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Consumer Behavior towards Scheduling and Pricing of Electric Cars Recharging: Theoretical and Experimental Analysis

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Consumer Behavior towards Scheduling and Pricing of Electric Cars Recharging: Theoretical and Experimental Analysis

PhD Dissertation

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Preface

This dissertation presents my PhD study carried out at the Department of Management Engineering at the Technical University of Denmark in the period from April 2013 to July 2016. The study was part of a large project entitled 'Consumer Acceptance of Intelligent Recharging'. I gratefully acknowledge the ForskEL program of the Danish Ministry for Climate and Energy for the financial support covering my study expenses.

This dissertation would not be possible without my supervisors' great guidance and support. I am grateful for my supervisor Associate Professor Sigal Kaplan for her great inspiration, motivation, guidance and for being truly accessible. I really learned a lot from the many discussions and talks we have thank had. I thank my co-supervisor Professor Carlo Giacomo Prato for providing very contractive comments and suggestions. I also thank my other co-supervisor Associate Professor Alexander Christopher Sebald for his constructive feedbacks and comments and for administratively arranging my six months visit at the Department of Economics at the University of Copenhagen.

For providing excellent environment for doing research, I would like to thank the then DTU Transport Department, which is integrated with the Department of Management Engineering few months before I finished my study. I thank all the staffs at the department for their excellent supports and for being nice colleagues. I specially thank Professor Mogens Fosgerau for supervising my first 9 months of the study during which he suggested me most of the courses I took and for suggesting Associate Professor Sigal Kaplan to be my supervisor. I also specially thank Stefan Mabit, who managed the project in which my study was a apart and who also co-authored in one of the papers, for his great and very kind help; Dereje Fentie for being a really nice friend, for the many discussions and talks we have had that helped me to make the dissertation better, for proof reading two of my papers, and generally for making my study stay at the department much better; Ismir Mulalic for being an excellent office-mate for two years and for his excellent support; Andres Jensen, who co-authored in one of the papers, for being a nice colleague and for translating the abstract of the dissertation in to Danish; Kira Janstrup for being a very nice office-mate during my last year of study; Linda Christensen for introducing the PhD project; Katrine Hjorth, Thomas J, Stefano, Abhishek, and all other staffs at the Department for being nice colleagues. I also specially thank Caroline Hartoft-Nielsen and Karen for their excellent and very kindly administrative help.

I had a pleasure to visit Institute of Transport and Economics at the Technical University of Dresden, Germany, from Oct. 2014 to Dec. 2016. I am grateful for

Abstract

This articled-based dissertation consists of five self-contained chapters. The first chapter presents the motivation of the dissertation and a summary of the four papers contenting the dissertation. Three of the chapters are applied microeconomics papers dealing with the economics of recharging electric cars. The last chapter deals with analysis of energy consumption rate and its determinants of electric cars under the hands of customers. A variety of techniques are used including analysis of field data, economics laboratory experiments and theoretical modeling with simulation.

Chapter one presents an introduction to the main parts of the dissertation and a summary of the articles contenting the dissertation.

Chapter two, 'The Economics of Workplace Recharging', proposes a microeconomic model of the demand for and supply of recharging facility at workplace (WPC), and uses the approach to shed light on the incentives and barriers employees and employers face when deciding on the demand for and supply of WPC. Using the model and simulation, the paper also examines the existence of WPC market under the current prices, and finds that no WPC contract exists that an employer is willing to offer and, at the same time, that the majority of employees are willing to accept. To overcome the lack of demand for or under-provision of workplace recharging, various remedies are discussed and suggested.

Chapter three, 'Myopic Loss Aversion Behavior under Ultimatum Game Framework in the Scheduling and Pricing of Electric Vehicle Recharging', proposes, and tests at laboratory, contracts about recharging BEVs combining the ultimatum game framework and the myopic loss aversion (MLA) behavioral hypothesis. The model represents the behavior of EV-owners trading-off between the amount of the discount on fee for postponing recharging, the risk of being eligible to the discount and the risk of not recharging the BEV on time for unforeseen trips. Findings from the experiment show that indeed individuals perform decisions exhibiting MLA behavior. The intuition from the result is that presenting time-of-use recharging price as long-term contracts may curtail MLA behavior and help BEV owners to choose cost minimizing recharging time

and, simultaneously, may help to reduce BEVs impact on the electricity grid system.

The fourth chapter, 'Using the Peer Effect in Scheduling and Pricing Electric Vehicles Recharging: Laboratory Evidence about Peer Effect in Risk-Taking', presents experimental evidence about peer effect in risk taking in general and, in particular, the use of peer effect in scheduling BEVs recharging. The study investigates whether individuals want to see the choices of others, if observing peers' choices influences the observers' choices, to what extent the peer effect is pervasive and who are being influenced by peers' choices as well as the role the type of peer information plays on peer effects. The results show that a lion share of individuals want to see peers' choices, but only a moderate percentage of them, mostly those with relatively lower scores in our math test (usually used to test cognitive ability) and lacking self-confidence, use the peers' choices to revise their intrinsic choices. The results reveal also that the type of peer information plays a significant role in peer effects.

The fifth chapter, 'Harnessing Big-Data for Estimating the Energy Consumption and Driving Range of Electric Vehicles', analyzes the electricity consumption of BEVs and its sensitivity to the various driving environments in the hands of customers. The results show that the energy consumption rate of BEVs is highly sensitive to weather conditions and to driving styles. The results may help individuals to make informed decisions about BEV choice, manufacturers to build trust with customers by provide more accurate information, and governments to design policies based on reliable information.

Dansk Resumé

Formålet med denne Ph.D. afhandling er at foreslå og eksperimentelt analyzere kontrakter mellem brugere af elbiler og udbydere af opladning til elbiler med henblik på at analyzere, hvordan brugernes adfærd bliver påvirket af pris og udskydelse af opladning, samt at analyzere elbilers strømforbrug i forskellige omgivelser. Afhandlingen består af fem uafhængige kapitler, hvor der er benyttet en bred vifte af metoder, såsom empirisk data-analyse, økonomiske eksperimenter samt teoretisk modellering med simulering.

Kapitel 1 giver en introduktion til emnet og beskriver, hvorfor det er relevant at analyzere elbiler og opladning. Kapitlet præsenterer et kort resumé af de fire artikler, som tilsammen udgør denne afhandling.

Kapitel 2, "The economics of workplace charging", foreslår en mikroøkonomisk udbuds- og efterspørgselsmodel for opladningsfaciliteter på arbejdspladser (WPC), og benytter denne fremgangsmåde til at belyse incitamenter og barrierer som arbejdsgivere og arbejdstagere står over for, når de fastlægger udbud af og efterspørgsel efter WPC. Ved hjælp af simuleringer med denne model undersøger artiklen desuden forekomsten af WPC under de nuværende vilkår, og konkluderer, at der ikke eksisterer nogen WPC kontrakt som en arbejdsgiver vil udbyde, og som størstedelen af arbejdstagerne samtidig vil efterspørge. Til slut foreslår og diskuterer artiklen forskellige måder, hvorpå man kan fremme udbud af og efterspørgsel efter WPC.

Kapitel 3, "Myopic Loss Aversion Behavior under Ultimatum Game Framework in the Scheduling and Pricing of Electric Vehicle Recharging", foreslår og afprøver vha. økonomiske eksperimenter kontrakter mellem brugere af elbiler og udbydere af opladning til elbiler, som kombinerer adfærdsteorierne inden for "Ultimatum game" og "Myopic Loss Aversion" (MLA). Modellen repræsenterer elbilbrugeres adfærd, når de afvejer, hvor meget de kan få i rabat for at udskyde opladning, risikoen for ikke at kunne få rabatten, samt risikoen for at elbilen ikke er opladet i tide til eventuelle uforudsete ture. Resultaterne viser, at respondenterne udviser MLA, og tyder på, at langtidskontrakter med specifikke priser for bestemte ladetidspunkter kan begrænse MLA adfærd og hjælpe

elbilbrugere til at vælge et prisoptimalt opladningstidspunkt og samtidig reducere elbilernes belastning på elnettet.

Det fjerde kapitel, " Using the Peer Effect in Scheduling and Pricing Electric Vehicles Recharging: Laboratory Evidence about Peer Effect in Risk-Taking", præsenterer eksperimentel dokumentation for gruppeeffekters generelle indflydelse på risikovurdering og, mere specifikt, betydningen af gruppeeffekter i forbindelse med planlægning af elbilers opladning. Artiklen undersøger, hvorvidt individer vil se andres beslutninger, om indsigt i andres beslutninger påvirker individets beslutning, i hvilken grad gruppeeffekten gør sig gældende, hvem der bliver påvirket af andres beslutninger, samt hvilken rolle en bestemt type information har på gruppeeffekten. Resultaterne viser, at en stor del af respondenterne gerne vil se andres beslutninger, men kun en begrænset andel - for det meste dem med lavere score i din matematik test (normalt bruges til at teste kognitive evne) og med lavere selvtillid - bruger andres beslutninger til at genoverveje deres umiddelbare beslutning. Resultaterne viser envidere, at der er stor forskel på effekten af forskellige typer af information, der deles i en gruppe.

Det femte kapitel, "Harnessing Big-Data for Estimating the Energy Consumption and Driving Range of Electric Vehicles", undersøger strømforbruget af elbiler under almindelige forhold. Artiklen analyzerer således, hvordan strømforbruget påvirkes af forskellige virkelige omgivelser. Resultaterne viser, at strømforbruget bliver meget påvirket af vejrforhold og kørestil. Resultaterne giver en større viden om elbilers forbrug, som både kan benyttes af potentielle købere før den endelige beslutning om at anskaffe en elbil, af producenter til at give et mere præcist og troværdigt billede af elbilernes egenskaber samt af myndigheder til at opbygge målsætninger baseret på pålidelig information.

Contents

1. Introduction

This section presents the motivation of the dissertation. The section presents the motivation and main results of each paper constituting the PhD thesis. An overview of the papers is also presented following a brief presentation of the methods applied in the study.

1.1. Motivation

At the time when the steadily increasing pollution from the transport sector (Eurostat, 2015; Hacker et al., 2009) is becoming a critical issue (BBC, 2015; Malykhina, 2015; Schofield, 2014), battery electric vehicles (BEVs henceforth) bring new opportunities in the transportation system. They use electricity that can be generated from sustainable sources such as hydro, wind and solar. They also pollute less than diesel and petro cars do even when the electricity for recharging comes from unsustainable sources (Hooftman et al., 2016; Nanaki and Koroneos, 2013). In addition to this, the BEV batteries offer potential to balance the electricity grid system by recharging the BEVs when electricity supply exceeds demand and/or by (possibly) de-charging the battery power back to the electricity grid system when demand exceeds supply and when BEVs are parked. Moreover, the BEVs could also be used to balance the power when there is prediction error in the renewable energy generators (Kempton and Tomić, 2005).

BEVs, however, also present new challenges. One of the main concerns about BEVs is that recharging (under the current technology) takes long time, from about 20 minutes to hours depending on the type of the recharging tool and on the battery type. Added to this is that the driving-range of currently available (and affordable by a representative car buyer) BEVs is limited. These result in driving-range anxiety (Franke and Krems, 2013a), making recharging time and place decisive issues (Bonges and Lusk, 2016; Lieven, 2015). The long recharging time makes on-the-road recharging costly because of the value of time (of the BEV user(s)), the parking fee associated with the long recharging time and of the distaste of waiting long time in the car while recharging the BEV in the

middle of the trip[1]. Certainly, BEVs can be recharged at residence while the BEV user doing household activities without almost any waste of valuable time for recharging. However, not all individuals have private parking to install recharging tool and even those who have private recharging tool at their residence may need to recharge at non-residential areas to extend the driving-range of the BEV for planned and unplanned trips[2] and when there are technical problems to recharge at residence. One suggested solution of addressing the recharging problem particularly for individuals without having private parking is to provide recharging service at workplace, which is considered as the second major recharging option next to residential recharging (Neubauer and Wood, 2014). However, this requires agreements at least between employers and employees about having recharging facility at workplace, workplace charging (WPC). There has been a literature gap that systematically analyzes the economics of the demand for and supply of recharging at workplace.

One objective of this dissertation is, thus, to propose a microeconomic model to investigate the demand for and supply of WPC. The model focuses on cost issues driving the supply of WPC on the employer side and user (net) benefits on the employee side. The model is used to shed light on the incentives and barriers employees and employers face when deciding on WPC. Using the model and simulation, the paper also examines the existence of WPC market under the current prices, i.e., whether a contractual agreement can be reached between employers and

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[1] Working in the car while the BEV is being recharged on the roadside may not be convenient, and it could even be distasting for the BEV user(s). The fee for recharging at (future) commercial recharging places may include parking fees since, under the current technology, recharging takes longer time in that charging only for the electricity and the service may not be profitable.

[2] Hahnel et al. (2013) find from 6 % (for work related) to 21 % (shopping) underestimates of trips, i.e., unplanned trips.

employees for WPC to exist without interventions from other economic agents, e.g., government and BEV makers.

Another challenge concerning BEVs is that the default recharging time, unfortunately, coincides with peak electricity consumption hours (Robinson et al., 2013). For example, recharging at residence (upon arrival from work) and using energy for household consumption, and recharging at workplace and using energy for office and company use. This could have a substantial effect on the electricity grid system (see, e.g., Grahn, 2013; Pan and Zhang, 2016). This apprehension necessitate investigating the ways to curtain BEVs impact on the electricity grid system and to save a substantial amount of electricity expansion cost that will be required to recharge a mass penetration of BEVs (Grahn, 2013; Hajimiragha et al., 2011; Waraich et al., 2013; Zhang et al., 2013). There have been numerous studies about smartly integrating BEVs in to the electricity grid system (see, e.g., Mwasilu et al., 2014; Waraich et al., 2013). Most of these studies focus on the feasibility, logistics and optimization algorithm of getting BEVs recharging smartly integrated with the grid system (Finn et al., 2012; Grahn and Soder, 2011; He et al., 2012; Hu et al., 2014). Most of these studies assumed, explicitly or implicitly, that BEV users will be willing to postpone charging and/or will accept their charging activity controlled by electricity suppliers in return for discounted fee for recharging (Pan and Zhang, 2016; Sundstrom and Binding, 2012). Empirical studies show, however, that individuals are bounded rational and that there are biases in decision-making (see, e.g., Holt and Laury, 2002; Kahneman and Tversky, 1979; Thaler et al., 1997) in that BEV users may not evaluate recharging decision on the bases of only the net gains from postponing recharging. These behavioral biases and bounded rationality, however, have received very limited attention in the emerging literature about BEV recharging (Caperello et al., 2013; Franke and Krems, 2013a).

The second objective of this study, thus, is to propose recharging contracts about smart integration of BEVs and to conduct

experiments tailoring behavioral biases to give insight about how to better induce BEV users to participate in smart integration of BEVs with the electricity grid system. One of the papers presents a behavioral model and experimental validation combining myopic loss aversion (MLA) behavioral hypothesis[3] (often used in financial investment literature) and an ultimatum game (UG) framework. Like individuals participating in financial assets investment, participating in smart integration of recharging involves making sequential decisions that may have the risk of losing more than the cost saving from discounted fee for recharging when unforeseen trips occur or if the individual need to revise initial trip plan while the BEV battery power is flat and is awaiting for recharging later at discount hours.[4] This, added with the small share of income of the recharging cost, may result in loss aversion and myopia behavior hindering participation in smart integrating of the BEV that needs treatment. The MLA and UG frameworks are combined and experimentally tested to enlighten on designing contracts about BEV recharging taking behavioral biases in to account. This may benefit BEV users to get discounted recharging fees and the electricity supplier to reduce the potential impacts of BEVs on the electricity system that also may benefit the society at large. The second paper that addresses

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[3] MLA combines the two concepts of loss aversion and mental accounting, where loss aversion is the tendency of individuals to be more sensitive to losses than to gains and mental accounting is the activity that individuals perform to evaluate alternatives and take decisions (Benartzi and Thaler, 1995).

[4] For example, if a BEV user arrives at home at, say, 5 pm with flat battery BEV and postpones recharging to, say, 9 pm in return for a discount, then there is a risk of paying more, say to a taxi or a higher distaste of not using the EV, if unforeseen trip that cannot be covered by the available battery power occurs before 9 pm.

behavioral issue is about peer effect in risk-taking that aims at giving insights about the use of peer influence in scheduling BEVs recharging.

Uncertainty about energy consumption rate (ECR henceforth) and its sensitive to the various driving environments in the hands of customers is also another setback of BEVs. Providing accurate information to people about the energy consumption rate of BEVs using real-world data where the drivers are the people themselves is crucial for individuals to make informed decisions and to build trust about BEVs, particularly in the current situation where big carmakers have been mistrusted after they have been found providing incorrect information about fuel efficiency (Kubota, 2016; Randazzo, S and Boston, W, 2016). Analyses of the factors affecting ECR of BEVs are also relevant to figure out the ways to improve the electricity efficiency of BEVs (analogous to fuel efficiency to conventional cars).

Insights into the factors that influence the ECR of BEVs have been scarce, mainly because of their recent market penetration. Most studies include technical analyses that investigate the effects of car components on the ECR (see, e.g., Duke et al., 2009) and studies using either only few BEVs or drivers and without full account of the weather condition (Birrell et al., 2014; Wu et al., 2015) mostly by stakeholders in BEVs. Large differences about fuel consumption of passenger cars are usually observed between the results of car manufacturers and the results observed in real-world driving (Huo et al., 2011).

The third objective of the dissertation is to analyze the energy consumption rate of battery electric vehicle using big-data consisting of each driving pattern of 741 drivers, weather condition during the trips, road type and drivers' households' characteristics.

To sum-up, the dissertation aims at giving insights about scheduling and pricing of BEVs recharging as well as about energy consumption of BEVs and its sensitivity to the various driving environments in the hands of the customers. In addition to contributing to the very scarce literature in economics about BEV recharging, the results from the study may give clues to better diffuse BEVs among urban dwellers and to curtain the

expected impacts of BEVs on the electricity grid system by designing and offering recharging and pricing options tailoring behavioral biases.

1.2. Methods

A variety of methods are used in this study. These include theoretical analyses, simulation, economics laboratory experiments and field data analyses.

To substantiate the theoretical findings about WPC and to examine the existence of a market for the employers to supply and the employees to demand for WPC without third party intervention, simulation is used in the analyses about WPC. Data about labor market, electricity tariff and cost of recharging tools is obtained from Germany.

Economic laboratory experiments are used in two of the papers consisting of the dissertation. As discussed in detail by Camerer (2011), laboratory experiments provide some unique advantages that complements field and other studies. For example, laboratory experiments are ideal to disentangle the effect of a treatment from other possible confounding factors that could be challenging to do so in field surveys. Well-designed experiments allow to truly drawing causal inferences without measurement error, allow neutralizing the effects of uncontrolled determinants and allowing controlling the information condition whenever required, and are easily replicable. There have been concerns and discussion about the external validity in terms of the ability to generalize the results of the economics lab experiment to the general population (Camerer, 2011; Levitt and List, 2007, 2009). Numerous studies have been also undertaken to investigate the laboratory-field generalizability of findings from economic laboratory experiments to the real world (Andersen et al., 2010; Beshears et al., 2011; Brookshire et al., 1987; Camerer, 2011), and most experiments demonstrated that laboratory findings could indeed be generalized to comparable field settings (Camerer, C., 2011). Thus, while the doubt about internal validity of the results from the experiments conducted for this dissertation is little, the magnitude of the numerical findings generalizability requires

further research, particularly from filed experiment using representative sample. A field survey representing the population will be an ideal future work and a nice complement to this study. However, it is difficult to currently find representative samples from the current BEV users since companies own a lion share of the BEVs and since early adopters may not represent the population.

Other methods applied in this dissertation include analyses using econometrics models for the experiment data and for the estimation of electricity consumption of BEVs.

1.3. Summary of studies

I now present a summary of the papers. The papers are also presented in the same order in the dissertation.

Paper 1: The Economics of Workplace Recharging

While residential recharging is the foreseen primary option even though limitations exist in large apartment buildings, workplace recharging opportunities are gaining increasing attention as the major secondary option, particularly for urban dwellers without having private parking place. WPC may have benefits for employees, employers, electricity suppliers and even for the society at large. For example, WPC could be an ideal recharging option for employees without having private parking. It is also expected to be the favorite alternative to public and commercial recharging stations for individuals having private parking but who need to extend the driving range of their BEVs recharged at residential areas. For employers, WPC can be a recruitment and retention tool and may attract more productive employees. For electricity suppliers, WPC has a potential for balancing the electricity grid system by recharging/de-recharging the batteries of BEVs according to the electricity balance condition during the working hours. However, there might also be social costs because employer-provided fringe benefits favoring car use may increase travel demand and so traffic congestion. By increasing electricity consumption during peak-periods the electricity overload problem could be aggravated and thereby an increase in electricity prices and inefficiency.

However, WPC related research is still in its infancy and to the best of our knowledge there is currently no systematic assessment of the economic rationale of WPC demand and supply. We propose a microeconomic model of WPC and use the approach to shed light on the incentives and barriers employees and employers face when deciding on the demand for and supply of WPC. In the model, we show the determinants of WPC demand and supply as well as the role that the electricity supplier (via electricity tariffs for companies and for recharging fees at residential and commercial sites) and the government (via income and energy taxes) play in affecting WPC provision. In addition to this, using the model and data calibration, we examine existence of WPC market without governments' or other agents' intervention. The simulation results show that under the current market conditions, there is no WPC contract that an employer is willing to offer and, at the same time, that the majority of employees is willing to accept. To overcome the lack of demand for or underprovision of WPC we discuss various `remedies', involving subsidies to recharging facility costs and adjustments in electricity tariffs or loading technologies. The results concerning remedies show that while incentives for the supply side of WPC are promising, incentives that aim at boosting the demand side of WPC are less feasible. A pure (non-distortionary) redistribution from employees to the employer may also help to overcome WPC underprovision since WPC generates private net-benefits when there is employer-paid recharging in that employees benefit from WPC but the employer does not.

Paper 2. Myopic Loss Aversion in the Response of Electric Vehicle Owners to the Scheduling and Pricing of Vehicle Recharging
(*Joint work with Sigal Kaplan, Alexander C. Sebald and Carlo G. Prato, and is accepted for publication at the Journal of Transportation Research Part D: Transport and Environment.*
Earlier version of the paper was presented at the 94th Annual Transportation Research Board meeting, Washington D.C. from January 11 – 13, 2015.)

Upward expectations of future electric vehicle (EV) growth pose the question about the future load on the electric grid system. This expected BEV growth is expected to load significantly the electric power grid system. Charging times are expected to coincide with peak hours of electricity demand for household consumption and industrial use. Demand side management of BEV charging, by encouraging EV-owners to

change their charging patterns in response to changes in electricity prices, is viewed as a possible solution to reduce grid overload at peak hours and to reduce investments in grid capacity expansion (Finn et al., 2012; Flath et al., 2014). Economic evaluations have shown that DSM of BEV charging has positive welfare effects. For example, smart charging grids in Finland could produce benefits of 227 EUR per vehicle per year (Kiviluoma and Meibom, 2010).

While existing literature on BEV charging demand management has focused on technical aspects and considered EV-owners as utility maximizers, this study proposes a behavioral model incorporating behavioral and psychological aspects relevant to EV-owners facing charging decisions and interacting with the supplier. The behavioral model represents utility maximization under myopic loss aversion (MLA) behavior in an ultimatum game (UG) framework with two players: EV-owner and the electricity supplier. We test the validity of the behavioral model by designing 3x2 (there treatments with two groups of participants for each treatment) economics laboratory experiment.

The main objective of the laboratory experiment is to investigate whether lessening the MLA behavior by providing contracts under UG framework and in long-term contract bases helps individuals to make better choices. Findings from the experiment show that individuals indeed reveal MLA behavior when taking BEV charging decisions. Thus, presenting long-term BEV charging contracts under UG framework may curtail MLA behavior and help BEV owners to choose cost-minimizing charging time by participating in discounted off-peak charging hours.

This study contributes to the literature about MLA behavior as well by considering MLA under UG framework that may have application in other areas such as trade and investment. We also extended the UG framework in situations where accepting the proposal entails risk for the responder. Moreover, while previous studies about MLA behavior considered a single individual, this is the first model exploring MLA behavior within a two-player UG framework and hence investigating MLA as related not only to the individual's gains or losses, but also to the individual's cautiousness in the proposal because of the need to consider the responder's strategy.

Paper 3. Using the Peer Effect in Scheduling and Pricing of Electric Vehicles Recharging: Laboratory Evidence about Peer Effect in Risk-Taking

Working paper.

Numerous theoretical studies (e.g., Banerjee, 1992; Bikhchandani et al., 1992; Leibenstein, 1950) and empirical studies (e.g., Avery and Zemsky, 1998; Bursztyn et al., 2014; Olaussen, 2009; Weizsäcker, 2010) have found that individuals are influenced by the choices and behavior of others. The insights into the effects of peer information on choice and on behavior have been used to guide individuals to take one choice or another (Hoff and Stiglitz, 2016). The peer effects play significant and lasting role in societies political, socio-economic and demographic aspects (Akerlof, 1997; Bardhan and Udry, 1999; Ellison and Fudenberg, 1995; Hoff and Stiglitz, 2016; Jones, 1984).

We design a laboratory experiment mimicking the real-world situation where BEV users may experience to tradeoff between the cost saving from postponing recharging towards off-peak electricity consumption hours and the risk of the current battery power not being enough for unforeseen trip occurrence. The standard economic theory prediction in this case is that individuals will make choices according to their risk preference without being influenced by peers' choices. This is so because observing peers' choices does not convey new information as the electricity tariff and the distribution of the unforeseen trip distance are common knowledge. Recent field and laboratory studies find, however, that the choices of individuals are affected by peers' choices even when the peers' choices do not convey new information and when there is no payoff commonality (Cooper and Rege, 2011; Chung et al., 2015; Gioia, 2016). For example, Allcott (2011) and Schultz et al. (2007) have found from filed experiments that households decreased (increased) energy consumption after learning that their consumption was higher (lower) than their neighbors consumption.

This study aims to shed light on whether and how peer effect may be used for policy-making in areas involving uncertainty in general and, in particular, about smooth integration of BEVs in to the electricity grid

system. By providing for the current BEV users attractive incentives and tips that helps to reduce the psychological barrier of postponing recharging and then, by sharing the charging experience and cost of these customers, electricity suppliers may induce the current and future BEV users to postpone recharging towards off-peak electricity consumption hours.

The study investigates whether individuals want to see the choices of others, if observing peers' choices influences own choices, to what extent the peer effect is pervasive and who (in terms of self-confidence and math test scores) are being influenced by peers' choices as well as the role the type of peer information plays on peer effects. We conducted five treatments tailoring peer information. In one treatment, risk-averse and risk-seeking participants received each other's choice. In the second treatment, each participant received the mean of the choices of all other participants excluding the recipient's own choice. In the third treatment, each participant received the same information as the second treatment but by framing the peer information as the choice of a peer instead of the mean choice of all participants. In the fourth treatment, each participant received the choices of two other participants to examine providing the choices of two peers looms larger peer effect than providing the choice of a peer. In the last treatment, each participant received the choice of randomly chosen participant.

The results show that a lion share of individuals wants to see peers' choices. However, only a moderate percentage of them, mostly those with relatively lower scores in our math test and lacking self-confidence, use the peers' choices to revise their intrinsic choices, implying that learning could be the main reason for peer effect. Accordingly, the use of peer effect in inducing individuals to choose one action or the other depends largely on the analytical ability and on the self-confidence on own decisions of the under-consideration decision problem of the target population. The results reveal also that the type of peer information plays a significant role in peer effects.

Paper 4. Harnessing Big-Data for Estimating the Energy Consumption and Driving Range of Electric Vehicles
(*Joint work with Carlo G. Prato, Sigal Kaplan, Stefan L. Mabit and Anders F. Jensen, and is under review at Journal of Transportation Research Part D: Transport and Environment.*
Earlier version of the paper was presented at the 95th Annual Transportation Research Board meeting, Washington D.C. from January 10 – 14, 2016.)

This study analyzes the electricity consumption rate, i.e., energy consumption per unit distance driven, of BEVs and its sensitivity to the various driving environments in the hands of customers. Analyzing the factors that affect the energy efficiency of vehicles is crucial to the overall efficiency improvement in the transport sector, one of the top polluting sectors at the global level. This may help individuals to make informed decisions about BEV choice, manufacturers to build trust with customers by provide more accurate information, and governments to design policies based on reliable information.

The results of the analysis measure the (unweighted) mean energy consumption rate of BEVs at about 0.183 kWh/km for BEV models used in this study. Energy consumption rate of BEVs is highly sensitive to the various driving environments. Particularly, the weather effect is strong with energy consumption rate in December being higher by about 65 %, on average, than the consumption rate in July or August. Moreover, the results of the analysis show that driving speed, acceleration and temperature have non-linear effects.

To summarize, the four papers contenting the dissertation are

1. Gebeyehu M. Fetene, Georg Hirte, Sigal Kaplan, Carlo G. Prato and Stefan Tscharaktschiew (2016). The Economics of Workplace Recharging. *Published at Journal of Transportation Research Part B: Methodology. Volume 88, June 2016, Pages 93–118. DOI: 10.1016/j.trb.2016.03.004*

2. Gebeyehu M. Fetene, Sigal Kaplan, Alexander C. Sebald and Carlo G. Prato (2015). Myopic Loss Aversion in the Response of Electric Vehicle Owners to the Scheduling and Pricing of Vehicle Recharging. A*ccepted for publication at Journal of Transportation Research Part D: Transport and Environment*

3. Gebeyehu M. Fetene (2016). Using the Peer Effect in Scheduling and Pricing of Electric Vehicles Recharging: Laboratory Evidence about Peer Effect in Risk-Taking. Working paper.

4. Gebeyehu M. Fetene, Carlo G. Prato, Sigal Kaplan, Stefan L. Mabit and Anders F. Jensen (2016). Harnessing Big-Data for Estimating the Energy Consumption and Driving Range of Electric Vehicles. *Under review at Journal of Transportation Research Part D: Transport and Environment. Earlier version of the paper is published at the proceedings of the 95th Annual Transportation Research Board meeting, Washington D.C. from January 10 – 14, 2016.*

In addition to the dissertation, I worked during my spare time on my previous master's thesis to get it published.

5. Fetene, Gebeyehu M., Søren B. Olsen, and Ole Bonnichsen (2014). "Disentangling the pure time effect from site and preference heterogeneity effects in benefit transfer: an empirical investigation of transferability." Environmental and Resource Economics 59.4 (2014): 583-611.

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2. The Economics of Workplace Recharging

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Abstract

To overcome the range-anxiety problem and further shortcomings associated with electric vehicles, workplace recharging (WPC) is gaining increasing attention. We propose a microeconomic model of WPC and use the approach to shed light on the incentives and barriers employees and employers face when deciding on demand for and supply of WPC. Calibration results using Germany data shown that, under the current market conditions, there is no WPC contract in that an employer is willing to offer and at the same time the majority of employees is willing to accept. To overcome the lack of demand or under provision of WPC, we discuss various `remedies' involving subsidies to recharging facility costs and adjustments in electricity tariffs for various types of customers or loading technologies. We find that direct subsidies to WPC facilities or subsidies combined with specific energy price policies could be a way to foster WPC provision. In contrast, measures on the employee side that may help to stimulate the demand for WPC turn out to be less feasible. Hence, our results suggest that in order to promote WPC it is more promising to support employers in offering WPC contracts than to provide employees an incentive to accept WPC contracts. The study therefore gives a rationale for public initiatives being undertaken to boost WPC provision, as e.g. in the case of the US.

2.1. Introduction

The market penetration rates of electric vehicles (EVs)[5] are still rather low (Rezvani et al., 2015) despite the number of public programs launched to promote their use (e.g., Mazur et al., 2015; Tanaka et al., 2014). Among the most important reasons are low battery performance and lack of recharging infrastructure implying limited and uncertain driving ranges – the so-called range-anxiety (Chéron and Zins, 1997; Dimitropoulos, A. et al., 2011; Franke and Krems, 2013a, 2013b; Kihm and Trommer, 2014; Rezvani et al., 2015). While residential recharging is the foreseen primary option even though limitations can exist in large apartment buildings with shared parking areas, workplace recharging (WPC henceforth) opportunities are gaining increasing attention as the major secondary option (Huang and Zhou, 2015; Neubauer and Wood, 2014). For example, more than 600,000 employees have had WPC access at more than 300 workplace sites in 2016 in the U.S. alone (U.S. Department of Energy, 2014a).

There are various reasons why WPC may be economically rational for employees as well as for employers and even socially desirable. From the perspective of the employee, analogous to workplace parking and other non-monetary advantages at the workplace, WPC might generate a fringe benefit if its net benefit to the employee exceeds net benefits from recharging elsewhere. For example, firms usually pay lower energy prices than households. If this cost advantage is (at least partly) forwarded to employees, they can charge at lower cost at the workplace than at home. This fringe benefit can also be considered as some kind of non-monetary income that is not subject to income taxation. Furthermore, by extending driving range of BEVs (Neubauer and Wood, 2014; Pearre et al., 2011), WPC opens up options drivers might not otherwise have, making it easier to manage special circumstances and, in the end, reducing the risk of not being able to perform additional unexpected trips (to the doctor, to the kindergarten etc.). WPC may also provide BEV users who live in multi-

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[5] In the present study, the acronym 'EV' generally refers to pure (plug-in) battery electric vehicles (EV). For simplicity, we only use 'EV' henceforth.

unit buildings recharging opportunities and, thus, may support BEV diffusion.

From the employer perspective, offering WPC might reduce costs if workers receiving fringe benefits are willing to accept lower wages and/or to pay recharging fees higher than the firm pays to the electricity supplier (Leibowitz, 1983). The provision of WPC could also reduce the operational costs of the firm's own car fleet once conventional fuel-powered cars are replaced by BEVs which e.g. could be charged overnight (Huang and Zhou, 2015). Despite cost issues, WPC can be a recruitment and retention tool (U.S. Department of Energy, 2014b). When the share of BEV commuters increase, employers that provide WPC may attract more productive employees.

Further, WPC provision may be a strategy for green corporate branding, thereby attracting new customers.[6] Last but not least, when the share of BEV commuters gets large, the provision of WPC could be necessary for firms located at places relatively far from residential areas and where recharging facilities are inaccessible.

In addition to potential benefits for employees and employers, social benefits may arise too. To the extent that WPC provision affects mode choice in favor of BEVs (Sierzchula, 2014), a reduction of adverse impacts such as noise, local pollution, and greenhouse gas emissions (GHG) can be expected (Thiel et al., 2010), even though in particular the latter is debated since the GHG reduction potential depends on the share of sources (e.g. coal vs. wind) for energy production (Buekers et al., 2014;

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[6] Corporate social responsibility from a more general perspective has indeed been found to induce employees to accept lower wages and work more unpaid hours (Boeri, 2008; Burbano, 2014). Similarly, green companies were shown to have more potential to recruit workers at lower wages than non- green firms (Brekke and Nyborg, 2008; Grolleau et al., 2012), to increase sales and profits (Grolleau et al., 2013) as well as job satisfaction and creativity (Spanjol et al., 2014). Higher labor productivity was observed in case of employers that adopted high environmental standards because employees increased their efforts when working for companies that are socially responsible (Delmas and Pekovic, 2013; Lanfranchi and Pekovic, 2014).

Proost and Van Dender, 2011, 2012). However, there might also be social costs because employer-provided fringe benefits favoring car use may increase travel demand and so traffic congestion (De Borger and Wuyts, 2009, 2011; Gutiérrez-i-Puigarnau and Van Ommeren, 2011; Potter et al., 2006; Shiftan et al., 2012; Shoup, 1997; Wilson, 1992). Moreover, as range-anxiety is getting less important in the presence of WPC, residential location of employees could be affected, thereby contributing to urban sprawl. Eventually, by increasing electricity consumption during peak-periods the electricity overload problem could be aggravated. Investment in peak load capacities paired with low electricity demand elasticities could then result in increasing electricity prices (Lyon et al., 2012).

Even when accounting for the potential disadvantages, it seems that the benefits of WPC dominate. To exploit the expected benefits, government and other state or city initiatives have begun to support WPC provision by offering subsidies to employers who launch workplace recharging programs (see e.g., CALSTART, 2013 for the US; OLEV, 2014 for the UK).[7] From an economic point of view, public interventions to boost WPC should be taken only if private actions are expected to be insufficient to generate WPC demand and supply. However, WPC related research is still in its infancy and to the best of our knowledge there is currently no systematic assessment of the economic rationale of WPC demand and supply.

Against this background, in this paper we propose an economic model of recharging BEVs at workplace and use the approach to shed light on the incentives and barriers employees and employers face when deciding on demand for and supply of WPC. It is shown that under market conditions and uncertainty regarding WPC's potential to foster a firm's attractiveness for environmentally orientated workers and customers, there is no WPC contract – defined as a package of wage and recharging

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[7] However, some of the programs have already expired, such as the 'Alternative Fuel Infrastructure Tax Credit' offered by the US federal government. It allowed employers to deduct up to 30% (but not to exceed $30,000) of the cost of the recharging equipment and installation (CALSTART, 2013).

fee offered by the employer – having the chance to be provided by the employer and, at the same time, to be accepted by the majority of employees.[8] We find that direct public subsidies to WPC facilities or subsidies combined with specific energy price policies could be a way to foster WPC provision. A pure (non-distortionary) redistribution from employees to the employer may also help to overcome WPC underprovision since WPC generates private net-benefits in those cases where employees benefit from WPC but the employer does not. In contrast measures on the employee side that may help to stimulate the demand for WPC turn out to be less feasible. Consequently, our results suggest that in order to promote WPC, it is more promising to support employers in offering WPC contracts than to provide employees an incentive to accept WPC contracts. The study therefore gives a rationale for public initiatives being undertaken to boost WPC provision, as e.g. in the case of the US.

The model focuses on cost issues driving the supply of WPC on the employer side and user (net) benefits on the employee side. The employer offers a cost-minimizing WPC contract encompassing a potential discount on wages earned by WPC using employees and/or a recharging fee to be paid by the workers in order to compensate the outlays of WPC provision. The employees in turn evaluate the contract offered and decide whether to accept this contract (i.e. whether to use the WPC option), taking into account energy prices, time costs for recharging and restrictions regarding the potential that non-home recharging can effectively be used.

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[8] We state 'majority of the employees' rather than 'all employees' because we do not know the 'true' distribution of the preferences with respect to WPC. We do the analyzes on the bases of pure economic reasons assuming uniform distribution of preferences (see below). If the average worker accepts WPC our finding is independent from the distribution. The firm will always provide WPC (respectively offer a specific contract) so long as it is beneficial for it and employees are interested in (even it is only a minority).

Our approach inherits from De Borger and Wuyts (2009, 2011), but there are important differences traced back to specific characteristics of BEV recharging in contrast to employer-provided parking or the provision of company cars: First, recharging can be split between home, workplace and public recharging implying also quantity decisions on the share of recharging at home and other places. In contrast parking is either at home when using transit or at the workplace/on-street when using a car. Second, range-anxiety in case of e.g. additional trips, battery power run-out due to bad driving environment (cold temperature), cost issues, and further aspects may force employees to charge their vehicles at places other than at home. This causes the generalized travel (commuting) cost to be expected values over the degree of range-anxiety, price dispersion etc. and so daily driving dependent on WPC features (availability in general and performance in relation to home and public recharging).

We proceed as follows: First, in Section 2 we suggest the theoretical model of employee's recharging choice and a cost minimization approach of employer's recharging supply. Subsequently we perform a comparative statics analysis showing how decisions on WPC interact with each other and respond to potential private and public actions. Since the comparative statics results are ambiguous in most cases in Section 3 we calibrate the model to German data and perform simulations. They show that WPC may raise the sum of consumer and producer rents but there is no way to achieve a Pareto improvement through private decisions. Therefore, we examine various 'remedies' that may help to overcome either the lack of demand or underprovision of WPC. The 'remedies' involve subsidies granted to employers to cover the facility and running costs of recharging stations, rebates on the electricity tariff paid by employer, variations in standard home and public recharging tariffs paid by the employees, and adjustments in labor income taxes. Section 4 presents conclusions and outlines directions for further research.

2.2. Analytical Framework

The model considers representative employees and employers as the two main types of agents. We assume that the employees generally made a car choice decision in advance in favor of BEVs and have full access to an EV.[9] The BEV can be charged at home (home place recharging –HPC),[10] at workplace (workplace recharging –WPC) and/or at commercial and public recharging stations (commercial/public recharging –CPC). In case that WPC is generally available and sufficiently attractive to be used, employees are assumed to recharge at the workplace rather than at public/commercial stations. Except for the case of employer-paid recharging, the employee has to pay for WPC provision and usage, either by a reduction of gross salary, through a recharging fee, or by combination of both. The concrete arrangement of the wage discount and the recharging fee forms the WPC contract offered by the employer (see below).

2.2.1. The employee's perspective: the demand for WPC

The employees maximize expected utility by choosing daily consumption of general goods, traveling, the usage pattern of recharging locations and, in the end, by deciding whether to demand WPC. Workers are heterogeneous with respect to their preference for WPC and, without loss of generality, earn only labor income. On each working day, the employee faces the requirement to recharge the BEV to accomplish aggregate daily travel distance, *D*. The recharging decision may involve a trade-off

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[9] This assumption implies that we do not consider the effect that WPC provision might make electric mobility in general more attractive such that total demand for BEVs increases. Even though this does hardly affect the present analyzes, it can be crucial when WPC is evaluated under an economic efficiency point of view. We will discuss this point in more detail in the concluding section.

[10] Note that HPC includes recharging access at multi-unit buildings, e.g. coordinated recharging access at off-street parking lots or garages that do not take time to search for unoccupied chargers.

between recharging locations based on economic (cost minimizing) reasons but can also be restricted to recharging at home regardless of whether recharging at non-home locations is preferable for cost reasons. For example, the worker might be forced to recharge at home (without looking at the recharging cost e.g. at work) to keep a minimum state of charge of the battery to ensure its functionality and efficiency (Neubauer et al., 2013), or to make sure that the battery load is sufficient to reach the next recharging station (chosen in the economic recharging decision) taking into account some risks for energy consumption arising from adverse weather conditions (EC Power, 2014). Let γ be the share of daily travel distance charged on the basis of the cost trade-off between recharging stations,[11] $d_0 = \left(1 - \gamma\right)D$ then is the basic amount of energy (in terms of daily travel distance) charged at home. The three-stage decision of a typical worker is as follows:

1. In the absence of WPC, workers decide on how to allocate the recharging of the required energy that is not covered by the minimum load d_0 between HPC and CPC such that it minimizes expected recharging expenditure. It is assumed that individual workers face an idiosyncratic daily shock on recharging costs at public stations with a zero expected value. Therefore, there is no discrete zero-one allocation between HPC and CPC but workers charge at both stations.[12] The share of HPC, denoted by $\beta^H\left(p^H, p^C\right)$

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[11] Put differently, γ can also be interpreted as the probability the employee expects to be forced to recharge the car during the day. Considering a full year, γ can be seen as the share of days with a shock to standard travel demand. It can also be interpreted as an indicator for the attractiveness of non-home recharging stations in general. If γ is low the employee will hardly ever consider the option of recharging elsewhere (non-home) even if there are price differentials.

[12] One can think of situations where the employee is forced to recharge at stations where he has to pay a price higher than expected because his primary station is closed, or because a traffic jam upfront or limited battery performance due to low temperature hampers reaching a cheaper station, or because range-anxiety forces the worker to charge during the day (non-home) despite

with $0 < \beta^H < 1$, depends on relative expected loading prices with p^H and p^C as the electricity tariffs [expressed in monetary units per BEV km traveled][13] related to recharging at home and at public stations,[14] respectively. We assume that $\frac{\partial \beta^H}{\partial p^H} < 0$ and $\frac{\partial \beta^H}{\partial p^C} > 0$. In the presence of WPC an equivalent decision is made where the HPC share now is $\beta^W\left(p^H, p^W\right)$ with $0 < \beta^W < 1, \frac{\partial \beta^W}{\partial p^H} < 0$ and $\frac{\partial \beta^W}{\partial p^W} > 0$, and p^W as the recharging fee the employer may decide to levy.[15] These relationships imply that in order to charge the daily travel distance not covered by d_0, BEV users are willing (respectively are forced) to charge outside home with shares $1 - \beta^H$ and $1 - \beta^W$ (see above) even if the expected prices of CPC, p^C, and WPC, p^W, exceed the price of HPC, p^H. Both shares,

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potentially higher cost. One can also think of energy price volatility during the day. These shocks may include idiosyncratic differences in the range-anxiety problem.

