Transportation Research Part C 69 (2016) 386–401

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

The impact of car specifications, prices and incentives for battery electric vehicles in Norway: Choices of heterogeneous consumers

Yingjie Zhang [b], Zhen (Sean) Qian [a,b,*], Frances Sprei [c], Beibei Li [b]

[a] Department of Civil and Environmental Engineering, Carnegie Mellon University, Pittsburgh, PA 15213, USA
[b] Heinz College, Carnegie Mellon University, Pittsburgh, PA 15213, USA
[c] Division of Physical Resource Theory, Chalmers University of Technology, 412 58 Göteborg, Sweden

ARTICLE INFO

Article history:
Received 20 April 2015
Received in revised form 19 May 2016
Accepted 19 June 2016

Keywords:
Electric vehicle
BLP model
Incentives
Heterogeneous consumers

ABSTRACT

Electric vehicles (EVs), specifically Battery EVs (BEVs), can offer significant energy and emission savings over internal combustion engine vehicles. Norway has a long history of research and government incentives for BEVs. The BEV market in Norway allows us to fully examine consumers' BEV choices influenced by car specifications, prices and government incentives (public bus lanes access, toll waiver and charging stations). The Random-Coefficient Discrete Choice Model (referred to as the BLP model) is applied to understand the choices of heterogeneous personal consumers and business buyers. Our study is instantiated on the entire EV sales data in Norway from 2011 to 2013, as well as a set of demographics at the municipality level. The results suggest significant positive effects of BEV technology improvement, space, toll waiver and charging station density on EV demand for both personal consumers and business buyers. However, the effects on business buyers may be generally less pronounced than on personal consumers. Interestingly, bus lanes access demonstrates a negative impact for personal consumers, possibly due to consumers' concern regarding bus lane congestion. In addition, preferences on the BEV price can vary statistically among consumers with different income levels. Compared to the BEV technology development, demographical features and municipal incentives may have generally less impacts on market shares within the BEV market.

1. Introduction

Electric vehicles (EV) convert roughly 60% of the electrical energy from the power grid to wheels, compared to 20% from gasoline to wheels for a regular gasoline car (Department of Energy, 2014). In addition, EVs have no singular required energy source as most internal combustion engines have, since electricity can be produced from a multitude of sources, allowing for a diversification of energy sources in transportation. Significant energy/emission savings and flexibility offered by EVs call for increasing EV adoption all over the world. However, EVs have limitations compared to their internal combustion engine counterparts. The barriers to their adoption are that, to name a few, EVs are more expensive, have limited ranges and have less infrastructure support.

* Corresponding author at: Department of Civil and Environmental Engineering, Carnegie Mellon University, Pittsburgh, PA 15213, USA.
E-mail addresses: yingjie@cmu.edu (Y. Zhang), seanqian@cmu.edu (Zhen (Sean) Qian), fsprei@chalmers.se (F. Sprei), beibeili@andrew.cmu.edu (B. Li).

http://dx.doi.org/10.1016/j.trc.2016.06.014
0968-090X/

Norway is one of the countries that have the highest Battery Electric vehicles (BEV) market penetration per capita with a record 14.5% of new cars sold being BEVs during the first quarter of 2014. A recent report shows that in April 2014, Norway was the first country where one in every 100 cars was purely electric (Radio, 2014). In fact, BEV sales in Norway have soared since 2010 (see Fig. 1) when established automotive manufacturers made an aggressive entrance into the Norwegian BEV market and supply-side shortage was no longer a constraint. Emerging BEV technology, such as battery capacity and power, has improved over the years. Such improvements not only extend the usage life of BEVs, but also make them more affordable, comfortable and powerful. It has been found that although BEVs were mostly bought as a second car in a household, people tend to use EVs as primary cars, especially for short daily trips (Klöckner et al., 2013).

In addition to BEV technology advancement and sufficient supply, one of the primary reasons that Norway has the greatest BEV market share is attributed to a variety of incentives for BEV only (some are for plug-in hybrid EV as well), including registration tax exemption, free parking, bus lanes access, exemption of toll roads, establishment of dense charging stations in the city, etc. The effective dates of most of those incentives are earlier than the current climate policies: exemption from registration tax from the 1990s, value-added-tax (VAT) exemption started in 2001, access to bus lanes from 2003, free parking from 1999 and waiver of toll roads from 1997. In June 2012, the Climate Policy Settlement was signed in the Norwegian Parliament to set an environmental goal of reducing average CO_2 emissions from new passenger cars to 85 g/km by 2020. The agreement states that all the current financial benefits of BEVs will be continued to the end of 2017.

The incentives, such as bus lanes access, waiver of toll roads and expansion of charging stations networks, could be discontinued after 2017. With the enormous increase of BEV sales, both politicians and consumers are concerned about whether those incentives would still benefit BEV adoption, and therefore should continue or not. A recent report (Figenbaum, 2013) summarized previous surveys of BEV sales in Norway, and found that those incentives indeed impacted consumers' choices of car purchase. Some respondents stated that they would move back to non-electric vehicles if the incentives were reduced or removed. However, it is unclear what the quantitative impacts of the incentives are on both the BEV and non-EV markets.

BEV specifications, prices and incentives may collectively affect two types of consumer choices: the choice between purchasing a BEV and an internal combustion engine vehicle, and the choice of what brand/model of BEV to purchase given availability of various BEVs. The effects vary among consumers, largely dependent on their demographics, such as income levels. For instance, wealthier consumers are more likely to afford a BEV with a long range than low-income consumers, and these BEVs require fewer charging stations. Therefore, the incentive of building new charging stations may or may not have substantial impact on wealthy consumers' choices. In another example, a price drop in high-end BEVs may lead to more BEV sales, but the effect may be minimal if the road toll is no longer waived for BEV drivers. In order to support policy making and BEV marketing, it is central to quantitatively estimate the effects of BEV specifications, prices and incentives to different consumers.

Our study aims to capture the effects of car specifications, prices and incentives on the BEV choices of heterogeneous personal consumers and business buyers. We have the luxury to possess both BEV specifications, prices and individual BEV sales data in Norway from 2000 to 2013 (Grnn Bil, 2015), of which sales are fairly significant across nearly all municipalities from 2011 to 2013. The data sets allow us to establish econometric models to understand the BEV market, namely, given that a consumer decides to purchase a BEV, what drives the choice of BEV and what are the impacts of the factors. On the other hand, due to the unavailability of regular vehicle sales data, unfortunately we are unable to model consumers' choices between a BEV and a regular vehicle. This paper serves as the first step to support policy making for BEV adoption by revealing the factors effecting market shares within the BEV market. Once the regular car sales data are collected, the latter choice can be further addressed in a separate paper.

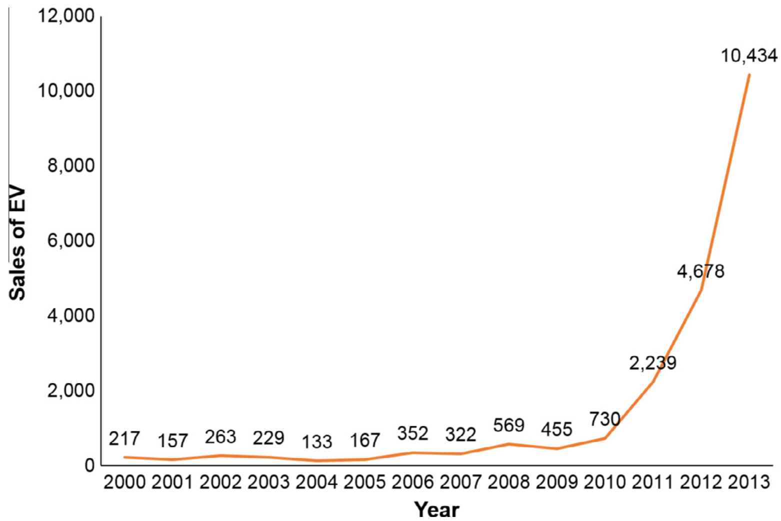

Fig. 1. 2000–2013 EV total sales in Norway.

