LOW EMISSION VEHICLES:
CONSUMER DEMAND AND FISCAL POLICY

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LOW EMISSION VEHICLES: CONSUMER DEMAND AND FISCAL POLICY

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door

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geboren te Athene, Griekenland

promotor: prof.dr. J.N. van Ommeren

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List of Acronyms

AFV	Alternative Fuel Vehicle
AIC	Akaike Information Criterion
CARB	California Air Resources Board
CMM	Class Membership Model
CNG	Compressed Natural Gas
FBEV	Full Electric Vehicle with Fixed Battery
FEV	Full Electric Vehicle
GLS	Generalised Least Squares
HEV	Hybrid Electric Vehicle
HPLCM	Hybrid Panel Latent Class Model
ICE	Internal Combustion Engine
LPG	Liquefied Petroleum Gas
LVSM	Latent Variable Structural Model
MWTP	Marginal Willingness To Pay
OLS	Ordinary Least Squares
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
PLCM	Panel Latent Class Model
PPP	Purchasing Power Parity
RUM	Random Utility Model
RUT	Random Utility Theory
SBEV	Full Electric Vehicle with Swappable Battery
SIC	Schwarz Information Criterion
SP	Stated Preference
WLS	Weighted Least Squares
WTP	Willingness To Pay

Preface

It often feels like it was few months ago, but it was actually much further in the past that, while still in Athens, I received an e-mail form Piet Rietveld offering me a PhD position at the Department of Spatial Economics. Conducting research on the early adoption of electric vehicles loomed like a fascinating opportunity for a PhD project and I accepted it with great excitement. Few years later, I look back at this life-changing moment, confident that I was right to be so excited. I truly enjoyed doing every single bit of this project.

I am indebted to Piet Rietveld for providing me the opportunity to embark on this journey, spend four wonderful years in Amsterdam and conduct my PhD research at the Department of Spatial Economics. Piet, I feel lucky that I had the chance to work under your supervision for three years and appreciate your warm and kind personality, your genuine smile, your positive energy and your sharp mind. You will always be a great source of inspiration for me.

Conducting empirical research under the supervision of Jos van Ommeren was an absolute pleasure. Jos, no doubt I learnt a lot from you. Your advice on econometric issues, drafting papers (especially how to reduce their length), formulating research questions and using time more efficiently were extremely helpful. However, this is not the main reason I feel so lucky for having you as a PhD supervisor and co-author. Neither the fact that *bijtelling* became the first Dutch word I learnt and the one I used most during my stay in Amsterdam. It is mostly your welcoming smile every time I dropped by your office, your generosity and politeness, and your relaxed approach to life and everyday problems that made me truly enjoy our collaboration. I sincerely hope that we will have the opportunity to work together again in the immediate future.

I am also very happy that I had the opportunity to work closely with Paul Koster. Paul, I have genuinely enjoyed our discussions about choice modelling, behavioural economics, welfare analysis, memory and cycling. Thank you for being so generous with your time, for sharing with me your ideas, knowledge, enthusiasm and concerns over modelling individual behaviour, and for accepting to be my co-author. I learned a lot from our discussions and I really look forward to having more of them soon.

I am grateful to the four members of my PhD Reading Committee: Stephane Hess, Gerard de Jong, Herman Vollebergh and Jan Rouwendaal for taking the time and effort to read my thesis and provide insightful comments on an earlier version of it. I sincerely appreciate it.

PhD life would have been less interesting without Friday afternoon discussions with Eric Kroes over company cars, the Toyota Prius, Italy, Paris, seafood and wine. Eric, many thanks for spicing up my Fridays and sharing with me all the secrets of plug-in electric cars and Italian wine.

I particularly enjoyed working on parallel projects with Marija Bočkarjova. Marija, our discussions about electric cars, diffusion of innovations, latent class models, questionnaire design, Qualtrics and Biogeme have been extremely useful. I really appreciate your input to, and advice on, the questionnaires used for the surveys. It was also fun – and often a big relief – to share with you the experience and burden of supervising MSc students.

Designing the stated preference surveys in Sawtooth would have taken much more time and effort, had it not been Anco Hoen and Mark Koetse who kindly shared with me the Sawtooth files used in their studies. I would like to thank Anco and Mark for the files and the extensive discussions we had on the design of the surveys. They were extremely useful. I would also like to thank Jasper Knockaert for his great help and advice on Biogeme and the estimation of hybrid choice models. I am also grateful to Jesper de Groote for translating an earlier version of Chapter 2 in Dutch for the purpose of its publication in *Tijdschrift Vervoerswetenschap*.

A big thank you to Coen Wartenhorst for his excellent IT support during the administration of the surveys. Coen, I am pretty sure that things would not have gone so well, if you were not there to patiently take care of all the details. Who else would be able to provide IT support even from a hospital room, right after suffering a nasty punch in a football game? I really appreciate it!

Many thanks also to Thijs Dekker for discussions and advice on the development and estimation of latent class and integrated latent class – latent variable models, and for sharing with me his passion for reinforcing the links between discrete choice modelling and welfare analysis. Thijs, I am also grateful for your comprehensive review of a much earlier version of Chapter 4. Your comments improved the paper significantly.

The Department of Spatial Economics is not only a unique place to do research, but also a community of amazing people, where making friends is hard to escape. I wish to thank everyone at the Department for making me feel like home right from the first day, for making me madly miss borrels since I left Amsterdam and for providing such a cosy workplace.

Martin, a big thanks for accepting to be my paranymph and taking the time to arrange multiple things around the defence! I really appreciate it. Many thanks also for driving us around São Miguel and for all the fun we had there (remember that amazing grilled fish? Harry, many thanks for the tip!).

Harry, Hugo and Maria, I was very lucky to share an office with you during almost the whole of my stay in Amsterdam. Thank you very much for your patience in dealing with my bad habit of having lunch (and multiple other meals…) behind my computer and for all the fascinating discussions we had about transport economics, life after PhD and, of course, food, beer and yerba mate.

Rujie and Zhiling, thank you for sharing with me so many fun facts about Chinese food and culture and the secrets of brewing tea. It was also very interesting to come to learn more about the labour market in China. Rujie, many thanks for introducing me to one of the most amazing teas I have tasted in my life. Zhiling, thank you very much for being so responsive to my questions about the details of the defence and the layout of this book.

Yuval, it was a real pleasure sharing with you the responsibilities of the Party Committee, the fun of organising events for the Department (including tiding up after every borrel), the pleasure of learning Dutch, an apartment in Berlin, and several boxes of delicious, crunchy nuts. It was also an honour and lots of fun to attend your wedding with Mari in Hungary. Many thanks for sharing these moments with me!

Ceren and Stefanie, I am very happy that both of you have been building successful careers in academia. I have to admit, however, that I have really missed dropping by your office on a weekly (or even daily) basis to discuss choice modelling in Biogeme, migration policy, Vienna, Istanbul, vegetarian food and restaurants. Stef, many thanks for commenting on an early draft of the survey questionnaire. I am also grateful to both of you for the impressive tolerance you showed to the never-ending contemplations of Yuval and me on the location, programme and menu of the next event for the Department.

Karolina, talking to you always made me feel better. Strangely, everything was looking much easier and less worrying after a chat with you. I am truly grateful for all your encouragement and support when struggling to revise Chapter 4 and when going through the hiring procedure at the OECD. I really enjoyed our discussions about environmental economics, travelling, Krakow, vodka, chocolate, and pierogi, and was among the lucky ones that had the pleasure to satisfy their sweet tooth with your Polish cheesecake. Delicious!

Ioanni, you are not only a great economist, modeller and programmer. You also have an exceptional sense of humour, which often makes bursting into laughter irresistible. I am also grateful for your extremely useful fitness tips and for convincing me to bring exercise back to my weekly routine.

Jan, Martijn, Or, Panayioti, Ridhwan, Ruben and Vincent, it was a pleasure sharing an office with you at different stages of my PhD studies. I really enjoyed our discussions about econometrics, GIS analysis, travel insurance, Indonesian food and tolling. Jan, many thanks for facilitating my search for the right command in Stata. Or, life would have been less spicy, had you not introduced me to cardamom-flavoured Greek-Turkish style coffee.

Elfie, Jenny and Mariska, many university departments around the world would really wish to have the administrative support you kindly offered on a daily basis. Many thanks for your timely and efficient response whenever I requested your help. I really appreciate it.

Crystallenia, Angele, Eleni, Niko, and Katerina, thank you very much for making homesickness seem like an exotic feeling during my four years in Amsterdam. I am very happy that that you have been my co-travellers in this journey and that we have had so many wonderful moments together. I wish that more of them are coming soon! Katerina, also many thanks for accepting to be my paranymph and for generously offering your time and skills to help me take care of all the little – and often not so little – things around the defence!

Manoli and Drew, it was a real pleasure spending time in and outside of the university with you. I hope that we will soon have the opportunity to see each other again in Amsterdam, Birmingham, Miami, Greece or elsewhere.

Life plays funny tricks on people sometimes, and Kelly and I got to know each other 2169 kilometres away from our little home suburb. Kelly, I feel blessed that I have had the pleasure to embark on this journey with you, to share with you all our good and bad moments, to enjoy your continuous support for every goal I set. Had it not been you and your truly remarkable patience, this journey would have felt much lonelier, more stressful and certainly less fun. Perhaps more importantly, I would still have not learned how to ride a bicycle. I feel very lucky to have you in my life and I wish that we have plenty of happy and unforgettable moments together in the future.

Afroditi and Petro, it is very difficult to find words to thank you for your unconditional love and support throughout my life. Let me try in Greek… Αφροδίτη και Πέτρο, ο Μέγας Αλέξανδρος υποστήριζε ότι «στους γονείς οφείλομεν το ζην, στους δε διδασκάλους το ευ ζην». Σας ευχαριστώ πολύ που μου έχετε δώσει κάθε δικαίωμα να πιστεύω ότι είχε άδικο και ότι και το ευ ζην οφείλεται σε μεγάλο βαθμό στους γονείς. Σας είμαι ευγνώμων για την απεριόριστη αγάπη σας και την αμέριστη στήριξη σας σε όποια προσπάθεια έκανα στη ζωή μου. Παρότι είμαστε μερικές χιλιάδες χιλιόμετρα μακριά, σας νιώθω πάντα δίπλα μου, και αυτό με γεμίζει χαρά και ενέργεια. Σας ευχαριστώ πολύ και εύχομαι να μοιραστούμε πολλές ακόμα χαρές στο άμεσο μέλλον.

It is with deep gratitude that I dedicate this book to the memory of Piet Rietveld.

Alexandros Dimitropoulos

Amsterdam – Paris – Athens

September 2016

Chapter 1

Introduction

1.1. Motivation and background

Climate change and air pollution are two of the most important environmental problems faced by the world today. Road transport is a major cause of both problems, as it is responsible for a considerable share of global emissions of greenhouse gases and air pollutants. Road transport accounts for about 17% of energy-related greenhouse gas emissions worldwide and is among the economic sectors experiencing the most rapid increases of emissions in the last decades (IEA, 2015; Sims et al., 2014). Road transport is also a major emitter of harmful air pollutants, such as nitrogen oxides and particulate matter. In 2012 only, outdoor air pollution was responsible for about 3.7 million premature deaths, mainly caused by cardiovascular and respiratory diseases. Besides, the adverse health effects of outdoor air pollution are much more pronounced in emerging economies, where demand for road transport is expected to grow significantly in the following decades (Sims et al., 2014; WHO, 2014). Scientists and policymakers generally agree that the need to drastically reduce air and greenhouse gas emissions from road transport is urgent. Although there is much less agreement across the scientific and policy community regarding the appropriate means to achieve these reductions, low emission vehicles will have a major part to play in the transition to sustainable road transport.

This thesis uses a wide and flexible definition of *low emission vehicles*. The term is used to denote cars whose tailpipe – in most cases CO_2 – emissions are low enough to allow them to be eligible for preferential fiscal treatment.[1] Even though the scope of the term varies among jurisdictions, low emission vehicles generally encompass electric cars and some other types of alternative fuel vehicles. However, the term often also includes cars driving on conventional fuel (e.g. petrol and diesel) with relatively low CO_2 emissions. Fiscal policy, and therefore also the definition of low emission vehicles, is usually determined by *type-approval* emission levels, i.e. emission measurements in controlled laboratory conditions, not real-world ones.

The early stages of the adoption process are key for the market prospects of innovative technologies, such as contemporary electric and other alternative fuel vehicles (Rogers, 2010). It is, thus, important that potential barriers to the early adoption of these technologies are well understood and that policies which can facilitate this process are put

[1] The terms "vehicle" and "car" are used interchangeably throughout the thesis. Passenger cars are the primary focus of the thesis, but sometimes interest extends to light commercial vehicles (the reader is prompted when this is the case). Heavy duty vehicles, two- and three-wheeled motor vehicles, and vehicles not used for road transport are out of the scope of the thesis.

in place. A first objective of this thesis is to contribute towards a better understanding of the factors hampering the early adoption of electric cars and other alternative fuel technologies. Consumer theory provides the background for the approach taken to achieve this objective. Consumers' vehicle choices are driven by their preferences for car and refuelling attributes. Next to traditional measures of costs of vehicle use, such as purchase and operating costs, additional *time* costs required to accommodate the refuelling specificities of alternative fuel vehicles are an important driver of consumer preferences.

Fiscal policy can play a pivotal role in overcoming barriers to the early adoption of low emission vehicles. Fiscal incentives for their early adoption can be justified on the – present and future – environmental and energy security benefits entailed by a successful adoption process, as well as on external benefits related to the fostering of innovation and investment in new technologies. The second objective of the thesis is to evaluate the effects of policies to promote the early adoption of low emission vehicles on consumer and manufacturer behaviour and economic welfare. The ultimate objective of this evaluation is to inform the design of future fiscal policies with similar ambitions. Fiscal policy analysis focuses to a large extent on incentives provided for the adoption of low emission vehicles by company car drivers, i.e. employees offered a – usually leased – car as fringe benefit in kind from their employers to meet their travel needs. This is due to the company car market's critical role in the diffusion of innovative technologies with relatively high capital costs in a number of countries.

1.2. Electric and other low emission vehicles

The scope of the thesis encompasses all motor vehicle technologies defined as low emission ones by fiscal policy. However, emphasis is often placed on electric vehicles, as they comprise the family of low emission technologies facing the highest expectations for ensuring a more environmentally sustainable future for road transport.[2]

Electric vehicle technologies also face the most significant barriers to consumer adoption, as their production is particularly costly and their driving and refuelling patterns do not closely resemble the ones of conventional cars. The relatively short distance most

[2] The environmental impact of electric cars also depends on the fuel used to produce electricity. When electricity generation is based on coal, for example, well-to-wheel CO_2 emissions may be higher for electric than for conventional cars. Analysis and discussion in this thesis generally focuses on tailpipe emissions, as they have been of primary interest to fiscal policy. For an earlier overview of the relative environmental benefits of electric car use when taking emissions of electricity generation into consideration, see e.g. Hacker et al. (2009).

electric cars can travel on a single charge and the long time required to recharge the battery imply that one may have to make important scheduling changes to fulfil one's travel needs. Furthermore, electric cars require drivers to get accustomed with a number of special features, such as vehicle charging, battery monitoring, silent driving at low speeds and rapid acceleration. The potential complexity of such changes in scheduling and driving patterns and the relatively high purchase costs of electric cars discourage the majority of consumers from considering most commercially available electric cars as viable alternatives for their mobility.

Electric vehicles

Electric vehicles do not comprise a novel family of technologies. The first experimental electric vehicles appeared in mid-1830s, while the first electric car powered by rechargeable batteries was constructed already in 1884. In fact, electric cars were much more popular than cars powered by internal combustion engines (ICE) in the beginning of the 20th century. Technological advances in ICE technologies and improved road infrastructure – which enabled travelling longer distances – were the critical factors that eventually determined ICE-powered cars' dominance over electric ones (Chan, 2007; Guarnieri, 2012). Following several decades of disregard of electric cars, interest temporarily arose again in the 1970s – due to the energy crises – and in early 1990s, due to the Zero Emission Vehicle programme enacted by the California Air Resources Board (CARB) (Chan, 2007; Kley et al., 2011). CARB's mandate led manufacturers to produce a new wave of electric cars, which were, however, eventually withdrawn from the market on the grounds of an alleged lack of consumer interest.

Interest in electric cars rekindled few years later, mainly due to mounting concerns over climate change and outdoor air pollution, and soaring oil prices. In contrast to previous revivals of interest which were geographically limited to the United States and perhaps a few other countries, electric cars are now in the spotlight in most developed and emerging economies, including the U.S., Europe, China and Japan. Motivated by consumers' increased awareness of climate change and its potential consequences, by generous fiscal incentives provided for the production and consumption of electric cars and by a desire to take the lead in a possible future transformation of the car market, virtually all major car manufacturers have embarked on the production of electric cars. In this endeavour, incumbent firms face growing competition from new players, such as Tesla Motors, whose core business is the production of electric cars.

Electric cars are – partially or fully – propelled by electric motors. They can mainly be categorised along two dimensions. The first dimension is the device used to power the electric motor. The two most popular devices used for this purpose are rechargeable battery packs and hydrogen fuel cells. Vehicles powered by battery packs which can be recharged from an external source are denoted as *plug-in electric vehicles* (PEVs), whereas the ones powered by fuel cells as fuel cell electric vehicles.[3] PEVs will be of particular interest in this thesis, as they are currently the most dynamic category of electric cars. More than 1.2 million plug-in electric vehicles have been sold worldwide between 2011 and 2015, while the rate of growth of PEV sales averages around 87% in the same period (Office of Energy Efficiency and Renewable Energy, 2016).

The second dimension along which electric vehicles can be categorised is the extent to which the car relies on the electric motor for its propulsion. The term *full electric vehicle* (FEV) will be used to denote cars powered exclusively by electric motors (see also Vollebergh and van der Werf, 2014). The Nissan Leaf and Tesla Model S are typical examples of FEV models. *Plug-in hybrid electric vehicles* (PHEVs) are vehicles with a plug-in option, which are propelled by both an internal combustion engine and one or more electric motors. Vehicles whose internal combustion engine is only used to power the electric propulsion system are often denoted as extended range electric vehicles. For the purposes of this thesis, the scope of the term PHEV also encompasses extended range electric vehicles. Commercially available PHEV models include the Chevrolet Volt and the Mitsubishi Outlander PHEV. The operation of both an internal combustion engine and an electric propulsion system is also a feature of *hybrid electric vehicles* (HEVs).[4] In contrast to PHEVs, however, HEVs cannot be recharged from an exterior power source. Typically, the former category also allows a much longer distance to be travelled on electricity than the latter. The Toyota Prius is perhaps the most popular HEV model. Figure 1.1 summarises the nomenclature of electric vehicles used in the thesis.

Other low emission vehicles

The definition of low emission vehicles is not limited to electric cars. The scope of the definition also extends to vehicles exclusively powered by internal combustion engines. Such vehicles may be driving on conventional fuel sources, i.e. petrol and diesel, or more unconventional ones, such as liquefied petroleum gas (LPG) and biofuels. Exogenous

[3] A full list of acronyms is provided in the beginning of the thesis.
[4] Hybrid electric vehicles first appeared as early as 1898 (Chan, 2007).

technological advances and volatility in oil prices have stimulated considerable improvements in the fuel efficiency of internal combustion engines. At the same time, stringent fuel efficiency standards and the increasing attention of fiscal policy to the potential environmental impact of new cars – especially to their type-approval CO_2 emissions – have further encouraged manufacturers to direct investment to fuel efficiency improvements.

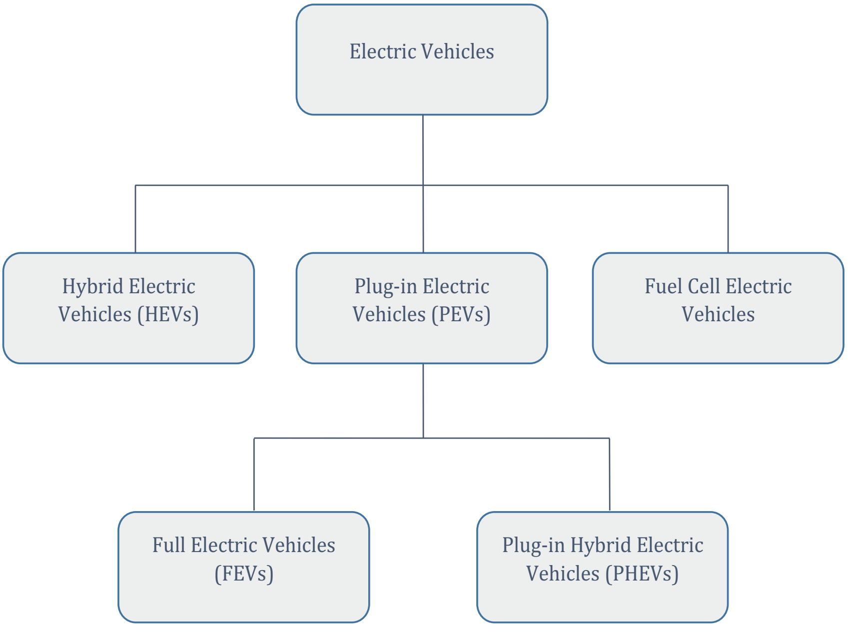

Figure 1.1: Nomenclature of electric vehicles used in the thesis.

The emphasis of fiscal policy on CO_2 emissions has induced a further shift towards diesel cars in a number of countries. Diesel engines are more efficient than their petrol-powered counterparts, allowing the emission of less CO_2 per kilometre driven. Diesel cars had already been benefitted by the levy of higher motor fuel taxes on petrol than diesel fuel (see also Harding, 2014a). However, a shift to diesel cars has two potentially important pitfalls: first, diesel cars cause significantly higher emissions of harmful pollutants, such as NO_x and particulate matter, than petrol cars (Harding, 2014a); second, their low operating costs – an outcome of relatively high efficiency and beneficial fiscal treatment – may result in drivers travelling more kilometres than they would do in petrol cars. Despite the *private* benefits associated with additional car travel, the external costs of this excessive car use, mainly in terms of congestion, air pollution and road accidents, are significant.

Low emission cars in the Netherlands

As we will see in the next section, Chapters 3-5 draw on empirical analyses for the Dutch car market. The Netherlands is of particular interest when it comes to low emission vehicles, as the Dutch government provides a diverse set of generous fiscal incentives for their adoption. Incentives provided in the private and, primarily, the company car market have been very effective in stimulating consumer demand for low emission vehicles (Kok, 2015). The Netherlands consistently ranks second in the world in the share of *plug-in electric vehicles* in new car sales (Cobb, 2014, 2015, 2016a). It was the largest market in terms of the number of registered PEVs in Europe until the end of 2015, before being surpassed by Norway in early 2016. However, the Netherlands is still the leading European market for *plug-in hybrids* with more than 80,000 PHEVs sold by April 2016 (Cobb, 2016b; RVO, 2016). It is also the country with the lowest average type-approval CO_2 emissions of new cars in the European Union (European Environment Agency, 2016).

The Netherlands has also set ambitious targets for the future CO_2 emissions of road transport and the market penetration of electric cars. The Energy Agreement for Sustainable Growth (*Energieakkord*) aspires that all new cars sold in the Netherlands as of 2035 will be able to travel (at least to some extent) without producing tailpipe CO_2 emissions (Sociaal-Economische Raad, 2013). The Agreement also aims that only cars driving exclusively on electricity will be eligible to be sold in the Dutch market from 2050 onwards. In addition, the *Green Deal Elektrisch Vervoer* 2016-2020 aspires that 50% of new car registrations will be plug-in and fuel cell electric vehicles already in 2025. About 30% of them are expected to be cars propelled exclusively by an electric motor.[5]

1.3. Structure of the thesis

The aim of the thesis is two-fold. Its first objective is to pinpoint the most important barriers to consumer early adoption of low emission vehicle technologies and provide estimates of the effects of these barriers on consumer demand. Its second objective is to evaluate the impact of fiscal policies recently implemented in the Netherlands and other European countries to stimulate demand for low emission vehicles on the behaviour of

[5] See http://www.greendeals.nl/wp-content/uploads/2016/04/GD198-Elektrisch-Rijden-2016-2020.pdf (in Dutch, accessed 16 May 2016).

manufacturers and consumers, and on economic welfare. All objectives are achieved through empirical analyses, which are based on advanced econometric methods. Figure 1.2 provides an outline of the four technical chapters of the thesis and summarises the data, methods and scope of vehicle ownership used in each chapter.

Chapter 2 addresses the first objective by focusing on driving range, i.e. the maximum distance that a car can travel on a full tank or a fully-charged battery. The short driving range of most electric vehicles and other alternative fuel cars is an important technological constraint on their ambition to serve the same travel needs as conventional cars. The chapter investigates consumer willingness to pay (WTP) for driving range using a meta-analysis of 33 stated preference studies. It also estimates the price reduction that consumers would require to compromise with cars with a range of 160 km – as currently common for commercially available electric cars – as compared to the price they would pay for their long-range conventional counterparts. In addition, Chapter 2 identifies the factual and methodological determinants of the variation in WTP estimates across examined studies. Ongoing and future stated preference studies looking into the trade-off between driving range and car purchase costs can benefit from the methodological suggestions provided at the end of the chapter.

Chapters 3 and 4 place special emphasis on *plug-in electric vehicles* (PEVs) and draw on the results of two new large-scale surveys among Dutch drivers. The surveys use choice experiments to elicit driver preferences for PEVs and internal combustion engine vehicles. Chapter 3 focuses on the first objective of the thesis and provides insights into the factors influencing private ownership of PEVs. Drawing on the stated choices of more than 1500 drivers of private cars, the chapter elicits consumer preferences for PEVs and internal combustion engine cars and estimates the trade-offs made between various vehicle attributes. Examined attributes include purchase price, driving range, refuelling time and time required to reach the nearest refuelling station.

Heterogeneity in consumer preferences and its link to drivers' socio-demographic background and psychological factors are studied with the help of latent class and hybrid latent class models. These models enable the identification of individual characteristics which increase the likelihood that a consumer will become an early adopter of a PEV. The role of environmental concerns in the formulation of consumer preferences for PEVs is of particular interest in this study. Furthermore, the chapter contributes to a better understanding of the sociodemographic factors determining individuals' environmental concerns.

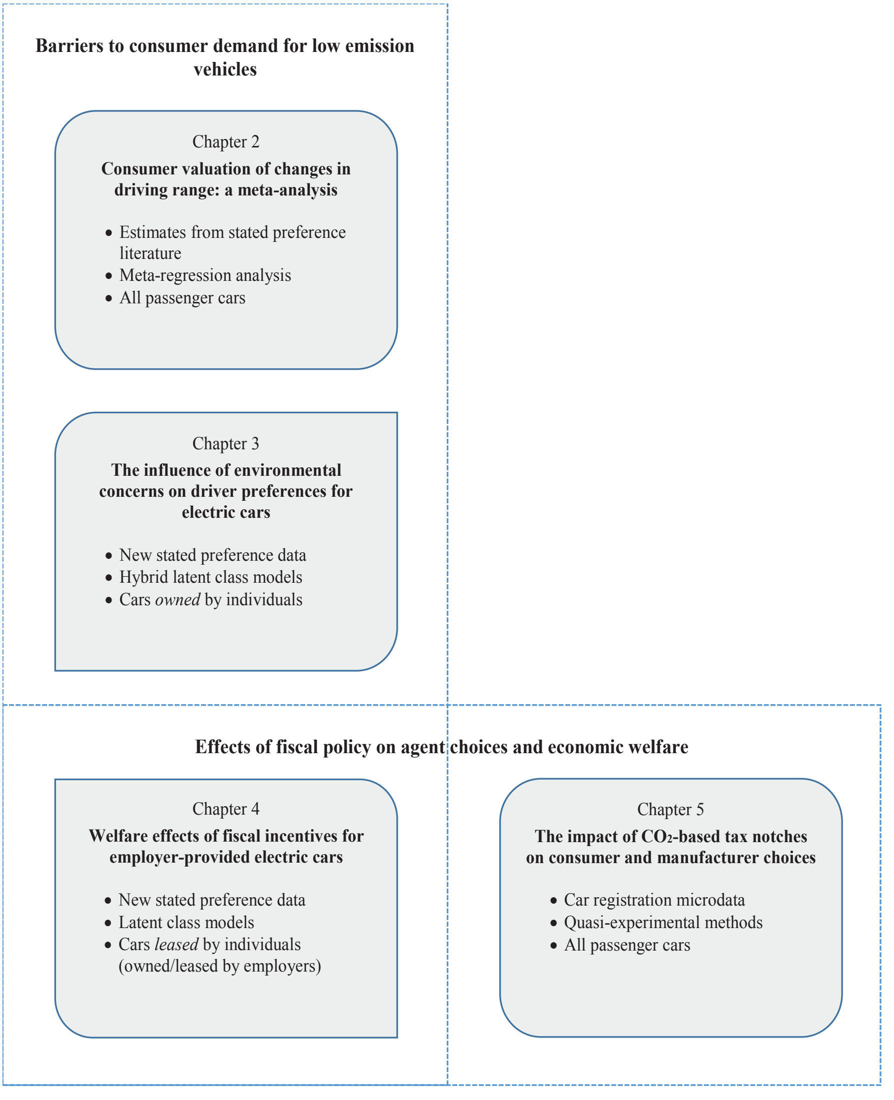

Figure 1.2: Outline of the thesis

In contrast to Chapter 3, which focuses on privately owned cars, the focal point of Chapter 4 is the company car market. *Company cars* are passenger cars offered as fringe benefits in kind by employers to employees and serving mainly employees' private travel needs (Copenhagen Economics, 2010). Employee's private use of the car is equivalent to an income increase and should be treated accordingly by the tax system. The amount added to employee's *taxable* income due to the private use of the company car usually depends on a tax rate levied on the car's purchase or list price (see also Harding, 2014b).

The company car market plays a critical role in the early adoption processes of PEVs and other low emission vehicles in a number of European countries. This is mainly due to employers and car leasing firms not only being the ones who incur the – typically high – upfront costs for the use of these vehicles, but also the ones who eventually bear the uncertainty about vehicles' resale price and operating costs. Fiscal policies to stimulate demand for low emission vehicles in the company car market have been popular in Europe.

Chapter 4 focuses on policies using reduced company car tax rates to accelerate consumer adoption of PEVs. Such policies are distortionary, as company car drivers are likely to opt for more expensive vehicles than the ones they would choose if tax advantages were designed to reflect PEVs' external benefits. The chapter develops an approach to estimate the immediate welfare effects of these policies, taking also into account preference heterogeneity. The approach is based on latent class modelling and is applied to estimate the welfare losses from the beneficial tax treatment of company PEVs in the Netherlands in 2014 and the potential welfare gains from marginal increases in company PEV tax rates. The welfare analysis is made under alternative assumptions of the size of PEVs' external benefits. The application draws on the stated vehicle choices of more than 800 Dutch *company car drivers*.

Fiscal treatment of cars often relies on schedules with discontinuities, also known as *notches* (see also Sallee and Slemrod, 2012). These schedules are increasingly based on measures of cars' potential environmental burden, such as their type-approval CO_2 emissions. Chapter 5 evaluates the impact of tax policies using notched schedules of type-approval CO_2 emissions on the behaviour of car manufacturers and consumers. The chapter considers a relatively wide range of low emission vehicles and focuses on achieving the second objective of the thesis. Using data on new car registrations for the period 2010-2014 in the Netherlands, the chapter first presents a graphical analysis of the impact of notches on consumer demand. It then uses a quasi-experimental econometric approach to analyse manufacturers' responses to notches. As notches in company car taxation can result in considerably more salient benefits to cars with CO_2 emissions right below the notch than notches in private car taxation, both types of analysis investigate whether consumers and manufacturers respond differently to notches in the company and private car market. In the absence of refined information about the ownership status of each car, the analyses distinguish between fuel technologies which are more likely to be adopted by company car drivers, i.e. diesel, or privately held, i.e. petrol.

Chapter 6 presents the conclusions of the thesis, discusses its policy implications and provides suggestions for future research on the economics of the transition to low emission road transport.

Chapter 2

Consumer valuation of changes in driving range: a meta-analysis

2.1. Introduction[*]

Growing concerns over climate change and local air pollution, increasing oil prices, as well as car industry's efforts to recover from the global economic crisis, appear as the main factors that have triggered a renewed interest in electric cars.[6] Some characteristics of full electric vehicles (FEVs), however, are likely to hamper their large-scale adoption. In addition to the substantially higher prices that consumers have to pay in order to acquire them, factors which have persistently been discussed in the literature include the short range they can travel on a fully charged battery, the long time needed for a battery recharge and the considerable costs required for the development of widespread charging infrastructure (e.g. Beggs et al., 1981; Dagsvik et al., 2002; Tompkins et al., 1998).

Several studies that examine consumer preferences for cars have emerged over the last decades, to provide insights into the potential market for full electric cars and other alternative fuel vehicles (AFVs), i.e. vehicles fuelled by energy carriers other than liquid petroleum products or by a combination of oil-derived and other fuels. The majority of these studies employ stated preference (SP) techniques to reveal households' and fleet-managers' preferences for AFVs (e.g. Bunch et al., 1993; Golob et al., 1997; Mabit and Fosgerau, 2011). Most of them consider driving range – the maximum distance that a vehicle can travel on a full tank or a fully-charged battery – as a determinant of preferences for cars. Their results typically suggest that short range is a notable reason for consumer scepticism towards FEVs and other AFVs.

There is no agreement in transportation literature on how important increases in range are for the adoption of AFVs. Consumer valuation for changes in driving range varies substantially among primary SP studies. This chapter employs a meta-analysis of 33 discrete choice and contingent ranking studies of consumer preferences for AFVs to provide valuable insights into the trade-off between vehicle range and purchase price and unravel the determinants of its variation. The measures used to capture this trade-off are the

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[6] The terms "car" and "vehicle" are used interchangeably throughout this chapter. The terms denote all body types of light duty vehicles, including vans, pick-up trucks and sport utility vehicles. Two- and three-wheelers, as well as heavy-duty vehicles, are not in the scope of the analysis.

willingness to pay for a one-mile increase in driving range and the willingness to pay (WTP) for an increase from 100 miles – the current driving range of most commercially available electric cars – to 150 and 350 miles. In addition to providing a comprehensive descriptive analysis of the variation of these measures, we use several meta-regression models to estimate the contribution of methodological and spatial factors to this variation.

