Willingness to delay charging of electric vehicles

Ricardo A. Daziano
School of Civil and Environmental Engineering
Cornell University, United States
daziano@cornell.edu

Abstract

Electrification of vehicles is becoming one of the main avenues for decarbonization of the transportation market. To reduce stress on the energy grid, large-scale charging will require optimal scheduling of when electricity is delivered to vehicles. 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. However, a challenge for successful introduction of coordinated deadline-scheduling of residential charging comes from the demand side: customers would need to be willing both to defer charging their vehicles and to accept less than a 100% target for battery charge. Within a coordinated electric-vehicle charging pilot run by the local utility in upstate New York, this study analyzes the necessary incentives for customers to accept giving up control of when charging of their vehicles takes place. Using data from a choice experiment implemented in an online survey of electric-vehicle owners and lessees in upstate New York (N=462), we make inference on the willingness to pay for features of hypothetical coordinated electric-vehicle charging programs. To address unobserved preference heterogeneity, we apply Variational Bayes (VB) inference to a mixed logit model. Stochastic variational inference has recently emerged as a fast and computationally-efficient alternative to Markov chain Monte Carlo (MCMC) methods for scalable Bayesian estimation of discrete choice models. Our results show that individuals negatively perceive the duration of the timeframe in which the energy provider would be allowed to defer charging, even though both the desired target for battery charge and deadline would be respected. This negative monetary valuation is evidenced by an expected average reduction in the annual fee of joining the charging program of $2.64 per hour of control yielded to the energy provider. Our results also provide evidence of substantial heterogeneity in preferences. 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 $5.16. 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.

Keywords: electric vehicles; smart charging; Bayesian inference; mixed logit.

1 Introduction

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 require optimal scheduling of when electricity is delivered to vehicles (Gonzlez-Garrido et al., 2019; Calearo et al., 2019; Andersen et al., 2018; Bitar and Xu, 2017; Arif et al., 2016). 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. From the demand side 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 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 Cornell researchers, OptimizEV: 1) determines exactly when to charge an EV within both a timeframe and target charge specified by the customer, 2) offers a discount based on how long an EV is left plugged in, and 3) ensures the EV is ready to go when needed.

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 Hardman et al., 2018; Daina et al., 2017b). 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 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 (Yang et al., 2016; Zoepf et al., 2013; Franke and Krems, 2013). In applied microeconometrics, mixed logit choice models (McFadden and Train, 2000) address unobserved heterogeneity in preferences through a parametric approach.

In this paper, our focus in on modeling choice of EV charging programs that implement optimal scheduling of EV charging (cf. Richter and Pollitt, 2018). In particular, we are interested in determining behavioral response to the idea of giving up control of EV charging by letting the electric utility to decide when to deliver electricity 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 and 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 designed for this study. Bayes estimation is an alternative approach to the more traditional maximum likelihood estimator, with many associated benefits 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 and Wand, 2010). Variational Bayes is implemented as an optimization problem rather than a sampling problem. 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 and McAuliffe, 2010; Depraetere and Vandebroek, 2017; Tan, 2017), recently in Bansal et al. (2020) we resolved major research gaps in terms of parameter recovery, finite-sample properties, and extensions to more general utility specifications and representations of unobserved preference heterogeneity. Across the VB implemtations in Bansal et al. (2020), VB-NCVMP-Δ (Depraetere and 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 The OptimizEV survey

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.

Before the start of the OptimizEV pilot, an online survey was launched to study charging preferences by residential customers that either own or are leasing an EV within and outside[1] the Tompkins County ESC footprint of the local electricity utility (Fig 1). The survey gathered categorical, attitudinal, and lifestyle information around current EV charging patterns and preferences.

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

[1] Across upstate New York, within the footprint of the local electricity utility.