This paper contributes to the literature in three ways. First, we adopt the state-of-the-art economic choice models to capture consumers' behavior in full details. Many studies have been dedicated into exploring the impacts of incentives on the EV market (Klöckner et al., 2013). Previous studies mainly focused on tax exemptions for hybrids (Diamond, 2009; Gallagher and Muehlegger, 2011) and applied linear regression methods to explore the effects of incentives or related technology improvement. However, simple linear models may be unable to capture consumer behaviors that vary significantly by individuals, locations and time. In this study, we will investigate the impacts of car specifications (speed, traveling range, number of seats, top speed, etc.), prices and incentives simultaneously on BEV purchases. We will specifically investigate the waiver of toll roads, bus lane access and charging stations networks as three main components of the existing incentives. Second, we also examine the effectiveness of BEV attributes and incentives on heterogeneous consumers who are distinguished by their income levels and purchase purposes (individual use or business use). By modeling the probabilistic preferences of different types of consumers, we are able to quantify the sensitivities of consumers' purchasing decisions. Third, since the BEV market is in its infant stage all over the world and EV sales data are usually unavailable, previous studies were heavily dependent on stated preference surveys or a small subset of full EV sales data. For this study, we use a full set of EV sales data in Norway from 2011 to 2013. To our best knowledge, this is the first such examination of this complete data set. This study can facilitate policy decision making about possible extension of BEV incentives. In addition, it also helps BEV-related programs, such as Transnova in Norway (http://www.transnova.no/english/), and BEV dealers with their marketing strategies. For example, our analysis of price elasticities among brands provides insights how to effectively price a BEV brand to influence its share in BEV market.

The rest of this paper is organized as follows. Previous relevant studies are reviewed in Section 2. We discuss our empirical econometric models in Section 3 with data descriptions and solutions to computation issues in Section 4. Section 5 presents our complete results by distinguishing consumer and business purchases. Finally, we conclude the paper in Section 6 with a summary of potential policy implications and future work.

2. Literature review

Many studies have been dedicated to exploring the impacts of incentives for alternative-fuel vehicles. Many look specifically at hybrids since these have been the longest on the market. There is still little empirical data on pure EVs and thus these have not been studied as extensively, yet. Gallagher and Muehlegger (2011) studied the effects of state Government incentives on hybrid vehicle sales in the US from 2000 to 2006. After omitting local incentive programs, they specifically focused on state sales tax waivers, income tax credits, non-tax incentives, rising gasoline prices and access to carpool lanes. They found that those tax incentives affected consumers' behavior and gasoline prices were positively correlated with the hybrid vehicle adoption, though there was no significant result for carpool lanes.

In addition to regression models, recently, other methods have been adopted to explore effects of EV sales, including agent-based models (Sullivan et al., 2009; Eppstein et al., 2011; Mueller and de Haan, 2009), consumer choice model (Santini and Vyas, 2005; Axsen et al., 2009; Bolduc et al., 2008), and diffusion rate and time series models (Cao and Mokhtarian, 2004; Al-Alawi and Bradley, 2013; Chandra et al., 2010). Beresteanu and Li (2011) studied hybrid vehicle sales in 22 municipalities. They adopted a random coefficient utility model in a market equilibrium model that takes into consideration both demand and supply side based on BLP (Berry et al., 1995). They found that both incentives and increasing fuel prices were significant in explaining increasing sales of hybrid cars. In a report on CO_2 reduction effect of fuel taxations in Europe, Cowi et al. (2002) combined sales statistics with socio-demographic data in a discrete choice Logit model. Many relevant studies have relied on Stated Preference (SP) surveys since there were few or no vehicles models available on the market or little sales data to perform conclusive analysis. Brownstone et al. (2000) and Axsen et al. (2009) combined stated and revealed preferences for alternative-fuel vehicles in a joint mixed Logit model. They presented advantages and disadvantages with both methods, and highlighted the risk for implausible forecasts with SP models. Axsen and Kurani (2013) perform a stated preference study in San Diego and find that PHEVs are the most attractive option between hybrids, PHEVs and BEVs. Recently a few studies investigated aggregated sales data using a cross-sectional regression analysis (Sprei and Bauner, 2011; Peter Mock, 2014; Sierzchula et al., 2014; Mersky et al., 2016). They all found that incentives played a role in the sales. However their effects were limited and hard to be quantified. Sierzchula et al. (2014) also included charging stations in the analysis and found them to be the single best predictor of EV sales. Vaggen Malvik and Ole Henrik Hannisdahl (2013) investigated Norway EV market. They tried to ascertain the driving reasons of EV sales. Their analysis was based on comparisons between Norway and other European countries and concluded that though the combination of incentives was important, the VAT tax exemption likely was the greatest factor. The history and effects of incentives in Norway was also presented in Figenbaum and Kolbenstvedt (2013). Overall, none of those studies examined the effects of all three factors altogether, traffic-related incentives, EV prices and car specifications. In addition, none of them considered individual heterogenous choices that may be affected by, for instance, their income levels.

3. Model and estimation

Our objective is to identify the impacts of car specifications and prices on BEV purchase by heterogeneous consumers and explore how the impacts vary with or without various municipal incentives. In this paper, we choose discrete choice models for two reasons: (i) personal preferences can be inferred from aggregate sales data, in a privacy-preserving manner; (ii) a choice model mimics consumers' purchasing decisions by modeling their utilities. Individual utilities represent consumers' preferences over various considerations while choosing different goods, and the utility concept is generally used in economics to reveal consumers' willingness to pay. In this section, we discuss our methodology to estimate the impacts of vehicle attributes and incentives using discrete choice models. To make this paper self-contained, we start off by briefly reviewing a discrete choice model with the assumption that all consumers are homogeneous in Section 3.1. In Section 3.2, we work with a more realistic model where consumers have distinct preferences that are dependent on their respective demographics and incentive benefits.

The following two assumptions are made throughout the paper, and they are further explained in later subsections.

Assumption 1. BEV consumers make choices of BEV products within each municipal market. In other words, consumers do not consider buying BEVs outside their living municipality.

Assumption 2. BEV consumers make choices of BEV products based upon their individual utilities that consist of three parts: utility of product specifications, utility of money and utility of municipal incentives.

3.1. Homogeneous consumers

To begin with, we briefly review the logit choice model (McFadden, 1972; McFadden and Train, 2000), by assuming that consumers within each market share identical preferences on car specifications, prices and BEV incentives. Suppose that we observe M municipal markets, each of which represents the BEV market in a municipality $m = 1, \ldots, M$. The m-th municipality has C_m consumers where consumers are denoted by index $i = 1, \ldots, C_m$. In each municipal market, there are J BEV products by brand $j = 1, \ldots, J$. We observe aggregated quantities of BEV sales, average price (P_j) and car specifications X_j of BEV product j, which is a vector of several individual features of the vehicle ($X_j = (x_{j1}, \ldots, x_{jk})$). The features include, but are not limited to, battery capacity, range, number of seats, top speed, etc. Each municipal market m has various types of EV incentives T_m. Here $T_m = (T_{m1}, \ldots, T_{mn})$ is a vector, each element of which denotes an incentive, such as bus lanes access, waiver of roadway tolls, etc. The utility (U^i_{mj}) of consumer i for BEV product j in the m-th municipality consists of three parts: utility of product, utility of money and utility of municipal incentives (Assumption 2). The consumer i does not consider purchasing BEV outside the m-th municipality market (Assumption 1), and therefore his/her utility is only related to features in the m-th market. We assume that each product feature in the vector X_j is associated with a weight indicating consumers' desirability towards that feature, so does each municipal incentive. As for utility of money, we assume it is linearly related to the prices of products. Based on this assumption, we consider the overall utility of the product as the aggregation of weighted utilities from the observed BEV product features (namely car specifications), BEV prices and BEV incentives, as well as an unobserved attribute ξ. Notice that in such a basic Logit model, the weights are identical across all consumers regardless of their demographics. Mathematically, the utilities are defined as follows,

$$U^i_{mj} = -\alpha \cdot P_j + \beta \cdot X_j + \gamma \cdot T_m + \xi_j + \varepsilon^i_{mj}, \tag{1}$$

where that ε is a stochastic error term following a Type I Extreme Value distribution. Note that β and γ are k and n dimensional vectors, respectively. The multiplication sign for the second term implies inner product of vectors. According to Assumption 1, the consumer can only choose from alternatives in the same municipal market. Therefore, the probability that a consumer i chooses product j in the m-th municipal market is:

$$P(choice^i_{mj}) = P(U^i_{mj} > U^i_{ml})(\forall l \text{ in municipal market } m, l \neq j). \tag{2}$$

Following McFadden (1972), we have:

$$P(choice^i_{mj}) = \frac{exp(-\alpha \cdot P_j + \beta \cdot X_j + \xi_j)}{1 + \sum_l exp(-\alpha \cdot P_l + \beta \cdot X_l + \xi_l)}, \quad i = 1, 2, \ldots, C_m, \tag{3}$$

where, without loss of generality, we set the utility of consumer i choosing a BEV brand other than $j = 1, \ldots J$ is constantly to zeros. In other words, we treat the other brands as the outside goods and normalize their consumers' utility to zeros. Since the consumers are homogeneous, the probability of purchasing BEV j, $P(choice^i_{mj})$, is identical among all consumers. Thus, we can ignore the superscript i and set $P(choice_{mj}) = d^{obs}_{mj}/d_{total_m}$, where d^{obs}_{mj} is the observed number of sales for product j in market m and d_{total_m} is the total number of BEV sales in market m, including a BEV brand other than $j = 1, \ldots, J$. Taking logs in Eq. (3), we can solve the system:

$$ln(d^{obs}_{mj}) = -\alpha \cdot P_j + \beta \cdot X_j + \xi_j. \tag{4}$$

Following Eq. (4), we can use any regression method with specific loss functions (e.g., ordinary least squares) to estimate β and α, and the effects of BEV specifications and prices to BEV sales for each brand and each market.