We believe that the meta-analysis presented here is a valuable complement to primary studies conducted in this field by means of: (i) synthesising the abundant amount of information residing in them, (ii) appointing the variation in willingness to pay (WTP) estimates across them to specific study characteristics, and (iii) providing methodological directions for future research efforts exploring consumer preferences for AFVs.

The remainder of the chapter is organised as follows. Section 2.2 presents an overview of the literature studying consumer preferences for AFVs, with a focus on driving range. Section 2.3 unravels the main contributions and limitations of meta-analysis in transportation research. Section 2.4 reviews the methodology for collecting relevant studies and provides summary statistics of the WTP for driving range. Section 2.5 discusses the results of several meta-regression models explaining the variation in WTP estimates in the literature. Section 2.6 draws implications for future research. Section 2.7 concludes.

2.2. Preferences for AFVs and willingness to pay for driving range

The application of stated preference techniques to the investigation of consumer preferences for alternative fuel vehicles (AFVs) has been of interest to economists for more than three decades (e.g. Dagsvik and Liu, 2009; Ewing and Sarigöllü, 1998; Morton et al., 1978), while the field seems to be recently gaining some popularity also in marketing science (e.g. Eggers and Eggers, 2011; Zhang et al., 2011). Stated preference (SP) methods have been identified from the beginning (Beggs et al., 1981) to be prominent candidates for the elicitation of consumer preferences for AFVs, as these methods can be used to study the prospects of alternatives that do not yet exist in the market.

Characteristics theory of value (Lancaster, 1966) provided the theoretical basis of stated preference methods, while random utility theory (McFadden, 1973) established the econometric foundations for their development and application. SP methods consider goods as bundles of attributes and individuals as utility maximising economic units. In the current context, individuals are invited to engage in a hypothetical purchase of a car and maximise their utility by selecting their preferred vehicle from a set of alternative options (discrete choice method) or by ranking the options presented to them (contingent ranking method). These options are presented as bundles of attributes, whose levels are varied among alternatives. In the context of vehicle choice, these attributes may comprise, for instance, fuel type, car body type, acquisition and operating costs, performance characteristics and environmental impact.

The stated choices or rankings resulting from such experiments are analysed on the basis of discrete choice or rank order models, such as the multinomial logit or the ordered logit model. Under specific assumptions, these models allow the computation of the effects of changes in the attribute levels on the probability of an alternative being chosen, as well as the estimation of welfare measures associated with changes in the attribute levels. A further discussion of the theory underlying the development, use and application of stated preference methods is beyond the scope of this chapter. Greene and Hensher (2010), Hensher et al. (2005) and Louviere et al. (2000) provide a solid and comprehensive analysis of relevant methods.

The first attempts to use discrete choice or contingent ranking methods to elicit consumer preferences for electric vehicles took place in the USA and Australia shortly before and after the second energy crisis of the 1970s (Beggs et al., 1981; Calfee, 1985; Hensher, 1982; Morton et al., 1978). These early studies use the results of surveys addressed to relatively small and non-representative samples and focus solely on electric cars as an alternative to petrol-fuelled vehicles. They examine individuals' trade-offs between vehicles' purchase price, operating costs and driving range, while ignoring consumers' sensitivity to variations in fuel availability and refuel time. They assume FEVs to have an average driving range of few tens of miles and survey only multi-vehicle households, as they expect that the availability of at least one extra car at their disposal will make them more tolerant to FEVs' range limitations. Their main conclusion is that FEVs' short driving range can indeed account for a strong impediment to their adoption.

Californian environmental legislation stimulated the revisit of this issue during the 1990s (e.g. Brownstone et al., 1996; Bunch et al., 1993; Golob et al., 1997; Greene, 1998; Segal, 1995). In the middle of that decade, stated preference surveys on electric and other alternative fuel vehicles were also conducted in Australia (Hensher and Greene, 2001), Canada (Ewing and Sarigöllü, 1998) and Norway (Dagsvik et al., 2002; Ramjerdi et al., 1996). One of the noteworthy deviations of these later studies lies with their consideration of other alternative fuel vehicle technologies apart from FEVs. These technologies generally yield less severe range limitations than FEVs, as well as less important deviations from drivers' mainstream refuelling behaviour. They include vehicles running on compressed natural gas (CNG), liquefied petroleum gas (LPG) and biofuels, while hybrid electric vehicles (HEVs) are also often taken under consideration. The 1990s studies have also added some novel elements in regard to the attributes examined in the choice or ranking settings consumers are confronted with. These attributes are particularly relevant to AFVs and concern refuel duration and timing, coverage of refuelling infrastructure, and emissions of greenhouse gases and air pollutants. The majority of these studies find that even though these attributes are significant determinants of consumers' vehicle choice, they are probably not ones of primary importance.

A third wave of studies, this time more evenly distributed across geographical regions, follows in the 2000s. Preferences for AFVs are also investigated in other European countries, such as Belgium (Knockaert, 2010), Denmark (Jensen, 2010; Mabit and Fosgerau, 2011), Germany (Achtnicht et al., 2012; Eggers and Eggers, 2011), Ireland (Caulfield et al., 2010), the Netherlands (Molin and Brinkman, 2010; Molin et al., 2007, 2012) and the UK (Batley et al., 2004; Batley and Toner, 2003), as well as in Eastern Asian developing economies, such as China (Dagsvik and Liu, 2009; Qian and Soopramanien, 2011), Hong Kong (Loo et al., 2006) and South Korea (Ahn et al., 2008). A number of additional studies are also conducted in California (e.g. Adler et al., 2003; Axsen et al., 2009; Nixon and Saphores, 2011) and Canada (e.g. Horne et al., 2005; Mau et al., 2008; Potoglou and Kanaroglou, 2007). Expectations for strong developments in the hydrogen fuel cell (HFC) technology often resulted in the inclusion of HFC vehicles in the choice experiments presented in these recent studies (e.g. Achtnicht et al., 2012; Mabit and Fosgerau, 2011; Mau et al., 2008).

Regardless of when the study was conducted, driving range usually appears as an important determinant of consumer choice between petrol-fuelled vehicles and AFVs. A closer look at the primary results, however, reveals that the implicit trade-off between range and purchase price varies substantially among studies, ranging from a few US dollars to hundreds of US dollars per additional mile. This implicit trade-off is the *effect size* of interest in this study. The measures we employ to capture this trade-off are the willingness to pay for a one-mile increase in driving range and the willingness to pay for a change from a reference level of 100 miles to 150 and 350 miles.

The willingness to pay for a marginal incremental change of driving range (MWTP) is defined as the negative of the ratio of marginal utilities of driving range and purchase price:

$$MWTP = -(\partial \mathrm{U}/ \partial R) / (\partial \mathrm{U}/ \partial P)\,, \tag{2.1}$$

where U is individual's stochastic utility function, encompassing the driving range of the vehicle, *R*, its purchase price, *P*, and a vector of other variables. When the utility function is linear in the purchase price and driving range variables (and no interactions among these two variables and other variables are considered), MWTP equals the negative of the ratio of the estimated coefficient of driving range, β_R, to the one of purchase price, β_P:

$$MWTP = -\beta_R / \beta_P\,. \tag{2.2}$$

MWTP estimates stemming from studies considering a non-linear in vehicle range, or purchase price, utility specification are dependent on the reference level at which the analyst calculates MWTP. This level is usually the mean of the driving range or the purchase price attribute employed in the SP experiment, which varies substantially among primary studies. This caveat of MWTP estimates can be particularly problematic for the comparison of values stemming from studies employing different utility specifications with respect to driving range or purchase price. A related measure which circumvents this problem is WTP for predetermined changes of driving range. The WTP for a change in driving range from R_0 to R_1 is the integral of MWTP:

$$WTP_{R_0 \to R_1} = -\int_{R_0}^{R_1} \frac{\partial \mathrm{U}/ \partial R}{\partial \mathrm{U}/ \partial P}\, \mathrm{d}R\,. \tag{2.3}$$

When the utility function is linear in driving range, WTP equals the product of marginal MWTP and the change in range. An investigation of official vehicle specifications reveals that the driving range of most currently available commercial FEVs is around 100 miles (Daziano, 2011). We compute WTP on the basis of two departures from this reference level: a 50-mile increase, which seems to be feasible in the short term for FEVs, and an increase to 350 miles, a driving range level similar to the one of an average car powered by conventional fuel.

Before proceeding with the introduction of the meta-analysis approach, we note that a number of studies conducted in California in the 1990s challenge the rationale behind the use of standard choice modelling methods for the elicitation of households' preferences for driving range. Research undertaken by Kurani et al. (1994, 1996) suggests that AFVs with a maximum range of 150 miles have the potential to gain a substantial share in new purchases of light-duty vehicles in California, provided that they are sold at a relatively low price premium above equivalent petrol-fuelled vehicles. Based on innovative types of interviews and surveys, they find the preferences of “hybrid households” to be highly unstable and sensitive to the provision of elaborate information on the use of AFVs and interactions with other people. Kurani et al. opine that the use of standard SP approaches to explore preferences for driving range is simplistic and inappropriate, as these methods fail to consider that consumers do not have well-developed preferences for driving range. Driven by their lack of experience with range limitations, individuals tend to anchor to the range of their current petrol-fuelled vehicle and overstate their willingness to pay.

At the same time, the outcome of recent field experiments with early adopters of FEVs in Berlin (Franke et al., 2012; Franke and Krems, 2013) reveals that consumer perceptions about their driving range needs can indeed be dynamic and sensitive to their experience with short-range cars. Most of experiment participants are found to be able to get accustomed to the short driving range of full EVs.

2.3. Meta-analysis

The term ‘meta-analysis’ denotes the synthesis of the findings of a well-defined collection of primary empirical studies by means of statistical methods (Glass, 1976). Meta-analysis has been gaining increasing popularity in transportation research during the last two decades, where it has been employed to review, for instance, literature on the value of travel time savings (e.g. Abrantes and Wardman, 2011; Wardman and Ibáñez, 2012; Zamparini and Reggiani, 2007) and the value of statistical life (de Blaeij et al., 2003), the externalities of transport activities (e.g. Button, 1995; Nelson, 2004; Quinet, 2004), the supply and demand of public transport (e.g. Brons et al., 2005; Holmgren, 2007) and the psychological determinants of car use (e.g. Gardner and Abraham, 2008).[7]

Three methodological pitfalls of meta-analysis have been of primary concern to researchers (see, for instance, Florax, 2002; Nelson and Kennedy, 2009; Stanley, 2001, 2005). These comprise selection and publication bias, heterogeneity among primary studies and heteroskedasticity, and correlation between the sampled effect sizes. Meta-analysis literature has proposed various ways to identify the existence of the aforementioned pitfalls and address them. Including fugitive literature, namely studies presented in conference papers, working papers, theses, dissertations, as well as reports prepared by government

[7] Meta-analysis has also been popular in the environmental economics literature (see e.g. Brouwer, 2000; van den Bergh et al., 1997).

agencies or private consulting firms, in the scope of the literature search is an initial step to mitigate the possibility of selection and publication bias. Once the study sample has been established, funnel graphs and Galbraith plots can be utilised to identify the possible existence of publication bias (Stanley, 2005).

In economics, pinpointing the main sources of heterogeneity in the effect size is often at least as important as the measurement of the effect size itself. This accounts for the popularity that meta-regression models have gained in meta-analyses performed in the transportation literature (e.g. Abrantes and Wardman, 2011; de Blaeij et al., 2003; Holmgren, 2007; Shires and de Jong, 2009). Meta-regression models are used to estimate the impact of observed sources of heterogeneity among primary studies – mostly modelled with dummy variables – on the effect size of interest. These sources usually concern characteristics of the commodity of interest (e.g. driving range), methodological considerations of the primary studies (e.g. model specification, estimation method), and contextual aspects, such as the time and location in which the study is carried out (Nelson and Kennedy, 2009).

In the context of meta-regression analysis, heteroskedasticity can be addressed by heteroskedasticity-robust variance-covariance estimators and by weighting approaches taking under consideration the precision with which effect sizes have been estimated in the primary studies (Florax, 2002). In the context of the latter, the inverse of the variances with which the effect sizes were estimated in the primary studies or, on their absence, the sample sizes employed therein can serve as weights. These weighting approaches can also moderate the effects of publication bias, as they lessen the influence of extreme effect-size estimates stemming from small-sample studies' extensive search for statistical significance (Stanley, 2005).

A less extensively discussed problem in meta-analysis is the correlation among the effect sizes arising from the aforementioned sources (Florax, 2002; Nelson and Kennedy, 2009). This caveat is particularly relevant for meta-analyses of welfare measures, where multiple sampling from the same study is dominating. In order to circumvent this problem, literature suggests the use of hierarchical regression methods or panel data procedures, which can further provide insights into the relevance of the distinction between a fixed and a random effect size. Essentially, the difference between the two concepts lies with the assumption of a fixed population effect size or of an effect size being a random draw from a normal distribution (Florax, 2002).

2.4. Descriptive analysis of the study sample and the effect sizes of interest

2.4.1. Collection of primary studies

SP studies examining consumer preferences for AFVs were collected via an extensive keyword-based search. We searched various paper and electronic sources, such as GoogleScholar, EBSCOHost, JSTOR and ProQuest, online databases (e.g. TRID and EVRI) and relevant conference websites (e.g. ETC, TRB and Kuhmo-NECTAR), as well as the websites of a large number of academic publishing companies, academic institutions, public agencies and private consulting firms. Furthermore, a handful of studies were obtained via personal communications with researchers.

Our search was completed at the end of 2011 and resulted in the collection of more than 80 studies. For a study to be included in our meta-sample, it should allow the computation of the WTP for a change in the driving range of a light-duty vehicle. A considerable share of the collected studies did not fulfil this criterion, either because they were not concerned with light-duty vehicles or because the derivation of the WTP for driving range was not possible, and were excluded from the meta-analysis.[8]

2.4.2. Descriptive analysis

Our meta-analysis draws on 33 primary studies, yielding 129 MWTP and 118 WTP estimates.[9] Some of these studies use stated preference (SP) data collected in the framework of other sampled studies. Consequently, the meta-analysis is based on the results obtained from the primary analyses of 21 different sets of SP data. Table 2.1 provides an overview of the primary studies used in the meta-analysis, including details about the location and time period in which the SP survey took place and the fuel technologies for which driving range was allowed to vary in the SP study design. It also presents the minimum, mean, and maximum estimate of WTP per mile derived from each

[8] Three interesting studies could not be accessed as they were not publicly available (Baumgartner et al., 2007; Morton et al., 1978; Train and Hudson, 2000). Some studies were excluded due to insufficient information about the characteristics of the primary samples (Hensher, 1982; Molin and Brinkman, 2010; Paleti et al., 2011; Train, 2008). In these studies, changes in prices or range were modelled as percentages of reference values, expressing the levels of consumers' current vehicle holdings or of the ones they intend to acquire next. However, these reference values were not reported in the study, rendering the derivation of MWTP and WTP impossible. The study by Mau et al. (2008) was excluded due to the fact that range was modelled in terms of time units (days) rather than distance units (miles).

[9] The difference of eleven estimates between MWTP and WTPs is due to the econometric model specifications used in Ewing and Sarigöllü (1998, 2000), Hidrue et al. (2011), and Parsons et al. (2011).

group of studies. MWTP estimates are standardised into PPP-adjusted 2005US$, to take account of international and intertemporal differences in consumers' purchase power. The annual consumer price index (CPI) and 2005 PPP index used for this purpose are provided by OECD (see also OECD and Eurostat, 2007). None of the examined studies reports that its sample of respondents includes drivers with experience with short-range vehicles, implying that our findings mainly draw on the preferences of individuals without experience with such driving range constraints.

Figure 2.1 illustrates the distribution of MWTP. Unweighted summary statistics for MWTP and WTP values are provided in the first row of Table 2.2. The MWTP for driving range is positively skewed with a mean value of 67 US$ and a median of 55 US$. The distributions of the two WTP measures are also skewed to the right. The mean WTP for an increase in range from 100 to 150 miles is close to 3,800 US$ with a median of 3,200 US$, while the value of an increase from 100 to 350 miles escalates to 17,200 US$ with a median of 13,100 US$ (see Table 2.2). This implies that consumers would be indifferent between an average conventional car and a 100-mile-range car if the latter was about 17,200 US$ cheaper than the former. Ceteris paribus, taking into account that a new car in the USA was costing, on average, around 28,400 US$ in 2005 (National Automobile Dealers Association, 2006), a 100-mile-range car should be offered in prices reduced by 61% in order to be competitive with its conventional counterparts.

The reduction in operating costs offered by the majority of AFVs, stemming from lower fuel and maintenance costs, is likely, however, to decrease these figures to a certain extent. Daziano (2011) discusses this issue in the context of a comparison among FEVs, petrol-fuelled and hybrid vehicles, while Delucchi and Lipman (2010) provide an elaborate analysis of the estimated lifetime costs of FEVs, Fuel-Cell and Plug-in Hybrid Vehicles. An intriguing aspect of FEVs and other AFVs is that while their cost advantage increases with annual mileage driven, annual mileage remains limited as long as their driving range is short.

Although providing an estimate of the magnitude of the effect sizes of interest, this first descriptive analysis does not take into consideration the strong correlation among estimates, induced by drawing multiple estimates from the same primary study or from studies analysing the same stated preference dataset (Florax, 2002; Stanley and Jarrell, 1989). Furthermore, it does not account for the heterogeneity underlying our study sample. It treats WTP estimates stemming from small, convenience samples as equivalent to estimates arising from much larger samples.

Table 2.1: Summary of the primary studies included in the sample.

Study	Location	Year of survey	Fuel Technologies whose driving range varies in study design[a]	Number of MWTP estimates	WTP per mile		
					Mean estimate	Lowest estimate	Highest estimate
Batley and Toner (2003)	Leeds, UK	2002	Unspecified	1	167	167	167
Batley et al. (2004)	Leeds, UK	2001	Unspecified	6	35	31	36
Beggs and Cardell (1980), Beggs et al. (1981)	USA	1978	CV, FEV	12	85	61	132
Brownstone and Train (1999), Brownstone et al. (2000), Kavalec (1999), McFadden and Train (2000)	California, USA	1993	CV, Methanol, CNG, FEV	11	99	58	202
Bunch et al. (1993)	California, USA	1991	AFV, PHEV, FEV	3	101	95	106
Calfee (1985)	California, USA	1980	FEV	1	195	195	195
Christensen et al. (2010), Mabit (2010), Mabit and Fosgerau (2011)	Denmark	2007	CV, Biodiesel, FEV, HEV [b]	4	20	18	23
Dagsvik et al. (2002)	Norway	1995	CV, LPG, FEV, PHEV	4	25	14	30
Daziano (2011), Hess et al. (2006), Train and Sonnier (2005), Train and Weeks (2005)	California, USA	2000	FEV	9	100	87	131
Ewing and Sarigöllü (1998, 2000)	Montreal, Canada	1994	FEV	12	21	17	24
Golob et al. (1997)	California, USA	1994	CV, Methanol, CNG, FEV	8	117	76	202
Hensher and Greene (2001)	Sydney, Australia	1994	CNG/LPG, FEV	4	23	14	31
Hidrue et al. (2011), Parsons et al. (2011)	USA	2009	FEV	9	55	29	82
Jensen (2010)	Denmark	2010	CV, FEV	2	20	20	20
Knockaert (2010)	Flanders, Belgium	2004	AFV, LPG, FEV, Hydrogen	9	39	31	45
Hess et al. (2012)	California, USA	2008	CNG, FEV	4	43	36	49
Molin et al. (2007)	Amsterdam, Netherlands	2006	Biodiesel, HEV, Hydrogen	1	8	8	8
Molin et al. (2012)	Netherlands	2011	FEV	2	44	43	45
Nixon and Saphores (2011)	USA	2010	CNG, FEV, HEV, Hydrogen	2	182	46	317
Qian & Soopramanien (2011)	China	2009	FEV	3	152	138	161
Ramjerdi et al. (1996)	Norway	1994	AFV, FEV	16	58	23	109
Tompkins et al. (1998)	USA	1995	CV, CNG/LPG, FEV, PHEV, Alcohol	6	64	44	102

Note: WTP per mile (MWTP) estimates are in PPP-adjusted 2005 US$. The analysis that follows is based on 21 (instead of 22) clusters of studies. Bunch et al. (1993) and Tompkins et al. (1998) are grouped in the same cluster, due to the use of a choice model pooling the SP data of the two experiments in the latter study.

[a] CV: Vehicle fuelled by conventional sources (petrol or diesel); HEV: Hybrid-electric vehicle; PHEV: Hybrid-electric vehicle with plug-in option; Unspecified: No information about the fuel technology of the alternatives is provided to respondents.

[b] The study by Christensen et al. (2010) considers only the subsample of respondents addressing binary choices between CVs and FEVs.

The funnel plot displayed in Figure 2.2 serves two purposes. The first is to provide insights into the possible existence of publication bias in our study sample. The second is to illustrate the importance of considering possible differences between the results of small sample and larger sample studies. The plot of the square root of the sample size[10] used in the primary study to the MWTP for driving range reveals that smaller sample studies inflate the mean MWTP, as they result in somewhat higher estimates than studies employing relatively large samples. The mean MWTP of the top 5% of sample sizes is approximately 31 US$, while the one of the top 10% is 52 US$, slightly lower than the median MWTP.[11] The fact that the plot is skewed to the right is an indication of possible existence of publication bias in our study. The examination of the distribution of the estimates of the other two WTP measures and the relevant funnel plots lead to similar results. Nevertheless, the insights provided by funnel plots are confounding when heterogeneity is present in the study sample (Stanley, 2005), as we will show later that it is the case here, so they cannot serve as evidence for the existence of publication bias per se.

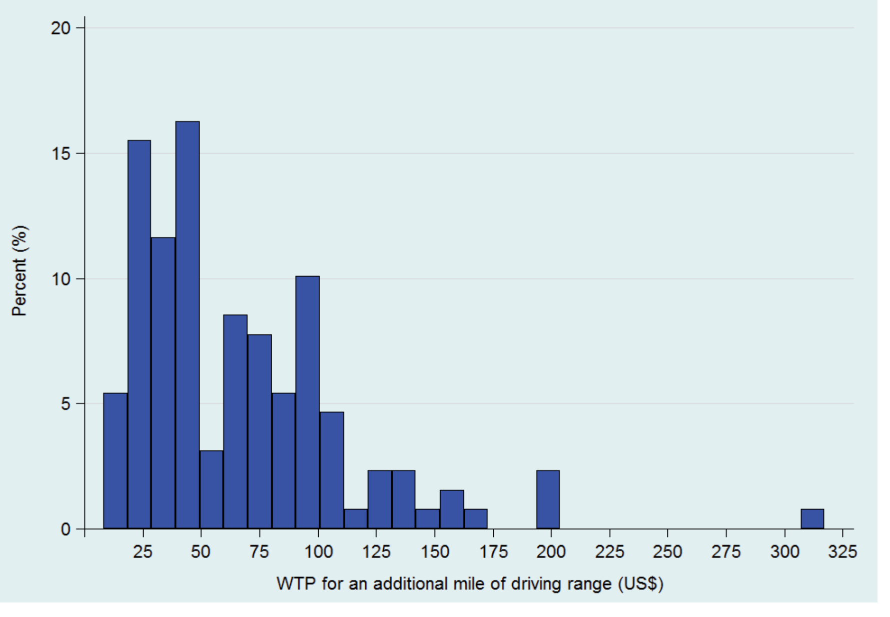

Figure 2.1: Distribution of MWTP.
Note: MWTP estimates are in PPP-adjusted 2005 US$.

[10] Sample size is defined as the number of observations used for the estimation of the relevant choice or ranking model and is equal to the number of choices made or the scenarios ranked by the total number of respondents.
[11] However, if an outlier observation is excluded from the top 10% of sample sizes, the resulting mean WTP is slightly lower than the one of the top 5% (about 30 US$).

Figure 2.2: Funnel plot for MWTP for driving range.

Note: The solid line illustrates the unweighted mean MWTP, whereas the dashed one the unweighted median MWTP.

The discussion provided above calls for the adoption of a weighting approach to mitigate the effects of correlation, heterogeneity and possible publication bias in the meta-sample. To this end, Table 2.2 compares unweighted and weighted summary statistics of MWTP and WTP to 150 and 350 miles. The results of two weighting schemes are presented. In the first scheme, estimates are weighted by the inverse of the number of estimates drawn per dataset, in order to take account of the sampling of multiple estimates per SP study. Hence, MWTP and WTP estimates are clustered in 21 datasets.[12] The second scheme employs a weighting approach aiming to mitigate the influence of both the correlation[13] and the heterogeneity among primary effects sizes present in our sample. The applied weights, w_{ij}, equal the products of the sample size, n_{ij}, used for the estimation of effect size i of dataset j, and the inverse of the number of effect size estimates, d_j, drawn from the dataset:[14]

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[12] Bunch et al. (1993) and Tompkins et al. (1998) are grouped in the same cluster, due to the use of a choice model pooling the SP data of the two experiments in the latter study. This clustering approach is adopted throughout our analysis.

[13] Although this approach seems to be taking into account the correlation among WTP estimates introduced by multiple sampling from the same dataset, Florax (2002) notes that it only mitigates the influence of heteroskedasticity, while leaving the impact of correlation unaffected.

[14] Meta-analysis literature suggests as ideal weights for this purpose the inverse of the variances with which effect sizes are estimated. Unfortunately, these could be computed only for very few MWTP estimates.

$$w_{ij} = n_{ij} / d_j \,, \tag{2.4}$$

Summary statistics do not reveal considerable differences in the means of the examined MWTP and WTPs between weighting schemes, but they do point to a modest overestimation of median effect sizes in the unweighted case.

Table 2.2: Summary statistics of WTP estimates under different weighting schemes.

Treatment of estimates	Marginal Willingness to Pay			Willingness to Pay 100-150 miles			Willingness to Pay 100-350 miles		
	Mean	Median	95% c.i.	Mean	Median	95% c.i.	Mean	Median	95% c.i.
Unweighted	66.9	54.8	49.3 - 84.5	3,795	3,242	2,774 - 4,817	17,227	13,078	12,634 - 21,819
Weighted by the inverse of the number of observations per dataset	74.5	45.2	48.1 - 100.9	3,807	2,661	2,657 - 4,958	17,025	11,293	11,182 - 22,867
Weighted by the product of the inverse of the number of observations per dataset and the sample size used in the primary study	66.5	41.7	29.0 - 103.9	3,887	3,230	2,328 - 5,445	16,799	10,186	8,322 - 25,276
Number of estimates		129			118			118	

Note: 95% confidence intervals are calculated on the basis of heteroskedasticity-robust standard errors, clustered by SP dataset. MWTP and WTP estimates are in PPP-adjusted 2005 US$.

As mentioned in Section 2.2, the studies considered in our meta-analysis do not reach an agreement on the way in which driving range enters consumer's utility function. Intuitively, MWTP should be a decreasing function of the car's range. It is very unlikely that a marginal increase in range from a reference level of 100 miles and from one of 500 miles has the same value to the consumer. It is striking, however, that the most commonly used specification assumes that the marginal utility of range is constant across range levels. Exceptions are Brownstone et al. (2000) and Bunch et al. (1993), who consider also a quadratic term for range in consumers' utility function, Calfee (1985), Hess et al. (2012), Jensen (2010), Kavalec (1999), Mabit (2010) and Mabit and Fosgerau (2011) who employ the logarithmic transformation of range in their utility function specification and Beggs et al. (1981), Ewing and Sarigöllü (1998, 2000), Hidrue et al. (2011) and Parsons et al. (2011) who use, inter alia, a dummy variable specification for range. Although Molin et al. (2007, 2012) test the performance of utility functions with effects-coded specifications for range, they fail to reject that they perform better than utility functions linear in range.

A graphical illustration of the mean MWTP per SP dataset against the mean driving range considered for the estimation of this MWTP (Figure 2.3) does not provide support

Following common practice in the field (e.g. Brons et al., 2008; de Blaeij et al., 2003), we instead use the sample sizes employed in the primary studies. A similar weighting approach in a meta-regression context is adopted by Van Houtven et al. (2007).

for the adoption of a utility function linear in driving range.[15] On the contrary, it shows that MWTP is a decreasing function of the average range level considered in the primary study, possibly linear in the inverse of the average range level. This finding provides some encouragement for the employment of a utility specification linear in the logarithmic transformation of range, while it does not oppose the adoption of a dummy codification scheme. It comes, however, in strong contradiction with the commonly used linear-in-range utility specification.

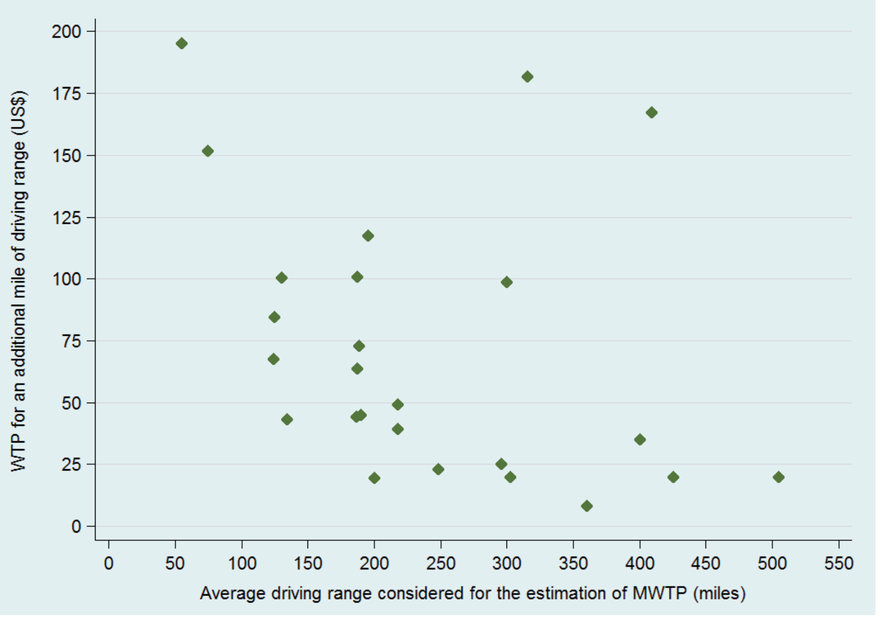

Figure 2.3: Mean MWTP for driving range per SP dataset against mean driving range.

A usually ignored element of consumer valuation of range is that it may well be sensitive to changes in the levels of refuel time and availability of refuelling infrastructure considered in the study. For instance, if the refuelling of AFVs takes only a few minutes and the density of refuelling infrastructure is high, it is reasonable to expect that driving range becomes much less important. Even though most studies consider at least one of these two attributes in their attribute set, only a few go further to acknowledge the dependence of range valuation on the levels assumed for these attributes (e.g. Ewing and

[15] Even though our study is based on 21 SP datasets, Figure 2.3 draws on 24 observations. The reason is that the mean driving range levels considered by Bunch et al. (1993) and the two models of Tompkins et al. (1998) differ among each other, and that the study by Ramjerdi et al. (1996) considers different mean driving range levels for FEVs and AFVs while also providing technology-specific marginal utilities for driving range.

Sarigöllü, 1998; Hidrue et al., 2011; Segal, 1995). The practical consideration of the relationship between these three attributes in consumer's mind would imply a non-linear formulation of the utility function, including interaction terms between driving range, refuelling duration and the coverage of refuelling infrastructure. Surprisingly, however, none of the examined studies explicitly mentions testing for interaction effects among these attributes.[16] This gap in empirical transportation literature suggests a promising opportunity for further research.

2.4.3. Heterogeneity among primary studies: bivariate analysis

Summary statistics on the valuation of driving range can provide valuable benchmarks to policy makers, manufacturers and researchers interested in the potential demand for AFVs. However, it is also important to acknowledge the heterogeneity in effect size estimates among primary studies, identify the study characteristics responsible for it and estimate their impact. Heterogeneity may be arising from factual differences among studies, concerning, for instance, spatial and temporal characteristics, or vehicle characteristics, such as fuel type and body type. It may further be stemming from methodological differences, such as differences in the design of the SP survey or the model used to analyse the SP data.

Table 2.3 provides descriptive information about the heterogeneity in primary WTP estimates across different groupings of studies. The groupings are based on: (i) the country in which the study was carried out, (ii) the time period in which the survey was conducted, (iii) the way in which range was assumed to enter consumers' utility functions, (iv) the minimum and maximum driving range levels considered in the study design, (v) the fuel technologies to which the marginal utility of driving range is relevant, (vi) the consideration or omission of a fast-refuelling option (especially when driving range varies only for FEVs), and (vii) the manner in which the marginal utilities of driving range and purchase price were modelled. For each grouping, the table presents the mean MWTP and WTPs per group, as well as the results of standard t-tests examining the statistical significance of the difference in means between the reference group and all other groups.

[16] Hidrue et al. (2011) and Parsons et al. (2011) are the only studies that standardise the driving range level that the refuel times presented to the respondents should be associated with (50 miles). With this approach, authors can provide estimates of MWTP for reductions in refuel time, holding driving range constant. Although this technique cannot provide insights into the sensitivity of the MWTP for an attribute to changes in another, it represents a first attempt to actively consider the dependence among these attributes in a choice experiment setting.

Table 2.3 employs a bivariate perspective; a multivariate analysis is provided in Section 2.5.

Table 2.3: Differences in means of WTP among different groups of studies.