[13] We consider a representative BEV with average energy intensity measured by kilowatt hours required to travel one kilometer [kwh/km]. Multiplying energy intensity with the price per unit of energy (which is typically expressed in monetary unit per kwh) then gives the energy price on a per km basis. For convenience, all energy prices (electricity tariffs) are therefore expressed in monetary unit per km throughout the paper. Note further that because the numerical analysis is related to the case of Germany, we use 'Euro (€)' as currency hereafter.

[14] Note that p^C could include parking fees in case the employee has to pay for parking while recharging the BEV at commercial/public recharging stations.

[15] Concerning workplace recharging idiosyncratic daily shocks on recharging costs with a zero expected value are assumed too.

however, decline as a response to higher non-home tariffs $\left(\dfrac{\partial \beta^H}{\partial p^C} > 0, \dfrac{\partial \beta^W}{\partial p^W} > 0 \right)$.[16]

2. Given this allocation the expected recharging costs are determined. By considering these costs, the worker maximizes expected utility by choosing daily consumption of general goods and traveling in the case that WPC is not available or not used (implying the recharging package $H = \{HPC, CPC\}$ and in the case that it is available (recharging package $W = \{HPC, WPC\}$,[17] yielding indirect utilities V^H and V^W, respectively.

3. In the last stage, the worker compares indirect utility achievable from recharging package H, V^H, and W, V^W, taking into account worker-specific idiosyncratic preference ε (assumed to have mean zero ($E(\varepsilon) = 0$)) he attaches to e.g. WPC in general and the contract the employer offers to him in particular (see below).

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[16] Drivers will put more effort in avoiding non-home recharging and so potential shocks at non-home stations or will plan their trips more carefully to reduce range-anxiety and so recharging at non-home stations.

[17] Another interesting recharging package is $CW = \{CPC, WPC\}$ as it involves the trade-off between both main non-home recharging opportunities. For convenience in the main part of the present study we focus on those packages involving HPC because (at least in the medium-term) individuals with access to HPC are most likely to buy a BEV at all (Hackbarth and Madlener, 2013). Nonetheless interested readers are referred to (Appendix 1 (A)) where we provide a comparative statics analysis regarding the package *CW* (in the same fashion as we will do it below).

In the following, we assume that the first stage decision is already made and consider only its outcome β^H and β^W.

In the absence of *WPC* ($H = \{HPC, CPC\}$), the expected daily recharging price per km is then given by

$$
\begin{aligned}
c^H &= (1-\gamma)\,p^H + \gamma\left[\beta^H p^H + (1-\beta^H)p^C\right] \\
&= d^H p^H + (1-d^H)p^C,
\end{aligned}
\tag{0.1}
$$

where $d^H = 1 - \gamma(1-\beta^H)$ and $1 - d^H = \gamma(1-\beta^H)$ is the expected share of energy charged at

commercial/public stations. Recharging at home only has share $1-\gamma$ and (per km) energy cost p^H. In contrast, with share γ recharging may also take place at non-home stations and recharging now also involves energy cost p^C associated with recharging at public stations.

When WPC is available ($W = \{HPC, WPC\}$), the expected daily recharging price per km can be written

$$
\begin{aligned}
c^W &= (1-\gamma)p^H + \gamma\left[\beta^W p^H + (1-\beta^W)p^W\right] \\
&= d^W p^H + (1-d^W)p^W,
\end{aligned}
\tag{0.2}
$$

where $d^W = 1 - \gamma(1-\beta^W)$ and $1 - d^W = \gamma(1-\beta^W)$. Note that by (0.2), as mentioned before, we assume for simplicity that if $\gamma > 0$ the employee meets his travel demand by recharging both at home and at the workplace without the need for recharging at public stations, i.e. once WPC is available, it fully replaces CPC.

In addition to the monetary cost, traveling involves time for driving and for recharging the battery of the EV. HPC and WPC are assumed to entail a cost-free time since the employee can basically do other things while

the car is being recharged.[18] In contrast, CPC implies additional time use due to queuing at recharging stations[19] and for recharging itself.

Denote by t_d the driving time per km, and by t_c the recharging time referring to the time the employee could not work while recharging, the total travel time per unit of distance D^i traveled is

$$t_D^i = \begin{cases} t_d + t_c\left(1 - d^H\right) & \text{if } i = H \\ t_d & \text{if } i = W \end{cases}, \quad (0.3)$$

Where $t_c(1 - d^H)D^H$ is the time saving due to the provision of WPC.

2.2.2. Second-stage decision: traveling

The employee derives utility from consumption of general goods and services, x, leisure, l , and travel, D.[20] His well- behaved utility function is

---

[18] This implies the assumption that there will be efficient coordination of recharging at home and at the workplace without affecting the employee's time (see e.g. the study of Huang and Zhou (2015) on WPC coordination).

[19] One can also think of situations where other (conventional internal combustion engine vehicle) drivers just block the public parking lot next to a public recharging stations. Of course even at the workplace congestion at recharging stations and so queuing cannot be ruled out but it is probably a minor problem compared with public recharging stations (Nichols and Tal, 2013).

[20] Note that, following standard approaches in transportation economics, we consider travel distance as component of utility since it increases the opportunity space (see, e.g., Bento et al., 2009; De Borger, B and Rouwendal, J, 2014; Golob et al., 1981; Parry and Small, 2005). The amount of travel does not (conventionally) increase utility by itself, though it could under certain conditions (Mokhtarian and Salomon, 2001), but it increases utility by raising the number of options one has for consumption, leisure activities, visits of friends/relatives, etc. (Anas, 2007; Rietveld and van Woudenberg, 2003), after controlling for the generalized cost of traveling. For example, for someone to eat dinner outside home, traveling one more km allows the individual to satisfy his taste for variety by increasing the number of restaurants to

$$U^i = U^i(x^i, l^i, D^i), i = H, W \qquad (0.4)$$

The (daily) monetary budget and time constraints, respectively, are,

$$x^i + c^i D^i = \omega^i(1 - \tau)t_w, \qquad i = H, W \qquad (0.5)$$

$$l^i + t_w + t_D^i D^i = T, \qquad i = H, W \qquad (0.6)$$

where t_w is fixed daily working time and T is the daily total time endowment. The price of goods/services (x) is normalized to unity. The hourly gross wage is either $\omega^H = \bar{\omega}$ or $\omega^W \leq \bar{\omega}$, where $\bar{\omega}$ is the market wage rate and ω^i is the wage rate paid by an employer not providing ($i = H$) and providing ($i = W$) WPC, respectively. The inequality with respect to ω^W indicates one part of the employer--employee WPC negotiation.

Substituting (0.5) and (0.6) into (0.4) yields

$$U^i\left(\omega^i(1 - \tau)t_w - c^i D^i, T - t_w\% - t_D^i D^i, D^i\right), \quad i = H, W. \qquad (0.7)$$

Differentiating (0.7) with respect to D^i gives the first-order condition

---

choose from, ceteris paribus. It has also been found empirically that an increase in commuting distance induces wage increase (Mulalic et al., 2014). The implicit assumption we made here is that the positive utility traveling gives by increasing options is proportional to distance traveled.

$$\frac{U_D^i}{\lambda^i} = \rho^i, \qquad i = H, W \tag{0.8}$$

where $\lambda^i \equiv U_x^i$ is the marginal utility of income (MUI) and ρ^i represents the generalized travel cost per km:

$$\rho^i = c^i + t_D^i \xi^i, \qquad i = H, W \tag{0.9}$$

with $\xi^i = U_l^i / \lambda^i \leq \omega^i$, as the value of time. Indirect utility then is

$$V^i = V\left(\omega^i \left(1 - \tau\right) t_w - c^i D^{i,*}, T - t_w - t_D^i D^{i,*}, D^{i,*}\right), \quad i = H, W. \tag{0.10}$$

2.2.3. Third-stage decision: location of recharging place

In the third stage the employee chooses the recharging option H or W that maximizes expected utility. For an employee, it is beneficial to charge the vehicle at the workplace if

$$V^W + \varepsilon > V^H. \tag{0.11}$$

Assuming that ε, the preference for WPC, is distributed uniformly over the interval $[-a, +a]$, the probability of WPC (respectively the share of employees preferring WPC) is given by

$$\theta = \frac{1}{2} - \frac{V^H - V^W}{2a}. \tag{0.12}$$

As can be seen from (0.12), a reservation utility level of $\bar{V} = V^H - V^W \leqq 0$ is needed to induce the (average) employee to use the WPC option provided by the employer through offering a certain WPC contract.

2.2.4. Comparative statics: Determinants of θ

In the following we present some of the comparative statics results concerning the impact a public authority, an employer and an electricity supplier might have in order to influence the probability of WPC. The comparative statics analysis is performed in the following order: (1): τ; (2): p^H; (3): p^C; (4): p^W; (5): t_c; (6): ω^W. While the labor tax τ is only in the sphere of the government, electricity tariffs p^H and p^C can be influenced by the electricity supplier as well as by the government (through energy taxes levied on top).[21] In contrast, the fee for recharging at the workplace p^W and a wage discount as part of a WPC contract (through offering a wage such that $\omega^W < \bar{\omega}$) are set by the employer. The recharging time at commercial stations can be influenced from several directions, e.g. private investment in more powerful (faster) public/commercial recharging stations, potentially stimulated by subsidies granted by the government; improvements in battery performance of the EV; all measures contributing to reduce or even avoid queueing at recharging stations such as expansion of parking space at stations. Let us now establish several lemmas illustrating the determinants of θ one after another, supported by a brief discussion. The analysis can be started by noting that for any exogenous variable α in (0.10):

$$\text{sign}\left(\frac{\partial \theta}{\partial \alpha}\right) \equiv \text{sign}\left(\frac{\partial V^W}{\partial \alpha} - \frac{\partial V^H}{\partial \alpha}\right). \qquad (0.13)$$

---

[21] If third parties were involved in providing commercial recharging stations, e.g. the carriers of conventional gas stations, they could also influence p C by levying a mark-up to cover their costs.

Lemma 1. *A higher labor tax increases the probability of WPC if differences in MUIs across the recharging regimes do not over- compensate wage differences:*

$$\frac{\partial \theta}{\partial \tau} > 0. \tag{0.14}$$

Proof. By applying the envelope theorem to (0.10) and using Roy's identity we have

$$\frac{\partial V^W}{\partial \tau} - \frac{\partial V^H}{\partial \tau} = \left(\lambda^H \bar{\omega} - \lambda^W \omega^W \right) t_w, \tag{0.15}$$

which implies that if $\left(\lambda^H \bar{\omega} - \lambda^W \omega^W \right) > 0$ $\left(\text{or } \dfrac{\omega^W}{\bar{\omega}} \dfrac{\lambda^W}{\lambda^H} < 1 \text{ where } \dfrac{\omega^W}{\bar{\omega}} \leq 1 \right)$ an increase in τ increases θ. $\square$

The result is intuitive and relates to the fringe benefit character of WPC. If the employer offers a WPC contract with wage discount, i.e. $\omega^W < \bar{\omega}$, a higher labor tax causes a larger tax burden when choosing recharging package H and thus, a combination of HPC and CPC, implying a higher probability of WPC by favoring recharging package W.

The effects of the electricity tariff for HPC are ambiguous. However, under certain assumption we can get some insights.

Lemma 2. *An increase in the electricity tariff for HPC increases the probability of WPC if generalized unit costs of CPC exceed those of WPC and vice versa (assuming $\beta^H = \beta^W$ and $\lambda^W D^W = \lambda^H D^H$ with symmetry of the functions β^H and β^W):*

$$\left.\frac{\partial \theta}{\partial p^H}\right|_{\beta^W \% = \beta^H, \lambda^W D^W = \lambda^H D^H} \begin{cases} > 0 & \text{if } p^C + \xi^H t_c > p^W \\ \leq 0 & \text{if } p^C + \xi^H t_c \leq p^W \end{cases}. \tag{0.16}$$

Proof. Applying the envelope theorem to (0.10) and using Roy's identity gives

$$
\begin{aligned}
\left(\frac{\partial V^W}{\partial p^H} - \frac{\partial V^H}{\partial p^H}\right) = \ & \lambda^H D^H \left(\frac{\partial c^H}{\partial p^H} + \xi^H \frac{\partial t_D^H}{\partial p^H}\right) - \lambda^W D^W \frac{\partial c^W}{\partial p^H} \\
= \ & (1-\gamma)\left(\lambda^H D^H - \lambda^W D^W\right) + \gamma\left(\lambda^H D^H \beta^H - \lambda^W D^W \beta^W\right) \\
& + \gamma\left(\lambda^H D^H \beta^H \varepsilon_{\beta^H}^{p^H} - \lambda^W D^W \beta^W \varepsilon_{\beta^W}^{p^H}\right) \\
& + \gamma\left[\lambda^W D^W \beta^W \frac{p^W}{p^H} \varepsilon_{\beta^W}^{p^H} - \lambda^H D^H \beta^H \left(\frac{p^C + \xi^H t_c}{p^H}\right) \varepsilon_{\beta^H}^{p^H}\right].
\end{aligned}
$$

If $\beta^H = \beta^W$, $\lambda^W D^W = \lambda^H D^H$, and if there is symmetry of the functions β^H and β^W implying identical price elasticities of β with respect to p^H, i.e. $\varepsilon_{\beta^H}^{p^H} = \varepsilon_{\beta^W}^{p^H}$, this is equivalent to

$$\left(\frac{\partial V^W}{\partial p^H} - \frac{\partial V^H}{\partial p^H}\right) = \underbrace{\left(\frac{p^C + \xi^H t_c - p^W}{p^H}\right)}_{>0} \left(-\varepsilon_{\beta^H}^{p^H}\right). \tag{0.17}$$

Since the own-price elasticity of the expected share of HPC, $\varepsilon_{\beta^H}^{p^H}$, is negative, an increase in p^H increases θ if $p^C + \xi^H t_c > p^W$. $\square$

An increase in the price of HPC shifts demand towards CPC and WPC. Since the former causes additional time costs in comparison to WPC the

probability of choosing WPC instead of CPC goes up. However, this does not hold if the fee for recharging at the workplace exceeds the generalized cost of CPC. Clearly, in this case CPC has a relative advantage over WPC, and an increase in the home recharging tariff (which decreases the share of home loading β^H) causes the probability of WPC to decrease.

Lemma 3. If the generalized cost of CPC does not exceed the electricity tariff of HPC by more than $\dfrac{1-\beta^H}{\left(\varepsilon_{\beta_H}^{p^C}\right)\dfrac{\beta^H}{p^C}}$, the probability of WPC increases with an increase in the recharging fee for CPC:

$$\frac{\partial \theta}{\partial p^C} = \begin{cases} > 0 & \text{if } \left(p^C + \xi^H t_c - p^H\right) < \dfrac{1-\beta^H}{\left(\varepsilon_{\beta^H}^{p^C}\right)\dfrac{\beta^H}{p^C}}. \\[4mm] \leq 0 & \text{otherwise} \end{cases} \qquad (0.18)$$

Proof. By applying the envelope theorem and using Roy's identity when partially differentiating (0.10) with respect to $p\,C$ we have

$$\frac{\partial V^W}{\partial p^C} - \frac{\partial V^H}{\partial p^C} = \gamma \lambda^H D^H \left[\underbrace{\left(1-\beta^H\right)}_{>0} + \beta^H \underbrace{\left(\frac{p^H - p^C - \xi^H t_c}{p^C}\right)\varepsilon_{\beta^H}^{p^C}}_{>0} \right]. \qquad (0.19)$$

Since the cross-price elasticity of the expected share of HPC, $\varepsilon_{\beta^H}^{p^C}$, is positive, an increase in p^C increases θ if the generalized costs of CPC are not much higher than the price of HPC, exactly speaking if $\left(p^C + \xi^H t_c - p_H\right) < \dfrac{1-\beta^H}{\left(\varepsilon_{\beta^H}^{p^C}\right)\dfrac{\beta^H}{p^C}}.$ $\square$

The implication is that by manipulating p^C through changing taxes or energy tariffs for CPC, the probability of WPC can be affected. According to (0.19) there are several effects. First, a change in p^C does not affect V^W because p^C is not an option under recharging package W. Hence, all effects of p^C on θ are channeled through its effects on V^H. Here two countervailing effects are relevant. First, an increase in p^C lowers V^H directly due to higher CPC costs (the first term in (0.19) where $1 - \beta^H$ is the share of CPC). Ceteris paribus, this causes the probability of WPC to increase. Second, p^C also affects the net benefits from HPC (the second term in (0.19) with share β^H of HPC). An increase in p^C shifts demand towards HPC, resulting in a decrease in demand for non-HPC recharging. If the cost of HPC is lower than the generalized cost of CPC, utility associated with recharging package H increases. This lowers the probability of WPC, ceteris paribus. The second effect is the stronger the larger the generalized cost advantage of HPC compared with CPC and the larger the elasticity of recharging at home with respect to p^C. As a result, the overall impact of p^C on θ depends on the relative strength of both effects, except in the case that recharging fee at HPC is higher than the generated cost of CPC in that an increase in p^C always increases the probability of WPC, ceteris paribus.

Lemma 4. The probability of WPC declines with an increase of the fee for recharging at the workplace if the fee is sufficiently small in comparison to the electricity tariff for HPC, ceteris paribus:

$$\frac{\partial \theta}{\partial p^W} = \begin{cases} < 0 & \text{if } \left(p^W - p^H \right) < \dfrac{1 - \beta^W}{\left(\varepsilon_{\beta^W}^{p^W} \right) \dfrac{\beta^W}{p^W}}. \\[2em] \geq 0 & \text{otherwise} \end{cases} \tag{0.20}$$

Proof. Partially differentiating (0.10) with respect to p^W, applying the envelope theorem and using Roy's identity yields

$$\frac{\partial V^W}{\partial p^W} - \frac{\partial V^H}{\partial p^W} = \gamma \lambda^W D^W \left[\underbrace{-\left(1 - \beta^W \right)}_{>0} - \beta^W \left(\frac{p^H - p^W}{p^W} \right) \underbrace{\varepsilon_{\beta^W}^{p^W}}_{>0} \right]. \tag{0.21}$$

Since the cross-price elasticity of the expected share of HPC when WPC is available, β^W, is positive, i.e. $\varepsilon_{\beta^W}^{p^W} > 0$, an increase in p^W reduces θ if $p^W < p^H$. $\square$

Intuitively, the employer can provide an incentive for workers to strengthen demand for WPC by lowering the recharging fee given that it is not too high initially (see evidence provided by Nichols and Tal, 2013; U.S. Department of Energy, 2014b). Again, two countervailing effects emerge. An increase in p^W directly reduces the probability for WPC (the first term in (0.21) where $1 - \beta^W$ is the share of WPC). However, it also affects the net benefits from HPC (the second term in (0.21) with share β^W of HPC). An increase in p^W shifts demand towards HPC. If the cost of HPC is lower than the recharging fee at the workplace, utility associated with recharging package H increases. This raises the probability of WPC, ceteris paribus. The second effect is the stronger the larger the generalized cost advantage of HPC compared with WPC and the larger the elasticity of recharging at home with respect to p^W. Hence, as in the previous case, the overall impact of p^W on θ depends on the relative strength of both effects.

Lemma 5. Measures that reduce the recharging time (at public stations) decrease the probability of recharging at workplace, ceteris paribus. That is

$$\frac{\partial \theta}{\partial t_c} > 0. \tag{0.22}$$

Proof. By applying the envelope theorem to (0.10) and using Roy's identity we have

$$\frac{\partial V^W}{\partial t_c} - \frac{\partial V^H}{\partial t_c} = \lambda^H D^H \xi^H \left(1 - d^H\right). \qquad (0.23)$$

Hence, presuming that $d^H < 1$ (which usually holds), a reduction in t_c reduces θ. $\square$

Obviously, the lower the time needed to recharge the BEV at public/commercial recharging stations, the lower the probability of WPC, ceteris paribus. This implies that a technological progress towards 'fast recharging' (respectively a larger share of public funds in favor of a more powerful public recharging infrastructure) will have a negative effect on the demand for WPC.

Lemma 6. A wage discount adopted by the employer as part of a WPC contract offer decreases the probability of WPC (put differently a raise of the wage ω^W raises the probability of recharging at the workplace, ceteris paribus):

$$\frac{\partial \theta}{\partial \omega^W} > 0. \qquad (0.24)$$

Proof. From applying the envelope theorem to (0.10) and using Roy's identity one obtains

$$\frac{\partial V^W}{\partial \omega^W} - \frac{\partial V^H}{\partial \omega^W} = \lambda^W \left(1 - \tau\right) t_w. \qquad (0.25)$$

Because $\tau < 1$, an increase in ω^W increases θ. $\square$

The comparative statics analysis clearly reveals that the probability of recharging at the workplace can be influenced by the employers, governments and electricity suppliers, and recharging facility providers through different channels. However, the employer's direct margin of influence is basically limited to the recharging fee p^W and the wage discount applied to a WPC using employee (discount on $\bar{\omega}$). The crucial

point now is that a certain combination of p^W and ω^W, being sufficiently attractive for the majority of BEV driving employees to accept WPC, may not necessarily be offered by the employer. We therefore now focus on the employer side and the link between both, the employer and the employee.

2.3. The employer's perspective: the provision of WPC

We consider a representative firm which has to decide whether to provide BEV using employees the opportunity to charge their vehicle at the workplace. We assume that WPC provision only affects (per employee) production cost but not productivity, the firm's aggregate labor stock or the number of sales in general.[22] Labor is the only input actually required for a given level of production of goods/services[23] and employees are generally paid their marginal product and so earn the hourly market wage rate $\bar{\omega}$ [24]. Employers, however, may make use of a

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[22] WPC is such a young 'phenomenon' so that evidence regarding its impact on e.g. labor productivity, recruitment, and firm sales is to the best of our knowledge not yet available. It is therefore debatable whether the impacts of the 'traditional' measures dignifying a company with an ecofriendly branding found in the literature (e.g. the firm's participation in the fair trade program, organic labeling, ISO 14001 standard; see the studies cited in the introduction) can be transferred on a one-to-one basis to the case of WPC provision. In fact, the green image of BEVs is not undisputed since their environmental performance heavily depends on factors such as battery production/recycling and sources (non-renewable vs. renewable energy) of power generation (see Buekers et al., 2014; Hawkins et al., 2013; Notter et al., 2010; Tessum et al., 2014; Thomas, 2009; Tscharaktschiew, 2015). Furthermore, abstracting from uncertain productivity or sales effects is actually even the more interesting case to consider because due the uncertainty involved it keeps firms on the safe side when deciding on WPC provision and the concrete arrangement of the contract. In the light of these facts we use some kind of 'backward induction' in the numerical part instead, assuming that a risk-averse employer abstracts from potential productivity effects when deciding on WPC provision. We can then calculate the 'critical' WPC productivity increment that would be needed to make the provision of WPC beneficial for the employer in a situation in which WPC otherwise would not have been provided.

[23] Broader capital costs (e.g. buildings, interior furnishings, machines, computer hard- and software), could easily be included as well but except for the capital cost of the recharging facility in the case of WPC (see below) they would add no significant further insights to the present analysis so that we solely focus on labor as the only primary input.

[24] We assume that provision of recharging facility at workplace is a result of a negotiation between individual workers and employers, not part of a labor compensation bargaining agreement between labor-unions and firms, in that the market wage rate will not be affected in the sense of, e.g., De Borger and Wuyts (2009, 2011) and Hashimoto and Zhao (2000).

wage discount such that $\omega^W < \bar{\omega}$ or may levy a recharging fee in case that employees receive a fringe benefit in the form of WPC. The combination of both then forms the contract $\{\omega^W, p^W\}$ the employer offers an employee who is interested in using WPC. For example, the employer could offer the contract $\{\bar{\omega}, 0\}$ which is obviously the special case of 'employer-paid recharging'.[25] In case that a positive recharging fee p^W based on usage is levied,[26] the firm is able cover a certain fraction of its own electricity cost, i.e. the tariff the employer pays to the electricity supplier, denoted by $\bar{p}$. The employer's net unit electricity cost associated with WPC (again expressed as cost per km) then is $(\bar{p} - p^W)$.

Note that if $\bar{p} < p^W$, WPC even generates revenue. Besides the employer's control variables captured by the contract $\{\omega^W, p^W\}$, WPC, once provided, has average annual capital costs $\bar{c}$ involving e.g. the pure facility cost of recharging infrastructure, installation cost, maintenance and administrative costs, land rent of the parking lots around the recharging stations[27]. Taking into account potential government programs which aim at supporting WPC provision through granting subsidies δ to recharging infrastructure expenditure, net capital costs are $(r\bar{c} - \delta)$, where $r = 1 + i$ denotes the unit capital cost (i is the

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[25] For the US the Workplace Recharging Challenge annual survey reports that 80 % (as of 2014) of employees get employer-paid recharging access (U.S. Department of Energy, 2014a).

[26] Instead of linking payments for recharging with actual usage one can also think of flat (fixed) recharging fees paid e.g. on a per month basis. However, the 2014 US Workplace Recharging Challenge annual survey reports that in those cases where recharging is not for free employees usually pay a fee based on usage (U.S. Department of Energy, 2014a).

[27] Average capital cost means that $\bar{c}$ crucially depends on the performance and capacity of the recharging station considered. The more powerful the recharging station (e.g. Level 1 vs. Level 2 charger) the larger the number of employees whose vehicle can be charged ultimately during a full workday (Huang and Zhou, 2015).

interest rate). The employer's daily cost per BEV using employee in case of WPC provision then is

$$\tilde{c} = \omega^W t_w + \left(\bar{p} - p^W \right) d^e + \frac{1}{k} \left(r\bar{c} - \delta \right), \qquad (0.26)$$

where k is a positive integer used to convert annual net capital costs into a comparable per day basis,[28] and

$$d^e = \left(1 - d^W \right) D^W \qquad (0.27)$$

is energy demand (again expressed in km) the firm expects each user to consume under WPC, with

$$d_\omega^e \equiv \frac{\partial d^e}{\partial \omega^W} = \left(1 - d^W \right) \frac{\partial D^W}{\partial \omega^W} > 0, \quad d_{\omega\omega}^e \equiv \frac{\partial^2 d^e}{\partial \left(\omega^W \right)^2} = \left(1 - d^W \right) \frac{\partial^2 D^W}{\partial \left(\omega^W \right)^2} < 0, \quad (0.28)$$

$$d_p^e \equiv \frac{\partial d^e}{\partial p^W} = \left(1 - d^W \right) \frac{\partial D^W}{\partial p^W} - \gamma D^W \frac{\partial \beta^W}{\partial p^W} < 0, \qquad d_{pp}^e \equiv \frac{\partial^2 d^e}{\partial \left(p^W \right)^2} > 0. \qquad (0.29)$$

However, on account of the employee's idiosyncratic preferences for WPC in general or a specific contract in particular, the employer cannot be completely sure that the contract will be accepted by the employee. Consequently, the firm constructs the contract based on expectations on the probability that the contract will be accepted (and fulfilled over a certain period of time and on the expected amount of recharging). The

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[28] In this sense, k could correspond to the number of working days in the contract period regarding the usage of the recharging facility.

employer's expected daily cost associated with WPC contract $\{\omega^W, p^W\}$ then is

$$C\left(\omega^W, p^W\right) = \underbrace{\left(1-\theta\right)\bar{\omega}t_w}_{\text{labor compensation for non-WPC users}} + \underbrace{\theta\left[\omega^W t_w + \left(\bar{p} - p^W\right)d^e + \frac{1}{k}\left(r\bar{c} - \delta\right)\right]}_{\text{labor compensation for WPC users}}$$

(0.30)

From (0.20) and (0.24) (assuming that the respective conditions are fulfilled) we know that

$$\theta_\omega \equiv \frac{\partial\theta\left(\omega^W, p^W, \boldsymbol{\alpha}\right)}{\partial\omega^W} > 0, \quad \theta_{\omega\omega} \equiv \frac{\partial^2\theta}{\partial\left(\omega^W\right)^2} < 0, \qquad (0.31)$$

$$\theta_p \equiv \frac{\partial\theta\left(\omega^W, p^W, \boldsymbol{\alpha}\right)}{\partial p^W} < 0, \qquad \theta_{pp} \equiv \frac{\partial^2\theta}{\partial\left(p^W\right)^2} \lesseqgtr 0. \qquad (0.32)$$

where $\boldsymbol{\alpha}$ denotes a vector of all other parameters being exogenous to the firm.

Based on the determinants of the employee's and employer's behavior we are now able to study the determinants of WPC provision and demand under various contract schemes $\{\omega^W, p^W\}$. We start with analytical expositions and subsequently, use numerical simulations to verify our findings and to shed light on ambiguous theoretical effects.

2.4. The joint perspective: WPC contracts

2.4.1. Employer-paid recharging

$$\left(WPC_1 = \left\{ \omega^W = \bar{\omega}, \, p^W = 0 \right\} \right)$$

The most obvious contract to consider is the case of employer-paid recharging, i.e. the employer neither makes a discount on wages offered to an employee being interested in WPC nor does he levy a recharging fee. The per-day expected labor cost incurred by an employer providing WPC with the contract offer $\{\bar{\omega}, 0\}$ then simplifies to

$$C\left(\bar{\omega}, 0 \right) = \bar{\omega} t_w + \theta^{\max} \left[\bar{p} d^{\max} + \frac{1}{k} \left(r\bar{c} - \delta \right) \right], \qquad (0.33)$$

where $\theta^{\max} = \theta(\bar{\omega}, 0)$ and $d^{\max} = d^e(\bar{\omega}, 0)$ represent the maximum share of employees choosing WPC and the maximum amount of energy charged under WPC if recharging is free of any costs to the employee. Not surprisingly it is the worst contract scheme for the employer because he is neither able to be compensated through lower wages nor through a contribution to the energy costs when employees charge their vehicle at the workplace. Hence, a cost-minimizing employer will offer this WPC contract only if the subsidy is high enough to finance fixed and variable costs of WPC, i.e. if $\delta \geq r\bar{c} + k\bar{p} d^{\max}$.

2.4.2. Wage discount only

$$\left(WPC_2 = \left\{ \omega^W \leq \bar{\omega}, \, p^W = 0 \right\} \right)$$

Now we examine the case where the employer offers a contract that comprising a wage discount and a predetermined zero recharging fee. The contract $\{\omega^W, 0\}$ leads to the cost function

$$C\left(\omega^W\right) = (1-\theta)\bar{\omega}t_w + \theta\left[\omega^W t_w + \bar{p}d^e + \frac{1}{k}(r\bar{c} - \delta)\right]. \quad (0.34)$$

Differentiating (0.34) with respect to the employer's choice variable ω^W yields the corresponding first-order condition (FOC) and second-order condition (SOC):

$$\text{FOC: } C_\omega = \theta_\omega\left[-(\bar{\omega} - \omega^W)t_w + \bar{p}d^e + \frac{1}{k}(r\bar{c} - \delta)\right] + \theta(t_w + \bar{p}d_\omega^e) = 0 \quad (0.35)$$

$$\text{SOC: } C_{\omega\omega} = \theta_{\omega\omega}\left[-(\bar{\omega} - \omega^W)t_w + \bar{p}d^e + \frac{1}{k}(r\bar{c} - \delta)\right] + 2\theta_\omega(t_w + \bar{p}d_\omega^e) + \theta\bar{p}d_{\omega\omega}^e,$$
$$(0.36)$$

where subscripts ω and $\omega\omega$ denote the first and second derivative, respectively.

Solving the FOC for ω^W and substituting (0.35) into (0.36) yields

$$C_{\omega\omega} = \left(2\theta_\omega - \theta_{\omega\omega}\frac{\theta}{\theta_\omega}\right)(t_w + \bar{p}d_\omega^e) + \theta\bar{p}d_{\omega\omega}^e. \quad (0.37)$$

The condition for cost minimization $C_{\omega\omega} > 0$ is fulfilled if $\left|d_{\omega\omega}^e\right|$ is not too large in magnitude.

The cost minimizing value of ω^W is then given by

$$\left(\omega^W\right)^* = \bar{\omega} - \frac{1}{\phi_\theta^\omega} - \frac{1}{t_w}\bar{p}d^e\left(\frac{\phi_d^\omega + \phi_\theta^\omega}{\phi_\theta^\omega}\right) - \frac{1}{kt_w}(r\bar{c} - \delta), \quad (0.38)$$

where $\phi_\theta^\omega = \frac{\partial\theta}{\partial\omega^W}\frac{1}{\theta} > 0$ and $\phi_d^\omega = \frac{\partial d^e}{\partial\omega^W}\frac{1}{d^e} > 0$ are, when multiplied by ω^W, the elasticities of θ and d^e with respect to the wage rate, respectively.

The compensation for offering WPC (the wage discount) then is:

$$\bar{\omega} - \left(\omega^W \right)^* = \frac{1}{\phi_\theta^\omega} + \frac{1}{t_w} \, \bar{p} d^e \left(\frac{\phi_d^\omega + \phi_\theta^\omega}{\phi_\theta^\omega} \right) + \frac{1}{kt_w} \left(r\bar{c} - \delta \right). \quad (0.39)$$

It is inversely related to the wage elasticity of the expected share of employees demanding WPC and proportionally related to the wage elasticity of energy demand when recharging. Note that by paying for WPC via a reduction of gross salary, the employer and the employee save $\tau \left(\bar{w} - w^W \right) t_w$ per day at the expense of government revenue.

By applying the implicit function theorem to the first-order condition (0.35), we can also find the effects of the other parameters on $\left(\omega^W \right)^*$:

$$\frac{d \left(\omega^W \right)^*}{d\bar{\omega}} = \frac{\theta t_w \phi_\theta^\omega}{C_{\omega\omega}} \geq 0, \frac{d \left(\omega^W \right)^*}{d\delta} = \frac{\theta \phi_\theta^\omega}{k C_{\omega\omega}} \geq 0,$$

$$\frac{d \left(\omega^W \right)^*}{d\bar{c}} = -\frac{\theta r \phi_\theta^\omega}{k C_{\omega\omega}} \leq 0, \frac{d \left(\omega^W \right)^*}{dr} = -\frac{\theta \bar{c} \phi_\theta^\omega}{k C_{\omega\omega}} \leq 0, \qquad (0.40)$$

$$\frac{d \left(\omega^W \right)^*}{d\bar{p}} = -\frac{\theta d^e \left(\phi_d^\omega + \phi_\theta^\omega \right)}{C_{\omega\omega}} \leq 0$$

The cost minimizing wage rate set by the employer $\left(\omega^W \right)^*$ increases with the market wage rate and the subsidy granted by the government to cover the capital costs of the recharging facility. However, it decreases with the recharging facility costs, and with employer's electricity costs. Moreover, in general one can see that the lower the wage elasticities of the expected share of WPC users and the electricity demand for WPC, the smaller the impact on the cost-minimizing value of $\left(\omega^W \right)^*$.

2.4.3. Recharging fee only

$$\left(WPC_3 = \left\{ \omega^W = \bar{\omega}, p^W \geq 0 \right\} \right)$$

Next we consider a contract where the employer cannot make use of a wage discount, e.g., due to collective wage bargaining, instead levying a recharging fee p^W. In this case, the contract is $WPC_3 = \left\{ \bar{\omega}, p^W \right\}$ and the cost function of the employer becomes

$$C\left(p^W \right) = \bar{\omega} t_w + \theta \left[\left(\bar{p} - p^W \right) d^e + \frac{1}{k} \left(r\bar{c} - \delta \right) \right]. \qquad (0.41)$$

The corresponding first- and second- order conditions are given by

$$FOC: C_p = -q d^e + \left(\bar{p} - p^W \right) \left(q d_p^e + d^e q_p \right) + q_p \frac{1}{k} \left(r\bar{c} - d \right) = 0 \qquad (0.42)$$

$$SOC: C_{pp} = -2 \left(\theta d_p^e + d^e \theta_p \right) + \left(\bar{p} - p^W \right) \left(2\theta_p d_p^e + d^e \theta_{pp} + \theta d_{pp}^e \right) + \theta_{pp} \frac{1}{k} \left(r\bar{c} - \delta \right).$$

$$(0.43)$$

Under reasonable parameter constellations and functional forms, it can be shown that the SOC is fulfilled so that the cost minimizing recharging fee set by the employer is:

$$\left(p^W \right)^* = \bar{p} + \frac{\left(r\bar{c} - \delta \right) \eta_\theta^{p^W} - k d^e}{k d^e \left(\eta_d^{p^W} + \eta_\theta^{p^W} \right)} \begin{cases} > \bar{p} & \text{if } r\bar{c} \geq \delta \\ \lessgtr \bar{p} & \text{if } r\bar{c} < \delta. \end{cases}$$

$$(0.44)$$

where $\eta_\theta^{p^W} = \frac{\partial \theta}{\partial p^W} \frac{1}{\theta} < 0$ and $\eta_d^{p^W} = \frac{\partial d^e}{\partial p^W} \frac{1}{d^e} < 0$ are, when multiplied by

p^W, the elasticities of θ and d^e with respect to the recharging fee, respectively.

The implication of (0.44) is that when choosing the recharging fee as part of a WPC contract while not making use of a wage discount, the employer will always levy a mark-up on own electricity cost if the capital costs of the recharging facility cannot be completely financed by a subsidy granted by the government. The mark-up will be the larger the smaller the subsidy.

By applying the implicit function theorem to the first-order condition in (0.42) we find the effects of the relevant parameters on $\left(p^W\right)^*$ as follows:

$$\frac{d\left(p^W\right)^*}{d\bar{p}} = -\frac{\theta d^e \left(\eta_d^{p^W} + \eta_\theta^{p^W}\right)}{C_{pp}} > 0, \qquad \frac{d\left(p^W\right)^*}{d\bar{c}} = -\frac{\theta r \eta_\theta^{p^W}}{kC_{pp}} > 0,$$

$$\frac{d\left(p^W\right)^*}{dr} = -\frac{\theta \bar{c} \eta_\theta^{p^W}}{kC_{pp}} > 0, \qquad \frac{d\left(p^W\right)^*}{d\delta} = \frac{\theta \eta_\theta^{p^W}}{kC_{pp}} < 0.$$

$$(0.45)$$

As can be seen, the higher the employer's costs associated with WPC provision (encompassing $\bar{p}$, $\bar{c}$, r), the higher the recharging fee levied by the employer will be. In contract, a higher subsidy induces the employer to levy a lower recharging fee. In each case the elasticities of the expected share of WPC users and their amount of electricity demand for recharging play an important role in setting the recharging fee. For example, the more elastic the employees respond to a higher recharging fee by avoiding WPC, the stronger the employer will increase the recharging fee as a response to higher capital costs of the recharging facility.

2.4.4. Fully flexible contract

$$\left(WPC_4 = \left\{\omega^W \leq \bar{\omega}, p^W \geq 0\right\}\right)$$

Eventually, the most flexible case is that the employer offers a contract $WPC_4 = \left\{\omega^W, p^W\right\}$. To cover the high cost of the recharging facility, the employer may exploit both instruments, a wage discount and the recharging fee, simultaneously. The first-order conditions with respect to the employer's decision variables ω^W and p^W are

$$C_\omega = \theta t_w - \left(\bar{\omega} - \omega^W\right)t_w\theta_\omega + \left(\bar{p} - p^W\right)\left(\theta d_\omega^e + d^e\theta_\omega\right) + \frac{1}{k}\left(r\bar{c} - \delta\right)\theta_\omega = 0$$

(0.46)

$$C_p = -\left(\bar{\omega} - \omega^W\right)t_w\theta_p + \left(\bar{p} - p^W\right)\ \theta d_p^e + d^e\theta_p + \frac{1}{k}\left(r\bar{c} - \delta\right)\theta_p - d^e\theta = 0.$$

(0.47)

The sufficient conditions for cost minimization are

$$C_{\omega\omega} > 0, \qquad C_{pp} > 0, \qquad C_{\omega\omega}C_{pp} > \left(C_{\omega p}\right)^2$$

(0.48)

Where

$$C_{\omega\omega} = 2\theta_\omega t_w - \theta_{\omega\omega}\left(\bar{\omega} - \omega^W\right)t_w + \left(\bar{p} - p^W\right)\left(2\theta_\omega d_\omega^e + \theta d_{\omega\omega}^e + d^e\theta_{\omega\omega}\right) + \frac{\theta_{\omega\omega}}{k}\left(r\bar{c} - \delta\right),$$

(0.49)

$$C_{pp} = -\theta_{pp}\left(\bar{\omega} - \omega^W\right)t_w + \left(\bar{p} - p^W\right)\left(2\theta_p d_p^e + \theta d_{pp}^e + d^e\theta_{pp}\right) + \frac{\theta_{pp}}{k}\left(r\bar{c} - \delta\right) - 2\left(\theta d_p^e + d^e\theta_p\right),$$

(0.50)

$$C_{\omega p} = \theta_p t_w - \left(\bar{\omega} - \omega^W\right) t_w \theta_{\omega p} + \left(\bar{p} - p^W\right)\left(\theta_p d_\omega^e + \theta d_{\omega p}^e + d_p^e \theta_\omega + d^e \theta_{\omega p}\right) - \left(\theta d_\omega^e + d^e \theta_\omega\right) + \frac{1}{k}\left(r\bar{c} - \delta\right)\theta_{\omega p}.$$
(0.51)

Under the conditions given in (0.46) - (0.48), the cost minimizing values of ω^W and p^W, denoted $\left(\omega_c^W\right)^*$ and $\left(p_c^W\right)^*$ with subscript c indicating the contract form that combines ω^W and p^W, are obtained by solving the FOCs in (0.46) and (0.47) simultaneously for ω^W and p^W (Appendix 1 (B)), implying

$$\left(p_c^W\right)^* = \bar{p} - \frac{\left(t_w \eta_\theta^{p^W} + d^e \phi_\theta^\omega\right)}{d^e\left(\phi_\theta^\omega \eta_d^{p^W} - \phi_d^\omega \eta_\theta^{p^W}\right)},$$
(0.52)

$$\left(\omega_c^W\right)^* = \bar{\omega} - \frac{d^e\left(\phi_d^\omega + \phi_\theta^\omega\right) + t_w\left(\eta_\theta^{p^W} + \eta_d^{p^W}\right)}{\left(\phi_\theta^\omega \eta_d^{p^W} - \phi_d^\omega \eta_\theta^{p^W}\right)t_w} - \frac{\left(r\bar{c} - \delta\right)}{k t_w}.$$
(0.53)

By applying the implicit function theorem for simultaneous equations on the FOCs given in (0.46) and (0.47), we have (for $C_{\omega p} \geq 0$) the following results (for derivation, see Appendix 1 (C)):

$$\frac{\partial\left(\omega_c^W\right)^*}{\partial\bar{\omega}} = \frac{\theta t_w\left(C_{pp}\phi_\theta^\omega - C_{\omega p}\eta_\theta^{p^W}\right)}{C_{pp}C_{\omega\omega} - (C_{\omega p})^2} \geq 0, \qquad \frac{\partial\left(p_c^W\right)^*}{\partial\bar{\omega}} = \frac{\theta t_w\left(C_{\omega\omega}\eta_\theta^{p^W} - C_{\omega p}\phi_\theta^\omega\right)}{C_{pp}C_{\omega\omega} - (C_{\omega p})^2} \leq 0.$$

Intuitively, the above result shows that an increase in the market wage rate results in an increase in wage rate that WPC users receive and a reduction in the fee they have to pay for recharging the EV, where the magnitude of the effect depends on the elasticities of the share of employees using WPC with respect to gross salary and fee for recharging, both of which are expected to be small.

$$\frac{\partial\left(\omega_c^W\right)^*}{\partial\overline{p}} = \frac{\theta d^e\left(C_{\omega p}\left(\eta_d^{p^W} + \eta_\theta^{p^W}\right) - C_{pp}\left(\phi_d^\omega + \phi_\theta^\omega\right)\right)}{C_{pp}C_{\omega\omega} - (C_{\omega p})^2} \le 0,$$

$$\frac{\partial\left(p_c^W\right)^*}{\partial\overline{p}} = \frac{\theta d^e\left(C_{\omega p}\left(\phi_d^\omega + \phi_\theta^\omega\right) - C_{\omega\omega}\left(\eta_d^{p^W} + \eta_\theta^{p^W}\right)\right)}{C_{pp}C_{\omega\omega} - (C_{\omega p})^2} \ge 0.$$

On the other hand, an increase in the electricity tariff that the employer pays to the electricity supplier reduces the wage rate the employer pays to the WPC users, but increases the fee the former collects from WPC users.

$$\frac{\partial\left(\omega_c^W\right)^*}{\partial\overline{c}} = \frac{r\theta\left(C_{\omega p}\eta_\theta^{p^W} - C_{pp}\phi_\theta^\omega\right)}{k\left(C_{pp}C_{\omega\omega} - (C_{\omega p})^2\right)} \le 0 \;,\; \frac{\partial\left(p_c^W\right)^*}{\partial\overline{c}} = \frac{r\theta\left(C_{\omega p}\phi_\theta^\omega - C_{\omega\omega}\eta_\theta^{p^W}\right)}{k\left(C_{pp}C_{\omega\omega} - (C_{\omega p})^2\right)} \ge 0,$$

$$\frac{\partial\left(\omega_c^W\right)^*}{\partial\delta} = \frac{s\left(C_{pp}\phi_\theta^\omega - C_{\omega p}\eta_\theta^{p^W}\right)}{k\left(C_{pp}C_{\omega\omega} - (C_{\omega p})^2\right)} \ge 0 \;,\; \frac{\partial\left(p_c^W\right)^*}{\partial\delta} = \frac{\theta\left(C_{\omega\omega}\eta_\theta^{p^W} - C_{\omega p}\phi_\theta^\omega\right)}{k\left(C_{pp}C_{\omega\omega} - (C_{\omega p})^2\right)} \le 0$$

The impacts of recharging facility installation/administration cost $\overline{c}$ and subsidies δ on the employer's decision variables have the expected sign but, intuitively, the price and wage elasticities of electricity demand do not play any role in the effect. Noteworthy in these comparative statics results is that, unlike the comparative statics analyzes we saw before when the employer uses only one of the two decision variables, the employer can exploit elasticities of both, θ and d^e (with respect to p^W and w^W) simultaneously.

