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Understanding EV Owners' Preferences Towards Enrolling in Smart Charging Programs

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ABSTRACT

Demand for electricity has been increasing in recent years, bolstered by growing adoption of electric vehicles (EVs). To smooth demand at peak periods, under demand response or "smart-charging" programs, power utilities can make electric vehicles extend or delay their charging. An EV owner can save money on their power bill by opting into such programs. However, it is not well known if EV owners would actually be willing to opt-in, given the radically different refuelling model between non-EVs and EVs. This investigation attempts to better understand EV owners' preferences towards enrolling in a particular smart charging program. We do this by constructing an adaptive contingent valuation survey that assesses savings amounts, among other variables. Through this method, we are able to quantify that more than half of EV owners are willing to participate in "smart-charging" for low monthly savings of five dollars or less.

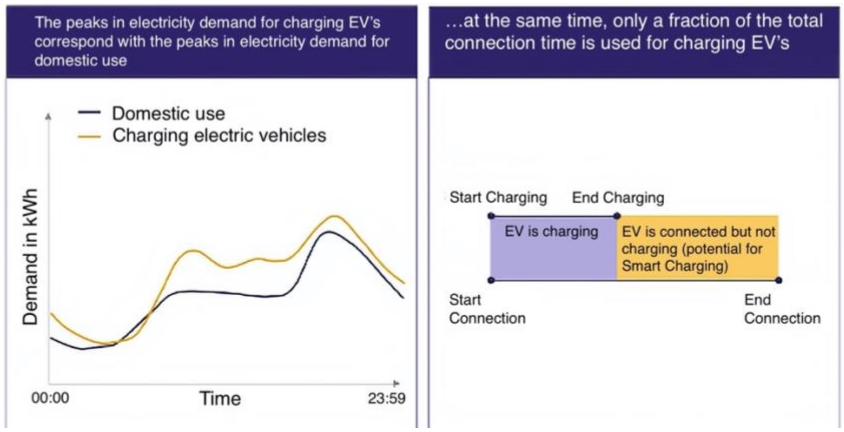
Introduction

The decision to acquire an electric vehicle (EV) involves two principal costs: the fixed cost of purchasing or leasing the vehicle along with any desired at home charging equipment and the variable or continuous cost of recharging the vehicle. At the moment, the cost of purchasing an electric vehicle is considerably higher than the cost of a purchasing a non-EV. The variable cost of recharging an electric vehicle, however, becomes comparable to paying for petrol for a non-electric car, which at times has even dipped below the cost of regular unleaded petrol. This presents a unique set of choices for consumers interested in purchasing or leasing a vehicle, who will be guided by a set of preferences. Before analysing these, it is important to recognize the aggregate effect of electric vehicles in energy grids.

Electric vehicles represent a large shock to the demand for energy. Some scholars estimate that if every driver in the US would switch from a gas-powered car to an EV, that the total electricity demand would increase by 25% (Faisal and Eatzaz 2011), with others estimating a higher increase of 50% in some regions (Davidson et al. 2019). Automobile manufacturers, such as Tesla, Nissan, and Chevrolet are fuelling this shift, empowered by incentives to reduce carbon emissions, along with the lower costs associated with maintaining car engines with fewer moving parts. Demand for energy is rising increasingly and with no sign of stopping, it is imperative that stakeholders in electricity and energy grids along the supply chain prepare themselves appropriately.

A novel approach to tackling this challenge is through demand response or managed charging programs. Under electric vehicle demand response programs, power companies send signals (through communication channels, such as mobile data networks) to charging EVs to smooth the aggregate demand of energy over a period of time. Depending on energy demand, electricity prices, and the potential to provide ancillary grid services, EVs can shift their charging schedule to reduce the cost of EV charging. The default charging option for EVs is typically the maximum rating of the charger. Therefore, when an EV owner/operator enrols in a demand response program, the net result is that the vehicle takes longer to complete a full charge. The additional time required is random but can easily be constrained by the owner/operator. A graphical demonstration of energy usage in a demand response program with EVs in provided in Figure 1-1.

Figure 1-1. Daily Electricity Demand and EV Charging



Smart Charging is a method to determine the optimal charging times for EV's such that the grid peak load is reduced while meeting the overall electricity demand.
Source: Youssef El Bouhassani, Retrieved from http://www.idolaad.nl/gedeelde-content/blogs/youssef-el-bouhassani/2018/pinpointing-the-smart-charging-potential.html

Although there has been technological progress through the development of EV-specific demand response programs, we do not completely know if electric vehicle owners would actually be willing to enrol in these. Electric vehicles do not recharge as quickly as regular non-electric cars refuel their gas tanks. Refuelling a regular non- electric car only takes a 5 to 15-minute visit to a petrol station. However, fully charging an EV can take anywhere from under 30 minutes to over a third of a day, depending on charging infrastructure, rate, and battery size. This fact leads to a prevalence of evening charging for electric vehicles (Weiller 2011), (Harris and Weber 2014), (Morrisey et al 2016). During the night, EV owners leave their vehicles plugged in while they sleep. In fact, a majority of electric vehicle owners are expected to charge their vehicles overnight (Duvall 2010), (Yilmaz and Krein 2013). Evidently, there is clearly a dissonance between the refuel/recharge finish times between regular cars and EVs. Demand response programs can extend the charge times for EVs as power to the vehicle may be curtailed for extended periods, further widening this gap. Because of this, it is not clear if EV owners would readily enrol in demand response programs. The influence of knowledge of the existence of demand response programs in the decision of purchasing an EV is also unknown.