Note that consumers would only make choices within each municipal market (Assumption 1). In other words, regardless of the choices of BEV product, a consumer gains the same benefits from municipal BEV incentives. Therefore, we cannot identify the effects of incentives by assuming homogeneous consumer preferences (In Eq. (3), the utility of incentives is canceled out). In addition, the homogeneity setting is not realistic in order to determine BEV choices that vary substantially within the population. For example, consumers' preferences on product prices are highly influenced by their income level. In the following subsection, we further discuss a heterogeneous discrete choice model that allows consumers to have diverse tastes within each municipality.

3.2. Heterogeneous consumers

In reality, consumers evaluate the same product differently and their utilities of purchasing the same product are therefore also different. Such differences stem from the diversity of consumers' demographic features. For example, income levels may partially explain why wealthy people are generally less price-sensitive than poor people. In our setting of the BEV markets, BEV incentives also affect the BEV market shares differently for different municipal markets. Compared to the municipalities with fewer charging points, a municipality with more charging points may offer BEV drivers more incentives to buy BEVs, and therefore the effects of charging points being an incentives are more pronounced.

To capture consumers' distinct preferences, we allow that the preferences of BEV prices and specifications to be functions of consumer demographics (particularly income) and municipal features (particularly municipal BEV incentives). In this paper, we follow the widely-used Random-Coefficient Model, referred to the *BLP* model introduced by Berry et al. (1995), Nevo (2001b), Oberholzer-Gee and Strumpf (2007), to extract consumers' heterogeneous preferences. The main idea of the *BLP* model is that consumers with different demographic characteristics treat the utility of the same product differently. In our setting, within the same municipality, consumers are homogeneous if and only if they are at the same income level. The income level affects the utility of money for consumers. Meanwhile, consumers with the same income level are still heterogeneous across municipalities because they are subject to different types of municipal features and BEV incentives, which affect the utility of the products.

The heterogeneous setting is an generalization of the homogeneous case. Again, we observe J BEV products (product index $j = 1, \ldots, J$). There are M municipal markets (market index $m = 1, \ldots, M$), each of which has C_m consumers and municipal BEV incentive T_m. Each BEV product j comes with its car specifications X_j and car price P_j. The unobserved attribute is captured by ξ_j and the random shock is denoted by ε. In the *BLP* model, the weights of the observed car specifications vary by the municipalities' features, represented by municipal incentives T_m. In addition, the weight of prices is a function of consumers' income levels (income level index $i = 1, \ldots, I$). Mathematically, for a consumer i in market m considering BEV product j, the utility function is described as:

$$U^i_{mj} = -\alpha(I^i) \cdot P_j + \beta(T^i_m) \cdot [X_j 1] + \xi_j + \varepsilon^i_{mj}. \tag{5}$$

The multiplication sign for the second term implies inner product of vectors.

The main difference between Eqs. (1) and (5) are in the weights. In the homogeneous case (Eq. (1)), the weights (α and β) are identical among all consumers in all markets, while in the heterogeneous case (Eq. (5)), the weights ($\beta(T^i_m)$ and $\alpha(I^i)$) vary among consumers in different markets. In order to separate the mean population preferences from the individual-specific preferences, we follow Li et al. (2011) to re-write $\beta(T^i_m) = \bar{\beta} + \beta_T T^i_m + \upsilon_\beta$ and $\alpha(I^i) = \bar{\alpha} + \alpha_I I^i + \upsilon_\alpha$, where $\bar{\beta}$ and $\bar{\alpha}$ are the means of the effects of incentives and car prices (for the lowest income level and without BEV incentives). α_I is a real-value coefficient capturing the effect of consumers' income levels on the utility of money. This effect is identical for all consumers in the same income level across all municipal markets. T^i_m is a $n \times 1$-dimension vector of BEV incentives for consumer i in his/her market m. β_T is a $(k+1) \times n$ matrix capturing various tastes of car specifications for different settings of incentives across municipalities, where k is the dimension of car specifications X_j. We augment X_j by one additional element 1 so that the last element of $\beta(T^i_m)$ indicates the utility of BEVs without any car specifications, analogous to the intercept in the linear regression model. υ_α and υ_β capture the unobserved heterogeneity. We assume these two unobserved variables follow a normal distribution with mean zero and a variance to be estimated.

Furthermore, we denote $\delta_j = \bar{\beta} \cdot [X_j 1] - \bar{\alpha} \cdot P_j + \xi_j$ the baseline utility of product j (for the lowest income level and without BEV incentives).

For each market m, the population income follows a distribution that is usually measured by census, and the incentives are predetermined as they are. We then derive the choice probability of BEV product j in the m-th market (the subscript market m is dropped for simplicity),

$$s_j = P(choice_j) = \int \frac{exp(\delta_j - \alpha_I I^i \cdot P_j + (\beta_T T^i) \cdot [X_j 1])}{1 + \sum_l exp(\delta_l - \alpha_I I^i \cdot P_l + (\beta_T T^i) \cdot [X_l 1])} \mathrm{d}P(I) \tag{6}$$

where, without loss of generality, we set the utility of consumer i choosing a BEV brand other than $j = 1, \ldots, J$ constantly to zeros.

We discuss in the next section how to compute this integral and to learn the unknown parameters δ_j, β_T, and α_I from the data.

3.3. Estimation process

Since there is no analytical method to solve Eq. (6), we apply the traditional iterative method of the *BLP* model to estimate unknown coefficients (Berry et al., 1995; Li et al., 2011; Nevo, 2000). The iterative estimation process can be divided into four steps:

Step 1: Initialize unknown parameters $\delta_j^{(0)}, \alpha_I^{(0)}$ and $\beta_T^{(0)}$ using randomly selected values. Set iteration index $v = 0$.

Step 2: Set iteration index $v = v + 1$. Determine the baseline utility of BEV product $j, \delta_j^{(v)}$.

Compute the market share of each product from Eq. (6) in each market. Unfortunately, the integral cannot be solved analytically and requires numerical approximation. To approximate this integral, we first use the distributions of income levels in each municipal market to generate a random consumer sample (with S being the sample size). Given the parameters $\theta^{(v-1)} \doteq (\alpha_I^{(v-1)}, \beta_T^{(v-1)})$, we calculate an unbiased estimator of the integral as follows (again the subscript market m is dropped for simplicity):

$$s_j(\delta_j|\theta^{(v-1)}) \sim \frac{1}{S}\sum_{i=1}^{S}\frac{exp(\delta_j - \alpha_I^{(v-1)}I^i \cdot P_j + (\beta_T^{(v-1)}T^i) \cdot [X_j 1])}{1 + \sum_l exp(\delta_l - \alpha_I^{(v-1)}I^i \cdot P_l + (\beta_T^{(v-1)}T^i) \cdot [X_l 1])} \tag{7}$$

Note that while generating consumer samples, we assume that the income of individuals is independent of each other, namely that the empirical distributions of income for all individuals are identically and independently distributed.

Eq. (7) computes the estimated market shares for each market given any $\delta_j, \alpha_I^{(v-1)}$ and $\beta_T^{(v-1)}$ in the v-th iteration. In addition, from the data, we observe the actual market shares of each product (s_j^{obs}). We use a contraction mapping method to find a $\delta_j^{(v)}$ conditional on $\theta^{(v-1)}$ to minimize the differences between the estimated and observed market shares. The following iterative approach is guaranteed to find $\delta_j^{(v)}$ such that $s_j(\delta_j^{(v)}|\theta^{(v-1)}) = s_j^{obs}$ (Berry et al., 1995). In each iteration r,

$$\delta_j^{(v),(r+1)} = \delta_j^{(v),(r)} + (ln(s_j^{obs}) - ln(s_j(\delta_j^{(v),(r)}|\theta^{(v-1)}))) \tag{8}$$

The iteration terminates when $\delta_j^{(v),(r+1)} = \delta_j^{(v),(r)}$ is achieved numerically.