Group	Marginal Willingness to Pay		Willingness to Pay	100 to 150 miles	100 to 350 miles
	Observations	Mean	Observations	Mean	Mean
Country/Region of survey implementation					
USA	65	90.1***	59	5,149***	22,788***
Canada	12	20.8***	7	1,131***	5,073***
Australia	4	25.0***	4	1,250***	6,250***
China	3	151.5***	3	7,577***	37,885***
Europe	45	*43.8*	45	*2,409*	*11,424*
Year of survey implementation					
1978 - 1989	13	93.2**	13	4,245	20,588
1990 - 1999	64	63.8	59	3,888	17,196
2000 - 2011	52	*64.1*	46	*3,548*	*16,317*
Treatment of driving range in the utility function					
Logarithmic	11	47.4	11	3,215	9,934***
Quadratic	8	93.4*	8	7,863***	24,944
Dummy-coded	21	40.6***	10	2,401**	9,624***
Linear	89	*73.2*	89	*3,658*	*18,289*
Driving range levels considered in the study					
Minimum range > 150 miles	13	21.5***	13	1,606***	6,608***
Maximum range < 100 miles	4	162.4***	4	6,771**	31,775
Max range > 100 miles & Min range < 150 miles	112	*68.8*	101	*3,959*	*18,017*
Fuel technologies to which marginal utility of range is relevant					
Marginal utility of range relevant to FEVs and other technologies	79	65.1	79	*3,765*	*16,621*
Marginal utility of range relevant only to FEVs	50	*69.8*	39	*3,856*	*18,454*
Availability of fast-charging option for FEVs					
Fast charging option unavailable for FEVs	14	78.6	14	3,929	19,646
Fast charging option available for FEVs	115	*65.5*	104	*3,777*	*16,901*
Distributional assumptions on the marginal utilities of range and price					
Lognormal distribution assumed for both marginal utilities	6	158.2**	6	7,910*	39,549**
Otherwise	123	*62.5*	112	*3,575*	*16,031*

Note: t-tests explore statistical significance in differences between a group's mean value and the mean of the reference group (last category of each grouping: relevant mean values reported in italics). t-tests do not impose the restrictive assumption that the variances between groups are equal. ***, ** and * indicate that the difference is statistically significant at the 1%, 5% or 10% level respectively. Means of MWTP and WTP are in PPP-adjusted 2005US$.

Valuations of driving range vary significantly among regions. The majority of studies are conducted in the USA and Europe. Our analysis shows that driving range has much higher importance for Americans than Europeans. In particular, the average MWTP in the USA is more than twofold the one in Europe. Possible reasons that might be explaining the higher importance of driving range in the USA are the higher range needs of Americans, due to longer distances that have to be travelled and lower densities of activities in urban environments, and the weaker emphasis they have placed on the development and use of transit (e.g. railway) infrastructure (Kenworthy and Laube, 1999). The divergence in driving range valuation between the two regions might also be partially attributed to the higher average income of Americans than Europeans (as approximated by GDP per capita) and the stronger association of feelings of freedom and independence with car trips in the USA than in Europe (FIA Foundation, 2003; World Bank, 2016). Furthermore, the annual distance travelled by a car in the United States is, on average, higher than the one of a car in the European countries included in our dataset (Euromonitor, 2012).

Even though we find that range valuations in Canada, China and Australia are also significantly different from the ones in Europe or the USA, the fact that these three countries are only represented by a single study in our sample renders the extraction of any such conclusion meaningless. The driving range levels considered in the study for China are notably low, whereas the ones for the study for Australia relatively high. Thus, the differences in effect size estimates shown above may be mainly related to differences in the driving range levels considered in the studies rather than among the countries where the studies were implemented.

Studies undertaken in late 1970s and early 1980s lead to significantly higher MWTP estimates than studies undertaken from 1990 onwards. Two facts should mainly account for this result. First, all studies carried out before 1990 and included in our study sample are conducted in the USA, where range valuations are higher. Second, driving range levels considered by these early studies are relatively low, inducing higher valuations of changes in range. In addition, in one of these early studies low range levels are explicitly related to other unappealing characteristics of FEVs, such as long refuel times and high battery replacement costs (Beggs et al., 1981).

Methodological differences among studies constitute an additional important source of variation in the effect sizes of interest. SP studies adopt a relatively diverse set of assumptions in their attempt to model consumer preferences for AFVs, as well as of approaches to elicit them. This divergence concerns, for example: (i) the behavioural assumptions made on the way in which driving range enters consumer's utility function, (ii) several aspects of the SP study design (e.g. fuel technologies and body types considered in the study, SP method selected to elicit consumer preferences, dimensionality of the choice design utilised) and the SP survey implementation (e.g. size of the surveyed sample and survey method employed), as well as (iii) the underlying assumptions of the choice model used to analyse the SP data. We present here only a limited number of methodological aspects which were found to have an influence on WTP estimates in the multivariate analysis that follows.[17]

The t-tests for differences in means between different utility specifications show that MWTP and WTP estimates are influenced by the assumptions imposed on consumers' utility functions. The use of dummies for different levels of range results in significantly lower WTP estimates than the ones derived from a linear specification. On the contrary, quadratic (in driving range) utility functions lead to higher WTP estimates than functions linear in range. Logarithmic specifications do not seem to lead to estimates significantly different from linear ones, with the exception of the WTP from 100 to 350 miles. This last finding, however, is not robust in the multivariate analysis presented in Section 2.5.

We further test for differences in WTP estimates between studies employing a narrower scope of driving range levels in the design of the SP study and ones eliciting consumer preferences for driving range in a wider, and more realistic for FEVs, interval. We find that studies employing a maximum driving range of 100 miles lead to considerably higher WTP estimates than studies allowing for higher maximum driving ranges. On the other hand, studies considering a minimum driving range of at least 150 miles result in notably lower WTP estimates than studies considering lower levels of minimum driving range. This emphasises the strong sensitivity of the WTP estimates to the driving range levels considered in the primary studies.

Different fuel technologies entail different range limitations and require different levels of change in drivers' refuelling behaviour. We test for differences between WTP estimates concerning solely FEVs and ones being relevant (also) to other fuel technologies. The former group encompasses WTP estimates from: (i) studies varying driving range levels only for FEVs, and (ii) FEV-specific estimates of the marginal utility of driving range. In contrast, the latter group contains WTP estimates derived from studies varying driving range levels (also) for other fuel technologies. Table 2.3 reveals that the differences in the means of the two groups are small and statistically insignificant.

[17] We note here that even though there are important reasons to believe that the valuation of range might vary substantially among car body types, mainly due to differences in the range-intensiveness of the household needs served by different body-types, body-type-specific range coefficients are very rarely provided in the examined literature (Bunch et al., 1993; Tompkins et al., 1998). Similarly, the study by Ramjerdi et al. (1996) is the only one considering differences in the valuation of driving range between the first and second car of the household, finding them to be substantial. We would encourage the devotion of more research efforts towards the investigation of differences in the valuation of driving range among different car body-types and travel needs.

The value of driving range might not be independent of the time needed to refuel the vehicle and the ease of finding available refuelling facilities. For instance, if the refuelling of AFVs takes only a few minutes and the density of refuelling infrastructure is high, it is reasonable to expect that driving range becomes much less important. Refuelling time is primarily relevant to FEVs, where three options are currently offered: (i) standard charging, taking usually between 6 and 10 hours for the charging of a 100-mile-range battery, (ii) fast charging, capable of bringing the charging duration of 80% of the battery capacity down to 20 minutes, and (iii) battery-swapping, which entails having the EV battery replaced within less than five minutes by a fully charged one at specialised stations. Battery-swapping essentially shifts the problem of long refuelling times to a possible problem of inadequate coverage of refuelling infrastructure. This obstacle is also relevant to other AFV technologies, such as CNG-powered vehicles and fuel-cell ones, especially during their early adoption phase.

Our meta-sample exhibits strong heterogeneity in the way refuelling time and availability of refuelling infrastructure are considered in the study design, while studies are not always clear in the way they treat these two attributes. Some studies consider at least one of them in their attribute set; others provide some relevant information in the text introducing respondents to the survey; while others seem to leave respondents uninformed about the levels of these attributes, probably inducing them to consider their levels equivalent to the ones of conventional fuel technologies. Studies are not always clear in the way they treat these two attributes. Our analysis shows that studies providing FEV-specific marginal utilities for driving range, while also limiting respondents' hypothetical refuelling options to a charging duration of 2 hours or more, lead to higher WTP estimates than the rest of the studies. Although this difference is not statistically significant in the bivariate analysis presented here, we do find significant differences in the multivariate analysis that follows.

The econometric model employed for the analysis of the SP data may also be an important determinant of the magnitude of effect size estimates. The econometric models utilised for the analysis of SP data range from the standard multinomial and exploded logit models, to logit models only partially bounded by the Independence of Irrelevant Alternatives (IIA) assumption, such as the nested logit, and to more flexible logit forms, such as the random parameter and latent class logit. Models making different distributional assumptions about the random component of the utility function, such as the multinomial probit, or models deviating from the random utility maximisation principles, such as the hierarchical-elimination-by-aspects model, have also been used to a limited extent in the examined literature.

In agreement with Hensher and Greene (2003) and Sillano and Ortúzar (2005), our analysis shows that random parameter logit models imposing a log-normal distribution on the marginal utilities of both purchase price and driving range result in substantially inflated mean MWTP and WTP values. This result stems from the long tail of the log-normal distribution. In order to avoid the inflation of mean WTP values when the marginal utility of an attribute is expected to have a specific sign, Hensher and Greene (2003) suggest the employment of constrained distributions, whereas Sillano and Ortúzar (2005) propose the use of consistency checks for individuals whose attribute coefficients are not of the expected sign and thereafter the employment of a normal distribution. Even though constraining the price coefficient to be fixed might also result in overestimated mean MWTP and WTP values, the magnitude of this overestimation is not usually as large as in the case where both coefficients are assumed to be log-normally distributed.

2.5. Meta-regression analysis

The bivariate analysis presented above is useful for the identification of possible factors affecting the magnitude of estimates of WTP for driving range, but a multivariate approach is required to disentangle the impact of each of these sources of variation on the effect sizes of interest. To this end, we employ a linear meta-regression model using the logarithmic transformations of MWTP and WTP estimates (in hundreds of 2005 US$) as dependent variables. Several reasons motivate the use of logarithmic transformations: (i) our study sample contains only positive effect size estimates, (ii) the distribution of estimates is heavily skewed to the right, and (iii) our sample contains some outlier values, reflecting exceptionally high MWTP and WTPs. Moreover, the logarithmically transformed figures are known to be less sensitive to the problem of heteroskedasticity (Konstantopoulos and Hedges, 2009). The distribution of ln(MWTP) is depicted in Figure 2.4.

2.5.1. Fixed effect-size meta-regression models

We consider two fixed-effect-size meta-regression model specifications for the explanation of the variation in MWTP for driving range.[18] The two specifications are different only in

[18] These models were selected among a large number of tested specifications. In this context, much care was taken to avoid high pairwise correlation levels among the explanatory variables, and, thus, address possible concerns about multicollinearity in the presented models.

the variables used to describe the levels of driving range considered in the primary study. In the first specification, the logarithm of MWTP estimate k is modelled as a function of the natural logarithm of average driving range, *ln(meanR)*, its interaction with a dummy variable indicating whether driving range levels are varied only for FEVs or also for other technologies in the primary study, *FEVrange*, and vectors of other variables.[19] This econometric specification can be formulated as follows:

$$\ln(MWTP_k) = \alpha_1 + \beta_{\mathrm{R}} \ln(meanR_k) + \beta_{\mathrm{REV}} FEVrange_k \ln(meanR_k) + \boldsymbol{\beta}_{\mathbf{L}_1} \mathbf{L}_k + \boldsymbol{\beta}_{\mathbf{D}_1} \mathbf{D}_k + \varepsilon_k , \qquad (2.5)$$

where **L** denotes a vector of dummy variables indicating the country of study, **D** denotes a vector of variables measuring selected aspects of the research design of the primary study, and ε is an error term with mean zero and given variance.[20] Parameters α_1, β_R and β_{REV} and vectors of parameters $\boldsymbol{\beta}_{\mathbf{L1}}$ and $\boldsymbol{\beta}_{\mathbf{D1}}$ shall be estimated by ordinary least squares and weighted least squares.

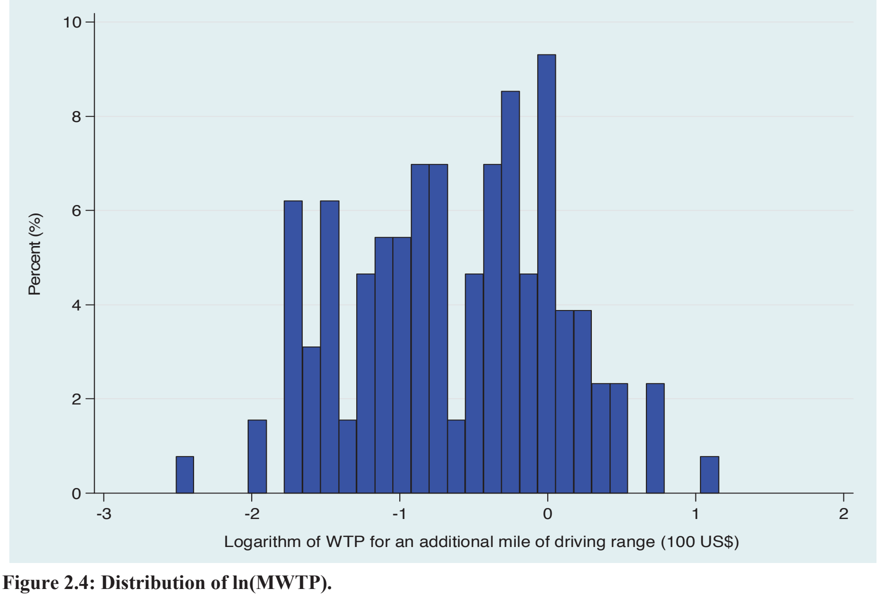

Figure 2.4: Distribution of ln(MWTP).
Note: MWTP estimates are in hundreds of PPP-adjusted 2005 US$.

[19] Average range is measured in hundreds of miles. Whenever fuel-type-specific marginal utilities of range are reported, average range concerns the fuel type for which the relevant marginal utility is estimated. We also tested a meta-regression model linear in the average driving range level considered in the study. Its performance is much worse and the coefficient of the average driving range is statistically insignificant. Our exploratory analysis shows that a meta-regression model linear in the inverse of average driving range can be alternatively utilised. The conclusions drawn from such a specification are similar to the ones presented here.
[20] In what follows, vector L takes the form of a scalar, indicating whether the study was conducted in the United States or elsewhere.

Motivated by the outcome of the bivariate analysis presented in Subsection 2.4.3, in Model 2 we employ two dummy variables to investigate the sensitivity of MWTP to the minimum and maximum driving range levels considered in the study. In particular, we distinguish studies employing a maximum level of driving range lower than 100 miles ($maxR_{100}$) and ones using a minimum driving range level higher than 150 miles ($minR_{150}$). We further look into MWTP's elasticity to the width of the interval within which driving range values vary in the primary study (*rangeR*), namely to the difference between the maximum and minimum driving range levels considered therein. Model 2 is, therefore, specified as follows:

$$\ln(MWTP_k) = \alpha_2 + \beta_{\mathrm{R_{max}}} maxR_{100_k} + \beta_{\mathrm{R_{min}}} minR_{150_k} + \beta_{\mathrm{RR}} \ln(rangeR_k) + \boldsymbol{\beta}_{\mathbf{L}_2}\mathbf{L}_k + \boldsymbol{\beta}_{\mathbf{D}_2}\mathbf{D}_k + \xi_k, \qquad (2.6)$$

where ξ is an error term with mean zero and given variance. Parameters α_2, β_{Rmax}, β_{Rmin} and β_{RR}, and vectors of parameters $\boldsymbol{\beta}_{\mathbf{L2}}$ and $\boldsymbol{\beta}_{\mathbf{D2}}$ are also to be estimated. The specification of Model 2 is also used to explain the variation in the estimates of WTP for increases from 100 to 150 miles and 350 miles.[21] In all models, the dependent variable is the logarithmic transformation of the effect size of interest. Table 2.4 summarises the definitions of the explanatory variables used in the meta-regression models, alongside with their weighted and unweighted mean values.

Table 2.5 presents the estimation results of the four meta-regression models. For all four models, we present the outcome of ordinary least squares (OLS) and weighted least squares (WLS) regressions. The weights used in WLS are as defined in Equation (2.4). Literature suggests that OLS should be used with caution in the context of meta-regression analysis, due to the dependence of observations drawn by the same study and the possible publication bias. On the contrary, WLS has several advantages over OLS in the current context. It can discount the effect of more poorly designed small-sample studies, mitigate the correlation among WTP estimates derived from the same study, lessen the influence of publication bias, while also take account of heteroskedasticity. Hence, the results of the WLS models form the basis of the subsequent discussion.

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[21] We do not present the results of meta-regression models for the two WTP measures following the specification of the first MWTP model, on the basis of both theoretical and empirical grounds. First, as the levels we employ here (150 and 350 miles) are independent of the mean driving range employed in the study, there is no reason to believe that these WTP measures are influenced by changes in mean driving range. Our empirical findings confirm this expectation, as meta-regression specifications following Model 1 have relatively low fit and the resulting coefficients of driving-range-related explanatory variables are statistically insignificant. On the contrary, estimates of the two WTP measures may well be affected by the boundaries considered for the driving range attribute, especially when these are lower than the 100-mile minimum boundary, or higher than the 150-mile or 350-mile maximum boundary, assumed here.

Table 2.4: Definitions and means of the explanatory variables used in the meta-regression analysis.

Variable	Description	Unweighted Mean	Weighted Mean
ln(meanR)	Natural logarithm of the average driving range level used in the study (measured in hundreds of miles).	0.68	0.84
ln(meanR) * FEVrange	ln(meanRange) interacted with a dummy reflecting whether the levels of the driving range attribute vary only for FEVs in the study or also for other fuel technologies.	0.15	0.11
maxR < 100miles	=1, if the maximum level of driving range considered in the study is less than 100 miles; =0, otherwise.	0.03	0.05
minR > 150 miles	=1, if the minimum level of driving range considered in the study is more than 150 miles; =0, otherwise.	0.10	0.34
ln(rangeR)	Natural logarithm of the width of the interval within which driving range values vary in the study (measured in hundreds of miles).	0.80	1.04
Quadratic	=1, if the utility function is assumed to be quadratic in driving range; =0, otherwise.	0.06	0.03
Logarithmic	=1, if the logarithmic transformation of driving range enters consumers' utility function; =0, otherwise.	0.09	0.30
Dummy-coded	=1, if a series of dummy variables are used to capture the effect of different driving range levels on consumers' utility; =0, otherwise.	0.16	0.14
No fast-charging option for FEVs	=1, if the marginal utility of range is specific to FEVs and there are only slow-charging options (more than 2 hours) considered in the study; =0, otherwise.	0.11	0.02
Ratio of lognormals	=1, if the WTP estimate stems from a random parameter logit model assuming lognormal distributions for both the marginal utility of range and the marginal utility of purchase price; =0, otherwise.	0.05	0.09
USA	=1, if the study is conducted in the USA; =0, otherwise.	0.50	0.46

Note: The weights used for the computation of weighted means are the products of the sample size employed in the primary studies with the inverse of the number of effect size estimates drawn per dataset, as described in Equation (2.4).

The results of the first meta-regression model suggest that the estimated MWTP is non-linearly decreasing in the driving range considered in the study and that it is particularly sensitive to changes in it. This finding urges for careful consideration and pre-testing of the driving range levels considered in relevant SP studies. Furthermore, it suggests that the minority of studies adopting a non-linear in range utility specification are likely to be better approximations of the way in which driving range enters consumers' utility function.

Model 1 further distinguishes between MWTP estimates stemming from studies varying driving range levels only for FEVs, or from FEV-specific estimates of the marginal utility of driving range, and MWTP estimates derived from studies varying driving range levels (also) for other fuel technologies. It is important to note that there is an almost 100-mile difference between the average driving range considered in the first group of estimates (153 miles) and the second one (252 miles). We find that the elasticity of MWTP with respect to driving range is significantly higher when estimates are derived from FEV-specific models than when they are derived from generic or other fuel-technology-specific models. This divergence in the elasticity values is not likely to be stemming from the FEV technology itself, as the FEV-specific driving range dummy is statistically insignificant when driving range levels are not considered in the econometric specification. Instead, it should be attributed to the significantly lower average driving range level employed in FEV-specific models. Thus, MWTP is elastic to increases in driving range in relatively low range values (around 150 miles), while inelastic in higher ones (about 250 miles). This result provides evidence that MWTP not only diminishes in driving range, but that it also diminishes at a decreasing rate. Our findings here are in agreement with the argument that driving range should enter consumer's utility function: (i) in a non-linear way, and (ii) not only as a stand-alone attribute, but also in interaction with other relevant attributes, such as refuelling time and coverage of refuelling infrastructure.

Meta-regression specifications following Model 2 confirm the insights provided in the bivariate analysis; studies employing a maximum driving range of 100 miles lead to considerably higher effect size estimates, whereas studies considering a minimum driving range of at least 150 miles result in notably lower MWTP estimates than studies considering higher maximum or lower minimum driving range values. Furthermore, meta-regression analysis shows that the two WTP measures are increasing in the width of the attribute range considered for driving range. This result holds after controlling for the two extreme cases described right above and confirms previous findings of choice modelling literature on the sensitivity of WTP to the attribute range considered (see, e.g. Hensher, 2004).

Once again, we find that the specification of the utility function with respect to driving range significantly affects MWTP and WTP values. This is well anticipated, of course, as the derivation of the WTP estimates is based on the form of the utility function adopted in the model. Different functional forms have different properties, which inevitably influence the magnitude of the estimates. Utility functions quadratic in driving range lead to higher effect size estimates than linear ones, being statistically significant only for the WTP from 100 to 150 miles. On the contrary, functions employing the logarithmic transformation of driving range result in significantly lower MWTP values. Their impact on the two WTP measures is much less pronounced. Functions considering dummy specifications have a negative and significant effect on MWTP mainly in OLS models. The insights provided by the WLS estimates are not very informative in this context.

Table 2.5: OLS and WLS estimation results for the logarithmic transformations of WTP estimates.

	Marginal Willingness to Pay (Model 1)		Marginal Willingness to Pay (Model 2)		Willingness to Pay 100-150 miles		Willingness to Pay 100-350 miles	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
ln(meanR)	*-0.441*** (0.185)	*-0.461*** (0.199)	-	-	-	-	-	-
ln(meanR) * FEVrange	*-0.905**** (0.317)	*-1.092*** (0.501)	-	-	-	-	-	-
maxR < 100miles	-	-	*1.524**** (0.174)	*1.774**** (0.186)	*1.363**** (0.385)	*1.933**** (0.479)	*1.420**** (0.384)	*1.909**** (0.453)
minR > 150 miles	-	-	*-0.568**** (0.142)	*-0.572**** (0.197)	*-0.462*** (0.200)	*-0.324* (0.254)	*-0.469*** (0.196)	*-0.378* (0.237)
ln(rangeR)	-	-	*0.110* (0.107)	*0.233* (0.137)	*0.227* (0.142)	*0.512**** (0.175)	*0.261** (0.150)	*0.516**** (0.169)
Quadratic [a]	*0.182* (0.132)	*0.244* (0.178)	*0.026* (0.179)	*0.072* (0.293)	*0.540**** (0.180)	*0.626** (0.334)	*0.049* (0.145)	*0.169* (0.247)
Logarithmic [a]	*-0.594**** (0.144)	*-0.457** (0.240)	*-0.560**** (0.140)	*-0.439*** (0.185)	*-0.071* (0.324)	*0.112* (0.310)	*-0.566** (0.316)	*-0.361* (0.300)
Dummy-coded [a]	*-0.061* (0.173)	*0.202* (0.302)	*-0.534**** (0.085)	*-0.414*** (0.148)	*-0.328*** (0.138)	*-0.022* (0.245)	*-0.533**** (0.119)	*-0.338* (0.197)
No fast-charging option for FEVs	*0.226** (0.127)	*0.303* (0.212)	*0.379**** (0.106)	*0.512**** (0.157)	*0.430**** (0.123)	*0.741**** (0.226)	*0.467**** (0.120)	*0.784**** (0.205)
Ratio of lognormals	*0.626** (0.341)	*1.224*** (0.521)	*0.546** (0.264)	*1.051*** (0.456)	*0.623*** (0.249)	*1.179**** (0.386)	*0.637*** (0.242)	*1.206**** (0.381)
USA	*0.654**** (0.141)	*0.636**** (0.211)	*0.742**** (0.112)	*0.626**** (0.194)	*0.641**** (0.136)	*0.465* (0.270)	*0.629**** (0.133)	*0.390* (0.244)
Constant	*-0.529*** (0.192)	*-0.630** (0.322)	*-1.015**** (0.110)	*-1.181**** (0.149)	*2.840**** (0.128)	*2.466**** (0.267)	*4.422**** (0.128)	*4.120**** (0.246)
Observations	129	129	129	129	118	118	118	118
R^2	0.66	0.72	0.74	0.83	0.65	0.67	0.64	0.70
R^2-adjusted	0.64	0.70	0.73	0.82	0.62	0.64	0.61	0.68
RMSE	0.42	0.48	0.36	0.37	0.41	0.45	0.41	0.44

Note: Robust standard errors, clustered by SP dataset, in parentheses. ***,** and * indicate that the parameter is statistically significant at the 1%, 5% and 10% level respectively. The weights used for the WLS are the products of the sample size employed in the primary studies and the inverse of the number of effect size estimates drawn per dataset, as described in Equation (2.4).
[a] Reference category comprises utility functions linear in driving range.

When the estimated marginal utility of driving range concerns only FEVs and the study context does not allow for a fast-charging possibility, consumer valuation of changes in driving range becomes significantly higher. Even though the exclusion of a fast-charging option constitutes an extreme case, this finding provides additional evidence for the interdependence of driving range and refuelling time attributes. This implies that for the AFVs whose refuelling duration can be long (e.g. FEVs), important reductions in consumers' disutility from short driving ranges can be achieved by options bringing refuelling time down to reasonable levels, such as fast-charging facilities and battery-swapping stations.

The meta-regression analysis confirms that random parameter logit models assuming a log-normal distribution for the marginal utilities of both purchase price and driving range result in substantially higher estimates of WTP. As this is probably an artefact of the shape of the log-normal distribution, practitioners are encouraged to seek alternative ways to ensure that the marginal utility of an attribute has the expected sign in a random parameter logit context. The guidance provided by Hensher and Greene (2003) and Sillano and Ortúzar (2005) can be useful in this context.

The econometric results further confirm that Americans value driving range substantially more than drivers in Europe and other countries. Their MWTP is around double the one of drivers elsewhere, while the two WTPs are also substantially higher. Still, the fact that the Australian, Canadian and Chinese WTP estimates are based on the results of a single study per country does not allow us to delve deeper into spatial differences in the valuation of changes in driving range. It should be noted that we also explored the impact of various contextual variables on MWTP and WTP estimates, such as: (i) the land area of the country where the study took place, (ii) the average distance travelled by car in the country of study and year of survey, and (iii) the modal share of the railway and the car in passenger transport therein. The effect of the last two variables was statistically insignificant in the examined specifications. The inclusion of land area in the explanatory variables of the meta-regression models was raising important multicollinearity concerns and, thus, the variable was discarded from the econometric analysis.

2.5.2. Random effect-size meta-regression analysis

It is also useful to provide insights into the random-effects panel-data counterparts[22] of the models presented in the previous subsection, as these models are more capable of taking into account the correlation among WTP estimates i, stemming from the same dataset j.[23] These can be formulated as follows:

$$\ln(MWTP_{ij}) = \tilde{\alpha}_1 + \tilde{\beta}_{\mathrm{R}} \ln(meanR_{ij}) + \tilde{\beta}_{\mathrm{REV}} FEVrange_{ij} \ln(meanR_{ij}) + \tilde{\boldsymbol{\beta}}_{\mathbf{L}_1} \mathbf{L}_{ij} + \tilde{\boldsymbol{\beta}}_{\mathbf{D}_1} \mathbf{D}_{ij} + u_j + \tilde{\varepsilon}_{ij}, \quad (2.7)$$

$$\ln(MWTP_{ij}) = \tilde{\alpha}_2 + \tilde{\beta}_{\mathrm{R_{max}}} maxR_{100_{ij}} + \tilde{\beta}_{\mathrm{R_{min}}} minR_{150_{ij}} + \tilde{\beta}_{\mathrm{RR}} \ln(rangeR_{ij}) + \tilde{\boldsymbol{\beta}}_{\mathbf{L}_2} \mathbf{L}_{ij} + \tilde{\boldsymbol{\beta}}_{\mathbf{D}_2} \mathbf{D}_{ij} + v_j + \tilde{\xi}_{ij}, \quad (2.8)$$

where all terms are defined as in Equations (2.5) and (2.6), u, v, $\tilde{\varepsilon}$ and $\tilde{\xi}$ are error terms with zero mean and given variance, and parameters $\tilde{\alpha}_1, \tilde{\alpha}_2, \tilde{\beta}_R, \tilde{\beta}_{REV}, \tilde{\beta}_{R_{\max}}, \tilde{\beta}_{R_{\min}}, \tilde{\beta}_{RR}$ and vectors of parameters $\tilde{\boldsymbol{\beta}}_{\mathbf{L}_1}, \tilde{\boldsymbol{\beta}}_{\mathbf{L}_2}, \tilde{\boldsymbol{\beta}}_{\mathbf{D}_1}, \tilde{\boldsymbol{\beta}}_{\mathbf{D}_2}$ are to be estimated. We use random-effects generalised least squares (GLS) to estimate these parameters. The results are presented in Table 2.6.

[22] In the meta-analysis literature, such models belong to the family of mixed-effect-size models.

[23] It should be noted that our dataset does not form a panel, but rather a sample of pooled data (Florax, 2002). We also attempted to employ a fixed-effects panel model. In agreement with existing meta-analysis literature (e.g. Nelson and Kennedy, 2009; Van Houtven et al., 2007), however, we found this option to be particularly problematic when explanatory variables do not vary substantially within studies, the study sample is relatively small and not all studies allow the derivation of multiple effect size estimates.

Table 2.6: Random-effects GLS estimation results for the logarithmic transformations of WTP.

	Marginal Willingness to Pay				Willingness to Pay			
	Model 1		Model 2		100-150 miles		100-350 miles	
ln(meanR)	*-0.398***	(0.183)	-		-		-	
ln(meanR) * FEVrange	*-0.850****	(0.321)	-		-		-	
maxR < 100miles	-		*1.559****	(0.289)	*0.814*	(0.609)	*0.893*	(0.594)
minR > 150 miles	-		*-0.789****	(0.300)	*-0.840***	(0.332)	*-0.831***	(0.333)
ln(rangeR)	-		*0.153*	(0.193)	*0.164*	(0.191)	*0.190*	(0.194)
Quadratic [a]	*0.141*	(0.232)	*0.138*	(0.233)	*0.649****	(0.193)	*0.134****	(0.047)
Logarithmic [a]	*-0.396****	(0.086)	*-0.407****	(0.124)	*0.467**	(0.259)	*-0.054*	(0.268)
Dummy-coded [a]	*-0.051*	(0.059)	*-0.136****	(0.045)	*-0.024*	(0.078)	*-0.119****	(0.035)
No fast-charging option for FEVs	*0.285***	(0.112)	*0.270****	(0.075)	*0.271****	(0.077)	*0.278****	(0.081)
Ratio of lognormals	*0.564*	(0.364)	*0.566*	(0.355)	*0.569*	(0.360)	*0.541*	(0.346)
USA	*0.678****	(0.205)	*0.624****	(0.185)	*0.365*	(0.246)	*0.342*	(0.246)
Constant	*-0.574****	(0.210)	*-1.022****	(0.168)	*2.988****	(0.201)	*4.565****	(0.205)
Observations	129		129		118		118	
R^2-overall	0.65		0.68		0.55		0.53	
R^2-within	0.16		0.16		0.31		0.15	
R^2-between	0.55		0.77		0.53		0.54	
$\hat{\sigma}_u$ or $\hat{\sigma}_v$	0.70		0.46		0.55		0.54	
ρ	0.84		0.70		0.78		0.78	
RMSE	0.29		0.30		0.29		0.29	

Note: Robust standard errors, clustered by SP dataset, in parentheses. ***,** and * indicate that the parameter is statistically significant at the 1%, 5% and 10% level respectively. Intraclass correlation, ρ, shows the proportion of the variance to be attributed to differences between studies, i.e. $\rho = \hat{\sigma}_u^2 / (\hat{\sigma}_u^2 + \hat{\sigma}_\varepsilon^2)\hat{\sigma}_v$.

[a] Reference category comprises utility functions linear in driving range.

For the majority of coefficients, WLS and random-effects GLS (RE-GLS) do not lead to substantially different outcomes. There are, however, some noteworthy differences, mainly concerning the models explaining the variation in WTP for an increase from 100 to 150 and 350 miles. First, the consideration of a maximum driving range level of 100 miles does not have a significant effect on the two WTP measures in the RE-GLS model. This also holds for the width of the attribute range considered for driving range. On the contrary, the consideration of a minimum driving range of more than 150 miles reduces WTP estimates substantially. WLS leads to exactly the opposite outcomes. It is also worth noting that the coefficient of the variable indicating whether WTP estimates stem from a model assuming that the marginal utilities of driving range and purchase price are log-normally distributed is statistically insignificant in all RE-GLS models.

2.6. Discussion and implications for future research

Driving range will of course be valued differently by different consumers. Even though the meta-analysis presented here adopts the perspective of the average consumer to provide insights into the WTP for driving range, it is reasonable to expect that the latter will vary with consumer's income, intensiveness of car use, and availability of other vehicles in the household. Other things being equal, consumers with lower incomes, shorter average travel distances, or more within-household vehicle substitution options are anticipated to have lower WTP for driving range than individuals with the opposite characteristics. In the context of the current meta-analysis, however, we cannot identify the impact of differences in such consumer characteristics on WTP. This is due to the lack of descriptive information about these characteristics in primary studies. Information about the average income or its distribution in the survey sample is unavailable in several studies, while very few of them provide adequate information about respondents' car use and their households' vehicle holdings.

The discussion above suggests that a meta-analysis can serve another purpose apart from synthesising the information provided in relevant literature and explaining the variation in the effect sizes of interest among studies. This purpose is to identify the limitations inherent in existing studies and formulate recommendations for future studies in the field. In this context, we would like to take this opportunity to make the following four suggestions for future studies eliciting consumers' stated preferences for driving range:

Thorough testing of the driving range levels used in the SP design: The levels of driving range used in the design of the SP study have a significant effect on the WTP for range derived by discrete choice analysis. It is, thus, important to thoroughly test the driving range levels considered for the design of the study in order to avoid arriving at extreme values of WTP for driving range.

