Adding more nuance, the heterogenous responses from the different groups indicate that people may react in the opposite direction to certain program attributes. These random effects are important to note as they will likely cause a lower sign-up rate than what is expected by third parties.

While incentives increase participation in our models for the two EV groups, results also suggest that a small but sizable number of both EV owners/lessees (26%) and EV interested buyers/lessees (14%) would definitely participate in smart charging without receiving any monetary incentives. Interestingly, when focusing solely on incentives from $0 to $1000 (in Section 5.2), we found that there also are diminishing returns when considering "definite" and "probable" participants of smart charging programs. This confirms the general trend in the sample enumeration results. In this way, we found that monetary incentives have a limit. The general population remains largely skeptical of smart charging programs and incentives with 38% saying they would definitely not participate with even a $1,000 incentive per year.

Altogether, these overarching results from our research suggest that a third-party operator could successfully develop a cost-effective smart charging program that shifts charging behavior, maintains strong participation, and decreases peak electricity demand. To answer this paper's title questions, incentives do make a difference in smart charging adoption. However, monetary and other types of incentives have limits, which suggests that universal opt-in will be hard to achieve, at present. While specific nuances of a program require piloting, the benefits of a smart charging program to consumers, utilities, and other stakeholders would be significant and worthwhile.

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8) Author Contribution

Stephen Wong: Conceptualization, Methodology, Formal analysis, Investigation, Writing - Original Draft, Writing - Review & Editing; **Susan Shaheen:** Conceptualization, Methodology, Writing - Review & Editing, Supervision, Project administration, Funding acquisition; **Elliot Martin:** Conceptualization, Methodology, Writing - Original Draft, Supervision, Project administration; **Robert Uyeki:** Conceptualization, Methodology, Writing - Review & Editing, Supervision, Project administration, Funding acquisition,

9) Appendix

Key Survey Question: Demand Response Participation – Full Prompt
In this scenario, you own a battery electric vehicle (BEV). You have the opportunity to participate in a demand response program. In this program, you will use an app on your smartphone to set a charging schedule (i.e., when the car must be ready for use) as well as the desired state of charge (i.e., 90% charged). Using this information, a third party will choose when your vehicle charges to match when electricity demand is low and the availability of renewable energy is high. At any point in time, you can override the charging decisions made by the V1G program.

If an error occurs during charging and you do not have sufficient charge at your scheduled departure time, you will be reimbursed for a ride through a ridesourcing company (Uber/Lyft) or a taxi. For your participation in the program, you will receive a yearly incentive.

Please select how likely you would be to participate in the demand response program for each of the following incentive levels. The incentive amount shown is how much you will be paid per year to participate in the V1G program.

10) References

ACS. (2020). American Community Survey 5-Year Estimates. US Census Bureau. https://data.census.gov/ce

Al-Obaidi, A., Khani, H., Farag, H. E. Z., & Mohamed, M. (2021). Bidirectional smart charging of electric vehicles considering user preferences, peer to peer energy trade, and provision of grid ancillary services. International Journal of Electrical Power & Energy Systems, 124, 106353. https://doi.org/10.1016/j.ijepes.2020.106353

Alvarez, J., Marcos, J., Lago, A., Nogueiras, A. A., Doval, J., & Penalver, C. M. (2003). A fully digital smart and fast lead-acid battery charge system. IEEE 34th Annual Conference on Power Electronics Specialist, 2003. PESC ’03., 2, 913–917 vol.2. https://doi.org/10.1109/PESC.2003.1218177

Asensio, O. I., & Delmas, M. A. (2016). The dynamics of behavior change: Evidence from energy conservation. Journal of Economic Behavior & Organization, 126, 196–212. https://doi.org/10.1016/j.jebo.2016.03.012

Axsen, J., Goldberg, S., & Bailey, J. (2016). How might potential future plug-in electric vehicle buyers differ from current “Pioneer” owners? Transportation Research Part D: Transport and Environment, 47, 357–370. https://doi.org/10.1016/j.trd.2016.05.015

Ayre, J. (2017, November 24). Top State In US For Electric Vehicle Concentrations [Blog]. CleanTechnica. https://cleantechnica.com/2017/11/24/top-state-us-electric-vehicle-concentrations-california/

Bailey, J., & Axsen, J. (2015). Anticipating PEV buyers’ acceptance of utility controlled charging. Transportation Research Part A: Policy and Practice, 82, 29–46. https://doi.org/10.1016/j.tra.2015.09.004

Ben-Akiva, M. E., & Lerman, S. R. (1985). Discrete Choice Analysis: Theory and Application to Travel Demand. MIT Press.