Step 3: Identify $\theta^{(v)} \doteq (\alpha_I^{(v)}, \beta_T^{(v)})$.

We use the Nelder-Mead Simplex algorithm (Li et al., 2011; Archak et al., 2007) to search for the gradients of the GMM objective function with respect to α_I and β_T given a set of instrumental variables (*IV*, denoted by a matrix *Z*). The basic intuition of IV methods is to find alternative IVs to substitute for the endogenous variable in the model, where the IVs should only be correlated with the endogeneous variable (i.e., price) but uncorrelated with the unobserved error term in the model. We use W as a design matrix including all BEV specifications and prices used in the baseline utility $\delta_j^{(v)}$, namely $W \doteq [W_1 W_2, \ldots W_J]$ where the j-th column $W_j \doteq [X_j, \quad -P_j]^T$. Let π denote the corresponding weight vector of W, namely $\pi \doteq [\bar{\beta}\ \bar{\alpha}]$. We define $\Phi = Z'Z$ and let ξ extract the unobserved error from the baseline utility, $\xi = \delta^{(v)} - \pi W$, where the baseline utility $\delta^{(v)}$ is a J-dimensional vector. The objective GMM function follows:

$$GMMObj = \xi' Z \Phi^{-1} Z' \xi. \tag{9}$$

As proved in Nevo (2000), given any $\delta^{(v)}$, the parameters in the mean utility function π can be expressed as a function θ:

$$\pi = (W'Z\Phi^{-1}Z'W)^{-1} W'Z\Phi^{-1}Z'\delta^{(v)}. \tag{10}$$

Step 4: If the GMM objective function is not minimized, then go back to Step 2.

Remark. By iterating steps 2 and 3, we obtain the "best" parameters given the initial starting values. A heuristic algorithm (namely the Nelder-Mead Simplex algorithm) is adopted to check whether the GMM objective function is minimized. If the GMMObj value does not decrease after a predetermined amount of iterations, then the GMM objective function is considered to be minimized.

4. Data and computational challenges

To evaluate the above model, we instantiate the framework with a unique data set containing complete information on Norwegian BEV sales. In the following subsections, we first discuss our data set, followed by detailed descriptions about how to fit the raw data to the model. Last but not least, we pinpoint several computational challenges associated with the *BLP* model in this study.

4.1. Data descriptions

Demand data: Sales data are obtained from Opplysningsrädet for Veitrafikken (Norwegian Road (www.ofv.no)), an umbrella organization of actors involved in road transport in Norway. Early data were supplied by GrØnn Bil (www.gronnbil.no, 'Green car') a project funded by the Norwegian organization aimed at diminishing the CO_2 emissions from the Norwegian transportation sector. This data set covers the entire BEV sales in Norway and contains various levels of information, including the sale's manufacturer and municipality, the vehicle's make/model, transaction time, purchase purposes (personal or business) and the gender of the buyer. Because the BEV sales prior to 2010 is minor due to premature BEV technology, this paper works with BEV sales from 2011–2013 to ensure model reliability. All the sales from 2011 to 2013 are aggregated into municipal level to fit the above model. In addition, the data are classified into two groups: personal sales and business sales. In this study, we only investigate 14 predominant brands. The 14 brands are: Buddy Electric, Renault, Citroen, Ford, Fiat, Mitsubishi, Nissan, Peugeot, Think, Tesla, Tazzari, Mia, Volkswagen, and BMW. Notice that Plug-in Hybrid Electric Vehicles (PHEV) are not included because they entered the market in late 2012, and the sales in 2013 were minor compared to BEV.

Municipalities: Administratively Norway is divided into 430 municipalities. For most census data, this is the lowest level of locality precision given. Unfortunately, municipalities have gone through several consolidation and merges from 2000 through 2013, which means that the data sets collected have inconsistent numbers of municipalities. For the purposes of this study municipalities and their sales and demographic data reflect the municipal borders at the end of 2013. Data from the previous years were merged together, from the constituent municipalities, into the borders of the more recent one. We found that 163 municipalities do not have EV sales from 2000 to 2013. This is because the division into municipalities and counties is an administrative division, thus a large share of these municipalities are not cities in the traditional meaning but rather rural areas, many with a very low number of inhabitants and thus no EV sales. In addition, many municipalities (especially those rural ones) do not have EV dealerships. To ensure data consistency, the municipalities with no sales of EVs have been excluded from the analysis. The final total of municipalities for personal consumers is 284, and 180 for business buyers.

EV product characteristics: Each brand has their car specifications, including top speed, car range, the number of seats and battery capacity (retrieved in 2013 from http://www.gronnbil.no/bilmodeller/). The attributes of the 14 brands EVs are shown in Table 1. In general, these specifications and prices are highly correlated. For example, the larger battery capacity, the more likely a BEV comes with a higher price. Each of those characteristics is normalized to the magnitude of 0 to 1. More details will be discussed in Section 4.3.

Incentive policies: As discussed above, Norway has a long history of providing policy incentives to encourage BEV adoption. The introduction dates of each incentive are summarized in Table 2. This paper only considers three main incentives: access to bus lanes, waiver of tolls and expansion of free public charging stations. We exclude tax exemption here because it is a nationwide policy and therefore does not allow spatial variations. Access to bus lanes and waiver of tolls are modeled as dummy variables where 1 indicates available and 0 otherwise. Note that the number of charging points within a municipality is positively correlated with its population. Thus, we consider the number of charging points per capita in this paper.

Income data: This data set comes from Statistics Norway (https://www.ssb.no/). The municipal income data contain percentages of seven levels of total gross household's income: (1) below NOK 150,000; (2) NOK 150,000~249,999; (3) NOK

Table 1
Car specifications of main BEV brands.

No.	Brands	Price (NOK)	Range (km)	Battery (kW h)	Number of seats	Top speed (km/h)	Market shares (%)
1	Buddy	173,700	120	14	3	80	0.96
2	Renault	191,980	210	22	5	135	1.28
3	Citroen	159,900	130	16	4	130	5.91
4	Fiat	289,000	113	15	4	120	0.18
5	Ford	218,000	160	23	5	135	1.62
6	Mitsubishi	192,700	130	16	4	130	12.79
7	Nissan	219,700	175	21	5	145	53.48
8	Peugeot	169,900	130	16	4	130	6.55
9	Think	244,000	160	23	4	110	0.99
10	Tesla	461,000	480	81	5	210	12.13
11	Tazzari	169,900	120	13	2	100	0.29
12	Mia	153,900	125	12	4	100	0.09
13	Volkswagen	187,000	160	18	4	130	3.41
14	BMW	249,900	190	18	4	150	0.30

Table 2
Norway incentives and introduction dates.

Incentives	Introduction date
Free public parking	1990s
Exemption from registration tax	1990s
Toll exemptions	1990s
Value added tax exemption	2001
Bus lane access	2003 (Oslo) and 2005 (Nationwide)
Reduced ferry rates	2009
Public EV charging station construction	009

250,000~349,999; (4) NOK 350,000~449,999; (5) NOK 450,000~549,999; (6) NOK 550,000~749,999; (7) NOK 750,000 and over. We establish discrete distributions of municipalities' income for each municipality in 2012 and apply it to our BLP model. To better interpret the coefficients in the following parts, we normalize the obtained mean household income to the magnitude of 0 to 1.

For ten major municipalities in Norway, we plot the market shares of eight main BEV brands from 2011 to 2013 with indications of the income levels and incentive policies in Fig. 2. As can be seen, Nissan, Tesla and Mitsubishi are the three BEV brands that dominant each market by the end of 2013. The variations on the market shares of all brands are fairly substantial from market to market. We will use the proposed BLP model to quantify the effectiveness of incentives and the impact of income level.

4.2. Heterogeneity generation

This section describes how to fit the data with *BLP* model, including car specifications, instrumental variables selections and generation of consumer samples.

In general, car specifications are generally correlated with car prices (see Table 3). Therefore, to avoid any potential collinearity issue, we only include the number of seats as the car specification that are not well interpreted by the price. Other specifications are treated as instrumental variables in the minimization of the GMM object function.

The integral in Eq. (6) is not analytical, so the market shares are estimated by numerical simulation (Nevo, 2000). For each municipal market, we generate 20 consumer samples, whose income is drawn randomly from the known income (discrete) distribution in his/her municipality. For the three incentives (i.e., bus lanes access, toll waivers and the number of charging stations), the values are assigned to each individual consumer depending on his/her municipality.