Testing of utility functions implying a positive and diminishing marginal utility of driving range: Our results reveal that MWTP for driving range decreases with increases in driving range and that the marginal rate of substitution of driving range for money is diminishing. Therefore, practitioners in the field are invited to test alternative utility functional forms which can accommodate this behaviour of MWTP. For example, this could be achieved by using the logarithmic transformation of driving range or the inverse of range in the specification of consumer utility function. A dummy variable specification of driving range levels can assist in getting richer information about non-linearities in WTP for driving range and its testing is, therefore, also encouraged.

Testing of interaction effects between driving range, refuelling duration and coverage of refuelling infrastructure: Intuitively, the value of driving range should not be independent from the time required to refuel the car and the availability of refuelling facilities. For instance, it is anticipated that high refuelling duration and low availability of refuelling infrastructure would result in higher WTP for the same change in driving range than low duration or high availability. More research efforts are needed towards the identification of the interaction effects between driving range, refuelling duration, and coverage of refuelling infrastructure.

Investigation of consumer heterogeneity in WTP for driving range: WTP for driving range can be expected to vary with consumer's income, intensiveness of car use, and availability of other vehicles in the household. Hence, the collection of information about respondents' income and household composition, as well as of elaborate data on the type and use of each car owned by the household, should constitute an essential part of the SP data collection process. This should be followed by the presentation of descriptive statistics for the relevant variables in the study, which will facilitate its comparison with other SP studies in the field. The possible impact of variation in (i) consumer income, (ii) annual (and if possible daily) distance travelled by the car in context and other cars owned by the household, and (iii) the hierarchical position of the car in household's vehicle fleet (e.g. primary vs. secondary car), on the variation of the WTP for driving range should also be part of the discrete choice analysis performed by researchers.

2.7. Conclusions

Following an unsuccessful attempt of large-scale introduction in the 1990s, electric vehicles have recently reappeared in the production line of manufacturing plants and the agendas of policy makers as environmentally sustainable alternatives to petrol-fuelled vehicles. However, literature investigating consumer preferences for alternative fuel vehicles suggests that technological breakthroughs permitting a substantially longer driving range than the one currently achievable by electric cars is of pivotal importance for their successful market penetration.

We perform a meta-analysis of 33 discrete choice and contingent ranking studies investigating consumer preferences for AFVs, in order to provide insights into the trade-off between driving range and purchase costs. Based on 129 marginal willingness to pay

(MWTP) estimates, we find that consumers are willing to pay about 67 US$, on average, for a one-mile increase in range. In line with intuition, but in contrast to common practice, we find evidence that MWTP for additional range can be best described as a decreasing function of vehicle range. It furthermore decreases at a diminishing rate. The analysis of 118 estimates of consumers' WTP for substantial increases of driving range derived from the same studies, reveals that a 100-mile driving range, as is currently common for FEVs, is heavily penalised by vehicle purchasers. We further show that the wide divergence in WTP estimates among primary studies can be mainly attributed to differences in the driving range levels considered, in other aspects of the study design, and in the country of study.

Ceteris paribus, our review suggests a very limited potential market for vehicles with a driving range at the level of most currently commercialised electric vehicles, unless they are offered at prices, on average, around 17,000 US$ lower than their long-range counterparts. It should be noted that this figure does not provide insights into consumers' WTP for FEVs per se, as this would require taking into account further differences between FEVs and conventional cars in our analysis. Nevertheless, under the condition that the large scale introduction of FEVs is a policy objective, our findings support the continuation of R&D efforts directed towards the reduction of EV battery costs and the development of advanced battery technologies permitting higher driving ranges. At the early stage of FEV adoption, developments in the supply side could be substantially assisted by policies aiming to increase drivers' awareness of their range needs and inducing them to use the range resources in their possession more efficiently (see also Franke and Krems (2013).

We further recommend that future studies in the field: (i) employ a rather wide scope of driving range levels in the SP study design, (ii) experiment with utility functional forms entailing a positive and diminishing marginal utility of driving range, (iii) explore the sensitivity of consumer valuation of driving range to changes in the time required to refuel the AFV and the coverage of refuelling facilities, and (iv) investigate whether the value of driving range is influenced by the body type, size and intended use of the vehicles entering respondents' choice sets. In light of the potential contribution of AFVs' to the reduction of environmental degradation and oil dependence, such insights will shed light on the mix of policy incentives required to accelerate their adoption by consumers.

Chapter 3

The influence of environmental concerns on driver preferences for electric cars

3.1. Introduction*

Plug-in electric vehicles (PEVs) have been enjoying the vigorous support of policy makers during the last decades, as their large-scale adoption is considered a promising means of confronting mounting concerns over environmental degradation, climate change, oil dependence and energy security.[24] This is reflected in recent attempts of the US and European governments to set ambitious goals for the penetration of PEVs in national car fleets. However, consumer adoption of PEVs, and especially full electric vehicles (FEVs), has long been hampered by relatively high acquisition costs, considerable uncertainty over developments in battery technologies, and drivers' reluctance to accept changes in their current refuelling behaviour.

Aiming to partially address these concerns, car manufacturers have recently developed intermediate solutions based on the parallel use of internal combustion engines (ICE) and electric propulsion systems, broadly labelled as plug-in hybrid electric vehicles (PHEVs).[25] At the same time, new refuelling concepts aiming to bring the PEV charging time down to the levels of the refuelling time of ICE-propelled cars, such as fast-charging and battery-swapping, have been developed and implemented worldwide. These developments have created the need for a fresh look at consumer preferences for PEVs, especially focussed on relevant vehicle attributes. Concurrently, it is important to understand which consumer characteristics are more likely to be associated with the profiles of candidate adopters of PEVs and target fiscal policies, communication strategies and marketing activities to drivers matching those profiles.

In this chapter, we study the influence of drivers' environmental concerns and sociodemographic background on their preferences for different types of PEVs and their attributes. To this end, we use a large-scale survey among Dutch drivers, where preferences for different vehicle technologies are elicited via a choice experiment and environmental concerns are reflected in drivers' responses to Likert-type questions. In

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* An earlier version of this chapter has been published in the Tinbergen Institute Discussion Paper Series (Dimitropoulos, 2014).

[24] As already noted in the Introduction of the thesis, the term plug-in electric vehicle (PEV) is used here to denote both *full electric vehicles* (FEVs), i.e. vehicles powered exclusively by electric motors, and plug-in hybrid and extended-range electric cars, i.e. vehicles propelled by both electric motors and internal combustion engines whose batteries can be recharged by plugging them into an electricity outlet. Vehicles with electric motors which cannot be plugged into an electricity outlet, such as hybrid electric vehicles (HEVs), are not considered as PEVs.

[25] Technological differences between plug-in hybrid EVs and extended-range EVs are not of primary interest in this thesis and we denote both with the encompassing term plug-in hybrids (PHEVs).

contrast to previous stated preference (SP) studies in the field, we distinguish between plug-in hybrids and two types of full electric cars, an FEV with a built-in battery and one whose battery can be swapped at specialised stations. Data are analysed with advanced panel latent class models (see also Kamakura and Russell, 1989; Greene and Hensher, 2003), where class membership is modelled as a stochastic function of drivers' socio-demographic characteristics and environmental concerns.

We consider two ways of treating concerns. First, we follow traditional practice in the use of Likert-type items in latent class membership models (e.g. Boxall and Adamowicz, 2002) and assume that the Likert scale accurately measures environmental concerns. As this approach has been criticised for resulting in biased estimates, we later relax this assumption and consider the possibility that individual responses to the relevant Likert-type questions are only approximate manifestations of consumers' underlying latent environmental concerns. Structural equation modelling techniques are then used to estimate concerns' impact on class membership.

This chapter aims to complement relevant stated preference literature by developing an intuitively appealing modelling framework to elicit driver preferences for state-of-the-art electric vehicle technologies and identify how the latter are influenced by drivers' environmental concerns and sociodemographic background. The study also provides insights into the sociodemographic factors affecting one's environmental concerns.

The remainder of the paper is organised as follows. Section 3.2 provides the background of our study. Section 3.3 describes the design and implementation of the survey, with emphasis on the choice experiment. Section 3.4 presents our modelling framework. Section 3.5 discusses the results of the empirical analysis. Section 3.6 concludes.

3.2. Background

In Chapter 2 we saw that stated preferences have played a central role in the study of consumer choice among alternative fuel vehicles (see e.g. Beggs et al., 1981; Brownstone and Train, 1999). At the same time, there is a growing literature investigating the influence of environmental concerns, attitudes and related psychological constructs on consumer choices. The discussion that follows focuses on studies examining the influence of these psychological constructs on vehicle choice. In stated preference literature, these constructs are usually assumed to be reflected in individual responses to rating questions, often used to form a Likert scale, or binary response ones. Somewhat confusingly, relevant constructs are not uniformly defined in this literature. A list of the psychological constructs used in relevant SP studies, following authors' terminology, is presented in Table 3.1. This overview further reveals that there is wide heterogeneity in the methods used by researchers to have these psychological constructs manifested. Researchers have thus far employed Likert scales, cluster analysis and direct use of rating scores for this purpose.

Two approaches have mainly been used to identify the impact of these constructs on consumer preferences for alternative vehicle types. The traditional approach deployed for this purpose is to include environmental concerns or attitudes as covariates in the random utility function of more environmentally sustainable alternatives (e.g. Ziegler, 2012) and/or let them interact with vehicle attributes related to the environmental performance of these vehicles (e.g. CO_2 emissions – see Achtnicht et al., 2012; Hackbarth and Madlener, 2013a). This way, the analyst can estimate, for instance, the influence of the construct on individuals' preferences for low emission vehicles or for relevant vehicle attributes. This approach is depicted in panel (a) of Figure 3.1. Following the establishment of latent class modelling in transportation and environmental economics (Boxall and Adamowicz, 2002; Greene and Hensher, 2003), researchers explored the possible contribution of such constructs in explaining individual membership in different latent classes. This approach allows the analyst to link one's environmental concerns or attitudes with one's probabilistic assignment to classes with certain preferences for more environmentally sustainable cars (e.g. Beck et al., 2013; Hidrue et al., 2011). Panel (b) of Figure 3.1 illustrates this approach.

Studies further differ in the modelling of the underlying psychological constructs as deterministic functions of the indicators used (e.g. scores to Likert scales) or as latent variables. In the former case, variables taking values equal to the (transformed) scores obtained by individuals (e.g. scores on a Likert scale or a Likert item) directly enter the random utility or the class membership model. In the latter case, the Likert items are assumed to be reflections of the underlying *latent* constructs. The influence of constructs on individual preferences is then estimated by the use of *hybrid choice models* (i.e. integrated choice - latent variable models, see also Ben-Akiva et al., 1999, 2002). The latter provide a framework whereby the explanatory potential of discrete choice models is enhanced by the use of latent variables. In this framework, latent variables are modelled as stochastic functions of individuals' observed characteristics (structural model), while their effect on observed indicators (e.g. Likert items) is explained through a set of measurement equations (measurement model).

Table 3.1: Overview of studies on the influence of environmental concerns and related constructs on vehicle choice.

Study	Psychological construct	Modelling	Treatment	Manifestation
Achtnicht et al. (2012)	Environmental Awareness	Random Utility Model	Measured	4-item Likert scale
Axsen et al. (2013)	Pro-environmental Lifestyle	Random Utility Model	Measured	Rating question
Beck et al. (2012)	Environmental Attitudes	Latent Class Membership Model	Measured	5 Likert items
Daziano & Bolduc (2013)	Environmental Concerns	Random Utility Model	Latent	14-item Likert scale
Ewing and Sarigöllü (1998, 2000)	Environmental Concerns	Random Utility Model	Measured	Likert scales & Cluster analysis
Hackbarth and Madlener (2013a)	Environmental Awareness	Random Utility Model	Measured	9-item Likert scale
Hackbarth and Madlener (2013b)	Environmental Awareness	Latent Class Membership Model	Measured	9-item Likert scale
Hidrue et al. (2011)	Environmentally Responsible Behaviour	Latent Class Membership Model	Measured	Rating question
Jensen et al. (2013)	Environmental Concerns	Random Utility Model	Latent	7-item Likert scale
Ziegler (2012)	Environmentally Responsible Behaviour	Random Utility Model	Measured	Rating question

The motivation behind the treatment of psychological constructs as latent variables is usually justified on attempts to enhance the insights provided by choice models and confront two econometric concerns, which, if valid, imply inconsistent parameter estimates. First, the scores to Likert items may well suffer from measurement error; second, they are likely to be endogenous, i.e. there might be unobserved factors influencing both vehicle choice and the choice of a specific level of agreement to a Likert-type question (see also Ashok et al., 2002; Daly et al., 2012).[26] In the context of identifying environmental concerns' influence on vehicle choice, applications of hybrid choice models can be found, for example, in Daziano and Bolduc (2013), who employ Bayesian

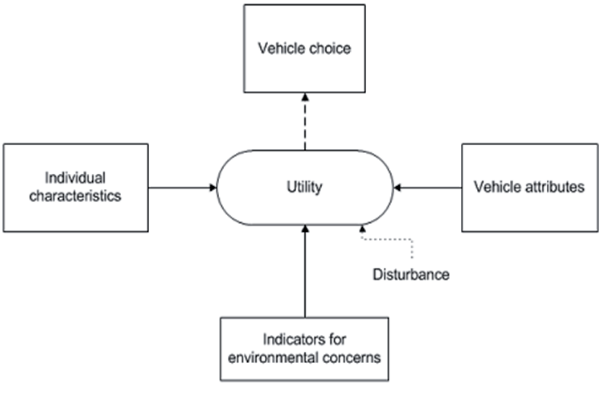
[26] In the current context, for instance, households with children are likely to have both higher environmental concerns (as they are concerned about the environmental conditions experienced by their children) and higher driving range needs (since they have to make more trips to satisfy the needs of their dependants).

estimation techniques, and Jensen et al. (2013). The approach developed in these studies is shown in panel (c) of Figure 3.1.

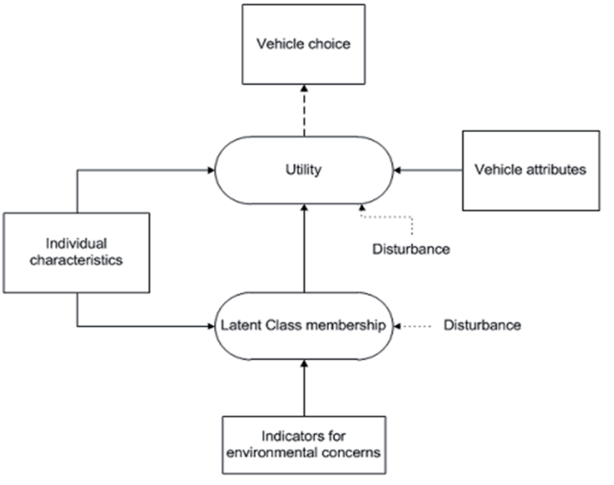
The studies cited in Table 3.1 generally find that environmental concerns and attitudes play an influential role in vehicle choice. Achtnicht et al. (2012) and Hackbarth and Madlener (2013a) show that higher environmental awareness is associated with a more positive view of alternative fuel vehicle technologies and a higher valuation of reductions in CO_2 emissions. Ewing and Sarigöllü (1998, 2000) illustrate along similar lines that environmentally concerned individuals are more likely to opt for more fuel efficient and electric vehicles, while Axsen et al. (2013) and Ziegler (2012) find that pro-environmental lifestyles and environmentally responsible behaviour are positively related to preferences for alternative fuel vehicles. In agreement to these studies, applications of integrated choice - latent variable models reveal that environmental concerns have a positive effect on drivers' likelihood to opt for PEVs (Jensen et al., 2013), or other types of alternative fuel vehicles (Daziano and Bolduc, 2013). The structural models used in these two studies indicate that one's level of environmental concerns and attitudes is positively correlated with one's age and education level. Daziano and Bolduc (2013) further suggest that females have higher environmental concerns than males.

Applications of latent class models show that individuals scoring higher in relevant Likert-type questions are more likely to belong to classes with stronger preferences for vehicles with low tailpipe emissions. Hackbarth and Madlener (2013b) and Hidrue et al. (2011) show that more environmentally aware consumers and individuals reporting to have recently made behavioural changes to help the environment are more likely to belong to classes with stronger preferences for PEVs and other alternative fuel vehicles and with higher willingness to pay for emission reductions. Beck et al. (2013) find that environmental attitudes and concerns play a critical role in the assignment of individuals to classes with different sensitivities to vehicle emission charges and preferences for diesel cars and hybrids.

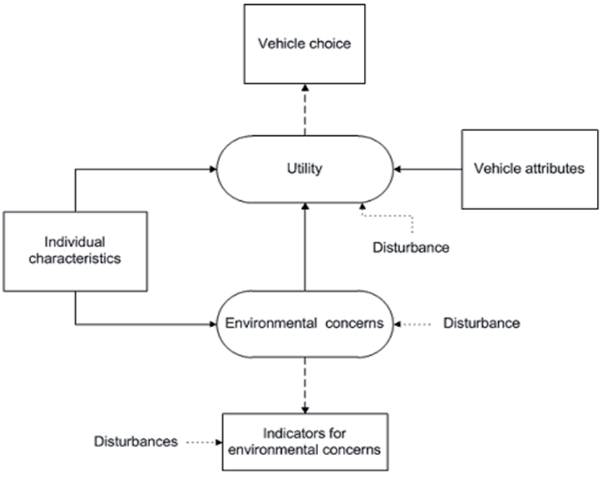
In what follows, the influence of environmental concerns on consumer vehicle choice is identified through *panel latent class models*. We focus on this family of models as they provide an informative framework for the study of consumer segments with different preferences for PEVs and their key attributes. Environmental concerns enter the class membership component, partially explaining individual's likelihood to belong to each class. We start by assuming that the scale used for environmental concerns provides accurate measurements of them (see panel (b) of Figure 3.1). We later relax this assumption and model concerns as a latent variable to take into account the possibility that the scale suffers from measurement error. To the best of our knowledge, the resulting *hybrid panel latent class model* has not been used before in the context of vehicle choice. A sketch of this approach is presented in panel (d) of Figure 3.1. In contrast to previous applications of hybrid panel latent class models (e.g. Hess et al., 2013; Mariel et al., 2015), individual characteristics are not restricted to have a direct effect *only* on the latent variable; instead, they also directly influence random utility and class membership. Before proceeding with the presentation of the methodology used in our study, we present the survey tool employed to collect the data.



(a)



(b)



(c)

(d)

Figure 3.1: Different approaches to identifying the influence of environmental concerns on vehicle choice.

Note: We use the general notation suggested by Walker and Ben-Akiva (2002). Rectangles denote observed elements, whereas ellipses latent ones. Solid arrows indicate structural relationships, dashed arrows measurement relationships, and dotted ones disturbances.

3.3. Data

We use data from a survey carried out between November 2012 and January 2013. Our survey was addressed by a sample drawn from TNS-NIPO's panel of motorists, a panel of Dutch vehicle owners with experience in filling in car-related questionnaires. The sample was stratified by the number of cars per household, their ownership status (private or company car) and their fuel type. TNS-NIPO was requested to draw a sample evenly distributed between single-car and multiple-car households, as well as between households having at least one company car and ones owning only private cars. Within these four categories, we asked for an adequate representation of households having at least one hybrid electric vehicle (HEV), as we were interested in examining possible differences in preferences between HEV drivers and drivers of cars propelled solely by an ICE.

3.3.1. Survey design

The survey was carried out with an online questionnaire developed in Sawtooth SSIWeb. The questionnaire comprised seven sections. The first section collected information about households' vehicle holdings and respondents' use of the car they drive mostly in. Respondents who were driving less often than once a week in household's cars and had a minor role in their household's vehicle choice making were asked whether they intended to purchase a car in the next 5 years. If they did not have that intention, they were automatically disqualified from the survey. Respondents were also asked a few questions about the car preceding the vehicle they currently drive mostly in. At the end of the first section, they were requested to state whether their next car choice would be made in the context of purchasing or leasing a vehicle. This chapter draws only on the responses of individuals reporting that they would *purchase a vehicle*.[27] The second section gathered details about the car that the respondent would buy next, such as whether it would be a new or second-hand car, its body and fuel type, its purchase price and the annual distance expected to be travelled in it.

Respondents were then introduced to the choice experiment. The context provided was that of their next car purchase, either being a replacement of the current vehicle or the adoption of an extra car. Following an elaborate presentation of the alternative types of propulsion systems and the vehicle attributes used in the study, respondents were given the opportunity to familiarise themselves with the choice experiment by means of an example

[27] Preferences of individuals stating that they would *lease a vehicle* are analysed in the next chapter.

choice scenario. Thereafter, they were invited to address 8 hypothetical choice scenarios. The design of the choice experiment is described in the next subsection. After answering the choice questions, respondents were asked to report how they made their choices, i.e. whether they considered all attributes or just a subset of them, or whether they were choosing at random.

The questionnaire also collected details about respondent's perceptions towards PEVs and about their hypothetical refuelling behaviour in case they adopted one of these technologies. It further examined respondent's experience with boarding and driving PEVs and HEVs, and invited them to express their level of environmental concerns and interest in innovative products through a number of Likert-type questions. Last, respondents were asked to report their gross household income and provide comments on the questionnaire layout and length. The time that respondents spent to handle different parts of the questionnaire was closely monitored, in order to provide us with a measure of how seriously they performed each task. Demographic characteristics of respondents were provided by TNS-NIPO.

The questionnaire launch was preceded by focus group discussions, a small-scale pretesting of the questionnaire with colleagues and a pretesting of the survey with 206 respondents. Following some minor adjustments to the questionnaire, 3900 invitations were sent to TNS-NIPO panel members. The number of complete responses collected was 2921, implying a response rate of 75%.[28] Slightly more than 15% of complete responses were excluded from the rest of our analysis, due to respondents' extremely fast handling of choice scenarios. All questionnaires with a median duration of response to the choice scenarios of less than 10 seconds were not further processed, as it would be hard to argue that these respondents actually made trade-offs between vehicle attributes. Of the remaining 2473 valid responses, 1514 concern the *purchase of a private car* (as opposed to a car lease). Thirteen individuals provided unreliable responses and were not further considered. Therefore, the responses of 1501 individuals are used in the rest of the analysis. An overview of respondents' background characteristics is provided in Appendix 3.A.

[28] The response rate is similar to other studies with the TNS-NIPO's panel of motorists (e.g. Hoen and Koetse, 2014). About 3.5% of respondents (134 individuals) were disqualified from the survey, as they reported that they made random choices in the choice scenarios.

3.3.2. Choice experiment

Before being introduced to the experiment, respondents were instructed to think about their next car purchase and treat all scenarios presented to them as real choice tasks. In each scenario, respondents were invited to choose their preferred option, assuming that the car model they were intending to purchase next was available in 4 versions: a plug-in hybrid (PHEV), an electric with fixed battery (FBEV), an electric with swappable battery (SBEV) and a version driving on respondents' preferred propulsion system and fuel (e.g. petrol, diesel, LPG, HEV, biofuels). When respondents reported that they would opt for a full electric car or a plug-in hybrid in their next car purchase, the fourth alternative was automatically set to a petrol-fuelled car. Respondents were instructed to assume that the four options were different only in the 9 attributes presented to them. Table 3.2 presents an overview of the attributes and attribute levels employed in the choice experiment. Details about the description of full electric vehicle and plug-in hybrid technologies provided to the respondents are offered in Appendix 3.B. We only mention here that PEVs were described as more environmentally sustainable alternatives than ICE-propelled cars, i.e. as vehicles with substantially lower emissions of CO_2 and air pollutants.

Apart from the propulsion system, the options differed with respect to 8 attributes, i.e. purchase price, fuel costs, residual value after 5 years, driving range, refuelling time at the station, charging time at home and work, extra detour time to reach the nearest refuelling station, and duration of exemption from the payment of the annual road tax. The *purchase price* of the ICE car was customised on respondent's selected price range.[29] The purchase price of the three other options varied around the price of the ICE car in accordance with the coefficients shown in Table 3.2. The price of PEVs included the costs of a charging cable and a standard home-charging unit. As the table shows, we also considered cases where PEVs were priced lower than ICE-propelled cars, in order to have the flexibility to examine a wider range of attribute trade-offs.

[29] Prior to addressing the choice scenarios, respondents were asked to select the anticipated price range of their next car from a list of possible ranges. The price ranges presented to respondents whose next purchase would be a second-hand car were narrower and lower than the ones of respondents opting for new cars. For each choice scenario, a random number was drawn from a uniform distribution defined in the interval between $1/100^{th}$ of the minimum value of that price range and 80% of $1/100^{th}$ of the maximum one. The resulting integer was then multiplied by 100 to present the respondent with a price rounded to hundreds of Euros. For example, if the respondent reported that their next car would fall in the price range €15,000-20,000, a random number was drawn in the interval [150,190]. The integer was then multiplied by 100 to provide a price between €15,000 and €19,000.

Table 3.2: Attributes and attribute levels used in the choice experiment.

Attributes	Attribute levels			
Propulsion system and fuel type	ICE or Hybrid	Plug-in hybrid	Fixed-battery electric car	Swappable-battery electric car
Purchase Price (€)	Customised on respondent's reported price range for next car purchase	0.8 * ICE 1.4 * ICE 2.0 * ICE	0.8 * ICE 1.4 * ICE 2.0 * ICE	0.8 * ICE 1.1 * ICE 1.4 * ICE
Fuel costs (€/100km)	Base value - 2.5 Base value Base value + 2.5	3.5 5.5 7.5	3 4.5 6	9 11 13
Residual value after 5 years (% of purchase price)	40 50 60	30 45 60	30 45 60	30 45 60
Driving range (kilometres)	600 750 900	500 700 900	100 300 500	100 300 500
Refuel time at station (minutes)	5	5	15 30 45	5
Charging time at home or work (hours)	N.A.	1.5 3 5	4 8 10	4 8 10
Extra detour time (minutes)	N.A.	N.A.	0 10 20	0 15 30
Annual road tax (years)	No exemption	No exemption Exemption for 2 years Exemption for 4 years	No exemption Exemption for 2 years Exemption for 4 years	No exemption Exemption for 2 years Exemption for 4 years

Note: ICE encompasses vehicles propelled solely by an internal combustion engine.

In regard to *fuel costs*, respondents were presented with three figures for each alternative; one indicating fuel costs per 100km, and two annual fuel cost figures based on the yearly distance expected to be travelled in their next car. The figures were calculated for the minimum and maximum of the expected distance range selected by respondents in a question preceding the experiment. The computation of the base value of the fuel costs/100km of the ICE car depended on the average fuel efficiency of the fuel type and propulsion system selected by the respondent and on retail fuel prices at the time of the survey.[30] Fuel costs of PEVs varied according to the values presented in Table 3.2. The fuel costs of the swappable-battery electric car were higher than the ones of the fixed-battery one and the plug-in hybrid as the former also included the rental price of the battery pack and the costs of using the battery-swapping stations.

In the Netherlands, cars remain on average under the ownership of the same individual for about five years. We thus assumed that the individual would have the

[30] We assumed that oil-derived fuel and biofuel prices would be more volatile than electricity prices and thus larger deviations were considered for the fuel costs of ICE-propelled cars than for the ones of PEVs. The smallest deviations were considered for fixed-battery electric cars, as fuel costs are least affected by changes in oil prices or the terms of battery-rental contracts. With the exception of petrol-fuelled ICE cars, where we considered different base values for compact and large cars, we employed a single base value per fuel type.

opportunity to sell their car at a satisfactory price at that time, reflected in the *residual value* of the car *after 5 years*. Since there is much uncertainty about the trajectories that the technology and prices of battery packs and other electric vehicle components will follow in the next years, we considered a wider range of depreciation rates for plug-in hybrids and full electric cars than for ICE-propelled cars.

Driving range varied for all alternatives. For plug-in hybrid technologies, we considered values spanning from the current situation of extended-range electric cars to the current situation of plug-in hybrids. For full electric cars, we employed driving range levels from as low as 100 km, slightly lower than the level advertised for most commercially available models, to 500 km, somewhat higher than the one estimated for the 85-kWh battery-pack of Tesla Model S.[31] *Refuel time at the station* denoted the time required to refuel the tank of the ICE car or the plug-in hybrid, to fast-charge the battery of the fixed-battery electric car, or to swap the batteries of the swappable-battery electric car at specialised stations. It varied only for the fixed-battery electric car, from 15 to 45 minutes for a full charge.

Standard *charging time at home or work* was substantially shorter for plug-in hybrids than full electric cars, due to their usually smaller battery-packs. It varied from 1½ to 5 hours for plug-in hybrids and from 4 to 10 hours for full electric cars. *Extra detour time* to reach the nearest fast-charging or battery-swapping station was essentially a measure of the availability of refuelling infrastructure, as it informed respondents about the extra time they would have to spend in searching for a quick alternative to standard home-charging if they adopted a full electric car (cf. Hoen and Koetse, 2014; Train, 2008).[32] As the investment required for the building of a battery-swapping station was at the time of the survey about 20 times higher than the one required for the installation of an AC fast-charging unit, we considered slightly higher levels of this attribute for swappable-battery than for fixed-battery electric cars.

The annual road tax constitutes a substantial share of the operating costs of a private car in the Netherlands. Its value primarily depends on the fuel type and weight of the car. It ranges from around €160/year for a very light, petrol-fuelled, car to more than

[31] See: http://www.teslamotors.com/models/options.

[32] An alternative approach employed in most previous studies (e.g. Achtnicht et al., 2012; Brownstone and Train, 1999) is to use an attribute presenting the availability of refuelling infrastructure as a percentage of the current availability of petrol stations. However, this approach does not inform respondents about the proximity of these refuelling stations to the routes they usually follow.

€2000/year for a diesel-fuelled car weighing more than 2 tonnes.[33] *Road tax exemptions* were provided at the time of the survey for cars with relatively low CO_2 emissions, including all PEVs.[34] The tax values presented to the respondents were customised on the size of the car they were most likely to purchase next and their preferred fuel type. No tax exemptions were considered for ICE cars. For PEVs we considered three cases: no tax exemption, and tax exemptions for 2 and 4 years.

Choice Question 1

The four options presented below are different versions of the same model. They differ only in the presented attributes.

	Option 1	Option 2	Option 3	Option 4
Fuel type	Plug-in hybrid	Petrol	Electric with fixed battery	Electric with swappable battery
Purchase price	€ 46,400	€ 23,200	€ 18,600	€ 25,500
Fuel costs	€ 3.50 per 100 km	€ 16.50 per 100 km	€ 6.00 per 100 km	€ 11.00 per 100 km
Annual fuel costs for travelling 10,000 km	*(€ 350 per year)*	*(€ 1,650 per year)*	*(€ 600 per year)*	*(€ 1,100 per year)*
Annual fuel costs for travelling 15,000 km	*(€ 525 per year)*	*(€ 2,475 per year)*	*(€ 900 per year)*	*(€ 1,650 per year)*
Residual value after 5 years	€ 20,900	€ 9,300	€ 11,100	€ 7,700
Driving range	900 kilometers	750 kilometers	300 kilometers	100 kilometers
Refuel time at the station	5 minutes	5 minutes	30 minutes	5 minutes
Refuel time at home or work	3 hours	Not applicable	10 hours	4 hours
Extra detour time	No extra time	No extra time	20 minutes	No extra time
Annual road tax	No exemption from road tax, €650 per year from the first year	No exemption from road tax, €650 per year from the first year	Exemption from road tax for 4 years, thereafter € 650 per year	Exemption from road tax for 2 years, thereafter € 650 per year

Please indicate below which option you would choose:

	Option 1	Option 2	Option 3	Option 4
Your choice →	○	○	○	○

Figure 3.2: Example of a vehicle choice scenario.

Note: In the example above, the respondent stated that his next purchase would be a new, medium-sized, petrol-fuelled car, costing €20,000-25,000. She would drive 10,000-15,000 km per year in it.

Regarding the design of the study, we used SSIWeb's *Complete Enumeration* method to generate a close to orthogonal design with 300 choice experiment versions (Sawtooth Software, 2008). To accommodate the attribute differences among the four propulsion systems presented to respondents, we used an alternative-specific design. The sequence of the four alternatives was randomised, whereas the attribute sequence was fixed to reduce the complexity of the task. Perl and HTML scripting was extensively used to accommodate the alternative-specific nature of the attribute levels and to customise

[33] The road tax for diesel and LPG cars is about twice as high as the one for petrol-fuelled ones, while the tax for CNG cars is about 50% higher than the one for the latter.

[34] From 2016 onwards, road tax exemptions are only provided for cars causing no tailpipe CO_2 emissions, i.e. full electric cars and hydrogen fuel cell vehicles (see e.g. http://www.anwb.nl/auto/autobelastingen/mrb).

monetary attribute values (purchase price, fuel costs, residual value and road tax) on respondents' statements for their next transaction. Figure 3.2 presents an example of a choice scenario.[35]

3.4. Methodology

We investigate consumer preference heterogeneity in the framework of panel latent class models (PLCMs). We believe that this class of models provides a more appropriate framework for our study than logit models based on continuous mixing distributions for two reasons. First, PLCMs do not require that specific distributional assumptions are imposed on taste parameters. Second, they provide a more structured and intuitively appealing framework to work with when the identification of potential adopters of new technologies and other groups of interest is of primary importance for the study, as it is here.

In this framework, we use PLCMs where class-membership is modelled as a stochastic function of driver's socio-demographic background, car use patterns and environmental concerns. Our baseline is a PLCM where environmental concerns are assumed to be accurately measured by the relevant Likert scale (see also panel (b) of Figure 3.1). The outcome of this model is then contrasted to the outcome of a hybrid panel latent class model (HPLCM), whereby we treat individuals' environmental concerns as unobserved (panel (d) of Figure 3.1). The HPLCM is developed in the spirit of Hess et al. (2013) and Hoyos et al. (2015), who apply analogous models in the context of rail travel and land-use policy valuation.

3.4.1. General formulation of the model

We now proceed with the general mathematical formulation of the models. The PLCM is presented first, followed by the HPLCM. We assume that, conditional on membership in class g, individual n behaves according to a random utility model when choosing alternative i in choice scenario s.[36] Utility is modelled in preference space and is of the form:

[35] About 24% of respondents reported that they considered all attributes when making a hypothetical vehicle choice, 55% stated that they considered a number of attributes, while 21% of respondents based their choices on a single attribute.