2.5. Simulation result

We have shown that the demand for and the supply of WPC are influenced through various channels but most effects depend on concrete parameter constellations. In the following we apply numerical simulations and examine the impacts of the different WPC contracts previously discussed on employees and employers. This allows us to evaluate the 'chances' of different contract schemes to be provided by employers and at the same time to be accepted by the majority of employees and, in the end, enables us to discuss what kinds of measures could help to overcome potential lack of WPC demand and supply.

2.5.1. Functional forms and data

To represent preferences of employees we adopt a Cobb-Douglas utility function

$$U\left(X^{i}, l^{i}, D^{i}\right) = \psi_{X} \log\left(X^{i}\right) + \psi_{l} \log\left(l^{i}\right) + \psi_{D} \log\left(D^{i}\right) \quad (0.54)$$

with parameters $\psi_{X}, \psi_{l}, \psi_{D}$ reflecting preference weights (full income shares) of general consumption, leisure, and mobility (captured by daily distance traveled).

The relative recharging shares were chosen such that they fulfill the required relationships between prices and recharging location distribution:

$$\beta^{H}\left(p^{H}, p^{C}\right) = \frac{1}{1 + \exp\left(p^{H} - p^{C}\right)}, \quad \beta^{W}\left(p^{H}, p^{W}\right) = \frac{1}{1 + \exp\left(p^{H} - p^{W}\right)}. \quad (0.55)$$

The employee's benefit from WPC access in general and the contract schemes in particular is evaluated by the equivalent variation (*ev*) measuring the amount of income necessary to compensate an employee

without access to WPC in order to reach equality with the utility level achievable when having access under a certain contract scheme, i.e.

$$V^{H}\left(\bar{\omega}(1-\tau)t_{w}+ev(\xi^{H},\rho^{H})\right)=V^{W}\left(\omega^{W}(1-\tau)t_{w},\xi^{W},\rho^{W}\right). \qquad (0.56)$$

The employer's (producer's) surplus of providing recharging at the workplace, denoted *ps,* is given by

$$ps=\bar{\omega}t_{w}-C\left(\omega^{W},p^{W}\right)=\left(\bar{\omega}-\omega^{W}\right)t_{w}\theta+\left(p^{W}-\bar{p}\right)d^{e}\theta+\frac{\delta-r\bar{c}}{k}\theta. \qquad (0.57)$$

The model is calibrated to Germany. The corresponding parameters are listed in Table 2.5.1.

Table 2.5.1. Parameterization

Description	Symbol	Value	Dimension
Transport data			
Degree of charging cost orientation	γ	0.7	%
Driving time[1]	t_d	0.025	h/km
Recharging time[2]	t_c	0.022	h/km
Prices, costs, taxes			
Market wage rate	ϖ	19.65	€ /h
Wage rate when WPC[3]	ω^W	≤ 19.65	€ /h
Electricity tariff for HPC[4]	p^H	0.052	€ /km
Charging fee WPC[3]	p^W	≥ 0	€ /km
Electricity tariff for CPC	p^C	0.091	€ /km
Electricity tariff paid by the employer[5]	$\bar{p}$	0.027	€ /km
Price general consumption goods	p^X	1	€ /unit
Labor tax rate	τ	0.40	%
Unit capital cost	r	1.30	€
WPC facility costs	$\bar{c}$	675	€ /EE∗year
WPC subsidy[6]	δ	≥ 0	€ /EE∗year
Other data			
Preference general consumption	ψ_X	0.47	–
Preference leisure	ψ_I	0.44	–
Preference mobility	ψ_D	0.09	–
Time endowment	T	18	h/day
Daily working time	t_w	8	h/day
Parameter WPC probability function	a	0.04	–
Number of contract days	k	225	days

WPC: Workplace charging   EE: Employee

[1] Implies average driving speed of $\frac{1}{t_d} = 40$ km/h.

[2] Implies a recharging time of 2.2 h for a driving range extension of 100 km.

[3] Depending on the WPC contract scheme.

[4] Assuming electricity price of 0.29 € /kwh and EV energy intensity of 0.18 kwh/km.

[5] Assuming that the employer's electricity cost is 52% of the employee's cost at home.

[6] In Section 3.2.1 (benchmark cases) $\delta = 0$; In Section 3.2.2 $\delta \geq 0$.

We assume that the employees under consideration use a representative BEV (car segment: 'compact')[29] with a nominal battery capacity of 24 kwh, nominal energy intensity (electricity consumption) of 14 kwh/100 km (Loisel et al., 2014)[30] and actual (on-the-road) energy intensity of 18

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[29] According to (Loisel et al., 2014) the 'compact' car segment has the highest share within the BEV car fleet (≈36% as of 2011).

[30] This corresponds to a Nissan Leaf according to the study of (Donateo et al., 2015).

kwh/100 km.[31] Assuming that the car is charged once and the battery is full, and taken into account that usable energy is lower than the battery's nominal capacity[32] this implies an average on-the-road daily driving range of around 100–110 km. The preference parameters in the utility function were then chosen such that a hypothetical scenario with fully recharging the vehicle at home (thereby avoiding potential idiosyncratic daily shocks on non- home recharging costs, i.e. $\gamma= 0$) results in an expected total daily travel distance of 60 km (25 km one-way commuting +10 km from further trips).[33] According to Donateo et al. (2015) and EC Power (2014), under a combination of certain adverse conditions, e.g. heavy traffic congestion in winter season (cold temperature), driving range can easily be only a fraction (around one-third to one-half) of the on-the-road driving range. In our case this would correspond to a daily driving range of less than 50 km. Importantly, even when the battery were fully charged in the morning[34] this would cause a considerable

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[31] Donateo et al. (2015) report that actual electricity consumption on the road can deviate considerably compared to that measured by the New European Driving Cycle (NEDC) and declared by the car manufacturers (actual energy consumption can be more than twice as high). Main reasons for the variations are traffic conditions, weather, average speed and acceleration, the usage of auxiliaries such as air conditioning. For example, all cars (EVs registered in Italy in 2013) listed in the study of Donateo et al. (2015) have nominal, i.e. as declared by the car manufacturers, energy electricity consumption below 17 kwh/100 km.

[32] A fraction of 80% is usually reported (see Lyon et al., 2012; Neubauer et al., 2013).

[33] Average one-way commuting distance (urban + rural areas) in Germany in 2009 amounted to about 17 km (BMVBS, 2013) where around two-thirds of the commuters traveled more than 18 km (BBSR, 2012). Meanwhile non-commuting related trips constitute a significant share on total trips (see Anas, 2007; MID (Mobilit¨at in Deutschland), 2008; Pearre et al., 2011) so that the assumption of 10 km is relatively conservative.

[34] Assuming a standard Level 1 home charger with voltage 120, amperage 12, and recharging power of 1.6 kw, it would take more than 12 hours to fully recharge the vehicle. Hence,

degree of uncertainty (range-anxiety) which might force a driver to charge his vehicle during the day at non-home locations, implying $\gamma > 0$. (e.g., see Rezvani et al., 2015). Besides, it is assumed that workers choose recharging places primarily by comparing costs at stations while limiting the fixed home recharging share to a moderate level of 30 %. We therefore set $\gamma = 0.7$ meaning that employees distribute 70% of the required energy between HPC and WPC or between HPC and CPC taking into account the tariffs at these recharging places.

Table 2.5.2: Contract schemes

Notation	Description	Contract
WPC_1	Employer-paid charging	$\left\{\omega^W, p^W\right\}_1 = \{\bar{\omega}, 0\}$
WPC_2	Wage discount, no charging fee	$\left\{\omega^W, p^W\right\}_2 = \{\leq \bar{\omega}, 0\}$
WPC_3	No wage discount, charging fee	$\left\{\omega^W, p^W\right\}_3 = \{\bar{\omega}, \geq 0\}$
WPC_4	Wage discount, charging fee	$\left\{\omega^W, p^W\right\}_4 = \{\leq \bar{\omega}, \geq 0\}$

WPC: Workplace charging.

Assuming average driving speed of 40 km/h, travel time then is $t_d = 0.025$ h/km. The recharging time at public/commercial recharging stations needed to expand the driving range by one kilometer is taken to be $t_c = 0.022$ hour implying a recharging time of around 130 min for a range

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assuming no power blackout, the employee would have to start recharging not later than let's say 7 p.m. to have a fully loaded battery available in the morning.

extension of 100 km.[35] Daily working time t_w is set at 8 hours and the daily time endowment T at 18 hours (24 –6 hours for recreation).

The electricity prices/tariffs $p^H, p^C, \overline{p}$ paid by households/workers/firms (including taxes and further fees) refer to the year 2013 and were taken from BDEW (2013). In line with current practice in Germany, we set electricity prices such that $p^H > \overline{p}$ meaning that the price paid by households exceeds the tariff paid by firms (the firm's rebate is around 48% compared with the private household tariff). The recharging tariff levied at public/commercial recharging stations in turn is assumed to be higher than the private household tariff. Pricing schemes at public stations are quite heterogeneous and mark-ups to standard home tariffs are observed to be considerable. Here we assume an excess over home tariffs in the order of three-quarters. The market wage rate is set at 19.65 €/h (average hourly gross earning of non-marginally employed persons working in the manufacturing industry and the service sector in Germany (Federal Statistical Office, 2014).

The recharging facility costs are very hard to pin down because they heavily depend on, in particular, the type of the recharging station. But even for the same type of recharging station, different brands lead to considerable price/cost dispersion. Moreover, a significant share of the total cost of more powerful stations can be attributed to installation cost (often 60–80%, according to (CALSTART, 2013; RMI, 2014) which in turn may differ regionally (e.g. electrician labor). We follow Huang and Zhou (2015) and assume a medium power Level 2 outlet as the most plausible charger for WPC. Based on an evaluation of several studies reporting cost

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[35] This bases upon the assumption that public recharging station are (on average) more powerful than those usually available at home. The per km recharging time of 1.3 min is derived by assuming a Level 2 charger with voltage 240, amperage 30, and recharging power of 8 kw (18 kwh/100 km BEV energy intensity divided by 8 kw recharging power).

estimates (Dong et al., 2014; Huang and Zhou, 2015; RMI, 2014; Schroeder and Traber, 2012), the cost of the recharging station hardware is taken to be 3000 € and all other costs associated with installation are assumed to amount to 4500 €.[36] Total facility cost then amount to 7500 €.[37] When additionally account is taken of the fact that the performance of a powerful Level 2 charger allows to serve 2–3 employees during an eight hours working day depending on their individual recharging demand[38] and that station lifetime can be assumed to be approximately 10 years (Schroeder and Traber, 2012), one obtains annual average facility cost of 375 € per WPC using employee. Adding regular maintenance and repair cost in the order of 300 €/per year (Schroeder and Traber, 2012) we arrive at $\bar{c}$ = 675 €/(employee ∗year). Eventually, because the employer's expected cost of WPC is given on a per day basis (see (0.30)) we use *k = 225* (number of contract days at which WPC is

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[36] Following the categorization of RMI (2014) aggregate installation cost breaks down as follows: 1000 € other hardware and materials; 3000 € electrician and other labor cost; 400 € mobilization (time for the electrician and others to get to the worksite and for preparation, including an initial on-site consultation); 100 € permitting.

[37] We assume that the firm provides parking space generally, i.e. regardless of whether it provides WPC. Consequently, rental costs of the parking lot are not imputed to the provision of WPC as additional cost and so not added to the facility costs. Aggregate installation cost then accounts for a share of 67% on total facility station cost which is line with usual 'installation cost/total cost' ratios reported by RMI (2014) .

[38] On the one hand a Level 2 charger with 8 kw power can in fact serve more than 2-3 employees because they will probably not arrive at workplace with an empty battery. On the other hand, some degree of coordination (of the firm and the worker) will probably be required to allow one charger to serve multiple employees (see the study of Huang and Zhou (2015) on workplace recharging facility coordination). Here we assume a conservative number of two employees being served by one charger considering that it could be most suitable for many workers to plug (the uncharged EV) and to unplug (the charged EV) during e.g. lunch time with minimum effect on working hours.

being used during the year) and $r = 1.30$ to convert annual facility cost $\bar{c}$ into a daily facility capital cost.

2.5.2. Results

2.5.2.1. Benchmark

In this subsection, we report the numerical results for the four contract schemes presented in the theoretical part ($WPC_1 - WPC_4$) relying on parameter values derived above. Table 2.5.2 summarizes the contract schemes and their main features.

The main results of the simulations are presented in Table 2.5.3. We display demand quantities X, l, and D; unit travel cost c, ρ; the endogenous value of time, ξ;[39] utility level U; the probability of WPC resulting from the employee's optimization, θ; the characteristic of the employer's cost minimizing contract offer, $\{\omega^W, p^W\}$; the employee's and employer's benefit from access and provision of WPC, *ev* and *sp*, respectively; and finally *WPC* induced aggregate (private) benefit.

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[39] Note that in all cases the endogenous value of time obtained is in line with empirical evidence suggesting that it is about half the hourly gross market wage rate (Small, 2012; Small and Verhoef, 2007; Wolff, 2014) and also reflects recent estimates regarding the valuation of travel time of German commuters (Obermeyer et al., 2013).

Table 2.5.3: Benchmark results of the different WPC contracts

Variable	Symbol	No WPC	WPC$_1$	WPC$_{2/4}$	WPC$_3$	Dimension
General consumption	X	91	93	86	91	units
Leisure	l	8.49	8.35	8.36	8.52	h/day
Mobility	D	52.71	65.88	65.54	59.18	km/day
Monetary travel cost	c	0.058	0.022	0.022	0.058	€/km
Generalized travel cost	ρ	0.349	0.284	0.265	0.310	€/km
Value of Time	ξ	10.15	10.50	9.71	10.07	€/h
Utility	U	3.417	3.439	3.403	3.428	units
Probability WPC	θ	—	0.82	0.30	0.65	%
WPC contract	$\{\omega^W, p^W\}$	—	19.65, 0	18.22, 0	19.65, 0.081	€/h, €/km
WPC employee benefit	ev	—	+7.88	−4.72	+3.77	€/EE*day
WPC employer benefit	ps	—	−4.02	+1.98	−2.11	€/EE*day
WPC benefit	$ev + ps$	—	+3.86	−2.74	+1.65	€/EE*day
WPC decision	employee	—	Majority	Minority	Majority	
	employer		No offer	Offer	No offer	

WPC: Workplace charging   EE: Employee.

In the case of employer-paid recharging (WPC_1), implying the WPC contract $\left\{\omega^W, p^W\right\}_1 = \left\{19.65, 0\right\}$, employees are better off (*ev = +7.88 €* per day) compared to a situation without WPC opportunities whereas employers are worse off, i.e. their expected net costs increase (*ps = −4.02* € per BEV using employee per day). On the one hand, a zero recharging fee causes the employer a net electricity cost burden and, in addition, increases the expected share of employees being interested in WPC which in turn imposes additional WPC capital facility costs. On the other hand, a zero recharging fee allows BEV users to charge their vehicle at work for free, thereby saving time and money at (more expensive) public recharging stations. Both, pure out- of-pocket travel costs as well as generalized travel costs decline despite a slight increase in the value of time. All in all the probability of WPC to be accepted by employees is *θ = 0.82* which is, not surprisingly, the highest number in comparison to all further contract schemes offered (see below). However, importantly, the contract won't be offered by a cost-minimizing employer facing uncertainty about WPC's potential to foster a firm's attractiveness for workers and customers. This outcome is even more important when

account is taken of the fact that the contract's overall net benefit is positive.

In the second contract scheme WPC_2 the employer makes a discount on wages while the recharging fee is assumed to be out of his control. On the one hand, reducing the wage saves the employer costs. On the other hand, the lower the employee's wage under WPC the less people will choose the WPC contract and work under higher wages thereby increasing the employer's cost. The cost minimizing discount was found to be 1.43 €/h implying a wage offer in the order of 18.22 €/h. The WPC contract offered by the employer is $\{\omega^W, p^W\}_2 = (18.22, 0)$ with a low probability ($\theta = 0.30$) of acceptance by the employees. Under this WPC contract, employees are now worse off while employers benefit. However, most importantly, the net effect is negative.[40]

Assume now that there is collective individual wage bargaining so that wages in the firm cannot deviate from outside wages. In that case, the employer can only use a recharging fee p^W to reduce the net costs of WPC provision. The cost minimizing recharging fee is found to be $p^W = 0.081$ and therefore the contract offered by the employer is $\{\omega^W, p^W\}_3 = \{19.65, 0.081\}$. The recharging fee of 0.081 €/km is higher than the electricity tariff the employee has to pay at home but slightly lower than what he

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[40] Note that with $\bar{p} > p^H$ (the electricity tariff the firm pays exceeds the private household tariff) rather than $\bar{p} < p^H$ as assumed here for the case of Germany, the cost minimizing wage discount will be even larger and, as a consequence, the probability of WPC to become accepted by the average employee even lower (see (0.40) along with (0.24)). For example, assuming $\bar{p} = 0.077$ (instead of $\bar{p} = 0.027$) results in a wage discount of 1.55 €/h (implying the contract offer $\{\omega^W, p^W\}_2 = \{18.10, 0\}$ and a probability of acceptance of only $\theta = 0.26$.

would have to pay at CPC where significant time costs accrue on top. Despite the recharging fee levied, the employees benefit from WPC_3 though they are worse off compared to employer-paid recharging (WPC_1). The recharging fee discourages WPC usage, reflected by a lower probability of WPC. In contrast the employer is now better off compared with WPC_1 mainly because of a net electricity revenue gain (the tariff he gets is higher that the tariff he pays to the electricity provider). However, in total the employer is worse off here too because the revenue gain is not sufficient to cover the WPC capital facility costs[41]. In the end this contract won't be offered by the employer though 65% of the employees would accept WPC_3.

Contract scheme WPC_4 is obviously the most flexible one. It allows the employer to make a discount on wages and to levy a recharging fee simultaneously. Surprisingly, the employer will not exploit this flexibility. More specifically the simulations suggest that once the employer applies a wage discount, there is no incentive to levy an additional recharging fee, thereby making WPC_4 fully equivalent to WPC_2. The cost minimizing contract offered by the employer is $\{\omega^W, p^W\}_4 = \{18.22, 0\}$. Obviously, in the present case the positive revenue effect of imposing a recharging fee on top is more than offset by the adverse effect on expected labor cost. The latter arises since a larger share of employees earning lower wages

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[41] Recall that we abstract from potential queuing at recharging stations (congestion) that may arise if demand for recharging at the workplace exceeds capacity. This might induce the employer to levy another fee on top (a 'congestion premium') to account for the queuing problem. This would shift some share of the employee's benefit towards the employer, thereby reducing the worker's willingness to accept WPC. The overall effect, however, depends on the level of queuing and the response of employees to potential recharging congestion fees. The more effective the coordination regarding the usage of chargers is, as assumed in the present study, the weaker will the queuing problem probably be (given demand and capacity).

due to the wage discount will reject the contract when a recharging fee is levied on top.

To sum up: the simulations of the different contract schemes reveal that under the plausible parameter constellations assumed and in the absence of interventions of whatever nature, *WPC* is likely to take place only in some cases at all with a minority of employees who have a high idiosyncratic preference for WPC. On the one side, in situations where *WPC* is beneficial from the (average) employee's perspective, there is no sufficient incentive for the employer to provide *WPC* (*WPC₁*, *WPC₃*). On the other side, in situations where *WPC* is beneficial from the employer's standpoint, there is no sufficient incentive for the majority of employees to use it, respectively to accept the corresponding contract offer (WPC₂, WPC₄).[42] This raises the question how to overcome the WPC underprovision or the lack of WPC demand such that supply of WPC and market demand coincides.

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[42] We considered another two contracts not reported here in detail. The contracts are extensions of WPC₃ and WPC₄ and entail the opportunity to deduct recharging expenses at the workplace from the income tax base (changing the monetary

budget constraint (0.5) to $x^W + d^W p^H D^W = (1-\tau)\left(t_w \omega^W - \left(1-d^W\right)p^W D^W\right)$

in case of access to WPC). Tax deduction of commuting expenses reduces the employee's income tax burden and is common practice in many countries (Hirte and Tscharaktschiew, 2013a; Wrede, 2009). One can easily see from Table 2.5.3 that the opportunity of tax deduction generates no further impacts as extension of WPC₄ where the recharging fee is set to zero by the employer. As regards WPC₃ it has been found that tax deduction on top has slightly beneficial effects from the employee's perspective but does not change the main finding that the employer does not have an incentive to offer this contract.

2.5.3. Remedies

Let us first consider the situations where the employer has been found to have no incentive to offer a WPC contract (WPC_1, WPC_3). Both contracts are characterized by the fact that wages are outside the employer's control which makes them the most likely WPC contract in a country with collective wage bargaining such as Germany. On the employer side, there are three obvious 'remedies' that may help to overcome the underprovision of WPC: (i) subsidizing facility capital cost; (ii) reducing the recharging tariff the employer has to pay to the electricity supplier; (iii) redistribution.

Clearly, both (i) and (ii) reduce the expected net cost of WPC provision and thus may support a contract offer. However, as Table 2.5.4 and Table 2.5.5 reveal (column 'Remedy (a)' entails the case of an increase in the subsidy only whereas column 'Remedy (b)' considers a subsidy accompanied by a reduction of the employer's energy tariff), measures must be strong to balance the employer's deficit associated with WPC provision.

Table 2.5.4: WPC_1 remedies

Variable	Symbol	Remedy (a)	Remedy (b)	Dimension
WPC facility subsidy	$\delta\uparrow$	1110[1]	878[2]	€/EE*year
Electricity tariff paid by the employer	$\bar{p}\downarrow$	–	0,000	€/km
Probability WPC before	θ	0,82	0,82	%
Probability WPC after	θ	0,82	0,82	%
WPC employee benefit	ev	+7,88	+7,88	€/EE*day
WPC employer benefit	ps	± 0,00	± 0,00	€/EE*day
WPC benefit	$ev + ps$	+7,88	+7,88	€/EE*day
WPC decision	employee	Majority	Majority	
	employer	Offer	Offer	

WPC: Workplace charging   EE: Employee
[1] Implies $(\bar{c} - \delta) = -435$ €/EE*year.
[2] Implies $(\bar{c} - \delta) = -203$ €/EE*year.

Table 2.5.5. WPC_3 remedies

Variable	Symbol	Remedy (a)	Remedy (b)	Dimension
WPC facility subsidy	$\delta\uparrow$	728[1]	655[2]	€/EE*year
Electricity tariff paid by the employer	$\bar{p}\downarrow$	–	0,000	€/km
Probability WPC before	θ	0,65	0,65	%
Probability WPC after	θ	0,65	0,65	%
WPC employee benefit	ev	+3,77	+3,77	€/EE*day
WPC employer benefit	ps	± 0,00	± 0,00	€/EE*day
WPC benefit	$ev + ps$	+3,77	+3,77	€/EE*day
WPC decision	employee	majority	majority	
	employer	Offer	Offer	

WPC: Workplace charging   EE: Employee
[1] Implies $(\bar{c} - \delta) = -53$ €/EE*year.
[2] Implies $(\bar{c} - \delta) = +20$ €/EE*year.

In the case of employer-paid recharging (WPC_1) a subsidy of 1110 € per worker per year (a) or a subsidy of 878 € plus a reduction of the electricity (used for BEV recharging) tariff $\bar{p}$ to zero (b) is needed to achieve a supply of *WPC* that will be accepted by the average employee. Given costs of 675 € per worker per year of the recharging facility, this means that the subsidy must exceed facility costs to cover electricity cost used for recharging BEVs. Only in case of WPC_3 a subsidy less than the facility cost is sufficient because here the employer also generates net recharging fee revenue. All in all the requirement of a relatively high subsidy highlights the importance of improving the coordination of recharging facility usage for making WPC sufficiently attractive for both, the employer and the employee.

Beside these policy instruments, a pure (non-distortionary) redistribution may help to overcome WPC underprovision. As our simulations suggest both contract schemes generate a private net benefit so that (Kaldor-Hicks) redistribution of some share of the employee's benefit in favor of the employer could in the end solve the underprovision problem, even without public initiatives such as public recharging infrastructure funding.[43]

Interestingly all in all it seems that some of the 'remedies' discussed have already proved effective. For example, even though experiences with WPC are still quite limited, the U.S. Department of Energy (2014b) reports that 80 % of employers who responded to its 2014 'Workplace Recharging Challenge' annual survey provided free recharging access.[44] Without (a mixture of) effective 'remedies' as discussed, our analyzes suggest that employer-paid recharging were unlikely to have been

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[43]One can think of e.g. widely spread information campaigns promoting the advantages of WPC for employees as this has happened recently on the employer side with the 'Employer BEV Initiative (EEVI)' in the US or various workshops organized in Germany. This might help to create some kind of a 'willingness-to-pay' awareness on the employee side.

[44] The share is reported to be 65% based on a statewide survey in spring 2013 of 79 public and private employers located in California (CPEVC, 2013).

created. However, another explanation for the dominance of employer-paid recharging could be that employers indeed have positive expectations on the potential spillover effects of WPC on labor productivity, worker recruitment and the number of sales.[45]

Now let us focus on situations in which the majority of the employees refuse to accept the employer's contract offer (WPC$_2$, WPC$_4$).

Table 2.5.6: WPC$_2$, WPC$_4$ remedies

Variable	Symbol	Remedy (a)	Remedy (b)	Remedy (c)	Remedy (d)	Dimension
Electricity tariff HPC	$p^H\uparrow$	0.088	–	–	–	€/km
Recharging time	$t^C\uparrow$	–	0.054[1]	–	–	h/km
Labor tax	$\tau\uparrow$	–	–	0.80	–	%
Electricity tariff CPC	$p^C\downarrow$	–	–	–	0.017	€/km
Probability WPC before	θ	0.30	0.30	0.30	0.30	%
Probability WPC after	θ	0.50	0.50	0.50	0.50	%
WPC employee benefit	ev	+0.00	+0.00	+0.00	+0.00	€/EE*day
WPC employer benefit	ps	+3.19	+2.71	+3.34	+3.26	€/EE*day
WPC benefit	$ev + ps$	+3.19	+2.71	+3.34	+3.26	€/EE*day
WPC decision	employee	Majority	Majority	Majority	Majority	
	employer	Offer	Offer	Offer	Offer	

WPC: Workplace charging   EE: Employee
[1] Implies a recharging time of $\approx$ 11 h for a driving range of 200 km.

As can be seen from Table 2.5.6, increasing the recharging fee at home ('Remedy (a)'), increasing the recharging time at CPC, e.g. by installing non-fast recharging facilities ('Remedy (b)'), increasing the labor tax ('Remedy (c)') and reducing the recharging fee at public/commercial recharging stations ('Remedy (d)')[46] achieve WPC provision as well as

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[45] For example, the employer could be intended to offer the contract despite its initially negative evaluation if WPC allows recruiting workers being sufficiently productive to offset the expected loss of WPC provision (about 4 € per employee per day or roughly 2% of the employee's hourly gross wage in our numerical example).

[46] Concerning the price of CPC, p^C, the extreme case discussed in **Lemma 3** arises. As p^C declines, e.g. overcoming the range-anxiety problem by recharging at (expensive) CPC stations becomes less expensive so that a (slightly) larger share than before will be charged there. According to the data, the cost gap between HPC and CPC is so high that this indirect effect

acceptance by the majority of workers while generating an overall benefit. However, the changes must be very drastic in comparison to current levels, questioning their capability to be accepted not only by the majority of employees but also by the majority of the society in general. For example, raising prices for electricity at home does also affect energy demand for other purposes such as cooking, warm water or heating and thus also affects non-EV users. The same applies to a higher labor tax which affects non-WPC employees as well and will exacerbate the distortions in the labor market, thereby inducing negative tax interaction effects.

2.5.4. Sensitivity Analysis

The previous analysis has discussed various 'remedies' to either overcome WPC underprovision or the lack of WPC demand resulting from the different benchmark WPC contracts offered and evaluated by representative employees and employers. In this subsection, we examine how robust the benchmark findings of Table 2.5.3 are with respect to variations in the employee's travel and energy consumption behavior and, thus, how general the potential 'remedies' discussed above are. The travel and the energy consumption behavior influence the extent to which WPC is demanded and the degree to which employees respond to differences in recharging tariffs. Both, therefore, may affect the implications of the WPC contracts in various ways.[47] To capture both margins of influence, in what follows we consider different assumptions on D, the employee's daily distance traveled, and γ, i.e. the degree to which the worker bases his recharging behavior on economic incentives.

(the shift towards more expensive CPC) outweighs the direct effect (the reduction in the price of CPC in general). This decreases the relative attractiveness in relation to WPC (respectively the recharging package W which is not directly affected by p^C but may also help to overcome range-anxiety).

[47] we focus on the employee (demand) side for the sensitivity analysis because in this case the implications of parameter variations are most uncertain in advance. The previous analyzes have made clear that in particular lower recharging facility costs on the employer (supply) side are crucial to foster WPC provision.

Figure 2.5.1 shows the impacts of variations in daily travel distance (horizontal axis)[48] for the WPC contracts under consideration. The left panels illustrate the employee's (*ev*) and employer's (*ps*) surplus (straight lines) as well as the aggregate effect (bars). The panels on the right-hand side depict the probability for WPC (left vertical axis) and, if applicable, a certain feature of the contracts (wage ω^W or recharging fee p^W on the right vertical axis). Because it turns out again that contracts WPC_2 and WPC_4 are equivalent, the figure shows three panels in the vertical direction. In each panel, the vertical dashed line indicates the benchmark situation (see Table 2.5.3).

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[48] Recall that travel distance D is in fact endogenous. We generated different levels of D by adjusting the preference weights (income shares) in the worker's utility function in such a way that the relative proportions between general consumption and leisure remain unaltered.
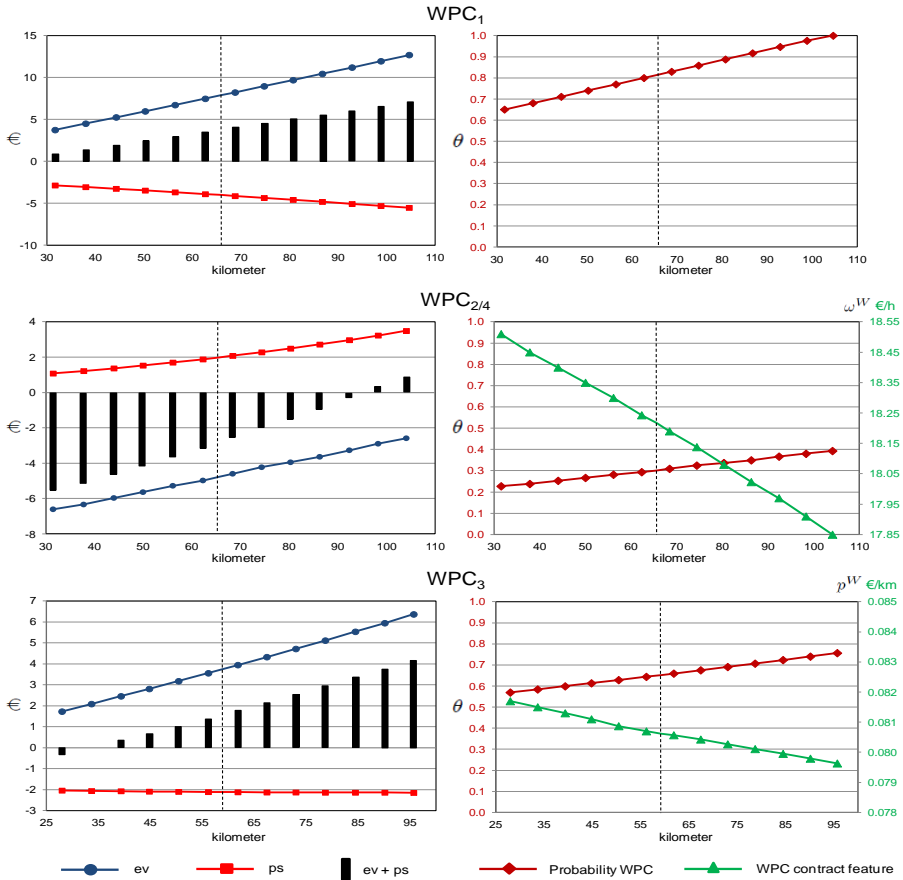
Figure 2.5.1: Sensitivity analysis of the different WPC contracts (daily travel distance)

Three noteworthy results stand out: First, at least in the distance range considered here, which we think is most plausible for traveling at workdays, *ev* and *ps* do not change their signs or graphically, the curves indicating *ev* and *ps* in the left panels do not intersect the center line (0 €). That is, if the employers/employees benefit or suffer from WPC, they do so regardless of the employee's daily travel distance (which in turn is proportional to the amount of recharging). This also implies that the main conclusion derived from Table 2.5.3 holds true, i.e. there is no WPC

contract an employer is willing to offer and at the same time the majority of employees is willing to accept. Second, travel distance does not affect the direction of the overall benefit from WPC ($ev + ps$) in the case of WPC_1, but in regard to $WPC_{2/4}$ and WPC_3 in case of very high ($WPC_{2/4}$) or very low daily travel distances (WPC_3). For example, as regards $WPC_{2/4}$, this implies that redistribution from the employer to the employee becomes an option to stimulate WPC demand when daily travel distance and, associated with it, recharging demand is high. Both, the employee and the employer benefit the more, the larger the travel distance. The former because he gets a larger recharging amount for free (recall that $WPC_{2/4}$ entails a zero recharging fee) and the latter because, as compensation for free recharging, he applies a stronger wage discount (respectively offers a lower wage, see the right panel related to $WPC_{2/4}$). Third, even though there is intuitively a positive relationship between travel distance and the probability of WPC (see the right panels), it is too weak to fundamentally change the employees' overall evaluation of WPC, put differently to turn a minority of employees accepting WPC into a majority and vice versa. As the right panels reveal, the curves indicating the probability of WPC are either below or above the vertical center line ($\theta = 0.5$) in the relevant distance range considered.

Now let us consider the case of a lower γ (0.2 compared to 0.7 of the benchmark case) meaning that the choice of the employees to charge at non-home locations is more restricted.

Table 2.5.7: Sensitivity analysis of the different WPC contracts ($\gamma = 0.2$)

Variable	Symbol	No WPC	WPC_1	$WPC_{2/4}$	WPC_3	Dimension
General consumption	X	91	92	86	91	units
Leisure	l	8.49	8.46	8.47	8.50	h/day
Mobility	D	57,87	61,78	61,32	59,92	km/day
Monetary travel cost	c	0,054	0,043	0,043	0,054	€/km
Generalized travel cost	ρ	0,318	0,299	0,284	0,307	€/km
Value of Time	ξ	10.14	10.23	9.64	10.12	€/h
Utility	U	3.426	3.432	3.405	3.429	units
Probability WPC	θ	–	0,59	0,20	0,55	%
WPC contract	$\{\omega^W, p^W\}$	–	19.65, 0	18.57, 0	19.65, 0.082	€/h,€/km
WPC employee benefit	ev	–	+2.26	−7.11	+1.13	€/EE*day
WPC employer benefit	ps	–	−2.47	+0.91	−2.02	€/EE*day
WPC benefit	$ev + ps$	–	−0.22	−6.20	−0.90	€/EE*day
WPC decision	employee		Majority	Minority	Majority	
	employer		No offer	Offer	No offer	

WPC: Workplace charging   EE: Employee.

Due to the fact that in this case employees can hardy exploit potential benefits of WPC, it is not surprising that they are worse off compared to the benchmark (see Table 2.5.7 in comparison to Table 2.5.3). However, in line with variations in travel distance, the direction of the effect remains unaltered for each WPC contract. That is, the employer benefits from $WPC_{2/4}$ whereas WPC_1 and WPC_3 make the employees better off. As regards the latter two contracts, it is still a majority that is supposed to accept WPC, even though the share is now smaller. However, there is also one major difference compared with the benchmark. While the overall benefit of WPC was positive for WPC_1 and WPC_3 in the benchmark, it is now negative in each of the contracts. Consequently, redistribution disappears as an option to ensure WPC provision when employers are worse off.

To sum up, the sensitivity analyzes suggest that our benchmark results summarized in Table 2.5.3 are quite robust with respect to the WPC contract induced distribution of gains and losses between employees and the employer. More precisely, we found that neither variations in D nor γ caused deviations from our main finding that each WPC contract is to the disadvantage for at least one party. As a consequence, the various 'remedies' discussed above are still needed to either overcome WPC underprovision or the lack of WPC demand. However, the overall private welfare effect of WPC may become negative if γ or D are sufficiently low.[49] This raises questions about the social desirability of WPC (see the discussion below).

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[49] Additional calculations reveal that the overall negative WPC benefit is about −0.22 €/EE *day in case of WPC 1 (see Table 2.5.7) and becomes positive again for γ > 0.23.

2.6. Discussion and Conclusion

In this paper, we proposed an economic approach to study incentives and barriers employees and employers face when deciding on demand for and supply of recharging BEVs at the workplace. We have shown that in the absence of public initiatives to support WPC provision and under uncertainty regarding WPC's potential to foster a firm's attractiveness for workers and customers, WPC contracts being sufficiently attractive to become accepted by the majority of employees won't be offered by an employer. On the other side, under these circumstances contracts offered by employers will only be accepted by a minority of employees, namely those who have a strong (idiosyncratic) preference for WPC. To overcome the lack of demand or underprovision of WPC we discussed various 'remedies', involving e.g. subsidies to recharging facility costs or adjustments in electricity tariffs. Our results suggest that is more promising to support employers, e.g. through subsidizing recharging facilities, in offering WPC contracts than to offer employees incentives to demand WPC. The study therefore gives a rationale for public initiatives being undertaken to boost WPC provision, as e.g. in the case of the US.

In case of proper adjustments, the basic structure of the model also allows an application to further issues such as the usage of an employer's resources for private purposes. The links to recharging cell phones, using the firm's web or IT resources or even corruption issues are straightforward. Adopting the terminology of the present paper, CPC can be seen as the purchase/consumption of a resource outside home, HPC as 'home production' or buying services that are only offered at home (e.g. WLAN) whereas using the employer's resources would be equivalent to WPC. The firm might offer two explicit or implicit contracts: $\left\{ \bar{\omega}, 0 \right\}$ if

there is no legal or illegal usage of its resources and $\left\{ \omega^W, p^W \right\}$ otherwise,

i.e. usage costs or sanctions are either a reduced wage (e.g. due to a layoff) and/or an additional fee or other sanction costs. The worker then decides which of the contracts he prefers, or put differently, whether he makes legal or illegal use of the firm's resource or whether he will not use firm's resources at all. In the end the approach then allows to analyze how the costs and benefits of legal/illegal behavior on the one side and respective compensations/countermeasures captured by the contract offered on the

other side are distributed among workers and companies and which measures could be taken to enhance outcomes for both agents.

The present analysis has focused on employee's and employer's costs and benefits while leaving aside any wider social effects of the implementation of WPC. Consequently, the paper cannot answer whether WPC per se, respectively measures taken to overcome the lack of demand or WPC underprovision, are also warranted on efficiency grounds. As outlined in the introduction, WPC may not only generate social benefits but may also cause adverse effects. The latter not only involves WPC's potential to increase traffic congestion or electricity demand at peak periods (peak-load problem), but also includes broader fiscal effects associated with WPC. For example, if subsidies to WPC facility costs are financed by distortionary taxes or if WPC provision boosts the demand for lower-taxed BEVs in general, WPC could in the end exacerbate the efficiency cost of the overall tax system.[50] Furthermore, the overall environmental impact of WPC needs to be analyzed in future research. At the extensive margin, the provision of WPC may induce individuals to use private car instead of (more environmentally friendly) public transit for commuting. At the intensive margin, WPC may provide incentives to replace conventional fuel powered cars by BEVs. The net environmental impact of WPC then depends on, among other things, the characteristics of the public transit system, fuel efficiency of the conventional fuel powered car replaced, social life-cycle costs of car types, sources of electric power generation (renewable vs. non-renewable). All in all, it is therefore not unequivocally clear whether a positive private net benefit

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[50] Estimates regarding the marginal welfare cost of raising public funds by labor taxation are usually reported to take values from 0.1 to 1.0 (see, e.g., Parry, 2002). Conditional on marginal welfare cost of taxation of 0.4 € per 1 € of revenue raised, a recharging facility subsidy of roughly 1100 €/year needed for WPC provision in case of 'Remedy (1)' would cause an excess burden of around 440 €/year. When divided by k = 225 to make it comparable to the numbers in Table 2.5.4, the daily welfare cost of taxation is around 2 € per employee using WPC. Moreover, even though not directly concerned with WPC, (Hirte and Tscharaktschiew, 2013b) and (Jenn et al., 2015) point to adverse fiscal effects in case of stronger BEV diffusion.

of WPC as we have found in some cases (see benchmark contracts WPC_1 and WPC_3) is accompanied by positive impacts on the society as a whole.

In the light of our findings WPC might also affect the welfare implications of general congestion pricing policies. According to the analyzes of De Borger and Wuyts (2009), congestion tolls may generate an extra efficiency gain when parking at the workplace is paid by the employer and public transport is available as an alternative to commuting by car. In case that public transport is subsidized, a higher congestion toll implies a side-welfare loss to the extent that it induces more (subsidized) public transport demand. This welfare loss, however, can be reduced if the change in travel mode choice in favor of transit lowers the demand for parking space at the workplace, provided that the distortion from employer-paid parking exceeds the distortive effect of transit subsidies. If, however, the positive net benefit of WPC (see e.g. contract WPC_1) in turn exceeds the adverse effect of providing parking space at the workplace for free, and taking into account that parking and recharging at the workplace are strongly complementary, the extra efficiency effect of the congestion toll through discouraging parking (and so WPC) could become even negative. Combining key elements of the present study with the approach of De Borger and Wuyts (2009) could give new insights into how to efficiently price a congestion externality under an increasing importance of electric mobility in general and recharging BEVs at the workplace in particular.

