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Research paper

Willingness to delay charging of electric vehicles

Ricardo A. Daziano

School of Civil and Environmental Engineering, Cornell University, United States

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ABSTRACT

Coordinated electric-vehicle charging can produce optimal, flattened loads that would improve reliability of the power system as well as reduce system costs and emissions. Optimal deadline scheduling of residential charging would require customers to defer charging their vehicles and to accept less than a 100% target for battery charge. To analyze the necessary incentives for customers to accept giving up control of when charging of their vehicles takes place, we use data from a choice experiment implemented in an online survey of electric-vehicle owners and lessees in upstate New York (N=462). The choice microdata allowed us to make inference on the willingness to pay for features of hypothetical coordinated electric-vehicle charging programs, exploiting Variational Bayes (VB) inference. Our results show that individuals negatively perceive the duration of the timeframe in which the energy provider would be allowed to defer charging. A negative monetary valuation is evidenced by an expected average reduction in the annual fee of joining the coordinated charging program of $2.66 per hour of control yielded to the energy provider. Our results also provide evidence of substantial heterogeneity in preferences, probably due to early-stage attitudes toward coordinated charging. For example, the 25% quantile of the posterior distribution of the mean of the willingness to accept an additional hour of control yielded to the utility is $4.72. However, the negative valuation of the timeframe for deferring charging is compensated by positive valuation of emission savings coming from switching charging to periods of the day with a higher proportion of generation from renewable sources. Customers also positively valued discounts in the price of energy delivery.

1. Introduction: coordinated charging and the OptimizEV pilot

Electrification of vehicles is becoming one of the main avenues for decarbonization of the transportation market. Even though there are clear environmental benefits of renewable-based electromobility, large-scale charging from high penetration of electric vehicles (EVs) will eventually require optimal scheduling of when electricity is delivered to vehicles (Andersen et al., 2018; Arif et al., 2016; Bitar & Xu, 2017; Calearo et al., 2019; González-Garrido et al., 2019). Optimal scheduling of electric vehicle charging has the potential to reduce load variance. In fact, coordinating EVs to charge at times when fewer people require electricity can effectively prevent stress on the power grid by reducing peak loads. Smart EV charging and the resulting flattened loads can improve reliability of the power system as well as reduce system costs and emissions. On the demand dimension of coordinated EV charging, residential customers would need to be willing both to delay charging their vehicles and to accept less than a 100% target for battery charge.

OptimizEV is a pilot program that NYSEG – the local electricity and gas provider in upstate New York – is running within the Energy Smart Community of Tompkins County, NY to precisely analyze residential optimal scheduling of the charging of electric vehicles. Following an algorithm developed by researchers of Cornell University (located in Tompkins County), the OptimizEV program is designed to: (1) determine exactly when to charge an EV within both a timeframe and target charge specified by the customer, (2) offer a discount based on how long an EV is left plugged in while letting the utility to decide when to actually charge the battery (according to the algorithmic optimal solution), and (3) ensure the EV is ready to go when needed. To inform the design of both the features of the OptimzEV pilot and the interface of the required smart EV charger, analysis of customer response to the idea of giving up control of charging of their EVs is essential.

From a perspective of demand-side dynamics (Chakraborty et al., 2019; Daina, 2018), there has been increasing interest in the literature regarding modeling EV charging behavior (for reviews, see Daina et al., 2017b; Hardman et al., 2018). Within this avenue of research, random utility maximization models have been used to explore response to smart EV charging services. For example, Daina et al. (2017a) built a model for joint decisions of EV charging and use (activity-travel) within the context of simplified (two-period) time-of-use pricing of electricity. Via a choice experiment in which respondents chose their target battery level and deadline to achieve the desired target given specific travel

E-mail address: daziano@cornell.edu.

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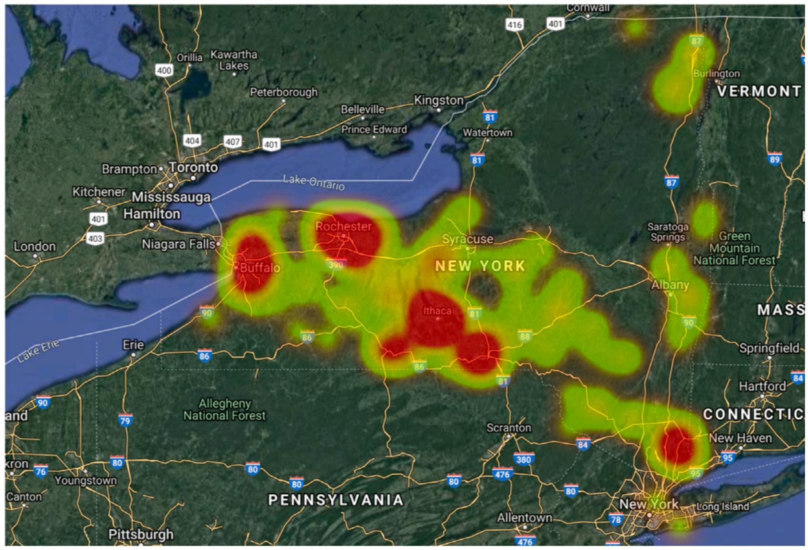

Fig. 1. Location of respondents to the OptimizEV survey in upstate New York.

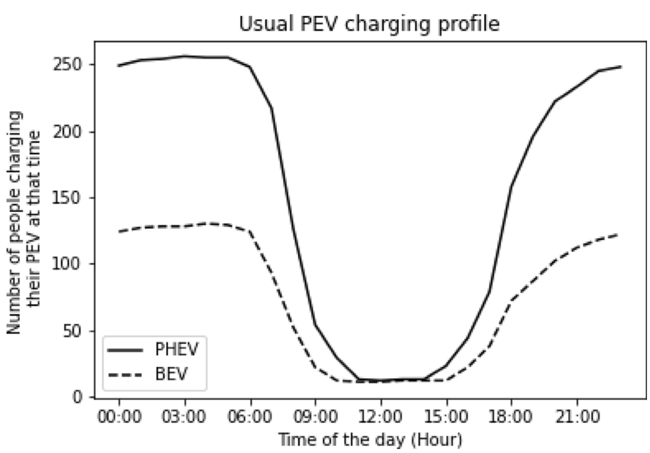

Fig. 2. Stated usual EV charging times.

Suppose that your electricity provider introduces a new PEV charging program

As part of the hypothetical PEV charging program:

① You will receive a Level 2 electric vehicle charger, which includes free installation and access to a charging management platform (mobile website) to manage the charging of your EV.

② In exchange for the installed charging unit, you will allow your electric utility to charge your vehicle at times of the day/night that will minimize stress on the electric grid while ensuring that your PEV is charged by the time you specify.

③ If you allow the utility to delay when your vehicle gets charged, you will receive a discount off of your electric delivery rate. Your supply rate will remain the same.

④ You can choose to not delay charging at anytime.