[36] The exposition of the model could also be made at the household, instead of the individual, level. For multivehicle households, choices are conditional on the availability and characteristics of the other vehicle(s). We opt for an exposition at the individual level as hypothetical choices were made for the vehicle that the respondent would mostly drive in, and as data on environmental concerns are collected at that level.

$$U^{g}_{nis} = \alpha^{g}_{i} + \boldsymbol{\beta}'^{g}\mathbf{X}_{nis} + \varepsilon^{g}_{nis}\,, \tag{3.1}$$

where U denotes random utility, $\mathbf{X}$ is a vector of variables related to individual n and alternative i at choice situation s, α_i is the alternative specific constant of i, $\boldsymbol{\beta}$ represents a class-specific vector of parameters, and ε is an idiosyncratic, unobserved by the researcher, component of utility, assumed to be i.i.d. Gumbel across individuals. Alternative specific constants α_i and vectors of parameters $\boldsymbol{\beta}$ are to be estimated. Conditional on her membership in class g, the logit probability that individual n chooses alternative i among J alternatives in scenario s, can then be expressed as:

$$P^{g}_{nis} = \frac{e^{\left(\alpha^{g}_{i} + \boldsymbol{\beta}'^{g}\mathbf{X}_{nis}\right)}}{\sum_{j=1}^{J} e^{\left(\alpha^{g}_{j} + \boldsymbol{\beta}'^{g}\mathbf{X}_{njs}\right)}}\,, \tag{3.2}$$

while the probability that she makes the sequence of choices that she is observed to make can be calculated as (Greene and Hensher, 2003):

$$P^{g}_{n} = \prod_{s=1}^{S} P^{g}_{nis}\,, \tag{3.3}$$

where S is the total number of choice scenarios addressed by the individual.

Individuals are probabilistically assigned to different classes according to a class membership model (CMM). Assuming that the random component of the membership likelihood function is also i.i.d. Gumbel, the logit probability that individual n is a member of class g among G classes is (Boxall and Adamowicz, 2002):

$$p^{*g}_{n} = \frac{e^{\delta^{*g} + \boldsymbol{\zeta}'^{*g}\mathbf{Z}_{n} + \theta^{*g}Q^{*}_{n}}}{\sum_{g=1}^{G} e^{\delta^{*g} + \boldsymbol{\zeta}'^{*g}\mathbf{Z}_{n} + \theta^{*g}Q^{*}_{n}}}\,, \tag{3.4}$$

where parameters and vectors of parameters of the *Gth* class (δ^{*G}, $\boldsymbol{\zeta}^{*G}$, and θ^{*G}) are normalised to zero to ensure identification (Greene and Hensher, 2003). In Equation (3.4), $\mathbf{Z}_n$ is a vector of observed socio-demographic characteristics and car use patterns of individual n, Q^{*}_{n} denotes environmental concerns, assumed to be accurately measured by the psychometric scale used, while class-specific constants δ^{*}, parameters θ^{*} and vectors of parameters $\boldsymbol{\zeta}^{*}$ are to be estimated. The unconditional probability that the individual makes the choices she is observed to have made is given by Equation (3.5):

$$L_{n_{PLCM}} = \sum_{g=1}^{G} p_n^{*g} P_n^{g} \, . \tag{3.5}$$

The assumption that the psychometric scale provides an accurate measurement of the psychological construct of interest might, however, be invalid. If the scale used for the construct suffers from measurement error, the parameter estimates of the PLCM will be biased. This econometric concern, as well as concerns about the validity of the assumption that the construct is exogenous, have led a number of researchers to consider psychological constructs in the framework of structural equation modelling. In this framework, the constructs of interest are modelled as latent variables (Walker, 2001). Latent variable Q is expressed as a stochastic linear function of individuals' observed characteristics according to the following structural equation:

$$Q_n = \boldsymbol{\gamma}' \mathrm{R}_n + \omega_n \, , \tag{3.6}$$

where $\mathbf{R}_n$ is a vector of observed socio-demographic characteristics of individual n – whose elements can be partially or fully shared with $\mathbf{Z}_n$ – and ω_n is a random component distributed normally with mean zero and standard deviation σ, which has to be estimated along with the vector of parameters $\boldsymbol{\gamma}$. The estimation of the model requires additional information about the latent construct, which is elicited from individuals' responses to attitudinal or perceptual (in this case Likert-type) questions.

In line with recent work by Daly et al. (2012) and Hess et al. (2013), we acknowledge the ordered structure of Likert-type data and employ ordered logit specifications in the measurement model used to analyse the responses to the indicators of interest. The probability that individual n provides response m to indicator I_t of the latent variable will then be:

$$\pi_{ntm} \equiv \mathrm{Prob}_n\left(I_t = m\right) = \frac{e^{\tau_{tm} - \lambda_t Q_n}}{1 + e^{\tau_{tm} - \lambda_t Q_n}} - \frac{e^{\tau_{t(m\text{-}1)} - \lambda_t Q_n}}{1 + e^{\tau_{t(m\text{-}1)} - \lambda_t Q_n}} \, , \tag{3.7}$$

where λ_t denotes the effect of Q on indicator I_t, and τ_{tm}, with m=0,…,M, are cut-off values to be estimated. For normalisation, τ_{t0} is set to -∞, τ_{tM} to +∞, and λ_1 to 1.

The logit probability that individual n is a member of class g among G classes will now be:

$$p_n^g = \frac{e^{\delta^g + \boldsymbol{\zeta}'^g \mathbf{Z}_n + \theta^g Q_n}}{\sum_{g=1}^{G} e^{\delta^g + \boldsymbol{\zeta}'^g \mathbf{Z}_n + \theta^g Q_n}}. \tag{3.8}$$

Assuming independence between the sequence of choices made in the experiment and the chosen levels of agreement to the attitudinal questions, the likelihood that individual n makes the sequence of choices she is observed to have made and that she provides the response to the indicators that she actually provided over classes will then be given by Equation (3.9):

$$L_{n_{HPLCM}} = \int_{\omega_n} \sum_{g=1}^{G} p_n^g P_n^g \prod_{t=1}^{T} \pi_{ntm} \phi(\omega_n)\, \mathrm{d}\omega_n, \tag{3.9}$$

where $\phi(\omega_n)$ is the density of ω_n and T is the total number of relevant Likert-type questions addressed by the individual. The log-likelihood for the sample will be:

$$LL_{(\bullet)} = \sum_{n=1}^{N} \ln(L_{n_{(\bullet)}}), \tag{3.10}$$

where $(\bullet)$ denotes PLCM or HPLCM and N the total number of individuals considered in the analysis.

The parameters of interest are estimated by maximising this log-likelihood function. All models were coded and estimated in PythonBiogeme 2.3 (Bierlaire, 2003, 2009). Regarding the desirable number of latent classes, it is determined by estimating models with different numbers of classes and comparing them on the basis of the meaningfulness of the yielded estimates and their performance with respect to the Schwarz Information Criterion (SIC, see also Gupta and Chintagunta, 1994).[37] It is worth noting here that this criterion is only of use for comparisons of models with the same treatment of the psychological construct. It is meaningless to compare the fit of a PLCM model with the fit of its HPLCM counterpart, as the latter not only explains the sequence of vehicle choices made by individuals, but also their responses to the indicators of environmental concerns.

3.4.2. PLCM specification

We now turn to the formulation of the PLCMs. The only difference between the PLCM and the HPLCM developed in this study concerns the treatment of *environmental*

[37] SIC = -2ln(LL_c) + $r$ln(N), where LL_c is the value of the log-likelihood function at convergence, and r is the number of parameters used in the model. For comparison purposes, we also report values of the Akaike Information Criterion: AIC = – 2(r-LL_c) (see Akaike, 1974).

concerns. The formulation of the random utility and class membership models is otherwise identical.

Random Utility Model

In the LCM specifications employed in this study, the formulation of random utility function does not vary among classes. All vehicle attributes used in the experiment enter the deterministic component of utility function linearly, with the exception of driving range, where the logarithmic transformation is employed instead. This conforms to the suggestions made in Chapter 2 and the empirical finding that the logarithmic specification performed significantly better than the linear one.

We also take into account possible income effects by considering interaction effects between price and the income category of the respondent. After experimenting with a number of different income categories, we distinguish only between drivers with low or average income, ones with higher income, and ones who preferred to keep their income category unrevealed. Descriptive statistics for annual gross household income are provided in Table 3.3 and Appendix 3.A.

Table 3.3: Description and descriptive statistics of the variables used in the models.

Variable	Description	Model component	Mean	Std. dev.
High income	Household's gross annual income ≥ € 77,500	RUM, LVSM	0.19	n.a.
Unreported income	Respondent did not report household's income category	RUM	0.07	n.a.
Female	Female respondent	CMM, LVSM	0.37	n.a.
Age	Respondent's age in years	CMM, LVSM	52.58	13.74
High education	Respondent has at least college / university education	CMM, LVSM	0.39	n.a.
Low driving needs	Annual distance expected to be travelled with next car < 15,000 km	CMM	0.57	n.a.
Often abroad	Respondent travels more than twice a year abroad by the car in context	CMM	0.24	n.a.
First car replacement	Next car will replace household's first car	CMM	0.83	n.a.
Long-term decision	Household's next car purchase will occur in more than 3 years	CMM	0.43	n.a.

Note: Sample size is 1501. All variables are binary, with the exception of age. RUM: Random Utility Model; CMM: Class Membership Model; LVSM: Latent Variable Structural Model.

Class Membership Model

Class membership is modelled as a function of individual's sociodemographic background, car ownership and use characteristics, and environmental concerns. Definitions and descriptive statistics of the variables employed in the class membership model are presented in Table 3.3. The selection of the variables used in the model and their functional form followed extensive search of possible specifications.[38]

3.4.3. Latent environmental concerns

We focus on a single latent variable: *environmental concerns*. *Environmental concerns* are specified as a stochastic function of individual's gender, age, education and income. Age is modelled as a continuous variable, whereas dummy variables are used to capture the influence of education and income. We distinguish highly educated individuals (i.e. individuals with at least college or university education) and high income households (i.e. households with annual gross income of at least €77,500). As the variables used in the structural model are also employed in the class membership or random utility model, descriptive statistics for them have been provided in Table 3.3. The table also provides information about the model components where the variables are used.

Table 3.4: Indicators used in the measurement model of latent environmental concerns.

Car use can have various effects. In your opinion, how serious are the following possible impacts of car use?			
		Mean	Std. dev.
$Ienv_1$	Noise caused by vehicle traffic.	3.54	1.15
$Ienv_2$	Local air pollution caused by vehicle traffic.	4.38	1.13
$Ienv_3$	Climate change caused by vehicle traffic.	4.14	1.26
$Ienv_4$	Environmental degradation caused by the extraction of oil and gas.	4.35	1.22

Note: Sample size is 1501.

Regarding the measurement model formulated for the latent variable, we deploy information from individuals' responses to 4 items assessing how serious different possible environmental impacts of car use are perceived. The text used for these items and their descriptive statistics are presented in Table 3.4. All items are measured on a scale from 1 to 6, where 1 indicates the lowest level of concern and 6 the highest. Internal consistency checks for the set of indicators presented in Table 3.4 suggest that they can reliably

[38] Among other variables, we tested the performance of various consumer characteristics, such as whether the consumer owns or rents the house she lives in, whether she commutes to work by the car in context, whether that car is the primary (or only) car of the household, as well as various characteristics of the municipality where the individual's dwelling is located, such as population, address density, and pollution levels (as measured by SO_x, NO_x and PM emissions). None of these variables, however, influence the results presented here.

manifest the underlying psychological construct. The four items used for the measurement of environmental concerns have a *Cronbach's α* of 0.859.

3.5. Empirical results

3.5.1. PLCM estimates

Table 3.5 presents the parameter estimates for the panel latent class model (PLCM). We tested PLCMs with 2-7 latent classes. Information about the statistical performance of the models is provided in Table 3.6. A comparison of the statistical fit of the models on the basis of SIC revealed that the 6-class model had the best statistical performance. However, our preferred specification is the model with 5 latent classes, as models with 6 or more classes resulted in inflated standard errors in small segments.[39]

As already noted, we examine variation in consumer sensitivity to purchase price changes according to their gross household income. Although we estimate a price parameter per class, the coefficients of interactions between price and income category are constrained to be the same across classes. This specification provides clearer insights than a more flexible specification where income effects are allowed to vary across them (in the latter, interaction effects were statistically insignificant in all classes). Individuals not reporting their household income are found to have a lower sensitivity to changes in vehicle price, which makes us suspect that they belong to higher income households (cf. e.g. van Ommeren et al., 2012).

The labels assigned to the classes are inspired by the estimates of the random utility parameters and the importance of consumer characteristics entering the class membership model. *Status quo captives* comprise the largest class, containing about 27% of the sample. While being open to new technologies, this class is very reluctant to relinquish the convenience of long driving range and short refuelling time offered by ICE-propelled cars. *Status quo captives* constitute the only class valuing fast-charging time (i.e. refuel time at station) and charging time at home or work. They are particularly sensitive to changes in fast-charging time, valuing a 1-minute reduction in the duration of each fast-charging action more than a 27-minute reduction in the duration of each home-charging one. Young and highly educated drivers and males are more likely to belong to this class. Their

[39] The smallest segment identified in the 6-class model encompassed about 10.6% of the sample. However, standard errors were peculiarly high for this class and only the estimates of price, fuel costs, resale value and driving range were statistically significant.

behaviour is grounded in their intensive car use, both within the national borders and abroad.

Table 3.5: PLCM estimation results.

	Status quo captives		Combustion engine diehards		Price conscious buyers		Full electric optimists		Plug-in hybrid enthusiasts	
Random Utility Model	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error
Plug-in hybrid [PHEV]	-0.193	(0.149)	-4.261***	(0.460)	0.248	(0.257)	0.864**	(0.380)	1.370***	(0.328)
Fixed-battery electric car [FBEV]	-1.154***	(0.389)	-5.961***	(1.160)	0.513	(0.364)	1.186**	(0.465)	-0.916	(0.649)
Swappable-battery electric car [SBEV]	-0.920***	(0.253)	-4.937***	(0.871)	0.083	(0.271)	0.860**	(0.409)	-0.071	(0.494)
Purchase price (1000 €)	-0.133***	(0.014)	-0.094***	(0.021)	-0.323***	(0.042)	-0.077***	(0.011)	-0.064***	(0.012)
Purchase price (1000 €) * Income > € 77,500 [a]	0.021**	(0.010)	0.021**	(0.010)	0.021**	(0.010)	0.021**	(0.010)	0.021**	(0.010)
Purchase price (1000 €) * Income unreported [a]	0.026**	(0.011)	0.026**	(0.011)	0.026**	(0.011)	0.026**	(0.011)	0.026**	(0.011)
Fuel costs (€/100km)	-0.150***	(0.014)	-0.089**	(0.040)	-0.097***	(0.030)	-0.190***	(0.042)	-0.246***	(0.043)
Annual road tax (*savings* in 1000 €)	0.070**	(0.029)	0.011	(0.078)	0.115*	(0.060)	0.173***	(0.037)	0.101**	(0.042)
Residual value of the car after 5 years (%)	0.028***	(0.003)	0.002	(0.008)	0.007	(0.005)	0.014***	(0.003)	0.021***	(0.007)
ln(Driving range) (km)	1.119***	(0.133)	0.355	(0.328)	0.845***	(0.124)	0.473***	(0.069)	0.638***	(0.175)
Extra detour time (10 min/refuelling action)	-0.402***	(0.103)	-0.010	(0.233)	-0.068	(0.071)	-0.070	(0.050)	-0.355***	(0.120)
Refuel time at station (10 min/refuelling action)	-0.280**	(0.109)	0.270	(0.176)	-0.099	(0.082)	-0.048	(0.053)	-0.093	(0.127)
Charging time at home/work (100 min/charging action)	-0.102**	(0.041)	0.067	(0.101)	-0.044	(0.036)	-0.020	(0.026)	-0.070	(0.069)
Class Membership Model			estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error
Environmental concerns	*Reference Class*		-0.190**	(0.090)	0.317**	(0.129)	0.388***	(0.113)	0.228*	(0.128)
Female			0.405**	(0.207)	0.679**	(0.266)	0.628**	(0.246)	0.141	(0.250)
Age			0.065***	(0.008)	0.008	(0.010)	0.012	(0.009)	0.016	(0.011)
High education			-0.561***	(0.183)	-0.306	(0.252)	-0.548**	(0.212)	-0.284	(0.219)
Low driving needs			0.479**	(0.192)	1.156***	(0.295)	0.052	(0.241)	0.297	(0.257)
Often abroad			-0.308	(0.205)	-0.789**	(0.315)	-0.450*	(0.236)	-0.240	(0.293)
First car replacement			-0.127	(0.287)	-0.887**	(0.328)	-0.442	(0.295)	-0.396	(0.338)
Long-term decision			-0.192	(0.178)	0.289	(0.247)	0.401*	(0.222)	0.032	(0.226)
Constant			-2.690***	(0.554)	-2.357***	(0.819)	-2.444***	(0.653)	-2.002***	(0.703)
Class size	*0.269*		*0.266*		*0.155*		*0.161*		*0.148*	
Parameters	93									
Observations (Individuals)	12008 (1501)									
Log-likelihood at convergence	-9281.0									

Note: Standard errors are heteroskedasticity-robust. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

[a] Parameter estimates are constrained to be equal among classes.

Table 3.6: Statistical performance of PLCMs with varying number of classes.

Latent Classes	Parameters	Log-likelihood at convergence	AIC	SIC
2	33	-10295.1	20656.2	20831.6
3	53	-9782.2	19670.5	19952.1
4	73	-9462.9	19071.8	19459.7
5	93	-9281.0	18748.0	19242.2
6	113	-9182.1	18590.1	19190.6
7	133	-9115.5	18496.9	19203.7

Note: AIC: Akaike Information Criterion; SIC: Schwarz Information Criterion.

The class of *combustion engine diehards* is of similar size to *status quo captives*. This class is, however, unwilling to consider PEV technologies, regardless of their characteristics. It encompasses older drivers who are not highly educated and have low environmental concerns. *Combustion engine diehards'* aversion to PEVs is not based on higher driving needs. This class is very unlikely to get behind the steering wheel of a PEV, unless they become the prevalent vehicle technology.

Price-conscious buyers take their name from their noteworthy sensitivity to changes in the purchase price of the car. Fuel technology is not a determinant of their choice and the operating costs of the vehicle have a secondary role in their decision-making process. Driving range is an important attribute for them, even though they value it less than other classes do. In short, this class of drivers would be willing to consider PEVs, provided that they were priced equivalently to their ICE-propelled counterparts. *Price-conscious buyers* are primarily females and their behaviour is in line with a higher probability that the car in context is not the primary car of the household. This is also in agreement with the low driving needs associated with one's membership in this class.

Full electric optimists are the most likely potential adopters of full electric cars. Amounting to slightly more than 16% of the sample, this is the only class preferring full electric cars from the rest of the alternatives. These drivers consider fixed-battery electric cars more attractive alternatives than swappable-battery ones. *Full electric optimists* are also the class placing the strongest emphasis on PEVs' exemptions from road taxes, implying that incentives provided for the adoption of full electric cars can be influential in the vehicle choices made by this class. Increases in driving range are also highly appreciated by these drivers. *Full electric optimists* have high environmental concerns, are more likely to be females, and have a longer-term view to the purchase of the next car, i.e. more than 3 years ahead. A further implication of the last finding might be that *full electric optimists* have considered optimistic scenarios for the performance of full electric cars more realistic than members of other classes.

Plug-in hybrid enthusiasts are likely early adopters of plug-in hybrids. This class corresponds to about 15% of the sample, who have high appreciation of reductions of vehicle operating costs. They are very sensitive to changes in fuel costs and resale value and suffer high losses from short driving range and long detour time. This renders full electric cars a less attractive option to them. On the contrary, plug-in hybrids' lower operating costs and similar levels of comfort in terms of driving range and refuelling needs with ICE-propelled cars make them an appealing alternative for this class. High environmental concerns are also a determinant of one's membership in *plug-in hybrid enthusiasts*.

Further insights into the sociodemographic composition of latent classes can be provided by the calculation of expected values for environmental concerns and the variables in vector $\mathbf{Z}_n$ of the class membership model for each class. These values are presented in Table 3.7. The expected value of each variable in class g is based on estimated prior class membership probabilities (see Equation (3.4)). Expected values can then be computed by the following formula (see also Hoyos et al., 2015):

$$\mathrm{E}[Y_n \mid g] = \frac{\sum_{n=1}^{N} \hat{p}_n^{*g} Y_n}{\sum_{n=1}^{N} \hat{p}_n^{*g}}, \tag{3.11}$$

where $\hat{p}_n^{*g}$ is the estimate of the probability of membership in class g obtained by the PLCM and Y_n is the variable of interest.

Table 3.7: Expected values of the variables used in the class membership model of PLCM.

Variable	Status quo captives	Combustion engine diehards	Price-conscious buyers	Full electric optimists	Plug-in hybrid enthusiasts
Environmental concerns (scale 1-6)	4.0	3.9	4.3	4.4	4.2
Female (%)	29.9	31.2	52.2	46.8	33.6
Age (years)	48.9	59.5	50.0	50.5	51.8
High education (%)	47.6	32.5	37.1	34.9	40.3
Low driving needs (%)	42.4	63.9	77.9	53.4	55.5
Often abroad (%)	31.4	24.9	13.6	20.7	25.5
First car replacement (%)	86.9	88.3	69.7	82.0	82.8
Long-term decision (%)	38.0	38.0	51.5	51.2	41.7

3.5.2. Hybrid PLCM estimates

Most of earlier studies of hybrid latent class models (e.g. Hess et al., 2013; Mariel et al., 2015) do not consider observed consumer characteristics in the class membership model. The underlying assumption behind their approach is that individuals' sociodemographic background and other characteristics influence their class membership probabilities only indirectly, i.e. via the latent variables. This relatively strong assumption also plays a pivotal role in supporting the argument that the use of latent variables can mitigate analyst's concerns about the endogenous nature of the observed measure. In fact, if this assumption is relaxed, and observed consumer characteristics are found to affect class membership both directly and indirectly, the use of latent variables does not address endogeneity. In other words, these observed characteristics cannot serve as *instruments* for the measurement of the latent variables.[40]

We relax this assumption and allow the same individual characteristics to enter both the class membership and the latent variable structural model.[41] Our estimates show that these characteristics may also have direct effects on class membership, thereby failing to manifest themselves as appropriate instruments for environmental concerns. This finding underlines the importance of rigorous testing of possible direct effects of the regressors of the latent variable structural model on class membership (or, equivalently, on utility, if the application follows the approach depicted in panel (c) of Figure 3.1). In general, arguments about the potential of hybrid choice models to address endogeneity concerns should be made with great caution, as the assumption of independence between the error term of the class membership model and the explanatory variables of the latent variable structural model is in principle untestable and might not always appear intuitive.[42]

Even though all modules of HPLCM were estimated simultaneously, we first present the estimates of the parameters of random utility and class membership modules (Table 3.8) and then the estimates of the structural and measurement model parameters (Table 3.9). A comparison of Table 3.8 with Table 3.5 immediately reveals that the parameter estimates of the HPLCM are very similar to the ones of PLCM, with the expected exception of the estimate for environmental concerns and, therefore, the one of the class-specific constant.[43] Confirming our expectations, the latter estimates are also *qualitatively* similar to the ones obtained through the PLCM.

[40] For relevant applications based on instrumental variables, see e.g. Petrin and Train (2010).

[41] To the best of our knowledge, the only other study adopting this approach is the one by Hoyos et al. (2015). In their specification, however, consumer sociodemographic characteristics do not have a significant direct effect on class membership and, thus, their impact on the class membership function is only manifested through the latent variables. An important difference between their study and ours is that the sociodemographic characteristics chosen by Hoyos et al. (2015) have very weak effects on class membership even in their PLCM specification. In sharp contrast, the sociodemographic characteristics considered here strongly affect latent class membership.

[42] For a wider discussion of the reasons why hybrid choice models may not be able to address endogeneity concerns, see Chorus and Kroesen (2014).

[43] The log-likelihood of the vehicle choice component at convergence is slightly lower than the one of the PLCM. This is an expected finding, as the HPLCM seeks for a set of parameter values which can explain both vehicle choice and responses to Likert items.

The upper panel of Table 3.9 shows the estimates of the structural model parameters. We find that females and highly educated individuals are more concerned about the environmental impacts of car use than males and individuals with lower levels of education. Similarly, environmental concerns increase with one's age, a finding probably reflecting one's increasing concerns about the environmental conditions faced by one's descendants, as well as about one's vulnerability to health risks stemming from the deterioration of the state of the environment. Even though environmental concerns are far from uniformly defined in relevant SP literature, these findings are in agreement with studies of environmental concerns or related constructs in the context of vehicle choice (Daziano and Bolduc, 2013; Jensen et al., 2013), or in other relevant contexts (Hess et al., 2013; Vredin Johansson et al., 2006).

Previous studies have not identified a significant impact of income on environmental concerns, but we find that representatives of households with relatively higher income have lower environmental concerns than representatives of households with lower income (see $\gamma_{\text{Income} > € 77{,}500}$ in Table 3.9).[44] This finding has important implications for policies and marketing strategies targeted at stimulating the demand for PEVs, as households who are likely to have the financial means to purchase them are not attracted by their labelling as environmentally friendlier products. These people might, however, be attracted to other special characteristics of PEVs, such as their innovativeness.[45]

The estimates of measurement model parameters (lower panel of Table 3.9) are consistent with our expectations, i.e. that individuals with higher environmental concerns would express a higher level of agreement with the four statements of Table 3.4. Environmental concerns are primarily reflected in concerns about climate change and local air pollution and secondarily in concerns about environmental degradation and noise. This implies that environmentally concerned individuals are more likely to be influenced by policies and campaigns emphasising the contribution of PEVs to the combat of climate change and local air pollution, rather than to other environmental problems exacerbated by the use of ICE-propelled cars.

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[44] We also experimented with other cut-off values defining high income households (e.g. €103,500/year). The results are very similar to the ones presented here. We also looked into differences in environmental concerns between low income households (gross household income < 32,500/year) and other household income categories, but we did not find any significant effects of low income on environmental concerns.

[45] Even though we tested for it, we did not find any statistically significant direct effect of high household income on class membership. The results produced by that model were almost unnoticeably different from the ones presented here.

Table 3.8: HPLCM estimation results.

	Status quo captives		Combustion engine diehards		Price conscious buyers		Full electric optimists		Plug-in hybrid enthusiasts	
Random Utility Model	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error
Plug-in hybrid [PHEV]	-0.193	(0.149)	-4.270***	(0.462)	0.252	(0.255)	0.868**	(0.377)	1.370***	(0.327)
Fixed-battery electric car [FBEV]	-1.165***	(0.391)	-5.967***	(1.150)	0.516	(0.363)	1.193**	(0.460)	-0.911	(0.645)
Swappable-battery electric car [SBEV]	-0.926***	(0.254)	-4.944***	(0.868)	0.084	(0.271)	0.867**	(0.405)	-0.074	(0.497)
Purchase price (1000 €)	-0.133***	(0.014)	-0.094***	(0.021)	-0.323***	(0.042)	-0.077***	(0.011)	-0.063***	(0.012)
Purchase price (1000 €) * Income > € 77,500 [a]	0.021**	(0.010)	0.021**	(0.010)	0.021**	(0.010)	0.021**	(0.010)	0.021**	(0.010)
Purchase price (1000 €) * Income unreported [a]	0.026**	(0.011)	0.026**	(0.011)	0.026**	(0.011)	0.026**	(0.011)	0.026**	(0.011)
Fuel costs (€/100km)	-0.150***	(0.014)	-0.090**	(0.040)	-0.097***	(0.029)	-0.190***	(0.041)	-0.246***	(0.043)
Annual road tax (*savings* in 1000 €)	0.071**	(0.029)	0.010	(0.078)	0.115*	(0.059)	0.173***	(0.037)	0.101**	(0.042)
Residual value of the car after 5 years (%)	0.028***	(0.003)	0.002	(0.008)	0.007	(0.005)	0.014***	(0.003)	0.021***	(0.006)
ln(Driving range) (km)	1.116***	(0.133)	0.346	(0.319)	0.848***	(0.123)	0.474***	(0.069)	0.633***	(0.178)
Extra detour time (10 min/refuelling action)	-0.400***	(0.103)	-0.004	(0.228)	-0.070	(0.071)	-0.070	(0.050)	-0.356***	(0.121)
Refuel time at station (10 min/refuelling action)	-0.275**	(0.109)	0.267	(0.174)	-0.100	(0.082)	-0.048	(0.053)	-0.094	(0.127)
Charging time at home/work (100 min/charging action)	-0.103**	(0.041)	0.066	(0.101)	-0.044	(0.036)	-0.020	(0.026)	-0.070	(0.069)
Class Membership Model			estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error
Environmental concerns (latent)			-0.151**	(0.067)	0.210**	(0.087)	0.259***	(0.076)	0.141	(0.090)
Female			0.419**	(0.207)	0.670**	(0.265)	0.617**	(0.245)	0.139	(0.250)
Age			0.065***	(0.008)	0.008	(0.010)	0.012	(0.009)	0.016	(0.011)
High education			-0.553***	(0.183)	-0.316	(0.252)	-0.560**	(0.212)	-0.286	(0.220)
Low driving needs	*Reference Class*		0.487**	(0.192)	1.158***	(0.295)	0.055	(0.241)	0.305	(0.257)
Often abroad			-0.310	(0.205)	-0.782**	(0.314)	-0.446*	(0.237)	-0.237	(0.292)
First car replacement			-0.124	(0.288)	-0.893**	(0.328)	-0.447	(0.296)	-0.395	(0.338)
Long-term decision			-0.190	(0.178)	0.284	(0.246)	0.401*	(0.221)	0.031	(0.226)
Constant			-3.391***	(0.504)	-1.197	(0.826)	-1.045*	(0.621)	-1.182*	(0.700)
Class size	*0.277*		*0.271*		*0.152*		*0.153*		*0.148*	
Parameters	121									
Observations (Individuals)	12008 (1501)									
Log-likelihood at convergence	-17042.4									
Log-likelihood vehicle choice component	-9308.3									
AIC	34326.7									
SIC	34969.7									

Note: Standard errors are heteroskedasticity-robust. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively. AIC: Akaike Information Criterion; SIC: Schwarz Information Criterion.

[a] Parameter estimates are constrained to be equal among classes.

Individual class membership probabilities are conditional on the values taken by the latent variable which are in turn also dependent on the realisations of ω_n. We simulate prior class membership probabilities using 10,000 draws of ω_n, in order to calculate the expected values of the HPLCM class membership model variables per class. These expected values are shown in Appendix 3.C, as they are largely similar to the ones presented in Table 3.7. Expected values of latent environmental concerns range between 0.32 for combustion engine diehards and 1.14 for full electric optimists.

3.5.3. Willingness to pay

Table 3.10 presents mean willingness to pay (WTP) estimates for each attribute and class. We only show here WTP estimates for the PLCM, as differences in class-specific mean WTP values between PLCM and HPLCM are trivial. Mean WTP values are computed as averages of the WTPs of all individuals. While WTP estimates for PEV technologies are strongly dependent on the model specification employed, it is interesting to note that all classes except *full electric optimists* rank PEV alternatives in accordance to their resemblance to ICE-propelled vehicles. Thus, plug-in hybrids are preferred to full electric cars and, among the latter, swappable-battery electric cars are slightly more attractive than fixed-battery ones.

Table 3.9: Latent variable model estimation results.

Structural Model

	estimate	std. error
γ_{Female}	0.446***	(0.087)
γ_{Age}	0.009**	(0.003)
$\gamma_{\text{High education}}$	0.293***	(0.093)
$\gamma_{\text{Income > € 77,500}}$	-0.307**	(0.111)
σ	1.509***	(0.097)

Measurement Model

Noise	estimate	std. error	*Climate change*	estimate	std. error
λ_1	1.000	-	λ_3	2.577***	(0.309)
τ_{11}	-3.695***	(0.241)	τ_{31}	-6.102***	(0.688)
τ_{12}	-1.349***	(0.197)	τ_{32}	-3.741***	(0.578)
τ_{13}	0.577***	(0.202)	τ_{33}	-0.607	(0.482)
τ_{14}	2.474***	(0.227)	τ_{34}	2.423***	(0.465)
τ_{15}	4.936***	(0.284)	τ_{35}	6.379***	(0.569)
Air pollution	estimate	std. error	*Environmental degradation*	estimate	std. error
λ_2	2.217***	(0.132)	λ_4	1.862***	(0.186)
τ_{21}	-7.075***	(0.567)	τ_{41}	-5.695***	(0.468)
τ_{22}	-4.412***	(0.446)	τ_{42}	-3.434***	(0.379)
τ_{23}	-1.368***	(0.403)	τ_{43}	-1.051***	(0.349)
τ_{24}	1.439***	(0.450)	τ_{44}	1.353***	(0.346)
τ_{25}	5.350***	(0.582)	τ_{45}	4.195***	(0.380)

Note: Sample size is 1501. Standard errors are heteroskedasticity-robust. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

WTP estimates for fuel costs range from around €306 per €1/100km saved for the class with the lowest driving needs, *price conscious buyers*, to €4421 per €1/100km saved for *plug-in hybrid enthusiasts*. This implies that consumers capitalise fuel savings of at least 3 years in the purchase price of the car (assuming an indicative annual distance travelled of around 10,000 km for *price conscious buyers*), while some classes even capitalise decades of fuel savings. An increase in the residual value of the car equal to 1%

of its purchase price is valued by only three classes (WTP ranges between €201 and €369), while *combustion engine diehards* and *price conscious buyers* do not consider it an important factor in their choice making process. A €1 saving of road taxes is appreciated differently by the classes, with values ranging from €0.4 (*price conscious buyers*) to €2.5 (*full electric optimists*). Variation in classes' valuation of this attribute essentially reflects variation in employed discount rates, as road tax exemptions reflect future savings.

