Response of electric vehicle drivers to dynamic pricing of parking and charging services: Risky choice in early reservations ☆

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ABSTRACT

When clusters of electric vehicles charge simultaneously in urban areas, the capacity of the power network might not be adequate to accommodate the additional electricity demand. Recent studies suggest that real-time control strategies, like dynamic pricing of electricity, can spread the demand and help operators to avoid costly infrastructure investments. To assess the effectiveness of dynamic pricing, it is necessary to understand how electric vehicle drivers respond to uncertain future prices when they charge their vehicle away from home. Even when data is available from electric vehicle trials, the lack of variability in electricity prices renders them insufficient for this analysis. We resolve this problem by designing a survey where we observe the stated preferences of the respondents for hypothetical charging services. A novel feature of this survey is its interface, which resembles an online or smartphone application for parking-and-charging reservations. The time-of-booking choices are evaluated within a risky-choice modelling framework, where expected utility and non-expected utility specifications are compared to understand how people perceive price probabilities. In the progress, we bring together theoretical frameworks of forward-looking behaviour in contexts where individuals were subject to equivalent price uncertainties. The results suggest that (a) the majority of the electric vehicle drivers are risk averse by choosing a certain price to an uncertain one and (b) there is a non-linearity in their choices, with a disproportional influence by the upper end of the price distribution. This approach gives new perspectives in the way people plan their travel activities in advance and highlights the impact of uncertainty when managing limited resources in dense urban centres. Similar surveys and analyses could provide valuable insights in a wide range of innovative mobility applications, including car-sharing, ride-sharing and on-demand services.

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1. Introduction

Mobility electrification can contribute to the decarbonisation of the transport sector but at the same time it may introduce an additional burden to the power grid, especially at the distribution level (Clement-Nyns et al., 2010). Such stresses

would be reduced if charging demand could be distributed smoothly in time and space. Demand management requires an intermediate agent that will function as a bridge between electricity market players and EV drivers. This aggregator, or Charging Service Provider (CSP) has to satisfy the target State Of Charge (SOC) for each EV individually and at the same time to optimize the charging activities subject to the local grid constraints (Sundström and Binding, 2011).

Fleet aggregation or smart charging is usually viewed as a service to the supplier side, whereas there is less interest for the demand side and the service proposition to the EV user. However, the Internet of Things (IoT) and the digitalization of the grid create a whole new set of opportunities for a customer-centric management of EV drivers with energy services that are tailored to personal consumption patterns (Giordano and Fulli, 2012). Similar personalization has been successfully implemented in other service industries, like e-commerce where recommender systems improve the experience of the users and yield substantial profits for the service providers (Qiu et al., 2015).

The challenge that follows this upsurge of sensing technologies and communication solutions in parking applications is how to exploit them in order to improve the level of service, optimize the utilization of resources (Zargayouna et al., 2016) and maximize the profits for the operators. One promising method in this direction is revenue management (RM).

Most of the existing studies on EV smart charging adopt standard exogenous assumptions for charging behaviour that do not correct for the endogeneity between the price of the service and charging choices. On the other hand, choice-based RM approaches, firstly introduced and theoretically developed by Talluri and van Ryzin (2004), explicitly capture the sensitivity of demand to price and other factors by using discrete choice models. Identifying heterogeneous segments of the relevant market, and calibrating the demand coefficients for these segments can significantly improve revenue performance (Garrow, 2010).

In previous work, the authors have presented a choice-based revenue management framework as an alternative approach to model charging coordination (Latinopoulos et al., 2015; Latinopoulos, 2016). The results of a microsimulation model based on this framework have shown that the net revenue for a charging service provider is higher compared to all uncontrolled scenarios and this improvement is in the range of 5–10%. The RM model depends on a reservation system, where customers have the chance to book a charging post 24 h in advance of their preferred arrival time at the parking facility.

This paper aims to unfold the behavioural process that takes place in such a reservation system and to model the response of EV drivers to dynamic pricing of parking-and-charging tariffs. Looking at different theoretical perspectives of intertemporal choices and decision-making under uncertain prices, it was found that there is a gap in the literature, especially for urban mobility problems. The suggested methodological framework addresses this gap, intending to achieve the following objectives:

- Measurement of drivers' *response to dynamic pricing* for out-of-home charging events.
- Understanding *attitudes towards risk* under different risky choice structures.

This framework heavily depends on data where the variability in electricity prices is adequate, in order to estimate the drivers' willingness to pay. However, the majority of electricity tariff programs offer either fixed or dual tariffs (i.e., differentiation between peak and off-peak overnight prices). Therefore, a secondary objective of the undertaken research is to design a survey instrument with stated choice exercises and observe how EV drivers respond to hypothetical booking scenarios.

The paper is structured as follows: Section 2 provides the context for parking-and charging pricing and reviews existing modelling approaches for behavioural response to dynamic pricing in other services, like airline tickets or residential electricity. Section 3 presents the survey and the choice experiments that have been developed in order to understand how people would respond to dynamic pricing in the context of electric mobility. In Section 4, the developed risky choice-modelling framework that captures the booking behaviour of the respondents is presented, while the results are demonstrated in Section 5. Finally, Section 6 concludes with the implications of these findings and the most promising directions for future research.

2. Background

2.1. Context of parking-and-charging pricing

Parking reservation systems are already applied in various contexts, from downtown, to airport and train station facilities. SpotHero (SpotHero, 2016), and JustPark (JustPark, 2016) are well-known real-time parking services that allow users to compare parking options and book a parking spot in advance.

Pierce and Shoup (2013) implemented a performance-based pricing technique and adjusted locational prices in order to achieve an on-street parking occupancy rate between 60% and 80% for each block in the area of interest at San Francisco, but the variation in prices is very slow. This project (SFPark) has shown the possibility of overcoming some of the political barriers to dynamic pricing policies in parking. Xerox (2016) has developed another algorithm that modifies prices according to historic data and predictions of parking demand. This algorithm has the same drawback with SFPark: it is impossible to anticipate short-term changes in demand since the prices are updated once every few weeks (Mackowski et al., 2015).

A parking operator that owns charging infrastructure has to bear a combination of fixed costs (e.g., EV supply equipment, parking lot alterations) and variable costs (e.g., the cost of electricity that varies with demand, time of day, local suppliers, etc.). The generated revenues, on the other hand, are dependent on electricity consumption and the duration of charging events. As it was elaborated in Williams and DeShazo (2014), pricing per kWh is subject to the sales volume induced by greater distances while pricing per hour is subject to the negative effect of higher charging rates. As a result, a price differentiation based on the charging rate (in kW) has the prospect to balance the counter effects of the two strategies above.

EV charging is an integrated service, in the sense that consumers evaluate both components (parking and electricity) and how they interact. Therefore, the tariffs could capture this *bundling* effect. Bundling is the strategy of assembling two or more products together as a package with a special price, and it is a form of non-linear pricing (Wilson, 1993). The CSP, as a third party in re-selling electricity, will have restrictions in price differentiation. The parking component of this bundle provides the flexibility that is required to dynamically change the price according to energy demand.

2.2. Response to dynamic pricing: review of modelling approaches

In a home-based electricity consumption context, it is potentially too complex for an individual to process dynamic prices and make an informed decision. A survey from IBM in 2011 revealed that 30% of the consumers did not understand the basics of their energy bill (IBM, 2011). Thus, it is typically assumed that a smart device is installed to control the appliances of the household (Mohsenian-Rad and Leon-Garcia, 2010; Samadi et al., 2010). Nevertheless, when a smart device is not available, individuals need to take a decision based on imperfect information about price fluctuations. In this case, it is likely that they will form subjective probabilities for future electricity prices based on their perception of past experiences.