⑤ Please note that you will be ensured of having a minimum charge in case of emergencies.

Fig. 3. Descriptive text about a charging program introducing the option to delay as shown in the survey.

needs for the day, the study provided evidence of large heterogeneity in charging preferences. This observation about large variability in behavior is also reported in previous work (Franke & Krems, 2013; Yang et al., 2016; Zoepf et al., 2013). Applied microeconometrics offers differing solutions to uncover and model variability in preferences and behavior; for instance, mixed logit choice models (McFadden & Train, 2000) address unobserved heterogeneity in preferences through a parametric approach. Mixed logit models are common in modeling EV purchases as well as response to EV charging contracts (e.g., Parsons et al., 2014).

In this paper, our focus in on modeling choice of smart EV charging programs that implement optimal scheduling of electricity delivery to the battery of the vehicle (cf. Richter & Pollitt, 2018). In particular, we are interested in determining behavioral response to the idea of residential customers giving up control of charging by letting the electric utility to decide when to deliver electricity to the EVs within a given time window and a pre-specified state of charge and deadline. In this regard, this work is related to how customers respond to terms of energy contracts including pricing, which in the literature there is also evidence of heterogeneous behavior (Richter & Pollitt, 2018).

To address and measure preference heterogeneity in the willingness to delay charging of electric vehicles, we propose a mixed logit model, which is fitted by Variational Bayesian (VB) methods using data from a choice experiment specifically designed for this study. Although the size of the microdata used in this study is standard, in anticipation of the massive revealed-preference data from the daily charging decisions of the actual pilot in this article we test the use of a scalable Bayes estimator. Bayes estimation is an alternative approach to the more traditional maximum likelihood estimator, with general associated benefits (Bansal et al., 2020) including direct inference on the full posterior distribution of individual-specific preference parameters that represent how tastes vary. Whereas Bayes estimators are typically simulated using Markov chain Monte Carlo (MCMC; Rossi, 2015; Rossi et al., 2012) posterior sampling, Variational Bayes methods have emerged as a scalable alternative to MCMC in the domains of probabilistic machine learning and computational statistics (Blei et al., 2017; Jordan et al., 1999; Ormerod & Wand, 2010). Variational Bayes is implemented as an optimization problem rather than a sampling problem (cf. MCMC). The objective of stochastic variational inference is to find an approximate parametric distribution of the model parameters such that the probability distance (typically measured in terms of the Kullback–Leibler divergence) between the exact posterior distribution and the variational distribution is minimal. A key challenge in the application of VB to posterior inference in discrete choice models is that the expectation of the logarithm of the choice probabilities – i.e., the expectation of the log-sum of exponentials – lacks a closed form, due to the lack of a general conjugate prior. Whereas VB posterior inference for mixed logit models has been analyzed in the literature (Braun & McAuliffe, 2010; Depraetere & Vandebroek, 2017; Tan, 2017), recently in Bansal et al. (2020) we resolved major research gaps in terms of parameter recovery,

	Bundle A	Bundle B	Bundle C
Brand of charging system	amazon	NYSEG	Google
Emission reductions per session	35 pounds of CO_2	35 pounds of CO_2	50 pounds of CO_2
Hours of **control yielded** to utility	4 hours	8 hours	8 hours
Payment for service (annual fee)	$90 per year	$50 per year	$25 per year
Discount per charging session at home	5% per session (**$0.98**/month)	10% per session (**$1.95**/month)	2% per session (**$0.39**/month)

Fig. 4. Choice card sample.

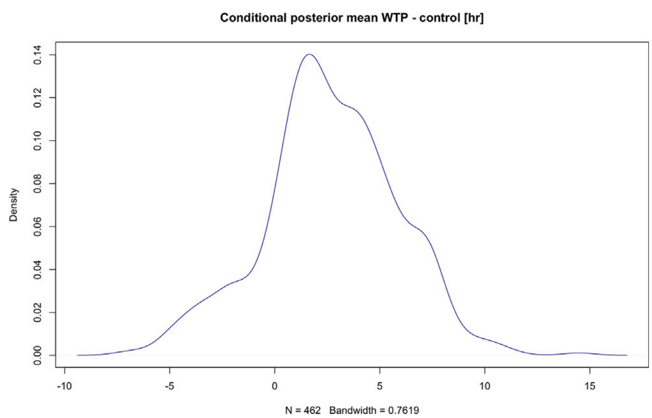

Fig. 5. Conditional distribution of the willingness to pay [in US $] to reduce in one hour the duration of period in which the utility controls EV charging.

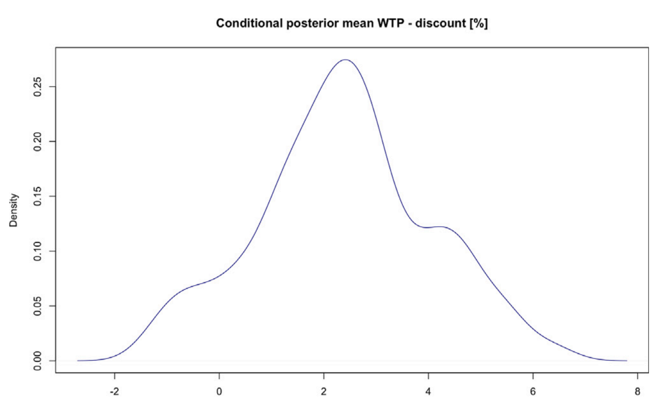

Fig. 6. Conditional distribution of the willingness to pay [in US $] for a one percent increase in the discount from participating in coordinated EV charging.

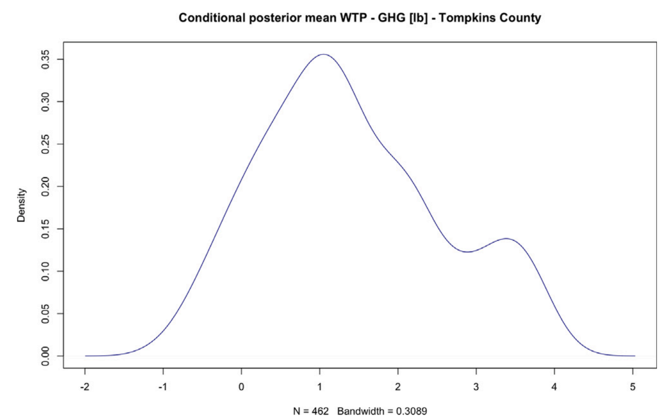

Fig. 7. Conditional distribution of the willingness to pay [in US $] by residents of Tompkins County for saving an additional pound of GHG emissions from participating in coordinated EV charging.

finite-sample properties, and extensions to more general utility specifications and representations of unobserved preference heterogeneity. Across the VB implementations in Bansal et al. (2020), stochastic VB inference implemented with nonconjugate variational message passing and the Delta-method (VB-NCVMP-Δ) (Depraetere & Vandebroek, 2017; Tan, 2017) is on average between 1.7 to 16.2 times faster than MCMC and MSLE, while performing nearly as well at prediction and parameter recovery. Thus, in this paper we explore preference heterogeneity in the responses to coordinated EV charging using VB-NCVMP-Δ inference.