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Appendix 1

Appendix A. The demand for WPC when HPC is not available

Individuals may not generally have private parking spaces at home to install their own private charger, e.g. at large apartment buildings where residents share parking areas. In this case, they have to share the recharging space with other individuals including non-EV users. This makes recharging at the place of residence costly since it may take time to search for an unoccupied recharging spot unless there is efficient coordination among individuals sharing the parking area.

In this section, we consider the demand for WPC when workers do not have own (or efficiently coordinated shared) recharging access at the place of residence.

In the absence of WPC, workers have to charge for the daily travel solely at CPC stations. In contrast, in the presence of WPC, they decide on allocating the required energy for the daily travel between CPC and WPC such that the recharging expenditure is minimized. As a consequence, workers have two options: $C = \{CPC\}$ and $CW = \{CPC, WPC\}$. The share of recharging at CPC, denoted by $\beta^C(p^C, p^W)$ with $0 < \beta^C < 1$ depends on the relative electricity tariffs for recharging at CPC and WPC, respectively, where $\dfrac{\partial \beta^C}{\partial p^C} < 0$ and $\dfrac{\partial \beta^C}{\partial p^W} > 0$. As above it is assumed that there is a basic load $d_0 = (1 - \gamma) D$ that is to loaded near home, i.e. at CPC (regardless of relative prices between CPC and WPC).

Accordingly, the expected daily recharging price per unit of distance, denoted c^j is given by

$$c^j = \begin{cases} p^C & \text{if} \quad j = C \\ (1-\gamma)p^C + \gamma\left[\beta^C(p^C, p^W)p^C + \left(1 - \beta^C(p^C, p^W)\right)p^W\right] & \text{if} \quad j = CW \end{cases}.$$

(A.1)

The corresponding total travel time per unit of distance, D^j , (i.e., travel time plus recharging time including the time for searching an unoccupied recharging spot), is given by (recall that WPC takes place without affecting the employee's time since he can work while the BEV is being charged)

$$t_D^j = \begin{cases} t_d + t_c & \text{if} \quad j = C \\ t_d + t_c\left[1 - \gamma + \gamma\beta^C(p^C, p^W)\right] & \text{if} \quad j = CW \end{cases}$$

(A.2)

Following similar procedures for the utility maximization problem that we saw in (0.4)–(0.10) , after replacing c^i by c^j and t^i_D by t^j_D, we compute comparative statics concerning the effects a public authority, an electricity supplier and the employer could have on the demand for WPC.

It is beneficial for the employee to charge at the workplace if

$$V^{CW} + \varepsilon > V^C. \tag{A.3}$$

where ε is the (unobserved) idiosyncratic preference for WPC representing several factors affecting the incentives to charge at the workplace, and

$$V^{CW} = V\left(\omega^{CW}(1-\tau)t_w - c^{CW}D^{CW,*}, T - t_w - t_D^{CW}D^{CW,*}, D^{CW,*}\right), \tag{A.4}$$

$$V^C = V\left(\omega^C(1-\tau)t_w - c^C D^{C,*}, T - t_w - t_D^C D^{C,*}, D^{C,*}\right). \tag{A.5}$$

With the equivalent assumption that ε is distributed uniformly over the interval [−a, + a] , the probability of WPC (respectively the share of employees preferring WPC) is given by

$$\tilde{\theta} = \frac{1}{2} - \frac{V^C - V^{CW}}{2a}. \qquad (A.6)$$

Thus, a reservation utility level of $\tilde{V} = V^C - V^{CW} \leqq 0$ is needed to induce the average employee to use the WPC option provided by the employer through offering a certain WPC contract.

The analysis of the effects of parameters and variables on the probability of WPC can be started by noting that for any exogenous variable α:

$$\text{sign}\left(\frac{\partial \tilde{\theta}}{\partial \alpha}\right) \equiv \text{sign}\left(\frac{\partial V^{CW}}{\partial \alpha} - \frac{\partial V^C}{\partial \alpha}\right). \qquad (A.7)$$

Lemma 7. *A higher labor tax increases the probability of WPC if differences in MUIs across the recharging regimes do not over- compensate wage differences:*

$$\frac{\partial \tilde{\theta}}{\partial \tau} > 0. \qquad (A.8)$$

The proof and intuition is similar to the effect of τ on θ that we saw in case of the recharging packages H and W (i = H is replaced by j = C and i = W by j = CW).

Lemma 8. Assume $\lambda^C D^C = \lambda^{CW} D^{CW}$. In this case, if the fee the employer levies on WPC exceeds the generalized costs of CPC by less than $\left(1 - \beta^C\right) / \left(-\varepsilon_{\beta^C}^{p^C}\right)\frac{\beta^C}{p^C}$, the probability of WPC increases with an increase in the tariff for CPC:

$$\frac{\partial \tilde{\theta}}{\partial p^C} = \begin{cases} > 0 & \text{if } p^W - p^C - \xi^{CW} t_c < \dfrac{1 - \beta^C}{\left(-\varepsilon_{\beta^C}^{p^C}\right)\dfrac{\beta^C}{p^C}}. \\[2em] \leq 0 & \text{otherwise} \end{cases} \qquad (A.9)$$

Proof.

$$\left(\frac{\partial V^{CW}}{\partial p^C} - \frac{\partial V^C}{\partial p^C}\right) = \lambda^C D^C \frac{\partial c^C}{\partial p^C} - \lambda^{CW} D^{CW}\left(\frac{\partial c^{CW}}{\partial p^C} + \xi^{CW}\frac{\partial t_D^{CW}}{\partial p^C}\right)$$

$$= \lambda^C D^C - \lambda^{CW} D^{CW}\left[\underbrace{1 - \gamma + \gamma\beta^C + \gamma\frac{\partial \beta^C}{\partial p^C}\left(p^C + t_c\xi^{CW} - p^W\right)}_{<0}\right]$$

If $\lambda^C D^C = \lambda^{CW} D^{CW}$ this is equivalent to

$$\left(\frac{\partial V^{CW}}{\partial p^C} - \frac{\partial V^C}{\partial p^C}\right) = \gamma\lambda^C D^C\left[\underbrace{\left(1 - \beta^C\right)}_{>0} - \frac{\beta^C}{p^C}\left(p^C + t_c\xi^{CW} - p^W\right)\underbrace{\varepsilon_{\beta^C}^{p^C}}_{<0}\right] \qquad (A.10)$$

Some algebra shows that this expression is positive if
$$p^W - p^C - \xi^{CW}t_c < \frac{1 - \beta^C}{\left(-\varepsilon_{\beta^C}^{p^C}\right)\frac{\beta^C}{p^C}} \cdot \square$$

The implication is that by manipulating p^C e.g. through changing taxes (the government) or energy tariffs (the electricity supplier and the CPC station owners) for CPC, the probability of WPC can be affected. If p^C increases, recharging package C = {CPC } becomes more expensive so that the probability for WPC goes up (the direct effect $(1 - \beta^C) > 0$). This effect strengthens (the more the larger $\left|\varepsilon_{\beta^C}^{p^C}\right|$) if WPC is relatively more attractive than CPC, put differently if the generalized price of CPC exceeds the recharging fee at the workplace.

Lemma 9. *The probability of choosing WPC declines with an increase in the recharging fee at the workplace if the fee does not exceed the generalized costs of CPC by more than* $\dfrac{1-\beta^C}{\left(\varepsilon^{p^W}_{\beta^C}\right)\dfrac{\beta^C}{p^W}}$:

$$\frac{\partial \tilde{\theta}}{\partial p^W} = \begin{cases} <0 & \text{if } p^W - p^C - \xi^{CW} t_c < \dfrac{1-\beta^C}{\left(\varepsilon^{p^W}_{\beta^C}\right)\dfrac{\beta^C}{p^W}}. \\[2em] \geq 0 & \text{otherwise} \end{cases} \qquad \text{(A.11)}$$

Proof.

$$\left(\frac{\partial V^{CW}}{\partial p^W} - \frac{\partial V^C}{\partial p^W}\right) = \lambda^C D^C \frac{\partial c^C}{\partial p^W} - \lambda^{CW} D^{CW}\left(\frac{\partial c^{CW}}{\partial p^W} + \xi^{CW}\frac{\partial t_D^{CW}}{\partial p^W}\right)$$

$$= -\lambda^{CW} D^{CW} \gamma \left[\left(1-\beta^C\right) + \left(p^C + \xi^{CW} t_c - p^W\right)\frac{\partial \beta^C}{\partial p^W}\right]$$

which is equivalent to

$$\left(\frac{\partial V^{CW}}{\partial p^W} - \frac{\partial V^C}{\partial p^W}\right) = \lambda^{CW} D^{CW} \gamma \left[\underbrace{-\left(1-\beta^C\right)}_{>0} - \left(p^C + \xi^{CW} t_c - p^W\right)\underbrace{\varepsilon^{p^W}_{\beta^C}\frac{\beta^C}{p^W}}_{>0}\right]$$

$$\text{(A.12)}$$

Some algebra shows that this expression is negative if

$$p^W - p^C - \xi^{CW} t_c < \frac{\left(1-\beta^C\right)}{\left(\varepsilon^{p^W}_{\beta^C}\right)\dfrac{\beta^C}{p^W}}. \quad \square$$

Note first that a change in p^W does not affect V^c because p^W is not an option under recharging package C. Hence, all effects of p^W on $\tilde{\theta}$ are channeled through its effects on V^{CW}. Here two countervailing effects occur. First, an increase in p^W clearly reduces the probability of WPC since it makes the recharging package C^W = {CPC, WPC} more expensive (the direct effect $(-(1 - \beta^c)) < 0$). However, an increase in the recharging fee at the workplace also induces the worker to switch (to some extent) to CPC within the recharging package C^W (the more the larger $\varepsilon_{\beta^c}^{p^W}$). If the generalized price of CPC is sufficiently low (relative to p^W), utility associated with recharging package C^W raises (compared to C) and this ceteris paribus increases the probability of WPC. The overall effect then depends on the strength of both countervailing effects.

Appendix B. Derivation for Equations (0.52) and (0.53)

For the fully flexible contract WPC_4 the first-order conditions with respect to the employer's decision variables ω^W and p^W are

$$\frac{\partial C}{\partial \omega^W} \equiv C_\omega = \theta t_w - (\bar{\omega} - \omega^W) t_w \theta_\omega + (\bar{p} - p^W)\ (\theta d_\omega^e + d^e \theta_\omega) + \frac{1}{k}(r\bar{c} - \delta)\theta_\omega = 0$$

(B.1)

$$\frac{\partial C}{\partial p^W} \equiv C_p = -(\bar{\omega} - \omega^W) t_w \theta_p + (\bar{p} - p^W)(\theta d_p^e + d^e \theta_p) + \frac{1}{k}(r\bar{c} - \delta)\theta_p - d^e \theta = 0$$

(B.2)

Solving (B.1) for p^W gives

$$p^W = \bar{p} + \frac{\theta t_w - t_w(\bar{\omega} - \omega^W)\theta_\omega + \frac{1}{k}(r\bar{c} - \delta)\theta_\omega}{(\theta d_\omega^e + d^e \theta_\omega)}$$

(B.3)

Substituting (B.3) in (B.2), we have

$$-t_w\left(\bar{\omega}-\omega^W\right)\theta_p+\left[\bar{p}-\left(\bar{p}+\frac{\theta t_w-t_w\left(\bar{\omega}-\omega^W\right)\theta_\omega+\frac{1}{k}(r\bar{c}-\delta)\theta_\omega}{\left(\theta d_\omega^e+d^e\theta_\omega\right)}\right)\right]\left(\theta d_p^e+d^e\theta_p\right)+\frac{1}{k}(r\bar{c}-\delta)\theta_p-d^e\theta=0$$

(B.4)

Canceling terms and regrouping gives

$$t_w\left(\bar{\omega}-\omega^W\right)\theta\left(\frac{\theta_\omega d_p^e-\theta_p d_\omega^e}{\theta d_\omega^e+d^e\theta_\omega}\right)-\frac{\theta t_w\left(\theta d_p^e+d^e\theta_p\right)}{\theta d_\omega^e+d^e\theta_\omega}+\frac{\theta}{k}(r\bar{c}-\delta)\left(\frac{\theta_p d_\omega^e-\theta_\omega d_p^e}{\theta d_\omega^e+d^e\theta_\omega}\right)-d^e\theta=0$$

(B.5)

Dividing the left-hand side and right-hand side of (B.5) by θ and collecting terms, we have

$$t_w\left(\bar{\omega}-\omega^W\right)\left(\frac{\theta_\omega d_p^e-\theta_p d_\omega^e}{\theta d_\omega^e+d^e\theta_\omega}\right)-\frac{t_w\left(\theta d_p^e+d^e\theta_p\right)}{\theta d_\omega^e+d^e\theta_\omega}+\frac{1}{k}(r\bar{c}-\delta)\left(\frac{\theta_p d_\omega^e-\theta_\omega d_p^e}{\theta d_\omega^e+d^e\theta_\omega}\right)-d^e=0$$

(B.6)

Multiplying both sides of (B.6) by $\theta d_\omega^e+d^e\theta_\omega$ gives

$$t_w\left(\bar{\omega}-\omega^W\right)\left(\theta_\omega d_p^e-\theta_p d_\omega^e\right)-t_w\left(\theta d_p^e+d^e\theta_p\right)+\frac{1}{k}(r\bar{c}-\delta)\left(\theta_p d_\omega^e-\theta_\omega d_p^e\right)-d^e\left(\theta d_\omega^e+d^e\theta_\omega\right)=0$$

(B.7)

Solving (B.7) for ω^W, we have

$$\omega^W=\bar{\omega}-\frac{d^e\left(\theta d_\omega^e+d^e\theta_\omega\right)+t_w\left(\theta d_p^e+d^e\theta_p\right)}{t_w\left(\theta_\omega d_p^e-\theta_p d_\omega^e\right)}-\frac{(r\bar{c}-\delta)}{kt_w}$$

(B.8)

Dividing the numerator and denominator of the second term on the right-hand side of (B.8) by θd^e gives

$$\omega^W = \bar{\omega} - \frac{d^e\left(\dfrac{d^e_\omega}{d^e} + \dfrac{\theta_\omega}{\theta}\right) + t_w\left(\dfrac{d^e_p}{d^e} + \dfrac{\theta_p}{\theta}\right)}{t_w\left(\dfrac{\theta_\omega}{\theta}\dfrac{d^e_p}{d^e} - \dfrac{\theta_p}{\theta}\dfrac{d^e_\omega}{d^e}\right)} - \frac{(r\bar{c}-\delta)}{kt_w} \qquad (\text{B.9})$$

After redefining terms, we arrive at (0.53). Now, substituting (0.53) for ω^W in (B.9) and simplifying gives (0.52).

Appendix C. Comparative statics for $(\omega^W)^*$ and $(P^W)^*$

In case of the fully flexible contract, WPC$_4$, the second-order conditions are given by

$$C_{\omega\omega} = 2\theta_\omega t_w - \theta_{\omega\omega}\left(\bar{\omega}-\omega^W\right)t_w + \left(\bar{p}-p^W\right)\left(2\theta_\omega d^e_\omega + \theta d^e_{\omega\omega} + d^e\theta_{\omega\omega}\right) + \frac{\theta_{\omega\omega}}{k}(r\bar{c}-\delta)$$
$$(\text{C.1})$$

$$C_{pp} = -\theta_{pp}\left(\bar{\omega}-\omega^W\right)t_w + \left(\bar{p}-p^W\right)\left(2\theta_p d^e_p + \theta d^e_{pp} + d^e\theta_{pp}\right) + \frac{\theta_{pp}}{k}(r\bar{c}-\delta) - 2\left(\theta d^e_p + d^e\theta_p\right)$$
$$(\text{C.2})$$

$$C_{\omega p} = \theta_p t_w - \left(\bar{\omega}-\omega^W\right)t_w\theta_{\omega p} + \left(\bar{p}-p^W\right)\left(\theta_p d^e_\omega + \theta d^e_{\omega p} + d^e_p\theta_\omega + d^e\theta_{\omega p}\right) - \left(\theta d^e_\omega + d^e\theta_\omega\right) + \frac{1}{k}(r\bar{c}-\delta)\theta_{\omega p}$$
$$(\text{C.3})$$

Using Cramer's rule, the effect of $\bar{\omega}$ on $\left(\omega^W\right)^*$ when $\left(\omega^W\right)^*$ is an interior solution is (where $C_{\omega\bar{\omega}}$ and $C_{p\bar{\omega}}$ are derived from (0.46) and (0.47), respectively):

$$\frac{\partial\left(\omega^W\right)^*}{\partial\bar{\omega}} = -\frac{\begin{vmatrix} C_{\omega\bar{\omega}} & C_{\omega p} \\ C_{p\bar{\omega}} & C_{pp} \end{vmatrix}}{\begin{vmatrix} C_{\omega\omega} & C_{\omega p} \\ C_{p\omega} & C_{pp} \end{vmatrix}} = -\frac{\begin{vmatrix} -\theta_\omega t_w & C_{\omega p} \\ -\theta_p t_w & C_{pp} \end{vmatrix}}{\begin{vmatrix} C_{\omega\omega} & C_{\omega p} \\ C_{p\omega} & C_{pp} \end{vmatrix}} \tag{C.4}$$

Assuming that the conditions for cost minimization are fulfilled (interior solution), we have (recall that $\theta_\omega \geq 0$, $\theta_p \leq 0$

$$\frac{\partial\left(\omega^W\right)^*}{\partial\bar{\omega}} = \frac{C_{pp}\theta_\omega - C_{\omega p}\theta_p}{C_{pp}C_{\omega\omega} - (C_{\omega p})^2} t_w \geq 0 \text{ if } C_{\omega p} \geq 0 \text{ or if } \left|C_{pp}\theta_\omega\right| \geq \left|C_{\omega p}\theta_p\right| \tag{C.5}$$

Similarly, we have

$$\frac{\partial\left(p^W\right)^*}{\partial\bar{\omega}} = -\frac{\begin{vmatrix} C_{\omega\omega} & C_{\omega\bar{\omega}} \\ C_{\omega p} & C_{p\bar{\omega}} \end{vmatrix}}{\begin{vmatrix} C_{\omega\omega} & C_{\omega p} \\ C_{p\omega} & C_{pp} \end{vmatrix}} = -\frac{\begin{vmatrix} C_{\omega\omega} & -\theta_\omega t_w \\ C_{\omega p} & -\theta_p t_w \end{vmatrix}}{\begin{vmatrix} C_{\omega\omega} & C_{\omega p} \\ C_{p\omega} & C_{pp} \end{vmatrix}} \tag{C.6}$$

$$\frac{\partial\left(p^W\right)^*}{\partial\bar{\omega}} = \frac{C_{\omega\omega}\theta_p - C_{\omega p}\theta_\omega}{C_{pp}C_{\omega\omega} - (C_{\omega p})^2} t_w \leq 0 \text{ if } C_{\omega p} \geq 0 \text{ or if } \left|C_{\omega\omega}\theta_p\right| \leq \left|C_{\omega p}\theta_\omega\right| \tag{C.7}$$

The effect of $\bar{p}$ on $\left(\omega^W\right)^*$ when $\left(\omega^W\right)^*$ is an interior solution is (where $C_{\omega\bar{p}}$ and $C_{p\bar{p}}$ are derived from (0.46) and (0.47), respectively):

$$\frac{\partial \left(\omega^W\right)^*}{\partial \overline{p}} = -\frac{\begin{vmatrix} C_{\omega\overline{p}} & C_{\omega p} \\ C_{p\overline{p}} & C_{pp} \end{vmatrix}}{\begin{vmatrix} C_{\omega\omega} & C_{\omega p} \\ C_{p\omega} & C_{pp} \end{vmatrix}} = -\frac{\begin{vmatrix} \theta d_\omega^e + \theta_\omega d^e & C_{\omega p} \\ \theta d_p^e + \theta_p d^e & C_{pp} \end{vmatrix}}{\begin{vmatrix} C_{\omega\omega} & C_{\omega p} \\ C_{p\omega} & C_{pp} \end{vmatrix}} \tag{C.8}$$

$$\frac{\partial \left(\omega^W\right)^*}{\partial \overline{p}} = \frac{\theta d^e \left[C_{\omega p} \left(\eta_d^{p^W} + \eta_\theta^{p^W} \right) - C_{pp} \left(\phi_d^\omega + \phi_\theta^\omega \right) \right]}{C_{pp} C_{\omega\omega} - (C_{\omega p})^2} \leq 0 \text{ if } C_{\omega p} \geq 0.$$
$$\tag{C.9}$$

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3. Myopic Loss Aversion Behavior under Ultimatum Game Framework in the Scheduling and Pricing of Electric Vehicle Recharging

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Abstract

Upward expectations of future electric vehicle (EV) growth pose the question about the future load on the electric grid system. While existing literature on BEV recharging demand management has focused on technical aspects and considered EV-owners as utility maximizers, this study proposes a behavioral model incorporating psychological aspects relevant to EV-owners facing recharging decisions and interacting with the supplier. The behavioral model represents utility maximization under myopic loss aversion (MLA) behavior in an ultimatum game (UG) framework with two players: EV-owner and the electricity supplier. We test the validity of the behavioral model by designing 3x2 economics laboratory experiment where a potential EV-owner faces either of three decisions: (i) rescheduling recharging time to be eligible for a given discount proposed by the supplier, (ii) proposing the amount of discount to request for recharging at hours set by the supplier, and (iii) proposing the amount of discount to request for supplier-controlled recharging, under two contract durations: daily versus weekly. Each of the three treatments were incentive compatible in that every participant was expected to reveal her true preference to the supplier since the amount of threshold that the supplier accepted was concealed. The main objective of the laboratory experiment is to investigate whether lessening the MLA behavior by providing contracts under UG framework and in long-term contract bases helps individuals to make better choices. Findings from the experiment show that individuals indeed reveal myopic behavior when taking BEV recharging decisions. Thus, presenting long-term BEV recharging contracts under UG framework may curtail myopic behavior and help BEV owners to choose cost-minimizing recharging time by participating in discounted off-peak recharging hours.

Key words: electric vehicles; recharging decisions; smart grid recharging; utility maximization; myopic loss aversion; ultimatum two-player game.

3.1. Introduction

While the market penetration of electric vehicles (EVs) has been negligible so far because of high unit costs and limited driving range, upward expectations exist for a future rapid BEV growth following the driving range improvements, purchase price reductions and government incentives (e.g., Andersen et al., 2009; Bonges and Lusk, 2016; Brady and O'Mahony, 2011; Dagsvik et al., 2009; Valeri and Danielis, 2015). Recent demand assessment studies predict reasonable market shares at around 4-10% for BEVs by 2020 (e.g., Brady and O'Mahony, 2011; Lebeau et al., 2012; Mendes et al., 2014), and suggest dominant market shares for BEVs by 2030-2050 in both Europe and the U.S. (e.g., Lebeau et al., 2012; Mabit and Fosgerau, 2011; Traut et al., 2013).

This expected BEV growth is expected to load significantly the electric power grid system. Recharging times are expected to coincide with peak hours of electricity demand for household consumption and industrial use (Axsen and Kurani, 2010), and even modest BEV shares (20-25% of the total vehicle fleet) are expected to increase the electricity load by roughly 30% in US (Amoroso and Cappuccino, 2012). Demand side management (DSM) of BEV recharging (i.e. encouraging EV-owners to change their recharging patterns in response to changes in electricity prices) is viewed as a possible solution to reduce grid overload at peak hours and to reduce investments in grid capacity expansion (Finn et al., 2012; Flath et al., 2014). Economic evaluations have shown that DSM of BEV recharging has positive welfare effects. For example, smart recharging BEVs in Finland could produce benefits of 227 EUR per vehicle per year (Kiviluoma and Meibom, 2011). Shifting recharging from peak to off-peak hours in the U.S. could generate savings ranging from $1.1 billion to $5.1 billion per year (Lyon et al., 2012); price-responsive recharging strategies in Singapore could turn estimated losses of 1000 SGD per vehicle per year into estimated profits of 21-130 SGD (Pelzer et al., 2014). Simulation-based feasibility evaluations have shown that DSM of BEV recharging helps to improve the grid system (Dallinger and Wietschel, 2012). Waraich et al. (2013) propose micro-simulation analyzes of

electricity demand considering price schemes. Optimization algorithms propose efficient BEV recharging scheduling under system optimization (e.g., Di Giorgio et al., 2014; Iversen et al., 2014); business models illustrated the efficiency of the optimization algorithms and the benefits of changing BEV recharging times (e.g., Kley et al., 2011).

While investigating the relevance and feasibility of smart integration of BEVs in to the grid system, previous studies assumed, explicitly or implicitly, that BEV users will be willing to postpone recharging and/or will accept their BEV recharging activity controlled by electricity suppliers in return for discounted fee for recharging. For example, in real-time and dynamic pricing, BEV owners are assumed to routinely seek information regarding the periodic price and adjust recharging time accordingly. However, empirical studies show that consumers generally prefer simple price schemes to dynamic and complex once (Dütschke, E., & Paetz, A. G., 2013). Moreover, postponing recharging hour could involve psychological or real driving-range anxiety concerning unforeseen trips occurrence during the postponement period (Bakker, 2011) that previous studies about recharging time do not account for.

When considering these aspects, and reflecting on the extensive evidence that individuals are bounded rational (see, e.g., Holt and Laury, 2002; Kahneman and Tversky, 1979; Thaler et al., 1997), the need to consider psychological aspects of EV-owners becomes evident. The issue of considering psychological aspects has received very limited attention in the literature, as the only considered psychological and behavioral aspects concern social etiquette (Franke and Krems, 2013) and resource replenishing behavior (Caperello et al., 2013).

This study contributes to the body-of-knowledge concerning BEV recharging by challenging the assumption that EV-owners are rational utility maximizers in their recharging decisions and hence examining the psychological aspects that are relevant to DSM contract selection and the development of realistic agent-based and optimization models otherwise

affected by the neglect of these psychological aspects. Specifically, this study proposes a novel behavioral model that presents utility maximization under myopic loss aversion (MLA) behavior in the context of an ultimatum game (UG) framework. The model represents the behavior of individuals (EV-owners) trading-off between the amount of the discount on fee for recharging, the risk of being eligible to the discount and the risk of not recharging the BEV on time for unforeseen trips. Moreover, the model considers MLA leading individuals to be risk averse in short-term decisions and differentiates itself from the 'deadline differentiated pricing' model (e.g., Bitar and Low, 2012; Bitar and Xu, 2013; Salah and Flath, 2014) where the supplier proposes a menu of deferral options and the consumer plays a role in specifying the menu that the supplier bargains with.

This study contributes to the MLA literature as well by considering MLA under UG framework that may have application in other areas such as trade and investment. We also extended the UG framework in situations where accepting the proposal entails risk for the responder. Moreover, while previous studies on MLA considered a single individual, this is the first model exploring MLA within a two-player UG framework and hence investigating MLA as related not only to the individual's gains or losses, but also to the individual's cautiousness in the proposal because of the need to consider the responder's strategy (Driesen et al., 2010). While previous studies on MLA considered only monetary decisions, this is the first model representing MLA for time-based decisions and hence looking into mental accounting for time as possibly similar to the one for money (Rajagopal and Rha, 2009). Instead of choosing the amount to invest in a risky asset for a given level of risk that previous MLA studies consider, we also consider choosing the level of risk to accept, like choosing among various stocks with varying return and risk level, for a given amount to invest.

The behavioral model is validated by an experimental economic laboratory setting that covers three decisions within two contract

durations. The three decisions concern (i) to postpone recharging time to off-peak periods for a discount proposed by the supplier, (ii) the amount of discount to request for off-peak recharging at times decided by the supplier, and (iii) the amount of discount to request for supplier-controlled recharging involving ambiguity concerning the recharging time. The two contract durations entail (i) a short-term (daily) framing and (ii) a long-term (weekly) framing. The three experiments tested whether the long-term contract framing lessens MLA behavior while controlling for possible confounding factors. In the first experiment, participants were requested to what extent they are willing to postpone recharging to be eligible to the discounted fee. In the second experiment, participants were requested to propose a discount for postponing the recharging while still facing the possible rejection by the supplier, the occurrence of unforeseen events and the aforementioned mobility constraints. In the third experiment, participants were requested to propose a discount to concede that the electricity supplier assumes the decision about the recharging time.

Findings from the experiment show that individuals indeed reveal MLA behavior when taking BEV recharging decisions. Thus, presenting long-term BEV recharging contracts, instead of merely presenting time-of-use pricing of electricity, may curtail MLA behavior and help BEV owners to choose cost-minimizing recharging time by participating in discounted off-peak recharging hours.

The paper is structured as follows. The next section presents the proposed behavioral model. The following sections introduce the experimental design and illustrate the results of the three experiments on BEV recharging decisions. The last section draws conclusions and suggests policy implications.

3.2. Behavioral model
3.2.1. A brief Overview of MLA and UG

MLA combines the two concepts of loss aversion and mental accounting, where loss aversion is the tendency of individuals to be more sensitive to losses than to gains and mental accounting is the activity that individuals perform to evaluate alternatives and take decisions (Benartzi and Thaler, 1995). In the literature, MLA refers typically to the way individuals evaluate a sequence of long-term risky investments that can also be evaluated in the short-term basis (Benartzi and Thaler, 1995; Thaler et al., 1997). Myopic individuals evaluate the transactions independently and reject them if each risky investment is separately unattractive, while non-myopic individuals evaluate the sequence in its entirety and reject the investments only if the aggregated net return is unattractive (Thaler et al., 1997). Accordingly, MLA implies that individuals reach different decisions according to the problem framing. Lessening MLA requires limiting evaluation frequency (i.e., the time horizon for transaction evaluation) for MLA individuals to perceive less the disutility of short-term losses, and/or decreasing decision flexibility (i.e., the individual has less ability to adjust the decision) for MLA individuals to tend towards the evaluation of a sequence of decisions as aggregate rather than as singular ones (e.g., see Gneezy and Potters, 1997; Thaler et al., 1997; Gneezy et al., 2003; Langer and Weber, 2008; Fellner and Sutter, 2009; Benzion et al., 2012; Kaufmann and Weber, 2013).

In the context of BEVs recharging, the way time-of-use pricing of electricity used for BEV recharging may affect BEV owners' response. The electricity tariff could be presented as self-selection daily choice problem, i.e., the electricity supplier simply announces the time-of-day tariff without requiring any formal contract, and the BEV owners choose the recharging time on daily bases. Alternatively, the tariff could be presented in long-term contract forms requiring the BEV owners to recharging at only the specified hours within the contract period to be eligible for the contract. Thus, according to the MLA hypothesis, presenting the tariff in

long-term bases may lessen MLA behavior, ceteris paribus. Lessening MLA may help BEV owners to choose the expected cost-minimizing recharging time/discount by trading-off between the aggregated cost saving from the discounted fee and the expected cost of not having the BEV charged on time.

On the other hand, an UG is a sequential bargaining, zero-sum game where the proposer and the responder are two players who passively bargain on sharing a sum of money. The proposer decides how the money is to be shared between the two players, and the responder decides to accept/reject the proposed shares (Kagel et al., 1996). Accepting implies that each player earns the agreed share, while rejecting entails no earnings for both players. The classical game theory prediction for the bargaining equilibrium solution is that the responder accepts any positive share, regardless of its amount, since this positive share is better than the zero earning associated to the rejection (ceteris paribus). Expecting this, the proposer offers the smallest positive unit, which is the equilibrium solution. The actual observation of empirical evidence suggests that the amounts proposed and rejected are affected by additional factors such as emotions, feeling of fairness, sense of punishment, sense of reciprocity, and to a lesser extent by demographic and cultural variables (e.g., Camerer and Thaler, 1995; Van't Wout et al., 2006).

A similar framework exists between BEV owners and electricity suppliers. Active (or passive) agreement between electricity suppliers and BEV owners concerning the discounted fee for scheduling recharging at times convenient for the grid system benefits both, though, unlike the classical UG framework, postponing recharging involves risk for BEV owners. In the model we present below, the BEV owner is the proposer about the amount of discount to request for postponing recharging. S/he trades-off between, on the one hand, claiming large share of the benefit from the discount and the corresponding high risk of the proposal being rejected by the supplier and, on the other hand, getting the small claim

proposal being accepted by the supplier, but risking that the discount claim is too small to cover the expected costs of unforeseen trip occurring during the postponement period.[51]

3.2.2.   The Proposed Model

Consider an individual facing a choice between (i) a consumption option having cost c at time t and (ii) a consumption option having cost $(c – g)$ at time $(t + \Delta t)$, where $0 \leq g \leq c$ and $\Delta t > 0$, but Δt is not too large to bear interest rate. The individual is the proposer (the BEV owner in our context) who offers a value g for choosing the second option to the responder (the electricity supplier) who decides whether to accept or reject the proposal. From the proposer's perspective, acceptance implies a potential gain, g, and rejection entails no gain. From the responder perspective, acceptance implies lower revenue by the amount g for an exogenous benefit, e.g. from smoothing electricity consumption that reduces average cost of supplying electricity. The responder accepts if g entails no less gain than the status-quo condition.

The proposer has two contrasting motivations towards deciding the size of g. On the one hand, a higher g implies a higher gain, but it entails also a lower acceptance probability, $\theta(g)$, of g, where θ is inversely related with g. On the other hand, a lower g implies a higher $\theta(g)$. However, extending the UG framework, in the case the responder accepts and the proposer postpones the consumption by Δt, a probability, $\alpha \geq 0$, exists that an unforeseen event occurs at an extra cost, e, and, thus, lower g may not be

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[51] The EV-owner proposing the discount amount bases on value-based pricing (Christopher M., 1982; Grewal et al, 2012) in that the discount amount depends on how much BEV owners value rescheduling recharging time. The electricity supplier, then, offers the discount for eligible BEV owners.

enough to cover the expected cost, αe. Thus, the expected cost of consumption at time $(t + \Delta t)$ equals $(c - g + \alpha e)$ for the proposer.

Accordingly, there are four possible outcomes for the proposer as also illustrated in figure 1:

- the proposer does not present the proposal, and hence experiences cost c at time t;

- the proposer proposes g that is rejected by the responder and, hence, experiences cost c at time t;

- the proposer proposes g that is accepted by the responder and no unforeseen event occurs and, hence, experiences cost $(c - g)$ and gain g at time $(t + \Delta t)$;

- the proposer proposes an amount g that is accepted by the responder, but an unforeseen event occurs and, hence, experiences cost $(c - g + e = c + s)$ at time $(t + \Delta t)$, where s is the net loss of the unforeseen event.
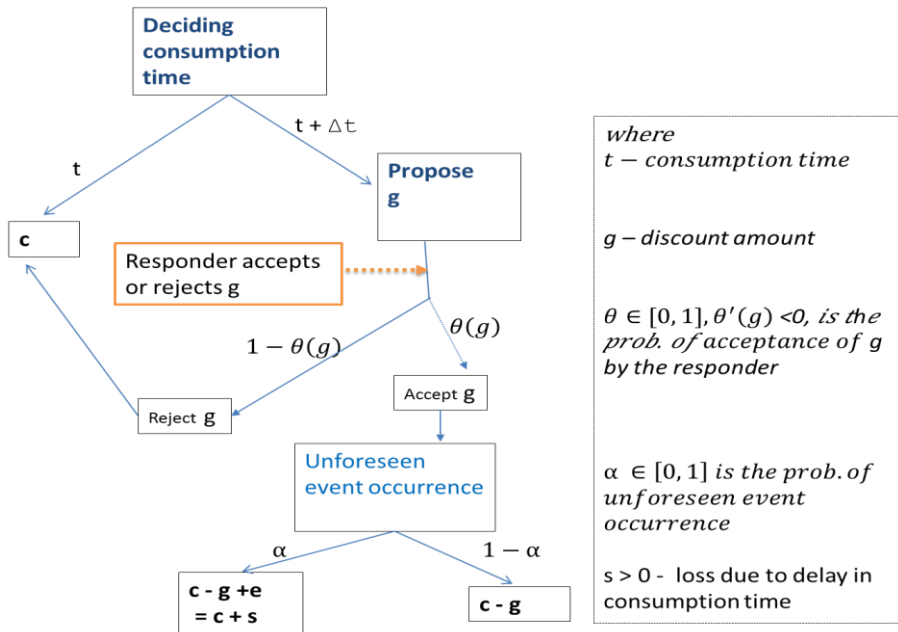
Figure 3.2.1. Choice of consumption time, discount proposal and the corresponded expected costs

The proposer faces a cost minimization problem that involves a decision whether to postpone consumption and, if so, to determine the amount of *g*, given the risk of the net loss, *s*. In the problem always exists a value of *g* that makes the cost at time (*t* + *Δt*) at most equal to the cost *c* at time *t*, and this assumption is realistic as risk averse proposers who prefer not to postpone consumption will propose a high value of *g* that will be rejected by the responder.

Thus, the proposer's expected cost as a function of the decision-making variable g, $C(g)$, is given by:

$$C(g) = \left[\theta(g)(1-\alpha)(c-g)\right] + \left[\theta(g)\alpha(c+s)\right] + \left[(1-\theta(g))c\right] \quad (3.1)$$

where the first term in the closed bracket represents the cost at time (t + Δt) diminished by the gain g given the responder acceptance of the proposal and the non-occurrence of the unforeseen event. The second term in the closed bracket represents the cost at time (t + Δt) given the responder acceptance of the proposal and the extra cost for the occurrence of the unforeseen event. The last term represents the cost at time t given the responder rejection of the proposal. The expression of the cost $C(g)$ may be rewritten to show the trade-off for the proposer between the incentive to demand a higher amount g in order to minimize the cost and the disincentive of a higher chance of rejection:

$$C(g)=\theta(g)\big[c-(1-\alpha)g+\alpha s\big]+\big(1-\theta(g)\big)c \qquad (3.2)$$

We assume for computational simplicity that (1- $\theta(g)$) has a uniform distribution with support *(0, b)*, where *b>0* is the maximum value that the proposer expects the responder to accept.

$$\theta(g)=\begin{cases} \dfrac{b-g}{b} & for \ \ g>0, b\neq 0 \\ 1 & for \ g\leq 0 \end{cases} \qquad (3.3)$$

The introduced UG framework (i.e., the higher the g, the higher the rejection of the proposal) may trigger aversion β of the discount proposal rejection, g, (and paying c). Thus, β and λ counteract each other. The proposer minimizes then the expected cost, c(g), given by

$$C(g)=\theta(g)\big[c-(1-\alpha)g+\alpha s\lambda\big]+\big(1-\theta(g)\big)c\beta$$

There exist at least three solutions for the value of g minimizing the expected cost depending on the framing of the choice problem and on the risk preference of the proposer: (i) a solution for a risk neutral proposer; (ii) a solution for a MLA proposer when the choice problem is presented without trying to lessen the MLA behavior; (iii) a solution for a MLA proposer when the choice problem is presented while trying to lessen the MLA behavior by framing the N decisions as aggregate.

For the **risk neutral proposer** ($\lambda = \beta = 1$), the expected cost function $C^n(g)$ (where the superscript n denotes risk neutrality) corresponds to

$$C^n(g) = \theta(g)\left[c - (1-\alpha)g + \alpha s\right] + (1 - \theta(g))c \quad (3.4)$$

The minimum amount, denoted by g^n, that a risk neutral proposer will propose is the amount that makes the expected cost $C^n(g)$ equal to the consumption cost, c, at time t, namely $g^n = s\alpha/(1-\alpha)$. Intuitively, g^n is independent of $\theta(g)$ but is dependent on the occurrence probability, α, of an unforeseen event. On the other hand, the expected cost minimizing value of g, denoted by g^{*n}, that a risk neutral proposer will propose is the amount that minimizes the expected cost function given in equation (3.4) and is given by[52]:

$$g^n = \frac{b}{2} + \frac{\alpha}{2(1-\alpha)}s \qquad (3.5)$$

Intuitively, g^n is higher for higher values of b that the proposer expects the responder to accept, and it increases with s due to unforeseen events, since higher values of g are required to compensate for higher expected

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[52] We are skipping the derivation and the second order condition since it is straightforward.

losses. It should be noted that the framing of the choice problem does not affect the choices of a risk-neutral responder.

For the MLA and rejection (of g) aversion proposer, the framing of the choice problem affects the amount g to be proposed. When the contract is presented without lessening the MLA behavior, i.e., the N decisions are presented as independent ones, the proposer weighs the expected loss, s, according to the degree λ of loss aversion and the expected cost of paying c by a degree β of aversion for the proposal rejection. The proposer minimizes then the expected cost, $C^m(g)$, given by

$$C^m(g) = \theta(g)\left[c - (1-\alpha)g + \alpha s\lambda\right] + (1 - \theta(g))c\beta \quad (3.6)$$

Minimization of equation (3.6) with respect to g and solving for g, denoted by g^m, gives:

$$g^m = \frac{b}{2} + \frac{1}{2(1-\alpha)}\left(\alpha s\lambda - c(\beta-1)\right) \quad (3.7)$$

There are worthy considering implications from the above result. First, for $\lambda=1$ and $\beta=1$, the cost-minimizing value converges to the value for the risk neutral proposer, i.e., $g^m = g^n$. Second, the degree of aversion towards rejection of the proposal discourages from proposing higher values of g. On the other hand, the degree λ of loss aversion increases g^m. It can be shown that g^m is either $g^m > g^n$ and is more likely to be rejected (by the responder) or is less $g*^m < g*^n$, overall resulting in at least as high expected cost of consumption as the risk-neutral proposer. Thus, β and λ counteracts each other on their effect on g^m inducing the proposer to reveal his true preference, which can be shown as:

$$\frac{dg^m}{d\lambda} = \frac{\alpha s}{2(1-\alpha)} > 0, \qquad \frac{dg^m}{d\beta} = -\frac{c}{2(1-\alpha)} < 0, \qquad \alpha \neq 1$$

(3.8)

where $\left|\dfrac{dg^m}{d\lambda}\right| > \left|\dfrac{dg^m}{d\beta}\right|$ for $as > c$, and vice versa.

An expected loss (αs) higher than cost c implies that g^m increases for increasing values of λ since loss aversion makes the postponement more expensive than the cost of rejection and hence drives the proposer towards a higher amount g to compensate higher expected losses. If ($as <$ c), then loss aversion with respect to s will be dominated by an aversion to rejection of the proposal. When $\alpha s = s$, the UG framework is expected to cancel out the loss aversion behavior that otherwise favors safer alternatives. The result is summarized as follows.

Hypothesis 1. *An MLA proposer proposes an amount g higher than the optimal value when ($\alpha s > c$) with the result being a higher probability of rejection of the proposal by the responder and, hence, a higher expected cost of consumption with respect to a risk neutral propose. Vice versa, an MLA proposer proposes an amount g lower than the optimal value when ($\alpha s < c$) with the result being a higher probability of acceptance of the proposal by the responder and, hence, a higher expected cost of consumption (due to the loss) with respect to a risk neutral propose.*

For the **MLA proposer with MLA lessening treatment**, the N decisions are presented as aggregate in the form of a long-term contract. The proposer minimizes then the cost function $C^t(g)$:

$$C^t(g) = \theta(g)\left[Nc + \sum_{v=0}^{N} \alpha^v (1-\alpha)^{N-v} \left(vs - (N-v)g \right)\gamma \right] + (1-\theta(g))Nc\beta$$

(3.9)

where γ corresponds to the degree λ of loss aversion if $(N-v)g - vs < 0$, and 1 otherwise. Equation (3.9) is obtained by following the probability rule. That is, out of N round, there is a chance with probability $(1-a)^N$ that unforeseen event will not occur at all and, hence, the expected cost will be Nc – Ng, there are N – 1 rounds with probability $a^1(1-\alpha)^{N-1}$ that there will be only one occurrence of unforeseen event and, hence, the expected cost will be Nc – (N – 1)g + s, and so on. If the proposal is rejected, then the expected cost is *Nc* multiplied by the psychological value to the rejection.