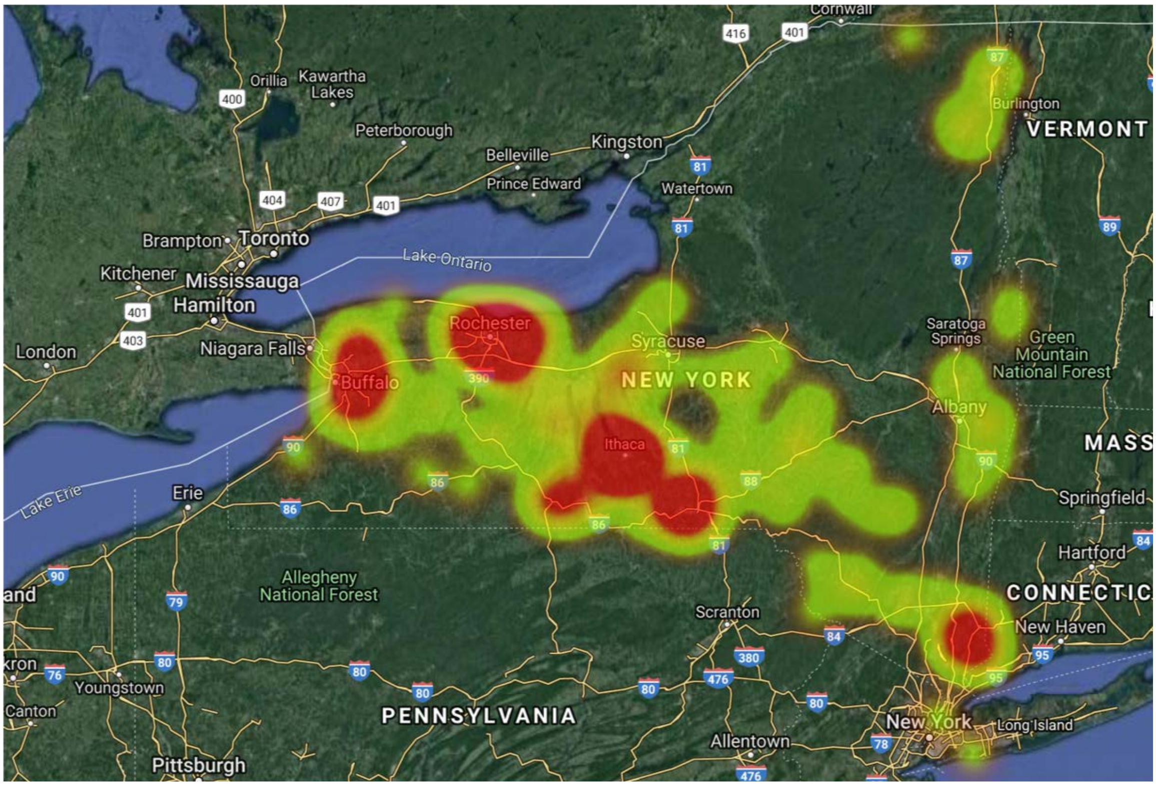


Figure 1: **Location of respondents to the OptimizEV survey in upstate New York**

that was included in the survey to determine the perceived trade-offs that EV owners are willing to make for smart EV charging.

Respondents to the survey (N=462) either own (69%) or lease (27%) mostly plug-in hybrids (PHEVs), with pure battery electric vehicles (BEVs) representing around one third of the sample (Fig. 2). 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. Other characteristics of the sample include: 55% have a graduate or professional degree; 90% live in a detached, single family home; 24% have onsite solar at home; 66% are employed full time; and 24% are retired.

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 $\geq \$25,000$ and $< \$35,000$	11%	8%
Household income $\geq \$35,000$ and $< \$50,000$	14%	14%
Household income $\geq \$50,000$ and $< \$75,000$	24%	19%
Household income $\geq \$75,000$ and $< \$100,000$	18%	14%
Household income $\geq \$100,000$	26%	29%
Homeowner	69%	75%

Table 1: **Sample Demographic Statistics**

2.2 Choice experiment

To elicit customer preferences around smart residential EV charging and deadline scheduling, a discrete choice experiment was designed mimicking some of the decisions expected from individuals participating in the OptimizEV program.

The choice experiment was presented to respondents as the electricity provider offering a smart EV charging program reproducing the characteristics of the OptimizEV pilot in terms of **GHG emission reductions per session**, **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 OptimizEV pilot is free, the experiment introduced a 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. Figure 2 shows a choice card sample.

	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)

Figure 2: **Choice card sample**

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), with a monetary incentive in the form of a discount per charging session which was presented as both a percentage reduction in the electricity delivery cost and customized expected dollar savings per month. Expected emission reductions were presented as pounds saved by charging session. At each choice situation, respondents had the possibility of choosing none of the bundles (i.e., keeping full control of charging). Brand of the charging system was included to determine brand equity.