The rest of the paper is organized as follows. Section 2 reviews the microdata, including details of the choice experiment that was implemented in the online OptimizEV survey. Section 3 provides a short description of the VB-NCVMP-Δ Bayes estimator that use to make inference on the degree of preference heterogeneity in preferences. Full details on the derivation of the estimator are provided in Bansal et al. (2020). Section 4 discusses point and interval estimates of marginal utilities and willingness to pay measures, with an emphasis of the extent of preference heterogeneity that is evidenced from the data. Finally, Section 5 concludes.

2. Data

2.1. Designing the OptimizEV pilot

As stated in the introduction, OptimizEV is a project by the local electricity company of Tompkins County in upstate New York. With a population of 101,564 (2010 US Census), Tompkins County comprises the college town of Ithaca, is home to Cornell University, and is now the first Energy Smart Community (ESC) in New York. The ESC project is a response to, first, the comprehensive energy strategy for New York Reforming the Energy Vision (REV), which mandates that 50% of New York's energy be generated by renewable sources by 2030, and second to the Energy Roadmap for Tompkins County, which aims at an 80% greenhouse gas reduction from 2008 levels by 2050. OptimizEV is a specific ESC initiative to test implementation of optimal scheduling of EV charging with the participation of 35 households that hold electric vehicles. The OptimizEV pilot is taking place over 2020–2021.

OptimizEV was conceived as follows. A participating customer would have the option to either keep full control of charging or let the electric utility control when charging of their electric vehicle takes place, every time that the EV is connected to their Electric Vehicle Supply Equipment (EVSE). If at a given EVSE session the customer agrees to give up control of charging, then loading profiles are determined by a coordinated EV charging algorithm based on the notion of deadline scheduling: right before beginning the charging sessions the customer inputs both their desired total charge and charging deadline (i.e., the time by which the requested energy must be delivered). As discussed in the subsection below, most current EV owners start their charging session immediately after connecting to their EVSE in the evening at home aiming for a full charge. The charging session usually is ready well ahead of when the load is really needed in the next morning. What OptimizEV allows customers to do is to let the electric company to optimize – from a whole grid perspective – when the electricity is delivered, while respecting the stipulated deadline. The longer the customer leaves their EV connected to the EVSE, the larger the potential flexibility offered back to the utility. There is no penalty or fee if the costumer decides to keep full control at a given charging session. The idea behind coordinated EV charging is that customers: (1) are flexible in terms of when their EV is charged, and (2) are willing to delay actual charging while their deadline is respected. In exchange for their flexibility, customers are offered a monetary incentive that is determined by the grid optimization algorithm. Additional benefits of coordinated charging, for which a customer could be willing to transfer control of their EVSE session to the electric utility, are emission reductions from flattening electricity generation.

2.2. The OptimizEV survey

To inform design and implementation of the OptimizEV pilot, an online survey was launched in September 2019 to study charging preferences by residential customers across upstate New York, both within and outside the Tompkins County ESC area.

The target population for the survey was EV owners and lessees within the footprint of the local utility that is running the OptimizEV pilot. The New York State Energy Research and Development Authority (NYSERDA) compiles data of EV registrations from the New York State Department of Motor Vehicles. 44% of the registration records had associated email addresses (1925 entries) that NYSERDA agreed to share with the local utility. 197 invitation emails bounced after the first contact. After a series of four reminders (scheduled biweekly for incomplete links) to complete the survey, a total of 462 individuals (Fig. 1) successfully completed the survey with responses that were assessed as valid for analysis.

Table 4 summarizes sociodemographic characteristics of the sample (N=462). Other characteristics include: 55% have a graduate or professional degree; 90% live in a detached, single family home (making charging at home a feasible option); 66% are employed full time, and 24% are retired.

The survey gathered categorical, attitudinal, and lifestyle information around current EV charging patterns and preferences. Respondents to the survey either own (69%) or lease (27%) mostly plug-in hybrids (PHEVs), with pure battery electric vehicles (BEVs) representing around one third of the sample. Of the 78% of respondents who typically leave their EVs plugged in until it is fully charged, 60% use a Level 1 charger at home. Most respondents stated to usually leave their vehicle charging over night, even those who own or lease a PHEV (Fig. 2).

In terms of ownership, the most popular make and model is the Toyota Prius Prime (37% among owners), followed by the Chevrolet Volt (14%), which are both PHEVs (which represent 67.6% of the total among owned electric cars). The most popular BEV is the Chevrolet Bolt (12%), followed by the Tesla Model 3 Long Range (11%). Among leased electric vehicles, the PHEV Chevrolet Volt (27%) is followed by the BEV Chevrolet Bolt (25%). Another goal of the survey was to inform design of the user interface of the mobile app to communicate with the OptimizEV smart chargers. In fact, the next subsection describes a choice experiment that was included in the survey to determine the perceived trade-offs that EV owners are willing to make for smart coordinated EV charging.

Before the choice experiment, the survey introduced the concept of optimal scheduling of EV charging as a hypothetical program offered by the electric utility. The actual text that was used to introduce the notion of delaying charging is shown in 3. The local electricity provider proposed this generic text to provide enough information about OptimizEV, while avoiding potential bias in the rollout of the actual pilot.

2.3. Choice experiment

To elicit customer preferences around smart residential EV charging and deadline scheduling, a discrete choice experiment was designed aiming at replication of some of the decisions expected from individuals joining the OptimizEV program. In fact, the choice experiment was presented to respondents as their electricity provider offering a smart EV charging program reproducing the expected characteristics of the OptimizEV pilot in terms of **GHG emission reductions per coordinated charging session**,[1] **hours of control yielded to utility (to decide when to charge)**, and **discount per charging session at home (when willing to delay EV charging)**. Even though participation in the actual OptimizEV pilot is free, the experiment introduced a hypothetical payment for the coordinated EV charging service (as an **annual fee**) with included installation of a free Level 2 charger with technical capability to coordinate charging. The provision of the free, smart Level 2 charger is essential to understand the consideration of a payment for the service.[2] Table 5 summarizes the attribute levels that were considered for a Bayesian efficient design of the experiment (Bliemer & Rose, 2010). Whereas priors were obtained from a pretest of the experiment, credible levels of the features were provided by the local electric utility from simulations of the program. Note that the discount per charging session is calculated with respect to delivery costs only, i.e. the cost for the utility to transport the electricity. Levels for the discount were presented as both a percent discount and savings per month in dollars that were customized based on current charging patterns of the respondent. Brand of the charging system was included at request of the electric utility for brand equity assessment.[3]

Fig. 4 shows a choice card sample. In addition to making a choice among the three hypothetical bundles (A–C), respondents could opt out (i.e., keeping full control of charging) at any of the 6 choice situations that were randomly assigned.