Solving for the cost minimizing value of g requires specific values for N and s. By taking example, however, we can observe that the effect of λ on g decreases with N. For example, for N = 2, the expected cost of proposing g amount, assuming that g > s, is given by

$$C^t(g) = 2\theta(g)\left[c - (1-\alpha)^2 g + \alpha^2 \lambda s + 2\alpha(1-\alpha)(s-g)\right] + 2(1-\theta(g))c\beta$$

After solving for the expected cost minimizing value, g^t, and computing comparative statics, we have

$$\frac{dg^t}{d\lambda} = \frac{s\alpha^2}{2(1-a^2)}, \quad \frac{dg^t}{d\beta} = -\frac{c}{2(1-\alpha^2)} < 0; \quad \alpha \neq 1 \tag{3.10}$$

And we can observe that

$$\frac{dg^t}{d\lambda} < \frac{dg^m}{d\lambda}, \quad \left|\frac{dg^t}{d\beta}\right| < \left|\frac{dg^m}{d\beta}\right|; \quad \alpha \neq 1,$$

where g^m is as given before in equation (3.8) when N =1. Thus, presenting the price discount in aggregates in terms of long-term contracts lessens both MLA behavior and the aversion to rejection of the

proposed amount behavior and, thus, behavioral hypothesis 2 follows.

Hypothesis 2. *Proposing N decisions as aggregate curtails MLA and aversion to proposal rejection behavior and implies higher gains g to the proposer with respect to the prospect of proposing N decisions as separate ones.*

Figure 2 summarizes the relationships between the amounts g proposed by the three proposers, i.e., the risk-neutral, MLA and MLA-treated, discussed above. The vertical axes represent the λ and β, and the horizontal axis presents g.
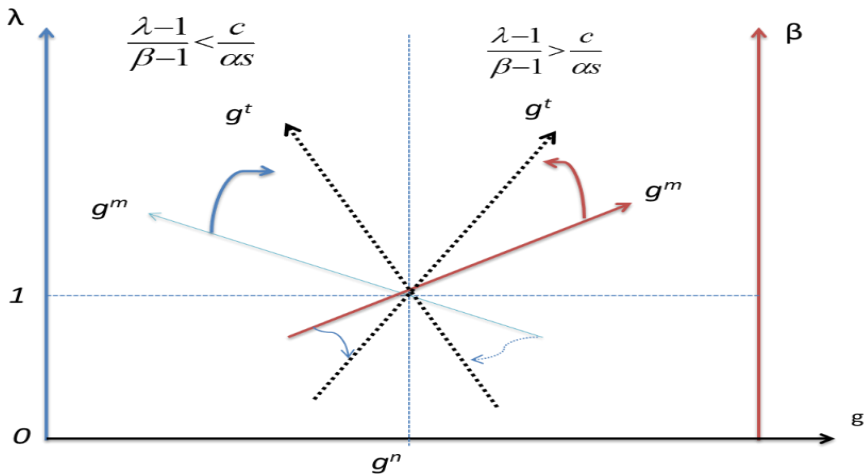
Figure 3.2.2. The role of lessening MLA under UG framework.

While a risk neutral proposer proposes an optimal amount g^n, an MLA proposer proposes an amounts g^m higher than g^n when $\alpha s > c$ and lower than g^n when $\alpha s < c$, and an MLA proposer with MLA lessening treatment proposes an amount g^t that is between g^n and g^m.

To sum up, we propose a model that may be of practical use in situations where there are gains from trade between two economic agents that occurs repeatedly and where the trade involves risk of loss to one of the agents. The UG framework, i.e., the threat of rejection of the proposal, discourages the proposer from claiming much higher shares of the gains from trade than the required amount to compensate expected losses that otherwise undermines the realization of the trade.

The model is also flexible in that it can be used to ask the maximum amount of risk that proposers are willing to take on to be eligible for a discount. For example, electricity suppliers could set c and g, as they usually do, and ask BEV users the maximum duration of time that they are willing to push recharging hours towards off-peak periods of electricity consumption to be eligible for a discount. The trade-off for the BEV users is between the incentive of deferring recharging for longer time towards the off-peak period to be eligible for the discount, and the disincentive of higher risk of not being able to use the BEV for unforeseen event in the cases that unforeseen trip (that requires recharging) occurs during the deferred period. The electricity supplier could then frame the contract in UG framework on long-term contract bases.

In the following section, we present results from a laboratory experiment with three treatments that we designed and conducted to test the claims of the results from the proposed model. In experiment 1, participants were asked to propose g for a given values of c, s and α, and where the distribution of θ is known to participants. In experiment 2, participants were presented the values of c, g and s and asked to propose (Δt) and, hence, α , to be eligible for the discount. A higher (Δt) implies a higher θ and higher α, creating the trade-off between both a higher acceptance probability of the proposed recharging time and the risk of losing s. In experiment 3, participants were asked to propose g for a given values of c and s to let the electricity supplier schedule recharging hour. However, unlike in Experiment 1, α is unknown in Experiment 3 so that the decision-making involves ambiguity.

3.3. Experimental Analysis

The main objective of the experiment is to investigate if enforcing long-term contracts curtail MLA behavior and a myopic-aversion to rejection behavior under the UG framework by inducing individuals to choose close to optimal risk level when compared with contracts designed without taking these behaviors in to account. The selection of an experimental economic setting is motivated by the aim of verifying the validity of the proposed behavioral model by isolating the effect of the treatment of interest (Falk and Heckman, 2009). A treatment group and a control group are defined to isolate the effect of the treatment while controlling for possible confounding factors that could influence the decision-making (Falk and Heckman, 2009). Arguably, the results from the experimental setting might be difficult to generalize to the general population (see, e.g., Levitt and List, 2007). However, there is no concern about the internal validity of the sample and about bias often prevalent in a field experiment because results tend to be associated with factors other than the treatment (see, e.g., Brookshire et al., 1987; Andersen et al., 2010; Camerer, 2011).

3.3.1. Experimental design

The experiment was conducted with the Z-tree statistical program (Fischbacher, 2007) at the Centre for Experimental Economics (CEE) of the University of Copenhagen under the standard laboratory economic settings for controlled experiments. The sample consisted of 147 individuals recruited within the CEE registered panel: the gender distribution was 57.8 % of men, age varied between 20 and 44 years old with mean age of 26.7 years old. Participants' mean self-reported income was 1430 USD, the employment distribution was between unemployed (21.1%), students (38.1%), students with also part-time job (29.9%), and employees (10.9%). The education level distribution had high percentages of Master (66.7%) and Bachelor (25.9%) degrees. The participants had previously participated in 2.8 experiments on average.

Participants were instructed to assume to be EV-owners with home BEV recharging availability. The treatment and control groups were given the same disposable income (110 tokens per day – per decision round) and the same mobility pattern in order to avoid biases from confounding factors. They were informed that the car battery empties every day at 6 pm when they return home from their daily activities, and requires recharging before the next planned trip the following day assumed to be at 9 am.

In the three experiments, participants faced the decision about whether to pay the amount c for recharging their BEV at time t (6 pm) and have it ready for unplanned trips, or to postpone recharging to time ($t+\Delta t)$ for a discount g. The UG was set up by allowing for the probability $\theta(g)$ that the supplier (represented by the computer) offers the discount g for postponing BEV recharging with reference to a threshold value. Participants were informed that, in the cases that the supplier agrees with postponing the BEV recharging, there is a probability, α, that an unplanned trip will occur before the recharging is completed and, hence, they will have to pay an extra cost, e, associated to the disutility of not travelling with their BEV at unforeseen trip occurrence time and experience a net loss s. Participants were also informed about general conditions: α does not depend on the amount g; α is not influenced by the supplier; daily earnings are independent; recharging days are independent and hence both θ and α do not depend from previous decisions of the same participant as well as decisions of other participants; decisions are taken individually with participants unaware of the decisions of their peers.

Each participant took part in one of six treatment conditions resulting from the combinations of the three decisions and the two contract durations (daily recharging decision for the control group and weekly recharging time decision for the treatment group), with completely randomized assignment to the treatments. In the daily contract duration, the participants performed 24 decisions representing 24 recharging days.

In the weekly contract duration, the participants performed only 3 decisions over the 24 recharging days (i.e., on days 1, 9 and 17) and each decision was valid for the next 8 recharging days. The two contract durations were deemed suitable to elicit myopic versus non-myopic behavior because habitually MLA is tested for 1-round versus 3-rounds (see, e.g., Hardin and Looney, 2012). It should be noted that alternative contract durations (e.g., daily versus monthly) is not expected to affect the sign of the results if not it strengthens as MLA testing is robust to different stakes and different return amounts (see, e.g., Camerer and Hogarth, 1999; Langer and Weber, 2005). Before starting the experiment, participants answered four control questions to make sure that they understand the decisions they are going to make, and clarifications were given to the small minority not answering correctly to these questions.

At the completion of the experiments, participants received cash corresponding to the tokens accumulated with their decisions. The cash payments removed the incentive compatibility bias associated to respondents not bearing the consequences of their choices in stated preference (SP) experiments (Wang et al., 2007). Participants were informed that the compensation would vary between 10 USD, representing a show up fee, and 87 USD, representing the total possible earnings from optimal choices: the actual earning varied between 17 and 51 USD with an average of 28 USD over an average duration of 50 minutes. Moreover, the cash payments at the end of the experiments removed the temporal discounting bias that might lead to choosing the immediate reward (Read, 2004).

3.3.2. Experiment 1: Acceptable discount for postponing the recharging time

3.3.2.1. Procedure

Experiment 1 was designed to test both Hypotheses 1 and 2 by asking participants to propose an amount g for given values of c, s, Δt and α, and a known distribution of $\theta(g)$. Recharging at peak hour t costed $c = 100$

tokens, which recalled the 99 Danish kroner charged by Clever A/S, one of the BEV recharging facility suppliers in Denmark. The cost c implied a default surplus, $s= 10$ tokens (i.e., the status qua gain from consumption), and it was risk-free because the supplier always accepts its maximum revenue and the EV-owner always charges the BEV upon arrival at home. Participants were asked to postpone recharging from 6 pm at which they arrive at home to 11 pm. The probability α of occurrence of an unplanned trip between he time period 6 pm and 11 pm is set at 66.67 % adopted from Thaler et al. (1997) in MLA inquiry that entails cost $e = g + s$, and hence a net loss of s = 10. Thus, for accepted proposals, participants have 33 % of saving the amount they proposed, g, and 66.67% chance of losing s = 10 tokens per round. A random number was drawn from a uniform distribution to simulate the acceptance or rejection of the proposed discount g. For accepted proposals, another random number, independent from the previous one, was drawn to simulate the occurrence (if lower than 0.6667) or the non-occurrence (if higher than 0.6667) of the unplanned trip. Accordingly, for accepted proposals participants had 33.33% probability of saving the amount g proposed and 66.67% probability of losing $s= 10$ for each day (decision round). This experiment was administered to two groups with daily and weekly contract conditions. The instructions used in the experiment are enclosed in the Appendix.

3.3.2.2. Results

Table 3.3.1 presents the results of the experiment in terms of average discount proposed as well as the share of risk-free choices and the corresponding cost savings for the two groups with daily and weekly contract. Overall, results show willingness to postpone the BEV recharging to 11 pm in exchange for a monetary gain while risking losses because of a 66.67% probability of occurrence of an unplanned trip before the BEV was recharged. Peak hour recharging was chosen only in 145 days (11.0% of the total recharging days), although guaranteeing a saving of 10 tokens and no risk of unplanned trip.

The results display a clear treatment effect. Except in the first-round decision, average proposals by the Weekly Group is closer to the optimal amount that a risk-neutral participant would take than the proposals by the control group (i.e., the daily Group). Compared to participants in weekly contracts, participants in daily contracts reflect "cautious player" behavior in choosing the risk-free option in a higher share of days and being risk averse to the possibility that the supplier might reject their proposal. Namely, participants tried to be eligible for discount by requesting lower amounts for postponing their recharging while assuming a 66.67% risk of an unplanned trip. The total average gain of the daily contract is 264.50 tokens, compared to 304.50 tokens for the weekly contract and 425.50 tokens for the risk-neutral proposer, suggesting a much larger extent of the myopia leading to sub-optimal decision.

To observe the significance of the differences, we use the non-parametric Mann-Whitney test. The fourth column reports z- values, which are a transformation of the Mann-Whitney U-value corrected for the presence of ties. The results indicate that the difference is statistically significant except on the very first decision round.

Table 3.3.1: Acceptable discount for postponing the recharging time to 11 pm

	Average discount requested in tokens (including the risk-free option)			Percentage of chosen risk free recharging days (i.e., recharging at 6 pm for a fee of 100 tokens) (%)		Money earned	
Decision round	Daily contract	Weekly Contract	Mann-Whitney test (z-value)	Daily contract	Weekly Contract	Daily contract	Weekly Contract
1-8	36.6	38.5	-0.130	9.3	17.9	10.2	12.2
9-16	34.6	39.7	-2.139**	17.6	0.0	10.7	13.2
17-24	34.7	41.0	-2.640***	18.1	3.6	12.2	13.9
all	35.3	39.7	-2.788***	15.0	7.1	11.1	13.1

*The symbols *, **, *** denotes 10 %, 5 % and 1 % level of significance.*

Figure 3.3.1 illustrates the effect of the MLA treatment as a comparison between the proposals of the two groups versus the optimal one.
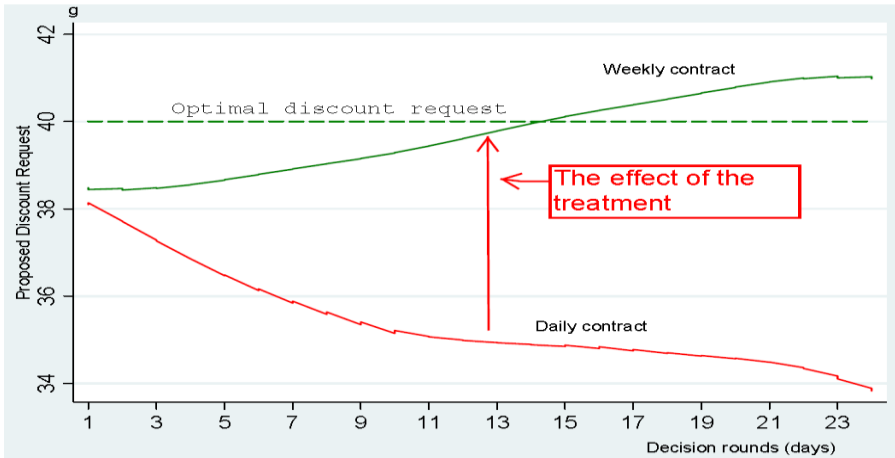
Figure 3.3.1. MLA treatment effect on the amount proposed to postpone the recharging time

Note. On the vertical y-axis is the proposed amount (g), the horizontal x-axis presents the decision rounds, the horizontal dotted line at g =40 denotes the cost-minimizing value that a risk-neutral participant would choose, the upward slopping 'weekly contract' line denotes the mean proposed value by the Weekly Group (the treatment group) and the remaining line denotes the mean proposed values over the 24 rounds of decisions by the daily Group (the control group). The difference between the two lines denotes the effect of the treatment.

The horizontal line at g = 40 denotes the cost minimizing value of the discount request, i.e., the proposal by a risk neutral individual. Framing the contract in long-terms bases has a visible effect on g, and the effect becomes stronger as both groups get experience. The participants in the daily group exhibited clear myopia behavior.

The effect of the treatment is clearly visible on Figure 3.3.1. Interestingly, the difference between participants in the daily and weekly contracts diverges as the participants get experience. While participants in the weekly contract gradually approximate the optimal value, g =40, participants from the daily contract myopically diverged away from it. Consistently with Hypothesis 1, participants were more averse to the

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rejection of proposals as (c >αs) and more myopic in decision-making while, consistently with Hypothesis 2, enforcing the treatment by presenting aggregate decisions lessened the myopic behavior. It should be noted that the participants in the weekly contracts had higher than optimal discount proposal in the last decision round, likely because of misjudgment of trends from the two previous decisions where they observed earnings increasing with the discount proposal increasing.

3.3.3. Experiment 2: Willingness to postpone the recharging time

3.3.3.1.   Procedure

Participants were requested to choose between recharging upon arrival at home at the peak hour t (6 pm) or postponing the recharging to off-peak hour (t + Δt). As in Experiment 1, each participant received 110 tokens per recharging day to save for himself /herself after paying costs associated with BEV recharging. They were informed that recharging at peak hour, t = 6 pm, costed c = 100 tokens, implies a default surplus equal to 10 tokens, and it is risk-free because the supplier always accepts its maximum revenue and the EV-owner never faces mobility constraints because of the BEV being charged upon arrival at home. Postponing the recharging to off-peak hour (t + Δt) earns a discount g =25 tokens regardless of the time Δt. Two contrasting risks are associated with the magnitude of Δt. First, the risk of the proposed recharging hour being rejected by the supplier when Δt is not far from the peak hour, t, where the further the proposed recharging hour from t, the higher is θ. Second, if Δt is accepted, there is the occurrence probability α of an unplanned trip existed, with α increasing linearly by 2% for every 15 minutes postponement. Occurrence of unplanned trip means they have to pay for tax that costs 35 tokens, meaning the risk of losing s = 10 tokens they could earn by recharging at 6 pm at free of risk. Participants were fully informed about the occurrence probability α of an unplanned trip prior to making the decision (the risk level is displayed on the computer screen along with the recharging time participants chose).

As in Experiment 1, random number was drawn from a uniform distribution to simulate the acceptance or rejection by the supplier. If the postponement of the recharging was accepted, another random number was drawn to simulate the occurrence of an unforeseen trip and compared with the level of risk they choose to accept. Unplanned trip occurs (does not occur) and the participant earns nothing (35 tokens) if the drawn number is less than α. Accordingly, the longer the participants postponed the recharging hour, the more likely they were going to obtain the discount g, but also the more likely they were incurring the extra cost e for the unforeseen trip. It should be noted that eq. (1) through (10) were expressed as a function of the decision variable Δt for the given g.

3.3.3.2. Results

Table 3.3.2 presents the results of the experiment in terms of average proposed recharging hours, the corresponding risk level that the proposers decided to take and the corresponding cost savings for the two groups with daily and weekly contract.

Overall, results illustrate willingness to postpone the BEV recharging in order to obtain the proposed discount of 25 % while risking losses because of a possible unplanned trip before the recharging was completed. Peak hour recharging, corresponding to a sure earning of 10 tokens and zero probability of an unplanned trip, was chosen only in 63 days (5.7% of the recharging days). Cost minimization disregarding myopia and the "cautious player" property (i.e., the risk neutral proposer) would lead to postponing the recharging to 10.30 pm, corresponding to a 36.0 % risk of an unplanned trip and a 36.0% supplier's acceptance

probability[53]. Participants tried to be eligible for discount by postponing BEV recharging to a later hour while assuming higher risk of an unplanned trip.

Compared to participants in weekly contracts, the participants in daily contracts showed myopia in taking higher risk aversion towards supplier rejection by both postponing more trips to off-peak hours and selecting later hours for BEV recharging.

Table 3.3.2. Postponing recharging time to be eligible for discount

	Average recharging hour including the risk-free option (Average accepted level of risk of an unplanned trip occurrence in parenthesis (in %))			Percentage of risk free choice (i.e., recharging at 6 pm for a fee of 100 tokens) (%)		Money earned	
Decision rounds	Daily contract	Weekly Contract	Mann-Whitney test (z-value)	Daily contract	Weekly Contract	Daily contract	Weekly Contract
1-8	11:42 pm (46.2)	10:07 pm (33.8)	6.452***	5.1	8.3	13.0	14.5
9-16	11:56 pm (47.5)	11:10 pm (41.4)	2.382**	1.7	8.3	13.0	14.0
17-24	11:54 pm (47.2)	11:32 pm (44.3)	0.456	1.7	8.3	11.7	11.7
all	11:50 pm (47.0)	10:56 pm (40.0)	Z=5.670***	3.0	8.3	12.5	13.3

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[53] The values c = 100, g =25, s = 35 − 25 =10 were inserted in the equations (3.4), and θ and α are as functions of Δt to solve for the cost minimizing time of recharging for redefined a risk neutral proposer. That is, C(g) is redefined as C(Δt) since time (of recharging) is a decision variable in this experiment.

The effect of the treatment is clearly visible in Table 3.3.2. Except in the last round (from 17 to 24), there is a statistically significant (by Mann-Whitney rank test) difference between the proposals of the two groups where the WG proposals were relatively close to optimal solutions.

We also present the difference in Figure 3.3.2. The dot and smooth curves are the proposal by the WG and the DG respectively while the horizontal dotted line at α = 36 % represents the optimal solution. The vertical axis presents the probability of unplanned trip occurrence and the acceptance probability of the proposed value (%), i.e., α that participants proposed to take on when they choose recharging time, and the horizontal axis presents the decision periods (days/rounds) that participants made.
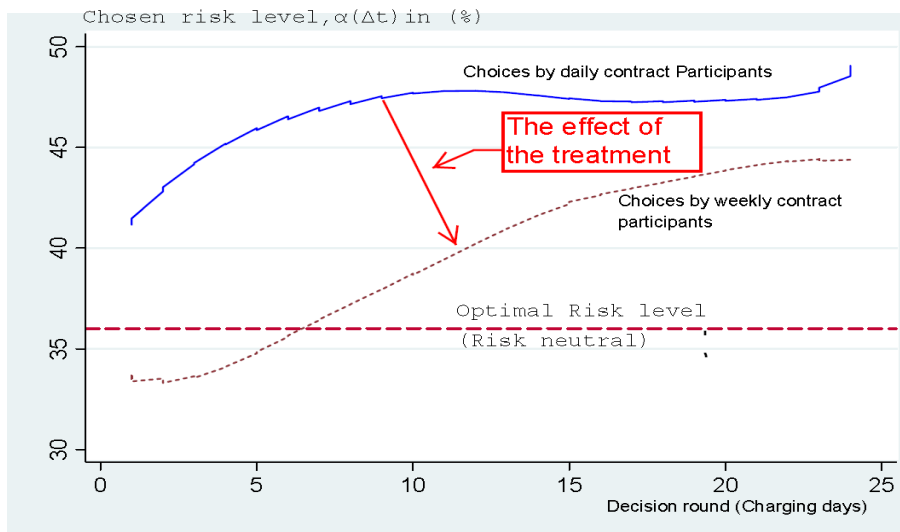

Figure 3.3.2. MLA treatment effect on the proposal of postponing the recharging time

Presenting recharging contract forms in terms of long term bases (weekly contract) lessens MLA behavior under UG framework, resulting in relatively close to optimal choice of time of recharging by participants who decided recharging time for a week than whose chose recharging time on daily bases

At least three notes worth considering on the Figure 3.3.2. First, Throughout the 24 rounds of decision, the proposed values by the WG participants are close to the optimal solution when compared with the proposals made by the DG participants indicating that the treatment of MLA behavior under UG framework helped participants to make better decision. Second, the DG participants where more averse to rejection of the proposals than to the risk of loss throughout the decision period whereas the WG were more averse to losses than to rejection of proposals in their very first decision, after which they showed more averseness to rejection of proposals than to losses. Third, the effect of the treatment decreases over repeated decisions as we can observe from the gradual convergence of the proposals by the WG towards the proposals by DG.

3.3.4. Experiment 3: Acceptable discount for supplier-controlled recharging

3.3.4.1. Procedure

Experiment 3 was designed to test Hypotheses 1 and 2 while having ambiguous decisions. Participants were requested to choose the amount *g* for given values of *c* and *s* upon agreeing to supplier-controlled recharging in which the supplier decides the recharging hour with the aim of optimizing the grid load. They were informed that the supplier could charge their vehicle at 6 pm, 11 pm, or 3 am, and that they could opt for recharging at peak hour *t* at the full cost *c* equal to 100 tokens and hence not experience any risk. Letting the supplier decide implied inconvenience due to the lack of behavioral control and ambiguity associated with the supplier-controlled recharging in that the participant did not know when the BEV will be ready for use (but the recharging is guaranteed for planned trips).

The second option of agreeing to supplier-controlled recharging bears two risks, namely the rejection of the proposal because the supplier considers it unprofitable and the risk of an unforeseen trip in the case that the amount g is accepted and the supplier schedules recharging hours at 3 pm or 11 pm. The acceptance probability of the amount g was set like in experiment 2. However, unlike the previous two experiments though, the magnitude of the probability α was unknown. Concerning α, they only know that α increases with postponement duration, and they do not have control over when to charge. Two random numbers were drawn independently from uniform distributions: the first to simulate the schedule time, and the second to simulate the occurrence of the unforeseen trip. Throughout the 24 rounds, they were not informed about the size of α, we simply informed them the scheduled recharging time and whether unplanned trip occurs. This experiment was administered to two groups with daily and weekly contract conditions.

3.3.4.2.   Results

Table 3.3.3 presents the results of the third experiment for the two contract conditions. Results illustrate the willingness to concede control to the supplier over the scheduling of BEV recharging in exchange for a monetary amount g and, hence, to agree not to know about the recharging hour and the probability of an unplanned trip. Peak hour recharging was chosen only in 60 days (5.4% of the total recharging days) regardless of the sure saving s of 10 tokens and the risk-free conditions. Practically, the participants were willing to wave their perceived behavioral control and deal with an ambiguous and ill-defined BEV recharging environment where the supplier has complete control over recharging time after guarantying timely recharging for planned trips. Interestingly, the share of risk-free recharging days was like the second experiment and lower than the first one, reflecting the possibility that the participants hypothesized the risk of an unplanned trip being lower than 50 %.

Table 3.3.3. Acceptable discount for supplier-controlled recharging

	Average discount requested			Percentage of chosen risk free recharging days		Money earned	
Decision round	Daily contract	Weekly Contract	Mann-Whitney test (z-value)	Daily contract	Weekly Contract	Daily contract	Weekly Contract
1-8	34.4	32.9	0.267	5.0	19.2	16.9	16.0
9-16	38.2	38.0	0.152	5.6	0.0	14.5	17.2
17-24	44.6	39.2	3.350***	2.0	0.0	19.4	15.1
All	39.1	36.7	2.141**	4.2	6.4	16.9	16.1

Note: The symbols *, ** & *** respectively denote 10 %, 5 % and 1 % level of significance.

Compared with the participants in weekly contracts, participants in daily contracts reflected higher "ambiguity aversion" in that they had a higher share of risk-free days in the decision-rounds from 9 to 24 and demanded higher amounts g for being willing to accept an ambiguous supplier-controlled recharging environment, and saved slightly more than the ones in weekly contract. It should be noted that presenting the decisions as aggregate in contexts where the participants are unaware of the risk level results in poor performance in comparison to contexts where the participants have a learning period about the risk level.

3.4.   Discussion and Conclusions

This study proposes a novel behavioral model representing utility maximization under MLA in the context of a two-player UG and presents an experimental economic application to validate the model. The application simulates EV-owners' recharging choice behavior for three stipulated decisions and two contract duration. The findings from the experiment show that framing decisions as aggregate and under UG framework contributes to lessening myopic behavior and implies higher recharging cost savings, except in the treatment where the risk of postponing recharging is ambiguous. Participants in the weekly contracts approximate cost minimization, while the myopia of the participants in the daily contracts leads to sub-optimal behavior from the EV-owner perspective.

While the primary objective of the three treatments we consider is to test the model prediction (i.e., lessening MLA under UG framework) under different scenarios, we believe that the proposed scenarios may also have practical application. The main point here is whether to merely announce time-of-use recharging fees (and to let the BEV users decide either postponing recharging for the discounted fee) or to present the discounted fees in long-term contract bases by inducing BEV users to reveal their true preference by framing the contracts under UG framework. Both the theoretical and experimental results favor the latter though there is a risk of less number of customers to choose not to postpone recharging time as we also saw in the result (the percentage of participants who chose to recharge at peak hours is higher in the weekly contract in Treatments 2 & 3). One solution for reducing the problem of getting less number of BEV users subscribing to the long-terms contract due to its less flexibility could be to allow for few exception days for the BEV users to recharging at any needy time.

Concerning the three contracts scenario, the first scenario in which the electricity supplier proposes the discounted recharging hours and the

BEV owners decide whether to postpone recharging is already in practice, except we consider the BEV drivers proposing the discount amount so that, at least in principle, all BEV drivers will participate in off-peak recharging. The electricity supplier can then select proposals that are not higher than its cost saving from smoothing electricity consumption. Its applicability could, however, be challenging since it is uncommon for consumers to propose prices and since price of energy is volatile in that BEV drivers may have to propose the discount amount regularly, which is tedious and time consuming.

The second scenario in that the electricity supplier asks BEV users to choose the recharging time to be eligible for the discounted fee seems more viable for application than the first scenario. The electricity supplier needs to announce the amount of the discount and the range of the period that makes eligible for the discount under the ultimatum game framework to induce BEV users to provide as long deferred recharging time as possible. Then, the supplier could provide the recharging service for selective number of BEV users depending on the electricity supply-demand balance at each point of time. For example, if electricity consumption begins to decline at 8 pm and continues decreasing until 6 am the following day, then the electricity supplier can start providing the recharging service for few of the BEV users starting from 8 pm, where the number of BEVs to be recharged continues increasing as demand falls. To do this, the supplier asks each BEV driver to postpone BEV recharging towards the late hours by stating that if the postponement is not long enough, the BEV user will not receive the discounted fee. Not specifying the time when the discount stars has advantage of reducing peak electricity consumption for recharging at the time the discount begins since, as discussed before, postponing further earns for BEV users nothing but the risk of unforeseen trip occurrence. The contract form enables the electricity supplier also to better predict the electricity demand at each point in time. The contract could be presented in long-term bases (with some flexibility) to reduce the MLA behavior in that BEV drivers; otherwise it could also be tedious for BEV users to daily think of

when to recharging, which could discourage them from participating at all. Its implementation would be straightforward in a future where EV-owners will access on-line management systems helping them in planning their recharging patterns taking their trip patterns and recharging fees in to account. This contract form has similarity with deadline differentiated pricing (Bitar and Xu, 2012) in that customers let the supplier know their deferred consumption period along with the deadline they need the product in return for discounted tariffs in that the supplier has flexibility to deliver the product.

The third scenario we consider is the supplier directly scheduling recharging hours is similar to "centralized control model" (see, e.g., Liu, C et al., 2012), except that we propose the BEV drivers to propose the discount amount. As the results revealed, presenting long terms contracts may not be effective in this case since the contract form does not let the BEV users know when their BEVs will be ready.

A word of caution is warranted for result interpretation as limitations to the study exist. Firstly, the experiment was conducted in a laboratory setting and the generalization of the results might be difficult even though a correspondence between laboratory   and field experiments has been verified for several similar experiments (Camerer, 2011). Secondly, the experiment controlled for incentive compatibility and temporal discounting biases, but the laboratory conditions might not reflect the actual electricity costs and mobility needs. Thirdly, the experiment was conducted with participants without prior experience as BEV-owners or users. However, the results have internal validity as the sample did not confound for experience and hence the MLA behavior emerges from an unbiased treatment. Lastly, the decisions in the experiment were taken individually and the participants were unaware of the decisions of their peers, while in reality word-of-mouth is a powerful market force. Accordingly, the results should be viewed as an indicative or diagnostic tool rather than a statistical analysis of the prevalence of the identified themes across the population of potential BEV-owners.

Bearing these limitations in mind, this study provides valuable insights for decision-makers and planners in the transportation and energy fields and these insights may be integrated into future agent-based and optimization models relying on more realistic behavioral rules representing BEV-owners' recharging behavior. A future research development could design a field experiment able to evaluate the contract framing effect via the observation of BEV-owners' behavior in terms of mobility and recharging patterns, while isolating the effect itself from the other factors playing a role in these patterns.

Acknowledgments

Appendix 2. Experimental Instructions

<u>Common instruction for all participants</u>

Welcome to this experiment about intelligent recharging of electric vehicles. The experiment will take about 1 hour and you will earn 50 DKK show up fee plus an additional sum that depends on your decisions in the experiment.

Assume that you use an electric car with a battery recharging option at home. The battery becomes empty at 6 pm when you are back from work/school. The next planned trip to work/school is at 9 am. Recharging the battery takes two hours, and, therefore, the battery can be charged between 6 pm and 7 am to make the car ready for the planned trip.

The electricity price depends on the hour in which you begin to charge. Postponing the time of recharging will give you a discount. However, there is a probability that you will have unplanned necessary trips before the car is charged. If such trips occur, you will pay taxi fee.

There are 24 recharging days in total and you are given 2640 points as endowment, i.e., 110 points per day, to pay for recharging the car and to earning the remaining money for yourself. The conversion rate is that 3 points = 1 Danish kroner (DKK). So, your earning from the experiment is

Earning= (2640 - Fees)*1/3 + 50 DKK,

where 'Fees' are the costs associated with recharging the car.

The points you saved will be converted to DKK and paid to you in cash immediately after the experiment. Your earnings from a day of recharging will not be affected by outcomes from other days of recharging. Your outcomes are also independent of the decisions of other participants in the experiment.

    i.   Experiment I Instruction: Request for Discount amount
    a) Only for the Control Group (Daily Contract)

There are 24 recharging days in total, and every day you can decide at which hour to charge your car. Recharging the car at 6 pm costs 100 points and thus, you will earn 110 - 100 = 10 points per day for making the decision.

The electricity supplier asks you to postpone the recharging time to 11 pm for a discount. You can decide the discount that you are willing to accept for postponing the recharging hour to 11 pm. However, the electricity supplier sets a random maximum value to be eligible for a discount. If you decided for a discount for postponing the recharging hour that is lower or equal to the supplier's threshold, you will get the discount.

If you do not postpone the time of recharging or if you decided for a discount for postponing the recharging hour that is greater than the supplier's threshold, you will not get the discount and you will pay 100 points per day and save 10 points per day.

If you get the discount after postponing the recharging hour from 6 pm to 11 pm, you will have a 66.67% probability of an unplanned trip to occur before the car is charged. If an unplanned trip occurs, you will pay a taxi fee equal to 110 - X, where X is the discount you decided. Thus, your earning on the day will be zero and you will loss the 10 points you could save by recharging at 6 pm. If an unplanned trip does not occur, you will get the amount X of discount you decide plus 10 points per recharging day.

The occurrence probability of an unplanned trip is always 66.67%. Every day, the computer randomly draws a number between 0 and 100, and the unplanned trip will occur if this drawn number is lower than 66.67%.

The occurrence probability of an unplanned trip does not depend on the electricity supplier, on the size of your discount bid, or on the decisions of other participants.

b) Only for the Treatment group (Weekly contract)

There are 24 recharging days in total, and you will make 3 decisions on days 1, 9 and 17 about the hour you begin to charge for 24 days, so that

each decision will be effective for 8 days. Recharging the car at 6 pm costs 100 points and thus, you will earn 110 - 100 = 10 points per day for making the decision.

The electricity supplier asks you to postpone the recharging time to 11 pm for a discount. You can decide the discount that you are willing to accept for postponing the recharging hour to 11 pm. However, the electricity supplier sets a random maximum value to be eligible for a discount. If you decided for a discount for postponing the recharging hour that is lower or equal to the supplier's threshold, you will get the discount for 8 consecutive days.

If you do not postpone the time of recharging or if you decided for a discount for postponing the recharging hour that is greater than the supplier's threshold, you will not get the discount and you will pay 100 points per day for 8 consecutive days.

If you get the discount after postponing the recharging hour from 6 pm to 11 pm, you will have a 66.67% probability of an unplanned trip to occur before the car is charged. If an unplanned trip occurs, you will pay a taxi fee equal to 110 - X, where X is the discount you decided. Thus, your earning on the day will be zero and you will loss the 10 points you could save by recharging at 6 pm. If an unplanned trip does not occur, you will get the amount X of discount you decide plus 10 points per recharging day.

The occurrence probability of an unplanned trip is always 66.67%. Every day, the computer randomly draws a number between 0 and 100, and the unplanned trip will occur if this drawn number is lower than 66.67%.

The occurrence probability of an unplanned trip does not depend on the electricity supplier, the size of your discount bid, or the decisions of other participants.

ii.   Experiment II instruction: Choosing the recharging time
a)   Only for the Control Group (Daily Contract)

There are 24 recharging days in total, and every day you can decide at which hour to charge your car. Recharging the car at 6 pm costs 100 points and thus, you will earn 110 - 100 = 10 points per day for making the decision.

The electricity supplier asks you to postpone recharging time for a discount fee. If you postpone the time of recharging to a later hour, you can get 25 points discount (i.e., you pay 75 points) and you will earn 110 - 75 = 35 points per day. However, the discount is available only in certain hours randomly selected by the electricity supplier. If you postpone the time of recharging after the supplier's threshold, you will get the discount. If you do not postpone the time of recharging or you postpone it earlier than the supplier's threshold, you will pay 100 points and save 10 points per day.

If you get the discount, you will earn 35 points per day only if there is no unplanned trip. However, an unplanned trip can occur before the car is charged, and you will pay 35 points for a taxi, and thus, you will loss the 10 points you could save by recharging at 6 pm.

The occurrence probability (out of 100 cases) of an unplanned trip depends on the recharging hour. A probability Y indicates that there is Y % chance of an unplanned trip to occur. For example, if you choose to charge at hour X where there is Y % chance of an unplanned trip to occur, then an unplanned trip will occur if the randomly drawn number is lower than Y. Every day, the computer randomly draws a number between 0 and 100, and the unplanned trip will occur if this drawn number is lower than the risk you choose to take.

The longer you postpone the recharging hour, the more likely you will get the discount, but also the higher is the chance of an unplanned trip to occur.

b) Only for the Treatment group (Weekly Contract)

There are 24 recharging days in total, and you will make 3 decisions on days 1, 9 and 17 about the hour you begin to charge for 24 days, so that each decision will be effective for 8 days. Recharging the car at 6 pm costs 100 points and thus, you will earn 110 - 100 = 10 points per day for making the decision.

The electricity supplier asks you to postpone recharging time for a discount fee. If you postpone the recharging time to a later hour, you can get 25 points discount (i.e., you pay 75 points) and you will earn 110 - 75 = 35 points per day. However, the discount is available only in certain hours randomly selected by the electricity supplier. If you postpone the time of recharging after the supplier's threshold, you will get the discount for 8 consecutive days.

If you do not postpone the time of recharging or you postpone it earlier than the supplier's threshold, you will pay 100 points for 8 consecutive days and save only 10 points per day. For example, if you postpone recharging time to an hour earlier than the supplier's threshold on day 1, you will not get the discount for days 1 to 8 and you will pay 100 points per day.

If you get the discount, you earn a potential 35 points per day only if there is no unplanned trip. However, an unplanned trip can occur before the car is charged, and you will pay 35 points for a taxi, and thus, you will loss the 10 points you could save by recharging at 6 pm.

The occurrence probability (out of 100 cases) of an unplanned trip depends on the recharging hour. A probability Y indicates that there is Y % chance of an unplanned trip to occur. For example, if you choose to charge at hour X where there is Y % chance of an unplanned trip to occur, then an unplanned trip will occur if the randomly drawn number is lower than Y. Every day, the computer randomly draws a number between 0 and 100, and the unplanned trip will occur if this drawn number is lower than the risk you choose to take.

The longer you postpone the recharging hour, the more likely you will get the discount, but also the higher is the chance of an unplanned trip to occur.

     iii.   Experiment III instruction: Letting the supplier control recharging hours
    a) Only for the Control Group (Daily Contract)

There are 24 recharging days in total, and every day you can decide at which hour to charge your car. Recharging the car at 6 pm costs 100 points and thus, you will earn 110 - 100 = 10 points per day for making the decision.

The electricity supplier offers a discount if you are willing to allow the supplier to set the recharging hour for you on a daily basis. The supplier could set the recharging hour at 6 pm, 11 pm, or 3 am, and will notify you the selected. You can decide the discount that you are willing to accept for the supplier to set your recharging hour.

However, the electricity supplier sets a random maximum value to be eligible for a discount. If you decide for a discount for letting the supplier schedule your recharging hour that is lower or equal to the supplier's threshold, you will get the discount. If you do not postpone the time of recharging or if you decided for a discount for letting the supplier schedule your recharging hour that is greater than the supplier's threshold, you will not get the discount and you will pay 100 points and save 10 points per day.

If the supplier accepts your discount bid and postpones your recharging hour to 11 pm or 3 am, there will be a probability of an unplanned trip to occur before the car is charged. If an unplanned trip occurs, you will pay a taxi fee equal to 110 - X, where X is the discount you decided. Thus, your earning on the day will be zero, and you will loss the 10 points you could save by recharging at 6 pm. If an unplanned trip does not occur, you will get the amount X of discount you decide plus 10 points per recharging day.

The occurrence probability of an unplanned trip depends on the recharging hour (i.e., the later the recharging hour, the more likely an unplanned trip to occur). Every day, after your recharging hour is scheduled, the computer will assign to you a number that depends on the hour you are scheduled to charge. Then, the computer randomly draws a number between 0 and 100, and the unplanned trip will occur if this drawn number is lower than the number assigned to you.

However, you will not know prior to your decision neither the hour scheduled by the supplier, nor the occurrence probability of an unplanned trip at 11 pm and at 3 am. The occurrence probability of an unplanned trip does not depend on the electricity supplier, on the size of your discount bid, or on the decisions of other participants.

b) Only for the Treatment Group (Weekly Contract)

There are 24 recharging days in total, and you will make 3 decisions on days 1, 9, 17 about the hour you begin to charge for 24 days, so that each decision will be effective for 8 days. Recharging the car at 6 pm costs 100 points and thus, you will earn 110 - 100 = 10 points per day for making the decision.

The electricity supplier offers a discount if you are willing to allow the supplier to set the recharging hour for you on a daily basis. The supplier could set the recharging hour at 6 pm, 11 pm, or 3 am, and will notify you the selected hour. You can decide the discount that you are willing to accept for the supplier to set your recharging hour.

However, the electricity supplier sets a random maximum value to be eligible for a discount. If you decided for a discount for letting the supplier schedule your recharging hour that is lower than or equal to the supplier's threshold, you will get the discount for 8 consecutive days. If you do not postpone the time of recharging or if you decided for a discount for letting the supplier schedule your recharging hour that is greater than the supplier's threshold, you will not get the discount and you will pay 100 points per day for 8 consecutive days and save only 10 points per day.

If the supplier accepts your discount bid and postpones your recharging hour to 11 pm or 3 am, there will be a probability of an unplanned trip to occur before the car is charged. If an unplanned trip occurs, you will pay a taxi fee equal to 110 - X, where X is the discount you decided. Thus, your earning on the day will be zero, and you will loss the 10 points you could save by recharging at 6 pm. If an unplanned trip does not occur, you will get the amount X of discount you decide plus 10 points per recharging day.

The occurrence probability of an unplanned trip depends on the recharging hour (i.e., the later the recharging hour, the more likely an unplanned trip to occur). Every day, after your recharging hour is scheduled, the computer will assign to you a number that depends on the hour you are scheduled to charge. Then, the computer randomly draws a number between 0 and 100, and the unplanned trip will occur if this drawn number is lower than the number assigned to you.

However, you will not know prior to your decision neither the hour scheduled by the supplier, nor the occurrence probability of an unplanned trip at 11 pm and at 3 am. The occurrence probability of an unplanned trip does not depend on the electricity supplier, on the size of your discount bid, or on the decisions of other participants.

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4. Using the Peer Effect in Scheduling and Pricing of Electric Vehicles Recharging: Laboratory Evidence about Peer Effect in Risk-Taking

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Abstract

This study investigates peer effect in risk-taking when observing the choices of peers does not convey new information and when there is no payoff commonality. We investigate whether individuals want to see the choices of others, if observing peers' choices influences own choices and who (in terms of self-confidence and analytical ability) are being influenced by peers' choices as well as the role the type of peer information plays on peer effects. We run a laboratory experiment tailoring peer information in five treatments. The result shows that most of the participants, 79 %, chose to see peers' choices. We find peer effects in risk-taking in that about 28 % of the participants changed their intrinsic choices after observing the choices of peers. Overall of the 10 rounds of decisions, in about 12 % of the total decisions that the participants made, they changed their initial choices towards the observed peers' choices every time they observed peers' choices while about 21 % of the participants chose even not to see the choices of peers. Interestingly, about 79 % of the participants who were frequently influenced by peers' choices were those who scored less than the mean score in the session in our math test and who were lacking self-confidence. The results reveal also that the type of peer information plays a significant role in peer effects. Thus, the use of peer effect in inducing individuals to choose one action or the other may depend largely on the analytical ability of the target population and on self-confidence that the individuals have on their analytical ability relatively to the analytical ability of the peer.

Key words: Peer effect, risk-taking, peer type, analytical ability.