The vast majority of studies that investigate the response to dynamic pricing can be found in the airline pricing literature. A typical evolution of prices for air tickets (Anderson and Wilson, 2003) can be seen in Fig. 1.

In case the customer is aware of this time distribution and has the ability to predict in which direction the current price is going to move, then there is a possibility for *strategic/forward-looking purchase behaviour*. On the other hand, if customers are not willing to delay their time of purchase and instead they prefer to make their buying choice immediately, they are characterized as *non-strategic* or *myopic*.

During the last decade, there has been an increasing interest to understand this strategic consumer behaviour towards intertemporal price discrimination. It is more straightforward to analyse the strategy that is followed by consumers, when products/services follow markdown-pricing policies (e.g., fashion retailers). Some individuals, instead of buying a product/service as soon as its price is below their perceived value for it, will wait for a price markdown to make their purchase (Elmaghraby et al., 2001; Nair, 2007; Su, 2007). However, for operators that share common features with airline companies, the consumers' strategy is based on their belief that a cheaper fare class that is currently closed, will re-open in the future.

Findings vary between different studies and it can be concluded that forward-looking behaviour is context-dependent (Osadchiy and Bendoly, 2015). In their laboratory experiments the authors examined the heterogeneity of participants regarding their risk perception by letting them choose between two different options: buy now or wait for a lower price, considering the probability of a sold-out.

Li et al. (2014), instead of assuming *a priori* that there are strategic customers in the airline industry, estimate their proportion and hypothesise forward-looking behaviour if it is significantly different than zero. They suggest that the above estimation can be achieved with two alternative methodological approaches: (a) with a Discounted Expected Utility (DEU) framework by estimating the discount factor, a "continuous measure of consumers' patience", which is computationally difficult due to identification issues and (b) by segmenting the market between myopic and strategic consumers and estimating their fractions. Baucells et al. (2016) deviate from the widely adopted DEU framework and use a generalised approach to model "buy-or-wait" decisions, in order to capture behavioural anomalies (e.g., *hyperbolic discount* or *sub-endurance effect*). Their generalised model collapses into a prospect theoretical approach for immediate purchases and, hence, it has similarities with the "buy-or-wait" risky choice framework presented in this paper.

In the next section this theoretical discussion is summarized and we highlight the key points that lead to the selection of a risky-choice approach, which is presented in Section 4. Before the modelling framework though, the course of action that was adopted, in order to design a stated preference survey to meet the data requirements, is outlined in detail.

3. Stated preference survey

The behavioural aspect that is examined in this paper is the response of EV drivers to the dynamic pricing of charging bundles. The respondents compare the price of their preferred charging option at the moment they check their smartphone with an uncertain future price and choose whether to book now or wait to make the booking later. It is assumed that an intermediary with incomplete information about the dynamic mechanisms provides respondents with objective probabilities for future prices. An analogous "delay purchase" option has been recently presented in the SP developed by Freund-Feinstein and Bekhor (2017) for air itinerary choices. However, the probability to defer choice depends only on current attributes (e.g., prices and cancellation fees) and not on information for future prices.

There are two elements that need to be stressed for intertemporal choice problems: the discounted utility and the bounded rationality. Most of the studies presented earlier, along with the majority of studies in the relevant literature,
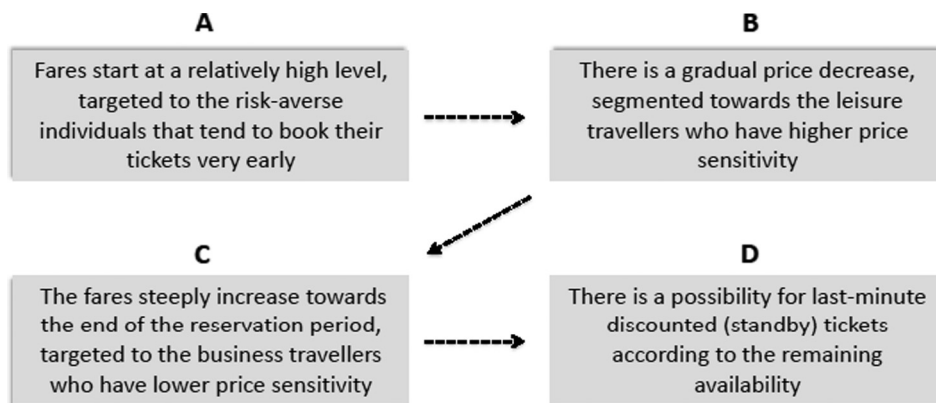
Fig. 1. Typical price profile in the airline industry, from the day a flight is posted to the day of departure.

use one or both of these elements to explain how individuals trade-off costs and benefits at different points in time. In our formulation we do not use a temporal discounting factor for charging-and-parking services because the daily booking horizon is small compared to other markets (e.g., air tickets or retail durable goods). Therefore, it is assumed that the effect of the drivers' "patience" is negligible compared to the mental cost and the cognitive abilities required to process price probabilities. Even when information regarding uncertain travel choices is explicitly provided to the travellers, it is observed that the assumptions of rational behaviour are systematically violated (Senbil and Kitamura, 2004; Avineri and Bovy, 2014). A comprehensive review of bounded rationality modelling approaches in the travel behaviour literature is presented in Di and Liu (2016).

The main focus of this section is the design of an SP exercise that will identify rationality (or irrationality) of EV drivers when confronted with risky outcomes.

3.1. Survey design

One aspect of SP experiments that has not received, so far, much attention in the literature is the discrepancy between the setting in which a choice is made in the real world and the setting in which it is made during the experiment. The typical setting for SP experiments is a table with two or more alternatives where the attributes of interest are listed for cross-comparison. The development of online shopping has created an artificial choice environment, which has a different presentation style. In Collins et al. (2012), the comparison between an interactive survey that was designed to resemble an air-ticket booking engine and a traditional SP design indicated that the realism of the former leads to better parameter estimates and lower variances in the random part of the utility.

The EV-PLACE (EV Plug and Charge) survey that is presented here includes two SP exercises: the charging game and the booking game (Fig. 2).

The setting for both exercises mimics the environment of a hypothetical online/smartphone application that could be used to reserve a charging place for an EV in advance, thus improving the presentational realism. The survey, which was administered online, includes a questionnaire that extracts information about the socio-demographics and the travel patterns of the respondents, as well as a debriefing section with some additional attitudinal questions.

The final sample is based on a mixed recruitment strategy, i.e., a combination of EV drivers that were identified by the researchers using various channels (forums and associations, EV trial participants and social media) and a panel of EV drivers and EV "considerers" recruited from a major provider of sample services for online surveys. The latter were recruited for participation if they have stated that they "seriously considered buying an electric vehicle during the last 12 months" and if they regularly parked in urban areas. The geographic coverage of the sample includes the United Kingdom and Ireland. The characteristics of the multiple recruitment channels are presented in Table 1.

Apart from presentational realism, the SP exercises must have a certain degree of "scenario realism". In other words, the hypothetical travel patterns need to be customized so that they resemble, as much as possible, to the respondents' actual travel patterns. A common practice in the literature is to first collect travel diary data and then use the observed behaviour to create individualized choice scenarios. However, the heterogeneity induced by the huge variety of travel patterns can lead to biased estimates in the presence of taste variation (Bradley and Daly, 2000). Moreover, the respondents might be unfamiliar with out-of-home charging scenarios, even if scenario realism is maximized.