Choosing a particular bundle of smart charging means that customers are willing to accept to give up control of charging their EV (hours of control yielded) in exchange for a monetary incentive, which appears in the form of a discount per charging session (presented as both a percentage reduction in the electricity delivery cost and a customized expected dollar savings per month). Expected emission reductions were presented as pounds saved by charging session.

[1] The utility estimates an upper bound of 73 pounds of CO_2e savings per session.

[2] Furthermore, the actual pilot with free participation for granting load control to the utility ended up implementing an app that displays the discount per charging session as a function of the elicited deadline by which a desired amount of energy must be delivered. The flexibility implied by the customer's inputs in terms of energy desired and deadline translates into the experimental attribute of 'hours of control yielded'.

[3] By request of the company, estimates of brand equity – which also act as a proxy for trust (c.f. Slade et al., 2015) – are kept private.

3. Methodology: variational Bayes inference for mixed logit

Because we expected substantial differences in how EV drivers would react to a hypothetical coordinated charging program, we decided to make inference at the individual level with a choice model that would allow us to make inference on unobserved preference heterogeneity. There are general benefits of using Bayesian inference for a mixed logit model, including direct sampling of conditional estimates at the individual level and derivation of posterior estimates of willingness-to-pay measures from marginal utilities. Variational Bayes (VB) methods have emerged as a computationally-efficient alternative to Markov chain Monte Carlo (MCMC) methods for scalable Bayesian simulation-aided inference. Our recent analysis in Bansal et al. (2020) shows that existing VB inference methods extended to the case of choice models with both invariant and individual-specific parameters perform as well as MCMC and MSLE at prediction and parameter recovery, but with important savings in estimation cost.[4] Stochastic VB inference with nonconjugate variational message passing and the Delta-method (VB-NCVMP-Δ) in particular is shown in our previous work to be up to 16 times faster than MCMC and MSLE. Due to the computing benefits of this later VB method in this paper we adopt VB-NCVMP-Δ for the estimation of a Bayesian mixed logit model, as specified below. Even though standard estimation would be appropriate in this study due to the scale of the stated preference data, we wanted to implement and test the VB estimator in anticipation of the large scale of the revealed-preference data coming from the actual OptimizEV pilot (with daily records of choices over multiple months).

Consider a standard discrete choice setup, where customer i faces a single choice among J alternatives, in each of T time periods. Adopting a general logit-type specification, the random truncated indirect utility[5] the customer extracts from alternative j in period (choice situation) t is:

$$u_{ijt} = \mathbf{x}'_{ijt}\boldsymbol{\gamma}_i + \varepsilon_{ijt} = \mathbf{x}'_{ijt,F}\boldsymbol{\alpha} + \mathbf{x}'_{ijt,R}\boldsymbol{\beta}_i + \varepsilon_{ijt}, \quad (1)$$

where $\mathbf{x}_{ijt}$ is vector of choice-specific features (attributes), $\boldsymbol{\gamma}_i$ is a vector of marginal utilities, and ε_{ijt} is an iid type-I extreme value preference shock. Under the econometric assumption that $\varepsilon_{ijt} \overset{iid}{\sim} \text{EV1}(0,1)$, the choice model is characterized by a conditional logit kernel. Following Bansal et al. (2020), the preference vector $\boldsymbol{\gamma}_i$ is partitioned into invariant (across decision-makers) parameters $\boldsymbol{\alpha}$ and customer-specific parameters $\boldsymbol{\beta}_i$, where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}_i$ are vectors of lengths L and K, respectively. To ensure conformability, the features vector $\mathbf{x}_{ijt}$ is partitioned into a component $\mathbf{x}_{ijt,F}$ associated with the invariant preferences $\boldsymbol{\alpha}$, and a component $\mathbf{x}_{ijt,R}$ associated with the customer-specific preferences $\boldsymbol{\beta}_i$, i.e. $\mathbf{x}_{ijt} = \begin{bmatrix}\mathbf{x}_{ijt,F} & \mathbf{x}_{ijt,R}\end{bmatrix}$. As in Bansal et al. (2020), the heterogeneity distribution of $\boldsymbol{\beta}_{1:N}$ is assumed multivariate normal, i.e. $\boldsymbol{\beta}_i \sim \mathcal{N}(\boldsymbol{\zeta}, \boldsymbol{\Omega})$ for $i = 1, \dots, N$, where $\boldsymbol{\zeta}$ is a vector of population means of marginal utilities, and $\boldsymbol{\Omega}$ is a covariance matrix.

For Bayes estimation, normal priors are adopted for both the invariant parameters $\boldsymbol{\alpha}$ and the vector $\boldsymbol{\zeta}$ of means of the customer-specific parameters. Due to superior noninformativity properties (Akinc & Vandebroek, 2018; Huang & Wand, 2013; Tan, 2017), a Huang's half-t prior (Huang & Wand, 2013) for the covariance matrix $\boldsymbol{\Omega}$ is adopted. Full details of the Bayes estimator exploited in this paper are found in our related paper Bansal et al. (2020), but the generative process of the Bayesian mixed logit specified above can be summarized in the following drawing process:

$$\boldsymbol{\alpha}|\boldsymbol{\lambda}_0, \boldsymbol{\Xi}_0 \sim \mathcal{N}(\boldsymbol{\lambda}_0, \boldsymbol{\Xi}_0) \quad (2)$$

$$\boldsymbol{\zeta}|\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0 \sim \mathcal{N}(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0) \quad (3)$$

$$a_k|A_k \sim \text{Gamma}\left(\frac{1}{2}, \frac{1}{A_k^2}\right), \qquad k = 1, \dots, K, \quad (4)$$

$$\boldsymbol{\Omega}|\nu, \boldsymbol{a} \sim \text{IW}(\nu + K - 1, 2\nu\,\text{diag}(\boldsymbol{a})), \quad \boldsymbol{a} = \begin{bmatrix}a_1 & \dots & a_K\end{bmatrix}^\top \quad (5)$$

$$\boldsymbol{\beta}_i|\boldsymbol{\zeta}, \boldsymbol{\Omega} \sim \mathcal{N}(\boldsymbol{\zeta}, \boldsymbol{\Omega}), \qquad i = 1, \dots, N, \quad (6)$$

$$y_{it}|\boldsymbol{\alpha}, \boldsymbol{\beta}_i, \boldsymbol{X}_{it} \sim \text{logit}(\boldsymbol{\alpha}, \boldsymbol{\beta}_i, \boldsymbol{X}_{it}), \qquad i = 1, \dots, N, \ t = 1, \dots, T_i, \quad (7)$$