Blair, B., Fitzgerald, G., & Dougherty, C. (n.d.). The State of Managed Charging in 2021. https://sepapower.org/resource/the-state-of-managed-charging-in-2021/

BMW. (2020). BMW ChargeForward: Electric Vehicle Smart Charging Program (pp. 1–47). BMW of North Ameirca, LLC. https://bmwchargeforwardreport.com/assets/BMW-ChargeForward-Report-R4-070620-ONLINE.pdf

BMW Group. (2021, March). BMW Group and PG&E Plug-In to Leverage Renewable Energy and Sustainably Power Electric Vehicles. https://www.press.bmwgroup.com/usa/article/detail/T0328209EN_US/bmw-group-and-pg-e-plug-in-to-leverage-renewable-energy-and-sustainably-power-electric-vehicles?language=en_US

Brown, M., Coe, S., Malme, R., Schare, S., Wikler, G., Pustinger, R., Maslowski, R., & Quinn, D. (2017). Evolution of Demand Response in the United States Electricity Industry. PLMA. https://www.peakload.org/assets/dr-dialogue/Evolution-of-DR-White-Paper.pdf

California Center for Sustainable Energy. (2013). California Plug-in Electric Vehicle Owner Survey. California Center for Sustainable Energy. https://cleanvehiclerebate.org/sites/default/files/docs/nav/transportation/cvrp/survey-results/California_PEV_Owner_Survey_Report.pdf

Cenex. (2021). Project Sciurus Trial Insights: Findings from 300 Domestic V2G Units in 2020. Cenex. https://www.cenex.co.uk/app/uploads/2021/05/Sciurus-Trial-Insights.pdf

ChargePoint. (2022). Smart Charging Stations. ChargePoint. https://www.chargepoint.com/en-ca/products/commercial

Clairand, J.-M., Rodríguez-García, J., & Álvarez-Bel, C. (2018). Smart Charging for Electric Vehicle Aggregators Considering Users’ Preferences. IEEE Access, 6, 54624–54635. https://doi.org/10.1109/ACCESS.2018.2872725

Coignard, J., Saxena, S., Greenblatt, J., & Wang, D. (2018). Clean vehicles as an enabler for a clean electricity grid. Environmental Research Letters, 13(5), 054031. https://doi.org/10.1088/1748-9326/aabe97

Con Edison. (2022). Electric Vehicle Charging Rewards | Con Edison. https://www.coned.com/en/save-money/rebates-incentives-tax-credits/rebates-incentives-tax-credits-for-residential-customers/electric-vehicle-rewards

CPUC. (2022a). Demand Response History in California. https://www.publicadvocates.cpuc.ca.gov/general.aspx?id=1422

CPUC. (2022b). Energy Division Resolution (E-5192). California Public Utilities Commission. Retrieved May 24, 2022, from https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M456/K322/456322989.PDF

Delmonte, E., Kinnear, N., Jenkins, B., & Skippon, S. (2020). What do consumers think of smart charging? Perceptions among actual and potential plug-in electric vehicle adopters in the United Kingdom. Energy Research & Social Science, 60, 101318. https://doi.org/10.1016/j.erss.2019.101318

Daina N, Sivakumar A, Polak JW, 2017, Electric vehicle charging choices: modelling and implications for smart charging services, Transportation Research Part C: Emerging Technologies, Vol: 81, Pages: 36-56, ISSN: 0968-090X

Dominion Energy. (2020). Smart Charging Infrastructure Pilot Program (pp. 1–3). Dominion Energy. https://www.dominionenergy.com/-/media/pdfs/virginia/save-energy/scip-faqs.pdf

DTE Energy. (2021). DTE Smart Charge (pp. 1–2). https://www.newlook.dteenergy.com/wps/wcm/connect/cc3f37d1-ab33-4c49-a4d8-47e6f3cba03e/SmartChargeBrochure.pdf?MOD=AJPERES

Enel X. (2022a). Fleet Charging Case Study. https://f.hubspotusercontent40.net/hubfs/4962241/_Commercial%20Content/Case%20Studies/091520-SMUDCaseStudy.pdf?__hstc=136157294.853ad149a379a7554db06db2d0fda1d5.1647370526237.1647370526237.1647370526237.1&__hssc=136157294.4.1647370526237&__hsfp=1843361320