In order to overcome these methodological issues, an intermediate solution between a generic and an individualised choice experiment is adopted. Respondents are classified in 96 socio-demographic groups based on a combination of their gender, age, employment status, marital status, parental status and residence location. Le Vine et al. (2011) used a similar classification to allocate the respondents to *avatars*, i.e., artificial characters that have similar socio-demographics with them.
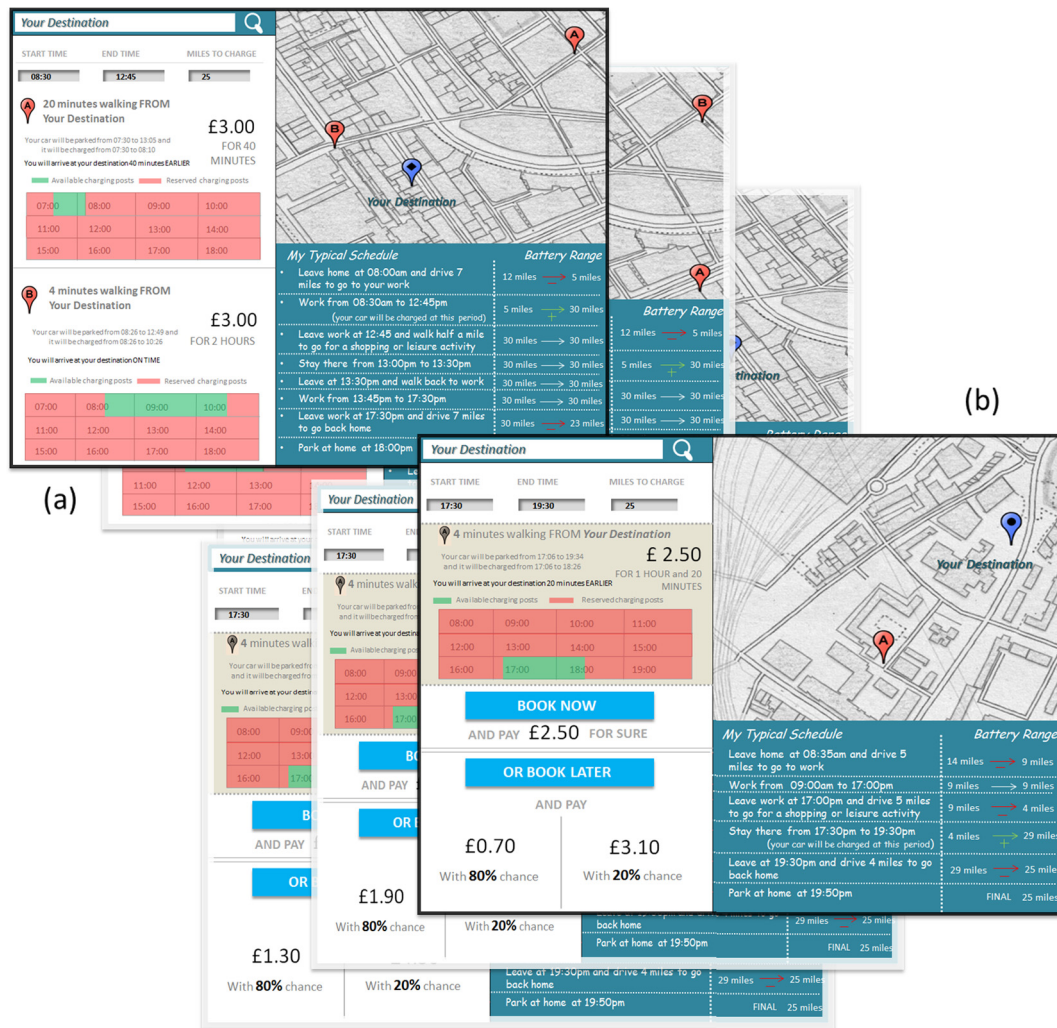
Fig. 2. Overview of SP exercises in the EV-PLACE survey: (a) Charging game and (b) Booking game.

Table 1
Characteristics of recruitment channels for the EV-PLACE survey.

	Recruitment channel			
	EV driver associations and forums	Electric vehicle trials	Social media (Facebook and Twitter)	Sample service provider
EV experience	All	All	All	Some of them
Licence holders	All	All	All	All
Sample representativeness	No	No	No	Yes
Geographical coverage	UK	UK and Ireland	UK	UK
Response rates	57.1%	57.1%	N/A[a]	60.2%
Sample size	20	16	11	216

[a] For this recruitment channel, it is possible to calculate the completion rate among people that contacted the researchers so that they get access to the survey. However, it's not easy to estimate the total number of persons that viewed the survey invitation originally.

An identical classification is performed for a sample of London drivers from the London Travel Demand Survey (LTDS), a survey carried out by Transport for London since 2005 (TfL, 2011) that combines personal and household questionnaires with a single-day travel diary. Finally, each EV-PLACE respondent is presented with a set of daily profiles (i.e., trip chains) that are more likely to be undertaken by an LTDS driver of the same socio-demographic group.

For each stated choice exercise, the respondents are presented with an instructional video that explains the various parts of the choice situations in Fig. 2. The blue[1] box on the bottom-right part embodies the activity schedule and it is based on the daily profile that the respondent had selected earlier. At the same time, it shows how the battery level of the vehicle changes as the person drives around.

The top-left part replicates the interface of an application that the EV driver would use to book a charging post in advance. The fields that should be completed for such an application are: the location of their destination (address or postcode), the preferred starting and ending time of the activity at this destination and the battery requirements after the activity is over (in miles). For the SP exercises, it is assumed that the respondents have already completed these fields, generating a list of charging bundles at the left part of the screen and a map with their location at the top-right part of the screen.

A total of 263 respondents completed the EV-PLACE survey. However, all individuals that completed the SP exercises in less time than the duration of the instructional videos were not further processed since it would be difficult to argue that they made actual trade-offs between the charging alternatives. The final sample size consists of 118 individuals, which correspond to 1062 observations for each SP exercise. Table 2 presents the composition of this final sample.

3.1.1. The charging game

The purpose of the charging game is to elicit the drivers' preferences for charging attributes in a hypothetical context where they provide the information described earlier so that a smart parking application offers them two charging alternatives that could accommodate their needs (options A and B in Fig. 2a).

Respondents are presented with nine choice situations where they have to select one of the two charging options. The four design variables of the charging game are: the *walking distance* from charging place to destination, the *price* of the charging offer (CP), the *duration* of the charging event and the *starting time* of the charging event.

Some scenario attributes, like the initial SOC and the charging amount, were adjusted for the various daily profiles according to the following constraints: (a) the charging amount should be deliverable with the existing infrastructure and (b) the tour would be infeasible without charging the EV during the day.

The attribute levels for the design variables, the statistical design and the estimation results of the charging game are thoroughly presented in Latinopoulos (2016). One of the key findings from the estimation is the existence of two distinctive segments: the "price-conscious" drivers and the "time-conscious" drivers.

3.1.2. The booking game

The structure of the booking game has a lot of similarities with the charging game. For example, the right-bottom and the top-left parts are identical. The main difference is that the respondent had already selected one of the charging bundles provided by the CSP (demonstrated in the shaded area of Fig. 2b) and the map indicates its location compared to the driver's destination.