Table 2 summarizes the attribute levels that were considered for a Bayesian efficient design of the experiment (Bliemer and Rose, 2010). Priors were obtained from a pretest of the experiment.

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 hours
	8 hours
	12 hours
Payment for service [annual fee in US$]	$5
	$10
	$50
	$90
	$300
Discount per charging sessions at home	1%
	2%
	5%
	10%
	20%

Table 2: **Experimental bundle features and levels**

3 Methodology: variational Bayes inference for mixed logit

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 analysis in Bansal et al. (2020) shows that existing VB variants extended to the case of invariant and individual-specific parameters perform as well as MCMC and MSLE at prediction and parameter recovery with important savings in estimation cost, with the exception of those variants relying on an alternative variational lower bound constructed with the help of the modified Jensen's inequality. Stochastic variational inference with nonconjugate variational message passing and the Delta-method (VB-NCVMP-Δ) in particular is shown to be up to 16 times faster than MCMC and MSLE.

Consider a standard discrete choice setup, where random-utility-maximizer decision-maker $n \in \{1,\dots N\}$ on choice situation $t \in \{1,\dots T_n\}$ chooses one alternative j in the choice set C_{nt}. Here, $V()$ denotes the representative utility, $\boldsymbol{X}_{ntj}$ is a row-vector of covariates, $\boldsymbol{\Gamma}_n$ is a collection of taste parameters, and ϵ_{ntj} is a stochastic disturbance. The assumption $\epsilon_{ntj} \sim \text{Gumbel}(0,1)$ leads to a multinomial logit (MNL) kernel. In this paper, we consider a general utility specification under which tastes $\boldsymbol{\Gamma}_n$ are partitioned into fixed taste parameters $\boldsymbol{\alpha}$, which are invariant across decision-makers, and random taste parameters $\boldsymbol{\beta}_n$, which are individual-specific, such that $\boldsymbol{\Gamma}_n = \begin{bmatrix}\boldsymbol{\alpha}^\top & \boldsymbol{\beta}_n^\top\end{bmatrix}^\top$, whereby $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}_n$ are vectors of lengths L and K, respectively. Analogously, the row-vector of covariates $\boldsymbol{X}_{ntj}$ is partitioned into attributes $\boldsymbol{X}_{ntj,F}$, which pertain to the fixed parameters $\boldsymbol{\alpha}$, as well as into attributes $\boldsymbol{X}_{ntj,R}$, which pertain to the individual-specific parameters $\boldsymbol{\beta}_n$, such that $\boldsymbol{X}_{ntj} = \begin{bmatrix}\boldsymbol{X}_{ntj,F} & \boldsymbol{X}_{ntj,R}\end{bmatrix}$. For simplicity, we assume that the representative utility is linear-in-parameters, i.e.

$$V(\boldsymbol{X}_{ntj}, \boldsymbol{\Gamma}_n) = \boldsymbol{X}_{ntj}\boldsymbol{\Gamma}_n = \boldsymbol{X}_{ntj,F}\boldsymbol{\alpha} + \boldsymbol{X}_{ntj,R}\boldsymbol{\beta}_n. \tag{1}$$

The distribution of tastes $\boldsymbol{\beta}_{1:N}$ is assumed to be multivariate normal, i.e. $\boldsymbol{\beta}_n \sim \mathcal{N}(\boldsymbol{\zeta}, \boldsymbol{\Omega})$ for $n = 1, \ldots, N$, where $\boldsymbol{\zeta}$ is a mean vector and $\boldsymbol{\Omega}$ is a covariance matrix. In a fully Bayesian setup, the invariant (across individuals) parameters $\boldsymbol{\alpha}$, $\boldsymbol{\zeta}$, $\boldsymbol{\Omega}$ are also considered to be random parameters and are thus given priors. We use normal priors for the fixed parameters $\boldsymbol{\alpha}$ and for the mean vector $\boldsymbol{\zeta}$. Following Tan (2017) and Akinc and Vandebroek (2018), we employ Huang's half-t prior (Huang and Wand, 2013) for covariance matrix $\boldsymbol{\Omega}$, as this prior specification exhibits superior noninformativity properties compared to other prior specifications for covariance matrices (Huang and Wand, 2013; Akinc and Vandebroek, 2018). In particular, (Akinc and Vandebroek, 2018) show that Huang's half-t prior outperforms the inverse Wishart prior, which is often employed in fully Bayesian specifications of MMNL models (e.g. Train, 2009), in terms of parameter recovery. The generative process of the fully Bayesian MMNL model is:

$$\boldsymbol{\alpha}|\boldsymbol{\lambda}_0, \Xi_0 \sim \mathrm{N}(\boldsymbol{\lambda}_0, \Xi_0) \tag{2}$$

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

$$a_k|A_k \sim \mathrm{Gamma}\left(\frac{1}{2}, \frac{1}{A_k^2}\right), \qquad k = 1, \ldots, K, \tag{4}$$

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

$$\boldsymbol{\beta}_n|\boldsymbol{\zeta}, \boldsymbol{\Omega} \sim \mathrm{N}(\boldsymbol{\zeta}, \boldsymbol{\Omega}), \qquad n = 1, \ldots, N, \tag{6}$$

$$y_{nt}|\boldsymbol{\alpha}, \boldsymbol{\beta}_n, \boldsymbol{X}_{nt} \sim \mathrm{MNL}(\boldsymbol{\alpha}, \boldsymbol{\beta}_n, \boldsymbol{X}_{nt}), \qquad n = 1, \ldots, N, \ t = 1, \ldots, T_n, \tag{7}$$

where (4) and (5) induce Huang's half-t prior (Huang and Wand, 2013). $\{\boldsymbol{\lambda}_0, \Xi_0, \boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0, \nu, A_{1:K}\}$ 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.

Stochastic variational inference 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 and Leibler, 1951) – to the posterior distribution of interest $P(\boldsymbol{\theta}|\boldsymbol{y})$. Thus, VB minimizes the KL divergence $q^*(\boldsymbol{\theta}) = \arg\min_q \{\mathrm{KL}(q(\boldsymbol{\theta})||P(\boldsymbol{\theta}|\boldsymbol{y}))\}$. Using the evidence lower bound (ELBO) $\mathbb{E}_q\{\ln P(\boldsymbol{y}, \boldsymbol{\theta})\} - \mathbb{E}_q\{\ln q(\boldsymbol{\theta})\}$, the estimation problem is recast as maximizing the ELBO. For choosing the functional form of the variational distribution $q(\boldsymbol{\theta})$, the mean-field family of distributions (e.g. Jordan et al., 1999) to factorize $q(\boldsymbol{\theta})$ can be exploited. The main result is that the ELBO can be maximized via a simple iterative coordinate ascent algorithm (Bishop, 2006), in which the variational factors are updated one at a time conditional on the current estimates of the other variational factors. Because the ELBO is convex with respect to each of the variational factors, the ELBO is thus guaranteed to converge to a local optimum (Boyd and Vandenberghe, 2004) and is expected to produce consistent estimates (Wang and 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):

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

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 $q^*(\boldsymbol{\beta}_n)$ are not members of recognizable families of distributions (due to the fact the conditional logit kernel does not have a general conjugate prior, Bansal et al. (2020)) and their updates require special treatment. The Delta (Δ) method (e.g. Bickel and Doksum, 2015) provides a simulation-based approximation based on a second-order Taylor series expansion.

4 Results

Logit-type choice models were used to derive estimates of customers' maximum 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 3 for both a conditional logit and a mixed logit model.

Smart EV charging bundle feature	Conditional Logit		Mixed Logit	
	Post. mean	Post. stdev	Post. mean	Post. stdev
Means				
Payment for service (annual fee in US$)	-0.0158200	0.0011050	-0.0193382	0.0015006
Hours of control yielded to utility for EV charging	-0.0381284	0.0072075	-0.0495393	0.0133526
Emission reductions per session [pounds]	0.0185446	0.0010609	0.0197761	0.0029181
Emission reductions per session [pounds] | Tompkins County	0.0077634	0.0017408	0.0233751	0.0058858
Discount per charging session at home [percentage]	0.0511575	0.0032177	0.0823401	0.0068904
Opt-out constant	-0.0145852	0.1133128	-0.6232797	0.4891341
Standard deviations				
Hours of control yielded to utility for EV charging			0.8313439	0.3828394
Emission reductions per session [pounds]			0.0426653	0.0029406
Discount per charging session at home [percentage]			0.0880205	0.0086275
Opt-out constant			3.3368670	0.3095830
Covariance				
Discount : GHG			-0.0081831	0.0044094
Discount : Control			0.0134810	0.0198757
Discount : OptOut			1.9616390	0.4555021
GHG : Control			-0.0410197	0.0177888
GHG : OptOut			-0.6049963	0.3442119
Control : OptOut			0.8313439	0.3828394
Loglikelihood at posterior means	-3260		-2607	