where Eqs. (4) and (5) induce Huang's half-t prior, $\{\boldsymbol{\lambda}_0, \boldsymbol{\Xi}_0, \boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0, \nu, A_{1:K}\}$ are hyper-parameters, and $\boldsymbol{\theta} = \{\boldsymbol{\alpha}, \boldsymbol{\zeta}, \boldsymbol{\Omega}, \boldsymbol{a}, \boldsymbol{\beta}_{1:N}\}$ is a collection of model parameters that need posterior distribution inference. Because of substantial gains in estimation costs, it is for $\boldsymbol{\theta}$ that stochastic VB inference is implemented. VB aims at finding a variational distribution $q(\boldsymbol{\theta})$ over the unknown parameters that is close – in the sense of the Kullback–Leibler (KL) divergence (Kullback & Leibler, 1951) – to the true posterior distribution of interest $P(\boldsymbol{\theta}|\boldsymbol{y})$. In fact, VB either minimizes the KL divergence $q^*(\boldsymbol{\theta}) = \arg\min_q \{\text{KL}(q(\boldsymbol{\theta})||P(\boldsymbol{\theta}|\boldsymbol{y}))\}$, or – equivalently – maximizes the evidence lower bound (ELBO) $\mathbb{E}_q\{\ln P(\boldsymbol{y}, \boldsymbol{\theta})\} - \mathbb{E}_q\{\ln q(\boldsymbol{\theta})\}$. Exploiting the mean-field family of distributions (e.g. Jordan et al., 1999) to find a partition of variational factors in the proposed $q(\boldsymbol{\theta})$, the ELBO can be maximized via a simple iterative coordinate ascent algorithm (Bishop, 2006). Because the ELBO is convex with respect to the variational factors, the ELBO is guaranteed to converge to a local optimum (Boyd & Vandenberghe, 2004) and is expected to produce consistent estimates (Wang & Blei, 2018).

For the parameters of a mixed logit model $\{\boldsymbol{\alpha}, \boldsymbol{\zeta}, \boldsymbol{\Omega}, a_{1:K}, \boldsymbol{\beta}_{1:N}\}$ the variational distribution can be factorized as (see Bansal et al., 2020):

$$q(\boldsymbol{\theta}) = q(\boldsymbol{\alpha}, \boldsymbol{\zeta}, \boldsymbol{\Omega}, a_{1:K}, \boldsymbol{\beta}_{1:N}) = q(\boldsymbol{\alpha})q(\boldsymbol{\zeta})q(\boldsymbol{\Omega})\prod_{k=1}^{K} q(a_k)\prod_{i=1}^{N} q(\boldsymbol{\beta}_i). \quad (8)$$

The optimal densities of the variational factors are given by $q^*(\theta_i) \propto \exp\mathbb{E}_{-\theta_i}\{\ln P(\boldsymbol{y}, \boldsymbol{\theta})\}$. However, we found that whereas $q^*(\boldsymbol{\zeta}|\boldsymbol{\mu}_\zeta, \boldsymbol{\Sigma}_\zeta)$, $q^*(\boldsymbol{\Omega}|w, \boldsymbol{\Theta})$, and $q^*(a_k|c, d_k)$ are common probability distributions, both $q^*(\boldsymbol{\alpha})$ and $q^*(\boldsymbol{\beta}_i)$ are not members of recognizable families of distributions because the conditional logit kernel lacks a general conjugate prior. The Delta (Δ) method (e.g. Bickel & Doksum, 2015) provides a simulation-based approximation based on a second-order Taylor series expansion that we have shown works well in practice (Bansal et al., 2020).

4. Results

4.1. Preferences over coordinated EV charging features

Logit-type choice models were used to derive estimates of customers' willingness to pay (WTP) for the features of experimental smart EV charging bundles. These WTP metrics reflect monetary valuation coming from the stated choices and the revealed preference mapping. The first step was to produce Bayes estimates of marginal utilities, which are presented in Table 6 for the selected Bayesian mixed logit specification after running a procedure that implemented a step-wise search based on minimizing the Bayesian Information Criterion BIC.[6] Appendix A presents estimates of baseline specifications, including a Bayesian conditional logit model without preference heterogeneity (Table 1), a conditional logit model with observed preference heterogeneity (Table 2), and a mixed logit model without observed preference

[4] The sole exception is for those variants relying on an alternative variational lower bound constructed with the help of the modified Jensen's inequality.

[5] Truncation of the utility function in the context of a discrete choice models refers to the consideration of the discrete choice alone without explicit reference to demand for continuous goods.

[6] The empirical strategy to find the best model was to start just with the experimental attributes – i.e. models without observed heterogeneity –, then introduce interactions of the attributes with sociodemographics and characteristics of the household (observed heterogeneity) and keep those that were interpretable and had credible intervals that did not include changes in sign. Finally, to address unobserved preference heterogeneity random parameters were considered, resulting in a mixed logit specification.

Table 1
Baseline conditional logit, no heterogeneity.

Smart EV charging bundle feature	Posterior estimates		95% credible interval	
	Post. mean	Post. stdev	Lower bound	Upper bound
Payment for service (annual fee in US$)	−0.0158	0.0011	−0.0179	−0.0136
Hours of control yielded to utility for EV charging	−0.0378	0.0072	−0.0519	−0.0237
Emission reductions per session [pounds]	0.0203	0.0010	0.0184	0.0222
Discount per charging session at home [percentage]	0.0510	0.0032	0.0447	0.0573
Opt-out constant	−0.0096	0.1132	−0.2314	0.2123
Loglikelihood at posterior means		−3270.1		
BIC		6595.7		

Table 2
Baseline conditional logit, observed heterogeneity.

Smart EV charging bundle feature	Posterior estimates		95% credible interval	
	Post. mean	Post. stdev	Lower bound	Upper bound
Payment for service (annual fee in US$)	−0.0160	0.0011	−0.0182	−0.0138
Hours of control yielded to utility for EV charging	−0.0444	0.0077	−0.0595	−0.0292
Hours of control yielded to utility | Smartmeter	0.0268	0.0122	0.0030	0.0507
Emission reductions per session [pounds]	0.0186	0.0011	0.0165	0.0207
Emission reductions per session | Tompkins County	0.0078	0.0018	0.0043	0.0113
Discount per charging session at home [percentage]	0.0510	0.0032	0.0447	0.0574
Opt-out constant	1.1578	0.2173	0.7320	1.5837
Opt-out heterogeneity				
Millennial	−1.4248	0.2231	−1.8620	−0.9876
Generation X	−0.8764	0.2022	−1.2728	−0.4800
Baby boomer	−0.5236	0.1774	−0.8712	−0.1759
Household income	0.0010	0.0004	0.0002	0.0017
Did not provide income information	0.5082	0.1561	0.2022	0.8143
Graduate or professional degree	−0.5099	0.1109	−0.7273	−0.2925
Time of use rate	−0.9005	0.4879	−1.8569	0.0558
Loglikelihood at posterior means		−3204.4		
BIC		6551.6		

Table 3
Baseline mixed logit, no observed heterogeneity.