Then, an intermediate agent takes the role of a price predictor and provides respondents with the following information:

- The probability of an increased future price and its value.
- The probability of a decreased future price and its value.

Once more, respondents are presented with nine choice situations where they have two alternatives: either to book now with a guaranteed price or to wait for a better deal, taking the risk of an increased cost. The charging attributes that were introduced for the previous SP exercise, apart from price, remain fixed along the booking period and across choice situations. Nevertheless, their values were shuffled for the various travel profiles in order to introduce variability in charging scenarios and examine the effect of this variability on individual responses.

There are three design variables and all of them are related to the price of the preferred charging option. More precisely they are: the probability of an increased price (P_i), the expected increase in price (E_i) and the expected decrease in price (E_d). It is straightforward to infer the probability of a decreased price (P_d), since $P_i + P_d = 1$. The three attribute levels for the design variables are presented in Table 3. The base price for the "book now" option was fixed at £2.50 and expected prices are evenly spaced above and below of this value.

The range of electricity unit costs for the "booking now" alternative, based on the fixed price and the charging amount, is £0.29/kWh–£0.42/kWh. The equivalent range for the "booking later" alternative is £0.08/kWh–£0.72/kWh. The main reason for the prices being higher than normal is that they should capture periods of simultaneous parking and electricity demand peaks, and as it was mentioned early they reflect a service bundle instead of parking and charging separately.

The booking game is based on an orthogonal design, contrary to the efficient design of the charging game. For the latter, the objective is to construct choice sets in a way that the estimated parameters from the choice model are generated with as small standard errors as possible (Louviere et al., 2000). Its selection is justified by the fact that efficient designs outperform orthogonal ones when there is information for the priors (this information comes from preliminary estimation at the pilot stage). On the other hand, an experimental design is defined as orthogonal when all the parameters are independently estimated and the attribute level balance criterion is satisfied. The reason for choosing this approach for the booking game is that

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[1] For interpretation of color in Fig. 2, the reader is referred to the web version of this article.

Table 2
EV-PLACE final sample properties.

Gender	Male	Female					
	71.2%	28.8%					
Age	<20	20–29	30–39	40–49	50–59	60–69	>70
	3.4%	27.1%	26.3%	18.6%	14.4%	5.1%	5.1%
Marital Status	Single	Married	Widowed	Divorced	Separated		
	30.5%	64.4%	1.7%	2.5%	0.8%		
Employment status	Full time	Part time	Self employed	Student	Unemployed	Other	
	65.3%	6.8%	5.1%	5.1%	5.0%	12.7%	
Education	No school	High School	Graduate	Post-graduate	Other		
	8.5%	22.0%	39.8%	24.6%	5.1%		
Place of residence	Inner London	Outer London	Rest of UK	Ireland			
	17.8%	11.9%	62.7%	7.6%			
Income	Very Low	Low	Average	High	Very High		
	6.8%	17.8%	39.0%	23.7%	12.7%		
EV access	Yes	No					
	57.6%	42.4					

Note: The income bands for UK participants were 1: £10,000 or less, 2: £10,001–20,000, 3: £20,001–40,000, 4: £40,001–70,000 and 5: More than £70,000. The same bands have been used for Ireland but with a different currency.

Table 3
Levels of the design variables presented to the respondents of the booking game.

Design variables	Attribute levels		
	Level 1	Level 2	Level 3
Probability of an increase in price (P_i)|Probability of a decrease in price (P_d)	20%|80%	50%|50%	80%|20%
Expected increase in price (E_i)	+24% (£3.10)	+48% (£3.70)	+72% (£4.30)
Expected decrease in price (E_d)	−24% (£1.90)	−48% (£1.30)	−72% (£0.70)

one of the design variables (i.e., the probability of an increased price) is not directly associated with an estimated parameter. Instead it is used to define the expectation of the possible future outcomes and has an indirect influence on the estimates of the other two parameters.

A full factorial design would consist of 3^3 = 27 choice situations. After choosing to have three levels[2] of price probability and taking the middle value of 50% as intuitive, the remaining two levels (20% and 80%) were selected arbitrarily but under the justification that they are not neither too close to the middle nor too extreme to have a deterministic effect on the final decision. For simplification purposes, since this is the second SP exercise for the respondents, a fractional factorial design is adopted with only a subset of those choice situations. Under the assumption that the interaction terms are negligible (Street et al., 2005), the Ngene (ChoiceMetrics, 2012) software was used to find an orthogonal design that enables the uncorrelated estimation of all main effects.

4. Modelling of risky choices in parking-and-charging reservations

4.1. Expected utility theory

EV-PLACE respondents are presented with a deterministic price ("BOOK NOW", the safe option) and with a random price ("BOOK LATER", the risky option). In particular, C_N is the deterministic price of the "booking now" option, C_D is the probabilistic decreased price of the risky option while C_I is the probabilistic increased price of the risky option.

The first modelling approach is based on Expected Utility Theory (EUT) that has been widely used in economics for choices with uncertain outcomes (gambles). According to this theory, the utility function of an individual is expressed as follows (Von Neumann and Morgenstern, 2007):

$$u(s^n) = \sum_{k=1}^{K} p_k^n v(s_k^n) \tag{1}$$

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[2] If one sought to examine the utility space of the probability attribute in more detail it would be necessary to use 5 levels (two above and two below 50%) resulting into a full factorial of $3^3 5^1$ = 45, or even 5^3 = 125 choice situations with five-level expected prices for a balanced design.

where $s^n = \{s_k^n; \; 1 \leqslant k \leqslant K\}$ is an alternative (or concept) characterized by a set of K possible outcomes, p_k^n is the probability associated with the kth outcome and $v(s_k^n)$ is the "value" of the kth outcome for prospect s^n.

In risky choices for transportation studies, EUT was often integrated with random utility models (RUMs) creating an *ad hoc* modelling approach. The integration of these two theories allows the modeller to represent simultaneously two distinct sources of uncertainty: the uncertainty of the observer and the uncertainty of the decision maker. Therefore, the integrated RUM-EUT model is formulated by adding an RUM-related error term ε^n to the value term of the EUT specification, i.e.:

$$u(s^n) = \sum_{k=1}^{K} p_k^n \left[v(s_k^n) + \varepsilon^n \right] \tag{2}$$

This model allows the explicit modelling of attitudes towards risk independently from the conventional RUM-like tastes (Bates et al., 2001; Liu and Polak, 2007). It is assumed that $\beta_i = \{\beta_{ir} 1 \leqslant r \leqslant R\}$ is a set of taste parameters related to the vector of observable attributes $X = \{x_m 1 \leqslant m \leqslant M\}$ that affect the choice behaviour. These taste parameters are representative of a riskless choice. Each individual i attaches a scalar value v_{ik}^n to the kth outcome of prospect s^n, which is a function of β_i, i.e., $v_{ik}^n = f(s_k^n, \beta_i)$. The scalar value u_i^n for prospect s^n is a function of v_{ik}^n, the probabilities related to prospect outcomes p_k^n and a set of additional parameters $\varphi_i = \{\varphi_{ir}; \; 1 \leqslant r \leqslant T\}$ that represent decision-making under risk. Therefore, it can be denoted as $u_i^n = g(v_{i1}^n, \ldots, v_{iK}^n, \; p_1^n, \ldots, p_K^n, \varphi_i)$. If some relaxation is allowed for EUT, each outcome s_k^n, instead of being evaluated based on its riskless value v_{ik}^n, can be evaluated based on a non-linear function $z(v_{ik}^n, \varphi_i)$. Consequently, the scalar value for prospect s^n can be transformed to:

$$u_i^n = \sum_{k=1}^{K} z(v_{ik}^n, \varphi_i) p_k^n + \epsilon_i^n \tag{3}$$

where ϵ_i^n is the unobservable component of the utility linked to prospect s^n and $v_{ik}^n = w_{ik}^n + \eta_{ik}^n$ is the combination of an observable and an unobservable component associated with the value function of outcome k.