In addition to the income levels, we also used another demographic feature, employment rate, to measure individuals heterogeneous preferences on price.

4.3. Computational challenges

We use Nevo's codes (Nevo, 2001a), written in Matlab, to estimate unknown parameters. In order to successfully fit our special data sets by the BLP model, the following issues are addressed to revise Nevo's codes:

1. *Singular matrix*: Car specifications are almost identical across all municipalities in Norway, and they do not vary by municipal markets. This can lead to matrix singularity during the process of parameter estimation. To address this issue, we use Moose-Penrose Pseudoinverse method (in Matlab code, we replace 'inv' with 'pinv' command).

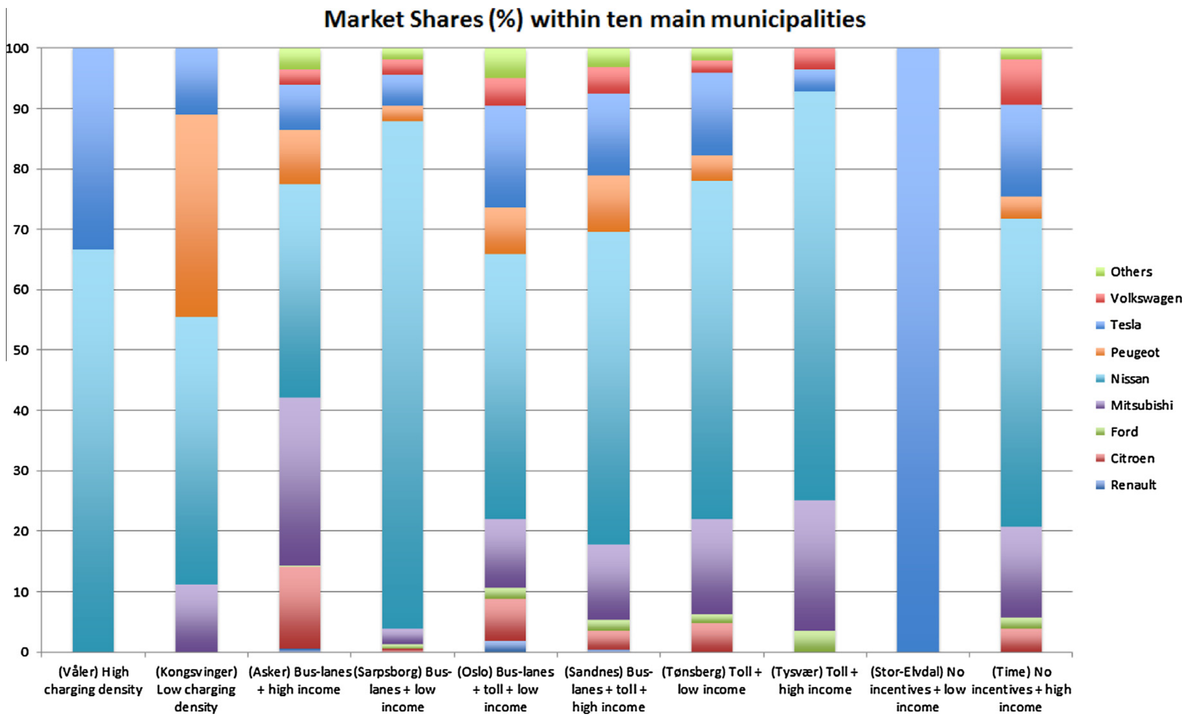

Fig. 2. Market shares (%) within ten main municipalities 2011–2013.

Table 3
Correlation matrix of car specification.

	Price	Range	Battery	Number of seats	Top speed
Price	1.000				
Range	0.8669	1.0000			
Battery	0.8966	0.9791	1.0000		
Number of seats	0.4172	0.4902	0.4545	1.0000	
Top speed	0.7806	0.8606	0.8289	0.6640	1.0000

2. *Starting values and search algorithm*: When we implemented the codes, we found that the final converged results are sensitive to the starting values, and different starting values may lead to different converged GMM objective function values. Knittel and Metaxoglou (2008) stated that starting values and search algorithms affect the estimated results. One of the main reasons stems from the local minimizing functions in Matlab. We apply the Nelder-Mead simplex search algorithm, widely used in previous studies (Li et al., 2011; Nevo, 2000). As for starting parameter values, we tried various sets to cover a wide range of spaces, and finally adopted the one yielding the minimum GMM objective function value.
3. *Zero market share*: When solving Eq. (6), we need to take the log transformation of market shares that requires market shares to be non-zero. However, since BEV sales are sometimes sparse, and some BEV brands were not sold in some municipalities, market shares can be zero in certain cases. With the consideration of the sensitivity of logarithm function, we replace those zero market shares with a very small number, namely 1e−20. Before we finalize this real number, we tried several small numbers and found that as long as the values are chosen sufficiently small, they would not affect the estimation results.

5. Results

This section discusses the results and policy implications.

5.1. Personal consumers

The case of personal consumer contains 3976 observations (284 municipal markets along with 14 brands). We finally choose to use the income levels to represent the choice heterogeneity for personal consumers. The reason is that, when using only the employment rate to measure the choice heterogeneity, we find most of the estimates are not statistically significant. In addition, the results report a much greater GMM function value than the results using only the income level. Literature also suggests the income feature is representative in heterogenous choices for consumers (Li et al., 2011; Nevo, 2000; Berry et al., 1995; Meza and Rempel, 2010).

The results of the estimation can be found in Table 4. The marginal utilities ($\bar{\alpha}$) for average consumers provided with no incentives is 150.1 and significant. The mean value is much greater than any interaction terms (β_T), implying that for average personal consumers, more seats generally increase consumers' utility for a BEV. As we show in Table 3, most car specifications are highly positively correlated with each other. In general, the increase of number of seats is correlated with the increase of battery capacity or top speed, which reflects BEV technology improvements to some extent (so we use the term, "vehicle technology", instead of "number of seats" in the table). The significantly positive coefficient (and a small standard deviation) implies that technology improvement of BEVs can effectively encourage BEV adoption.

The mean coefficient of price is negative, −0.0785, for a consumer with the lowest income. However, its robust standard errors are of comparable magnitude, 0.0647. This implies that higher BEV prices may hinder BEV adoption, but not significantly. Consumers with an average income do not have significant preferences over product prices given that they decided to

Table 4
Results of personal consumers.

Variable	Mean	Std. Dev.	Interaction with individual features			
			Bus lanes access	Toll waiver	Charging stations	Income
Price	−0.0785	−1.0929***	–	–	–	0.8283***
	(0.0647)	(0.0495)	–	–	–	(0.1879)
Vehicle technology	150.0958***	−1.5674***	−0.8536***	0.4902***	0.8039***	–
	(0.0131)	(0.3590)	(0.0342)	(0.0258)	(0.0001)	–
Constant	−122.4629***	1.0287***	1.5430***	0.3769***	0.1388***	–
	(0.0131)	(0.0668)	(0.0394)	(0.0269)	(0.0001)	–
GMM Obj	0.0055242					

Note: The asymoptotically robust standard errors of estimates are shown in parenthesis.
Significant levels: ** $p < 0.05$; * $p < 0.1$.
*** $p < 0.001$.

purchase a BEV. In fact, the income-price interaction coefficient is 0.8283, positive and significant, indicating that consumers with higher income tend to be less price-sensitive. As mentioned in Section 4.1, income data is normalized between 0 and 1 while the actual incomes range from 0 to 950,000 NOK. Thus, 0.01 unit of normalized income change (9,500 NOK) increases the effect of BEV prices by 0.008, which is approximately 10% higher when compared to the average price effects among all consumers. Although the absolute value of the coefficient of interaction between prices and income is larger than that of the mean coefficient of price, the negative coefficient on unobserved demographics makes the total mean effect negative, which is consistent with the general observation where the price is negatively correlated with the demand. This result is also supported by some stated preference studies (e.g., Hidrue et al., 2011).

Estimates of heterogeneity around the means are presented in the next few columns. The column labeled as "Std Dev.", the standard deviation from the corresponding mean, captures the effects of the unobserved consumer demographic types. The unobserved effects of vehicle technology are significant and negative, indicating that included incentives cannot explain perfectly the heterogeneity in the coefficients. Some other heterogeneity, including tax exemption, municipal employment rate, etc., would still affect consumers' heterogeneous weights of utility from the product. However, the absolute coefficients values of "Std Dev." are much smaller than mean values, suggesting that compared to the technology improvement, demographics features and municipal incentives have considerably smaller impacts on BEV market shares.