This investigation attempts to provide insight into determining the factors that could lead potential EV owners to be willing to be opt in to demand response programs. We do this by constructing and delivering a contingent valuation survey. In this survey, we ask respondents questions meant to elicit their willingness to enrol in a demand response program. We repeatedly asked respondents to answer this question while increasing or decreasing the amount of money they would save on a monthly basis. This savings amount is described simultaneously with the estimated monthly cost of charging an EV, calculated according to the respondent's commuting profile. Ultimately, we are able to quantify bounds of the monetary value that respondents assigned to having their charging EV enrolled in a hypothetical demand response program.

Related Work

Demand response is a term used to describe a group of technologies that allow power companies to control periodic rises in the demand for electricity that may be hard to meet. For example, if a power utility is experiencing an unexpected rise in demand for electricity in a certain region, it may send signals for devices with low usage priority in that region to power down. In (Albadi and El-Saadany 2008) researchers elaborate on the use of demand response within different contexts and system scales. The authors describe tangible benefits of demand response programs here, along with the daily dynamics of electricity pricing through a simulated case study. Demand response has gained prevalence in recent years due to the steady increase of demand for electric energy and power companies' challenge to supply this demand. The urgency of the energy crisis is illustrated in (Schmidt 2017). Here, researchers expose figures regarding energy dynamics within the United States, underscoring projections of the impact of electric vehicles. A stark finding is that the Sacramento Municipality Utility District has recognized that about 17% of the company transformers may need to be replaced as a result of EV-related overloads, at a mean cost of $7,400 per electric transformer. Researchers conduct special analysis considering the ability of electrical vehicles to provide stability to the grid if dynamic charging systems for EVs are properly and sustainably implemented. They present the figure that EVs in demand response environments can lower the speed and voltage fluctuation in a grid by up to 80% and also extend critical clearing times (which are the times in which the grid remains stable despite peak demand) by 20-40%.

Although EVs can strain infrastructure and increase electricity costs, EVs can also provide support to the electric grid in the future and help reduce total system costs. With customer consent, EV charge controllers can shift EV charging towards periods of low demand or low electricity prices; this flexibility could also be managed by aggregators and offered as capacity or ancillary services in wholesale markets. In some cases, vehicles could even discharge power to serve the grid; this is referred to as vehicle-to-grid (V2G) power. V2G power is a type of demand response technology since it can provide further supply of energy to homes, businesses, or the local distribution grid in times of peak demand. This facilitates the alignment of supply and demand in the energy market, allowing for more efficient energy prices. Moreover, outfitting EVs with V2G abilities allows for the theoretical reduction of the total cost of an EV since V2G owners may be compensated for power reserve support. In turn, this would allow for the closer approximation of the cost of owning an EV over time to the cost of owning a non-electric car over time. A Toyota RAV4 EV could generate almost $2,554 on a yearly basis by providing reserve service to the grid (Kempton and Tomic 2005). In an Indonesia-based investigation, researchers estimated that providing such ancillary services could even reduce the cost of charging by over half (Huda and Koji 2020)

In one study, researchers estimated the willingness of consumers to pay for V2G EVs with contract requirements (Parsons et al. 2014). These contract terms stipulated a required "plug-in time" and "guaranteed minimum driving range". These contract terms would assure that V2G EVs could provide a form of reserve power to the electric grid while giving the owners of these vehicles the security of having a guaranteed minimum charge. Researchers administered a web-based stated preference survey to U.S. households with choice experiments and contingent valuation. The data were used to develop an estimate for consumers' willingness to pay for conventional electric vehicles with no V2G capability. This paper claims to be the first to empirically evaluate whether V2G power makes EVs seem more attractive on the market, finding that contract requirements are unlikely to make V2G power competitive under current market conditions. To counter this, other contract approaches are proposed.

In another related paper (Will and Schuller 2016), researchers focused on relating consumer behaviour with "smart charging" for EVs. Specifically, they sought to understand how users perceive control interventions in their charging behaviour and what are the main factors fuelling the acceptance of a "smart charging" program. With data obtained from 237 early adopters of EVs in Germany, the authors identified significant correlations between pertinent factors of smart charging acceptance. They found that German early adopters would accept smart charging more if they understood that it contributed to increased grid stability.

Other studies cover the current electric vehicle market in the United States, along with financial and network incentive dynamics. (Li 2016), develops and estimates the structural model of vehicle demand and charging network investment to quantify the impact of a uniform charging standard for EVs. (Clinton and Steinberg 2016) estimates the effects of financial incentives for purchasing electric vehicles on actual buying rates. (Holland et al. 2016) conducts a choice experiment for new EV purchases, highlighting results through the lens of environmental benefits through reduced emissions. (Li et al. 2017) analyses network effects in the electric vehicle market to better frame policies that finance EV charging station deployment.