Table 3: **Bayes estimates of marginal utilities and nuisance parameters**

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. 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. For those attributes that exhibited evidence of unobserved preference heterogeneity, the mixed logit results include estimates of standard deviations and covariance of the individidual-specific parameters. In addition to posterior means for Bayesian point estimation, posterior standard deviations 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.

From the conditional logit estimates, assuming a homogeneous sample, we derived a negative willingness to pay of $2.41 (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). 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. The mixed logit estimates provide evidence that customers exhibit heterogeneity in their response to delay charging. Table 4 summarizes the posterior distributions of the means of the conditional individual-specific willingness to pay for features of the smart EV charging bundles.

Smart EV charging bundle feature		Quantiles				
	mean	5%	25%	50%	75%	95%
Hours of control yielded	-2.6402	-10.1578307	-5.1629931	-2.5081686	0.3422097	4.0608275
Pounds of GHG saved	1.1203	-0.9067813	0.1207043	1.1770988	2.0434324	3.1993851
Pounds of GHG saved | TC	2.2680	0.2409586	1.2684442	2.3248387	3.1911723	4.3471250
Percent discount	4.2160	-0.07823991	2.18870337	4.21784134	6.30973925	8.40490967

Table 4: **Mean and selected quantiles of mean conditional willingness to pay estimates at the individual level [US $ per year]**

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 $2.64, which is close to the conditional logit estimate), 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 $4.21 in associated annual fee. Each marginal pound in emission savings is also positively valued. 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 $2.27 in the annual fee by customers in Tompkins County (cf.the average $1.12 for customers outside Tompkins County). To give an idea of the magnitude of the environmental benefits, an upper bound for emission savings comes from shifting 100kWh 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.

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 4 show that there is substantial heterogeneity. Figure 3 shows, for instance, the conditional posterior distribution of the mean willingness to give up an additional hour in controlling EV charging.

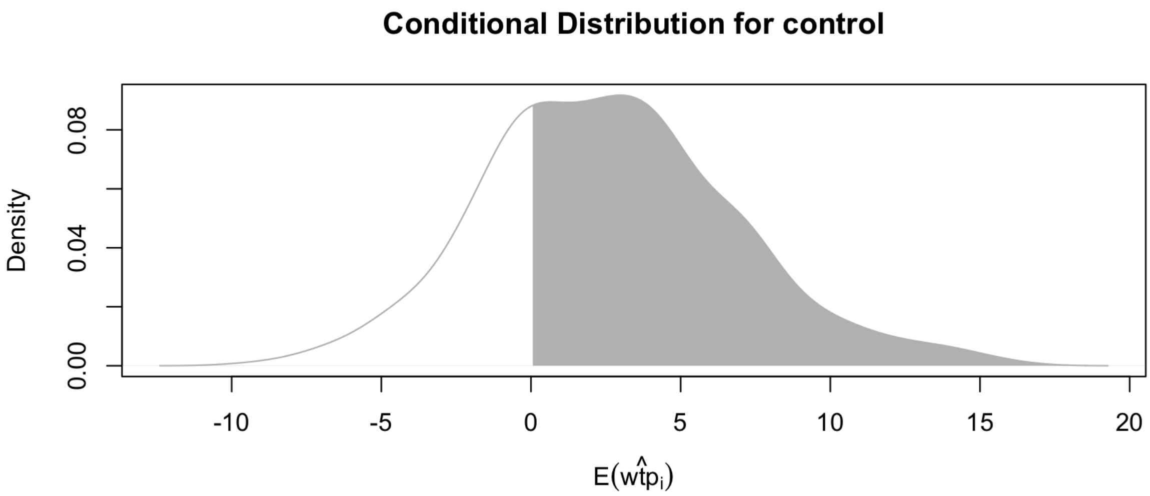
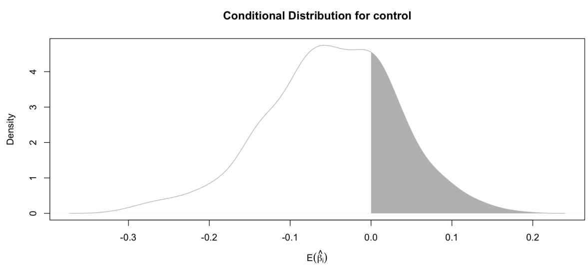
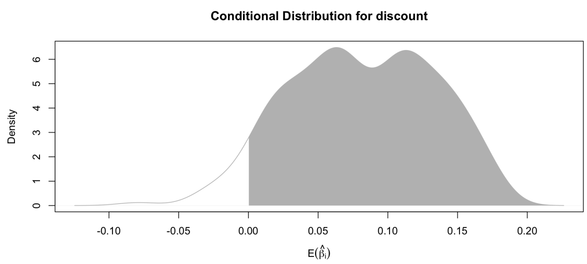