Smart EV charging bundle feature	Posterior estimates		95% credible interval	
	Post. mean	Post. stdev	Lower bound	Upper bound
Payment for service (annual fee in US$)	−0.0320	0.0030	−0.0379	−0.0262
Hours of control yielded to utility for EV charging	−0.0834	0.0165	−0.1159	−0.0510
Emission reductions per session [pounds]	0.0315	0.0034	0.0248	0.0382
Discount per charging session at home [percentage]	0.0937	0.0085	0.0770	0.1103
Opt-out constant	−1.2208	0.1821	−1.5778	−0.8639
Standard deviations				
Payment for service (annual fee in US$)	0.2018	0.0175	0.1676	0.2361
Hours of control yielded to utility for EV charging	0.0510	0.0037	0.0438	0.0582
Emission reductions per session [pounds]	0.1127	0.0101	0.0928	0.1326
Discount per charging session at home [percentage]	0.0421	0.0033	0.0357	0.0485
Covariance				
Discount : GHG	−0.0226	0.0111	−0.0444	−0.0009
Discount : Control	0.0055	0.0044	−0.0032	0.0142
Discount : Payment	0.0503	0.0219	0.0075	0.0931
GHG : Control	0.0170	0.0043	0.0085	0.0254
GHG : Payment	0.0276	0.0198	−0.0112	0.0664
Control : Payment	−0.0393	0.0225	−0.0833	0.0048
Loglikelihood at posterior means		−2572.7		
BIC		5280.2		

heterogeneity (Table 3). Whereas the standard MCMC sampler was used for the conditional logit estimates, for the mixed logit model with individual-specific and invariant parameters the VB-NVMP-Δ estimator introduced in Section 3 was used. Despite having detailed information about the respondents, their electric vehicles, and their EV charging patterns very few interactions representing observed preference heterogeneity were kept in minimizing BIC. In fact, applying a frequentist approach to parameter significance most of the interactions result in observed preference heterogeneity that is not statistically significant. For example, interactions that were excluded when minimizing BIC and that were not significant in the frequentist sense included whether the car was PHEV or BEV, battery capacity in kWh, vehicle miles traveled (on a representative weekday and monthly total), and hours the vehicle is usually left plugged in. As discussed in the conclusions, one explanation of this lack of interaction effects may be due to respondents being exposed for the first time to the notion of potentially delaying their charging as part of a coordinated EV charging program. Another explanation is the use of a single experiment that was not customized, besides savings in dollars, to the customers' vehicle characteristics and behavior. Under a frequentist view, the interactions in the selected

Table 4
Sample demographic statistics.

Respondent characteristics	Tompkins County (N = 104)	Outside Tompkins (N = 358)
Male	58%	73%
Millennial	19%	22%
Generation X	30%	22%
Baby Boomer	44%	47%
Older Generations	7%	8%
Household income < \$25, 000	8%	16%
Household income ≥ \$25, 000 and < \$35, 000	11%	8%
Household income ≥ \$35, 000 and < \$50, 000	14%	14%
Household income ≥ \$50, 000 and < \$75, 000	24%	19%
Household income ≥ \$75, 000 and < \$100, 000	18%	14%
Household income ≥ \$100, 000	26%	29%
Homeowner	69%	75%

Table 5
Experimental bundle features and levels.

Bundle features	Levels
Brand of charging system	NYSEG
	Amazon
	Google
Emission reductions per session	10 pounds of CO_2
	35 pounds of CO_2
	50 pounds of CO_2
	70 pounds of CO_2
Hours of control yielded to utility	4 h
	8 h
	12 h
Payment for service [annual fee in US\$]	\$5
	\$10
	\$50
	\$90
	\$300
Discount per charging session at home*	1%
*Savings in dollars were also presented,	2%
pivoted around current charging patterns	5%
	10%
	20%

specification would be statistically significant at the 95% level of confidence. Matching the Bayesian approach, Table 6 presents the lower and upper bounds of the 95% credible intervals of each model parameter.

The adopted specification of the indirect utility function considers observed preference heterogeneity for the valuation of emission reductions per session. The environmental benefit of delaying EV charging was effectively interacted with an indicator for those respondents residing in Tompkins County. There is empirical evidence supporting the fact people in Tompkins County are more environmentally aware than residents of other areas of upstate New York. The higher valuation of emission reductions per session when willing to delay EV charging among Tompkins County residents is compatible with these individuals being more environmentally conscious. Furthermore, the revealed preference data will serve as means for external validity of the analysis presented in this paper.

The posterior means across both specifications are as expected: on average customers prefer a lower annual fee, fewer hours of control yielded to the electric utility for it to decide when to charge the electric vehicle, larger emission savings, and a higher discount. In terms of observed preference heterogeneity, people in Tompkins County exhibit a higher valuation of emission savings, a result that is consistent with Tompkins County having residents that are more environmentally aware. For those features that exhibited evidence of unobserved preference heterogeneity, the mixed logit results include estimates of standard deviations and covariance of the individual-specific parameters. In addition to posterior means for Bayesian point estimation, posterior standard deviations and 95% credible interval estimates are also included as a measure of uncertainty. To give an idea of model fit, the loglikelihood function evaluated at the posterior means is also displayed. Both the loglikelihood at the posterior means and BIC can be contrasted with those of the baseline models in Appendix A.

4.2. Inference on willingness to pay for program features

From the marginal utility estimates in Table 6, it is possible to derive a negative willingness to pay of \$2.65 (in the annual fee of the program) for each hour increase in the timeframe for which the customer is giving up control of charging of their EV (cf. Richter and Pollitt, 2018).[7] This negative estimate can be seen as an expected rebate in the annual fee that the customer accepts in exchange for their willingness to delay charging. As supported from current charging patterns, most EV owners leave their cars plugged in at home overnight. For optimal flexibility of smart charging, electric utilities would like to control when charging takes place over that whole period (while respecting the stated charging target). However, the negative estimate of the valuation of hours of control yielded to the electric utility means that customers are less likely to enroll in a smart EV charging program with an extensive period of time where customers are expected to give up control.

Although willingness to pay estimates can be derived from postprocessing the chains of the marginal utilities, Table 7 summarizes the posterior of the population willingness to pay metrics for the selected mixed logit model, recast in willingness to pay space. The mixed logit estimates provide evidence that customers exhibit substantial heterogeneity in their response to delay charging.

A known benefit of implementing a Bayes estimator of a mixed logit model is direct inference on the individual-specific parameters, considering the sequence of choices elicited by the same individual. Table 8 summarizes quantiles of the posterior distributions of the means of the conditional individual-specific willingness to pay for features of the smart EV charging bundles.