(T&D World 2016) represents a study of one of the first demand response technologies implemented by an auto manufacturer and a power utility in the real world. In this investigation, BMW partners with a California-based utility, PG&E (Pacific Gas and Energy), to test a demand response pilot program. In this program, San Francisco Bay area BMW i3 electric vehicle owners opt-in to allow PG&E to adjust the charging rate of their EVs when the grid becomes saturated with electric demand. The BMW i3 vehicles are controlled through a cellular network-based control system. Researchers highlight successes in reducing electric demand at target levels yet recognize the necessity of testing the system at a larger scale. On another front, (Castelvecchi 2015) introduces the potential of augmenting the stability and capacity of the electric grid by incorporating energy storage points manufactured by Tesla along the grid.

Although demand response technologies have the potential to smooth demand in times of peak grid usage, it is not certain if electric vehicle owners would be willing to participate. If EV owners are able to accrue savings on their monthly electric bills by participating in demand response programs, theoretically there should be a minimum savings amount someone would require in order to participate. To estimate minimum savings for EV owners to participate in demand response technologies, contingent valuation can be an appropriate method. Contingent valuation is a survey-based economic method that involves the use of sample surveys (questionnaires) to elicit the willingness of respondents to pay for hypothetical projects or programs (Portney 1994). There are many forms of conducting contingent valuation surveys, which generally depend on the way questions are asked.

In *open ended* contingent valuation questions, respondents are asked to directly value a certain good or program (e.g. What is the max you would pay for x good?).

In *referendum* contingent valuation, respondents are asked a series of binary questions to mark preference (e.g. Under this new law, taxes would increase by $20 for good x. Will you vote for this proposal? “Yes” and “No” are the only possible answers). Next, in *payment card* contingent valuation, respondents are presented with a field with a series of numbers representing valuations. For example, given a series of numbers from $0 to $100, participants may be asked to identify which are the highest amounts of which they would be willing to pay for a particular good.

Finally, there is *bidding* contingent valuation. Under bidding, a survey presents respondents with a quantified valuation of a good, program or service. The participant would then be asked if they would be willing to accept or deny the good at the given price level. If the method is increasing bidding and the participant denies, the survey asks the participant the same question but, instead, increases the price amount. This process is repeated in increasing bidding until either the participant accepts a given price or denies at an established upper price bound. Under decreasing bidding, the survey asks a respondent to accept or deny a good or service at a given price. If the respondent denies, the bidding immediately ends. If the respondent accepts, the survey continues with a lower price at each round until either a lower bound is reached or the participant accepts a price. Bidding contingent valuation differs from referendum contingent valuation by repeating questions with different valuations as opposed to focusing on a single question with a single valuation.

This investigation differentiates itself from the presented works by focusing on a specific objective: monetarily quantifying the willingness of EV owners to opt- in to demand response programs. We attempt to understand how much a person would need to save on their monthly power bill in order to opt into a demand response program that would lead their EV to finish charging at a later time, closer to their morning commute departure time. We explore the effects of changes in EV charging finish times on a person’s willingness to enrol their EV in demand response. Furthermore, we explore the effect of the choice of a label for a demand response program on the willingness to enrol. We also test how knowledge of demand response within the context of electric vehicles affects a person's intention on purchasing or leasing an electric vehicle for their next vehicle acquisition.

Technical Approach

We conducted a web-based, stated preference survey in 2018. The survey was distributed to United States residents across the entire country through the Amazon MTurk platform and through a link shared in various EV Owner Facebook groups. The survey included a set of choice experiments: one evaluating the amount of money required to enrol the charging of an EV to a demand response program and another covering the effect of knowledge of EV demand response charging on the choice of a future vehicle. In this process, we tested how the choice of name of the demand response program affected the willingness of respondents to enrol. In addition, we studied the sensitivity of enrolment with respect to the proximity of the charging finish time to the time in which a respondent would begin their daily commute. We also evaluated the effect of our survey and the knowledge of alternative or smart charging of EVs imparted by our survey on respondents' desire to acquire an electric vehicle for their next vehicle purchase or lease.

The survey began by asking respondents to identify their current commuting profile. If respondents drove a vehicle at least once a week, they were required to share their estimated daily total driving time and daily total mileage. The survey then asked all respondents to specify the time at which they left their homes to begin their commutes and the time at which they arrived at their household after completing daily obligations and responsibilities. We also asked respondents to share the earliest time that they left their household to begin their commute in a typical week.

After respondents had identified their commuting profile, the survey performed a choice experiment between regular EV charging and demand response EV charging, applying bidding contingent valuation. This choice is based on similar choice experiments in (Portney 1994) and (Parsons et al. 2012). In this section, we asked respondents to envision that they had just purchased an electric vehicle. We informed them that the next series of questions would involve choosing between two options for charging their EV at home. If respondents had previously indicated that they never drove a vehicle to commute, they were asked to imagine a certain scenario before the following questions. Specifically, they were asked to imagine that they commuted 30 miles on a daily basis, taking a total of 50 minutes of time (15 miles/ 25 minutes each-way), reflecting the average commute in the US according to the US Census Bureau.

After the survey had informed respondents of the question conditions, it followed with the first question of bidding contingent valuation. In this question block, a table appeared comparing the consequences of choosing between two distinct charging options for an EV. The first charging option was the regular option, with no effects of demand response. The second option involved enrolling a charging EV into a demand response program. Precisely, the table displayed the differences regarding the type of charging, the completion of charging, and monthly cost of charging. Below this table, a few sentences offered a summary of these differences, highlighting the difference in cost and time, before asking for a preference between the two charging options. **Figure 3-1** and **Figure 3-2** illustrate sample questions.