Figure 3: **Conditional distribution of the willingness to accept [in US $] an additional hour of control yielded to utility for EV charging**

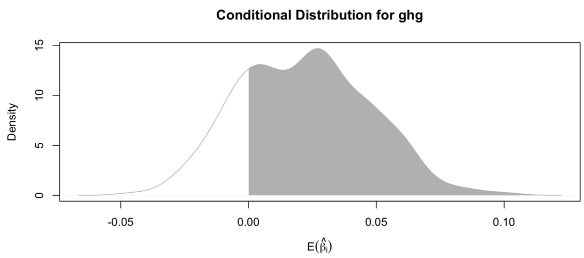
The resulting heterogeneity in the valuation of the features of the smart EV charging bundles comes from posterior distributions of the conditional estimates of the marginal utilities at the individual level. These distributions are displayed in Figure 4.



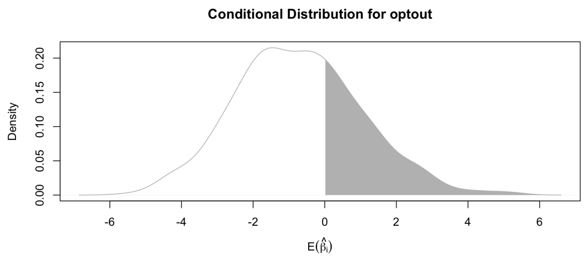
(a) Hours of control yielded to utility for EV charging



(b) Percent discount



(c) Pounds of GHG emissions saved



(d) Opt-out constant

Figure 4: **Conditional distributions of mean marginal utilities at the individual level**

Finally, as an additional way to visualize the extent of how preference vary in the population, Figure 5 displays – in increasing order – the conditional estimates of the individual-specific willingness to pay for reducing in one hour the timeframe in which the electricity utility takes control of 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.