JEL Classification: C91. C92. D03. D81. D83. Q49

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4.1. Introduction

Individuals may change behavior and their choices when they observe the actions and choices of others (Bernheim and Exley, 2015; Festinger, 1954). Some individuals need a reference for their action to reduce the distaste from not acting according to the established norm (Akerlof, 1997; Jones, 1984). They may also adjust their behavior and choices to socialize with others and to avoid direct or indirect social sanctions (Akerlof, 1997; Kremer and Levy, 2008; Noussair and Tucker, 2005). Peers' choices sometimes convey (perceived or real) new information about the choice alternatives that help individuals to update their beliefs (Bikhchandani et al., 1992; Ellison and Fudenberg, 1995; Eyster and Rabin, 2014). Joining others may also provide social utility and social learning (Bursztyn et al., 2014) and even may involve payoff complementarity (Fu, 2004; Hurkens and López, 2014). Lack of self-confidence and low analytical ability in decision-making contribute also for people to seek reference for their decisions, to imitate the choices of others and to change behavior when they observe the choices and behavior of others (Eyster and Rabin, 2014; Offerman and Schotter, 2009).

Insights into the effects of peer information on choice and on behavior can be used to guide individuals to take one choice or another (Hoff and Stiglitz, 2016). The peer effects play significant and lasting role in societies political, socio-economic and demographic aspects (Akerlof, 1997; Bardhan and Udry, 1999; Ellison and Fudenberg, 1995; Hoff and Stiglitz, 2016; Jones, 1984).[54]

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[54] Peer effects have been documented in various activities including labor productivity (Falk and Ichino, 2006; Jones, 1984), brand of products choice (Bearden and Etzel, 1982; Childers et al., 1992), recreational site choice (Olaussen, 2009; Stephen M. and Ditton, 1992), household energy consumption (Allcott, 2011; Schultz et al., 2007), public good contribution and donation (Bernheim and Exley, 2015; Chen et al., 2010; Zafar, 2011), financial investments (Bursztyn et al., 2014; Hong et al., 2005), criminal and unhealthy activities (Carrell et al., 2008; Clark and Lohéac, 2007; Duncan et al., 2005; Gaviria and

This study aims to shed light on whether and how peer effect may be used for policy-making in areas involving uncertainty in general and, in particular, about smooth integration of electric vehicles (EVs) in to the grid system. Sensitivity of the driving range of BEVs to the driving environment[55] and the long recharging time of the relatively affordable BEVs induce uncertainty and anxiety about whether the available battery power is enough to cover both foreseen and unforeseen trips. This driving range uncertainty, added with the low price elasticity of fuel demand (Lin and Prince, 2013), may make discount recharging tariffs for postponing recharging towards off-peak electricity consumption hours less attractive. This will have alarming effect on the electricity grid system by increasing grid overload that could result in inefficiency and pollution, since peak electricity consumption hours usually coincide with the default recharging time. By providing for the current BEV users attractive incentives and tips that helps to reduce the psychological barrier of postponing recharging and then, by sharing the charging experience and cost of these customers to upcoming customers, electricity suppliers may induce smart integration of BEVs. For example, BEV users may consider postponing recharging if they find that they are paying higher cost than their peers while having similar BEV and not driving longer daily trips than their peers. Of course, the contract should not affect mobility; it should rather aim at reducing the psychological driving range anxiety. However, it is important to investigate how pervasive is the peer effect, who in terms of behavior are influenced by peers and how to present peers' choices that this study aims at giving insight.

We design a laboratory experiment mimicking the real-world situation where BEV users may tradeoff between the cost saving from postponing recharging towards off-peak electricity consumption hours, assumed to

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Raphael, 2001), in transport (Arentze and Timmermans, 2008; Axhausen, 2008; Belgiawan et al., 2013; Den Braven et al., 2012; Dugundji et al., 2008; Ettema et al., 2011; Kim et al., 2014), on strategic games (Georg, 2008) and so on.

[55] Fetene et al. (2016) find as large as 65 % of BEV energy consumption difference between summer and winter.

be between 21:00 and 6:00, and the risk of the current battery power not being enough for unforeseen trip occurrence. We asked participants to choose the amount of kilometers to buy electricity for BEV recharging for unforeseen trips. The distance of the unforeseen trip, D, that they were informed to occur before 21:00 was assumed to be uniformly distributed between 0 and 60 km. The participants were informed that the electricity tariff that is needed to drive one km distance costs *10 cents* for recharging the BEV before 21:00 and costs zero after 21:00. On the other hand, not buying enough electricity costs *15 cents* for using taxi for each unit of travel distance that the amount of electricity they chose to buy falls short of D. They were informed to assume that the battery power currently available in the BEV is enough only for planned trips. Thus, recharging both less and more than the amount required to cover the posterior travel distance is costly. (The detailed instruction provided to the participants can be referred in Experimental Instructions).

The standard economic theory prediction in this case is that individuals will make choices according to their risk preference without being influenced by peers' choices. This is so because observing peers' choices does not convey new information as the electricity tariff and the distribution of the unforeseen trip distance are common knowledge. Recent field and laboratory studies find, however, that the choices of individuals are affected by peers' choices even when the peers' choices do not convey new information and when there is no payoff commonality (see, e.g., Cooper and Rege, 2011; Chung et al., 2015; Gioia, 2016). The desire for reducing social regret in case individuals earn lower posterior payoffs than the peers' earnings (Cooper and Rege, 2011), relative income concern and conformity preference (Lahno and Serra-Garcia, 2015) are attributed for the observed peer effects.

We start by first asking an open question in the literature about whether individuals choose to see the choices of others at all. Two counteracting explanations could be provided for (not) choosing to see the choices of others. On the one hand, some may choose to see peers' choices to have a reference against which they can evaluate their choices and they could correct any errors they may have done. Others may not know the best choice for themselves in that they seek the choices of others to make better choices. On the other hand, individuals with strong intrinsic

preference and having self-confidence on their choices may not choose to see peers' choices to avoid the distaste in cases if they become unlucky while the peers with perceived inferior choice may become lucky. Other individuals may consider peers' choice information as spam since seeing the choices of others does not convey new information. Provision of peers' choice information without asking for their consent may annoy the latter types of individuals, and it may even result in boomerang effect when the peers information is shared between individuals with different social status, e.g., income (Beshears et al., 2015). Thus, asking for individuals consent whether they want to receive peers' choice information could be better than providing the information without asking for their consent.

We next examine whether those who choose to see peers' choices actually use the peer information to revise their intrinsic choices, i.e., if the peer effect exists. The important question here is how large the percentage of individuals is using the peer information, which may help to examine how prevalent is the pure peer effect to worthy consideration in wide policy-making and which is usually overlooked in the literature. Related to this, we investigate whether the analytical ability for the problem at hand and self-confidence are attributed for peer effect.

We then investigate whether and to what extent (with reference to intrinsic choice) individuals adjust their intrinsic choices towards the choice of others. For example, how individuals do react to two levels of peer information that vary in magnitude with reference to their intrinsic choices? That is, do they continuously adjust their choice towards the choices of peers if own intrinsic choices differ from that of peers' or is there a threshold level beyond which peer effects declines or even disappear perhaps because they are viewed as too costly to conform or as 'noise'? Knowing the extent individuals adjust their choices towards the choices of peers is relevant to be selective to the types of peers' choices information to provide to individuals to direct their choices and behavior.

To investigate this, we conducted two treatments. In the first treatment, called the *Nonrandom-peer* treatment, the most risk-averse and the most risk-seeker (with reference to the median choice) received each other's choice, the second most risk-averse and the second most risk-seeker

received each other's choice, etc. until the last two individuals with the closest choices from each side of the median choice were shown each other's choice. In the second treatment, called the *Population-as-a-peer* treatment, each participant received the mean of the choices of all participants excluding own choice. However, the mean choice was presented as if it is a choice of a randomly matched peer. If individuals imitate peers' choices, then the *Population-as-a-peer* treatment results in strong peer effect and the sample choices will have lower diversion (or even zero standard deviation in the case of complete imitation) than the Nonrandom-peer treatment, which results in a mere exchange of choices between paired participants. The implication would be that the choices of individuals can be diverted towards the intended outcome by selectively providing peers' choices that is equivalent to the target level of choice. On the other hand, if individuals only partially and monotonically reduce their choice difference from the peers' choice, then the Nonrandom-peer treatment may result in a stronger peer effect than the other treatment. We also conducted a third treatment, called the *Two-peer* treatment, which is similar to the Nonrandom-peer treatment except participants in the *Two-peer* treatment received the choices of two peers instead of a peer. We expect a higher peer effect in the *Two-peer* treatment than in the Nonrandom-peer treatment since seeing the choices of two peers may induce more participants who are around the margin in terms of self-confidence when they observe the choice of a peer.

Finally, we investigate if the types of peers play a role in peer effect. For this, we conduct a fourth treatment, called the *Population* treatment, in that participants received the same information as the participants in the *Population-as-a-peer* treatment, but by framing differently as 'the mean choice of all participants excluding your choice'. The difference between the two treatments is only the framing of the peer information either as 'the mean choice of all participants' or 'the choice of a peer'. Thus, any difference between the two treatments is attributed to whether participants valued the 'population representative' and 'a peer' information differently. For example, while individuals lacking self-confidence will be almost equally influenced by the two types of peer choice information, individual with marginally higher self-confidence than those influenced by peers' choices may be influenced more by the average choice of all participants than by a peers' choice.

The last treatment we have is a *Random-peer* treatment in that we match participants randomly. This treatment helps to examine whether tailoring of the peer information instead of matching randomly plays a role in the peer effect. Finally, we have a control group who made decisions without receiving peer information that we use it to investigate the overall peer effect. We run the experiment with 215 participants, and each participant made 10 rounds of decisions of the same type.

We find that about 79 % of the participants chose to see others' choices, where the figure drops to 58 % in the fourth round. In terms of using the peer information, about 28 % of the participants changed their intrinsic choices in the first round after observing the choices of peers, where the percentage drops to the lowest, 6.4 %, in the seventh round and to about 12 % overall. Interestingly, most of the participants, 79 %, who persistently changed their initial choices whenever observing peers' choices were among participants who scored less than the median score of the participants. Looking at the factors that may induce the peer effects, we find a statistically significant inverse effect of level of education, analytical ability, self-confidence and experience. Thus, though the peer effect exists, it affects a moderate percentage of individuals who lack self-confidence and/or with relatively lower ability, implying that social learning is the main reason for peer effect.

The peer effect observed in 12 % of the decisions increased the overall risk-taking by more than 1.6 units on average and reduced the overall standard deviation by about one unit when compared with the control group participants who did not observe peers' choices. While 51 % of the participants increased risk-taking by, on average, 10 units, about 49 % of the participants reduced risk-taking by, on average, 12.3 units after observing peers' choice. We find limited imitation, only about 10 % of the overall 12 % peer effects that we observed and was mostly by participants with relatively lower math scores (88.9 %) or by participants lacking self-confidence (72.2 %). In the remaining 90 % of the revisions that the participants made after seeing peers' choices, they traded off between their intrinsic choices and conforming the choice of the peers, and they reduced each unit own choice difference from the peer's choice by about 0.65 units, on average. A random effects Poisson regression shows that the peer's choice difference from the intrinsic choice has a

non-linear effect on the amount of intrinsic choice that participants substitute for conforming the peers' choice.

Concerning the type of peer information role in peer effects, we find a higher mean risk-taking (in the direction of the risk-neutral choice) in the *Population* treatment than in the Population-as-a-peer treatment. The choices by the participants in the *Population* treatment is statistically different from that of the control group while we do not find a statistically significant difference between the choices by Population-as-a-peer treatment and by the control group. This may indicate that providing the choices of well-trusted peers plays a significant peer effect even though the choices of peers do not convey new information. We also find a clear difference between the Nonrandom-peer treatment and the Population-as-a-peer treatment. Risk-taking was higher and the diversion within the treatment was lower in the Nonrandom-peer treatment than in the population-as-a-peer treatment.

Organization of the remaining sections of the paper is as follows. Section 4.2 presents a brief review of the related literature. A simple theoretical model of analytical under risk in the presence of the choices of peers is presented in section 4.3 to substantiate the experiment and to better understand the peer effects when peer information does not convey new information and nor there is any means of the choices of peers having effect on the outcome of the decision-maker. Section 4.4 presents the experimental design. The results from the study are presented in section 4.5 while section 4.6 concludes the paper along with discussion of the results.

4.2. Related literature

Our paper contributes most directly to previous studies about peer effect in general and, in particular, to studies about peer effect in risk-taking when there is no social utility and when accessibility of the choices of peers does not convey new information related to the decision-making problem. There have been emerging studies from controlled laboratory, field and neuroscience experiments that mainly focus on disentangling the causes for peer effects in risky decisions in the presence of complete information in the sense that the peer choice information does not convey new information.

Gioia (2016) investigated the role group identity plays on peer effect in risk-taking when there is no payoff commonality and when peers' choice does not convey new information. By matching participants in groups of three through different matching protocols (randomly, allowing interaction by exchanging text messages and based on their painting preference), she find that participants took risker (safer) decisions when both of the two peers in the group made riskier (safer) decisions. She also finds that observing the choice of a peer with similar identity, painting preference, increases the magnitude of the peer effects.

Using neuroscience controlled laboratory experiment, functional neuroimaging, participants chose between paired lotteries after observing the choices of two peers, Chung et al. (2015) find that participants chose safer (risker) lotteries when both of the peers in the group chose safer (risker) lotteries, but not when the choices of the two peers were mixed (one risker and one safer). They also find that the peer effects diminish as the difference between risk-taking preferences of the pairs gets larger. That is, risk-averse (risk-seeking) individuals conform more of risk-averse (risk-seeking) peers than they do to a risk-seeking (risk-averse) peers.

Similarly, Lahno and Serra-Garcia (2015) find peer effects in risk-taking using controlled laboratory experiment in a panel of repeated lottery choices where they disentangle the peer effects as relative payoff concern (envy) and conformity preference. In one of their treatments, the 'Random treatment', the participants were informed that the peers

choices were randomly assigned and in other treatment, the 'Choice treatment', the peers chose the lottery. They find about 15 % more switches between two lotteries towards the choices of peers in the 'Choice treatment' than in the 'Random treatment'. This result is comparable with our result in that we find peer influences in the 12 % of the decisions that participants made. They also find that imitation is more frequent in the direction of safer options. Unlike other related studies, the payoffs of the participants in the Lahno and Serra-Garcia (2015) study were correlated in that a single random draw determined the payoffs of both the observer and the peer.

Similarly, in a series of lottery choices under risk and ambiguity, Cooper and Rege (2011) find that the likelihood of switching gambles towards the group members' choices increased by 15 % when the lagged choice of the majority of the (six) group members' disagreed with the individual's lagged choice. They attribute the causes for the peer effects as the 'social regret' preference in that the regret of losing being less intense when being one of the losers than when being the only loser inducing participants to follow the group choice.

Bougheas et al. (2013) find a lower variability among decisions taken by participants who consulted each other of the three group members they were randomly assigned to when compared with the decisions taken in isolation. They do not, however, find average risk-taking difference between the treated and the untreated groups of participants. Another interesting result they find is that average risk-taking was higher with the mentioning of the expected value during the group discussion in one of the treatments where participants within a group had to make identical decision with payoff commonality, which could give clue about the type of individuals having influence in group decision-making.

Another notable example is a field experiment by Bursztyn et al. (2014) involving a large stake investment in a risky asset in that they disentangle the peer effect in to social learning (i.e., learning from others about the products' quality) and social utility (i.e., 'joint consumption' of the product, e.g., chatting about the asset together). In one treatment that they used to disentangle the social learning effect from the social utility effect, participants were informed that a family member or a friend was

interested in investing on the asset but did not succeed in getting the chance to invest in, which signals the quality of the assets. In the other treatment, participants were informed that their family member or friend interested in and invested on the asset. They compared the results from the two treatments and with the control group treatment who were not informed about peers' choices to disentangle the learning effect from the social utility effect. Another interesting result they find, which is consistent with our result, is that social learning had a statistically significant influence only among financially unsophisticated participants.

Our study differs from and complements the above mentioned and other related studies in peer effect in risk-taking. Firstly, instead of providing the peer information without asking the participants' consent that previous studies did, we asked 68 % of the participants in the treatments to make choices about whether they wanted to see peers' choices and, we investigate the factors that influence the probability of wanting to see the choices of others. Secondly, we examine the extent that individuals adjust their intrinsic choices to reduce their choice gap from the peers' choices. Thirdly, we investigate whether lack of self-confidence relative to the peer in decision-making and analytical ability are the behavioral reasons for the peer effect. Finally, by introducing different types of peers' choice information through matching protocols (randomly, based on risk-preference and framing), we investigate the role the peer type plays on in peer effects.

The results from this study may give insights about whether and to whom to provide peer information and whether to be selective to the type of peer information to provide to the various categories of the society in investment, new technology adoption, in various contracts including in BEV recharging and de-charging and health-promotion behavior.

4.3.   Theoretical Framework

In this section, we propose a simple model about how individuals may update their intrinsic choices towards the choices of others depending on their self-confidence and on their social interaction preference. Our model follows standard models in conformity preference and the peer effects in general by Bernheim (1994), Hoff and Stiglitz (2016) and by Jones (1984).

Consider a set of N individuals having heterogeneous risk preference and facing similar decision-making problem that involves uncertainty. Everyone chooses a normal good consumption x from a compact set of X to maximize utility. (In the context of our experiment, x denotes the amount of kilometers the participant buys electricity for and the utility could be the direct and the derived-utility from travelling (Anas, 2007)).

Consider a utility function that allows ordering individuals according to their degree of risk preference based on their intrinsic choice, for example a power utility function. Let the intrinsic utility maximizing value of x be denoted by $r_1, r_2, ..., r_n, r_{n+1}, ..., r_N$ in ascending order of risk preference, where r_n is the choice by a risk neutral individual, $r_i > r_n$ for $i = 1, 2, ..., n-1$ are the choices of risk-averse individuals and $r_j < r_n$ for $j = n+1, n+2, ..., N$ are the choices of risk-seeking individuals. Here the 'r's represent both type of individuals in terms of risk preference and their intrinsic utility-maximizing values of x. Thus, the r_i's are the Intrinsic Blissing Points (IBP)[56] that are based on intrinsic preference and that maximize utility in the absence of peer choice information. Accordingly, any value of x that differs from r_i decreases the intrinsic utility of individual i. This preference is presented in a value function given by[57]

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[56] The term IBP is from (Bernheim, 1994).

[57] This formulation is similar to the one given by Bernheim (1994) except we categorize individuals in terms of risk-preference instead of by esteem (social status).

$$g(x) = g(x - r_i) \qquad (4.1)$$

where g(x) is assumed to be twice differentiable, concave, symmetry with reference to $x = r_i$ and achieves a maximum at $x = r_i$ (the *IBP*).

Now let's examine how the intrinsic choices of individuals are influenced by observing the choice, s_j, of a peer type of j. Observing s_j may induce the individual to compare own choice with the choice of the peer for reasons such as social interaction effect (Cooper and Rege, 2011) and lack of self-confidence in decision-making (Bénabou and Tirole, 2002). The taste of conformity is summarized by a value function,

$$R(x) = \beta_{ij} R(x - s_j), \, j \neq i \quad (4.2)$$

where R(x) is assumed to be twice differentiable, concave and symmetric with reference to $x = s_i$ and achieves a maximum at $x = s_i$ (the Social Blissing Point, *SBP*), s_j is the observed choice of others and the parameter $0 \leq \beta_{ij} \leq 1$ is the relative weight that individual i attaches to the taste of conformity to peer information of type j (Zafar, 2011).

Given the intrinsic and conformity preferences, the individual chooses x to maximize total indirect utility given by

$$\max_{x \in X} V\left(x, r_i, s_j\right)$$

where

$$V_i\left(x, r_i, s_j\right) = \lambda_i g\left(x - r_i\right) + \beta_{ij} R\left(x - s_j\right), \, j \neq i \qquad (4.3)$$

Where λ_i, $0 \leq \lambda_i \leq 1$, is the measure of how well-formed is the intrinsic preference, i.e., self-confidence in decision-making when the individual evaluates won choice relative to the choice of others.

Equation (4.3) states that the amount of intrinsic choice the individual is willing to give up to adjust his/her choice towards peer j's choice depends on the strength of intrinsic preference mechanism relative to conformity preference (Jones, 1984), β_{ij}, on the individual's self-confidence relative to the confidence s/he has on the decision-making ability of others (Offerman and Schotter, 2009), λ_i, on the type of the peer such as a stranger, a relative, a random person, or a representative of the community j (Zafar, 2011), and on the magnitude of the difference between r_i and s_j. V(.) attains its maximum value at V(0), i.e., when $r_i = s_j$, which is consistent with previous studies, e.g., by (Akerlof, 1997).

If we assume β_{ij} and λ_i are exogenous, then the utility-maximizing choices would then be characterized by the following first order condition:

$$\lambda_i g'\left(x - r_i\right) + \beta_{ij} R'\left(x - s_j\right) = 0. \qquad (4.4)$$

Therefore, the optimal consumption amount is a function of r_i, s_j, β_{ij} and λ:

$$x_{0i}^* = h\left(r_i,\ s_j, \beta_{ij}, \lambda_i\right) \qquad (4.5)$$

where x_{0i}^* is the solution for equation (4.4), i.e., the reaction function of individual i as a function of the peer's choice, s_j.

The first order condition for indirect utility maximization intuitively states that the total utility is maximized when the consumer chooses x in such a way that the marginal disutility from choosing a different value than the *IBP*, x =r_i, equals the marginal utility from conformity.

The indirect utility maximization problem is also depicted in Figure 4.3.1, where *i* observes the choices of *j*. The indifference contours are circular and symmetric with respect to the blissing point at $x = r_i$, point A, for intrinsic preference and at $x = r_j$, point B, for conformity preference. The intrinsic preference maximizing value is x_i^*; whereas, the social preference maximizing value is s_j^*, and thus, the individual trades-off

between x_i^* and s_j^* to maximize the joint preference. The dotted line $\overrightarrow{AB}$ depicts the utility-maximizing path, given in equation (4.5). It connects the IBP and the SBP along which the indifference curves from the two types of preferences are tangent of each other. The joint utility-maximizing value can be at any point on the $\overrightarrow{AB}$ depending on the values of r_i, s_j, β_{ij} and λ_i.
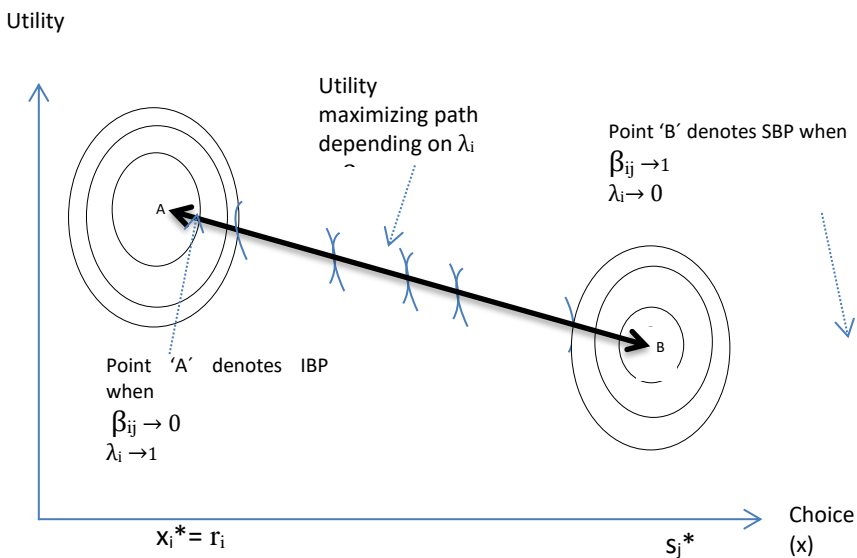
Figure 4.3.1. Utility maximization problem under conformity preference**.**

Our primary interest in this framework is on the effect of the type and magnitude of the absolute difference between the social choice and the intrinsic choice, $\left| r_i - s_j \right|$, on the mount of intrinsic maximizing value that individuals substitute for conformity.

Applying the implicitly theorem on (4.4), we have

$$\frac{dx}{ds_j} = \frac{\beta_{ij}R''(x-s_j)}{\lambda_i g''(x-r_i) + \beta_{ij}R''(x-s_j)} \geq 0$$

(4.6)

Note that, $\frac{dx}{ds_j} > 0$ implies that individual i does not make identical choice when separately observing two distinct choices of a peer. In extreme cases, $\frac{dx}{ds_j} = 0$ for homo-economicus individuals and $\frac{dx}{ds_j} = 1$ for imitators, for example, for individuals with $\lambda = 0$. For intermediate solutions, the following propositions are in order.

Proposition *1: Suppose that* β_{ij} *and* λ_i *are exogenous as we assumed so far*[58] *and that* $r_i < s_1 < s_2$ *, where s_1 and s_2 are peer information of the same peer type. Let $x_{0i}*$, $x_{1i}*$ and $x_{2i}*$ respectively be the indirect utility maximizing*

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[58] The assumption that β_{ij} and λ_i are exogenously determined that we assume for simplicity is a restrictive assumption that may not hold always. For example, Akerlof (1997) shown that there is an inverted U-shaped relation between confirming peers' choice and the amount of choice intrinsic choice difference from peers' choice. Using a modified version of the gravitational model of motion, Akerlof (1997) show using three individuals that when two of the persons position initially fairly close to each other and if the value of social exchange is sufficiently high relative to the value of the intrinsic choice, then there will be a stable solution in the short run where individuals changing positions. However, either of them will not be affected by a third individual positioning at far distance when the social preference relative to the intrinsic preference is weak and when their choice is initially far from the optimal value. In this case, β_{ij} and λ_i are endogenous and the predictions of our model may not apply.

values without peer information, with observing s_1 and with observing s_2. Then, $x^*_{0i} \leq x^*_{1i} \leq x^*_{2i}$. Similarly, if $r_i > s_1 > s_2$, then $x^*_{0i} \geq x^*_{1i} \geq x^*_{2i}$.

Proof: When s_1 is observable, $\lambda_i g'\left(x - r_i\right) + \beta_{ij} R'\left(x - s_1\right) \geq 0$ at $x = x_{0i}* = r_i$ $< s_1$ since $g'(y) = 0$, but $R'\left(x - s_1\right) \geq 0$ $\forall x : x \leq x^*_{1i}$. This implies that the utility-maximizing value of x is greater than $x_{0i}*$ when s_1 is observable. Thus, $x^*_{0i} \leq x^*_{1i}$. Similarly when $s_2 > s_1$ is observable, $\lambda_i g'\left(x - r_i\right) + \beta_{ij} R'\left(x - s_1\right) \geq 0$ at $x = x_{1i}*$ since $g'(y) = 0$, but $R'\left(x - s_1\right) \geq 0$ $\forall x : x \leq x^*_{2i}$, implying that $x^*_{1i} \geq x^*_{2i}$. The proof for $r_i > s_1 > s_2$ follows similar procedure. □

Accordingly, the higher is the difference between the intrinsic choice and the observed peers' choice, the higher will be the amount of intrinsic choice to give up for conformity. The implication of Proposition 1 is that

$$\frac{d\left(r_i - x_i\right)}{d\left|r_i - s_j\right|} \geq 0, i \neq j \qquad (4.7).$$

The result is intuitive. Provided that individuals obtain positive utility from confirming peers' choices, an increase in the choice gap from the peers' choice should not decrease the amount of intrinsic choice individuals substitute for conformity preference.

Proposition 2: Consider a set of individuals arranged in ascending order of their intrinsic choice as in r_1, r_2, ..., r_n, r_{n+1}, ..., r_N, where r_n is the median choice, under the following two scenarios. Scenario (I) Individuals with choices: r_1 and r_N, r_2 and r_{N-1}, ..., r_{n-1} and r_{n+1} receive each other' choice and the individual with the median choice receives a confirmation of own choice. Scenario (II) each individual receive the median choice, r_n. Then,

   a) Under imitation, peer information in Scenario II results in a mere change of location in terms of choice distance between matched

individuals without affecting the central tendency and the diversion of the sample choice. Whereas, peer information in Scenario I substantially reduces the diversion in risk-taking.

    b) *Suppose that there is no imitation of peers' choice but adjustment of choice towards peer's choice, that the reaction function given in (4.5) is linear[59] and that the intrinsic choices are fairly symmetric with respect to the median. Then, there is a threshold value in the amount of intrinsic choices that an individual gives up to adjust their choices towards the peers' choice such that peer information in Scenario I reduces the dispersion of the sample more than peer information in Scenario II does.*

Proof. Suppose that individual i receives either the median choice, r_n, or a peer's choice, s_j, but not both. Assume for simplicity that the choices r_i and s_j are symmetric with respect to the median choice as shown in Figure 4.3.2. If all individuals are imitators, then exchange of peer choice information between individual i and individual j merely changes the location in terms of choice distance of individuals in that individual i adapts the choice of individual j and vice versa without affecting the distribution and the central tendency of the choice. This concludes the proof for scenario part (a).

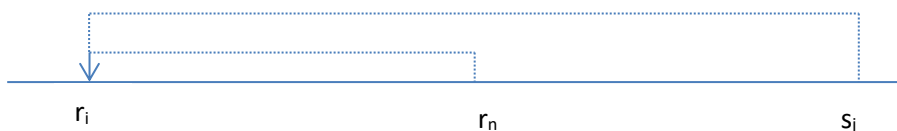**Figure 4.3.2. Median versus preference based peer choice information**

Considering (b), the assumption that choices are symmetric with respect to the median choice implies that the choice distance from r_i to s_j is twice the choice distance from r_i to r_n under Scenario II. Let $y = |r_i - r_n| = |r_n - s_j|$ and

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[59] Bernheim (1994) and Jones (1984) also used linear reaction functions.

let α, 0≤ α≤1, be the proportion of y that the individual chooses to reduce his/her choice gab from r_n, where α = 0 implies no peer effect and α=1 implies imitation. The assumption that the reaction function is linear implies that if (αy) is the amount of the intrinsic choice the individual gives up for getting closer to r_n, then (2αy) will be the amount to give up when the individual receives s_j. What we want now to show is that there is a value of 'α' such that provision of s_j is better than provision of r_n in terms of inducing individual i to choose a value that is closer to r_n. Thus, providing s_j is better than providing r_n in terms of inducing choices towards r_n if and only if:

$$2\alpha y - y < y - \alpha y \qquad \Leftrightarrow \alpha < \frac{2}{3}.$$

Generally, for $\delta = \dfrac{|r_i - s_i|}{|r_i - r_n|}$ and a linear reaction function, the sample diversion from providing s_j is smaller than from providing r_n if

$$\delta\alpha y - y < y - \alpha y \qquad \Leftrightarrow \alpha < \frac{2}{\delta + 1} \qquad \square$$

Thus, if individuals reduce each unit of their intrinsic choice differences from the peers' choices by $\alpha < \dfrac{2}{\delta + 1}$, then the sample diversion under the Nonrandom-peer treatment is lower than under the Population-as-a-peer treatment.

The model provides the following testable hypotheses that we tested using laboratory experiment.

Hypothesis 1: The magnitude of intrinsic change in the Nonrandom-peer treatment is higher than that of the Population-as-a-peer treatment since $|r_i - s_i|$ is higher in the former treatment. This follows from Proposition 1.

Hypothesis 2: The sample diversion under the Nonrandom-peer treatment is lower than under the Population-as-a-peer treatment if imitation is infrequent in the treatments. This follows from Preposition 2.

Hypothesis 3: The peer effect is stronger for individuals lacking self-confidence than for those having more confidence, both relative to the median individual in terms of confidence. This follows from the magnitude of λ_i.

4.4. The Experimental Design

4.4.1. The Decision-Making Problem

The decision-making problem of the participants involved choosing the amount of kilometers to buy electricity for unforeseen trips. They buy the electricity for recharging BEVs. They were informed that electricity is time-of-use priced such that the amount that enables to drive one km costs 10 cents and zero cents respectively for charging the car during 6:00 to 21:00 and during 21:00 to 6:00. Thus, it is always cheaper to charging the car between 21:00 and 6:00 unless the amount charged during this period is not enough to cover the daily trips. They were informed to assume that the car has enough battery power to drive to just planned trips they have today until 21:00. However, unforeseen trips may occur before 21:00 for that they had to buy electricity for. Not buying enough electricity costs *15 cents* for each unit of travel distance that the amount of electricity they chose to buy falls short of the posterior trip distance. Thus, recharging both less and more than the amount required to cover the posterior travel distance was costly. However, the actual distance of the unforeseen trips was unknown at the time of decision and, thus, the decision-making problem involved uncertainty. In particular, they were informed that the unforeseen trip distance, D, is uniformly distributed with support (*0*, *60*) *km*.

Then, the decision-making problem of the participants was to choose the amount of electricity to buy, denoted by *x*, to minimize the expected cost given by

$$c(x) = \underbrace{10\,x}_{electricity\ cost} + \underbrace{15(D-x)Pr(D \geq x)}_{cost\ of\ insufficient\ purchase} + \underbrace{10(x-D)Pr(D < x)}_{implicit\ cost\ of\ excess\ purchase}$$

$$(4.8)$$

Given that $D \sim U(0,60)$ so that $Pr(D < x) = \dfrac{x}{60}$ and E(D) = 30, the expected cost, E [c(x)], is given by

$$E\left[c(x)\right] = 450 - \frac{35}{2}x + \frac{5}{12}x^2 \qquad (4.9)$$

This is a U-shaped, convex function with a minimum at *x =21*.

Considering the endowment the participants were given to earn cash money after paying for the cost in (4.9), a risk-neutral individual chooses x to maximize

$$Earning = Endowment\text{-}450 + \frac{35}{2}x - \frac{25}{60}x^2 \qquad (4.10)$$

The endowment amount was 1300 cents for each round, which implies that s/he chooses $x_n^* = 21$ with the corresponding expected cost of 266.25; whereas, risk-averse and risk-seeking individuals respectively choose $x^* > 21$ and $x^* < 21$.

4.4.2. The Procedure

The experiment was conducted from 06 to 18 May 2016 at the Laboratory for Experimental Economics (LEE) at the Department of Economics, University of Copenhagen using the zTree software package (Fischbacher, 2007). A total of 215 students (87.4 %) and non-students (12.6%) recruited from the LEE registered panel participated in 11 sessions. The mean age of participants was 25 years (minimum 19, maximum 36) and 48.5 % of them were male.

Upon arriving at the LEE site, participants were briefed about the general procedures in the laboratory and they were randomly assigned using cards into computers. Instructions of the experiment were provided to participants in printed papers and also were displayed on computer screens. Each session lasted between 45 minutes and 75 minutes. To

make sure that the participants understood the decision-making problem correctly, we asked each of them to answer four control questions, and the laboratory assistants briefed those who sought help answering the questions.

After correctly answering the mandatory control questions, participants started the main experiment that lasted 10 rounds. The basic experimental setting was identical for all participants, except the type of peer information presented to participants in the treatments. Participants had to always perform the same task: to choose the amount of km to buy electricity for unforeseen trip that is uniformly distributed between 0 and 60 km, inclusive. They received 1300 cents for each round of decision to save for themselves after paying 10 cents for each km they bought electricity for and 15 cents for each distance unit that the amount of km they chose to buy electricity for falls short of posterior unplanned trip distance. To determine the actual cost participants had to pay at each round, traveling distance of unforeseen trips, D, was drawn randomly from a uniform distribution with support (0, 60) independent of the previous rounds and independent of each other of the participants.

All participants were allowed to see the outcomes of their immediate choices as well as the outcomes of all previous rounds of decisions in a table that showed the amount they chose, the realized outcome of distance, the cost they paid for traveling and the corresponding earnings. In addition to that, they received non-informative information mentioning whether the amount they chose is lower or higher than the realized outcome. However, they did not observe the outcomes of other participants.

At the end of the experiment, participants completed a short questionnaire. After which, we called them individually based on their computer number and received their earning plus a show up fee of 50 Danish kroner in another room. On average, participants earned 140 Danish kroner.

4.4.3. The Treatments

The primary goal of our experimental design was to investigate if tailoring the peer choice information plays a role in peer effect. The experiment consisted of five treatments and a control group. Each participant remained in the same treatment throughout the 10 rounds of decisions and each of them participated only in one treatment. The experiment consisted of two main stages. In the first stage that lasted 10 rounds of decisions and is the actual research phase, participants made choices and received the choices of peers if they were eligible and were willing to receive peers' choices as discussed below. In the second stage, participants' relative self-confidence and analytical ability was determined according to math tests that we asked participants and that we found from the internet.

Stage 1: All participants in the treatment group had to first make their choice before receiving the choices of peers. While making their decision, participants in all treatments were not sure if they were to get peer choice information since they were informed that there is 5 % chance that they may not get peer choice information. We did this to induce participants to consider their initial choice as the final decision. After they decided the amount to buy and confirmed it, a random number from a uniform distribution was drawn in each of the 10 rounds of decisions independently for each participant and across rounds of decisions to determine if the participant was to receive peer choice information. Participants with assigned random numbers greater than or equal to 0.05 were eligible to receive one of the peer choice information.

Instead of providing the peers' choices without asking for their consent like previous studies did, we asked 68 % of the participants in the first two and in the last two rounds of decisions to choose whether they would like to see peers' choices. For the remaining 32 % of the participants and for the 68 % of the participants from rounds three to round eight, we provided the peer information without asking for their consent to investigate if making the peer choice information available as default option makes a difference on peer effect when compared with participants who receive peer information by choice. However, as shown

in Table 4.5.3, we do not find a statistically significant difference (*p-value = 0.343*) between the two treatments.

Concerning individual treatments, the *Population* treatment and the *Population-as-a-peer* treatment were conducted in similar sessions by grouping at random the participants in to the two treatments with equal size. Then, each of eligible participants (i.e., those who chose to see and were drawn to see peer choice information) received the mean of the choices of all participants in the same session, excluding the participant's own choice. The only difference between the two treatments is the framing of the peer information either as 'the mean of the choices of all participants excluding your choice' or 'the choice of a peer'. An exception is the provision of the 25th and 75th percentiles and the standard deviation of the choices in one of the three sessions to the *Population* treatment, but such information did not affect results in that we merged the data. Thus, any difference between the two treatments is attributed to whether participants valued the 'population representative' and 'a peer' information differently.

In the *Nonrandom-peer* treatment, we first ranked participants using their intrinsic choice that the made before knowing whether they would receive the choices of others. Then, each eligible participant received the choice of a peer in such a way that the most risk-averse (with respect to the median choice) and the most risk-seeking participants received each other's choices, the second most risk-averse and the second most risk-seeking participants received each other's choices, etc. until the last two participants with the closest choices to the median choice received each other's choice[60]. This matching was conducted throughout the 10 rounds

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[60] Note that we labeled an individual as risk-averse or as risk-seeker based on his/her choice relative to the median choice, and thus, the labeling may not reflect the general risk preferences of the participants.

of decision in that each participant might not receive the choices of the same person throughout the 10 rounds of decisions.

The *Two-peer* treatment is like the Nonrandom-peer treatment except participants in the former treatment received the choices of two peers such that the most risk-averse individual received the choices of the two most risk-seeking peers, and a risk-seeing individual received the choices of the most two risk-averse peers, etc.

In the *Random-peer* treatment, participants were matched randomly in to groups of two, and each participant remained in the same group throughout the 10 rounds of decision. This treatment is included to investigate whether tailoring the peer information makes a difference on the peer effect when compared with random matching.

Finally, we have a Control group who made decisions without receiving peer information that we use it to investigate the overall peer effect. A summary of treatments is presented in Table 4.

Table 4. A summary of treatments

Treatments	Provided peer information type	No. of sessions	No. of participants
Control group	No peer info	2	39
Population	Mean of choice the session (and S.D., 25th and 75th percentiles of the sessions)	3	27
Population-as-a-peer	Mean of choice the session		27
Nonrandom peer	Choice based on a risk preference	2	50
Random peer	A randomly chosen peer choice	2	22
Two-peer	The choices of two peers that are selected based on risk preference	2	50
Total		11	215

Stage 2: The purpose of this stage was to determine the relative confidence and analytical ability (in terms of math test scores) of participants so as to investigate if these attributes contribute for the peer effects. We followed a similar experimental design used by Falk et al. (2006)[61] to examine the relative analytical ability and self-confidence of participants. After the first stage is completed, we asked participants in the treatments to answer eight math questions, which we found in the internet. They were allowed to use calculators. Example of the questions include "What is the probability of getting all heads in tossing a fair coin

twice times; give a whole number answer that solves $x^2 = 1$; etc." The test questions are enclosed in the Appendix 3.iii (a). They were rewarded 100 cents for each of the questions they correctly answered and they had a total of 200 seconds to answer as many questions as they could. The questions are not difficult to answer for the participants who were at least Bachelor degree students.

Looking at the answers, 3.4 % of the participants correctly answered all questions within the given time while, in the other extreme, 2.8 % of them answered no question correctly. On average, they answered four questions correctly, and the median and mode were also four. The

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[61] There are some differences between Falk et al. (2006) tests and ours. First, the tests are different: they used multiplication question between a one digit and two digits numbers while we used various tests that we found from the internet. Second, they asked a series of questions that the participants could answer as many questions as they can within 5 minutes while we restricted the questions numbers to 8 and the time to answer the questions to 3.3 seconds. Third, they showed the results of the tests to the participants before asking them to self-assess their performance while did not show the results since showing the results would help them to better self-assess their performance. For example, 3.4 % of the participants answered all questions correctly and, hand we showed their performance, they would definitely know their relative performance.

distribution of participants scoring from zero to eight is fairly symmetrical with respect to the mean as shown in the Appendix 3. Iii (b).

To examine self-confidence, we asked participants to choose between two lotteries after the math test was completed. *Lottery (A) win 500 cents with 50 % probability and zero otherwise.* Lottery *(B) where a 'high type' had 80 % probability of winning 500 cents and zero otherwise while a 'low type' has 20 % of winning 500 cents and zero otherwise.* A *'high type' participant is the one who answered at least as many questions correctly as half of the participants did and a 'low type' participant is the one who answered less questions correctly than half of the participants did.* We never used the terms 'high type' and 'low type' in the experiment to avoid biases: we simply asked them to choose between the lotteries. Lotter (B) was presented as 'win 500 cents with 80% probability if you answered as many questions correctly as HALF of the participants or win 500 cents with 20 % probability if you answered less questions correctly than HALF of the participants in the previous questions'. Obviously, participants who were confident in their performance relative to the performance of the median participant choose lottery B since the winning chance in lottery B (80 %) was higher than the winning chance in lottery A (50 %) while participants lacking self-confidence relative to the performance of the median participant choose lotter A since the winning chance of lottery A (50 %) is higher than the winning chance of lottery B (20 %) for low type participants.

Interestingly 49.4 % of the participants chose Lottery B over lottery A while the remaining 50.6 % chose Lottery A. About 72 % of the participants correctly predicted that they are low type and the remaining 28 % over-assessed their relative performance, probably indicating risk-seeking preference. On the other hand, 65.4 % of the participants correctly predicted that they were high type and the reaming 34.6 % of them under-assessed their relative performance, probably indicating risk-aversion behavior. We also find that male participants had higher self-confidence (58 % of them) than female participants had (41 %).

4.5. Results

In this section, we present the results. We first present the result about whether participants chose to see the choices of others. Following this, existence of peer effects and its variations across the treatments are presented.

4.5.1. The desire to see the choices of others

To observe whether individuals want to see the choices of other participants, we asked 120 of the participants in rounds 1, 2, 9 and 10 to choose either they want to see peers' choices. We asked them to make the choice after they made decision about how many kilometers to buy electricity for unplanned trip but before they knew the type of peer information to receive if they chose so.

Figure 4.5.1 shows that most of the participants (79 %) chose to see the choices of others in the first round. Unsurprisingly, the percentage declined by 9 % in the second round after those who chose to see peers' choices observed the type of peer information and after receiving outcomes for the first round decision. Then, from rounds three to eight, we provided the peer information without asking for their consent. When we asked them again in round 9 about whether they wanted to see peers' choices, the percentage of participants who chose to see peers' choice still remains high, 64 %, slightly declining to 58 % in round 10. Tabulation of the panel data show that 78 % of the participants who chose to see the choices of peers in one round also chose to see in other rounds. And for those who chose not to see in one round, 69 % of them persistently chose not to see the choices of peers throughout the rounds.