Using the RUM-EUT specification above and assuming a riskless form for the value function, the utility functions for the two booking alternatives are given in **Model 1** by:

$$u_i^{NOW} = ASC^{NOW} + \beta_C C_n + \beta_X' \boldsymbol{X} + \varepsilon_i \tag{4}$$

$$u_i^{LATER} = ASC^{LATER} + \beta_C [P_I C_I + (1 - P_I) C_D] + \varepsilon_i \tag{5}$$

where ASC^{NOW} and ASC^{LATER} are the alternative specific constants, P_I is the probability for an increase in future price, $(1 - P_I)$ is the probability for a decrease in future price, $\boldsymbol{X}$ is the vector of personal attributes and β_X' is the vector of the associated parameters, β_C is the sensitivity to price and ε_i is the error term related to the analyst's observations. For this riskless choice, the value function in Eq. (3) is linear and there are no risk-related φ_i parameters to estimate. The two prospect outcomes that characterize the value function $v_{ik}^{LATER} = f(s_k^{LATER}, \beta_i)$ are an increase in future price s_1^{LATER} and a decrease in future price s_2^{LATER}.

There are several formulations that can be used for the non-linear transformation of the value function in Eq. (3). One typical transformation is when the individuals are characterized by Constant Absolute Risk Aversion (CARA), i.e., the value outcomes of a particular prospect do not affect the risk attitudes for this prospect. The functional form of CARA is $z(x) = (1 - e^{-ax})/a$ where a positive *alpha* expresses risk proneness whereas a negative *alpha* expresses risk aversion. Following the framework in Liu and Polak (2007), CARA was adopted to investigate the decision maker's attitude towards risk in the dynamic pricing environment of the booking game. With this non-linear transformation, the utility function of the risky alternative becomes (**Model 2**):

$$u_i^{LATER} = ASC^{LATER} + \beta_C \left[P_I (1 - e^{-aC_I})/a + (1 - P_I)(1 - e^{-aC_D})/a \right] + \varepsilon_i \tag{6}$$

A few decades ago, non-EUT approaches started to emerge because of the first convincing arguments that expected utilities are not representative of observable choices. The popularity of non-EUT applications in the transport domain has been steadily growing since then (Senbil and Kitamura, 2004; Hess et al., 2008). The most prominent non-EUT methods are Rank-Dependent Expected Utility Theory (RDEU) and Prospect Theory (PT). The general idea for these methods is that individuals tend to misperceive the real probability distribution, thus, objective probabilities are transformed into subjective ones with the use of weighting functions.

4.2. Rank-dependent expected utility theory

In RDEU this weighting function $w(\cdot)$ depends on the ranking of prospective outcomes (Quiggin, 1982). Therefore, for a prospect $s^n = (s_1^n, s_2^n, \ldots, s_k^n; \; p_1^n, p_2^n, \ldots, p_k^n)$ where $s_1^n \leqslant s_2^n \leqslant s_k^n$ are the possible outcomes, ranked from the worst to the best, the expected utility can be written as:

$$u(s^n) = \sum_{k=1}^{K} w(s_k^n) v(s_k^n) \tag{7}$$

and the utility for the risky alternative, based on a linear value function (**Model 3**) and a CARA transformation (**Model 4**) are respectively:

$$u_i^{LATER} = ASC^{LATER} + \beta_C[w(P_I)C_I + (1 - w(P_I))C_D] + \varepsilon_i \tag{8}$$

$$u_i^{LATER} = ASC^{LATER} + \beta_C[w(P_I)(1 - e^{-aC_I})/a + (1 - w(P_I))(1 - e^{-aC_D})/a] + \varepsilon_i \tag{9}$$

The decision weights are given by:

$$w(s_k^n) = \begin{cases} \pi(p_k^n, p_{k+1}^n, \ldots, p_K^n) - \pi(p_{k+1}^n, p_{k+2}^n, \ldots, p_K^n) & \text{if } 1 \leqslant k < K \\ \pi(p_K^n) & \text{if } k = K \end{cases} \tag{10}$$

where $\pi(\cdot)$ is the increasing weighting function with $\pi(0) = 0$ and $\pi(1) = 1$. Moreover, $\pi(p_k^n, p_{k+1}^n, \ldots, p_K^n)$ is the weight associated with obtaining outcome k or better than k. In other words, the decision weight expresses the difference between the distortions of cumulative probabilities. For the ranking effect, it is assumed that individuals pre-process how good each outcome k is. Since there are two possible outcomes for the future prices in the booking game, k is either equal to 1 or 2.

If $\pi(\cdot)$ is convex then individuals demonstrate optimistic or risk-prone behaviour. On the other hand, if it is concave they demonstrate pessimistic or risk-avert behaviour. It is possible that the weighting function is not strictly convex or strictly concave and, hence, it has a mixed specification. The most commonly encountered in the literature are the inverse S-shaped weighting functions. A typical function that results into an inverse S-shaped curve is the following:

$$\pi(p_k^n) = \frac{(p_k^n)^\gamma}{((p_k^n)^\gamma + (1 - (p_k^n)^\gamma)^{\frac{1}{\gamma}}} \quad \text{with } \gamma > 0.290 \tag{11}$$

where γ is a parameter that defines the form of the inverse S-shape. This mixed curvature typically suggests that the decision makers over-weight small probabilities while they underweight large probabilities. Models 3 and 4 are formulated based on the weighting function above.

4.3. Prospect theory

According to Prospect Theory, which was introduced by Kahneman and Tversky (1979), the outcomes of a gambling choice can be interpreted as gains or losses compared to a specific reference point. The existence of a reference point is appealing due to various behavioural hypotheses, like the tendency of decision makers to maintain their status quo (*endowment effect*) or the habit to compare the possible outcomes with the status quo (*anchoring effect*).

The prospect $s^n = (s_1^n, s_2^n, \ldots, s_K^n)$ is split into losses $s^{n-} = (s_1^{n-}, s_2^{n-}, \ldots, s_i^{n-})$ and gains $s^{n+} = (s_i^{n+}, s_{i+1}^{n+}, \ldots, s_K^{n+})$ based on the outcome's relative position to the reference point s_{ref}^n. Therefore, the utility function has now two parts, which can be expressed as:

$$u(s_k^n) = \begin{cases} \left(v(s_k^{n+}) - v(s_{ref}^n)\right)^\delta \\ -\lambda\left(v(s_{ref}^n) - v(s_k^{n-})\right)^\zeta \end{cases} \tag{12}$$

where $\delta, \zeta < 1$ are parameters that reflect the degree of diminishing sensitivity and λ is an indication of loss aversion, if greater than one. One of the main findings in PT studies is the asymmetry in preferences between gains and losses, towards loss-avert behaviour.