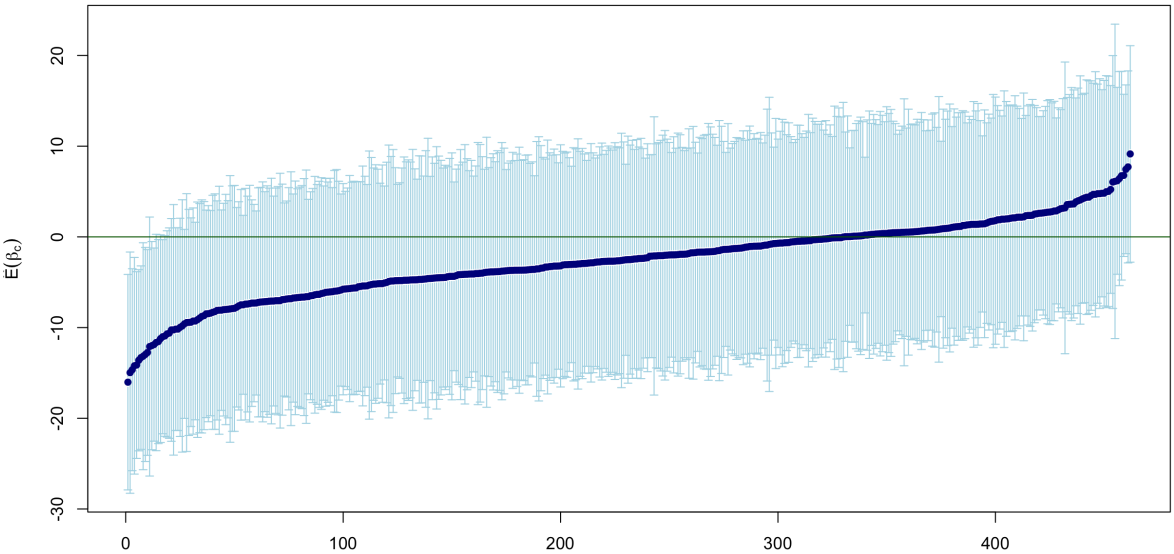


Figure 5: **Credible intervals of the conditional estimates at the individual level of the WTP [in US $ per year] for reducing an hour of control yielded to utility for EV charging**

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 are being designed by researchers and energy providers. Coordinated EV charging requires incentives to persuade residential customers to delay charging and to potentially accept a lower charge target for their electric vehicles. This current study has analyzed response to an actual pilot program – OptimizEV – in upstate New York. Results from survey data and a choice experiment before the roll-out of the actual pilot have provided evidence that 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. However, 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. Future work will include the consideration of more flexible representations of unobserved preference heterogeneity for modeling the survey data, as well as modeling revealed preferences coming from those 35 households involved in the actual pilot.

Acknowledgments

The OptimizEV survey was supported by NYSEG, the New York State Energy Research and Development Authority (NYSERDA), and the National Science Foundation (NSF; Grant PFI:BIC 1632124). Estimation software was the result of the collaborative work published as (Bansal et al., 2020). Charleen Heidt (NYSEG) and Briana Amoroso (Taitem Engineering) helped with the design of the questionnaire and the definition of the requirements of the choice experiment.

References

Akinc, D. and Vandebroek, M. (2018). Bayesian estimation of mixed logit models: Selecting an appropriate prior for the covariance matrix. *Journal of choice modelling*, 29:133–151.

Andersen, P. B., Sousa, T., Thingvad, A., Berthou, L. S., and Kulahci, M. (2018). Added value of individual flexibility profiles of electric vehicle users for ancillary services. In *2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*, pages 1–6.

Arif, A., Babar, M., Ahamed, T. I., Al-Ammar, E., Nguyen, P., Kamphuis, I. R., and Malik, N. (2016). Online scheduling of plug-in vehicles in dynamic pricing schemes. *Sustainable Energy, Grids and Networks*, 7:25 – 36.

Bansal, P., Krueger, R., Bierlaire, M., Daziano, R. A., and Rashidi, T. H. (2020). Bayesian estimation of mixed multinomial logit models: Advances and simulation-based evaluations. *Transportation Research Part B: Methodological*, 131:124 – 142.

Bickel, P. J. and Doksum, K. A. (2015). *Mathematical Statistics: Basic Ideas and Selected Topics, Volumes I-II Package*. Chapman and Hall/CRC.

Bishop, C. (2006). *Pattern Recognition and Machine Learning*. Information Science and Statistics, Springer Nature Textbooks ? HE site. Springer-Verlag, New York.

Bitar, E. and Xu, Y. (2017). Deadline differentiated pricing of deferrable electric loads. *IEEE Transactions on Smart Grid*, 8(1):13–25.

Blei, D. M., Kucukelbir, A., and McAuliffe, J. D. (2017). Variational Inference: A Review for Statisticians. *Journal of the American Statistical Association*, 112(518):859–877.

Bliemer, M. C. and Rose, J. M. (2010). Construction of experimental designs for mixed logit models allowing for correlation across choice observations. *Transportation Research Part B: Methodological*, 44(6):720–734.

Boyd, S. and Vandenberghe, L. (2004). *Convex optimization*. Cambridge university press.

Braun, M. and McAuliffe, J. (2010). Variational Inference for Large-Scale Models of Discrete Choice. *Journal of the American Statistical Association*, 105(489):324–335.