As the logarithmic specification of driving range is used in drivers' utility function, we show the mean WTP values for three relevant levels of range, 100, 300 and 500 kilometres.[46] The value of an additional kilometre of driving range varies from €27 to €115 at a range of 100 km, to values between €5 and €23 at a range of 500 km. Even though reductions in detour time are only appreciated by *status quo captives* and *plug-in hybrid enthusiasts*, a 1-minute reduction in the detour time spent per fast-refuelling action is valued between €318 and €638. This implies that expansions of the coverage of fast-charging or battery-swapping infrastructure which would lower detour times would be highly appreciated by more than 41% of drivers. Notably, *plug-in hybrid enthusiasts*' WTP for reductions in detour time is double the one of *status quo captives*. Reductions of fast-charging and home charging time are only valued by *status quo captives*. At a value of €221/minute, reductions of fast-charging time can bring noteworthy benefits to this class, while at a value of €486/hour, generous cuts in home charging time would be needed to make PEVs more attractive to these drivers.

So far, we looked at WTP at the class level. It is however, interesting to provide insights into class-membership weighted WTP estimates and the differences emerging in this context between PLCM and HPLCM. We focus on alternative specific constants and investigate how the distribution of class-membership weighted WTP for fixed-battery EVs, swappable-battery EVs and plug-in hybrids differs between PLCM and HPLCM. The expressions used to calculate individual-specific WTP values for PEV technology *A* are:

$$WTP_{n_{A_{PLCM}}} = \sum_{g=1}^{G} \hat{p}_n^{*g} WTP_{A_{PLCM}}^{g} \tag{3.12}$$

for PLCM, and:

$$WTP_{n_{A_{HPLCM}}} = \sum_{g=1}^{G} \hat{p}_n^{g} WTP_{A_{HPLCM}}^{g} \tag{3.13}$$

for HPLCM.

[46] The average driving range level used in the study is 512.5 kilometres.

Table 3.10: Mean estimates of willingness to pay per class: PLCM.

Willingness to pay (in €) for	Status quo captives	Combustion engine diehards	Price-conscious buyers	Full electric optimists	Plug-in hybrid enthusiasts
Plug-in hybrid [PHEV]	*ins.*	-48,854.8	*ins.*	12,411.9	24,618.8
Fixed-battery electric car [FBEV]	-9128.1	-68,334.4	*ins.*	17,032.5	*ins.*
Swappable-battery electric car [SBEV]	-7277.5	-56,599.4	*ins.*	12,348.2	*ins.*
Fuel costs (€/100km)	-1189.2	-1015.4	-305.9	-2732.8	-4420.7
Residual value (% of purchase price)	224.9	*ins.*	*ins.*	201.4	368.8
Driving range (km) at 100 km	88.5	*ins.*	26.7	68.0	114.6
Driving range (km) at 300 km	29.5	*ins.*	8.9	22.7	38.2
Driving range (km) at 500 km	17.7	*ins.*	5.3	13.6	22.9
Refuelling time at station (min)	-221.4	*ins.*	*ins.*	*ins.*	*ins.*
Charging time at home/work (min)	-8.1	*ins.*	*ins.*	*ins.*	*ins.*
Extra detour time (min)	-317.6	*ins.*	*ins.*	*ins.*	-637.7
Annual road tax (savings in €)	0.6	*ins.*	0.4	2.5	1.8

Note: The term *ins.* denotes statistically insignificant estimates.

The histograms presented in Figures 3.3 to 3.5 present the distribution of WTP estimates for the three PEV technologies. In all cases, panel (a) depicts PLCM estimates, while panel (b) HPLCM ones. PLCM results in slightly lower, in absolute terms, mean and median WTP estimates for all technologies. On the contrary, the distribution of PLCM estimates has substantially higher variance and is more negatively skewed than the distribution of the HPLCM ones. The fact that HPLCM estimates are more concentrated around mean values provides an additional argument about the attractiveness of HPLC modelling in this application.

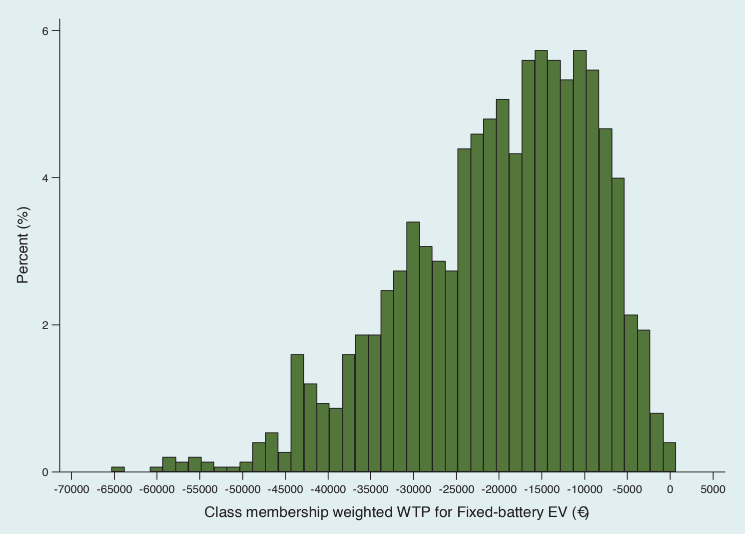
3.6. Conclusions

Despite the fact that more than three decades have passed since the introduction of stated preference methods to the analysis of consumer preferences for full electric vehicles (FEVs) (Beggs and Cardell, 1980), the same barriers to FEV adoption identified in the 1980s studies still play an important role in consumer reluctance to adopt them. Their large-scale adoption is still conditioned on expectations for technological breakthroughs permitting substantial reductions in EV battery costs, increases in driving range, and decreases in the time needed to recharge vehicle's battery (see also Chapter 2). Recent developments to address these concerns by the car industry and mobility service providers include the construction of car alternatives combining the merits of conventional vehicles with the ones of plug-in electric ones (e.g. plug-in hybrids), and the building of facilities where drivers can swap the depleted battery of a full electric car with a fully-charged one at the same time needed to refuel a conventional car with petrol.

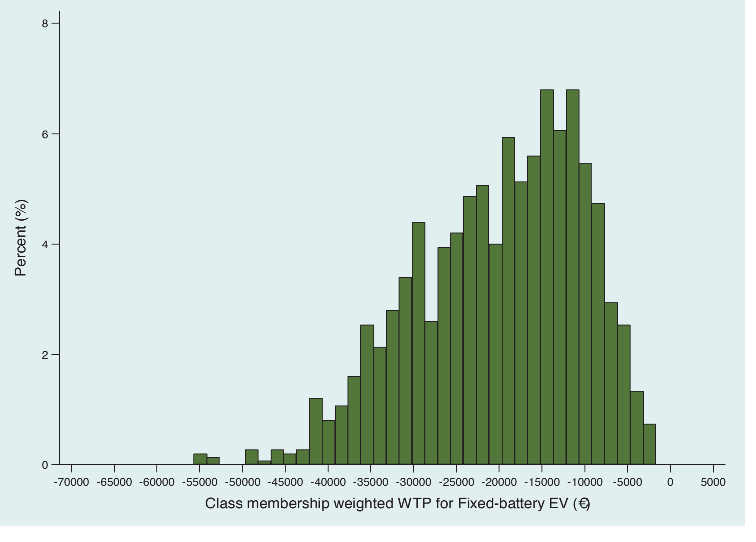
Motivated by these developments, we conduct a choice experiment to provide insights into driver preferences for different types of plug-in electric vehicles (PEVs). In doing so, we are especially interested in identifying the influence of drivers' environmental concerns – as manifested in their responses to Likert-type questions – on their preferences for PEVs. Our empirical analysis is based on the use of advanced panel latent class models, which enable the identification of consumer segments being more likely to become PEV adopters. Environmental concerns enter the class membership model, thereby influencing drivers' likelihood to fall into each latent segment. The presented approach also allows the estimation of the impact of sociodemographic characteristics on environmental concerns and is robust to possible errors arising in the measurement of the latter.

Drawing on the responses of about 1500 Dutch drivers, we find that full electric vehicles are still far from attractive for the majority of consumers, who seek for PEV alternatives whose attributes resemble the ones of ICE-propelled cars. To this end, the recently introduced plug-in hybrid and extended-range EVs have considerable potential to mitigate drivers' concerns over short driving ranges and long charging times. In contrast, swappable-battery electric cars are not considered significant improvements to their fixed-battery counterparts by any of the segments identified in our study. An encouraging finding for full electric cars is that we detect a non-negligible share of drivers (ca. 16% of the sample) who have strong preferences for them. This segment is characterised by high environmental concerns, but also by a longer-term view to the adoption of the next car.

Our findings reveal that drivers' environmental concerns have strong and positive influence on their preferences for PEVs. Policies and communication strategies built around the environmental benefits of PEVs can attract highly concerned drivers' attention and stimulate them to consider PEVs as viable alternatives to ICE-propelled vehicles. Women, highly educated and older drivers are more likely to exhibit high environmental concerns, and are thus more likely to be attracted by the aforementioned means, while individuals belonging to households with relatively high income are less likely to do so.

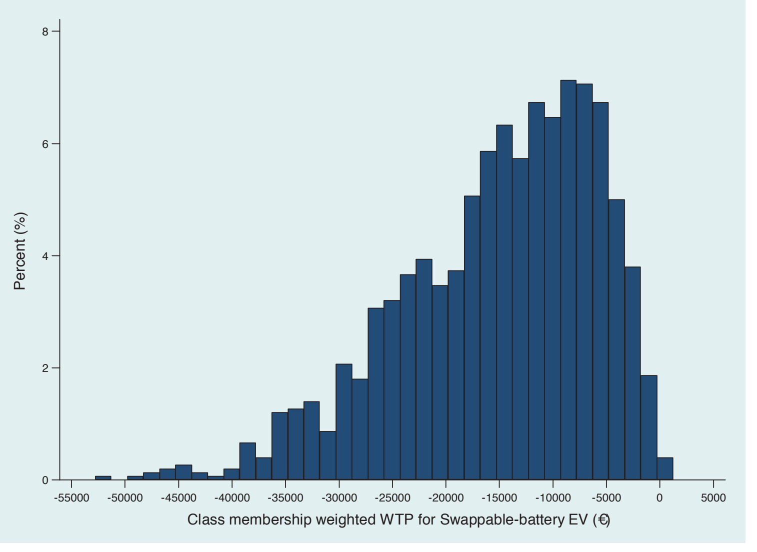


(a) PLCM

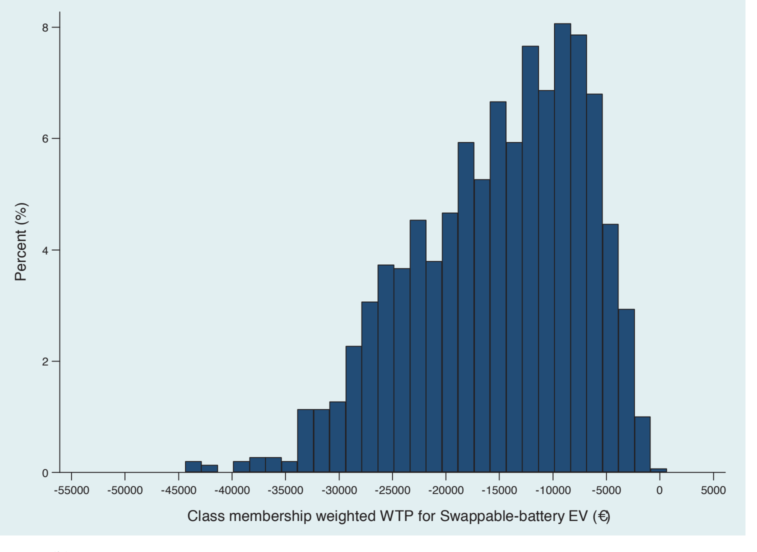


(b) HPLCM

Figure 3.3: Distribution of class membership weighted mean WTP for fixed-battery EVs.

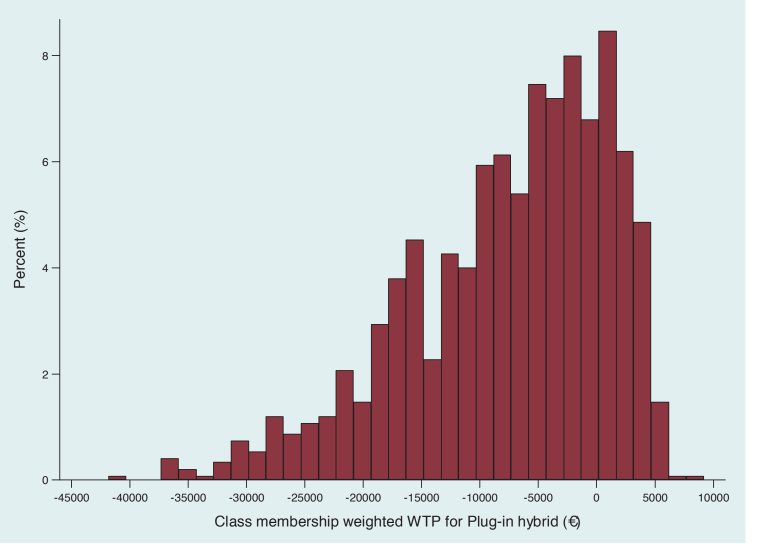


(a) PLCM

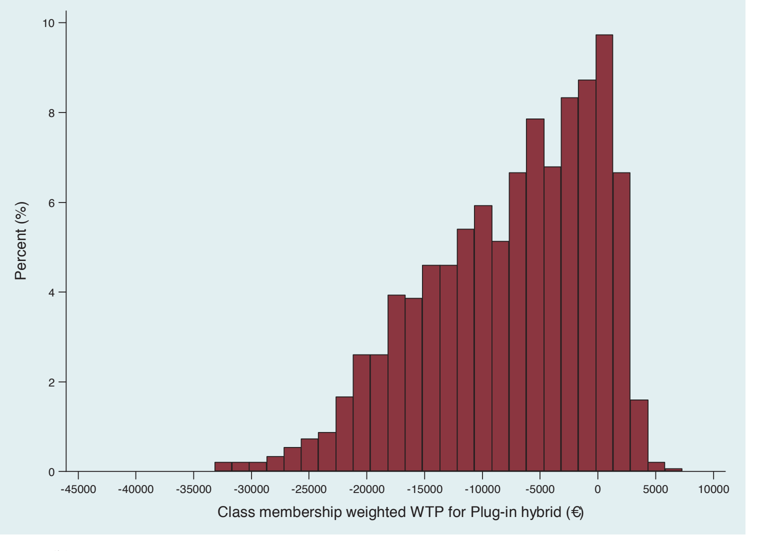


(b) HPLCM

Figure 3.4: Distribution of class membership weighted mean WTP for swappable-battery EVs.



(a) PLCM



(b) HPLCM

Figure 3.5: Distribution of class membership weighted mean WTP for plug-in hybrids.

Our findings and suggestions are conditional on PEVs being more environmentally sustainable alternatives than ICE-propelled vehicles. Even though PEVs can provide important environmental improvements in urban environments, it is not equally clear whether they can currently contribute to the combat of climate change and environmental deterioration. This strongly depends on the carbon content of the energy sources used for electricity generation and the environmental performance of the manufacturing procedures used to produce battery packs and other PEV components. If drivers are desired to keep considering PEVs as greener transportation means than ICE-propelled vehicles, it is of utmost importance that they are convinced that the lifecycle environmental impact of PEVs is noticeably lower than the one of their ICE-propelled counterparts.

Appendix 3.A: Sociodemographic background of respondents

Table 3A.1 presents the main sociodemographic characteristics of the sample.

Table 3A.1: Sociodemographic characteristics of the sample.

Characteristic	Frequency	Characteristic	Frequency
Sex		*2011 Gross household income (€)*	
Male	0.63	Less than 20,000	0.04
Female	0.37	20,000 - 32,500	0.14
Age		32,500 - 51,300	0.30
18-25	0.01	51,300 - 77,500	0.25
26-35	0.11	77,500 - 103,800	0.13
36-45	0.19	103,800 - 155,100	0.05
46-55	0.24	155,100 or above	0.01
56-65	0.25	Unreported	0.07
66 +	0.19	*Household size*	
Highest level of education followed		1	0.13
Primary and lower secondary	0.22	2	0.47
Higher secondary vocational	0.25	3	0.14
Higher secondary professional	0.13	4	0.19
College / University bachelor	0.27	5	0.05
Masters / PhD	0.12	6 or more	0.02
Unreported	0.005		

Appendix 3.B: Description of the PEV technologies presented in the experiment

Before presenting respondents with the choice scenarios, we provided them a description of the PEV technologies. The fixed-battery electric vehicle (FBEV) was described as a car with a built-in battery pack. Due to the purchase of the battery-pack, the FBEV was usually more expensive than its ICE counterpart. However, its operational costs were much lower. The FBEV could be either charged at a standard charging point at home or work or at special fast-charging stations. Standard charging would take several hours, while fast-charging would bring the battery to full charge in substantially less than one hour.

The electric vehicle with swappable battery (SBEV) was different from FBEV in two aspects. First, the battery pack should be rented by the driver. Second, while the SBEV adopter could use standard charging at home or work, fast-charging was not possible. Instead, the driver would have to exchange the depleted battery with a new one at specialised battery-swapping stations. This procedure would take the same time required to refuel an ICE car. Respondents were also offered the opportunity to watch a video of the battery-swapping procedure, in order to familiarise themselves with it.

The PHEV was described as a vehicle running on both oil-derived fuel and electricity, thereby incorporating both plug-in hybrid and extended-range technologies. Respondents were informed that the PHEV could run on electricity for a few tens of kilometres. Once the battery was almost depleted, the PHEV would run solely on oil-derived fuel. No fast-charging or battery-swapping option was offered for PHEVs.

Respondents were further informed that PEV technologies ran on automatic transmission and that driving electric was almost silent. PEVs were also described as more energy efficient and as having substantially lower (plug-in hybrids) or no (full electric cars) *direct* emissions of air pollutants, CO_2 and particulate matter. Respondents were also instructed to assume that the battery packs would be recycled at the end of their lifespan.

Appendix 3.C: Expected values of the variables of the HPLCM class membership model

Table 3C.1 presents the expected values of the variables entering the class membership model of HPLCM. They are calculated according to the HPLCM equivalent of Equation (3.11).

Table 3C.1: Expected values of the variables used in the Class Membership Model of HPLCM.

Variable	Status quo captives	Combustion engine diehards	Price-conscious buyers	Full electric optimists	Plug-in hybrid enthusiasts
Latent environmental concerns	0.52	0.32	1.03	1.14	0.87
Female (%)	29.8	31.3	52.3	46.8	33.5
Age (years)	48.9	59.4	50.0	50.5	51.9
High education (%)	47.7	32.5	37.1	34.7	40.4
Low driving needs (%)	42.6	64.8	77.4	52.5	55.1
Often abroad (%)	31.3	24.8	13.7	20.9	25.6
First car replacement (%)	87.1	88.8	69.1	81.6	82.6
Long-term decision (%)	38.2	39.0	50.7	50.5	41.3

Chapter 4

Not fully charged: welfare effects of tax incentives for employer-provided electric cars

4.1. Introduction[*]

In Europe, around half of new vehicle registrations concern *company cars*, i.e. passenger cars offered as fringe benefits in kind by employers to employees and serving mainly employees' private travel needs (Copenhagen Economics, 2010). Company cars are usually leased by firms and offered to employees under contracts of a predetermined duration – typically 3 to 4 years. These contracts normally cover all operating costs of the car, including fuel costs. Employee's private use of the car is equivalent to an increase in her annual taxable income. Even though taxation rules vary widely among countries, the amount added to employee's income usually depends on a *company car tax rate* levied on the car's purchase or list price (see also Harding, 2014b).[47]

One of the most important reasons for company cars' widespread use is their beneficial tax treatment. From employers' perspective, the provision of company cars does not increase social security contributions, as other forms of employees' remuneration do. On the employees' side, the increase in their taxable income is usually much lower than employers' costs for the compensation of their private travel expenses, as the applicable company car tax rates are set at lower than optimal levels (Gutiérrez-i-Puigarnau and van Ommeren, 2011). This implicit subsidy for employees is further reinforced in taxation systems where the fuel costs of the private use of the car are also covered by employers, but are not taken into account in the calculation of employees' taxable income (Copenhagen Economics, 2010).[48] Recent empirical literature, however, reveals that the beneficial tax treatment of company cars is distortionary, resulting in employees opting for more expensive cars (Gutiérrez-i-Puigarnau and van Ommeren, 2011), driving more kilometres (Shiftan et al., 2012), and expanding their household fleet (van Ommeren and Gutiérrez-i-Puigarnau, 2013).

The company car market is not only the driving force of changes in the car fleet of many European countries, including Germany, the Netherlands, Sweden and the UK, but also the main diffusion channel for alternative fuel vehicles. The latter can be grounded in

[*] This chapter is based on joint work with Jos N. van Ommeren, Paul R. Koster and Piet Rietveld. Earlier versions of it have been published in the *Journal of Environmental Economics and Management* and the Tinbergen Institute Discussion Paper Series (Dimitropoulos et al., 2014, 2016).

[47] For example, given a 20% company car tax rate for a vehicle with a list price of €35,000, and a marginal income tax rate of 42% (which is commonly applicable in the Netherlands), the annual tax payment that the driver has to make for this fringe benefit is 42% × 20% × €35,000 = €2940.

[48] Examples of such taxation systems can be found in the Netherlands and Spain, and under conditions, France and Germany. Business-related fuel expenses are in most countries fully tax-deductible for firms.

two main arguments. First, company car drivers do not have to incur the (typically high) upfront costs for the use of these vehicles. Second, the uncertainty about vehicle's resale price and operating costs is thereby shifted from the car user to the employer or the car leasing firm. In view of the potential contribution of alternative fuel vehicles to the pursuit of environmental and energy security goals, European governments have attempted to accelerate their adoption in the company car market by providing generous tax incentives for drivers, firms and car leasing companies.

Several European countries have designated special rules for the taxation of the benefit in kind arising from the private use of low emission company cars, either by adjusting the considered value of these vehicles or by tailoring the company car tax rates levied on them. For example, tax authorities in Germany and Sweden consider *list prices* of plug-in electric company cars that are substantially lower than their market prices when calculating employees' addition to taxable income (ACEA, 2013). In other countries, such as Belgium, France, the Netherlands, and the UK, the *company car tax rate* is itself a function of the car's type-approval CO_2 emissions.[49] The latter tax treatment implies that the environmental benefits of low emission vehicles are considered to vary with the list price of the car. However, the environmental costs of CO_2 emissions do not have a one-to-one relationship with car prices. An unintended consequence of this form of tax treatment is that company car drivers are likely to opt for more expensive vehicles than they would do if tax advantages for electric cars reflected their actual external benefits. This results in welfare losses, as the marginal social costs of these vehicles will be higher than their marginal social benefits.

In the Netherlands, the country we focus on, cars emitting less than 50 gCO_2/km have been exempt from registration and road taxes. More importantly, however, the private use of company cars with very low CO_2 emissions has been subject to especially low tax rates. Until the end of 2013, the private use of these cars was not taxed at all, while in 2014, the company car tax rate was raised to 4% for full electric cars and 7% for plug-in hybrids.[50] This incentive was among the main determinants of the successful penetration of

[49] Unless otherwise stated, when we henceforth refer to cars' CO_2 emissions, we consider the type-approval measurements of tailpipe CO_2 emissions (in grams of CO_2 per kilometer).
[50] To facilitate comparison, the median company car tax rate in the Netherlands was 20% in 2012 (VNA, 2013). Building on the example provided in the first footnote, a zero company car tax rate entails annual tax savings for the driver equivalent to €2940. As demand elasticities can be high in the car market (see e.g. Bento et al., 2009; Gutiérrez-i-Puigarnau and van Ommeren, 2011; Train and Winston, 2007), we expect that these tax incentives can cause strong demand responses.

plug-in electric vehicles (PEVs) in the car market; for example, 95% of the ca. 28,700 PEVs registered in the Netherlands in 2013 were company and fleet cars (RVO, 2014).[51]

To the best of our knowledge, empirical assessments of the welfare effects of the favourable tax treatment of electric and other low emission vehicles in the company car market have thus far been missing. This chapter provides a first attempt to estimate the welfare effects of such tax advantages, focussing on policies aiming to promote the adoption of PEVs through reduced company car tax rates. Our empirical approach is built around data from a new survey among Dutch company car drivers, which elicited their preferences for three different types of PEVs. These stated choice data enable us to analyse drivers' sensitivity to changes in the applicable company car tax rates and other vehicle characteristics.

Following the estimation of the choice model and its recalibration on the basis of 2014 market data, we estimate the welfare losses from the adopted tax treatment relative to two benchmarks. The first benchmark, benchmark A, is based on the assumption that the external benefits of electric cars are fully compensated by their exemption from registration and road taxes (which applies to PEVs on top of company car tax advantages). The second benchmark, benchmark B, assumes that there are additional external benefits in the future from the adoption of PEVs in the company car market in terms of positive network externalities, technological innovation and concomitant *future* environmental benefits (see also Vollebergh and van der Werf, 2014). To be explicit, we assume that these benefits are substantial and justify deductions of €10,000 from the list price of a full electric car and €6500 from the list price of a typical plug-in hybrid.[52] Given both benchmarks, the welfare losses from the current scheme are estimated to be sizeable and even higher than the changes in drivers' tax expenses implied by these adjustments. We also estimate the welfare gains from *marginal* increases in the 2014 company PEV tax rates and show that they are substantial.

[51] A full list of the acronyms used in the study is presented in the beginning of the book. The term plug-in electric vehicle (PEV) is used here to denote both *full electric vehicles* (FEVs), i.e. vehicles powered exclusively by electric motors, and plug-in hybrid and extended-range electric cars, i.e. vehicles propelled by both electric motors and internal combustion engines whose batteries can be recharged by plugging them into an electricity outlet. The technological differences between plug-in hybrid EVs and extended-range EVs are not of primary interest in this study and we denote both with the encompassing term *plug-in hybrids* (PHEVs). Vehicles with electric motors which cannot be plugged into an electricity outlet, such as hybrid electric vehicles (HEVs), are not considered as PEVs for the purposes of this study.

[52] The list-price deductions for full electric cars coincide with the deductions allowed for in Germany.

Preference heterogeneity has a central role throughout our analysis. We use an adapted version of the latent class model popularised by Kamakura and Russell (1989). The model enables the identification of groups of potential early adopters of the technologies of interest and pinpoints the socio-demographic factors contributing to the likelihood that individuals belong to these groups. Differences in the contribution of each group to the welfare effects of tax policy adjustments are important and reveal that potential early adopters of PEV technologies would mainly be responsible for the identified welfare losses.

The rest of the chapter is organised as follows. Section 4.2 describes the stated choice experiment and provides summary statistics for the sample. Section 4.3 presents the methodology used to elicit company car driver preferences and estimate the welfare effects of changes in the taxation of company PEVs. Section 4.4 discusses heterogeneity in company car drivers' preferences for PEVs, while Section 4.5 evaluates the welfare effects of changes in company PEV tax rates. Section 4.6 concludes.

4.2. Data

The welfare implications of changes in the tax treatment of PEVs in the company car market can be evaluated through the analysis of revealed and stated preference data. Appropriate revealed preference data are, however, unavailable for this purpose (cf. Klier and Linn, 2013). The main reason for this is that registrations of company cars are usually made under the name of firms or car leasing companies. This has several shortcomings, the most important of which is that it does not allow the identification of the driver of the vehicle. Another important shortcoming is that such data do not enable a reliable distinction between company and fleet cars, i.e. cars serving solely business trips.

Our empirical approach is, therefore, built around a new dataset of stated vehicle choices of Dutch company car drivers in an experimental setting. The data stem from drivers' responses to an online questionnaire inviting them to make hypothetical choices between company cars propelled by different propulsion systems. The two following subsections provide details about the design of the questionnaire, the online survey, and the choice experiment, while the third subsection presents sample descriptive statistics.

4.2.1. Survey design

The survey was carried out between November 2012 and January 2013 with a sample drawn from the panel of motorists of TNS-NIPO. To that end, we used a comprehensive online questionnaire developed in Sawtooth SSIWeb (Sawtooth Software, 2008). The design of the survey is described in detail in Section 3.3.1 of Chapter 3. In contrast to Chapter 3, however, this chapter draws on the responses of individuals reporting that their *current car* is a company car and that their *next car* will also be a company car. These respondents were presented with a different choice experiment from the one presented in the previous chapter and faced various questions regarding their current car lease contract and the one they were expecting to engage in next.

Following a detailed presentation of the alternative types of propulsion systems and the vehicle attributes used in the study, respondents were invited to choose their preferred alternative in 8 hypothetical choice scenarios. We remind the reader that respondents were later asked to report how they made their choices, i.e. whether they considered all attributes, just a subset of them, or whether they chose an option at random. The time that respondents spent to handle different parts of the questionnaire was closely monitored, in order to provide us with a measure of how seriously they addressed the questionnaire.

The study was preceded by focus group discussions, a small-scale pretesting of the questionnaire and a pilot survey with 206 respondents from the same panel of motorists. As already noted in Chapter 3, the response rate was ca. 75%. We had to further exclude 154 responses from the rest of our analysis, due to respondents' extremely fast handling of choice scenarios. All questionnaires with a median duration of response to the choice scenarios of less than 10 seconds were not further considered, as it is unlikely that these respondents engaged in trade-offs between vehicle attributes. Of the remaining 885 responses, 40 were considered unreliable,[53] resulting in 845 complete responses being used in the remainder of the analysis.

4.2.2. Choice experiment

Respondents were initially instructed to think about their next company car and treat the choice scenarios presented to them as real choice tasks. They addressed 8 choice scenarios inviting them to choose their preferred option among 4 versions of the same car: a plug-in hybrid (PHEV), a full electric with fixed battery (FBEV), a full electric with swappable battery (SBEV) and a version driving on respondents' preferred propulsion system and fuel (e.g. petrol, diesel, LPG, HEV, biofuels).[54] When respondents reported that their next car would be a full electric car or a plug-in hybrid, the fourth alternative was automatically set

[53] Most of these drivers reported that a zero company car tax rate applied to them.

[54] Appendix 3.B of Chapter 3 summarises the description of full electric vehicle and plug-in hybrid technologies provided to the respondents.

to a petrol-fuelled car. They were further instructed to assume that the four options were different only in the 8 attributes presented to them and that fuel costs would be paid by their employer.[55] Table 4.1 presents an overview of the attributes and attribute levels used in the choice experiment. These were determined on the basis of a comprehensive literature review (see also Chapter 2) and deliberations with colleagues. The selection of attribute levels aimed at the presentation of realistic scenarios, on the one hand, and at the elicitation of driver preferences across a wide range of possible attribute values, on the other.

Table 4.1: Attributes and attribute levels used in the choice experiment

Attributes	Attribute levels			
Propulsion system and fuel type	ICE or Hybrid	Plug-in hybrid	Electric with fixed battery	Electric with swappable battery
List price (€)	Customised on reported price range for next car	0.8 * List price ICE 1.4 * List price ICE 2.0 * List price ICE	0.8 * List price ICE 1.4 * List price ICE 2.0 * List price ICE	0.8 * List price ICE 1.1 * List price ICE 1.4 * List price ICE
Company car tax rate (%)	14 20 25	0 7 14	0 7 14	0 7 14
Employee's annual net contribution (€)	0 1200 3600	0 1200 3600	0 1200 3600	0 1200 3600
Driving range (kilometres)	600 750 900	500 700 900	100 300 500	100 300 500
Refuel time at station (minutes)	5	5	15 30 45	5
Charging time at home/work (hours)	N.A.	1.5 3 5	4 8 10	4 8 10
Extra detour time (minutes)	N.A.	N.A.	0 10 20	0 15 30

Note: ICE encompasses vehicles propelled solely by an internal combustion engine. *Employee's annual net contribution* is made to the employer to cover part of the monthly expenses made for the provision of the company car.

Apart from the propulsion system, the four options differed with respect to the following seven attributes: list price, company car tax rate, employee's annual net contribution, driving range, refuel time at the station, charging time at home, and detour time required to reach the nearest fast-charging or battery-swapping station on top of the time needed to access the nearest petrol station. The *list price* of full electric cars and plug-in hybrids included the costs of a charging cable and a standard home-charging unit. The list price of the conventional car (internal combustion engine – ICE – or HEV) was

[55] Only 3% of our sample reports that the fuel costs associated with the private use of the car are (partially) paid by themselves.

customised on respondent's selected price range.[56] The price of the three other options varied around the price of the conventional car in accordance with the coefficients shown in Table 4.1. We also considered cases where PEVs were priced lower than conventional cars, in order to be able to examine trade-offs for a wider range of attribute levels.

Dutch regulation requires company car drivers to be taxed for their private use of the car when it exceeds 500 kilometres per year.[57] The addition to driver's taxable income due to the private use of the company car is calculated as the product of the list price of the car and a *company car tax rate* which currently depends on vehicle's type-approval CO_2 emissions (cf. Koetse and Hoen, 2014). Until the end of 2013, all employees who acquired company cars with tailpipe CO_2 emissions of less than 50 g/km directly qualified for a 5-year exemption from taxation on the private use of the car. At the same time, rates of 14%, 20%, and 25% apply to vehicles with higher tailpipe emissions of CO_2. These values provide the basis for the levels considered in the design of our study, where company car tax rates vary between 14% and 25% for conventional cars, while between zero and 14% for PEVs.

We further presented respondents with the actual annual tax payment they would have to incur under the considered list price and company car tax rate to facilitate their comparison of different alternatives. In the Netherlands, two income tax rates are applicable for this purpose depending on driver's income, 42% and 52%.[58] As information about the income tax rate category within which respondents fall was unavailable, they were presented with annual tax figures for both categories. These figures are calculated as the product of list price, company car tax rate and income tax rate.

Employees usually make substantial private use of the company car and are often asked to contribute to the monthly expenses made by the employer for this purpose. The magnitude of this contribution usually depends on the price of the car. Koetse and Hoen

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[56] Before engaging in the choice scenarios, respondents were asked to select the anticipated price range of their next company car from a list of possible ranges. For each choice scenario, a random number was drawn from a uniform distribution defined in the interval between 1/100th of the minimum value of that price range and 80% of 1/100th of the maximum one. The resulting integer was then multiplied by 100 to present the respondent with a price rounded to hundreds of Euros. For example, if the respondent reported that their next car would fall in the price range €20,000-€25,000, a random number was drawn in the interval [200,240]. The integer was then multiplied by 100 to provide a price between €20,000 and €24,000.