Figure 3-1. Sample contingent valuation bidding question, asking respondent to choose between "Option A" and "Option B" charging options

	Option A	Option B
Charging Type	Car charges immediately when plugged in	Car charges when electricity is inexpensive
Charging Completion	Car is finished charging **1.3 hour(s) after you arrive home**, approximately by **6:15PM**	Car is finished charging by **7:00AM, one hour** before you typically leave in the morning.
Monthly Cost	**$25.16**	**$5.16**

Option A charges your vehicle immediately, while Option B charges your vehicle when electricity is less expensive. Under Option B, you save $20 per month. Which option do you prefer?

Option A

Option B

Figure 3-2. Sample contingent valuation bidding question, asking respondent to choose between "Normal Charging" and "Smart Charging"

	Normal Charging	Smart Charging
Charging Type	Car charges immediately when plugged in	Car charges when electricity is inexpensive
Charging Completion	Car is finished charging **1.7 hour(s) after you arrive home**, approximately by **6:00PM**	Car is finished charging by **6:30AM, two hours** before you typically leave in the morning.
Monthly Cost	**$33.54**	**$13.54**

Normal Charging charges your vehicle immediately, while Smart Charging charges your vehicle when electricity is less expensive. Under Smart Charging, you save $20 per month. Which option do you prefer?

Normal Charging

Smart Charging

Randomization

Within the bidding contingent valuation, the questions respondents received varied in three fundamental ways. The first factor was the labelling of the two charging options. These were either “Regular Charging” and “Smart charging” or “Option A” and “Option B”. The second factor was the finish time of the alternate charging option (i.e. the option labelled "Smart charging" or "Option B"), which varied between one hour before the respondent’s previously indicated regular departure time from home and two hours before the regular departure time. The third and final factor was the savings incurred by choosing the alternate charging option. Under decreasing bidding contingent valuation, this savings amount began at $20 and decreased to $1.

Otherwise, under increasing bidding contingent valuation, the savings began at $1 and increased to $20. The intervals of savings between rounds of bidding contingent valuation are described **in Table 3.1**, along with a summary of all the variations in questions presented in the bidding contingent valuation section of the survey. We randomly selected one variation per row for each respondent, uniformly at random.

Table 3.1. Variations within contingent valuation questions. Each variation was independently randomly assigned among its two options.

Variation	First variation	Second Variation
Labels of charging options	“Regular Charging” and “Smart charging”	“Option A” and “Option B”
Finish time of alternate charging option	1 hour before indicated regular departure	2 hours before indicated regular departure
Savings amounts	$20, $15,$10, $5, $1	$1, $5, $10,$15,$20

We chose these variations to identify three distinct relationships. The first variation tested the effects of labelling of charging, while the second tested for time sensitivity. If one respondent was assigned decreasing bidding contingent valuation, the survey would continue asking them the same question while decreasing the amount of savings for smart charging/ option B. This would continue until the respondent indicated preference for the regular charging option/ option A OR the minimum savings amount was accepted. If the respondent was assigned increasing bidding contingent valuation, then the survey would finish once the respondent indicated preference for smart charging/ option B over regular charging/ option A or they preferred regular charging/ option A despite smart charging/ option B yielding an upper bound of savings of $20. Each variation was independently assigned to each respondent uniformly at random at the beginning of the survey.

The survey also asked respondents about their likelihood of purchasing or leasing an electric vehicle. The survey asked a set of questions to this purpose either towards the beginning of the survey (right after the introduction) or towards the end (after the conclusion of the bidding contingent valuation section). At the very end of the survey, all respondents were asked to identify their age group and income level. We chose to ask this question at the very end to prevent any induced bias respondents may have in internalizing a demographic quality. The survey flow can be closely observed in Figure 3-3.