The utility function for the risky alternative is now:

$$u_i^{LATER} = ASC^{LATER} + \beta_{C(gain)}(1 - P_I)(C_{Ref} - C_D)^\delta + \beta_{C(loss)}P_I(C_I - C_{Ref})^\zeta + \varepsilon_i \tag{13}$$

where C_{Ref} is the reference price, which is assumed to be equal to the fixed price of the "book now" option. This fixed value is possibly not representative of the current recharging costs of EV drivers, yet, it is the reference point based on which the comparisons are made for the booking game.[3] The sensitivity to cost is now divided into two coefficients, $\beta_{C(gain)}$ and $\beta_{C(loss)}$, according to the relative position of the outcome with respect to C_{Ref}. Two models are estimated: **Model 5**, where δ and ζ are fixed to one in order to capture only reference dependence and **Model 6**, where they are not fixed to allow the estimation of diminishing sensitivity.

5. Results

The models described in the previous section were estimated with BIOGEME 2.2 (Bierlaire, 2003). In Latinopoulos (2016), after estimating two MNL models, one for the respondents recruited by the service sample provider and one for the respon-

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[3] The λ parameter for loss aversion is not included in this specification since the model was unidentifiable.

dents recruited by the researchers, it was found that the parameters of the charging game are of different scale and there is a higher variance for the error term related to the former. In order to combine the observations from the two sub-samples, capturing this variance heterogeneity, a scale parameter (η) was estimated.

Table 4 provides information about the personal characteristics, the travel characteristics and the revealed driving/charging behaviour that were included in the final models, along with their descriptive statistics. Their selection is the result of an extensive search of possible specifications.

The EV-PLACE survey included additional attitudinal questions to capture the drivers' perception of flexibility for the underlying activities and their perception of planning their travel in advance. Factor analysis of the 16 psychometric indicators collected allowed the identification of four latent constructs: *Schedule flexibility*, *perceived mobility necessity*, inclination towards *pre-planning* travel activities and tendency to *search for parking at the last moment*. Alternative specifications have been tested, where these latent constructs entered the utility function as a combination of the Likert-scale values of the associated indicators. Among the four latent variables, only schedule flexibility was found to improve the explanatory power of the models, hence it enters the final specifications with the other variables in Table 4. The indicators that define the combined score of schedule flexibility are:

- I_1: I could have changed my departure time at the beginning of the day (earlier or later).
- I_2: I could have performed the first activity of the day in another location.
- I_3: I could have performed the first activity of the day at another time.
- I_4: I could completely cancel the first activity of the day.

Looking at the results of the booking game, 67.9% of the observed choices are in favour of the safe option and 32.1% in favour of the risky option. This is in agreement with previous findings from road pricing, suggesting that individuals tend to choose a certain price over an uncertain one (Bonsall et al., 2007) or that they dislike uncertainty per se (Lindsey, 2011). For 56.4% of the respondents that have chosen not to gamble, the current price was lower than the expected future price, suggesting a rational decision. On the other hand, the remaining 43.6% were risk-averse even if the rational decision would be to wait. Among the "book later" choices, 80.9% were based on a higher probability of gain, while 19.1% took the risk even if the probability of gain was lower.

The estimation results for the various specifications discussed in the previous section are presented in Table 5. The alternative specific constant for the "book now" option is positive expressing an implicit preference for the safe choice, i.e., a tendency towards myopic behaviour. The coefficient for the charging price is negative and statistically significant, a rather intuitive result.

According to the estimated parameters, older individuals tend to choose the safe option compared to younger individuals. The findings are similar for employed individuals. Under a different risky context, Daina (2014) has also found that older groups and full-time employed persons demonstrate a higher risk aversion, reflected by their increased sensitivity to a range anxiety latent construct. Parents and people with a higher education level are more likely to exhibit strategic behaviour. Individuals that undertake work-based tours are characterized by a more conservative response, while those that own or lease an electric vehicle have a higher willingness to wait for a better offer.

The myopic behaviour of EV drivers who stated that they charge their vehicle more than once per day could be justified by the planning burden associated with comparing dynamic prices every time they charge. Moreover, EV drivers that have been charging their vehicle for free are strongly inclined towards the safe option, possibly because they are less willing to risk an increased charging price. Experienced EV drivers, i.e., individuals that have been driving an EV for more than a year, have a higher likelihood of being strategic. On the other hand, EV loyal enthusiasts (as they are defined in Table 4) exhibit a more myopic behaviour. Finally, individuals that have been regularly driving long distances with their EV prefer the "book later" choice. This behaviour is possibly an outcome of their higher familiarity with risky situations, due to the fact that they repeatedly strain the limits of their battery range.

The goodness-of-fit for Model 2 is slightly lower than Model 1 and there is no significant difference in the parameter estimates. This relatively small differentiation could be attributed to overfitting and it might be useful to cross-validate the estimated values with another sample, in order to investigate this possibility. Likewise, the adjusted $\bar{\rho}$ has not improved for Models 3, 4, 5 and 6 while the signs and magnitudes of the parameter estimates were similar to the EUT models. The price coefficients for Models 5 and 6 agree with the *a priori* expectations, i.e., the sensitivity to price is positive when the outcome is framed as a gain and negative when it is framed as a loss. The absolute ratio of the two coefficients $\left| \frac{\beta_{C(loss)}}{\beta_{C(gain)}} \right|$ does not suggest a loss aversion (0.63 < 1 for Model 5 and 0.41 < 1 for Model 6), contrary to what is usually observed in PT studies. The *alpha* parameter for Models 2 and 4 is not significant but this is likely due to the fact that risk aversion is already captured by the "book now" constant, which is positive and significant.

The parameter γ is statistically significant for both Models 3 and 4. As it was explained in the previous section, it contains information about the individuals' perceptions of the probabilities for future prices. For $\gamma = 1$ there is a linear relationship between objective and subjective probabilities, thus, the distortion in these models ($\gamma \approx 1.3$) is small. However, in this case, the weighting function is S-shaped, instead of the commonly encountered inverse S-shape. In other words, individuals are observed to slightly underweight low probabilities and overweight high probabilities. The relationship between objective and subjective probabilities for Model 3 (it is almost the same for Model 4) can be seen in Fig. 3.

Table 4
Descriptive statistics and information for the variables that enter the models.

Variable	Description	Mean	Std dev
Personal characteristics			
Age over 60	Dummy variable for age higher than 60	0.05	0.22
Employed	Dummy variable for employed (Reference categories: Unemployed, Students, Retired and Unable to work)	0.84	0.37
Having children	Dummy variable for respondents that have children	0.56	0.50
Education: University Graduate	Dummy variable for university graduates (Reference categories: No schooling, High school, other education)	0.62	0.49
EV access	Dummy variable for owning or leasing an EV	0.54	0.50
Number of activities	Number of daily activities in the trip chain	1.44	0.65
Number of searches	Number of searches ("clicks") before selecting a travel profile (min: 0–max: 3)	0.21	0.65
Travel characteristics			
Travel profile: Everyday	Dummy variable for undertaking the selected travel profile every day (Reference categories: Less frequently)	0.05	0.21
Travel weekday	Dummy variable for respondents that have reported a weekday for their travel profile	0.79	0.40
Work based tour	Dummy variable for tours that include a working activity	0.65	0.48
Driving/charging behaviour			
Charging frequency: More than once a day	Dummy variable for charging EV more than once a day (Reference categories: Charging EV less than once a day, Non-EV drivers)	0.06	0.23
Charging cost: free	Dummy variable for current daily cost of recharging (Reference categories: Less than 50p, 50p–£1, £1–£2, £2–£4, more than £4, Non-EV drivers)	0.03	0.16
Driving EV: More than a year	Dummy variable for respondents that drive EV more than a year (Reference categories: drive EV less than a year, Non-EV drivers)	0.16	0.37
EV loyal enthusiast	Respondents that give a 9 or 10 score to the question: "From a scale of 1–10, how likely is that you would recommend your EV to a friend or colleague?"[a]	0.27	0.44
EV daily mileage: more than 40 miles	Dummy variable for respondents that drive more than 40 miles a day with an EV: (Reference categories: drive less than 40 miles a day with EV, Non-EV drivers)	0.07	0.25

[a] Based on the Net Promoter Score (NPS), a management tool that measures customer satisfaction (https://en.wikipedia.org/wiki/Net_Promoter).