Enel X. (2022b). JuiceBox Level 2 EV Charger & Charging Station | Enel X. https://evcharging.enelx.com/ca/en/products/juicebox

ENMAX. (2022). ENMAX EV charging program. https://www.enmax.com/ev

Frendo, O., Graf, J., Gaertner, N., & Stuckenschmidt, H. (2020). Data-driven smart charging for heterogeneous electric vehicle fleets. Energy and AI, 1, 100007. https://doi.org/10.1016/j.egyai.2020.100007

Gallo, A. (2014, November 19). A Refresher on Net Present Value. Harvard Business Review. https://hbr.org/2014/11/a-refresher-on-net-present-value

García-Villalobos, J., Zamora, I., San Martín, J. I., Asensio, F. J., & Aperribay, V. (2014). Plug-in electric vehicles in electric distribution networks: A review of smart charging approaches. Renewable and Sustainable Energy Reviews, 38, 717–731. https://doi.org/10.1016/j.rser.2014.07.040

Green, L., Fry, A. F., & Myerson, J. (1994). Discounting of Delayed Rewards: A Life-Span Comparison. Psychological Science, 5(1), 33–36. https://doi.org/10.1111/j.1467-9280.1994.tb00610.x

GreenFlux. (2022). GreenFlux Smart Charging. GreenFlux. https://www.greenflux.com/

Henriksen, I. M., Throndsen, W., Ryghaug, M., & Skjølsvold, T. M. (2021). Electric vehicle charging and end-user motivation for flexibility: A case study from Norway. Energy, Sustainability and Society, 11(1), 44. https://doi.org/10.1186/s13705-021-00319-z

Hilo. (2022). Pilot project: Smart Charging. Hilo. https://www.hiloenergie.com/en-ca/pilot-project-smart-charging/

Huber, J., & Weinhardt, C. (2018). Waiting for the sun—Can temporal flexibility in BEV charging avoid carbon emissions? Energy Informatics, 1(1), 49. https://doi.org/10.1186/s42162-018-0026-2

International Energy Agency. (2022, May 30). Global EV Outlook 2022. IEA. https://www.iea.org/reports/global-ev-outlook-2022/executive-summary

Jargstorf, J., & Wickert, M. (2013). Offer of secondary reserve with a pool of electric vehicles on the German market. Energy Policy, 62, 185–195. https://doi.org/10.1016/j.enpol.2013.06.088

Jia, W., & Chen, T. D. (2021). Are Individuals' stated preferences for electric vehicles (EVs) consistent with real-world EV ownership patterns? Transportation Research Part D: Transport and Environment, 93, 102728. https://doi.org/10.1016/j.trd.2021.102728

Kempton, W., & Letendre, S. E. (1997). Electric vehicles as a new power source for electric utilities. Transportation Research Part D: Transport and Environment, 2(3), 157–175. https://doi.org/10.1016/S1361-9209(97)00001-1

Kiviluoma, J., & Meibom, P. (2011). Methodology for modelling plug-in electric vehicles in the power system and cost estimates for a system with either smart or dumb electric vehicles. Energy, 36(3), 1758–1767. https://doi.org/10.1016/j.energy.2010.12.053

Kurczewski, N. (2022, March 29). How Much Does it Cost to Charge an Electric Car? Kelley Blue Book. https://www.kbb.com/car-news/how-much-does-it-cost-to-charge-an-ev/

Lancsar, E., & Louviere, J. (2006). Deleting 'irrational' responses from discrete choice experiments: A case of investigating or imposing preferences? Health Economics, 15(8), 797–811. https://doi.org/10.1002/hec.1104

Latinopoulos C, Sivakumar A, Polak JW, 2017, Response of electric vehicle drivers to dynamic pricing of parking and charging services: risky choice in early reservations, Transportation Research Part C: Emerging Technologies, Vol: 80, Pages: 175-189, ISSN: 0968-090

Lopes, J. A. P., Soares, F. J., & Almeida, P. M. R. (2010). Integration of electric vehicles in the electric power system. Proceedings of the IEEE, 99(1), 168-183.