Figure 3-3. Survey flowchart walkthrough

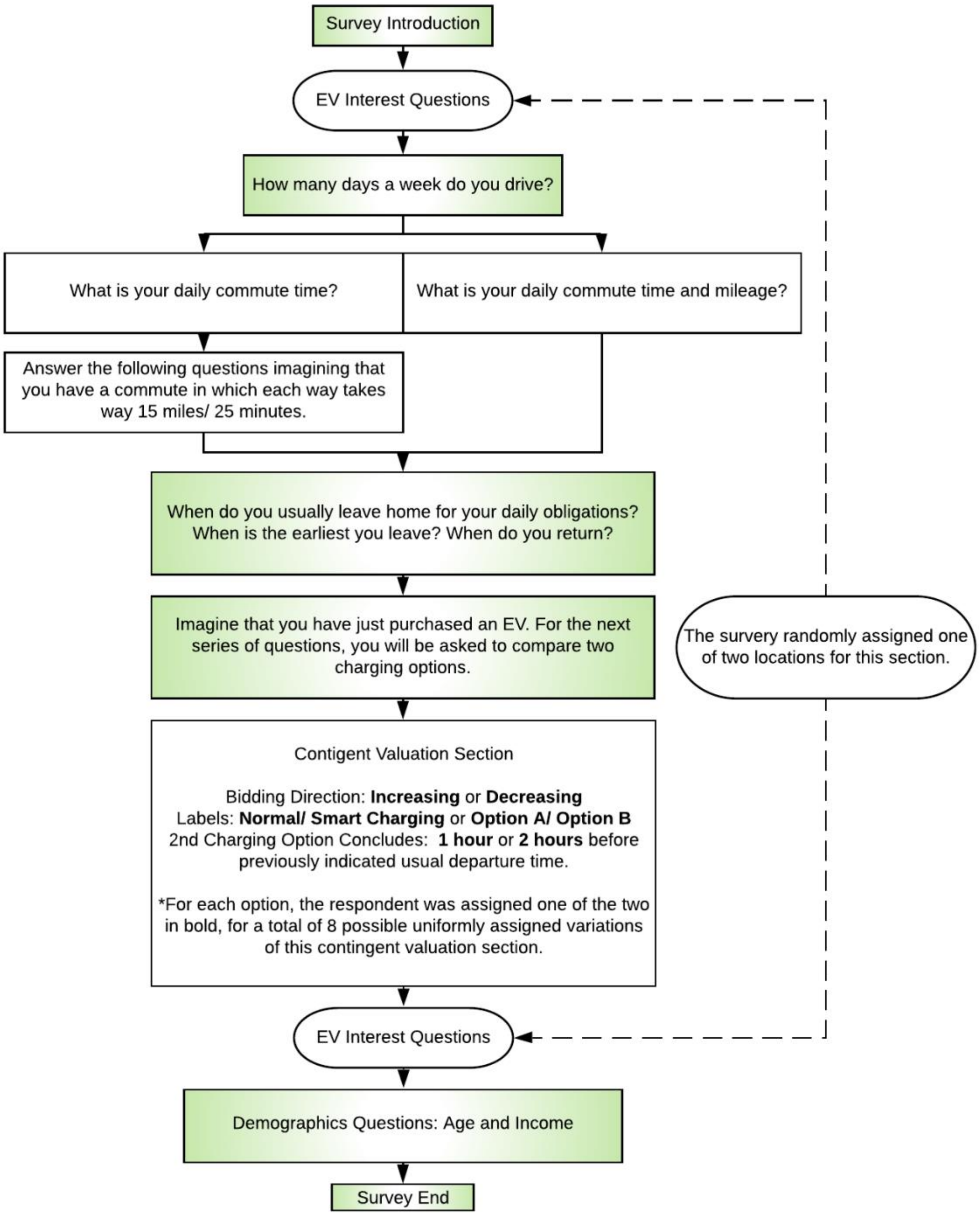


Table 3.2. Attributes used in charge cost and time calculations

Attributes	Values
Kilowatt hours per mile	$\frac{1}{3.5} \approx 0.29$ kWh per mile
Cost per kWh	\$0.27
Time to charge a kWh	$\frac{1}{3.3} = 0.\overline{30}$ hours per kWh
Default days commuted in a week	5 days
Default total daily commute distance	15 miles

Choice of Parameters and Attributes

Our choice of parameters, illustrated in **Table 3.2**, stem from specific reasoning and decisions. According to the United States Census Bureau American Community Survey Data of 2017, the average American's commute to work is 26.9 minutes and covers an average distance of 16 miles. We rounded these amounts to the nearest multiple of 5 in an effort to reduce the mental math a respondent would exercise in remembering these numbers. The measure of kilowatt hours of battery used up per mile travelled and the time to charge an EV battery one kilowatt hour stem from an approximate average in the current electric vehicle market.

The price of charging a kilowatt hour involved some considerations. The average annual price of electricity in the United States in 2019 was 12.86 cents per kilowatt hour, according to the U.S. Energy Information Administration. The states that have the lowest electricity prices, though, are comparatively more rural than the states' cities in which most electric vehicle owners are concentrated in. Here, the price of electricity is higher. The average annual price of electricity in New York is 14.78 cents per kilowatt hour, in California, 16.14 cents per kilowatt hour. In Hawaii, the annual average price of electricity reaches almost 30 cents per kilowatt hour.

We chose 27 cents per kilowatt hour in our study. This is approximately a high measure of the current retail price in Eastern Massachusetts, based on retail prices in coastal urban and suburban areas, where EV adoption is highest.

Calculation of Monthly Cost of Charging EV

The monthly cost of charging an EV was calculated in the following manner:

$$M = \delta * \mu * \kappa * \theta * \frac{\tau}{7}$$

δ represents the total distance covered in one day in miles (to and from commute destination). We multiply this amount by the number of kWh required to travel one mile ($\mu = \frac{1}{3.5}$), followed by multiplying by the cost of electricity of charging one kWh ($\kappa = 0.27$). This yields the daily cost of charging a vehicle for its total daily miles covered. To get the monthly cost, we then multiply this amount by the average number of days in a month ($\theta = \frac{365.25}{12}$)times the portion of days per week driven, represented by tau over 7.

Delivery of Survey

We delivered the survey to two different populations: 1) current electric vehicle owners and 2) US Residents on the Amazon Mechanical Turk (MTurk) platform. We sourced the electric vehicle owners by sending a link and short description of the survey and its purpose to various Facebook groups of EV owners in different regions in the United States. These electric vehicle owners voluntarily completed the survey without a monetary incentive. The MTurk respondents were offered $1 for completing the survey. The overwhelming majority of the MTurk respondents were not electric vehicle owners, since we only filtered for a location within the United States. We received 202 unique responses from the MTurk platform and 262 unique responses from electric vehicle owner Facebook groups. This gave us a total of 464 observations.