Figure 4.5.1. Percentage of participants who chose to see peers' choices.

The large percentage of participants choosing to see the choices of peers may not be surprising since peer choice information was provided free of cost. Participants who are confidence of their own choice may even choose to see the choices of others for curiosity or to double check their choices and to correct any errors. More importantly, seeing the choices of others is a rational choice for participants who are not sure of whether they choose the optimal choice for themselves (Eyster and Rabin, 2014).

To identify the factors inducing individuals to choose to see the choices of others, we estimated the following linear probability model (LMP), which provides good estimates of partial effects (Wooldridge, 2010).

$$y_i^l = \alpha + X_i \beta + \varepsilon_i^l \tag{4.11}$$

where y_i^1 is a dummy variable indicating whether individual i wanted to see the choices of peers. The parameters α and β (β is a vector) are the population parameters to be estimated and ε_i^l is an error term. X_i is a vector of covariates including a gender dummy taking a value one for male participants and zero for female, age, an education dummy taking a value one for being a masters student or higher level of education and zero otherwise, learning denoting the decision rounds, self-confidence is a dummy taking one for self-assessed self-confident participants and zero otherwise, and the 'high type' is a analytical ability (as examined by math

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scores) according to our test and taking a value one for participants correctly answering more than the median participant and zero otherwise. Table 4.5.1 reports the LPM estimates of the wanting to see the choices of peers[62].

Table 4.5.1. The probability of wanting to see the choices of peers

Dependent variable: Wanted to see the choices of peers			
Independent Variables	Estimates	Standard error (Robust, HC3)$^{\zeta}$	t-value
Gender (dummy: 1 = male)	-0.08*	0.044	-1.86
Age	0.01	0.009	1.2
Education (dummy: 1 = maters student or higher level of education)	-0.17***	0.044	-3.84
Learning	-0.02***	0.005	-3.44
Relative self-confidence (dummy: 1 =self-confident)	0.13***	0.044	3.03
Decision-making ability (dummy: 1 =high type)	-0.17***	0.046	-3.64
Constant	0.66***	0.205	3.21
N	480		
F(6, 473)	6.83		0.000
The symbols *, **, *** respectively indicate the 10 %, 5 % and 1 % statistically significant differences. ζ denotes heteroskedasticity-robust standard errors.			

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[62] The estimates from logit model are similar in terms of statistical significance of the covariates, and, as expected the coefficients of the logit model are large (about 5 times) than the LPM estimates. We choose to present the LPM estimates for easy of interpretation of coefficients.

Table 4.5.1 shows that most of the estimates are statistically significant and have the expected sign. They are also jointly significant (*p-value =0.000*). We find statistically significant gender difference in wanting to see the choices of peers: ceteris paribus, male participants are less interested in seeing the choices of peers than women participants do. The largest marginal effect comes from the level of education and analytical ability. As expected, the participants with relatively higher education achievements or higher ability wanted less to see the choices of peers than their counterparts. As we also saw in Figure 4.5.1., participants chose less to see the choices of others as they get experience (learning). Probability unexpected result is that participants who stated that they have relatively higher self-confidence wanted more to see the choices of others. However, wanting to see the choices of others does not necessarily mean using the peer information to update own choice, which we discuss later. The coefficient for age of the participants is not statistically significant.

The next important question to ask is whether and who uses the peer information among those who chose to see and for who we provided peers' choices without consent.

4.5.2. The peer effect

What is probably most important for policy use of the peer effect is whether and who uses the peer information to revise intrinsic plans and choices. We present below the overall choices participants made, the observed peer effect and its determinants as well as peer effects over the treatments.

4.5.2.1. The Overall Result

Over all the 10 rounds of decisions, participants chose to buy 29.3 units on average, 9.3 units more than the expected cost-maximizing value. Most of the participants (77.5 %) chose more than what a risk-neutral individual would chose, probably an indication of risk-aversion behavior. Whereas, a minority of them (about 12.6 %) chose to buy less than the payoff-maximizing value, and the rest (9.9 %) chose the expected cost minimizing value.

Table 4.5.2 reports a summary statistics of the treatments including for the control group and for the overall samples. The null hypothesis that the choices made by the samples for all the treatments including the control group over the 10 rounds of decisions are from the same distribution is rejected by the non-parametric Kruskal-Wallis equality test (*p-value = 0.0021*)[63]. We also conduct a Mann-Whitney test taking all the treatment samples as one group and the control group as the second group, and still the null hypothesis of the two samples are from the same distribution is also rejected at 5 % level of significance (*p-value= 0.0281*).

To investigate whether the observed difference is because of the unlikely sampling problem in that the samples in different treatments have systematic difference before the treatment, we conduct a randomization test using the choices participants made before they received the choices of peers. Interestingly, we do not found statistically significant difference across the treatments including the control group (Kruskal-Wallis equality test, *p-value = 0.3553*). This is not surprising since participants were randomized across treatments. Thus, any difference across treatments after participants received the choices of peers can be attributed purely to the peer effects.

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[63] Kruskal-Wallis (or Mann-Whitney for two sample) testis a non-parametric method used to test whether two or more samples of equal or different size originate from the same distribution. We cannot use the parametric t-test and F-test since it assumes that the distributions come from the normal distribution while the lower- and upper-bounds are 0 and 60 in the observation.

Table 4.5.2. The overall result

Treatments	Mean Choice	Standard deviation	No. of observations	Two-sided Mann-Whitney test (z-values)
Control group	30.9	11.34	390	-
Population	27.5	11.74	270	2.869 ***
Population-as-a-peer	29.8	11.40	270	0.049
Nonrandom-peer	28.8	10.70	500	1.955 *
Random-peer	27.5	10.81	220	3.624 ***
Two-peers	30.1	9.77	500	0.615
All treatments	29.3	10.90	2150	chi-squared = 23.772 *** (Kruskal-Wallis Test)

The symbols *, **, *** respectively indicate the 10 %, 5 % and 1 % statistically significant differences.

Though the magnitude of the mean choice difference is small, it seems that the peer effects generally induce more risk-taking when compared with the control group participants who made choices in isolation. The overall mean choice by the control group, 30.9 units, is higher than the mean choice by all treatments taken together, 29.3, as well as the mean choice of each of the treatments. This mean choice difference is observed despite the fact that the mean choice of the control group at the first round is the second lowest, 27 units, when compared with the mean choices of the treatments before the participants observed peers' choices.

The peer effect is clearly observed in Figure 4.5.2 where the vertical axis presents the mean choice and the horizontal axis presents rounds of

decisions starting from '0' to 10. Round '0' denotes the first round when all participants made choices before receiving peer information.
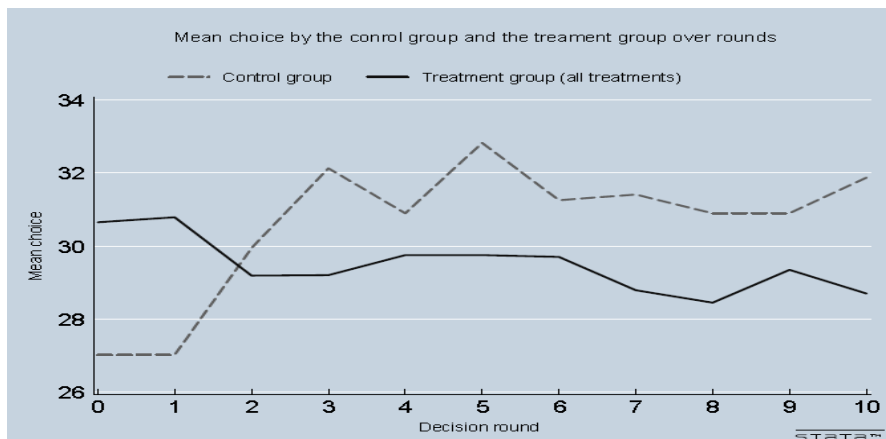
Figure 4.5.2. The overall peer effect

Figure 4.5.2 shows that provision of peers' choices induced participants to change their intrinsic choice. The peer effect increased risk-taking (i.e., the amount of kilometer participants chose to buy electricity for unplanned trip decreased). Overall, participants in the control group myopically increased their mean choice of about 27 units in round 1 to 30.9 units overall in the 10 rounds while the participants in the treatments group reduced their intrinsic mean choice in round 1, 30.5 units, to 29.3 units overall in the 10 rounds during which they received peers' choices. It seems that the peer effect is not observed in the first round as the mean choice of the treatments group is almost the same in round 0 and in round 1. This arises because while 20 participants reduced their intrinsic choices by 13.45 units, on average, 18 participants increased their choice by 13.61 units, on average, resulting in only a 0.6 mean choice difference between the intrinsic choice and the choice after observing peer' choices. Otherwise, the largest peer effect in terms of the percentage of participants influenced by peers' choices is observed in the first round as shown in Figure 4.5.3 in the upcoming section-

To determine the significance of the differences between each treatment and the control group, i.e., the peer effect, we use the Mann-Whitney test.

As we can observe the z-values in the last right column of Table 4.5.2, the difference is statistically significant except for the *Two-Peer* and the *Population-as-a-peer* treatments. Looking at the differences within the five treatments, the *Population* and the *Random-peer* treatments have the lowest mean choices while the *Two-Peer* treatment has the highest. The Kruskal-Wallis Test rejects the null hypothesis that the distributions of the five treatments came from the same distribution (*p-value = 0.0006*). In terms of standard deviation, the *Population* treatment has the largest followed by the *Population-as-a-peer* treatment.

4.5.2.2.   Prevalence and determinants of peer effect

Of all the 1498 decisions that participants were eligible to see the choices of peers and to revise their intrinsic choices afterwards, they revised their choices in 183 decisions (about 12 %) every time they saw the choices of peers indicating the direct peer effects. Figure 4.5.3 presents the percentage of decisions across rounds that the direct peer effect is observed, i.e., the percentage of decisions that participants revised their intrinsic choices after observing peers' choices. As expected, the highest peer effect was observed in the first round (28 %), after which it declined continuously up to the 7th round in that only 6.4 % of the participants made revision as participants got more and more experience and, then, the peer effect moves up and down in the last three rounds of decisions.
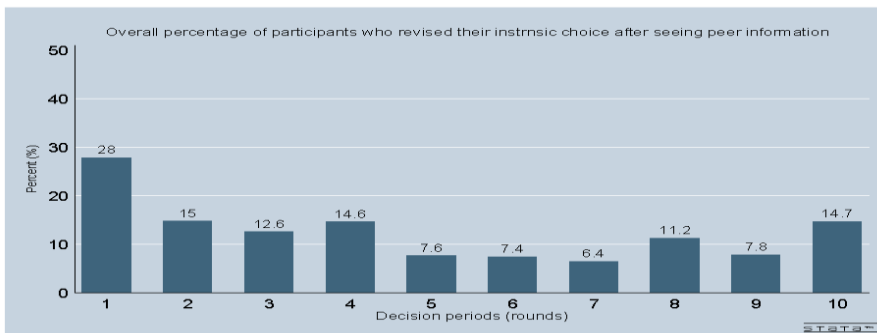

Figure 4.5.3. Percentage of revisions of intrinsic choices after seeing the choices of peers

There is considerable persistency from round to round in terms of not changing the intrinsic choice after observing the peer information. About 90 % of those who did not change their intrinsic choice in one round did not also change their choices in the next round, while only about 26 % of those who revised their choice in one round persistently revised their choices in the next round after observing the choices of peers.

Concerning the differences across treatments in terms of revising intrinsic choices, the overall percentage of participants who revised their intrinsic choice is fairly similar across treatments, the maximum being 14.8 % in the Nonrandom-peer treatment and the minimum being 10.5 % in the Population-as-a-peer treatment. However, there was considerable difference among treatments when we compare the revisions across rounds, the maximum difference being between the Nonrandom-peer treatment (23.4 %) and the Random-peer treatment (0 %) on the 4th round of decision.

There is also an indirect peer effect in that the choices of peers that participants saw in the previous round(s), call $t-1$, may affect the decision they made on the next round(s), call t, where $t > 1$. To examine the indirect peer effects, we compare the choices that participants made without changing their choices in response to seeing the choices of peers with the choices of the Control Group. The Mann-Whitney test shows that there is a statistically significant indirect peer effect (P-value = 0.0448). We present the magnitude of the indirect effect in Appendix 3 (C) in that we can observe that the overall choices by the Treatment Group after the indirect peer effect begins (the second decision round) is lower than that of the choices by the Control Group thought out the nine relevant (for observing the indirect peer effects) rounds of decisions except for the ninth round at which the choices between the two groups almost match.

We next investigate the factors behind the reason for the peer effect inducing an overall 12 % revision of intrinsic choices as well as the factors that affect the extent individuals change their intrinsic choice to reduce the choice gap with the observed peers' choice. We estimate a random

effects LPM[64] to estimate the probability if peer effect is observed given by

$$y_{it}^2 = \alpha_t + X_{it}\theta + c_i + \varepsilon_{it}^2 \quad (4.12)$$

where y_{it}^2 is a dummy variable indicating whether the peer effect is observed (i.e., whether individual i revised his/her decision at round t), α_t a time-variable intercept, X_{it} are covariates that vary across decision rounds and/or across individuals, c_i is time-invariant individual heterogeneity and ε_{it}^2 is idiosyncratic error.

And we estimate random effects Poisson model to estimate the amount of intrinsic choice participants given up to adjust their choices towards peers' choice. We choose a Poisson model since 88 % of the dependent variable's observation are zero (i.e., no direct peer effects) and the remaining are integers with considerable repetitions, e.g., 4.27 % fives, 2.18 % tens, etc. for which Poisson model is preferable (Wooldridge, 2010). The random effects Poisson model is given by

$$E\left(y_{it}^3 / X_{it}\right) = \alpha_i \, exp(\, X_{it}\beta \,), \qquad y_{it}^3 = 0,1,2,...,60 \;, \qquad (4.13)$$

where α_i is the individual specific effects and is assumed to be gamma distributed with a mean of 1 and a variance of η.

As covariates, we use:

- 'Peer information by choice' – a dummy variable taking the value one for participants where peer choice information is presented if they chose to receive and taking the value zero when peer

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information is presented without asking for the participants consent to receive peers' choices,

- '|x-y|' - the absolute difference between the participant's choice, x, and the observed peers' choice, y, (non-linearly),

- 'regret' - a lagged absolute difference between choice and the realized outcome and

- Learning, gender, education, relative self-confidence and analytical ability– as defined before.

We have tested for differences among treatments by including treatment dummies but none of them are statistically significant both individually and jointly and thus, we omitted the dummies from the estimation. The estimation results from the random effects LPM and random effects Poisson estimates are presented in below.

Table 4.5.3. The probability of observing the peer effects and the magnitude of the peer effects

Dependent variable	Probability of being influenced		Absolute amount of intrinsic choice change	
	(Random effects LPM)[a]		(Random effects Poisson model)[b]	
	Estimates		Estimates	
Peer information by choice	0.0214 (0.95)		0.138 (0.53)	
Relative self-confidence	-0.0178 (-0.70)	(-	-0.159 (-0.48)	(-
High type	-0.0685*** (-2.83)		-0.986** (-1.97)	
Gender	-0.0185 (-0.75)		-0.251 (-0.74)	
|x-y|	0.00954*** (3.57)		0.130*** (4.51)	
$(x-y)^2$	-0.000154** (-2.17)		-0.00153** (-2.33)	
Regret	0.00109 (1.28)		0.00200 (0.23)	
Education	-0.00698 (-0.29)		-0.131 (-0.40)	
Learning	-0.00576 (-1.44)		-0.0385 (-1.09)	
Constant	0.0878** (2.26)		-0.829* (-1.74)	
Lnalpha			1.970***	(11.71)
N	1358		1358	

t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The superscripts 'a' and 'b' respectively denote that cluster robust and bootstraps (100) standard errors are used.

Table 4.5.3 shows that the covariates are jointly statistically significant. Looking at individual estimates, intuitively, participants with relatively

higher analytical ability and having relative self-confidence are less influenced by the choices of peers though the latter is less precisely estimated, probably because of the high correlation between the two variables. Further looking at the data, we find that about 79 % of the pees effects are observed among participants of 'low type' who constitute 52.5 % of the participants. Similarly, about 62 % of the peer effects are observed among participants lacking relative self-confidence. Analytically less able individuals are more likely to make errors and to make more random choices than analytically able individuals (Andersson et al., 2015; Eyster and Rabin, 2014)). Consistent with this, we found that the standard deviation (= 14.4) of the choices by participants who revised their intrinsic choices is larger than the standard deviation (= 12.5) of the choices who did not revise their choice for the decisions they made before receiving peer information. This result is in line with Hypothesis 3. Bursztyn et al. (2014) find a similar result in a well-designed field experiment in that social learning has a statistically significant effect on risk-taking among financially unsophisticated investors, but not among financially sophisticated investors.

As we can see on the random effects Poisson model estimates in Table 4.5.3, analytical ability has also a statistically significant (inverse) effect on the magnitude of the peer effects, i.e., on the mount of intrinsic choice participants substituted for getting closer to the peers' choices. Thus, the main reason behind being influenced by the choices of peers in the absence of payoff complementarities and social utility may be are lower analytical ability and lack of self-confidence relative to the peer.

Another factor contributing for peer effect is the magnitude of the individual's choice from the peer choice. The probability of making revisions towards the choices of the peer increases as the difference between owns choice and the peer's choice increases. However, there is a threshold beyond which, the probability declines as the gap between the choices increases. One explanation for this may be that when individuals (at the margin in terms of analytical ability) observe significant differences between their choices and the peers' choices, then they may start doubting their own analytical ability and adjust their choice towards peers' choices. However, if the peers' choices are too far,

then they may doubt the peer's analytical ability instead of theirs in that the probability of the peer influence declines.

Expectedly, regret on own previous decision increases the probability of being influenced by peers' choices while learning (experience) and higher education level reduce the probability. However, all regret, education and learning are less precisely estimated.

We next examine the extent individuals adjust their choices towards peers' choice. A further look of the data show that 10 % of the observed peer effects were imitations in that participants adapted peers' choices. The rest of the observed revisions are adjustments towards the peer information in that they substituted some of their intrinsic choice for getting closer to the choices of peers. We find that participants reduced each unit of their choice difference from the peers' choices by 0.65 units, on average. As we can see on Table 4.5.3, the individuals' choices absolute difference from the peers' choices difference, however, has a non-linear effect on the amount of intrinsic choices individuals substituted for getting closer to the observed peers' choices.

4.5.2.3. A Population representative versus a random peer effects

In this section, we investigate whether providing the same peer choice information either as 'a peer's choice', the *Population-as-a-peer* treatment, or as 'the mean choice of all the participants excluding the individual's choice', the *Population* treatment, makes a different in the peer effect.

Figure 4.5.4 reports the mean choices of the two treatments and the control group across the 10 rounds of decision. The graph at decision round '0' denotes the mean intrinsic choices that the participants made at the very first of decision before the participants in the two treatments received Peers' choices. At round 0, the mean choice of participants in the P*opulation* treatment, 31.1 units, is lower than the other treatment, 32.4 units. However, we fail to reject the hull hypothesis of equality of distributions of the two sample before the peer treatment is introduced (a two-sided Mann-Whitney test, p-value = -0.429).

Figure 4.5.4. A peer versus peers effect

The graph shows that after 'round 1', the mean choice of the *Population-as-a-peer* treatment is at least as high as that of the *Population* treatment. More interestingly, while the mean choice of the latter treatment gradually decreases towards the choice of a risk-neutral individual, the mean choice of the former treatment lacks a clear patter and oscillates around 29 units particularly after the fourth round. The overall mean choice of the *Population* treatment, 27.5 units, is lower than that of the *Population-as-a-peer* treatment. Moreover, while we fail to reject the hull hypothesis that there is no statistically significant peer effect in the *Population-as-a-peer* treatment (Mann-Whitney test, p-value =0.9610), we reject the same hull hypothesis for the *Population* treatment (p-value = 0.0053). Thus, there is an interesting and clear difference between the two treatments despite the fact that the participants received identical peer information.

4.5.2.4. Matching the risk-averse with the risk-seeker

We now test the first two hypotheses about the magnitude of peer effect and the peer effect on convergence of choices towards the median choice in the Nonrandom-peer versus in the Population-as-a-peer treatments. We already saw before that while we fail to reject the null hypothesis that

the samples from the control group and the Population-as-a-peer treatment came from the same distribution (*p-value = 0.9610*), we rejected the same hypothesis for the control group and the Nonrandom-peer treatment (*p-value = 0.0505*).

Figure 4.5.5 presents the differences in peer effects between the two treatments in terms of the percentage of peer effects observed over the 10 rounds of decisions. There is a clear difference between the two treatments in that, except on decisions rounds one and seven, the peer effect is higher in the Nonrandom-peer treatment than in the Population-as-a-peer treatment throughout the rounds of decisions, which is in line to Hypothesis 1 and Preposition 2 (b).
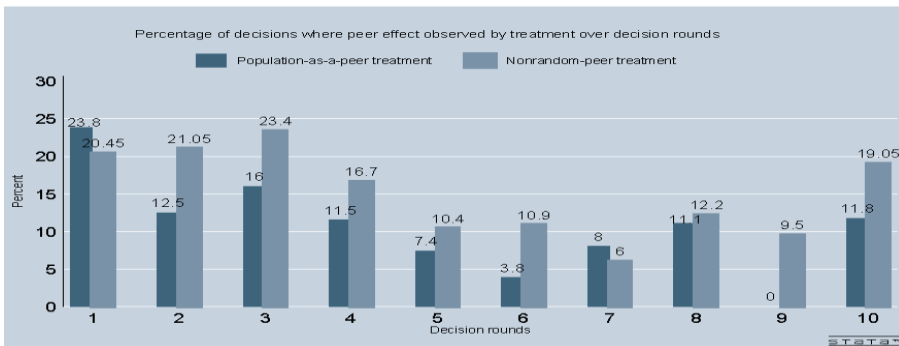
Figure 4.5.5. Risk preference based versus median choice peer effects

Moreover, the peer effect in the Nonrandom-peer treatment contributes for the median absolute deviation and the standard deviation of the sample to decrease by 3.5 units, respectively, from 10.9 to 7.4 units and from 14.2 to 10.7 units. Whereas the peer effect in the Population-as-a-peer treatment contributed the same diversion measures to decrease by only 1.5 units each, which is in line to Preposition 2 (b) and Hypothesis 2. However, we saw before that the absolute choice difference from the peer' choice has a non-linear effect in that there is a threshold level beyond which the peer effect declines both in terms of percentage of individuals being influenced by peers and the amount of intrinsic choice

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they give up to get closer to peers' choices.

Actually, peer effect in terms of percentages of participants being influenced by peers' choices in the Nonrandom-peer treatment is higher than that of the Population treatment as well throughout the 10 rounds of decisions, except on the first round as we can see on Figure 4.5.6. Overall, while the peer effect is observed in about 14.8 % of the observations in the Nonrandom-peer treatment, the percentage is 10.7 % for the Population treatment and 10.5 % for the Population-as-a-peer treatment. Thus, providing the choices of a peer systematically in such a way that the most risk-averse and the most risk-seeking individuals observe each other's choice, the second most risk-averse and the second most risk-seeing individuals receive each other's choice, etc. induces higher peer effect than providing the mean choice the population.
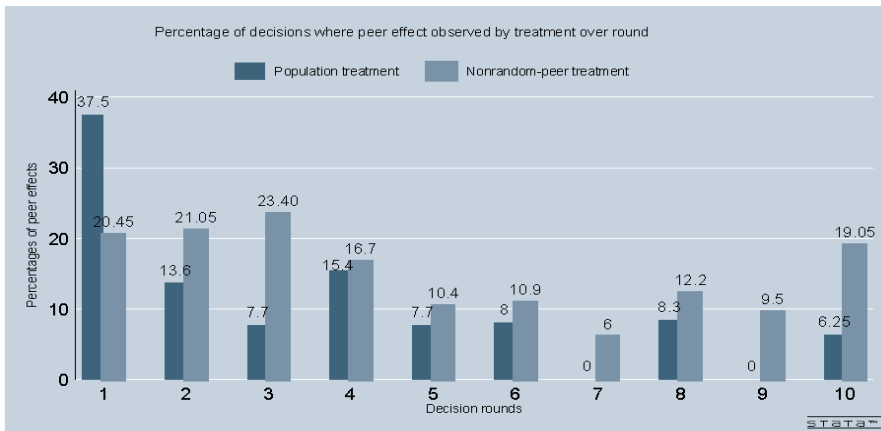

Figure 4.5.6. Nonrandom-peer versus Population treatments

4.6.   Conclusion

This study contributes to the emerging field and laboratory studies about peer effect in risk-taking when peers' choices do not convey new information and when there is no payoff commonality and social utility.

The first purpose of the study is to observe if individuals choose to see the choices of others at all given that seeing the choices of others does not convey new information about the decision-making problem. Asking for individuals consent if they want to receive (controllable) peer information is better than providing without consent not to annoy participants who do not want to observe peers' choices and to reduce any boomerang effect. For example, Beshears et al. (2015) find in a field study about pension saving that providing the choices of high earning employees to low income employees resulted in oppositional reaction in that the latter decreased their contribution to pension after receiving the contributions of the former. Even in our study where oppositional reaction is unlikely to occur since the participants received the choices of anonymous participants, 21 % of the participants chose not to see peers' choices, where the percentage grows up to 42 % after participants observed peers' choices in previous rounds of decisions. Unsurprisingly, however, a lion share of them chose to see peers' choices. Participants who are confidence of their own choice may even choose to see the choices of others for curiosity or to double check if they made errors. More importantly, seeing the choices of others is a rational choice for participants who are not sure of whether they choose the optimal choice for themselves (Eyster and Rabin, 2014). We find that male participants, participants with lower analytical ability and those with higher education level are less interested in observing peers' choices.

The second purpose of this study is to examine the pervasiveness of the peer effects, and to investigate the factors that (not) induced the peer effects. This is important for policy use of the peer effects. The large interests in seeing peers' choices that we saw before does not, however, lead to using the peer information to revise the intrinsic choices. We find that participants changed their choices in about 12 % of the overall decisions whenever they saw the choices of peers. We call this the direct peer effect whereas there we also found indirect peer effect in that the

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choices that the peers made in previous rounds influences the choices that the peer choice recipients made on the next round. In real life where the probability of gain/loss is not clearly known, the percentage of individuals being influenced by peers could be higher since peers' choices may convey new (real/perceived) information about the quality of the choices. For example, Bursztyn et al. (2014) find social learning effect increasing the number of participates invested in a risky asset by 29 %.

Insights about the behavior of individuals who are influenced most frequently by the choices of others is worth considering for the use peer effect in policy making. Interestingly, we find that the peer effect is significantly higher among participants with relatively lower math score. Specifically, we find that of all the direct peer effects in that participants changed their choices whenever they observed the choices of peers, 79 % was by the participants who scored less than the median score in the math test that we asked participants to solve. One implication of this result is that, one may improve the choices of these individuals through consultation or by providing better choices of peers.

Peer effects may have both intended and unintended outcomes. We find that while the peer effects helped to increase the earning of participants in 89 decisions by increasing mean risk-taking from 38.2 to 25.9 units, it reduced the influenced-participants' earnings in 92 decisions by reducing mean risk-taking from 20.2 units to 30.1 units. (Recall that lower purchase amount implies higher risk taking in our experiment). Zafar (2011) find also that charity contribution could be boosted or reduced by showing higher (lower) contributions of others. Similarly, Falk and Ichino (2006) find that labor productivity could be increased (reduced) by showing higher (lower) performances of others as did household energy consumption (Schultz et al., 2007). The results show how selective one as to be in terms of choosing the individuals used to induce peer effects since some individuals may follow the choice of the peers without giving due emphasis for the quality of the peer choice information.

Another interesting result we find is that the peer type plays a significant role in peer effects. We find that while framing peers' choice information as 'mean choice of all participants' induced a significant peer effect, providing the same information as a choice of a peer dose not result in a

statistically significant risk-taking. Moreover, while the mean choice of the latter treatment gradually decreased towards the choice of a risk-neutral individual, the mean choice of the former treatment lacks a clear patter. Thus, there is an interesting and clear difference between the two treatments even though the participants received similar peer information except the framing difference. Similarly, we find that the largest peer effect in terms of percentage of participants influenced by peers' choices is observed in the Nonrandom-peer treatment where the most risk-averse and the most risk-seeing participants received each other's choice, the second most risk-averse and the second most risk-seeking participants received each other's choice, etc.

To sum-up, we find that most participants choose to see the choices of others. Only a moderate percentage of the participant who received peer information either by choice or by default changed their choices every time they saw the choices of peers while some of them referred the choices of peers they observed in previous rounds to make their choice in the next round instead of revising their choices every time they saw peers' choices. Most of the direct peer effects were observed among participants with relatively lower analytical ability or among participants lacking self-confidence relative to peers' decision-making ability, probably indicating that the main reason for the peer effects in the context of this study could be lack of decision-making ability or lack of self-confidence relative to the peers in decision-making ability. Accordingly, the use of peer influences to induce individuals to choose one or the other action may largely depend on the analytical ability of the society at large. Moreover, providing the average choice of the community may have a stronger peer effect when compared with providing the choices of random individuals.

Acknowledgment

Appendix 3

A) Supplementary results

  i. The probability of wanting to see the choices of peers

Table 4.A. Logit model – The probability of wanting to see the choices of peers

Dependent variable: Wanted to see the choices of peers			
	Estimates	Standard error (Robust, HC3)$^{\zeta}$	z-value
Gender	-0.41	0.225	-1.81
Age	0.05	0.045	1.17
Education	-0.87	0.233	-3.73
Learning	-0.09	0.026	-3.43
Relative self-confidence (dummy: 1 =self-confident)	0.70	0.230	3.02
Decision-making ability (dummy: 1	-0.84	0.233	-3.58
Constant	0.68	1.073	0.63
N	480		
R^2	0.07		
F(6, 473)	6.83		0.000

The symbols *, **, *** respectively indicate 10 %, 5 % and 1 % statistically significant differences. ζ denotes heteroskedasticity-robust standard errors.

Table 4.A.2. Random logit - Probability of being influenced by peers

Dependent variable: Probability of being influenced by peers' choices			
(Random effects logit)			
Covariates	Estimates	Std. Err.	Z-values
Peer information by choice	0.31	0.3012	1.04
Relative self-confidence	-0.20	0.3687	-0.55
High type	-1.21***	0.4207	-2.87
Gender	-0.43	0.3422	-1.25
$|x-y|$	0.13***	0.0319	4.04
$(x-y)^2$	0.002***	0.0008	-2.87
Regret	0.01	0.0085	1.5
Education	-0.06	0.3423	-0.16
Learning	-0.08*	0.0405	-1.91
Constant	-3.16	0.5045	-6.26
/lnsig2u	.7726717		
sigma_u	1.471579		
Rho	.3969533		
Wald chi2(7)	42.72		
Prob > chi2	0.0000		
N	1358		

Likelihood-ratio test of rho=0: chibar2(01) = 62.41 Prob >= chibar2 = 0.000
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

a)   Test Questions

1. What is the probability of getting all heads in tossing a coin three times?

2. Which number complete the following series: 144   121   100   81   64?

3. A trader buys coffee for $1200 and sells it for $1500. For each bag of coffee, he earns a profit of $50. How many bags of coffee did he has?

4. Mary, who is twelve years old, is four times as old as her brother. How old will Mary be when she is twice as old as her brother?

5. Choose the number that is 1/4 of 1/2 of 1/5 of 200

6. What is the expected value of getting 50 with probability of 50% and getting 10 with probability of 50%?

7. Give a whole number answer that solve $x^2 = 1$

8. What is the expected value of getting 80 with 50% probability and losing 60 with 50% probability?

Histogram of correctly answered math tests
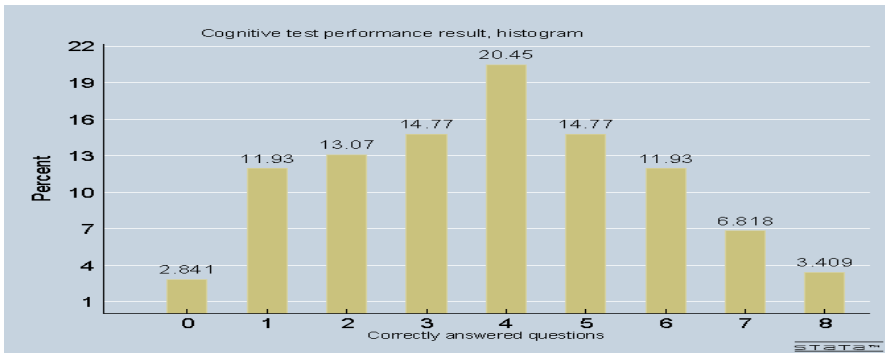
Figure 4.B.1. Histogram of correctly answered tests. The bare heights denote the percentage of participants correctly answering the corresponding number of questions. About 2.8 % of the participants answered no questions correctly while about 3.4 % of them correctly answered all 8 questions.
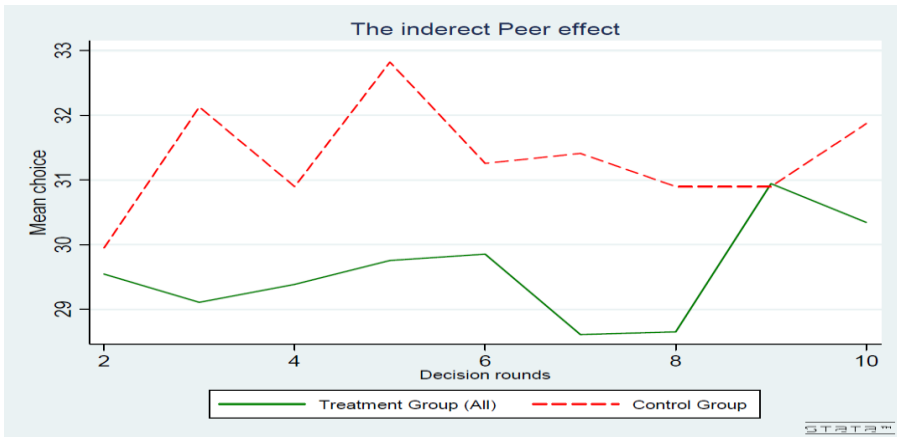
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Figure 4.C. The indirect peer effect. The indirect peer effect in that the choices of peers that participants saw in the previous round(s), call *t-1*, may affect the decision they made on the next round(s), call *t*, where *t > 1*. The graph compares the choices that participants in all treatments combined made without changing their choices in response to seeing the choices of peers with the choices of the Control Group.

B) Experimental Instructions

1. General Instruction

Welcome. Thank you for your participation.

The purpose of this experiment is to analyze decision making under risk. The experiment will take about an hour. You will earn a considerable sum of money that depends on the decisions you will make in the experiment. The experiment ends with a short questionnaire and you will be called for cash payment individually after the experiment is over.

Please refrain from talking or trying to communicate by any means with other participants once the experiment begins. If you have any questions or problems at any point during the experiment, please raise your hand

and one of the laboratory   assistants will come to you and answer your questions in private. Participants intentionally violating the rules may be asked to leave the experiment and will not be paid.

Description

In this experiment, you will be buying electricity to charge electric car. For that, consider that you an electric car that uses electricity instead of fuel. Charing the car battery is similar to charging a mobile phone battery. Electricity is time-of-used priced such that a unit of electricity used to drive one km costs 10 cents if you charge between the time 6:00 and 21:00 and Zero otherwise.

Consider that the battery level available at the moment you are making decision is just enough (not more not less) to cover planned trips you have until 21:00. However, unplanned trip may occur before 21:00 for that you need to buy electricity now. If you do not buy electricity now, then you have to cancel the trip, use a taxi, or order a fast charging of your EV. Each of these alternatives costs higher cents per km distance that the amount of electricity you buy is short of the unplanned trip distance than the electricity tariff.

Travel cost and your task

Electricity needed to travel one kilometer (km) costs **10 cents**. Thus, if you buy electricity for **X** km, you will pay **10*X** cents. Whereas, if the amount **X** that you buy is less than the **actual distance**, **D**, that you have to travel, then you have to pay **15 cents** for each kilometer distance that X falls short of D. Thus, total cost of travel is

$$Total\ cost\ =\ \begin{cases} 10*X & if\ D \leq X \\ 10*X + 15(D-X) & if\ D > X \end{cases}$$

,

where X is the amount of km that you buy electricity for and D is the actual distance of the unplanned trip.

The unplanned trip distance, D, is **uniformity distributed between 0 and 60 km, inclusive**. That is, it can be 0, 1 km, 2 km, ..., 60 km, where each number has equal chance of occurrence. The realization of the actual distance of the unplanned trip is simulated by a computer randomly drawing a number between 0 and 60 after you make a decision.

Knowing this, **your task** is to decide for how much kilometers to buy electricity for so that you can earn high cash from the experiment.

[Peer information here, given below]

Payoffs

The amount of money that you earn in this experiment depends on the decisions you will make. You are given **1300 cents** for each round of decision for you to pay for travel and to save the rest for yourself. Specifically, your earnings (in cents) per decision round are calculated as follows:

Your earning = 1300 – Total cost

In total, you will be making 10 rounds of decisions.

Note that your earning from the experiment exclusively depends on your choice and will not be affected by the choices of other participants. Your earnings and decision in one round will not be also affected by other rounds. For example, you cannot use the amount of km you buy electricity for in a round for other rounds. Similarly, the random draw of a number to detriments the actual distance is independent across rounds of decisions and across participants.

You can use the computer calculator by clinking on the calculator button

on your screen that looks like

Enjoy the experiment!

[The peer information]

[To the Population Treatment]

After you make a decision, you may get the chance to see the average (mean) choice of all participants. Your choice is not included in the calculation. A random number draw determines whether you will get the peer information. If you are drawn to see the information, you may be asked whether you would like to see the information. If you choose to see and if you get this information, you may revise your initial choice if you want, but you **MUST** consider each of your decisions as the final decision since it is highly likely that you may not get the information.

[To the Population-as-a-peer, Nonrandom-peer and Random-peer treatments]

After you make a decision, you may get the chance to see the choice of another participant. A random number draw determines whether you will get the information. If you are drawn to see the information, you may be asked whether you would like to see the information. If you choose to see and if you get this information, you may revise your initial choice if you want, but you **MUST** consider each of your decisions as the final decision since it is highly likely that you may not get the information. Moreover, if you get the information, the other peer whose choice you observe will not get your choice.

[To the Two-peer Treatment]

After you decide, you may get the chance to see the choices of two participants. A random number draw determines whether you will get the information. If you are drawn to see the information, you may be asked whether you would like to see the information. If you choose to see and if you get this information, you may revise your initial choice if you want, but you **MUST** consider each of your decisions as the final decision since it is highly likely that you may not get the information. Moreover, if you get the information, the other participants whose choices you observe will not get your choice.

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5. Harnessing Big-Data for Estimating the Energy Consumption of Electric Vehicles

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Abstract

Analyzing the factors that affect the energy efficiency of vehicles is crucial to the overall efficiency improvement in the transport sector, one of the top polluting sectors at the global level. This study analyzes the energy consumption rate of battery electric vehicle (EVs) and provides insight into the factors that affect energy consumption by harnessing big data from real-world driving. The analysis considers four data sources: (i) driving pattern data collected from 741 drivers over a two-year period; (ii) drivers' characteristics; (iii) road type; (iv) weather conditions. The results of the analysis measure the (unweighted) mean energy consumption rate (ECR) of electric vehicles at about 0.183 kWh/km. We find that weather condition has a very strong effect on the ECR of EVs: on average, trips in December consume as high as 65 % more energy than the trips do in July or August, where the overall winter season trips mean ECR is higher by 39 % than that of the summer season trips. Moreover, the results of the analysis show that driving speed, acceleration and temperature have non-linear effects on the energy consumption rate, while season and precipitation level have a strong linear effect. The findings from this study enlighten the consumers to be more informed and manufacturers to be more aware about the actual utilization of battery electric vehicles.

Keywords: fully battery electric vehicles, energy consumption rate, driving range, driving environment

5.1. Introduction

As the transport sector is one of the largest contributors of greenhouse gas at a global level (see, e.g., Alessandrini et al., 2012; Zahabi et al., 2014), there have been efforts by car-makers, car drivers and governments to improve fuel efficiency, to reduce pollution and to limit dependence on fossil fuel. For example, some of the EU and US governments have set standards that limit the pollution level of cars and they use incentives and taxes to induce car manufacturers to produce, and car users to use fuel-efficient vehicles (Kono et al., 2008). China has planned to take millions of old cars off roads to improve air quality (Duggan, 2014). Battery electric vehicles (henceforth, BEVs) are considered as one alternative to curtail pollution from the sector and to reduce dependence on the scarce and insecure petroleum since the electricity needed to charge BEVs can be obtained from renewable resources such as wind, solar power and hydro.

However, the market penetration rate of BEVs has been lethargic, mainly because of high purchase prices, limited recharging infrastructures, limited driving range coupled with long recharging time, uncertainties concerning driving range and battery life, and risk aversion behavior in adopting new technologies (see, e.g., Egbue and Long, 2012; Birrell et al., 2014; Kihm and Trommer, 2014). Uncertainty plays a role when factoring in that customers have limited knowledge about the performances of BEVs and their sensitivity to driving environments, adversely affecting the demand for BEV (Birrell et al., 2014). Accordingly, providing insight into the factors that affect the energy (electricity for BEVs) consumption rate (ECR), i.e. the amount of electricity consumption per unit distance, and the corresponding driving range of BEVs under different driving environments is very relevant to support, on the one hand, consumers in choosing appropriate vehicles that suit their needs, and, on the other hand, manufacturers in distinguishing and targeting different customers depending on the driving environments that the customers live and move in.

Insights into the factors that affect the ECR and information about the driving range of conventional vehicles have been provided extensively, as the fuel consumption of conventional cars is well-documented in both the

theoretical literature (Nam and Giannelli, 2005; Mellios et al., 2011) and in the empirical literature (Ericsson, 2001; Brundell-Freij and Ericsson, 2005; Hu et al., 2012). Existing studies show that the fuel consumption rate of conventional vehicles is affected by road width (Brundell-Freij and Ericsson, 2005; Yao et al., 2007; Kono et al., 2008; Hu et al., 2012), road grade (Nam and Giannelli, 2005; Wang et al., 2008), traffic congestion and speed limits (Brundell-Freij and Ericsson, 2005) as well as by traffic information provided to drivers (Kono et al., 2008; Fotouhi et al., 2014). Existing studies also illustrate that driving patterns (in terms of speed and acceleration profiles) are the main factors affecting fuel consumption of conventional vehicles (Ericsson, 2001; El-Shawarby et al., 2005; Nesamani and Subramanian, 2006; Wang et al., 2008; Heide and Mohazzabi, 2013). Moreover, a number of studies have provided mathematical and technical detailed accounts of the effects of different car characteristics on the fuel consumption of conventional cars (see, e.g., Brundell-Freij and Ericsson, 2005; Nam and Giannelli, 2005; Heide and Mohazzabi, 2013; U.S.E.P.A., 2014). It should be noted that the effects of car features on fuel consumption are usually taken into account during the design of the vehicle by the manufacturers, and are usually made available to the consumers during the purchase of the vehicle (Kono et al., 2008; Ben-Chaim et al., 2013).

The factors that affect the ECR of hybrid electric vehicles (HEVs) that use both fuel and rechargeable batteries have been provided to a lesser extent. For example, winter season (in Canada) has been related to a decrease of 20 % in the fuel efficiency of HEVs, and the overall fuel economy of HEVs with respect to conventional vehicles has been evaluated as possibly overweighed by the poor performance of HEVS in cold weather locations (Zahabi et al., 2014). The temperature has been found as relevant in other studies that have focused also on the driving environment (Fontaras et al., 2008; Alvarez and Weilenmann, 2012; Lohse-Busch et al., 2013), while technical features such as the power ratio of HEV components and the applied control strategy have been demonstrated analytically related to the ECR of HEVs (Banjac et al., 2009).