Whereas on average accepting a delay in when EV charging takes place (as measured by an additional hour in the time window where the electric utility controls charging) is associated with an expected rebate in the annual fee of \$2.65, other features exhibit a positive valuation. For example, each percent increase in the discount offered as incentive to join the smart EV charging program is valued on average by an incremental \$2.39 in associated annual fee. Each marginal pound in emission savings is also positively valued, on average. As previous studies in the area have indicated, inhabitants of Tompkins County seem to be more environmentally conscious. In this study, this fact is represented by a higher valuation of emission savings: a marginal improvement in emission savings from the use of cleaner electricity production is reflected by a willingness to pay additional \$1.40 in the annual fee by customers in Tompkins County (cf.the average \$0.44 for customers outside Tompkins County). To give an idea of the magnitude

[7] The Bayes population WTP estimates can be derived from either postprocessing the draws from the posterior distributions of the respective marginal utilities or from recasting the parameters to willingness-to-pay space, which is the approach adopted in this work.

Table 6
Bayes estimates (posterior means) of marginal utilities and nuisance parameters for the selected mixed logit model.

Smart EV charging bundle feature	Posterior estimates		95% credible interval	
	Post. mean	Post. stdev	Lower bound	Upper bound
Means				
Payment for service [annual fee in US$]	−0.0327	0.0030	−0.0385	−0.0268
Hours of control yielded to utility for EV charging	−0.0945	0.0185	−0.1307	−0.0583
Emission reductions per session [lb]	0.0269	0.0037	0.0196	0.0341
Emission reductions per session [lb] | Tompkins County	0.0196	0.0070	0.0059	0.0334
Discount per charging session at home [percentage]	0.0937	0.0084	0.0772	0.1102
Opt-out constant	0.5779	0.5333	−0.4674	1.6232
Standard deviations				
Payment for service [annual fee in US$]	0.2005	0.0181	0.1650	0.2359
Hours of control yielded to utility for EV charging	0.0499	0.0037	0.0426	0.0572
Emission reductions per session [lb]	0.1117	0.0102	0.0917	0.1316
Discount per charging session at home [percentage]	0.0424	0.0033	0.0359	0.0488
Covariance				
Discount : GHG	−0.0201	0.0111	−0.0418	0.0017
Discount : Control	0.0061	0.0044	−0.0024	0.0147
Discount : Payment	0.0500	0.0249	0.0011	0.0989
GHG : Control	0.0128	0.0047	0.0035	0.0220
GHG : Payment	0.0180	0.0208	−0.0228	0.0587
Control : Payment	−0.0446	0.0254	−0.0944	0.0051
Loglikelihood at posterior means		−2547.6		
BIC		5317.1		

Table 7
Bayes population estimates of willingness to pay for the selected mixed logit.

Smart EV charging bundle feature	Posterior WTP estimates		95% credible interval	
	Post. mean	Post. stdev	Lower bound	Upper bound
Means				
Hours of control yielded to utility for EV charging [$/h]	−2.6531	0.4772	−3.5884	−1.7179
Hours of control yielded to utility | Smartmeter [$/h]	1.0246	0.7021	−0.1504	2.1995
Emission reductions per session [$/lb]	0.4663	0.1462	0.1798	0.7528
Emission reductions per session [$/lb] | Tompkins County	0.6590	0.1792	0.3077	1.0104
Discount per charging session at home [$/%-point]	2.3598	0.2273	1.9144	2.8053
Standard deviations				
Hours of control yielded to utility for EV charging [$/h]	4.9182	0.5066	3.9252	5.9111
Emission reductions per session [$/lb]	1.4051	0.0939	1.2210	1.5892
Discount per charging session at home [$/%-point]	2.6644	0.2466	2.1812	3.1477
Loglikelihood at posterior means		−2547.6		
BIC		5317.1		

Table 8
Mean and selected quantiles of mean conditional willingness to pay estimates at the individual level [US $ per year].

Smart EV charging bundle feature		Quantiles				
	mean	5%	25%	50%	75%	95%
Hours of control yielded (as rebate)	2.6582	−3.2821	0.8545	2.4908	4.7243	7.4774
Pounds of GHG saved	0.4380	−1.2599	−0.4294	0.2792	1.2218	2.6006
Pounds of GHG saved | TC	1.4032	−0.2948	0.5357	1.2443	2.1869	3.5657
Percent discount	2.3870	−0.6052	1.3442	2.3710	3.3827	5.2867

Table 9
Posterior means of the incremental willingness to pay estimates [US $] for hypothetical smart EV charging programs.

	Program features per charging session			Max WTP [$]	
	Discount	Control yielded	Emission savings	Outside Tompkins	Tompkins County
Program 1	5%	8 h	10 lb	−4.9506	4.7014
Program 2	5%	8 h	35 lb	5.9994	39.7814
Program 3	10%	8 h	10 lb	6.9844	16.6364
Program 4	10%	8 h	35 lb	17.9344	51.7164
Program 5	5%	12 h	10 lb	−15.5834	−5.9314
Program 6	5%	12 h	35 lb	−4.6334	29.1486
Program 7	10%	12 h	10 lb	−3.6484	6.0036
Program 8	10%	12 h	35 lb	7.3016	41.0836

of the environmental benefits, an upper bound for emission savings comes from shifting 100 kWh for fully charging the largest EV battery from on-peak to off-peak times. For upstate NY, this switching results in roughly 73 pounds of avoided CO_2e per session. Thus, a key outcome from the mean estimates is that whereas allowing the utility to delay charging is negatively perceived, the negative effect can actually be offset by the incentive (discount) and environmental benefits. However,

Table 10
Selected quantiles of the posterior distribution of the relative risk of opting out, mixed logit.

Mixed logit		Quantiles				
Relative risk of opting out	Mean	5%	25%	50%	75%	95%
Millennial	0.1658	0.0569	0.1011	0.1432	0.2029	0.3643
Generation X	0.1832	0.0669	0.1101	0.1597	0.2315	0.3736
Baby boomer	0.4223	0.1749	0.2775	0.3805	0.5162	0.8141
Household income	1.0023	1.0008	1.0017	1.00235	1.0030	1.0039
Did not provide household income	2.9456	1.3703	2.0514	2.7542	3.5331	5.3456
Monthly electricity bill	0.9949	0.9913	0.9936	0.9950	0.9964	0.9983
Graduate or professional degree	0.5250	0.3155	0.4185	0.5014	0.6127	0.8021
Time-of-Use rate	0.3397	0.0336	0.0100	0.1979	0.3819	1.1185

it should be mentioned, that valuation of environmental benefits may be affected by both hypothetical and desirability bias.

Although, most of the posterior distributions of the individual-specific willingness to pay measures are consistent with the signs of the mean estimates, the quantiles reported in Table 8 show that there is substantial heterogeneity. Fig. 5 shows, for instance, the conditional posterior distribution of the mean willingness to pay to regain one hour of controlling EV charging. Whereas the most of the individuals in the sample exhibit a negative willingness to pay (expecting a compensation or rebate in the annual fee, as discussed above), some individuals have a positive valuation that is independent of the benefits (discount and emission savings) that are associated with delaying charging.

Fig. 6 displays the conditional posterior of the mean willingness to pay for an increase in the offered discount. Fig. 7 shows the conditional posterior of the mean willingness to pay for one pound of GHG emission savings from coordinated EV charging for an individual in Tompkins County.