The results suggest that when the probability of an increased price is small, it weighs less than its objective value (i.e., 0.2 and w(0.2) < 0.2 and 1 − w(0.2) > 0.8), reflecting optimism for the individuals who are more likely to be risk-prone. Following the same logic, when the probability of a decreased price is small, individuals show pessimism and tend to be risk averse. Since the value of γ is closer to 1 for high probabilities, it can be deduced that the main distortion happens at the left part of the S-shaped function.

The statistical significance of the δ and ζ parameters indicates an asymmetrical response to price increases and price decreases from the fixed price of the "book now" option. This asymmetry can vary between the loss and the gain space with $\delta < 1$ reflecting a diminishing sensitivity to lower future prices and $\zeta > 1$ reflecting an increasing sensitivity to higher future prices. The shifts in the utility function relative to changes in future prices are presented in Fig. 4.

The asymmetry mentioned earlier is visible both in absolute terms and in the shape of the function. For example, an 80% decrease in price (+80% gain) results into a utility increase of 3 units while an analogous increase in price (−80% loss) results in utility decrease of 1 unit. Moreover, the relationship is almost linear in the gain space and concave in the loss space, with the latter suggesting an increase in the absolute marginal utility as the difference from the reference point increases. In other words, a £2.00 increase of charging price, instead of being twice as bad as an £1.00 increase, has a stronger negative effect on drivers. As Bonsall et al. (2007) observe, "people's behaviour is more than proportionally influenced by the upper end of a price distribution".

This result is in contradiction with the supposition put forward by prospect theory that the value function for losses should be convex and relatively steep. Interestingly, Hess et al. (2008) also found different relationships in the gain/loss asymmetry for changes in different attributes.

Since the goodness-of-fit is similar for all models, it's not clear if the non-linear transformations lead to improved models. In order to examine if there is a superior specification two additional metrics are compared for Models 1–4: the Bayesian Information Criterion (BIC) and the likelihood ratio test. For the latter, Model 1 is considered to be the restricted model and the other specifications are characterized as general. The PT specifications (Models 5 and 6) are not included in the comparison because they are non-nested; hence, they cannot be a parametric generalisation of any of the other models.

The additional metrics are included in Table 5. It is observed that Model 1 has the best model fit based on the BIC metric and the LR test (the null hypothesis that the restricted model is true is not rejected for any general model at the p = 0.1 significance level). Nevertheless, the differences are minor. Similar comparative analysis of EU and non-EU methods in the context of travellers' choice for hypothetical unreliable train services was undertaken in Michea and Polak (2006). In both studies, regardless to the comparative performance of alternative risky choice frameworks, each alternative offers additional behavioural insights. Moreover, most specifications support the hypothesis that individuals tend to systematically distort objective probabilities in risky situations.

Table 5
Estimates of EUT, RDEU and PT specifications with linear and non-linear value functions accounting for systematic heterogeneity.

Variables	Model 1 (EUT, linear)		Model 2 (EUT, non-linear)		Model 3 (RDEU, linear)		Model 4 (RDEU, non-linear)		Model 5 (PT, fixed δ and ζ)		Model 6 (PT, not fixed δ and ζ)	
	Coef[b]	Std error	Coef	Std error	Coef	Std error	Coef	Std error	Coef	Std error	Coef	Std error
ASC$_{NOW}$	1.49[*]	0.805	3.27[*]	1.94	3.07[*]	1.68	6.23[*]	3.49	2.14[**]	0.927	2.76[**]	1.03
ASC$_{LATER}$	0	Fixed	–[***]	–[***]	–[***]	–[***]	–[***]	–[***]	–[***]	–[***]	–[***]	–[***]
CP [£][a]	−1.12[**]	0.162	−3.47[**]	1.08	−2.84[**]	0.552	−4.49[**]	1.60	2.92[**]/ −1.83[**]	0.497/ 0.485	3.21[**]/ −1.33[**]	0.856/ 0.514
Age over 60	2.45[**]	0.653	2.46[**]	0.653	2.53[**]	0.679	2.55[**]	0.680	2.47[**]	0.654	2.55[**]	0.677
Employed	1.20[**]	0.544	1.21[**]	0.545	1.26[**]	0.567	1.27[**]	0.567	1.21[**]	0.544	1.26[**]	0.565
Having children	−0.55[*]	0.322	−0.55[*]	0.323	−0.55[*]	0.329	−0.56[*]	0.332	−0.56[*]	0.324	−0.59[*]	0.331
Education: University	−0.97[**]	0.320	−0.98[**]	0.323	−0.98[**]	0.325	−1.00[**]	0.329	−0.98[**]	0.324	−1.00[**]	0.329
EV access	−0.85[*]	0.509	−0.86[*]	0.511	−0.91[*]	0.534	−0.93[*]	0.537	−0.87[*]	0.512	−0.92[*]	0.533
Number of daily activities	−0.27	0.229	−0.27	0.230	−0.27	0.233	−0.27	0.235	−0.27	0.231	−0.27	0.235
Number of profile searches	0.32[*]	0.196	0.32[*]	0.198	0.33[*]	0.198	0.33[*]	0.200	0.32[*]	0.198	0.33[*]	0.200
Travel profile: Every day	1.02	0.720	1.03	0.722	1.02	0.739	1.04	0.743	1.04	0.724	1.04	0.743
Travel day: Weekday	0.54	0.370	0.55	0.371	0.54	0.382	0.55	0.383	0.55	0.372	0.55	0.383
Work based tour	0.92[**]	0.387	0.93[**]	0.388	0.96[**]	0.401	0.97[**]	0.402	0.93[**]	0.388	0.97[**]	0.401
Schedule flexibility	−0.04	0.032	−0.04	0.032	−0.04	0.033	−0.04	0.033	−0.04	0.032	−0.04	0.033
Charging frequency: More than once a day	0.91[*]	0.548	0.92[*]	0.552	0.89	0.555	0.90	0.560	0.92[*]	0.553	0.91	0.560
Charging cost: Free	5.04[**]	2.39	5.10[**]	2.38	5.18[**]	2.51	5.25[**]	2.51	5.11[**]	2.380	5.23[**]	2.500
Driving EV: More than a year	−1.01[**]	0.323	−1.02[**]	0.324	−1.02[**]	0.327	−1.03[**]	0.330	−1.02[**]	0.325	−1.04[**]	0.330
EV loyal enthusiast	0.79[**]	0.322	0.80[**]	0.324	0.80[**]	0.327	0.81[**]	0.330	0.80[**]	0.325	0.82[**]	0.330
EV daily mileage: More than 40 miles	−1.07[**]	0.414	−1.09[**]	0.417	−1.06[**]	0.420	−1.09[**]	0.424	−1.09[**]	0.418	−1.09[**]	0.424
Scale for recruitment channel (η)	0.416[**]	0.0771	0.415[**]	0.0762	0.400[**]	0.076	0.400[**]	0.074	0.414[**]	0.076	0.397[**]	0.074
Risk attitude parameter (a)	–	–	0.155	0.128	–	–	0.20	0.140	–	–	–	–
Distortion of probabilities (γ)	–	–	–	–	1.30[**]	0.293	1.32[**]	0.259	–	–	–	–
Diminishing sensitivity: gain (δ)	–	–	–	–	–	–	–	–	1	Fixed	0.960[**]	0.249
Diminishing sensitivity: loss (ζ)	–	–	–	–	–	–	–	–	1	Fixed	2.010[**]	0.641
Number of estimated parameters	19		20		20		21		20		22	
Number of individuals	118		118		118		118		118		118	
Number of observations	1062		1062		1062		1062		1062		1062	
Null log-likelihood	−736.122		−736.122		−736.122		−736.122		−736.122		−736.122	
Final log-likelihood	−546.489		−545.749		−545.526		−544.518		−545.340		−543.597	
Likelihood ratio index ρ	0.258		0.259		0.259		0.260		0.259		0.262	
Adjusted likelihood ratio index $\bar{\rho}$	0.232		0.231		0.232		0.232		0.232		0.232	
BIC	1255.37		1230.86		1230.41		1235.36		–		–	
LR test	Restricted model		1.48		1.93		3.94		–		–	