Insights into the factors that influence the ECR of BEVs have been scarce, mainly because of their recent market penetration. Most studies include technical analyzes that investigate the effects of car components on the

ECR (see, e.g., Duke et al., 2009) and reports by car manufacturers and other stakeholders. Large differences about fuel consumption of passenger cars are usually observed between the results of car manufacturers and the results observed in real-world driving (Huo et al., 2011), mainly because manufacturers test cars by performing a long and continue test drive from a fully charged battery to a completely flat battery, thus, ignoring basic real-world energy expenditures such as the energy used to overcome the inertia force to propel a parked car and the energy used to cool down a propelling car for each short trips. A limited number of studies have focused on the ECR and the driving range of BEVs: ECR of BEVs was estimated by taking into account driving patterns and car features from GPS data, and in-city driving was deemed more energy efficient than freeway driving (Wu et al., 2015); ECR of BEVs was compared by considering the driving range reported by the manufacturer versus the actual driving range of drivers (Birrell et al., 2014). However, these studies present limitations: (i) the study samples consisted respectively of one (Wu et al., 2015) and 11 drivers (Birrell et al., 2014), with obvious consequences on the possibility of generalizing findings as the authors point out; (ii) the data collections did not cover both the winter and summer seasons simultaneously; (iii) the data analyzes did not control for possible confounders, with obvious consequences on the possibility of assessing whether the differences were caused by other factors.

As aforementioned, the uncertainty and the consequent anxiety about the driving range and the ECR of BEVs is one of the major barriers to their wider market penetration. It is therefore essential to provide insights into the actual ECR and driving range of BEVs under different driving environments as well as the factors that affect them. Providing accurate information to people about the ECR of BEVs using real-world data where the drivers are the people themselves is crucial not to damage the credibility and sustainability of BEVs, particularly in the current situation where big carmakers are facing challenges for incorrectly reporting the fuel economy of the cars they make. (For example, carmakers Volkswagen and Mitsubishi Motors are expected to pay billions of dollars fine and compensation fees for measuring fuel efficiency incorrectly (Randazzo & Boston, 2016; Kubota 2016).). Analyzes of the factors affecting ECR of BEVs is also relevant to figure out the ways to improve the electricity

efficiency of BEVs (Wu et al., 2015). The current study contributes to the existing literature by analyzing real-world data collected over a two-year period in Denmark. Namely this study addresses questions about the ECR of BEVs considered in this study, the sensitivity of BEVs to various driving environments including speed and acceleration profiles, wind speed, temperature, and precipitation.

Big data are used for providing answers to these questions. More than a quarter of a million trips performed by 741 BEV drivers have been analyzed in the current study. The data were collected over a two-year period between January 2012 and January 2014 by Clever A/S, an electric mobility operator in Denmark, using three models of BEVs, namely Citroen C-Zero, Peugeot Ion and Mitsubishi iMiev. The data contained information for each trip about vehicle positioning (i.e., longitude, latitude), driving patterns (i.e., speed profile, acceleration profile), battery charge level, time and duration of the trip, and road characteristics after map-matching. Data included also information about the weather conditions during each trip as well as the drivers' household characteristics. The analysis focus on the computation of the ECR and the corresponding driving range of BEVs from the large sample of trips in real-world driving conditions, and the estimation of the effects of driving patterns, road characteristics and weather conditions on the ECR of BEVs from the estimation of individual-specific fixed effects econometric models. Moreover, the analysis proposes a simple formula that allows consumers to compare BEVs and conventional vehicles in terms of fuel (electricity) cost under varying intensity of the winter season. The current study contributes to the literature about energy efficiency of BEVs by overcoming limitations of existing studies: (i) the sample of the study is significantly larger than previous studies with about 2.3 million km driven; (ii) the seasonal variation is accounted for, as the study period covers two summer and three winter seasons; (iii) the weather effects are considered, as the study looks at the effect of temperature, precipitation and wind speed; (iv) the actual driving patterns are analyzed, as the speed and acceleration profiles are collected for each trip; (v) econometric models are used to disentangle the effect of each variable on the ECR after controlling for possible confounders.

The remainder of this paper is structured as follows. The next section presents the data collection and the methods used to compute the ECR of BEVs and to estimate the model of the ECR of BEVs. Then, the results of the computation and the estimation are presented, and conclusions and further research directions are offered in the last section.

5.2. Methods

5.2.1. Data Collection

Four data sources were used for this paper: (i) driving patterns collected from GPS data loggers installed on 200 BEVs used by 741 drivers[65] for 276,102 trips and about 2.3 million km travelled; (ii) drivers' characteristics obtained from registration during receiving BEVs for 3 to 6 months drive; (iii) road characteristics collected from the map-matching of the GPS data with the Danish road network; (iv) weather information obtained from the Danish Meteorological Institute (DMI). Clever A/S collected the driving pattern data from customers who have been driving BEVs for a period of 3 to 6 months in a project called "test-en-elbil" (in English: "test an electric car") where Danish drivers were invited to drive BEVs and were proposed an agreement to collect information about their trips during the period. The data were collected using GPS during the period from January 2012 to January 2014, and the GPS data loggers were mounted on three fully BEV models, namely Citroen C-Zero, Peugeot Ion, and Mitsubishi iMievst, which are technically identical.

Variables related to driving patterns (i.e., speed profiles, acceleration profiles), date and time of each trip, distance and duration of each trip, geographical coordinates of each trip, and percentage change in the battery charge level for each trip, were extracted from the data logger.

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[65] The total number of individuals participated in the project was higher than 741, but the number of drivers with relevant data for this paper is 741. Each driver had been using a BEV for 3 to 6 months, after which, the BEV was given to other drivers.

Time-of-day periods and seasonal variation were defined on the basis of the date and time stamps of the GPS loggers.

Variables related to income and demographic characteristics of drivers' households were collected during the registration process for testing BEVs. The drivers were men (56%), had average age of 44 years old, and heterogeneous distribution of self-reported income, 48% of them declared a yearly income higher than the then mean national income.

Controlling for the road and traffic characteristics revealed cumbersome since road grade and traffic congestion are dynamic even within a trip. However, it was considered that road grade is not relevant to Denmark as one of the flattest countries in the world, and we use rush hour as a proxy to traffic congestion hours. Moreover, it was discerned whether each trip was performed on a highway in order to account for road variability.

Controlling for the weather conditions revealed also cumbersome because weather varies dynamically across time and location even for a single trip. It was considered that a driver could experience different types and level of weather conditions, but the changes would have marginal effects when considering that most trips in Denmark are rather short. Accordingly, and similarly to existing literature, we use the mean values for temperature, precipitation, wind speed and visibility during each trip as reported by DMI. A descriptive statistic of the variables is presented in Table 5(B) in the Appendix.

Considering the initially registered 276,102 trips, the data cleaning process implied looking for missing values and possible errors in the variables. In particular, 10,977 trips had missing information about the battery charge status, 10,420 trips had unreliable information with extremely low or high values of battery charge level variation, and 9,394 trips had missing information concerning the identity of the driver. Following the data cleaning process, the data analysis focused on 239,247 trips for the descriptive part and 229,853 trips for the regression part.

5.2.2. Data analysis method

5.2.2.1. Measuring the energy consumption of electric cars

This study examine the performance of BEVs in terms of ECR (analogous to the fuel consumption rate for conventional cars). Namely, the ECR is calculated as the ratio between the power consumed during the trip and the distance traveled:

$$ECR = \frac{Power\ consumed\ (kWh)}{Distance\ traveled\ (km)} \qquad (5.1)$$

The lower is the ECR, the better is the energy efficiency. In this study, the data contained the percentage change in battery charge level before and after each trip, which implied that the value obtained from the data collection had to be multiplied by the watt-hour of the battery of the vehicle (which is 16 kWh as reported in the specification of the cars) in order to obtain the power consumed in kWh.

Given the ECR, the driving range of BEVs was computed as follows:

$$Driving\ Range = \frac{Power\ of\ a\ fully\ charged\ BEV\ (kWh)}{ECR\ (kWh/km)} \qquad (5.2)$$

It should be noted that the driving range depends on the battery capacity, the car performance, or both. Accordingly, a higher driving range would not necessarily indicate that the BEV performs better in terms of ECR, but could possibly relate to a higher battery capacity that comes at a heftier price. For this reason, comparing ECR between BEVs provides more correct insight into the energy efficiency of BEVs. To reduce (the possible) error in obtaining ECR using equation (5.1), for example if it is not technically possible to use the whole battery power of the BEV (e.g., for the sake of the battery-life), one can also compute the ECR in percentage terms (denoted by ECR^p) by dividing the percentage change in the battery-recharging-status at end of the trip by the trip distance traveled. That is,

$$ECR^P = \frac{B_0 - B_1}{D} \; , \tag{5.3}$$

where B_0 and B_1 are the battery recharging status at the beginning and end of the trip, respectively, and D is trip distance in km.

The driving range of the BEV is then simply found by dividing 100 (representing fully charged battery) by ECR^P, i.e., driving range = 100/ECR^P. Note that $ECR^P > 1$ for BEVs with shorter than 100 km mean driving range and $ECR^P < 1$ for BEVs with longer than 100 km mean driving range, and thus, ECR^P cannot be used to compare the energy efficiency of different types of BEVs.

5.2.2.2. Modeling analysis of the ECR of BEVs

Explaining the factors that affect the ECR of BEVs under different driving environments is relevant to consumers for choosing vehicles that suit their driving needs and to manufacturers to distinguish and target market segments according to driving environments. Accordingly, this study provides the estimation of a model that unravels the sign and magnitude of the factors that affect the ECR.

There could be unobservable (latent) characteristic of individuals that vary across individuals but are similar across trips by an individual, which are potentially correlated with one or more of the independent variables. An unobserved effects model was used because this is the most suitable model for panel data as the ones collected in this study (Wooldridge, 2010). Accordingly, an unobserved individual specific effect model was estimated to explain the ECR variation, which controls for unobserved variables that are invariant across trips of a driver. A general model that can be used to estimate the factors explaining the variation in ECR can be given by

$$ECR_{it} = \theta_t + X_i\beta + S_{it}\lambda + W_{it}\alpha + Y_{it}\delta + Z_{it}\gamma + \phi_i + \upsilon_{it} \tag{5.4}$$

where ECR_{it} is the ECR in trip t *by* driver *i* (i = 1, 2, 3, ...,N denoting the drivers), X_i is a row vector of the characteristics of the vehicle used by individual *i*, S_{it} is driving characteristics (e.g., speed of driving and acceleration and traffic congestion of individual i in trip t, W_{it} is a row vector of weather variables that may vary among individuals *i and* across trips *for an individual*, Y_{it} is a row vector of road characteristics that may vary across individuals *i and* across trips *t*, Z_{it} is a row vector of household characteristics that could vary across individuals *i* and across trips t, ϕ_i is individual-specific unobserved effect that is trip-invariant but varies across individuals, v_{it} is the idiosyncratic error term with mean zero and is (assumed to be) uncorrelated with any of the explanatory variables, and the column vectors α, λ, β, γ and δ contain the population parameters to be estimated. The inclusion of the intercept allows for the aggregate ECR to vary over time.

The choice of the appropriate model among unobserved effects models mainly depends on how the ϕ_i is correlated with the explanatory variables. The random effects model is preferred to fixed effects model when ϕ_i is uncorrelated with explanatory variables, and when the main variables of interest are dummies. Whereas the fixed effects model is preferred when there is strong correlation between the unobserved factors and the explanatory variables included in the model. One way of choosing between random and fixed effects models is to conduct the Hausman test (Wooldridge, 2010). Having found that the fixed effects model is preferred to random effects model via a Hausman test for the data collected in this study, a fixed effects model was estimated to investigate the factors that explain the variation of *ECR.* Correspondingly, the explanatory variables X_i, and Z_i and the latent variable, ϕ_i, were canceled out by trip-demeaning given that these variables did not vary across the trips of a driver. Accordingly, the model we estimated is given by

$$ECR_{it} - \overline{ECR}_i = \left(\theta_t - \overline{\theta}_t \right) + \left(W_{it} - \overline{W}_i \right)\tilde{\alpha} + \left(S_{it} - \overline{S}_{it} \right)\lambda + \left(Y_{it} - \overline{Y}_i \right)\tilde{\delta} + v_{it} - \overline{v}_i$$

, (5.5)

where the bars subtracted on each corresponding variable denotes the mean of each variable computed over trips by each driver individually.

For example, $\overline{ECR}_i = \dfrac{1}{T} \sum_t ECR_{it}$, $\bar{W}_i = \dfrac{1}{T} \sum_t W_{it}$, and so on, where T is the number of trips by individual i for i = 1, 2, 3, ...,741. This transformation enables to cancel out the time-invariant latent variable that could bias the estimation results otherwise, and the model provides consistent estimates regardless of the correlation between the latent variable and the explanatory variables (Wooldridge, 2010).

5.3. Results

In this section, the results from the data analyzes are presented. The main results presented in this section include descriptive statistics results about the trips, ECR (by different categories), and result from the fixed effects model estimation of the factors explaining ECR variation.

5.3.1. Overview of trips by BEVs

On average, each driver had 307.1 trips during the average 90.7 days that the individuals used BEVs. This is equivalent to a mean of 3.4 trips per day per driver, which is higher than the 2.73 average number of trips in 2014 in Denmark obtained from the Danish National Survey (Christiansen & Skougaard, 2015). Concerning the length of the trips, about 50% of trips were less than 5 km, and only about 1 % of the total trips were over 50 km, where the mean trip distance is about 9 km as shown in Figure 5.3.1. A possible reason for the short trip distances in our data could be the way that a trip is defined in our data: a trip constitutes when the vehicle starts moving until it stops and the engine is set off. For example, an individual shopping on the way from workplace to home is considered as having two trips: one from workplace to the supermarket and the other from the supermarket to home while it is most likely regarded as a trip in surveys. This may also explain the relatively larger per day average trips we observe in our data. Another possible reason for the short trip distances could be the fact that about 39% of Danes commuted less than 5 km in 2013 (Denmark Statistics, 2014), and another reason may be that the customers had a range anxiety problem and used the BEV for short distances.
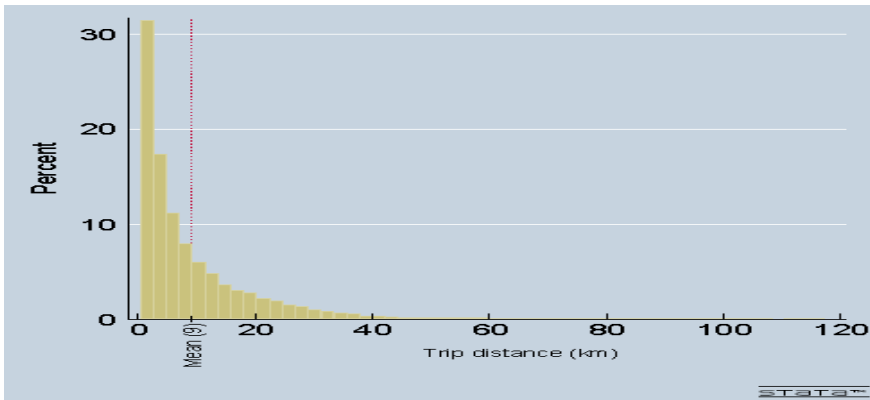
**Figure 5.3.1.** Trip distances (in km) histogram observed in the data

Related to frequency of recharging, a lion share of drivers did not recharge their BEVs upon the arrival from each trip: the frequency of recharging observed in the data is 21.4 % of the total number of trips. This means that, on average, drivers had been recharging their car after using the BEVs for about 4.7 trips. Given the observed short trip distances, it is not surprising that a great share of individuals did not recharge the BEVs upon arrival from each trip. It is however interesting that the infrequent recharging does not correspond to waiting for having an empty battery: the mean and the median of battery charge status when the recharging was performed were, respectively, 55.5% and 56%, namely individuals recharged their BEVs well before risking to have their batteries empty.

The time-of-day trip patterns by BEVs could be also of interest, for example, to observe whether BEVs had been used for daily routine trips in that, we expect, trips by BEVs to have similar trip-time pattern to the general population. Figure 5.3.2 and Figure 5.3.3 respectively present the kernel density of the frequency of trips with the BEVs in our sample and trip patterns by passenger car from the Danish National Survey according to the departure time of the trips. These densities show similarity that most of the weekday trips in both cases were performed during the peak hours in the morning (i.e., 7.00 am - 8.30 am) and in the afternoon (i.e., 3.00 pm - 5.30 pm). The same applies also for the weekends, as most of the weekend trips were performed between 9.00 am and 5.00 pm. This

could indicate that, like conventional cars, BEV had been used for routine trips at least for the data that we used.
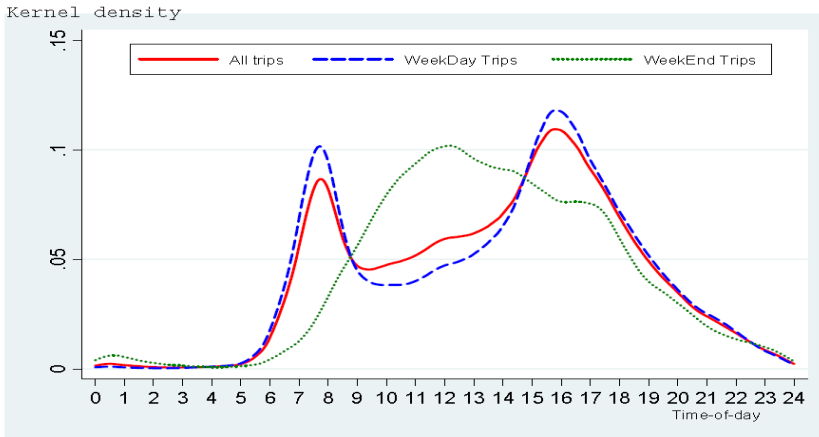
Figure 5.3.2. Departure time of trips by BEVs, kernel density
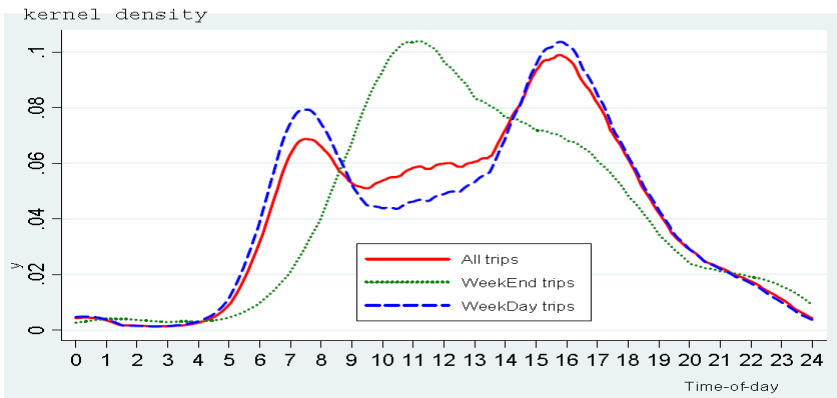
Figure 5.3.3. Departure time of trip computed from the 2013 Danish National Travel Survey

*Source: Own computation using the 2013 Danish National Travel Survey*

5.3.2. Observed ECR of BEVs

5.3.2.1. Overall ECR

Figure 5.3.4 shows that the distribution of the ECR presents high heterogeneity. The mean ECR in the sample is about 0.183 kWh/km, namely each km traveled consumes on average 183 Watt-hour (= 0.183 kWh). The corresponding driving range of the 16 kWh BEVs considered in this study is about 87.4 km.[66] About 80 % of the trips consumed between 0.113 kWh/km and 0.274 kWh/km electricity consumption rate, where the median ECR is about 0.169 kWh/km and the standard deviation is about 65. A possible reason for the heterogeneity is the difference in driving environments whose investigation motivated the modeling of the variation of the ECR presented later. Moreover, we found that only about 7 % of the trips could achieve the 150 km maximum driving range of the BEVs reported by the New European Driving Cycle (NEDC) test (Peugeot-iOn, 2015). (Using the mean ECR, we present a comparison between conventional cars and BEVs in terms only of fuel (electricity) cost for running the car. Interested readers can refer Appendix A for the result.)

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[66] We also computed ECR in terms of percentage battery consumption changes, i.e., ECR^P, as given in equation (5.3), and interestingly, we found similar result that ECR^P = 1.14, which means that the recharging status of the battery decreases, on average, by about 1.14 for each km distance traveled. The corresponding driving range is 100/1.14 = 87.7 km.
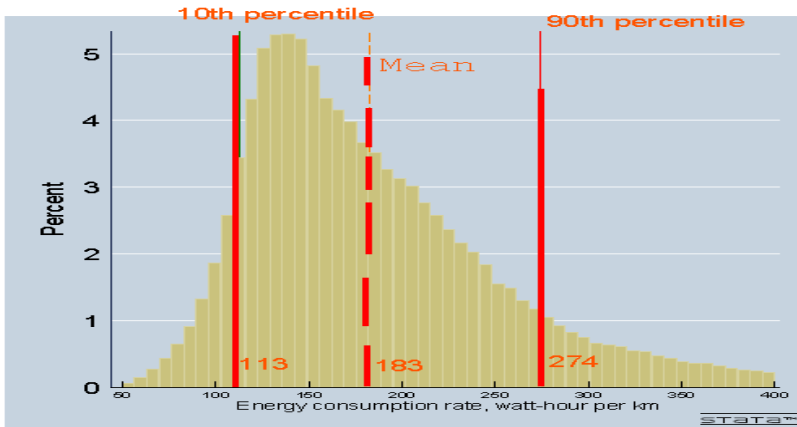
Figure 5.3.4: The distribution of ECR, and observed versus reported ECR of BEVs

5.3.2.2.   ECR by season

The ECR was computed for the summer and the winter seasons, where winter in this paper context represents months from November to March, both inclusive, and the rest of the months are considered as summer. Results from this paper reveal that ECR is higher, and, consequently, the driving range is shorter in winter with respect to summer: the average ECR is about 0.157 kWh/km during the summer and about 0.219 kWh/km during winter, with an observed 39.5% increase in electricity consumption in winter per km driven.

Both a parametric t-test and a non-parametric Mann-Whitney test proved the difference to be statistically significant, and the difference is higher than the 20% reported in Canada for hybrid vehicles (Zahabi et al., 2014).

 Figure 5.3.5 presents the monthly variation of ECR along with the mean temperature across the months. The Figure clearly reveals that the mean ECR is highly sensitive to weather conditions. For example, the mean ECR is higher by about 65 % in December than in July (or in August).

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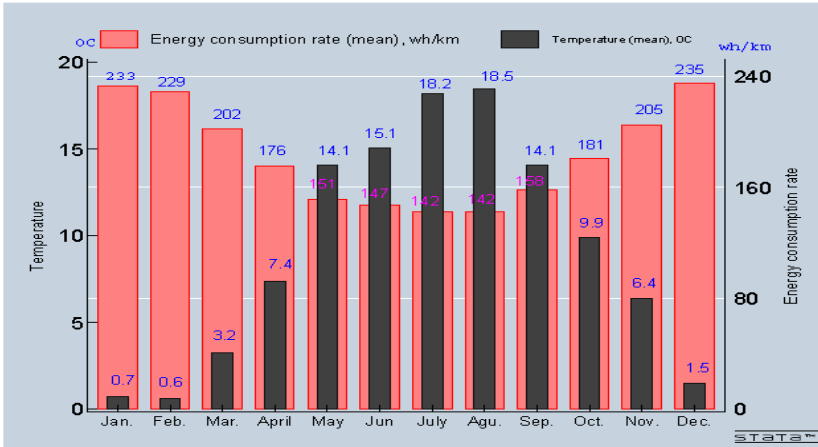
Figure 5.3.5: Mean ECR (in watt-hour per km) and the men temperature (in ⁰C) by month. The monthly mean ECR is presented on the y-axis to the right and the monthly mean temperature recorded during the trips is presented on the y-axis to the left.

5.3.2.3.   ECR by trip distance

As driving patterns could vary with the trip distance (Fosgerau, 2005), and in turn the distance could affect the ECR (Ericsson, 2001), it is relevant to consider the ECR for different trip distances in order to know for which trip distances BEVs are, on average, more energy efficient. The distribution of the distances in the trips analyzed in this study suggested considering short trips (less than 2 km), medium trips (between 2 and 10 km) and long trips (longer than 10 km).

Table 5.3.1 presents the mean, median and percentiles of the distributions of ECR and driving range for the three trip distance bands considered. Obviously, it emerges that the mean ECR decreases (and consequently the mean driving range increases) with the increase of the trip distance: for example, on average short trips consume 40 Wh/km more energy than medium trips do and 57 Wh/km more energy than long trips do. The difference is observed for all percentiles except the lower one, and it is statistically significant according to both a parametric t-test and a non-parametric Mann-Whitney test. Roughly speaking, these findings suggest that BEVs are more energy-efficient for individuals with

relatively longer commuting distance rather than ones with shorter commuting distance (less than 10 km).

Table 5.3.1: ECR and driving range of BEVs by trip distance

	Short Trips (< 2 km)		Medium Trips (≥ 2 & < 10 km)		Long Trips (≥ 10 km)	
	ECR (Wh/km)	Driving range (km)	ECR (Wh/km)	Driving range (km)	ECR (Wh/km)	Driving range (km)
Mean	223	*82*	183	*96*	166	*102*
5 percentile	112	*143*	111	*144*	114	*141*
25 percentile	162	*99*	136	*117*	134	*119*
Median	209	*76*	169	*95*	159	*101*
75 percentile	281	*57*	222	*72*	192	*83*
95 percentile	366	*44*	298	*54*	238	*67*
Standard dev.	79	*30*	59	*28*	39	*23*
No. obs.		54,161		108,605		73,809

5.3.2.4. *ECR by road type*

As road characteristics have an effect on the fuel economy of conventional and hybrid vehicles (Brundell-Freij and Ericsson, 2005; Ericsson, 2001; Zahabi et al., 2014), ECR was computed for highway and non-highway trips.

Table 5.3.2: ECR and driving range of BEVs by road type

	Trips on highways		Trips not on highways	
	ECR (Wh/km)	Driving range (km)	ECR (Wh/km)	Driving range (km)
Mean	174	*96*	187	*94*
5 percentile	121	*132*	111	*144*
25 percentile	145	*111*	138	*116*
Median	168	*95*	172	*93*
75 percentile	198	*81*	223	*72*
95 percentile	243	*66*	318	*50*
Standard dev.	39	*21*	63	*29*
No. obs.	16,369			210,984

Table 5.3.2 presents the mean, median and percentiles of the distributions of ECR and driving range for the two road types considered. No clear difference emerges between driving on highway or non-highway roads, although the average ECR is slightly lower for highway portions of the trips. More specifically, while the 5th and 25th percentiles of the ECR of trips on highway are higher (and consequently the driving ranges are shorter) than for trips on non-highways, the opposite is observed when looking at the mean, median, 75th and 95th percentile of the ECR of BEVs. However, the differences are not statistically significant according to both a parametric t-test and a non-parametric Mann-Whitney test.

It is very important to note that the observed differences in ECR and the corresponding driving ranges by trip distance (short, medium and long), season (winter versus summer), and route type (dummy for highway) that we discuss above are mean comparisons without controlling for

other cofounding factors. It is importance to conduct further analysis to disentangle the impacts of each factor by controlling for other confounding factors that affect ECR. For this end, we conducted regression analysis that is presented in later section of the paper.

5.3.3. Estimates of the ECR

Table 5.3.3. presents the estimation results of the unobserved individual specific fixed effects model from 229,853 trips. Interestingly, most of the explanatory variables are statistically significant and have the expected sign also when considering non-linearity in their relation to the ECR. The model estimates present effects on the ECR, i.e., electricity consumption per km traveled, which means that the potential effects when considering yearly travel distances are considerably high.

The most important determinants of energy consumption rate of BEVs are found to be driving patterns (acceleration and speed of driving, both non-linearly) and seasonal variation (a winter dummy), temperature (non-linearly) and precipitation. It should be noted that the lower the ECR is, the better is the fuel efficiency, ceteris paribus, and, thus, estimates with negative signs (and that are statistically significant) indicate the variables having a positive effect in terms of fuel efficiency and driving range.

Table 5.3.3: ECR model estimates: Fixed Effects model[67]

Dependent variable: ECR (watt hour/km)

Explanatory Variables	Estimate	Cluster Robust std. error	p-value
Mean driving speed (m/s)	-19.000	0.365	0.0000
Mean driving speed square	0.761	0.015	0.0000
Median acceleration (m/s^2)	55.521	7.156	0.0000
Median acceleration square	27.828	9.150	0.0020
Trip distance (km)	-1.110	0.062	0.0000
Trip distance square	0.010	0.001	0.0000
Winter (dummy: 1 = trip during winter season)	14.687	0.364	0.0000
Highway (dummy: 1 = trip on highway)	0.534	0.381	0.1610
Rush hour (dummy: 1 = trip during rush-hours of traffic)	-1.926	0.204	0.0000
Battery level at trip start (%)	3.401	0.206	0.0000
Battery level at trip start square	-0.056	0.003	0.0000
Battery level at trip start cube	0.0003	0.000	0.0000
Temperature (^{0}C)	-4.807	0.040	0.0000
Temperature square	0.081	0.002	0.0000
Wind speed (m/s)	0.695	0.042	0.0000
Visibility duration in the journey (minutes)	-0.118	0.005	0.0000

[67] We also estimated the energy consumption rate in percentages (see equation (5.3) for details) directly computed from the battery recharging status changes after the trip. The result is presented in Appendix C (Table 5.C). Note, however, that the coefficients are not directly comparable since the dependent variables are different: ECR versus ECR^P.

Precipitation (mm)	5.287	0.229	0.0000
Constant	135.489	6.378	0.0000
R-square: within	0.2714	sigma_u	20.0258
R-square: between	0.7020	sigma_e	44.8110
R-square: overall	0.4078	Rho	0.1665
Number of observations	229,853		

An interesting finding from the model estimation is that the mean driving speed presents a quadratic term, namely trips at both very slow and very fast speed increases the ECR (and, correspondingly, decreases driving range), where the ECR minimizing driving speed according to our estimation is 12.5 m/s (= 45 km/h)[68], ceteris paribus. Driving at slower speed than at an ideal speed may increase ECR since more energy could be required for keeping the BEV moving for a longer period, while a possible reason for the high speed of driving consuming higher energy could be linked to the higher per unit time energy consumption. To substantiate this finding, we also run a non-parametric locally weighted scatter plot smoothing estimation of the effect of speed of driving on ECR. Figure 6 presents the fitted curve, where the horizontal axis represents the driving speed and the vertical axis represents the ECR. The model predicts that trips with mean driving speed of between 45 and 56 km/h (minimum at about 52 km/h) demonstrate relatively lower ECR at least for the driving environment considered in this study, which is lower than

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[68] Similar result is obtained from the estimation of ECR^P (see Table 5.C. in Appendix C for comparison and equation (5.3) about computation of ECR^P), indicating the (possible) measurement error converting the energy consumption rate from battery recharging status indicator to watt-hours is ignorable since ECR^P is not subjected to such measurement error.

the fuel saving driving speed for conventional vehicles of 65 km/h (El-Shawarby et al., 2005).[69]
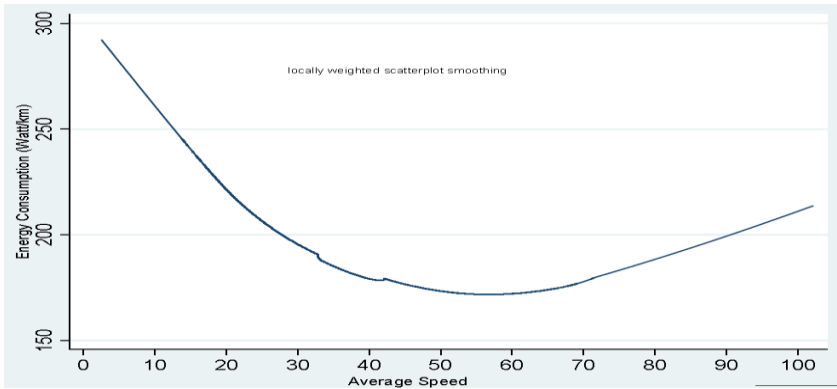
Figure 5.3.6: The effect of driving speed on the ECR of BEVs

Table 5.3.3 reveals also that acceleration is the most important determinant of ECR in terms of marginal effect. It increases ECR at an increasing rate, ceteris paribus. A number of studies also found significant impact of acceleration on fuel consumption rate of conventional and hybrid cars. See, for example, Zahabi et al. (2014). Besides to testing the impact of acceleration on ECR of BEVs, the contribution of this paper is to indicate the non-linearity of the impact.

The seasonal variation has a significant impact on the ECR, with a higher ECR in winter with respect to summer, even when controlling for the weather effects such as temperature, precipitation, and wind. Thus, the winter dummy variable presented in the table should be interpreted as variable denoting seasonal variations such as snow on the street and

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[69] This result seems a contradiction to physics which states that ECR should increase strictly monotonically with driving speed, and thus, the interpretation of the result requires consciousness. By speed and ECR relationship, we are referring the effect of average speed of trips (not the speed variation within a trip) on the corresponding ECR.

energy consumption for heating/cooling the car, which we do not control for.

Another interesting result from the model estimation is that the outside temperature has a non-linear U-shaped effect on the ECR, namely driving at both too low and too high temperature affects (negatively) the energy efficiency of BEVs. This finding is in line with the results presented by Lohse-Busch et al. (2013) that observed an increase of about 100% in the ECR of BEVs in a controlled laboratory experiment with temperature falling from 70 °F to 20 °F. However, Birrell et al. (2014) do not find any relation between temperature and ECR, possibly because there was not enough variation in the temperature for a study conducted between May and October. It should be noted that previous studies did not consider non-linearity that appears intuitively relevant, as lower temperatures require more energy for warming the vehicle, etc., and higher temperatures need more energy for cooling the vehicle, etc. Ceteris paribus, our mode predicts that the most favorable temperature in terms of energy efficiency of BEVs is about 29.7 °C. Similar result is obtained from the estimation of ECR^p in the Appendix for comparison (see Table 5 (C)).

Wind speed and precipitation have positive and statistically significant effect on ECR, whereas visibility (sunshiness) has a positive and statistically significant effect. Driving on highway does not seem to have a statistically significant effect. This may not be surprising since the main differences between driving on highways and on non-highway streets, speed of driving and acceleration, are already controlled for. We also found that trip distance has a U-shaped effect on ECR, where both too short and too long trips are associated with high ECR, ceteris paribus. Still another interesting result is that driving BEVs during traffic rush-hour has a negative effect on ECR, ceteris paribus, which is consistent with previous studies, for example, by Wu et al. (2015), because of the de-generating characteristic of BEVs' batteries once other variables affecting ECR channeled through rush-hour driving (such as speed of driving and acceleration) are controlled for.

Moreover, it is very interesting that the initial level of the battery has a polynomial (third degree) effect on the ECR. Specifically, individuals can

observe different rates of battery power consumption for driving in the same environment for the same distance, just because of a different battery charge level at the beginning of the trip. Figure 7 presents a locally weighted scatterplot smoothing estimation of the battery power depletion rate per km distance traveled, which was obtained by running-line least squares smoothing with 0.80 bandwidth (i.e., 80% of the observation is used to estimate each point of the curve). The graph reveals that the depletion rate of the battery power is polynomial, and the rate of depletion per km traveled is very high (mean value equal to 1.22% of the battery per km traveled) when the battery power is about 100% charged, then declines at a higher rate as the battery power decreases until the local minimum (equal to 1.17% per km) when the battery power is about 77%, and then gradually increases until the local maximum (equal to 1.12% per km) after which the depletion rate is slow. The information from this graph could help BEV customers in having a better feeling for the range that they would be able to drive with the battery power they are left with. There is also the possibility that new BEV customers would be worried by observing that a fully charged battery drops very quickly after only a short drive.
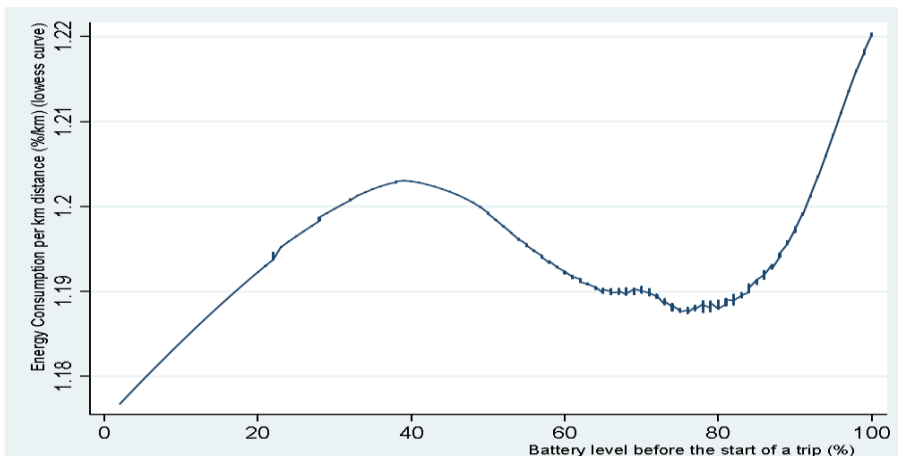
Figure 5.3.7. Depletion of the battery power

Finally, the paper is not without limitations. The main limitations of the paper attributes to potential measurement errors. One of the limitations

is that most of the trips in the data used in this study are short, mean trip distance is about 9 kilometers. As we saw in Table 5.3.1, this may overestimate ECR if participants in this data collection systematically used BEVs for short trips than the trips they actually have or if the participants were individuals in the population who generally have short trips when compared with the population representatives (i.e., if there is a self-selection problem that we do not check for due to insufficient data). Another potential measurement error could come from the way energy consumption was measured: it was measured in terms of percentage changes on the charging status of the battery in that the marginal changes in energy consumption in units of energy was not observed. In this case, a trip that reduced the amount of the battery power from 80.49 to 79.51 percentage points could be observed as consuming the same amount of energy to a trip that reduced the amount of the battery power from 79.51 to 79.49 percentage points since the charging status displayer could show that each of the trips consumed 1 % of the battery power by reducing the charging status from 80 % to 79 %. Moreover, we assumed that all the 16-kWh battery power of the BEVs used in the data is useable while in practice there could be a minimum amount of energy reserved for technical that is not usable for driving (Clever A/S, 2016).

We still get consistent estimates from the fixed effects models since the measurement errors on the energy consumption rate, the dependent variable, are mechanical that are serially uncorrelated and they are uncorrelated across individuals in that the trip-demeaning removes the errors. We expect minimal measurement error problem among covariates, which otherwise cause inconsistency in estimates, since the variables were mechanically measured including speed of driving, acceleration, weather variables and road types.

5.4. Conclusions

This study presents energy consumption and its determinants of battery electric cars by harnessing big data obtained from a variety of sources. The study is innovative in its investigation of a very large number of drivers, an immense number of trips (over 230,000) and km travelled (about 2.3 million), and a great number of sources of information concerning trip details, roads, weather and seasons.

The findings from this study provide insight into the actual energy efficiency of BEVs. The overall mean ECR is about 0.183 KWh/km, which for a traditional battery capacity of 16 KWh of a Citroen C-Zero corresponds to a mean driving range of about 87 km, far less than the driving range of 150 km maximum driving range set at the New European Driving Test. The consumption of electricity is significantly higher in winter, as the ECR increases by about 39.5 % with respect to summer conditions, which for countries with longer (shorter) winters implies a lower (higher) driving range. Most relevantly, the findings from the calculation of the ECR allow understanding where the price of electricity should be for consumers to have convenience from an energy cost perspective of purchasing a BEV rather than a conventional vehicle.

The most significant findings from this study provide insight into the effect of several variables on the ECR variation. Remarkably, some variables have quadratic effects. This appears logical for example for temperature, given that more energy needs to be spent to warm the vehicle at lower temperatures and to cool it down at higher temperatures, and for speed, given that more energy requires to be spent to move the vehicle from lower speeds and to maintain higher driving regimes. Optimal values for the temperature at 29 °C and for the driving speed at about 52 km/h are found from the model estimation results, and these are on the one hand good indicative values for potential consumers of BEVs who might want to maximize the use of their battery and hence their vehicle. Interestingly, the battery charge level at the beginning of the trip has a polynomial effect that indicates how the battery level decreases drastically for full charge rather than for lower charge levels, and these are on the other hand not so good indicative values for potential customers of BEVs who might want not to take chances given anxiety about the performance of the vehicles.

The results from this study could be used in order to perform a cost-benefit analysis of the introduction of BEVs under different market penetration scenarios, to estimate more accurately the level of emissions of BEVs in comparison with conventional vehicles (while accounting the emissions related to the recharging), and to predict more precisely the driving range of BEVs that causes the anxiety hindering most consumers to prefer BEVs over conventional vehicles. Specifically, the results indicate that optimal driving speed and acceleration within given weather conditions can be selected by consumers in order to have energy efficient vehicles guaranteeing to reach the destination without the need for recharging.

Acknowledgments

Appendix 4

Appendix A: How cheap is to drive BEVs in terms of fuel (electricity) cost?

Having the mean ECR from the analyzed data allows formulating an equation for the (rough) comparison of BEVs and conventional vehicles in terms of fuel efficiency, at least in the Danish driving environments considered in this study.

Consider the mean ECR of BEVs analyzed in the data, 0.183 kWh/km. The average cost of electricity used to drive one km is 0.183 P_e, where P_e is the recharging fee per kWh of electricity. Thus, a consumer who is comparing a BEV and a conventional car based only on fuel cost has to buy a BEV if and only if

$$0.183 P^e \leq v P^f , \qquad (5.6)$$

where P^f is the per litter fuel price and v is the average fuel consumption per kilometer of a conventional car.

For example, if the fuel cost P^f = 11 DKK/liter (i.e., current price of gasoline in Denmark) and if v = 0.05 liters (i.e., 20 km/liter), then it would be cheaper to drive a BEV if and only if the electricity tariff P^e ≤3 DKK/kWh.

Table 5.B. Descriptive Statistics of variables

Variable	No. Obs.	Mean	Std. Dev.	Min	Max
Trip distance (km)	242335	8.94	10.37	0.40	117.15
Mean driving speed (m/s)	242335	10.70	4.08	0.71	28.49
Median acceleration	242335	0.28	0.13	0.04	4.80
Battery level at trip start (%)	242335	73.96	21.11	2	100
Temperature (^{0}C)	240030	9.24	7.35	-20.60	31.7
Wind speed (m/s)	240030	4.64	2.49	0	29.1
Visibility duration in the journey (minutes)	240030	18.62	23.34	0	60.00
Precipitation (mm)	240030	0.08	0.43	0	23.80
Highway (dummy: 1 = trip on highway)	232882	0.08	0.27	0	1
Winter (dummy: 1 = trip during winter season)	242335	0.41	0.49	0	1
Rush hour (dummy: 1 = trip during rush-hours of traffic)	242335	0.40	0.49	0	1

Appendix C. Estimating ECR$_p$

Table 5.C. Estimation of energy consumption rate per km distance traveled (in terms of percentage change in the battery recharging status)

Dependent variable: Energy consumption (in %) per km Variables	Coef.	Cluster robust Std. Err.	P>t
Mean driving speed (m/s)	-0.125162	0.002	0.0000
Mean driving speed square	0.005109	0.000	0.0000
Median acceleration (m/s2)	0.3685535	0.032	0.0000
Median acceleration square	0.2002235	0.037	0.0060
Trip distance (km)	-0.005766	0.000	0.0000
Trip distance square	0.000000	0.000	0.0000
Temperature (0C)	-0.030126	0.001	0.0000
Temperature square	0.000506	0.000	0.0000
Wind speed (m/s)	0.004327	0.000	0.0000
Visibility duration in the journey (minutes)	-0.000738	0.000	0.0000
Precipitation (mm)	0.033106	0.002	0.0000
Highway (dummy: 1 = trip on highway)	0.003320	0.003	0.2690

Winter (dummy: 1 = trip during winter season)	0.091853	0.006	0.0000
Rush hour (dummy: 1 = trip during rush-hours of traffic)	-0.012167	0.002	0.0000
Battery level at trip start (%)	0.019350	0.001	0.0000
Battery level at trip start square	-0.000312	0.000	0.0000
Battery level at trip start cube	0.000002	0.000	0.0000
Constant	1.522922	0.027	0.0000

Number of observations	230617	sigma_u	0.12973
corr(u_i, xb)	0.1254	sigma_e	0.28877
R-square: within	0.2709	rho 0.167927	
R-square: between	0.7032		
R-square: overall	0.4075		

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