Calearo, L., Thingvad, A., Suzuki, K., and Marinelli, M. (2019). Grid loading due to ev charging profiles based on pseudo-real driving pattern and user behavior. *IEEE Transactions on Transportation Electrification*, 5(3):683–694.

Chakraborty, D., Bunch, D. S., Lee, J. H., and Tal, G. (2019). Demand drivers for charging infrastructure-charging behavior of plug-in electric vehicle commuters. *Transportation Research Part D: Transport and Environment*, 76:255 – 272.

Daina, N. (2018). Modelling the user variable. *Nature Energy*.

Daina, N., Sivakumar, A., and Polak, J. W. (2017a). Electric vehicle charging choices: Modelling and implications for smart charging services. *Transportation Research Part C: Emerging Technologies*, 81:36 – 56.

Daina, N., Sivakumar, A., and Polak, J. W. (2017b). Modelling electric vehicles use: a survey on the methods. *Renewable and Sustainable Energy Reviews*, 68:447 – 460.

Depraetere, N. and Vandebroek, M. (2017). A comparison of variational approximations for fast inference in mixed logit models. *Computational Statistics*, 32(1):93–125.

Franke, T. and Krems, J. (2013). Understanding charging behaviour of electric vehicle users. *Transportation Research Part F: Traffic Psychology and Behaviour*, 21:75–89.

Gonzlez-Garrido, A., Thingvad, A., Gaztaaga, H., and Marinelli, M. (2019). Full-scale electric vehicles penetration in the danish island of bornholm,Äîoptimal scheduling and battery degradation under driving constraints. *Journal of Energy Storage*, 23:381 – 391.

Hardman, S., Jenn, A., Tal, G., Axsen, J., Beard, G., Daina, N., Figenbaum, E., Jakobsson, N., Jochem, P., Kinnear, N., Pltz, P., Pontes, J., Refa, N., Sprei, F., Turrentine, T., and Witkamp, B. (2018). A review of consumer preferences of and interactions with electric vehicle charging infrastructure. *Transportation Research Part D: Transport and Environment*, 62:508 – 523.

Huang, A. and Wand, M. P. (2013). Simple marginally noninformative prior distributions for covariance matrices. *Bayesian Anal.*, 8(2):439–452.

Jordan, M. I., Ghahramani, Z., Jaakkola, T. S., and Saul, L. K. (1999). An Introduction to Variational Methods for Graphical Models. *Machine Learning*, 37(2):183–233.

Kullback, S. and Leibler, R. A. (1951). On Information and Sufficiency. *The Annals of Mathematical Statistics*, 22(1):79–86.

McFadden, D. and Train, K. (2000). Mixed MNL models for discrete response. *Journal of applied Econometrics*, 15(5):447–470.

Ormerod, J. T. and Wand, M. P. (2010). Explaining Variational Approximations. *The American Statistician*, 64(2):140–153.

Richter, L.-L. and Pollitt, M. G. (2018). Which smart electricity service contracts will consumers accept? The demand for compensation in a platform market. *Energy Economics*, 72:436–450.

Rossi, P. (2015). bayesm: Bayesian inference for marketing/micro-econometrics, 2012. ***URL:*** *http://CRAN. R-project. org/package= bayesm. R package version*, pages 2–2.

Rossi, P. E., Allenby, G. M., and McCulloch, R. (2012). *Bayesian statistics and marketing*. John Wiley & Sons.

Tan, L. S. L. (2017). Stochastic variational inference for large-scale discrete choice models using adaptive batch sizes. *Statistics and Computing*, 27(1):237–257.

Train, K. E. (2009). *Discrete Choice Methods with Simulation*. Cambridge University Press, 2nd edition.

Wang, Y. and Blei, D. M. (2018). Frequentist consistency of variational bayes. *Journal of the American Statistical Association*, pages 1–15.

Yang, Y., Yao, E., Yang, Z., and Zhang, R. (2016). Modeling the charging and route choice behavior of bev drivers. *Transportation Research Part C: Emerging Technologies*, 65:190–204.

Zoepf, S., Mackenzie, D., Keith, D., and Chernicoff, W. (2013). Charging choices and fuel displacement in a large-scale demonstration of plug-in hybrid electric vehicles. *Transportation Research Record*, (2385):1–10. cited By 29.