The 4th to 6th columns present the effect of incentives for various BEV products on average consumers. The estimates suggest that while an average consumer may like more seats (equivalently more power, more battery capacity, etc.), the marginal valuation is reduced in municipalities with public bus lanes, but is higher in municipalities with toll waivers and denser charging stations. In Norway, public bus lanes are available in only 25 municipalities, most of which are major areas with early BEV adoption and larger public transportation networks. An increasing amount of BEVs accessing the bus lanes can contribute to a substantial capacity reduction for both buses and BEVs, which in turn would only decrease the utility of BEV products gained from such an incentive policy. The heterogeneous weight of toll waivers and number of charging points are significant and positive. The toll roads are expensive in Norway (e.g., 600–1000 €per year in Oslo), so the waiver of tolls encourages more consumers to buy BEVs. Among the three incentives, we find that the number of charging points has the greatest and most significant interaction coefficients. Note that the incentive of charging station is represented by the number of charging points per capita, less than 0.01. This positive effect seems to indicate establishing charging infrastructure is the most efficient way for BEV adoption among the three incentives. The denser charging station networks a municipality has, the more BEVs are likely to be sold. Sierzchula et al. (2014) found similar results at the national level.

5.2. Business buyers

Table 5 shows the results for business buyers with 2,520 observations (14 brands in 180 municipalities). In personal buyers case, income is assumed to be the factor that affects consumers' preferences on BEV choices. However, this is no longer applicable for business buyers because company managers do not make decisions directly based on the household income. Instead, companies' preferences may be highly relevant to their business performance. Due to the data limitation, we are unable to observe the performance information of each company. Fortunately, the overall economic condition of a municipality can partially reflect the business performance within the municipality. Thus, in this case, we replace the income with an macro-economic matrix: employment rate at the municipality level. The data were obtained from the Norway statistics (www.ssb.no) in 2012.

The mean coefficients of price is negative but insignificant, indicating that business buyers are probably not sensitive to BEV price changes. The coefficient of the interaction term between the price and the employment rate is significant and positive. Since the employment rate is an approximation of the business performance within each municipality, this interaction coefficient suggests that companies with better performance would have lower price sensitivity. The significant negative

Table 5
Results of business consumers.

Variable	Mean	Std. Dev.	Interaction with individual features			
			Bus lanes access	Toll waiver	Charging stations	Employment rate
Price	−0.2211	−1.0498***	–	–	–	1.0584***
	(0.2766)	(0.1172)	–	–	–	(0.2160)
Vehicle technology	102.0723***	−0.6149	0.1097*	1.6813***	1.1505***	–
	(0.1349)	(0.7613)	(0.0563)	(0.0418)	(0.0002)	–
Constant	−83.2379***	0.1087	0.0067	1.0161***	0.9628***	–
	(0.1349)	(0.3304)	(0.0653)	(0.0465)	(0.0001)	–
GMM Obj	0.00048381					

Note: The asymoptotically robust standard errors of estimates are shown in parenthesis.
Significant levels: ** $p < 0.05$.
* $p < 0.1$.
*** $p < 0.001$.

estimate of standard deviation of price coefficient indicates that there remains significant unobserved demographic heterogeneity, which may include the purpose of use, capital of the company, types of business, and so on. This unobserved heterogeneity can lead to the negative effect of prices on BEV demands.

In addition, coefficients of all the interaction terms between the vehicle technology and the incentives are positive, indicating that the municipal incentives would generally encourage more businesses to adopt BEVs. Among the three included incentives, charging station density has the greatest impact and is the most effective. Both toll waiver and bus lane access are insignificant. Therefore, business buyers may not be effectively incentivized by these two incentives when choosing which BEV to purchase.

5.3. Comparisons

Generally speaking, car specifications, prices and incentives have similar impacts on BEV sales for both individual consumers and business buyers. However, their impacts on business BEV sales are milder than personal consumers. Establishing charging infrastructure is the most efficient way for BEV adoption among the three incentives, but the effects for business buyers are not as pronounced as for consumers. When comparing the mean coefficient of vehicle technology, we find that business buyers value technology improvement less than the personal buyers. The insignificant and positive interaction terms among bus lane access, toll waiver, and "vehicle technology" suggest that business buyers may not be as sensitive as individual consumers when taking advantage of those two incentives. One should keep in mind that the sales numbers to business consumers is much lower than to personal consumers since the VAT exemption does not affect them (Figenbaum and Kolbenstvedt, 2013).

5.4. Price elasticity of demand (personal consumers)

We are interested in investigating the effects of BEV prices on the BEV market shares in Norway as part of marketing strategy evaluation. As derived in Nevo (2000), the elasticities of the market share of the j-th BEV product with respect to the k-th BEV price in each municipal market m are (the subscript market m is dropped for simplicity):

$$\begin{aligned}\eta_{jk} &= \frac{\partial s_j P_k}{\partial P_k s_j} = \left(\frac{P_k}{s_j}\right)\frac{\partial}{\partial P_k}\left(\int \frac{exp(\delta_j - \alpha_I I^i \cdot P_j + \beta_T T^i \cdot [X_j\ 1])}{1+\sum_l exp(\delta_l - \alpha_I I^i \cdot P_l + \beta_T T^i \cdot [X_l\ 1])} \mathrm{d}P(I)\right) \\ &\approx -\left(\frac{P_k}{s_j}\right)\frac{1}{S}\sum_{i=1}^{S}(\bar{\alpha} + \alpha_I I_m^i)(-s_{ij}\cdot s_{ik} + 1\{k == j\}\cdot s_{ik}),\end{aligned} \tag{11}$$

where $s_{ij} = exp(\delta_j - \alpha_I I^i \cdot P_j + \beta_T T^i \cdot X_j)/(1+\sum_{l=1}^{J} exp(\delta_l - \alpha_I I^i \cdot P_l + \beta_T T^i \cdot X_l))$ is the probability of individual i purchasing product j. Eq. (11) represents own-price elasticity if k equals to j, otherwise, it is the across-price elasticity. The price elasticities can be predicted for each municipal market. In this paper, we select the City of Oslo as a representative example of urban areas to demonstrate some interesting findings.

Table 6 presents the estimated own- and cross-price elasticities among all the brands in the City of Oslo, except for BMW which is not sold in Oslo. The reason we exclude BMW is that the computation of price elasticities requires non-zero market share in the denominator (Eq. (11)). Each element on the j-th row and k-th column gives the elasticity of brand j with respect to the change in the price of brand k. It is clear that the diagonal values are own-price elasticity while the others are cross-price elasticities.

Renault, Ford, Fiat and Mia are the four BEVs with by far the greatest own-price elasticities, greater than negative 10. Their market shares in BEV can change by at least 10% if their prices changes by 1%. The sales of those four brands are minor with less than 1% of market shares in Olso, and therefore the sales are sensitive to their prices. Tesla (Brand No. 10) has the highest price with the highest vehicle technology (represented by largest number of seats, highest top speed, etc.). The cross-price elasticities of all brands induced by Tesla and Nissan are the highest among all brands. However, price change in those minor brands does not seem to affect the BEV market as much as the price change in Tesla/Nissan. It seems Mia sales are impacted the most by price changes of the remaining brands. Overall, it suggests that higher priced BEV brands with greatest market share may have higher substitutional effects. Tesla can be considered more as luxury products which normally have a higher price elasticity.

5.5. Incentive elasticity of demand (personal consumers)

One of the major advantages of the structural econometric model is in counterfactural effects analysis. Here we build three counterfactural simulations respectively for the three BEV incentives. First, since toll waiver and bus lane access are denoted as binary indicators, the effects of these two incentives in the market share of BEV product j can be expressed as (the subscript market m is dropped for simplicity):

$$s_j^{sim} - s_j^{true} = \frac{1}{S}\sum_{i=1}^{S}\frac{exp(\delta_j - \alpha_I I^i \cdot P_j + \beta_T T_{sim}^i \cdot [X_j\ 1])}{1+\sum_l exp(\delta_l - \alpha_I I^i \cdot P_l + \beta_T T_{sim}^i \cdot [X_l\ 1])} - s_j^{true}, \tag{12}$$

Table 6
Price elasticity within the BEV market.