Results

Table 4.1. Summary of overall respondent observations

	Random Participants	Targeted Participants	All
N	202	241	443
% EV owners	4.29	95.02	55.98
% high EV interest	38.12	94.61	68.85
Daily VMT	44.11	24.67	35.25
VMT (Std. Dev.)	35.59	19.84	30.99
Est. Monthly Charging Cost	98.14	48.51	75.51
Cost (Std. Dev)	80.62	46.82	71.68
Median Earliest Departure Time	7:30 am	7:00 am	7:00 am
Range	[5:00 am, 4:00 pm]	[5:00 am, 5:15 pm]	[5:00 am,4:55 pm]
Median Normal Departure time	8:00 am	7:30 am	7:45 am
Range	[5:45 am, 3:00 pm]	[5:30 am, 12:00 pm]	[5:30 am,1:58 pm]
Median Return Time	5:15 pm	5:30 pm	5:30 pm
Range	[9:15 am, 7:59 pm]	[10:00 am, 8:00 pm]	[9:31 am,8:00 pm]
Median Income Group	$50,000 to $74,999	$100,000 to $149,999	$75,000 to $99,999

241 people responded to our survey targeted towards electric vehicle owners, which was distributed in various EV owner Facebook groups based in the United States. We classified this population as **targeted participants**. Targeted participants received no compensation for completing the survey and did so voluntarily. 202 people replied to our survey that was distributed to United States residents through the MTurk platform, who we classified as **random participants**. Random participants received $1 for completing the survey. Electric vehicle ownership was very high among the targeted population and very low among random participants, as expected, at 95% and 4%, respectively. A summary of the responses from both groups of respondents can be found in **Table 4.1**.

In this section, we present and evaluate the stated preferences of both random and targeted participants. We begin by evaluating participants' interest into purchasing or leasing an EV for their next vehicle acquisition. Afterwards, we classify participants' daily vehicle miles travelled (VMT) in an effort to assess how comparable participants' daily VMT is to the general US population's daily VMT. Then, we present the findings of the survey's contingent valuation to calculate the upper and lower bounds of the monthly savings required for respondents to participate in smart charging. Next, we assess the smart charging participation rates of each participant group, followed by a comparison of the participation rates when offering a one- or two-hour buffer between the conclusion of charging and a participant's regular departure time. We follow by analysing the distribution of participants with respect to the minimum reservation price to enrol in smart charging. We conclude by analysing the correlations of participating in smart charging for low monthly savings with two explanatory variables: the difference between a respondent's regular and earliest departure times and the quality of a respondent's earliest departure time being after the promised smart charging finish time.

Interest in EV Acquisition

When considering their next vehicle acquisition, a high interest[1] in purchasing or leasing an electric vehicle remained very high among the targeted population, at 94.6%. This signals a large index of satisfaction with electric vehicle ownership and implies that targeted participants will strictly remain within the electric vehicle market after experiencing EV ownership. Comparatively, 38% of random participants revealed high EV interest. Both figures are meaningful since they reflect the long run transition of the personal vehicle market. Almost 4 out of every 10 of our random respondents (overwhelmingly not EV owners), were highly considering an EV.

Vehicle Miles Travelled (VMT)

The average daily Vehicle Miles Travelled of our respondents was comparable to the general US population. The average daily VMT of the targeted population centred itself at 24.67 miles, with a standard deviation of 19.84 miles. This figure is slightly lower than the daily VMT figure of 29.5 miles per day (σ=21.7) of electric vehicles found in Idaho National Laboratory's EV Project, a comprehensive EV usage study, presented in (Boston and Werthman 2016). Neither figures are too far off from the average daily VMT in the United States in general, which is about 30 miles per day for one-vehicle households and 40 miles for the first vehicle in two-vehicle households. (US Department of Transportation 2017). The average household in the US owns about 1.97 cars (Sivak and January 2018). Households with electric vehicles have higher car ownership, with 83% to 89% of households owning two or more vehicles (Shahan 2018). The gap between the daily VMT of our targeted respondents and the national average can potentially be attributed to non-electric vehicles acting as substitutes in the < 10-mile gap for EV owners. However, the commuting profile between purely non-electric vehicle households and our targeted respondents could simply differ by this amount.

Savings Requirement for Smart Charging

With data from increasing and decreasing contingent valuation, we were able to calculate the bounds towards our respondents' valuation of smart charging. These calculations followed the intuition that, for example, if someone was not willing to participate for \$0, \$1, or \$5, but was willing to participate for \$10, then the lower bound on their valuation would be \$5, and the upper bound, \$10. We calculated the lower bounds of the minimum savings required for smart charging in the following manner:

$$LB = -1 * G_0 + 1 * G_1 + 5 * G_5 + 10 * G_{10} + 15 * G_{15}$$

[1] We defined people with high interest as those indicated would "Probably" or "Definitely" consider an EV for a next car purchase. The options were "Probably", "Definitely", "Unsure", "Probably Not", and "Definitely Not".

where G_0 is the amount of people accepting to enrol in "smart charging" or "Option B" charging at zero dollars of savings on their monthly electric bill, G_5 is the amount of people accepting to enrol for a savings of five dollars, and so forth. We calculated the upper bound of required savings in a similar fashion:

$$UB = 1 * G_0 + 5 * G_1 + 10 * G_5 + 15 * G_{10} + 20 * G_{15}$$

After these calculations, targeted participants demonstrated a lower bound savings requirement of approximately \$2.92 per month and an upper bound savings requirement of \$5.73 per month. Random respondents required, on average, slightly more to enrol in smart charging, with a lower bound of \$3.42 of savings per month and an upper bound of \$6.77 of savings per month. We observed a lower bound of \$3.24 and an upper bound \$6.33 for respondents with informative labels. Our survey asked these respondents to choose between "Regular Charging" and "Smart Charging" as opposed to choosing between "Option A" and "Option B".