Lyon, T. P., Michelin, M., Jongejan, A., & Leahy, T. (2012). Is “smart charging” policy for electric vehicles worthwhile? Energy Policy, 41, 259–268. https://doi.org/10.1016/j.enpol.2011.10.045

Mallette, M., & Venkataramanan, G. (2010). Financial incentives to encourage demand response participation by plug-in hybrid electric vehicle owners. 2010 IEEE Energy Conversion Congress and Exposition, 4278–4284. https://doi.org/10.1109/ECCE.2010.5618472

Muehlegger, E., & Rapson, D. (2018). Understanding the Distributional Impacts of Vehicle Policy: Who Buys New and Used Alternative Vehicles? https://escholarship.org/uc/item/0tn4m2tx

Multi-State ZEV Task Force. (2018, August 2). About the ZEV Task Force. https://www.zevstates.us/about-us/

Niesten, E., & Alkemade, F. (2016). How is value created and captured in smart grids? A review of the literature and an analysis of pilot projects. Renewable and Sustainable Energy Reviews, 53, 629–638. https://doi.org/10.1016/j.rser.2015.08.069

Noel, L., Zarazua de Rubens, G., Kester, J., & Sovacool, B. K. (2019). History, Definition, and Status of V2G. In L. Noel, G. Zarazua de Rubens, J. Kester, & B. K. Sovacool (Eds.), Vehicle-to-Grid: A Sociotechnical Transition Beyond Electric Mobility (pp. 1–31). Springer International Publishing. https://doi.org/10.1007/978-3-030-04864-8_1

Nova Scotia Power. (2022). Electric Vehicle Smart Charging Pilot. Default. https://nspower.ca/cleanandgreen/innovation/smart-grid-nova-scotia/chargepoint-home-flex-ev-charging-system

Parsons, G. R., Hidrue, M. K., Kempton, W., & Gardner, M. P. (2014). Willingness to pay for vehicle-to-grid (V2G) electric vehicles and their contract terms. Energy Economics, 42, 313–324. https://doi.org/10.1016/j.eneco.2013.12.018

Pearre, N. S., & Ribberink, H. (2019). Review of research on V2X technologies, strategies, and operations. Renewable and Sustainable Energy Reviews, 105, 61–70. https://doi.org/10.1016/j.rser.2019.01.047

Plug ’N Drive. (2022). Electric Vehicle (EV) Smart Charging Pilot Program. Plug’n Drive. https://www.plugndrive.ca/electric-vehicle-smart-charging-pilot-program/

Pratt, R. M., & Bernal, L. E. (2018). Distribution System V1G PEV Charging Impacts Report (PNNL-27206). Pacific Northwest National Lab. (PNNL), Richland, WA (United States). https://doi.org/10.2172/1480851

Richardson, D. B. (2013). Electric vehicles and the electric grid: A review of modeling approaches, Impacts, and renewable energy integration. Renewable and Sustainable Energy Reviews, 19, 247–254. https://doi.org/10.1016/j.rser.2012.11.042

SCE. (2022). Charge Ready. Southern California Edison. https://www.sce.com/evbusiness/chargeready

Schmalfuβ, F., Mair, C., Dobelt, S., Kampfe, B., Wustemann, R., Krems, J. F. & Keinath, A. (2015). User responses to a smart charging system in Germany: Battery electric vehicle driver motivation, attitudes and acceptance. Energy Research & Social Science. 9 (2015), 60-71.

SDG&E. (2022). Electric Vehicle Pricing Plans | San Diego Gas & Electric. https://www.sdge.com/residential/pricing-plans/about-our-pricing-plans/electric-vehicle-plans

Shahan, Z. (2017, May 4). US Electric Car Sales By State—Who's #1, Ohio Or California? CleanTechnica. https://cleantechnica.com/2017/05/04/us-electric-car-sales-state-whos-1-ohio-california/

Shell. (2022). Shell RechargePlus: Managed Smart Charging for Electric Vehicles. https://www.shell.us/business-customers/shellrechargeplus.html

SmartCharge Rewards. (2022a). Join a SmartCharge Rewards Program. SmartCharge Rewards. https://www.smartchargerewards.com/sign-up/

SmartCharge Rewards. (2022b). SmartCharge Georgia. SmartCharge Georgia. https://www.smartchargerewards.com/georgia/

SmartCharge Rewards. (2022c). SmartCharge Nashville. https://www.smartchargerewards.com/nashville/