[57] This condition holds for around 97% of the company car drivers who completed the questionnaire. To ensure that the *company car tax rate* attribute is consistently considered across respondents, drivers who were not taxed for the use of the company car at the time of the survey were excluded from the rest of the analysis.

[58] Lower income tax rates are applicable to brackets of lower income, but these brackets are only relevant for a tiny minority of company car drivers.

(2014) report that employees' contribution from their *gross* monthly earnings usually varies between zero and €400. We adopt a wider range and consider values up to €300 (annualised to €3600) for *employee's net contribution*, independent of the fuel technology in context.

Driving range varied for all alternatives. For plug-in hybrids, we considered values spanning from the current situation of extended-range electric cars to the one of plug-in hybrids. For full electric cars, we employed driving range levels from as low as 100 km, slightly lower than the level advertised for most commercially available models, to 500 km, somewhat higher than the one estimated for the 85-kWh battery-pack of Tesla Model S.[59] *Refuel time at the station* denoted the time required to refuel the tank of the conventional car or the plug-in hybrid, to fast-charge the battery of the fixed-battery EV, or to swap the batteries of the swappable-battery EV at specialised stations. It varied only for the fixed-battery EV, from 15 to 45 minutes for a full charge.

Standard *charging time at home or work* was substantially shorter for plug-in hybrids than full electric cars, due to their usually smaller battery-packs. It varied from 1½ to 5 hours for plug-in hybrids and from 4 to 10 hours for full electric cars. *Extra detour time* to reach the nearest fast-charging or battery-swapping station was essentially a measure of the availability of refuelling infrastructure, as it informed respondents about the extra time they would have to spend in searching for a quick alternative to standard home-charging if they adopted a full electric car (cf. Koetse and Hoen, 2014; Train, 2008). As the investment required for the building of a battery-swapping station is currently about 20 times higher than the installation of an AC fast-charging unit, we considered slightly higher levels of this attribute for swappable-battery EVs than for fixed-battery ones.

Regarding the design of the study, we used SSIWeb's *Complete Enumeration* method to generate a close to orthogonal design with 300 choice experiment versions (Sawtooth Software, 2008). To accommodate the attribute differences among the four propulsion systems presented to respondents, we used an alternative-specific design. The sequence of the four alternatives was randomised, whereas the attribute sequence was fixed to reduce the complexity of the task. Perl and HTML scripting was extensively used to accommodate the alternative-specific nature of the attribute levels and to customise them in accordance with respondents' stated values for their next transaction. Figure 4.1 presents an example of a choice scenario.

[59] See also http://www.teslamotors.com/models/options.

Choice Question 1

The four options presented below are different versions of the same model. They differ only in the presented attributes. The annual costs of the company car are equal to the sum of annual tax payment and your annual net contribution.

	Option 1	Option 2	Option 3	Option 4
Fuel type	Diesel	Electric car with fixed battery	Electric car with swappable battery	Plug-in Hybrid
List price	€ 22,000	€ 30,800	€ 24,200	€ 44,000
Company car tax rate	25%	0%	14%	7%
- ***Annual tax payment: 42% rate***	*€ 2310 per year*	*€ 0 per year*	*€ 1420 per year*	*€ 1290 per year*
- ***Annual tax payment: 52% rate***	*€ 2860 per year*	*€ 0 per year*	*€ 1760 per year*	*€ 1600 per year*
Employee's contribution	€ 0 per year	€ 3600 per year	€ 1200 per year	€ 1200 per year
Driving range	750 kilometres	300 kilometres	100 kilometres	500 kilometres
Refuel time at the station	5 minutes	30 minutes	5 minutes	5 minutes
Charging time at home or work	Not applicable	8 hours	10 hours	3 hours
Extra detour time	No extra detour time	10 minutes	15 minutes	No extra detour time

Please indicate below which option you would choose:

	Option 1	Option 2	Option 3	Option 4
Your choice →	○	○	○	○

Figure 4.1: Example of a vehicle choice scenario.

Note: In the example above, the respondent stated that his next company car would be a new, medium-sized, diesel-fuelled car, costing €20,000-€25,000. The example is translated from Dutch.

4.2.3. Descriptive statistics

Table 4.2 provides the main descriptive statistics of the sample used in the empirical analysis.[60] It mainly consists of males (ca. 82%) and highly educated drivers (61%). An important share (15%) of the sampled drivers belongs to high-income households with gross annual earnings greater than €103,800. The mean age of respondents is 44 years. These results are in general agreement with earlier studies of the Dutch company car market (Ecorys, 2011). Furthermore, the distribution of our sample's gender, age, and education level is similar to the one reported by Koetse and Hoen (2014) for their sample of Dutch company car drivers. Relevant statistics for the population of company car drivers are not available, as there is no relevant census or regular survey.

[60] Note that the sample used in the econometric analysis is 756 individuals. The exclusion of around 10.5% of respondents from the econometric analysis is justified in Section 4.4. Descriptive statistics of the full sample are very similar to the ones reported here.

Table 4.2: Sample descriptives.

Variable	Percentage	Variable	Percentage
Demographic Characteristics		Characteristics of respondent's current car (cont.)	
Sex		*Fuel type*	
Male	0.82	Petrol	0.36
Female	0.18	Diesel	0.54
Age		Hybrid	0.10
18-24	0.00	LPG	0.00
25-34	0.18		
35-44	0.36	Next company car characteristics	
45-54	0.30	*Fuel type*	
55-64	0.15	Petrol	0.26
65 +	0.00	Diesel	0.53
Education (completed)		Hybrid	0.14
Primary and lower secondary	0.07	LPG	0.00
Higher secondary vocational	0.20	Plug-in Hybrid	0.03
Higher secondary professiona	0.12	Full Electric	0.02
Bachelor	0.41	CNG / Biofuels	0.01
Masters / PhD	0.20	Unknown	0.02
Unreported	0.00	*Segment*	
2011 Gross household income (€)		Small	0.06
Less than 32,500	0.02	Medium-sized	0.46
32,500 - 51,300	0.18	Large / Estate	0.33
51,300 - 77,500	0.36	MPV	0.09
77,500 - 103,800	0.22	SUV	0.03
103,800 - 155,100	0.12	Van	0.01
155,100 or above	0.03	Sports / Luxury	0.01
Unreported	0.06	*Annual distance travelled (km)*	
		< 20,000	0.10
Characteristics of respondent's current car		20,000 - 30,000	0.24
Applicable company car tax rate (%)		30,000 - 40,000	0.32
14	0.30	40,000 - 50,000	0.21
20	0.38	> 50,000	0.12
25	0.32		

Table 4.2 also provides summary statistics about variables that are used in the class membership model, described in the next sections. The majority of respondents currently drive in diesel-fuelled cars (54%), while a minority drives in HEVs, such as the Toyota Prius (10%). Compared to the population of leased cars in 2012 (VNA, 2013), diesel cars are slightly overrepresented (by around 4 percentage points), while petrol-fuelled cars are underrepresented by about 8 percentage points. We also aimed for an overrepresentation of

HEVs (approximately 5 percentage points) to enable us to study the preferences of these drivers in more detail. Turning to the company car tax rate, the most common category is the 20% tax rate, followed by 25% and 14%. This distribution is in close agreement with national statistics for company cars registered in the period 2010-2012 (RAI Vereniging and BOVAG, 2013).

Diesel-fuelled cars also have the lion's share in respondents' preferences for the fuel type of their next company car. The characteristics of this fuel technology (e.g. long range and low fuel costs) render it especially suitable for the needs of company car drivers. Slightly less than 5% of respondents state that their next company car will be a PEV. Two-thirds of them will opt for a plug-in hybrid and one-third for a full electric car. This already indicates that even though PEVs have not yet passed the early-adoption stage, there is non-trivial interest in these vehicles. Due to their long range and important similarities to conventional cars, plug-in hybrids currently appear as the most attractive PEV technology for company car drivers.

Respondents' choices for the segment of their next company car and the annual distance expected to be travelled confirm that they are heavy car users who place emphasis on comfort and good performance. The need for long range and increased comfort are relatively high for company car drivers, rendering larger cars more suitable for their needs. Sample statistics confirm this expectation, as medium-sized cars are the most popular segment in drivers' choice for their next company car, followed by large/estate cars and multi-purpose vehicles.

4.3. Methodology

We now turn to a discussion of the methodological approach developed to elicit company car driver preferences for PEVs and estimate the welfare effects of changes in their beneficial tax treatment. Consumer heterogeneity has a central role in our modelling framework.

4.3.1. Modelling preference heterogeneity

We investigate consumer preference heterogeneity using a panel latent class model, i.e. a finite mixture model which allows for repeated observations by the same individual (Kamakura and Russell, 1989). Class membership is modelled as a stochastic function of consumer socio-demographic and behavioural characteristics. Conditional on membership in class *g*, company car driver *n* behaves according to a random utility model when choosing alternative i in choice scenario s. Utility is modelled in willingness to pay (WTP) space (see e.g. Scarpa and Willis, 2010; Train and Weeks, 2005) and is of the form:

$$U_{nis}^{g} = \beta^{g}(M_{nis} - \boldsymbol{\omega}'^{g}\mathbf{X}_{nis}) + \varepsilon_{nis}^{g}, \tag{4.1}$$

where U stands for random utility, M is the monetary attribute used for the calculation of the WTP, $\mathbf{X}$ is a vector of the (levels of the) other attributes used in the experiment, β and $\boldsymbol{\omega}$ represent class-specific parameters and vectors of WTPs to be estimated, and ε is an idiosyncratic component of utility which is unobserved by the researcher, and assumed to be i.i.d. Gumbel across individuals.[61]

Individuals are probabilistically assigned to different classes according to a class membership model (CMM). Assuming that the random component of the membership likelihood function is also i.i.d. Gumbel, the logit probability that individual n is a member of class g among G classes is (Boxall and Adamowicz, 2002):

$$p_{n}^{g} = \frac{e^{\delta^{g} + \boldsymbol{\xi}'^{g}\mathbf{Z}_{n}}}{\sum_{g=1}^{G} e^{\delta^{g} + \boldsymbol{\xi}'^{g}\mathbf{Z}_{n}}}, \tag{4.2}$$

where the normalisations $\delta^{G} = 0$ and $\boldsymbol{\xi}^{G} = 0$ for class G are required to ensure identification (Greene and Hensher, 2003). In Equation (4.2), $\mathbf{Z}_n$ is a vector of socio-demographic and behavioural characteristics of individual n, while class-specific constants δ and vectors of parameters $\boldsymbol{\xi}$ are to be estimated. For further details about the estimation of the panel latent class model, we refer to Section 3.4.1 of Chapter 3, Boxall and Adamowicz (2002) and Greene and Hensher (2003). The desirable number of latent classes is determined by estimating models with different numbers of classes and comparing them on the basis of the meaningfulness of the yielded estimates and their performance with respect to the Schwarz Information Criterion (SIC, see Gupta and Chintagunta, 1994).

4.3.2. Estimation of welfare effects

The estimates of the PLCM can serve as a basis for the evaluation of the welfare effects of changes in the policy framework governing the adoption of environmentally friendlier vehicle technologies. We show here how they can be used for the assessment of the welfare implications of changes in the company car tax rates applicable to PEVs in 2014 in

[61] Despite the fact that $\boldsymbol{\omega}$ is also allowed to vary across fuel technologies for specific attributes (fuel technology constant and driving range) in the econometric analysis that follows, we suppress here subscript i to simplify the notation.

the Netherlands. The developed approach is of relevance to countries which have linked company car taxation with vehicle environmental performance, a practice which has been relatively popular in Europe.

We assume that the number of company cars in the market is exogenously determined and focus on the demand for alternative fuel technologies. The car market is perfectly competitive and the supply of PEVs and conventional cars is fully elastic.[62] This assumption is plausible in the context of the Dutch car market, as its size is relatively small. Provided that the demand for company PEVs is not completely inelastic, changes in their taxation entail changes in social welfare. We estimate the welfare losses induced by distortionary taxation using the two benchmarks briefly discussed in the introduction.

The first benchmark, benchmark A, assumes that the external cost savings caused by PEVs (e.g. in terms of lower tailpipe emissions of CO_2, air pollutants and lower noise levels) are fully compensated by the exemption of these cars from registration and road taxes. Support for this assumption is found in tax policies applied in the Dutch *private* car market to encourage the purchase of PEVs, where the principal tool used at the national level is their exemption from these taxes. Because the external benefits of PEVs are fully reflected in their exemption from registration and road taxes, there is only a distortion through the use of too low company car tax rates.

Our second benchmark, benchmark B, assumes that there may be additional external future benefits from the fast penetration of PEVs in the company car market, which are not reflected in these exemptions (e.g. benefits associated with network externalities – related, for example, to the higher demand for (fast-) charging infrastructure – technological innovation and accompanying future environmental benefits). Here it is assumed, for example, that the additional external benefits in the future from the adoption of PEVs justify deductions of €10,000 from the list prices of full electric cars and €6500 from the list prices of plug-in hybrids.

Economic theory suggests that the addition to employee's income due to the private use of the company car should fully reflect the difference between car's operating costs and the increase in employee's productivity stemming from its use (see Clotfelter, 1983; Katz and Mankiw, 1985).[63] Accordingly, the optimal company car tax rate is the one

[62] See Berry et al. (1995) and Verboven (2002) for discussions of alternative market structures.

[63] The operating costs of the company car encompass all costs incurred by the employer for the provision of the company car and comprise fuel costs and leasing costs, where the latter reflect car depreciation, maintenance costs, insurance costs and road taxes.

whose product with the list price of the car yields this difference (Gutiérrez-i-Puigarnau and van Ommeren, 2011). We make a very conservative estimate and assume that the welfare-optimal tax rate is the one most commonly applied to company cars in the Netherlands, i.e. 20%.[64] If income effects of price changes are negligible (and the tax rate on labour income is at its welfare-optimal level), this framework entails that the subsidisation of company PEVs through lower tax rates is distortionary and leads to welfare losses.

We are interested in the net welfare effects of changes in the company PEV tax rates from their 2014 levels. Net welfare, *W*, is given by the difference between social benefits and costs. In this case, the former are captured by consumer surplus, *CS*, whereas the latter by the distortionary implicit subsidy *D*. This implicit subsidy is equal to the difference between the optimal addition to employee's income due to the use of the PEV (here assumed to be equal to 20% of its acquisition price) and the consumer price implied by the applicable company car tax rate in 2014. An increase of a PEV tax rate from its 2014 level will yield two effects. First, it will result in a reduction in consumer surplus. Second, it will lead to a decline in the implicit subsidy provided for the use of the PEV. We now look closer into these two effects.

When utility is linear in income, the expected consumer surplus is equal to the monetary equivalent of the logsum, plus an unknown constant (see e.g. de Jong et al., 2007; Small and Rosen, 1981).[65] Latent class models offer a key advantage over continuous logit mixtures in regard to the computation of the expected consumer surplus, as there is a closed-form expression for it. In particular, *CS* can be computed as the class membership probability weighted average of the consumer surpluses of the three latent classes, i.e.:

$$CS_n = \sum_{g=1}^{G} p_n^g [-\frac{1}{\beta^g} \ln(\sum_{j=1}^{J} e^{\beta^g (M_{nj} - \boldsymbol{\omega}'^g \mathbf{x}_{nj})})] + \psi , \qquad (4.3)$$

where ψ is a constant.

[64] Other studies (see e.g. Gutiérrez-i-Puigarnau and van Ommeren, 2011) argue that the tax rates should be much higher than 20% to reflect the expenditure actually incurred by employers for the use of these cars. As tax rates were varied in the experiment between 0 and 25%, we perform a welfare analysis within these boundaries. If the optimal level of the company car tax rate is higher than the one taken into account here, the welfare losses induced by reduced company car tax rates for PEVs are underestimated here.

[65] This assumption is supported by our data, as no statistically significant differences in the marginal utility of income were identified between different income groups.

At the same time, for each latent class g and PEV technology k, the implicit subsidy per company car is equal to the product of the probability that k is chosen with the difference between the optimal addition to employee's taxable income and the one considered in 2014. When lower than optimal tax rates are levied on all PEV alternatives (as was the case in 2014 in the Netherlands), the total amount implicitly subsidised per class will be reflected in the sum of the relevant amounts per alternative. The (class membership probability) weighted average of the subsidised amounts per class yields the total amount of annual subsidy implied by the applicable company car tax rates:

$$D_n^A = \sum_{g=1}^{G} p_n^g \sum_{k=1}^{3} P_{nk}^g [(t_{\text{ICE}} - t_k) LP_{nk} - M_{nk} (1-\tau)^{-1}], \tag{4.4}$$

where P_{nk}^g is the probability that driver n chooses alternative k conditional on membership in class g; t_{ICE} is the (optimal) tax rate applicable to conventional (ICE-propelled) cars; t_k is the tax rate applicable in 2014; LP_{nk} and M_{nk} denote the list price of alternative k and driver's own contribution in its operating costs respectively, and τ is the marginal income tax rate. M_{nk} is zero for ICE-propelled cars and τ is set to its most common value in the Netherlands, i.e. 42%. For benchmark B, the implicit annual subsidy provided by the 2014 tax scheme takes the following form:

$$D_n^B = \sum_{g=1}^{G} p_n^g \sum_{k=1}^{3} P_{nk}^g [t_{\text{ICE}} (LP_{nk} - S_k) - t_k LP_{nk} - M_{nk} (1-\tau)^{-1}], \tag{4.5}$$

where S_k is a tax-free allowance for PEVs, reflecting these external benefits. This tax-free allowance is independent of LP_k, but varies with technology k, as different PEV technologies may have different external benefits.

Welfare losses from 2014 company PEV tax rates

The social benefits induced by current company car tax rates can be estimated by the compensating variation, i.e. the increase in drivers' income which would be required to keep them at their initial level of utility after the increase of the tax rates to their optimal levels. In the context of latent class models, the compensating variation (CV) can be computed according to the following formula (Boxall and Adamowicz, 2002; Hanemann, 1982):

$$CV_n = \sum_{g=1}^{G} \frac{p_n^g}{\beta^g} [\ln(\sum_{j=1}^{J} e^{\beta^g (M_{nj}^0 - \boldsymbol{\omega}'^g \mathbf{x}_{nj}^0)}) - \ln(\sum_{j=1}^{J} e^{\beta^g (M_{nj}^1 - \boldsymbol{\omega}'^g \mathbf{x}_{nj}^1)})], \tag{4.6}$$

where superscript 0 refers to the situation where company car tax rates are set at their optimal level, and superscript 1 to the applicable rates in 2014. The welfare losses per company car can then be computed as the mean value of the difference between CV_n and D_n across company car drivers.

Welfare improvements from marginal increases in 2014 company PEV tax rates

As drastic changes to company car taxation may not always be feasible in the short-run, we also estimate the welfare improvements that can be achieved by marginal upward adjustments of company PEV tax rates from their 2014 levels. A marginal increase in the tax rate of a PEV alternative of type q (with $q \in \mathbf{K}$={PHEV, FBEV, SBEV}) will yield a reduction in consumer surplus equal to:

$$\frac{\partial CS_n}{\partial t_q} = \sum_{g=1}^{G} p_n^g \omega_t^g P_{nq}^g , \tag{4.7}$$

where t_q is the tax rate for PEV alternative q, and P_q^g is the probability of choice of q conditional on membership in latent class g.[66]

At the same time, when the positive externalities of PEVs are considered to be fully reflected in exemptions from registration and road taxes, this marginal increase of the tax rate of q will reduce the implicitly subsidised amount by:

$$\frac{\partial D_n^A}{\partial t_q} = -\sum_{g=1}^{G} p_n^g P_{nq}^g \left\{ LP_{nq} + \beta^g \omega_t^g \sum_{k=1}^{3} [((t_{\text{ICE}} - t_k) LP_{nk} - M_{nk}(1-\tau)^{-1})(1-P_{nk}^g)^y (-P_{nk}^g)^{(1-y)}] \right\}, \tag{4.8}$$

where y is a binary variable taking the value of 1 if k=q, and 0 otherwise.[67] The change in net welfare implied by a marginal change in the tax rate of alternative q will be equal to the change in consumer surplus (Equation (4.7)) net of the change in the implicit subsidy (Equation (4.8)), i.e.:

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[66] We note here that:

$$\partial[\ln(\sum_{j=1}^{J} e^{\beta^g (M_{nj} - \boldsymbol{\omega}'^g \mathbf{x}_{nj})})] / \partial t_q = -\beta^g \omega_t^g e^{\beta^g (M_{nq} - \boldsymbol{\omega}'^g \mathbf{x}_{nq})} / \sum_{j=1}^{J} e^{\beta^g (M_{nj} - \boldsymbol{\omega}'^g \mathbf{x}_{nj})} = -\beta^g \omega_t^g P_{nq}^g .$$

[67] Note that for k=q:

$$\partial[P_{nk}^g (t_{\text{ICE}} - t_k) LP_{nk}] / \partial t_q = [(t_q - t_{\text{ICE}}) LP_{nq} - M_{nk}(1-\tau)^{-1}] \beta^g \omega_t^g P_{nq}^g (1 - P_{nq}^g) - LP_{nq} P_{nq}^g ,$$

and for $k \neq q$: $\partial[P_{nk}^g (t_{\text{ICE}} - t_k) LP_{nk}] / \partial t_q = [(t_{\text{ICE}} - t_k) LP_{nk} - M_{nk}(1-\tau)^{-1}] \beta^g \omega_t^g P_{nk}^g P_{nq}^g .$

$$\frac{\partial W_n^A}{\partial t_q}=\sum_{g=1}^{G} p_n^g P_{nq}^g \left\{ LP_{nq} + \omega_t^g \left\{ 1+\beta^g \sum_{k=1}^{3} [((t_{\mathrm{ICE}}-t_k) LP_{nk} - M_{nk}(1-\tau)^{-1})(1-P_{nk}^g)^y (-P_{nk}^g)^{(1-y)}] \right\} \right\}. \qquad (4.9)$$

Likewise, when PEVs are considered to provide additional future external benefits, S_k, to the ones covered by exemptions from registration and road taxes, the equivalents of Equations (4.8) and (4.9) are given below:

$$\frac{\partial D_n^B}{\partial t_q}=-\sum_{g=1}^{G} p_n^g P_{nq}^g \left\{ LP_{nq} + \beta^g \omega_t^g \sum_{k=1}^{3} [(t_{\mathrm{ICE}}(LP_{nk}-S_k) - t_k LP_{nk}) - M_{nk}(1-\tau)^{-1})(1-P_{nk}^g)^y (-P_{nk}^g)^{(1-y)}] \right\}, \qquad (4.10)$$

$$\frac{\partial W_n^B}{\partial t_q}=\sum_{g=1}^{G} p_n^g P_{nq}^g \left\{ LP_{nq} + \omega_t^g \left\{ 1+\beta^g \sum_{k=1}^{3} [(t_{\mathrm{ICE}}(LP_{nk}-S_k) - t_k LP_{nk}) - M_{nk}(1-\tau)^{-1})(1-P_{nk}^g)^y (-P_{nk}^g)^{(1-y)}] \right\} \right\}. \qquad (4.11)$$

4.4. Empirical results

Table 4.3 presents the estimation results of the panel latent class model (PLCM). For comparison purposes, we also show the results of a multinomial logit (MNL) model. All models were coded and estimated using PythonBiogeme 2.3 (Bierlaire, 2003, 2009). We tested PLCMs with 2, 3, 4 and 5 latent classes. The model with 3 latent classes resulted in the lowest value of SIC and in intuitively appealing estimates and is, hence, our preferred specification. PLCM clearly outperforms MNL in terms of statistical fit. Its principal merit, however, is that it provides insights into preference heterogeneity and links it to heterogeneity in individual characteristics. Before discussing the estimation results, it is worth noting that all respondents choosing the same technology in all choice scenarios were excluded from the econometric analysis.[68] The behaviour of these respondents has, thus, been interpreted as an expression of decision heuristics, arising, for instance, due to the complexity of the choice task (Sælensminde, 2006).[69] This interpretation renders respondents' choices inconsistent with the assumptions underlying the use of compensatory models.[70]

[68] In our data, 77 individuals (9.1%) chose the ICE car and 12 respondents (1.4%) the PHEV in all scenarios. When these respondents are included in the econometric analysis, a class of 13-17% of the sample is identified by the latent class model. All estimated parameters of that class are statistically insignificant. Comparing MNL models estimated on the full set of valid responses (845 individuals) and the subset of responses which exclude respondents choosing the same technology in all choice scenarios (756 individuals), we observe that the differences in WTP estimates between the two samples are not statistically significant, with the exception of the estimates of alternative specific constants.

[69] This interpretation is supported by our data. About two-thirds of these respondents reported that they considered only one attribute in the choice scenarios. The share of respondents reporting that they did so in the sample finally used in the econometric analysis is notably lower (about 9%).

[70] However, it is also possible that this behaviour is consonant with random utility theory (RUT). That would be true if differences in attribute levels between the technology always chosen by the respondent and the

4.4.1. Random Utility model results

The random utility model is estimated in WTP space. The monetary attribute used to derive WTP estimates (*M*) is *employee's annual net contribution* to company car's costs. This attribute was selected because it reflects a payment that has to be fully incurred by the company car driver, in contrast to other monetary attributes (list price of the car and addition to driver's taxable income) where the final costs incurred depend on driver's annual income. The alternative specific WTP estimates presented in Table 4.3 reveal that conventional technologies are generally preferred to PEVs, closely followed by their nearest alternative in terms of performance and refuelling behaviour, plug-in hybrids. In sharp contrast, full electric vehicles fall far behind plug-in hybrids. A closer look at the WTP estimates, however, manifests substantial heterogeneity in preferences among classes and reveals where the class labels stem from.

The first class draws on the preferences of almost 27% of the sample and comprises a group of *potential early adopters* of PEV technologies. Membership in this group reveals one's indifference between conventional cars and plug-in hybrids and relatively low utility losses suffered from the adoption of full-electric vehicles. The second class corresponds to about 30% of the sample and encompasses a group of *conventionalists*. These are drivers who have a strong preference for conventional technologies and attach high values to the driving range of the car. The third class is the largest (around 43% of the sample) and reflects the preferences of *the hesitant majority* of company car drivers. This class has only a marginal preference for conventional cars over PHEVs, but derives considerable disutility from full electric cars. Later in this subsection, we elaborate on the preferences of *potential early adopters* as they are the most interesting group for the welfare analysis that follows. WTP estimates of the other two classes can be interpreted analogously.

Valuation of monetary attributes

Drivers appear very sensitive to changes in company car tax rates, thereby confirming that tax incentives are a powerful tool for the stimulation of the demand for PEVs in the hands of policy makers. Differences in the sensitivity to changes in tax rates among classes are generally rather small. It seems that only *potential early adopters*

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other alternatives were simply not adequately large to make the respondent opt for another alternative (see e.g. the experimental work by Cairns and van der Pol, 2004). In that case, the demand of those respondents for all alternatives would be fully inelastic within the range of attribute levels examined. This implies that changes in PEV taxation would yield no welfare effects for them. The results of the welfare analysis under this alternative interpretation of non-trading behaviour are available from the authors.

exhibit a slightly lower sensitivity, with a point estimate equivalent to around 75% of the one of the other two classes. On the contrary, the three classes show substantial heterogeneity in their sensitivity to company car's list price. *Conventionalists* are consistently the most responsive class to changes in tax rates and list prices. This might be a reflection of differences in the *personal* income between members of this class and members of other classes. However, we cannot test the validity of this hypothesis as data on respondents' income is only available at the *household* level.

Table 4.3: Estimation results of the MNL and Latent Class model

	Multinomial Logit		Latent Class Model					
			Potential early adopters		Conventionalists		Hesitant majority	
Random Utility Model								
	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error
Employee's annual net contribution (1000 €)	-0.433***	0.012	-0.507***	0.048	-0.277***	0.048	-0.697***	0.050
	WTP estimate	std. error	WTP estimate	std. error	WTP estimate	std. error	WTP estimate	std. error
Components of addition to taxable income								
Company car tax rate (%)	-0.181***	0.008	-0.147***	0.017	-0.202***	0.046	-0.194***	0.016
List price (1000 €)	-0.062***	0.004	-0.056***	0.010	-0.186***	0.039	-0.031***	0.007
Alternative specific constants								
Plug-in hybrid [PHEV]	-0.598***	0.141	0.618	0.405	-1.714**	0.819	-0.284	0.248
Full electric: fixed battery [FBEV]	-6.047***	0.492	-3.322***	0.874	-11.442***	2.670	-7.025***	0.957
Full electric: swappable battery [SBEV]	-5.631***	0.411	-2.891***	0.807	-8.667***	2.260	-6.739***	0.859
Driving range (100 km)								
Conventional & PHEV	0.259***	0.031	-0.010	0.073	0.789***	0.193	0.182***	0.056
FBEV & SBEV	1.072***	0.059	0.856***	0.109	1.479***	0.407	1.205***	0.148
Detour time (10 min/refuelling action)	-0.567***	0.073	-0.396***	0.110	-1.172**	0.452	-0.666***	0.132
Charging time at station (10 min/charging action) [a]	-0.279**	0.108	-0.199**	0.096	-0.199**	0.096	-0.199**	0.096
Charging time at home/work (100 min/charging action)	-0.113***	0.040	-0.031	0.053	-0.378	0.236	-0.148**	0.065
Class Membership Model								
			estimate	std. error	estimate	std. error		
Constant	-	-	-0.988***	0.286	-0.130	0.224		
Individual characteristic								
Age < 35 years	-	-	-0.367	0.321	-0.592*	0.313		
Annual gross household income ≥ €103,800	-	-	-0.672*	0.391	-0.064	0.303		
Current car is hybrid	-	-	-0.009	0.372	-1.250**	0.576	*Reference Class*	
Annual distance with next car < 20,000 km	-	-	1.049**	0.419	0.556	0.469		
Next car: small / medium-sized	-	-	0.789***	0.277	0.104	0.276		
At least 1 acquaintance drives a plug-in hybrid	-	-	0.429	0.283	-0.682**	0.336		
Class size	-		*0.265*		*0.304*		*0.431*	
Parameters	11		45					
Observations (Individuals)	6048		6048 (756)					
Log-likelihood at convergence	-5609.0		-5121.7					
McFadden's rho-squared	0.331		0.389					
Adjusted McFadden's rho-squared	0.330		0.384					
Schwarz Information Criterion (SIC)	11,313.8		10,541.7					

Note: WTP estimates are annual amounts in €1000. Standard errors are heteroskedasticity-robust. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.
[a] The WTP for charging time at the station is constrained to be equal among latent classes.

Valuation of driving range and refuelling time attributes

The findings of the meta-analysis of Chapter 2 revealed that utility is non-linear in driving range. We, thus, allow the WTP for driving range to differ between full electric vehicles and their longer range counterparts, i.e. plug-in hybrids and cars propelled only by internal combustion engines, as the levels employed for the two sets of technologies span different ranges.[71] Station refuelling time is the only attribute whose WTP is restricted to be fixed among classes.[72] The WTP estimate for this attribute amounts to approximately €20/min.

A closer look at the WTP estimates of the three time attributes reveals that a consistent ranking of their importance is made by drivers. The WTP for a 1-minute reduction in extra detour time is higher than the WTP for an equal decrease of station fast-charging time, which in turn considerably exceeds the WTP for the same reduction in home/workplace charging time. This is an intuitive finding, reflecting the fact that the opportunity costs of detouring, refuelling at the station and charging at home/workplace differ substantially from each other, as the range of other activities that drivers can perform while engaging in these refuelling-related actions varies widely. While detouring, the main activity that can be performed is driving, whereas while charging at the station, other activities like working, enjoying a meal or engaging in some form of entertainment can be undertaken. The opportunity costs of charging at home or workplace approach zero as drivers can carry out the activities they would anyway do while the car is being charged.

Potential early adopters

Potential early adopters consider PHEVs equivalent to conventional cars and incur moderate losses from the adoption of full electric cars. While they attach no value to increases in the range of plug-in hybrids and conventional cars, they achieve important gains from increases in the driving range of full electric vehicles. Their annual WTP for it is around €9/km.[73] *Potential early adopters* derive no utility from increases in home-charging time. They are, however, sensitive to changes in the extra detour time required to reach a fast-charging facility or a battery-swapping station. Their willingness to pay for a 1-minute reduction in detour time is about €40 (note that the net contribution attribute is in

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[71] We also considered a logarithmic transformation of driving range (see also Chapter 3), but the piecewise linear form presented here resulted in a significantly better model fit. For similar reasons, we also dropped the idea of using categorical variables for each level of driving range. The piecewise linear formulation has also been identified to perform better in other related studies (see e.g. Jensen et al., 2013).

[72] A more flexible specification, where the WTP for station refuelling time is allowed to be different among classes, does not reveal statistically significant differences between classes. We, thus, prefer the more parsimonious specification presented here.

[73] Assuming a 4-year duration of the use of the company car, the total willingness to pay for a 1 km increase in driving range would be about 34 Euros (2012 prices). This is equivalent to about 55 US$/mile (in 2005 PPPs), which is well in the range of values presented in Chapter 2 (see e.g. Table 2.2).

1000 Euros). These findings highlight that policies directed to the expansion of fast-refuelling facilities can be an effective stimulus for the early adoption of full electric cars, which can partially substitute tax reductions aimed at triggering their demand. Such policies might further lead to savings of public spending for the stimulation of the adoption of electric vehicles, as the financing of this expansion might be delivered via public–private partnerships or private initiatives.

4.4.2. Class membership model results

The class membership model (CMM) explains individuals' class membership by their socio-demographic background and car ownership and use patterns. The presented model is the outcome of extensive search among model specifications.[74] In regard with socio-demographic characteristics, only income and age are found to have an effect on these probabilities, significant only at the 10% level. In particular, drivers with relatively high gross annual household income, which is defined as income above €103,800, are less likely to belong to the group of potential early adopters than drivers with lower income. This is in contrast with studies on the private car market suggesting that high-income households are more likely to become early adopters of innovative environmentally friendlier technologies (e.g. Qian and Soopramanien, 2011), but concurs with previous empirical findings rejecting this hypothesis (e.g. Bunch et al., 1993; Hidrue et al., 2011).