Participation in Smart Charging

As noted in the "Fraction Participating" column, a high percentage of survey respondents were willing to participate in "Smart Charging" or "Option B" for some amount of monthly savings.

We identified an overall high participation rate in smart charging for respondents across both populations. As seen in **Table 4.2**, 84% of all respondents chose to participate in "smart charging" or "Option B" for at least one amount of savings. The participate rate was comparable between both random and targeted participants, at 86% and 83% respectively. We observed the highest participation rate for respondents with informative labels at 87%, hinting towards an attractive effect of the phrase "smart charging".

We sought to understand the number of respondents who would participate in smart charging for a low amount of monthly savings on their electric bill. As seen in **Table 4.3**, among all respondents, 53% chose to participate for less than \$5 of savings. 55% of targeted respondents (of which 95% are EV owners) chose to participate for this amount. Random participants chose to participate for the same savings at a slightly lower rate, at 51%. Overall, we observed a participation rate for smart charging with low monthly savings among a weak majority of respondents.

Table 4.2: Participation Rates and Savings Requirement Bounds

	Fraction Participating	Savings Requirement (Lower Bound)	Savings Requirement (Upper Bound)
Total	0.84	3.16	6.22
Standard Error	(0.02)	(0.23)	(0.30)
Confidence Interval		[2.71,3.60]	[5.62,6.81]
Random Participants	0.86	3.42	6.77
Standard Error	(0.02)	(0.32)	(0.43)
Targeted Participants	0.83	2.92	5.73
Standard Error	(0.02)	(0.31)	(0.42)
Increasing Valuation	0.86	3.37	6.28
Standard Error	(0.02)	(0.34)	(0.45)
Informative Labels	0.87	3.24	6.34
Standard Error	(0.02)	(0.32)	(0.43)

Table 4.3: Participation Rates for Low Monthly Savings with Regressions

	All	Random	Targeted
Fraction that participates for $5 or less	0.53	0.51	0.55
Percentage change of participation with Two Hour vs One Hour Buffer	0.07	0.04	0.10
Standard Error	(0.05)	(0.06)	(0.05)
Confidence Interval	[-0.03,0.17]	[-0.11,0.19]	[-0.04,0.23]
Regressor for participation according to difference between earliest and normal departure times	-0.01	-0.02	-0.01
Standard Error	(0.005)	(0.005)	(0.005)
Confidence Interval	[-0.02, -0.003]	[-0.03, -0.005]	[-0.02, -0.0004]
Regressor for participation if earliest departure time is within 1 to 2-hour buffer	0.17	0.14	0.19
Standard Error	(0.06)	(0.09)	(0.08)
Confidence Interval	[0.04,0.30]	[-0.06,0.34]	[0.02,0.37]

Comparison of Effects of One to Two Hour Buffers

To recall, in our survey we informed respondents that, under “smart charging” or “Option B”, their electric vehicle would conclude charging either one or two hours before the time in which they would regularly depart for their commute towards daily responsibilities. For a monthly savings of $5 or less, we observed that, when offered a two-hour buffer instead of a one-hour buffer, 7% more respondents would participate. This figure underscores the increase in enrolment observed when respondents have added time flexibility close to their departure time. Within the two main respondent groups, targeted respondents would participate at a higher rate with a two-hour buffer, with 9.7% more participating at low savings (≤ $5). EV owners thus demonstrate a degree of sensitivity to the finish time of their EV charging. Random respondents, too, more readily participated in smart charging when offered a two-hour buffer, with 4% more participating.