	Buddy	Renault	Citroen	Fiat	Ford	Mitsubishi	Nissan	Peugeot	Think	Tesla	Tazzari	Mia	Volkswagen
Buddy	−1.20975	0.083823	0.042435	0.068357	0.092474	0.054198	0.131909	0.045218	0.058024	0.286953	0.018487	0.036875	0.048295
Renault	0.196895	−16.0706	0.545381	0.723371	2.360994	0.66148	3.356011	0.572054	0.65469	4.512163	0.105767	0.478438	0.594729
Citroen	0.016158	0.088406	−0.90256	0.04432	0.094069	0.038244	0.133865	0.032598	0.039073	0.215292	0.010317	0.026986	0.034261
Fiat	0.737885	3.324237	1.256467	−41.8231	3.727245	1.702888	5.322481	1.363445	1.988687	13.19586	0.473536	1.080061	1.501993
Ford	1.021106	11.09876	2.727978	3.812732	−81.8498	3.349837	16.58753	2.871818	3.385951	23.62165	0.556213	2.388077	3.00509
Mitsubishi	0.01336	0.069416	0.024758	0.038886	0.07478	−0.74869	0.106505	0.026314	0.033239	0.193593	0.008547	0.02155	0.027987
Nissan	0.006739	0.072992	0.017961	0.02519	0.076746	0.022074	−0.50738	0.018913	0.022343	0.156	0.003674	0.015721	0.019799
Peugeot	0.01488	0.080141	0.028173	0.041565	0.085584	0.035128	0.121821	−0.83269	0.036292	0.203454	0.009508	0.024591	0.031432
Think	0.149385	0.717569	0.26419	0.474311	0.789458	0.347166	1.125953	0.283934	−8.4708	2.442167	0.095762	0.228429	0.307807
Tesla	0.034931	0.233837	0.068829	0.148811	0.260411	0.095604	0.371709	0.075263	0.115472	−1.88817	0.020822	0.058893	0.083977
Tazzari	0.092605	0.225551	0.135731	0.219744	0.252323	0.173684	0.360245	0.144727	0.18632	0.856803	−3.77322	0.1179	0.154722
Mia	0.419049	2.314648	0.805406	1.137041	2.457694	0.99348	3.496934	0.849207	1.008281	5.497897	0.267472	−23.4556	0.890649
Volkswagen	0.019817	0.103893	0.036922	0.057096	0.111672	0.046589	0.159024	0.039194	0.049059	0.283072	0.012674	0.03216	−1.11341

The estimates are computed under the personal consumer case for the City of Oslo.
It should be noted that price elasticities are estimated within the BEV market.

Table 7
Incentive elasticity within the BEV market.

	Buddy	Renault	Citroen	Fiat	Ford	Mitsubishi	Nissan	Peugeot	Think	Tesla	Tazzari	Mia	Volkswagen	BMW
Toll charge	−0.007901898	0.085514	−0.03113	0.047863	0.100799	−0.05575	−0.31298	−0.03875	0.033725	0.089229	0.004587	0.025905	−0.02179	0.042072
No bus access	−0.00026824	0.075935	−0.02651	0.055599	0.090461	−0.04981	−0.32771	−0.03382	0.040182	0.061706	0.013261	0.029925	−0.0165	0.048445
CP elasticity	−0.07244328	0.270204	−0.00542	−0.05874	0.286986	−0.01738	0.408354	−0.00842	−0.03587	0.652413	−0.09614	−0.00343	−0.01386	−0.03722

The estimates are computed under the personal consumer case for the City of Oslo.
CP: charging points. The elasticity is based on the number of charging points per 10,000 persons.
It should be noted that incentive elasticities are estimated within the BEV market.

where s_j^{sim} is the predicted market share of BEV j with simulated incentives T_{sim}^i and s_j^{true} is the actual market share of BEV j extracted from data.

The variable indicating the number of charging points per capita is continuous. Thus, the counterfactural effect of the number of charging points per capita in market share of BEV product j is defined as follows (the subscript market m is dropped for simplicity):

$$\Delta_j^C = \frac{\partial s_j}{\partial C_m} \approx \frac{1}{S}\sum_{i=1}^{S}\beta_C \cdot s_{ij}\left(X_j - \sum_{l=1}^{S} X_l s_{il}\right), \tag{13}$$

where C_m denotes the number of charging points per capita in the municipal market m and β_C denotes the parameter for the charging points. Similar to that in price elasticity analysis,

$$s_{ij} = exp(\delta_j - \alpha_I I^i \cdot P_j + \beta_T T^i \cdot [X_j\ 1])/(1 + \textstyle\sum_{l=1}^{J} exp(\delta_l - \alpha_I I^i \cdot P_l + \beta_T T^i \cdot [X_l\ 1])). \tag{14}$$

The incentive elasticities of demand are shown in Table 7 for the City of Oslo. It should be noted that these are elasticities within the BEV market. The city currently has toll waivers and bus lane access for BEVs. We predict the market share changes if either incentive is removed. Interestingly, we find significant heterogeneity in incentive policy impact on different brands, especially for Renault, Ford, Nissan and Tesla. For example, if all BEVs have to pay tolls, then Nissan, as the best-selling BEV brand, can lose 31% of its market share in BEV market where a major market share shift goes to Renault, Ford and Tesla. A similar prediction is applied to the case where we hypothetically remove the incentive of bus lane access. On the other hand, increasing charging station density in Oslo can significantly increase the market shares of Tesla (with an exceptionally long range), Nissan, Ford and Renault (all three being a good compromise of competitive prices and relatively long ranges). It is interesting to note the difference between Nissan and Tesla, the two major brands. Compared to Nissan, Tesla is not as affected by the changes in the local incentives implying that those that purchase the Tesla might be doing it more because they like the vehicle (even if the tax exemptions can play a role in making it more affordable) rather than it being an electric vehicle that gets certain perks. The Nissan Leaf on the other hand may be more dependent on these incentives.

6. Conclusions and discussion

Norway has a long history of research and government incentives for BEVs, and it also has the largest BEV market of the world, on a per capita basis. Unlike many survey-based studies, we have the luxury to obtain entire BEV sales data in Norway from 2000 to 2013. To better leverage such a data set to evaluate consumers' behavior, we apply Random-Coefficient Logit Model, *BLP* model (a well-established methodology for demand estimation from economics and marketing literature), to capture the choices of heterogeneous consumers in full details. The model generates an estimate of how much each incentive contributes to the impacts of car specifications and prices on BEV sales, for personal consumers with different income levels and for business buyers with different employment rates.

We analyze two independent groups of consumers: personal and business BEV sales. From the results, we find that both groups have similar taste over BEV technology improvement, prices and incentives. Business buyers, however, can be less influenced by those impacts than personal consumers. We consider three incentives, bus lanes access, waiver of toll roads and the density of charging stations for each municipality. Most incentives have positive impacts on BEV sales. One exception, though, is that bus lanes access could have negative impact for personal consumers. Some previous surveys (e.g., Prosam, 2009) suggest the opposite effect. Our results could be explained by consumers' concerns about the potentially heavy traffic on public bus lanes, due to the increasing number of BEVs on the roads. Again, the impacts of those incentives to EV adoption for business buyers are slightly milder than for personal consumers. Of the three incentives, we found that the number of charging points has the greatest and most significant effect on BEV sales.

In addition, our results also show that BEV price preferences are significantly heterogeneous among consumers with different demographic features. Individual consumers with a higher income would be statistically less price-sensitive than those with lower income. Compared to the BEV technology development (such as travel range, number of seats and engine power), demographics features and municipal incentives have generally less impacts on BEV market shares.

For the City of Oslo, Renault, Ford, Fiat and Mia are the four BEVs with the greatest own-price elasticities. The cross-price elasticities of all brands induced by Tesla and Nissan are the highest. However, price change in the minor brands does not seem to affect the BEV market as much as a price change in one of the major brands (such as Tesla and Nissan). Interestingly, we find significant heterogeneity in incentive policy impact on different brands, especially for Renault, Ford, Nissan and Tesla. If all BEVs have to pay tolls or do not have access to bus lanes, then Nissan, as the best selling BEV brand, can lose 31%-32% of its market share in the BEV market where a major market share shift goes to Renault, Ford and Tesla. On the other hand, increasing charging station density in Oslo can significantly increase the market shares of Tesla (with an exceptionally long range), Nissan, Ford and Renault (all three being a good compromise of competitive prices and relatively long range or exceptionally long ranges). Note that what this research estimates is the marginal effect of charging station density. In the long run when the charging station density is sufficiently high, the charging station density intuitively would have negative impact on expensive BEVs such as Tesla with long ranges. However, at present, the charging station supply is still not developed to the coverage that can meet the potential BEV demand. Users range anxiety will be primarily addressed by adding more charging stations and having a long-distance range BEV, both of which are more complementary than substitutional. Therefore, a long range BEV can still benefit from the marginal increase in the charging station density at this time.