4.3. Simulated scenarios of total willingness to pay

Taking the posterior means of the WTP estimates at the individual level discussed in the previous subsection, Table 9 shows the posterior means of the total willingness to pay, as a monthly fee, for hypothetical coordinated EV charging programs. Each program is defined by considering likely features per charging session in terms of the experimental attributes of percent discount in the delivery cost, hours of control yielded to the utility to decide when to charge the car, and GHG emission savings. Because we were able to identify observed heterogeneity in responses to the programs based on whether customers lived in Tompkins County or not, we derived posterior distributions for the incremental monthly fee customers would be paying as maximum premium for participation in the program.

A positive incremental willingness to pay indicates that on average customers perceive benefits from the program and are likely to join and pay a positive premium, whereas a negative valuation is associated with average customers not being likely to participate unless they receive further compensations beyond the included percent discount in the electricity delivery cost. For example, a representative Tompkins County EV user would be likely to join Program 1 and would accept an increase in their bill of up to almost $5. However, for the same program, a customer outside of Tompkins County would likely opt out unless they receive a monthly reduction in their bills. When emission savings go from 10 (Program 1) to 35 pounds (Program 2), representative customers in both areas not only are likely to join but also the environmental gains are such that the premium that could be charged increases substantially. Program 5 is similar to Program 1, with the only difference being an increase in the hours where the utility would be able to control charging (Program 5 adds 4 additional hours of control). Even in Tompkins County, a representative customer would be unlikely to join Program 5.

4.4. Opting out of smart EV charging programs: observed heterogeneity

We explored observed heterogeneity in the decision of opting out of the offered coordinated EV charging programs by interacting the opt-out constant with sociodemographics. Table 10 summarizes posterior quantiles of the relative risk of opting out from the selected mixed logit model

We were able to identify an effect among those customers who currently have a Time-of-Use rate, those that completed a graduate or professional degree, an income effect, as well as a nonlinear effect of age — grouped in generations. As working definition of age generations we adopted cutoffs that are standard in marketing in the US, namely: millennials (born between 1981 and 1996), Generation X (1965–1980), and baby boomers (1946–1964). Those born before 1946 were grouped together and left as reference. As it can be seen from the relative risk estimates, ceteris paribus younger individuals are much more likely to join a program of optimal scheduling of EV charging. In fact, most of the variables make customers less likely to opt out, with the exception of income.[8] The increase in the odds of joining a coordinated EV charging program is substantially higher for millennials (7.03 times higher than for those older than baby boomers), followed by those in Generation X (6.46 times higher), and baby boomers (3.37 times higher). The odds of joining the coordinated EV program are increased by 3 times, on average, for customers that completed graduate or professional studies, and are 4 times higher for customers with a Time-of-Use rate.

Each $10,000 increase in household income increases the odds of opting out by 0.23%, but a substantial increase in the odds of 195% is found for those individuals who did not provide income information.

5. Conclusions

A new energy landscape is emerging with the development of technology that both optimizes power systems in real time and addresses climate change, and customer engagement is essential to fully take advantage of technological change. Furthermore, successful design and deployment of energy-saving programs and services crucially depends on an accurate characterization of customer preferences.

Within this new energy landscape, and given the expected impacts on energy load profiles of large-scale charging of electric vehicles, coordinated EV charging programs – where electricity delivery is optimized to reduce grid stress – are being designed by researchers and energy providers. Coordinated EV charging requires incentives to persuade residential customers to delay charging to avoid peak charging times and to potentially accept a lower charge target for their electric vehicles.

This current study has analyzed response to the prototype of an actual pilot program of coordinated EV charging – OptimizEV – in upstate New York. Results from survey data and a choice experiment

[8] Odds ratios of opting out that are less than 1 can be recast as odds ratios of joining by using the multiplicative inverse plus 1, or by recoding the specification such that covariates that reduce the odds of opting out are introduced in the bundles to represent joining in.

before the roll-out of the OptimizEV pilot have provided evidence that on average customers would expect a monetary compensation (per hour of control yielded) for their willingness to defer charging and let the electricity provider to decide when to deliver energy to the battery. However, both monetary discounts in delivery charges and emission savings from delaying charging to off-peak hours can offset disutility of giving up control of when charging takes place. A net positive valuation of the program is supported by simulated scenarios that consider likely characteristics per EV charging session in terms of percent discount, hours of control yielded to the electric utility, and emission savings.

From a technical perspective and using Variational Bayes inference on conditional willingness-to-pay metrics at the individual level, this study also has provided strong evidence of substantial preference heterogeneity, both in terms of expected monetary valuation of features of coordinated EV charging programs and uncertainty in the determination of those estimates.

Limitations. The substantial unobserved heterogeneity in preferences captured by the selected mixed logit model reflects in part uncertainty regarding a charging program that not only did not exist at the time of the survey but also first introduced the concept of coordinated EV charging among current EV drivers in the region. In fact, even though coordinated EV charging was defined in the survey before the choice experiments, the local electric utility decided to present the notion of delaying charging of electric vehicles in a succinct way to avoid behavioral bias in eventual participants of the actual pilot. Furthermore, even though the pilot is being offered without an annual fee, for the derivation of welfare measures the experiment included an annual fee for participation in the smart EV charging program with the incentive of receiving a level-2 charger. Because of unfamiliarity with delaying charging of their electric vehicles, stated responses need to be treated with caution and only analyzed as early response by a sample of relative early adopters to a newly developed program. That posterior means have expected signs is reassuring in the sense that the concept of coordinated charging was understood by participants. However, difficulty of capturing observed preference heterogeneity in expected controls (such as battery size) is an indication of EV drivers not being familiar with the hypothetical program. Besides, unobserved heterogeneity may be masking attitudes to the OptimizEV program. Finally, the use of a multivariate normal distribution to represent preference heterogeneity may introduce unexpected signs in the tails of the posterior distributions of willingness to pay.

Future work will include the consideration of more flexible representations of unobserved preference heterogeneity that depart from mutivariate normal assumptions for modeling the survey data, as well as modeling revealed preferences coming from those 35 households involved in the actual load-shifting pilot. We expect that observed preference heterogeneity that was difficult to capture in the models with the early-response data used in this article will be elicited in the revealed preferences that are being currently collected, allowing us to control for variables such as battery capacity in kWh and vehicle miles traveled and to disentangle preference heterogeneity from attitudes and other unobserved factors. The revealed preference data that eventually we will have for analysis will require a scalable estimator such as the variational Bayes estimator tested in this paper due to: (1) the large number of transactions being recorded, and (2) the possibility of integrating updates of the choice model to produce personalized recommendations to the EV customers.

CRediT authorship contribution statement

Ricardo A. Daziano: Conceptualization, Data analysis to writing and revising.

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Appendix A. Benchmark models

See Tables 1–3.

Appendix B. Tables

See Tables 4–10.

Appendix C. Figures

See Figs. 1–7.

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