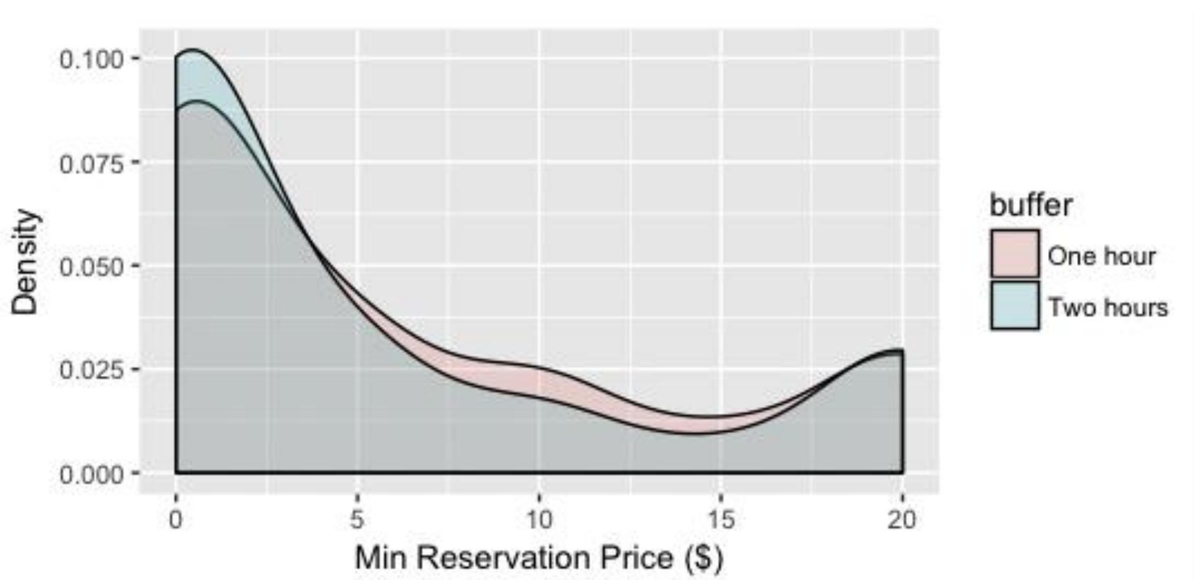
Minimum Reservation Price

The minimum reservation price is the minimum amount of monthly savings required for a survey participant to enrol in “smart charging” or “Option B”. The minimum reservation price is calculated by:

$$\sum_{i \in [0,5,10,15,20]} S_i E_i$$

where E_0 is the first enrolment group, in which respondents across both increasing and decreasing valuation have a minimum reservation price of S_0 = \$0. E_5 is the second enrolment group, with minimum a minimum reservation price of S_5 = \$5 and so forth. We then calculate the distribution of respondents per enrolment group, underscoring the differences in distribution with respect to the one- or two-hour buffer amount. This yields **Figure 4-1**. Upon inspection, we can observe a decreasing density curve, reflecting a strong propensity to enrol in smart charging for low monthly savings. When comparing the buffer amounts, we see a higher distribution of survey participants choosing to enrol in smart charging for low monthly savings when offered the longer, two-hour buffer. We can also observe a higher distribution of respondents centred on the middle minimum reservation price of \$10, for the one-hour buffer. This follows intuition since people would assign a higher cost to smart charging as their cars finish charging closer to their departure time.

Figure 4-1: Minimum Reservation Price Density



By offering a two-hour buffer, there was a higher density of participants choosing to participate in “Smart charging”/ “Option B” for low monthly savings. Note that all participants are included in this figure. For the purposes of this graph, those who did not choose to participate for any amount are lumped into the 20-dollar minimum reservation price group.

Regression Analysis

Throughout our data, the difference between a respondent's regular departure time to begin their commute and the earliest departure time varied. We sought to evaluate the effects of this difference with participation rates at low monthly savings (≤ \$5). We thus ran the Δ (Earliest Departure, Normal Departure) regression, having our binary dependent variable be 1 if a respondent participates for low monthly savings and 0 otherwise. Our explanatory variable was the difference between a respondent's normal departure time and their earliest departure time, as indicated in their responses.

After their calculations, as seen in **Table 4.3**, all regression coefficients were negative when considering the respondents in aggregate and also when divided between targeted and random respondents. This follows intuitively: when respondents have higher variance in their departure times, they become less interested in participating. Importantly, it becomes harder to commit to a form of smart charging when your schedule is more unpredictable.

For our second regression, we tested the relationship between participation at low monthly savings and if a respondent's car would be finished charging before their indicated earliest departure time. The dependent variable followed the previous definition while this new, binary explanatory variable was 1 if a respondent's earliest departure time was *after* the time survey promised the EV would be finished charging and 0 otherwise. All regression coefficients were positive, indicating a positive correlation between a car finishing charging before the very earliest time a respondent would use the car. This positive value also follows intuitively since we expect more people to participate in smart charging if their schedules are always unaffected with smart charging's finish time. The regression coefficient value was comparatively large for our targeted population, at 0.19. For random respondents, this figure laid at 0.14 and over all respondents, at 0.16.

Conclusion

We designed a contingent valuation survey to estimate the amount of savings required for electric vehicle owners in the United States to enrol in a hypothetical smart charging program. In this hypothetical smart charging scenario, the charging of a vehicle would conclude one or two hours before a survey participant's normal departure time towards their commute, with the added benefit of a monthly savings on an electric utility bill. We distributed the survey to electric vehicle owners and random participants. Over 80% of survey participants across both populations chose to participate for some amount of monthly savings, with a majority choosing to participate for low monthly savings of five dollars or less. Respondents were also more likely to enrol in the hypothetical smart charging program for lower amounts if offered a two-hour buffer rather than a one-hour buffer between the conclusion of smart charging and their indicated commute departure times.

We tested for the effect of the choice of label for charging options and found that participants were more likely to enrol in the hypothetical charging program if it was labelled informatively as "smart charging" and not generically, as "Option B". In addition, a higher variability between a participant's earliest and regular departure time was negatively correlated with committing to smart charging at low monthly savings. Having a car always finish charging before the earliest departure time, on the other hand, was positively correlated with committing to smart charging at low monthly savings.

The results of this investigation are promising since they indicate a high participation rate in "smart" charging programs for considerably low monthly savings. This is a positive sign for electric utilities and EV manufacturers that can design and apply demand response programs to optimize and smooth aggregate demand for electricity. This study also highlights the transition of the personal vehicle market towards electric vehicles, with survey data that demonstrate high satisfaction of EV owners within the EV market and high interest from non-EV owners.

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