In general, our research provides several policy implications using the Norwegian data. It is found that bus lane access and toll waiver promote the market shares of BEVs. With the increasing usage of EV, however, the benefits brought by the bus lane access may become less attractive for personal consumers. Furthermore, charging station expansion has the greatest and most significant effects for BEV sales, for both personal consumers and business users. The charging station density in Norway, though leading worldwide, is yet to fully address the range anxiety for users. Our research provides the sensitivity of charging station density in BEV market shares in different municipalities. Such knowledge will be helpful for decision makers to evaluate the cost and benefits in building a charging station network.

Our research has several limitations. First, because data regarding the cross-market variations of BEVs are not available, we use approximation methods to complete the estimation procedure, which may lead to some imprecision issues. They can be improved in the future research by collecting more detailed information and applying other search algorithms, e.g., Generalized Pattern Search, Mesh Adaptive Direct Search (Knittel and Metaxoglou, 2008). Second, we only investigate three types of incentives in Norway BEV market that possesses the most BEV-related incentive policies. As some previous research mentioned, tax exemption is non-trivial in the expansion of BEV markets, which can also concluded from the coefficients of unobserved demographics in our model. Since BEV markets are quickly expanding across the world, future work can also compare incentives and BEV characteristics between various countries. Last but not least, the paper only studies the BEV market due to unavailability of regular car sales data. Within the BEV market, we have studied the relative market share of all major BEV brands. However, the effects of car specifications, prices and incentives to the total BEV sales compared to regular car sales are still unknown. We are actively collecting regular car sales data in Norway to conduct further analysis for the full market.

Acknowledgements

This research was partially supported by Berkman Faculty Development Grants and Traffic21 Research Institute at Carnegie Mellon University. The authors would like to thank three anonymous reviewers for their thoughtful and constructive comments.

References

Al-Alawi, B.M., Bradley, T.H., 2013. Review of hybrid, plug-in hybrid, and electric vehicle market modeling studies. Renew. Sustain. Energy Rev. 21, 190–203.
Archak, N., Ghose, A., Ipeirotis, P.G., 2007. Show me the money!: deriving the pricing power of product features by mining consumer reviews. In: Proceedings of the 13th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, pp. 56–65.
Axsen, J., Kurani, K.S., 2013. Hybrid, plug-in hybrid, or electric: what do car buyers want? Energy Policy 61, 532–543.
Axsen, J., Mountain, D.C., Jaccard, M., 2009. Combining stated and revealed choice research to simulate the neighbor effect: the case of hybrid-electric vehicles. Resource Energy Econom. 31 (3), 221–238.
Beresteanu, A., Li, S., 2011. Gasoline prices, government support, and the demand for hybrid vehicles in the United States*. Int. Econom. Rev. 52 (1), 161–182.
Berry, S., Levinsohn, J., Pakes, A., 1995. Automobile prices in market equilibrium. Econometr.: J. Econometr. Soc., 841–890
Bolduc, D., Boucher, N., Alvarez-Daziano, R., 2008. Hybrid choice modeling of new technologies for car choice in canada. Transport. Res. Rec.: J. Transport. Res. Board 2082 (1), 63–71.
Brownstone, D., Bunch, D.S., Train, K., 2000. Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. Transport. Res. Part B: Methodol. 34 (5), 315–338.
Cao, X., Mokhtarian, P., 2004. The Future Demand for Alternative Fuel Passenger Vehicles: A Diffusion of Innovation Approach. University of California, Davis–Caltrans Air Quality Project, Final Report.
Chandra, A., Gulati, S., Kandlikar, M., 2010. Green drivers or free riders? an analysis of tax rebates for hybrid vehicles. J. Environ. Econom. Manage. 60 (2), 78–93.
Cowi, A. et al., 2002. Fiscal measures to reduce co2 emissions from new passenger cars. Technical report, Directorate General Taxation and Customs Union, European Commission.
Department of Energy, 2014. All-electric vehicles. <http://www.fueleconomy.gov/feg/evtech.shtml>.
Diamond, D., 2009. The impact of government incentives for hybrid-electric vehicles: evidence from us states. Energy Policy 37 (3), 972–983.
Eppstein, M.J., Grover, D.K., Marshall, J.S., Rizzo, D.M., 2011. An agent-based model to study market penetration of plug-in hybrid electric vehicles. Energy Policy 39 (6), 3789–3802.
Erik Figenbaum, M.K., 2013. Electromobility in norway – experiences and opportunities with electric vehicles. <https://www.toi.no/publications/electromobility-in-norway-experiences-and-opportunities-with-electric-vehicles-article32104-29.html>.
Figenbaum, E., Kolbenstvedt, M., 2013. Electromobility in Norway-experiences and opportunities with electric vehicles, number 1281/2013.
Gallagher, K.S., Muehlegger, E., 2011. Giving green to get green? incentives and consumer adoption of hybrid vehicle technology. J. Environ. Econom. Manage. 61 (1), 1–15.
Grnn Bil, 2015. Bev and phev sales and population. <http://www.gronnbil.no/english/>.
Hidrue, M.K., Parsons, G.R., Kempton, W., Gardner, M.P., 2011. Willingness to pay for electric vehicles and their attributes. Resource Energy Econom. 33 (3), 686–705.
Klöckner, C.A., Nayum, A., Mehmetoglu, M., 2013. Positive and negative spillover effects from electric car purchase to car use. Transport. Res. Part D: Transport Environ. 21, 32–38.
Knittel, C.R., Metaxoglou, K., 2008. Estimation of Random Coefficient Demand Models: Challenges, Difficulties and Warnings Technical report. National Bureau of Economic Research.
Li, B., Ghose, A., Ipeirotis, P.G., 2011. Towards a theory model for product search. In: Proceedings of the 20th International Conference on World Wide Web. ACM, pp. 327–336.
McFadden, D., 1972. Conditional logit analysis of qualitative choice behavior. Technical report.
McFadden, D., Train, K., 2000. Mixed mnl models for discrete response. J. Appl. Econometr. 15 (5), 447–470.

Mersky, A.C., Sprei, F., Samaras, C., Qian, Z.S., 2016. Effectiveness of incentives on electric vehicle adoption in norway. Transport. Res. Part D: Transport Environ. 46, 56–68.

Meza, S., Rempel, M., 2010. Effect of income heterogeneity on price response during the diffusion of wireless service in multiple markets. Available at SSRN 1664480.

Mueller, M.G., de Haan, P., 2009. How much do incentives affect car purchase? agent-based microsimulation of consumer choice of new cars. Part i: Model structure, simulation of bounded rationality, and model validation. Energy Policy 37 (3), 1072–1082.

Nevo, A., 2000. A practitioner's guide to estimation of random-coefficients logit models of demand. J. Econom. Manage. Strategy 9 (4), 513–548.

Nevo, A., 2001a. Computer codes for blp model. <http://faculty.wcas.northwestern.edu/ane686/supplements/rc_dc_code.htm>.

Nevo, A., 2001b. Measuring market power in the ready-to-eat cereal industry. Econometrica 69 (2), 307–342.

Oberholzer-Gee, F., Strumpf, K., 2007. The effect of file sharing on record sales: an empirical analysis. J. Polit. Econ. 115 (1), 1–42.

Peter Mock, Z.Y., 2014. Driving electrification a global comparison of fiscal incentive policy for electric vehicle. ICCT.

Prosam, 2009. Trafikk i kollektivfelt: kapasitet og avvikling. Technical report, Prosam rapport No. 176.

Radio, N.P., 2014. Norway takes the lead in electric cars (with generous subsidies). <http://www.npr.org/blogs/parallels/2014/03/11/288611696/norway-takes-the-lead-in-electric-cars-with-generous-subsidies>.

Santini, D.J., Vyas, A.D., 2005. Suggestions for a new vehicle choice model simulating advanced vehicles introduction decisions (avid): Structure and coefficients. Center for Transportation Analysis, Argonne National Laboratory. ANL/ESD/05-1.

Sierzchula, W., Bakker, S., Maat, K., van Wee, B., 2014. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. Energy Policy 68, 183–194.

Sprei, F., Bauner, D., 2011. Incentives Impact on ev Markets – Report to the Electromobility Project. Viktoria Institute, Gothenburg.

Sullivan, J.L., Salmeen, I., Simon, C., 2009. Phev marketplace penetration: an agent based simulation.

Vaggen Malvik, Hävard, Ole Henrik Hannisdahl, G.B.W., 2013. The future is electric! – the ev revolution in norway explanations and lessons learned. In: Presented at the ECEEE Summer Study.