[a] For Model 5 and Model 6 the charging price is divided in $\beta_{C(gain)}$ and $\beta_{C(loss)}$ for gains and losses compared to the fixed price.
[b] Two asterisks ([**]) indicate that the coefficient for this parameter is statistically significant at the p < 0.05 level, whereas one asterisk ([*]) indicates that the coefficient is statistically significant at the p < 0.10 level.

6. Conclusions and future directions

Despite the vast amount of information that is collected with real-time parking applications, there is a lack of dynamic pricing methods that exploit this information to optimize the system performance. Moreover, it is crucial to develop behavioural models that capture the response of individuals to these dynamic pricing methods in order to assess their feasibility and adjust them accordingly.

This paper presents a risky-choice framework that aims to interpret the booking behaviour of EV drivers when parking-and-charging prices vary dynamically or, in other words, to measure their willingness to wait for future reductions in price. This framework consists of six models based on three theoretical approaches that cover a wide range of attitudes towards risk: EUT, RDEU and PT. The data required in order to estimate these models were collected with the assistance of an online SP survey instrument that is also presented here.

The EV-PLACE survey is the first that evaluates parking choices under the consideration of EV charging characteristics. Furthermore, unlike most EV studies that focus on the strategic choice of vehicle purchase, the interest is shifted towards
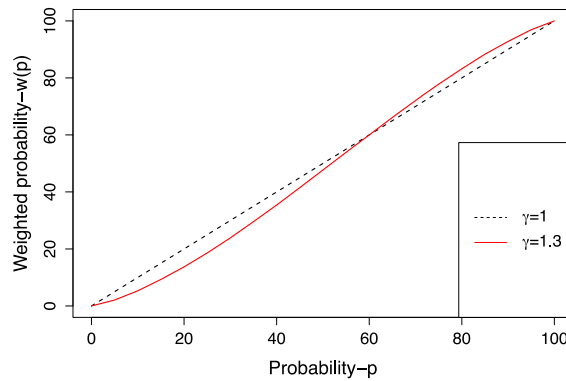
Fig. 3. Objective and subjective probabilities for risky outcomes of dynamic pricing.

the tactical every-day choices in using and charging an EV. The two main innovative elements of the survey presented in this paper are: out-of-home charging preferences and response to dynamic pricing (DP).

The results suggest a propensity of individuals to be risk-averse, since the majority of them preferred the safe option to the risky one. However, it is observed that specific demographic groups, like for example young and educated individuals, are more likely to exhibit forward-looking behaviour. Moreover, the non-EUT approaches imply some nonlinearity in the attitudes towards risk, and this might have significant implications for more complex pricing environments.

As pointed out by Talluri and van Ryzin (2005), failing to incorporate strategic behaviour in pricing could lead to significant revenue losses, especially with increasing availability of information for the customers. Like in the airline industry, there is a possibility that third parties will use pricing data to produce price trend forecasts and feed this information back to the customers. Consequently EV drivers might delay their charging post reservation in the expectation of a cheaper charging bundle. The presented framework, if applied in practice, will allow CSPs to link the attitudes towards risk with personal characteristics and, thus, to improve their dynamic pricing tools.

Optimal pricing in the presence of forward-looking customers is typically modelled with game-theoretical approaches. Lei and Ouyang (2017) propose a dynamic Stackelberg game for the parking pricing and reservation problem with deterministic parameters of demand. They stress the importance of capturing drivers' choice under uncertainty in optimizing system performance. A conceptual framework where the estimated proportions of myopic and forward-looking drivers are used as input to a stochastic game of charging coordination is discussed in Latinopoulos (2016).

One limitation of the survey is that the binary choices that take place in the booking game are not representative of a real booking application. For example, if an individual wants to buy an air ticket and the price increases, he has the ability to opt-out and search for a similar flight in a competitive airline company. In the interactive survey of Collins et al. (2012) the respondents have the capability to search, sort and filter the various alternatives. Apart from the presentational realism, which is fairly achieved for the EV-PLACE survey, the functionality of such a dynamic interface offers a wide range of new opportunities. For example side actions of the respondents, like attribute valuation from sorting or searching time and strategy can now be identified. The development of an equivalent tool for EV parking/charging services is a cumbersome task but quite appealing for future research.

The low penetration of EVs in the British market together with the great difficulty in tracing the drivers posed a constraint in terms of sampling for the online survey. The sample was complemented with EV considerers, i.e., individuals that are
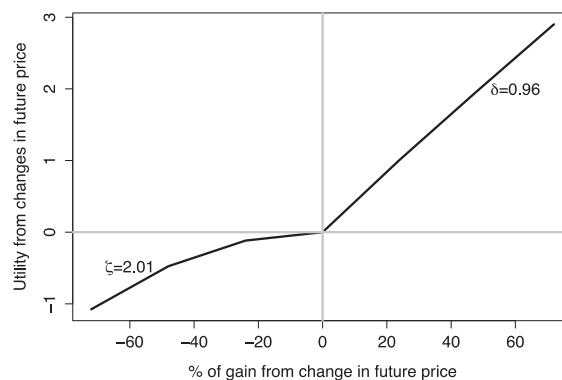

Fig. 4. Asymmetrical preferences towards gains and losses compared to the reference price.

potential future buyers of electric vehicles. Both drivers and considerers belong in the general profile of "early adopters", which have distinct characteristics compared to the broader population. Therefore, it is difficult to generalise the empirical results and use the choice models for prediction purposes, without performing a cross validation with a larger dataset. Nevertheless, the estimated parameters can have a direct operational impact. Therefore, their value for the CSP lies in the proper understanding of charging behaviour of their customers for each respective period, rather than in long-term predictions for the mass market.

Similar applications to the one presented in this paper can be designed for other existing and emerging mobility services. For example, car-sharing customers can reserve a vehicle in advance and some operators offer discounts to incentivize early reservations. Moreover, the spatiotemporal variability of travel patterns creates an imbalance in the availability of vehicles at car-sharing stations. This problem can be solved by physically relocating the vehicles to balance supply with demand. Nevertheless, IoT and dynamic pricing offer the possibility for more efficient solutions that will create added value for both users and operators.

Acknowledgements

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