SmartCharge Rewards. (2022d). SmartCharge New Brunswick. SmartCharge Rewards. https://www.smartchargerewards.com/smartchargenewbrunswick/

SmartCharge Rewards. (2022e). SmartCharge PGE. SmartCharge PGE. https://www.smartchargerewards.com/smartchargepge/

Sovacool, B., Axsen, J., & Kempton, W. (2017). Utilities and Electric Vehicles: Evolving to Unlock Grid Value. SEPA. https://sepapower.org/resource/utilities-electric-vehicles-evolving-unlock-grid-value/

Sovacool, B. K., Noel, L., Axsen, J., & Kempton, W. (2018). The neglected social dimensions to a vehicle-to-grid (V2G) transition: A critical and systematic review. Environmental Research Letters, 13(1), 013001. https://doi.org/10.1088/1748-9326/aa9c6d

Spencer, S. I., Fu, Z., Apostolaki-Iosifidou, E. & Lipman, T. E. (2021). Evaluating smart charging strategies using real-world data from optimized plugin electric vehicles. Transportation Part D: Transport and Environment, 100 (2021), Article 103023.

Szinai, J. K., Sheppard, C. J. R., Abhyankar, N., & Gopal, A. R. (2020). Reduced grid operating costs and renewable energy curtailment with electric vehicle charge management. Energy Policy, 136, 111051. https://doi.org/10.1016/j.enpol.2019.111051

Tal, G., Raghavan, S., Karanam, V., Favetti, M., Sutton, K., Ogunmayin, J., Lee, J., Nitta, C., Kurani, K., Chakraborty, D., Nicholas, M., & Turrentine, T. (2020). Advanced Plug-In Electric Vehicle Travel and Charging Behavior Final Report (p. 184). UC Davis. https://web.cs.ucdavis.edu/~cjnitta/pubs/2020_03.pdf

Tomić, J., & Kempton, W. (2007). Using fleets of electric-drive vehicles for grid support. Journal of Power Sources, 168(2), 459–468. https://doi.org/10.1016/j.jpowsour.2007.03.010

Train, K. E. (2009). Discrete Choice Methods with Simulation. Cambridge University Press.

Ueckerdt, F., Brecha, R., & Luderer, G. (2015). Analyzing major challenges of wind and solar variability in power systems. Renewable Energy, 81, 1–10. https://doi.org/10.1016/j.renene.2015.03.002

U.S. Department of Energy. (2015). Final Technology Performance Report: Pecan Street Smart Grid Demonstration Program. U.S. Department of Energy. https://www.energy.gov/sites/prod/files/2016/12/f34/Pecan-Street-SGDP-FTR_Feb_2015.pdf

U.S. Department of Energy. (2022). Alternative Fuels Data Center: Maps and Data—U.S. Plug-in Electric Vehicle Sales by Model. https://afdc.energy.gov/data/10567

Wang, J., Liu, C., Ton, D., Zhou, Y., Kim, J., & Vyas, A. (2011). Impact of plug-in hybrid electric vehicles on power systems with demand response and wind power. Energy Policy, 39(7), 4016–4021. https://doi.org/10.1016/j.enpol.2011.01.042

Wang, Y., Li, J., Jiang, J., & Niu, L. (2005). Management information system of charging station for electric vehicle (EV). 2005 International Conference on Electrical Machines and Systems, 1, 857-860 Vol. 1. https://doi.org/10.1109/ICEMS.2005.202660

Washington, S. P., Karlaftis, M. G., & Mannering, F. (2010). Statistical and Econometric Methods for Transportation Data Analysis, Second Edition. CRC Press.

Will, C. & Schuller, A. (2016). Understanding user acceptance factors of electric vehicle smart charging. Transportation Research Part C: Emerging Technologies, 71 (2016), 198-214.

Xcel Energy. (2021, September 30). Xcel Energy announces new electric vehicle smart charging pilot with automakers | Press Releases | Xcel Energy. https://co.my.xcelenergy.com/s/about/newsroom/press-release/xcel-energy-announces-new-electric-vehicle-smart-charging-pilot-with-automakers-MCAMWGE6254FFLNEAWSFYXMYBQA4

Zhang, T., Pota, H., Chu, C. & Gadh, R. (2018). Real-time renewable energy incentive system for electric vehicles using prioritization and cryptocurrency. Applied Energy, 226 (2018), 582-594.