Similar to other studies in the field (e.g. Ewing and Sarigöllü, 1998; Hidrue et al., 2011), our estimates show that younger drivers have a significantly lower probability to be *conventionalists*. In particular, we find that drivers younger than 35 years old are less likely to belong to this group than older individuals. We do not find significant differences in the probabilities to belong to one of the classes between the remainder age categories.

A relatively underexplored issue in SP studies on alternative fuel vehicle choice is the impact of current car ownership and use on stated choices. As already noted, we sampled an adequate number of individuals currently driving in a company HEV, in order to be able to explore differences in preferences between them and drivers of conventional cars. Our findings show that these drivers are indeed much less likely to be

[74] For example, we tested the performance of other socio-demographic variables, such as gender, education and household size, residence location characteristics (population density of the municipality of residence), car ownership characteristics (number of cars owned by the household), and car use patterns (e.g. availability of a fixed working location, commuting distance, availability of parking spot at home or workplace, frequency of travelling abroad, frequency of using a tow-hitch) in the estimation of the CMM. However, none of these variables led to significant improvements in model fit or had a statistically meaningful effect on the class membership probabilities.

conventionalists. Even though this result refers to people *currently driving* in an HEV and not individuals who report that their *next car* will probably be an HEV, it is in line with other studies revealing that drivers interested in HEVs are unlikely to fall within classes oriented to conventional vehicles (e.g. Hidrue et al., 2011).

Ceteris paribus, it is expected that drivers who travel relatively short distances would be more likely to adopt electric vehicles, as they can more easily address driving range limitations. Our findings support this hypothesis, as individuals planning to drive less than 20,000 kilometres per year in their next company car are significantly more likely to belong to the group of *potential early adopters* than drivers who plan to drive more than this. This finding is in agreement with Koetse and Hoen (2014), who show in the framework of an MNL model with interaction effects that preferences of Dutch company car drivers for driving range, net annual contribution and different propulsion technologies depend on the annual distance travelled.

In agreement with Hidrue et al. (2011), we find that individuals who indicate that their next car will most likely belong to the small or medium class have a significantly higher probability to belong to the class of *potential early adopters* than drivers intending to adopt larger company cars. Several reasons could explain this finding. First, it might be a reflection of consumer perceptions of PEVs as smaller cars. This would have been the signal that well-informed consumers would have received from the Dutch car market at the time of the survey, as almost all PEV models available at that time belonged to these two categories. Another reason could be that there is some correlation between the desired body type of the car and the driving range needs of the driver. Even though we control for the effect of small annual distances driven by the company car on the class membership probabilities, that variable might not be comprehensively capturing the impact of driving range needs on those probabilities.

There is a growing literature investigating the influence of social networks and word of mouth on the adoption of PEVs (see e.g. Axsen et al., 2013; Urban et al., 1996). Our analysis provides support to the findings of this literature and reveals a positive social influence for plug-in hybrids. In particular, we find that individuals who have at least one acquaintance (e.g. friend, neighbour or colleague) who drives in a plug-in hybrid are less likely to be *conventionalists* than people who are not aware of anyone driving in such a vehicle in their close social environment.[75] This is an encouraging finding for the future demand for plug-in hybrids, as it shows that the experiences of first adopters are rather positive, inducing their colleagues and acquaintances to also take a more positive view of this technology. In our sample, around 81% does not have any acquaintances driving in plug-in hybrids, whereas 14% report that they know only one person driving in them and 5% declare knowing more drivers of plug-in hybrids. We also investigated the impact of social influence in the case of full electric cars, but probably due to the small number of respondents who had an acquaintance driving in a full electric car (7.5% of the sample) we did not find any significant effect of this variable on class membership probabilities.

4.5. Welfare effects of the taxation of electric company cars in 2014

The estimates confirm that drivers are highly sensitive to adjustments in company PEV tax rates and, therefore, the latter can be effective in triggering demand for PEVs. However, this high sensitivity also implies that these adjustments may have substantial social welfare effects. These will be estimated on the basis of the analytical results provided in subsection 4.3.2. For the welfare analysis to be relevant, however, we first need to ensure that when the model is simulated on the basis of the 2014 attribute values, the overall choice probabilities of PEVs approximately equal the ones observed in the 2014 company car market. To do so, we work as follows.

We first simulate the PLCM using the point estimates of the parameters and WTPs presented in Table 4.3 and the attribute values best resembling the characteristics of the car models available in the market (see Section 4A.1 of Appendix 4.A for details). As the simulated model predicts higher market shares for PEVs than the ones observed in the 2014 company car market (see Section 4A.2 of Appendix 4.A for a discussion of the 2014 market shares),[76] we recalibrate the alternative specific constants for each class, so that the predicted shares of the model approximately equal the observed ones. The recalibration of constants is performed using an iterative process (Train, 2009, p. 33). In this process, special care is taken that the adjustments of alternative specific constants are uniform across classes, i.e. that constants are reduced by the same amount in each class. Table 4.4

[75] It could be argued that a driver's awareness of acquaintances driving in PEVs also captures some implicit prior interest in PEV technologies. Unfortunately, there is no way that we can differentiate between the effect of such prior interest and the one of social influence in our data.

[76] Note that this finding is not unexpected, as respondents were instructed to assume that the four alternatives presented to them were identical, with the exception of the attributes used in the experiment. In reality, however, only a limited number of PEV models were available in the market in 2014, and most of them did not have exact ICE counterparts.

presents the estimated means of choice probabilities for ICE-propelled cars, plug-in hybrids and full electric vehicles (combined fixed-battery and swappable-battery ones). The class-size weighted averages are approximately equal to the ones observed in the company car market.

Table 4.4: Estimated means of choice probabilities for alternative fuel technologies.

Latent class	ICE-propelled cars	PHEVs	FEVs
Potential early adopters	0.881	0.078	0.040
Conventionalists	0.975	0.024	0.001
Hesitant majority	0.927	0.072	0.001
Class-size weighted average	0.928	0.059	0.012

Note: FEVs include both fixed- and swappable-battery electric cars.

The welfare analysis is based on the recalibrated model and the attribute values presented in Table 4A.1 of Appendix 4.A. As noted earlier, here we consider that none of the respondents choosing the same vehicle technology in all scenarios behaves according to RUT.[77] Before proceeding with the presentation of the estimated welfare effects, we discuss the values considered for the parameter S_k. Inspired by the maximum discounts considered in this context in Germany, one of the few countries where this approach is employed, we set S_k equal to €10,000 for full electric cars and €6500 for plug-in hybrids. These discounts may seem rather generous, but the aim of the analysis is to uncover the welfare implications of linking company car tax rates with vehicle environmental impact, even in the scenario that their external benefits are valued very highly.

There are at least two reasons why the use of higher discounts for full electric cars than for plug-in hybrids may be justified. First, the exemption of PEVs from registration and road taxes may not reflect the higher external environmental benefits – in terms of reduced CO_2 emissions and air pollution[78] – provided by full electric cars compared to plug-in hybrids. As the type-approval CO_2 emissions of plug-in hybrids are on average about 2/3 lower than the emissions of the average new car in the Netherlands – 110 g/km in 2013 (Stichting BOVAG-RAI Mobiliteit, 2014) – the discount for them amounts to about 2/3 of the discount considered for full electric cars. Second, the adoption of full

[77] The main findings and conclusions of the chapter are not sensitive to this assumption.

[78] Electricity generation is mainly based on natural gas in the Netherlands and, thus, driving on electricity can result in lower emissions than driving on petrol or diesel. However, the level of emissions from electricity generation also varies with the time of the day when charging occurs.

electric cars is more likely to stimulate investments in public charging and battery swapping infrastructure than the adoption of PHEVs, which can also drive on petrol or diesel. Such investments may well facilitate the further penetration of PEVs, as the necessary infrastructure will already be in place.

Estimated welfare losses from 2014 company PEV tax rates

Table 4.5 reveals that the annual welfare losses due to the linking of vehicle environmental performance with company car tax rates are not negligible. The top panel of the table shows estimates based on benchmark A, the benchmark assuming that the environmental benefits of PEVs are fully reflected in their exemption from registration and road taxes (i.e. the annual implicit subsidy is computed on the basis of Equation (4.4)). The bottom panel reveals estimates based on benchmark B, which assumes that PEVs provide additional external benefits in the future to the ones reflected in these exemptions (see Equation (4.5)). The weighted average welfare loss per company car amounts to €159/year in the first case and €70/year in the second one. As expected, welfare losses are higher for the class which is more likely to opt for PEVs, i.e. *potential early adopters*. Important losses are also incurred by the *hesitant majority*, while welfare effects for the class of *conventionalists* are much more moderate.

Considering that there are about 600,000 company cars in the Netherlands which also serve drivers' private travel needs (RAI Vereniging and BOVAG, 2013), the aforementioned amounts imply that annual welfare losses of around €95 million are suffered under the first assumption, and €42 million under the second one. The estimated welfare losses also account for the lion's share of the reduction in implicit subsidies. As the tax revenues foregone by the beneficial tax treatment of PEVs would correspond to only 42-52% (income tax rates for the majority of drivers) of implicit subsidies, it is striking that in most cases welfare losses even outweigh the foregone revenues.

Estimated welfare improvements from marginal increases in 2014 company PEV tax rates

Table 4.6 presents estimates of welfare gains arising from marginal increases in the tax rate for plug-in hybrids and full electric vehicles. The top panel of the table presents estimates based on Equations (4.8) and (4.9), while the bottom one estimates computed by Equations (4.10) and (4.11). Estimates of marginal changes in consumer surplus are based on Equation (4.7). Annual welfare gains of around €35 per company car could be achieved by a 1-percentage-point increase in the tax rate for plug-in hybrids, under the assumption that the environmental benefits of PEVs are fully reflected in exemptions from registration and road taxes. When additional future external benefits are considered, annual gains are slightly lower; in the area of €28 per company car. The corresponding annual welfare gains from increases in the tax rate for full electric cars are significantly lower; ca. €4.5 and €3 per company car respectively. Welfare gains from changes in the tax rate of plug-in hybrids are principally driven by the *hesitant majority*, while *potential early adopters* are mainly responsible for gains from increases in the tax rate for full electric cars.

Table 4.5: Estimated annual welfare losses per company car from the 2014 tax scheme.

Latent class	Estimated welfare losses of the 2014 scheme			
Benchmark A: External benefits of PEVs fully reflected in exemptions from other taxes	CV	Implicit Subsidy (D^A)	Change in Welfare (W^A)	Welfare change/ Implicit Subsidy
Potential early adopters	€ 159.0	€ 412.8	-€ 253.7	61.5%
Conventionalists	€ 47.5	€ 85.9	-€ 38.5	44.8%
Hesitant majority	€ 90.3	€ 268.0	-€ 177.7	66.3%
Class-size weighted average	€ 97.1	€ 256.1	-€ 159.0	62.1%
Benchmark B: Additional future external benefits of PEVs taken into consideration	CV	Implicit Subsidy (D^B)	Change in Welfare (W^B)	Welfare change/ Implicit Subsidy
Potential early adopters	€ 137.0	€ 230.2	-€ 93.3	40.5%
Conventionalists	€ 29.5	€ 52.7	-€ 23.2	44.0%
Hesitant majority	€ 87.3	€ 172.8	-€ 85.5	49.5%
Class-size weighted average	€ 84.4	€ 154.4	-€ 70.0	45.4%

Note: Additional external benefits in the future justify deductions of €10,000 from the list prices of full electric cars and €6500 from the list prices of plug-in hybrids.

In light of the size of the fleet of company cars in the Netherlands, the annual welfare gains from a 1-percentage-point increase in the company car tax rate for plug-in hybrids would amount to about €21 million (€17 million for benchmark B). A 1-percentage-point increase in the company car tax rate for full electric cars would yield a welfare gain of about €2.7 million (€1.8 million for benchmark B). Yet, in all cases the potential average welfare gains exceed the marginal tax revenues raised by the increase in company PEV tax rates.

Discussion

There are several reasons to believe that our estimates are lower bound. First, we make the very conservative assumption that the 20% company car tax rate is optimal whereas previous studies indicate that the optimal tax rate is substantially higher and about 35% (Gutiérrez-i-Puigarnau and van Ommeren, 2011). Consequently, there is much more overconsumption in the company car market in terms of car expenditure and usage than assumed here. Second, we assume that exemptions of PEVs from registration and road taxes are justified, due the environmental cost savings that PEVs can offer in comparison to their conventional counterparts. If these exemptions are more generous than assumed here, welfare losses from the tax incentives provided for PEVs would be higher.

Table 4.6: Estimated annual welfare gains from marginal increases of PHEV and FEV tax rates per company car.

Latent class	Marginal change in the tax rate of PHEVs				Marginal change in the tax rate of FEVs			
Benchmark A: External benefits of PEVs fully reflected in exemptions from other taxes	Change in CS	Implicit Subsidy Change (D^A)	Change in Welfare (W^A)	Welfare/ Implicit Subsidy change	Change in CS	Implicit Subsidy Change (D^A)	Change in Welfare (W^A)	Welfare/ Implicit Subsidy change
Potential early adopters	-€ 11.5	-€ 52.4	€ 40.9	78.1%	-€ 5.9	-€ 20.2	€ 14.3	70.8%
Conventionalists	-€ 4.9	-€ 15.2	€ 10.3	67.9%	-€ 0.2	-€ 0.4	€ 0.2	52.9%
Hesitant majority	-€ 13.9	-€ 63.2	€ 49.3	78.0%	-€ 0.2	-€ 0.7	€ 0.5	72.7%
Class-size weighted average	-€ 10.6	-€ 45.9	€ 35.3	77.0%	-€ 1.8	-€ 6.4	€ 4.5	71.3%
Benchmark B: Additional future external benefits of PEVs taken into consideration	Change in CS	Implicit Subsidy Change (D^B)	Change in Welfare (W^B)	Welfare/ Implicit Subsidy change	Change in CS	Implicit Subsidy Change (D^B)	Change in Welfare (W^B)	Welfare/ Implicit Subsidy change
Potential early adopters	-€ 11.5	-€ 46.2	€ 34.7	75.1%	-€ 5.9	-€ 14.9	€ 9.0	60.4%
Conventionalists	-€ 4.9	-€ 13.5	€ 8.6	63.8%	-€ 0.2	-€ 0.3	€ 0.1	36.8%
Hesitant majority	-€ 13.9	-€ 51.9	€ 38.0	73.2%	-€ 0.2	-€ 0.5	€ 0.3	57.4%
Class-size weighted average	-€ 10.6	-€ 38.9	€ 28.3	72.8%	-€ 1.8	-€ 4.7	€ 2.9	61.1%

Note: Additional external benefits in the future justify deductions of €10,000 from the list prices of full electric cars and €6500 from the list prices of plug-in hybrids.

Third, we ignore the distortionary supply effect which might arise from the eventual sale of company PEVs at the second-hand market. The destiny of PEVs in the second-hand car market is strongly dependent on the existence of the necessary charging infrastructure. Hence, it is likely that the majority of company PEVs will be sold in the domestic market, as the Netherlands provides a wider coverage of charging facilities and has more convenient geographic characteristics for the use of PEVs (shorter average distances and flatter hillslopes) than other European countries. Provided that consumers have strong preferences for better performance, in terms of e.g. longer driving range, than the one provided by most currently available PEVs (see e.g. Hidrue et al., 2011; Hoen and Koetse, 2014), there may well be higher welfare losses in the long-run than the ones estimated here. Fourth, we ignore possible welfare costs of public funds.

4.6. Conclusions

This chapter develops an approach to estimate the immediate welfare effects of policies which use reduced company car tax rates to promote the adoption of low emission vehicles. The approach is built around new stated preference data from Dutch company car drivers and a panel latent class model which allows for preference heterogeneity. The approach is applied to estimate the welfare losses from the beneficial tax treatment of company plug-in electric vehicles (PEVs) in the Netherlands in 2014 in light of two alternative benchmark assumptions. First, we assume that the environmental benefits of PEVs are fully compensated by their exemption from registration and road taxes (which applies to PEVs on top of company car tax advantages). We then consider that there might be additional external benefits in the future from the adoption of PEVs in the company car market (e.g. in terms of positive network externalities, technological innovation and accompanying future environmental benefits) that are not reflected in these exemptions. These additional benefits would justify generous reductions in the list prices of PEVs. We also estimate the welfare gains from marginal increases in the 2014 company PEV tax rates, under both aforementioned assumptions.

We find that potential early adopters of company PEVs, comprising almost one quarter of our sample, will primarily opt for plug-in hybrid and extended-range EVs. They are more likely to be found among company car drivers travelling relatively short annual distances but less likely to be part of high-income households. At the early stage of adoption, governmental intervention through reductions in company car tax rates emerges as a very effective strategy for the stimulation of PEV demand. However, our estimates reveal that the provided tax advantages also lead to important welfare losses, which are even higher than the foregone tax revenues. Depending on the assumption made for the magnitude of external benefits provided by PEVs, these annual welfare losses are estimated to be between €42 million and €95 million.

We further show that the welfare gains from marginal increases in the company car tax rates of plug-in hybrids can be substantial (in the area of €17-21 million per year). The welfare effects of marginal increases in the tax rates of full electric vehicles are less acute. Our findings generally provide little support for the stimulation of the adoption of company PEVs *through reduced company car tax rates*. Policies based on reductions of PEV list prices, *solely determined on the basis of PEVs' external benefits* are far less distortionary and appear therefore to be more desirable from a welfare perspective.

At the stage of early adoption of new technologies, the scarcity of market data highlights the importance of using alternative data sources to assess the welfare implications of policy changes. In this chapter, we show how stated preference data can be effectively used to evaluate the welfare effects of changes in the taxation of innovative and environmentally friendlier company cars. Similar approaches can be used, for example, to assess the welfare effects of subsidies for innovative vehicle technologies in the private car market (e.g. hydrogen vehicles), or subsidies for using more environmentally friendly modes to commute to work (e.g. subsidies for commuting by public transport).

Appendix 4.A. Supplementary material for the welfare analysis

4A.1. Attribute levels used in the baseline scenario

Table 4A.1 shows the attribute levels used in the baseline scenario for PLCM simulation. The selected attribute levels closely resemble the situation of the company car market in 2014. Even though the table is mostly self-explaining, we provide further details with respect to two monetary attributes. First, we note that the list price of conventional cars is individual-specific and is customised on drivers' anticipated price range of their next company car. Second, the net contribution of employees is zero in the case of conventional vehicles. Their gross contribution for PEVs is computed as the difference between the annual lease price of a PEV and the one of its conventional counterpart.[79] The expected net contribution of the employee for the company car is then calculated by subtracting the applicable tax from gross contribution. To this end, we use the income tax rate level usually applicable in the Netherlands, i.e. 42%.

Table 4A.1: Attribute levels used in the baseline scenario of the simulation of the PLCM.

Attributes	Attribute levels			
Propulsion system and fuel type	ICE or Hybrid	Plug-in hybrid	Electric with fixed battery	Electric with swappable battery
List Price (€)	Mean value of reported price range for next car	Price of most popular model per segment [a]	Price of most popular model per segment [a]	Price of most popular model per segment [a b]
Company car tax rate (%)	20	7	4	4
Employee's annual net contribution (€)	0	(Lease price of PHEV - Lease price of ICE car) × (1-Income tax rate) [c]	(Lease price of FBEV - Lease price of ICE car) × (1-Income tax rate) [c]	(Lease price of SBEV - Lease price of ICE car) × (1-Income tax rate) [c]
Driving range (kilometres)	900	Driving range of most popular model per segment [a]	Driving range of most popular model per segment [a]	Driving range of most popular model per segment [a]
Refuel time at station (minutes)	5	5	30	5
Charging time at home or work (hours)	N.A.	4	8	8
Extra detour time (minutes)	0	0	10	30

Note: ICE encompasses vehicles propelled solely by an internal combustion engine.
[a] Indicative list prices and driving ranges of the most popular models per segment are provided in Table 4A.2.
[b] Where prices of electric cars excluding battery costs were publicly available (e.g. Renault models and Nissan Leaf), they were used as proxies for the prices of SBEVs. For the segments that such information was unavailable, we presumed (based on the comparison of models for which we had information about the price of the model with and without the battery) that list prices of SBEVs are equal to 80% of the prices of the corresponding FBEVs.
[c] Lease prices concern contracts of 4-year duration, for maximum annual distance of 35,000 km, and inclusive of fuel costs. Lease prices were obtained from www.directlease.nl, except for the price of Renault Zoe which was extracted from http://www.leaseprijsonline.nl. Lease prices for the two versions of Renault Kangoo Z.E. were imputed by multiplying the ratios of List Price (Renault Kangoo Z.E.)/List Price (Renault Zoe) by the lease price of Renault Zoe.

[79] When the lease price of a PEV is lower than the one of its conventional counterpart, this difference is set equal to zero. The underlying assumption here is that the driver is required to contribute to company car's operating costs only if these exceed the ones of the representative conventional alternative of the segment.

Table 4A.2: Overview of PEV models available in 2014 in the Netherlands

	Body type	List price (€)	Driving range (km)	Segment for which it is used in the welfare analysis
Plug-in hybrids and EREVs				
Mitsubishi Outlander PHEV	SUV	44,000	800	*SUV, MPV, Van*
Volvo V60 PHEV	Station wagon	64,000	900	*Large, Luxury*
BMW i8	Full-size luxury car	149,000	900	*Sports*
Opel Ampera EREV	Compact car	48,500	900	-
Toyota Prius PHEV	Compact car	39,500	900	*Medium-sized*
BMW i3 EREV	Subcompact car	40,000	300	*Small*
Full electric cars				
Renault Kangoo Z.E.	Small van	29,500	130	*Van*
Renault Kangoo Maxi Z.E. 5	MPV	33,000	130	*MPV, SUV*
Tesla Model S [a]	Full-size luxury car	69,000	300	*Large, Luxury, Sports*
Ford Focus EV	Compact car	40,000	max. 162	-
Kia Soul EV	Compact car	33,000	max. 212	-
Nissan Leaf	Compact car	30,000	150	*Medium-sized*
VW e-Golf	Compact car	36,000	130-190	-
BMW i3	Subcompact car	35,500	130-160	-
Renault Zoe	Subcompact car	26,000	150	*Small*
Smart 4-2 Coupe EV	Subcompact car	24,000	max. 145	-
VW e-Up	Subcompact car	26,000	80-160	-

Note: EREV denotes an extended range electric vehicle. The table shows only models emitting less than 50 gCO_2/km, which sold at least 10 cars in 2014. Prices concern the most economical version of the model, and are rounded to the nearest €500. Prices were accessed in January 2014, except for the ones of BMW i8, Kia Soul EV, VW e-Golf and VW e-Up, because the models became available later in 2014. They were extracted from www.directlease.nl and from car manufacturers' original websites.
[a] The cited price concerns the version equipped with a 60 kWh battery.

4A.2. Approximation of PEV shares in the 2014 company car market

The exact market shares of different PEV types in the company car market are not known at the time of this study. We use information from various official sources to approximate them. RVO (2015) suggests that there were 2664 full electric cars and 12,245 plug-in hybrids registered in the Dutch market in 2014, out of a total of about 390,400 new car registrations.

Data from RAI Vereniging and BOVAG (2013) for the period 2007-2012 reveal that on average around 1/3 of new car registrations per year concern cars to which company car tax rates are applicable. Around 63% of the PEVs registered in the market in 2012 fall under this category. Assuming that the 2014 proportions will not be very different from previous periods, we infer that PEVs amount to around 9400 company cars, i.e. about 7.2% of the ca. 130,000 registrations (ca. 1/3 of 390,400 registrations) for which company car tax rates are applicable. We further assume that the share of company plug-in hybrids in the total number of company PEVs is approximately the same with their share in total PEV registrations, i.e. ca. 82.1%. Thus, plug-in hybrids are estimated to account for ca. 5.9% of company car registrations, while full electric cars to around 1.3%. Table 4A.3 summarises the PEV shares in the 2014 company car market.

Table 4A.3: Estimated shares of PEVs in the 2014 company car market.

All cars					Company cars (estimated)		
PHEVs	PHEVs (%)	FEVs	FEVs (%)	Total	PHEVs (%)	FEVs (%)	Total
12,245	3.1%	2664	0.7%	390,402	5.9%	1.3%	130,000

Chapter 5

The impact of CO_2 emission based tax notches on consumer demand and manufacturer choices

5.1. Introduction[*]

It is not difficult for car manufacturers to manipulate type-approval emissions. The 2015 Volkswagen emissions scandal (EPA, 2015) revealed that they might even deploy illegal practices to make their models comply with regulatory standards. However, manufacturers rarely need to resort to illegal practices to manipulate emissions. Current emission testing procedures often allow them enough flexibility to fine-tune specific car models so that their type-approval emissions do not exceed predetermined cut-off points. The New European Driving Cycle (NEDC), for example, allows the use of special tyres and the manual control of brakes during the testing procedure (Mock et al., 2014).[80] This has resulted in an increasing gap between type-approval and real-world emissions which can sometimes be dramatic; in fact, it is not rare for the level of real-world emissions to be 50% higher or even multi-fold the level of type-approval ones. This increasing divergence has costly environmental and health implications and should be of major concern for policymakers.

The divergence between type-approval and real-world emissions becomes all the more important as environmental policy is increasingly based on type-approval emissions to stimulate demand for less polluting cars. Taxation of car ownership and use has seen major changes during the last decade. It has evolved from targeting heavier, more powerful and more expensive passenger cars towards targeting cars with a higher environmental burden (Klier and Linn, 2015). In doing so, many tax systems employ schedules with discontinuities, often labelled as notches (see also Kleven and Waseem, 2013; Slemrod, 2010).

Despite their alleged appeal in terms of administrative simplicity, notches lead to inefficient outcomes when the externality intended to be corrected by the tax is a continuous function of the underlying measure (Sallee and Slemrod, 2012). The external costs of an additional gram of CO_2 per kilometre travelled, for example, are invariant to the location of the vehicle in the distribution of CO_2 emissions per kilometre. For a notch set at 100 gCO_2/km, it is difficult to see why the additional external costs of CO_2 implied by a car emitting 100 gCO_2/km (vs. a car emitting 99 gCO_2/km) would be different from the ones of a car emitting 102 gCO_2/km (vs. a car emitting 101 gCO_2/km). Notches induce

[*] This chapter is based on joint work with Jos N. van Ommeren.

[80] NEDC will be replaced with new testing procedures, better reflecting the real-world emissions of tested car models, in the near future.

behavioural responses by economic agents which depend on agents' location relative to the point at which the discontinuity occurs. This chapter focuses on the Dutch car market and investigates the effects of tax notches on consumer demand and manufacturers' choices.

Notches are widely used in car taxation. In this chapter, we look into two types of taxes: the car registration and the company car tax. The Dutch system features two types of notches in both taxes, a quality-based and a quantity-based one. Both types are based on attributes determining, among others, the environmental performance of the vehicle. The quality-based notch distinguishes between diesel cars and vehicles driving on other fuel types, such as petrol or LPG.[81] Within these two categories, tax liability is determined on the basis of a notched schedule of vehicle's type-approval CO_2 emissions.[82]

We use rich car registration data covering the period from January 2010 until July 2014. We first show that there is marked bunching of car registrations on the tax-favourable side of the notches. Bunching is especially prevalent for diesel cars. For example, we observe that the percentage of diesel cars registered *exactly on* the notch in 2013 is about 40%. We then exploit the fact that these notches are changed on a regular basis and use a quasi-experimental approach to examine whether manufacturers respond strategically to these changes. We find significant differences in manufacturers' responses depending on fuel technology. Diesel cars are much more likely to just make it to the favourable side of the cut-off point than cars with petrol engines. As diesel cars are primarily popular among company car drivers, we conclude that it is primarily notches in company car taxation that induce strategic responses from car manufacturers. This becomes more disconcerting when considered along with recent evidence that the divergence between type-approval and real-world CO_2 emissions of diesel company cars in the Netherlands exceeds 50% (Tietge et al., 2015). Even though manufacturer responses can take a number of different forms, we provide evidence that they need not introduce new car model specifications to manipulate CO_2 emission cut-off points; they often just have to fine-tune *existing* car model specifications to allow them to cross to the tax-favourable side of the notch.

The rest of the chapter is organised as follows. Section 5.2 illustrates the popularity of notches in car taxation. Section 5.3 describes the data used in the study. Section 5.4

[81] This quality-based notch was removed in the beginning of 2015.

[82] Unless otherwise stated, when we henceforth refer to cars' CO_2 emissions (in grams CO_2 per kilometre) in this chapter, we consider the type-approval measurements of tailpipe CO_2 emissions of the New European Driving Cycle (NEDC) tests. These measurements are widely used in car taxation policy in many EU countries, including the Netherlands.

presents evidence of bunching of car registrations below notches, while Section 5.5 outlines our empirical strategy and interprets the results of the analysis. Section 5.6 concludes and discusses policy implications.

5.2. Distortionary tax incentives for low emission vehicles

5.2.1. Distortionary tax incentives

In Europe, car taxation has been increasingly based on vehicles' type-approval CO_2 emissions (see also ACEA, 2014; Adamou et al., 2014). One of the main driving forces of this trend has been European Union's commitment to challenging environmental goals for 2020 (see e.g. European Commission, 2010). In this framework, many European countries use some form of tax policy which is based on notches to stimulate demand for low emission vehicles. Notched tax policies are extensively used by tax authorities worldwide, probably due to their appealing simplicity and transparency. However, these virtues come at the expense of a loss in economic efficiency, especially in cases where a notched schedule is used to approximate a smooth continuous one (Sallee and Slemrod, 2012). Notched policies imply that marginal changes in the behaviour of economic agents can result in private net benefits or costs which substantially outweigh the external benefits or costs of these behavioural changes. This leads to inefficient outcomes. Put in another way, despite marginal changes in behaviour implying similar marginal changes in external costs or benefits, agents located around notches are strongly incentivised to change their behaviour in order to move to the tax-favourable side of a notch, whereas agents located away of the notch have almost no incentive to change their behaviour.

Examples of notched CO_2-based tax policies can be found in several European countries. One of them is the French feebate programme, denoted as *Bonus/Malus écologique*, which stimulates the purchase of low emission vehicles through the provision of a rebate, while discouraging the purchase of high emission vehicles through a fee (d'Haultfoeuille et al., 2014). In 2013, passenger cars emitting between 61 and 90 grams CO_2/km were awarded a rebate of €550, whereas the ones emitting between 91 and 105 gCO_2/km a rebate of only €200 (ADEME, 2013). This structure creates a strong incentive for manufacturers whose cars emit slightly more than 90 gCO_2/km to make small adjustments to their vehicles to make them qualify for a higher rebate. However, manufacturers have no incentive to lower the emissions of a model emitting e.g. 89 gCO_2/km, even though the marginal external costs of a gram of CO_2/km is the same for a model with emissions of 91 gCO2/km and for one with 89 gCO2/km. The importance of these cut-off values is further increased when they are used to distinguish cars with good (bonus) environmental performance from the ones with average performance or to stigmatise the ones with bad (malus) environmental performance (see also Sallee and Slemrod, 2012).

A list of examples of car tax policies with notches in Europe would also include the company car tax rates applied in France, the Netherlands and the UK; the annual circulation tax in Germany, Greece, the Netherlands and the UK; the registration tax in the Netherlands; and the grants for the purchase of alternative fuel vehicles in Italy (cf. ACEA, 2014). In the following subsection, we elaborate on notches in car taxation policies in the Netherlands, the country of focus in this chapter.

5.2.2. Tax incentives for low emission vehicles in the Netherlands

In the Netherlands, the national government provides various tax incentives to stimulate demand for low emission vehicles by households and firms. These incentives can be broadly categorised in policies targeted to soften the upfront burden to adopters and ones aiming to reduce the recurrent costs of car use. Two types of taxes are applicable when purchasing a car in the Netherlands, a car registration tax (*Belasting van personenauto's en motorrijwielen* or BPM) and VAT. VAT currently adds an extra 21% to car's pre-tax price, while BPM adds on average another 17%. The latter figure varies widely, however, depending on car's fuel type and CO_2 emissions. During the last decade, the formula used for the calculation of BPM has been regularly adjusted by the tax authorities, mainly to help achieve environmental policy objectives. Since the beginning of 2009, a full exemption from BPM is applied to cars with relatively low CO_2 emissions. These are defined as cars with CO_2 emissions per kilometre below a cut-off value. Until the end of 2014, distinct cut-offs applied to diesel cars (including hybrid-electric variants) and cars driving on other fuel types. The cut-off values have been adjusted downwards on a yearly or half-yearly basis since 2012. Table 5.1 provides a summary of the cut-off points used since 2010. Changes in cut-off points from July 2012 onwards were announced in June 2011.

Low emission passenger cars were also exempted from the annual road tax (*Motorrijtuigenbelasting* or MRB) in the period 2010-2013. MRB is an important element of cars' annual operating costs, amounting to around €500 for a typical average-sized petrol-fuelled car and €1200 for its diesel-fuelled counterpart. The cut-off values rendering a passenger car eligible for exemption from MRB were 110 gCO_2/km for petrol cars and 95 gCO_2/km for diesel ones. The exemption remained in place for passenger cars emitting up to 50 gCO_2/km, i.e. all full electric cars and the majority of plug-in hybrids, until the end of 2015.[83]

Table 5.1: Evolution of cut-offs bellow which a car is eligible for exemption from BPM: 2010-2014.

Fuel type	Jan 2010	July 2012	Jan 2013	Jan 2014
Petrol	110	102	95	88
Diesel	95	70	70	70

Note: Maximum levels of type-approval CO_2 emissions (g/km, according to NEDC cycle) entailing full exemption from BPM.
Source: Adapted from Kok et al., 2014.

Firms and company car users can also benefit from targeted policies. The company car market primarily consists of cars provided from employers to employees under lease contracts of a predetermined duration (see also Gutiérrez-i-Puigarnau and van Ommeren, 2011). Company cars mainly serve private travel purposes and, thus, constitute a fringe benefit on which income tax is levied. The amount added to employee's income due to the private use of a company car depends on a tax rate which is levied on the car's list price. The basic company car tax rate in the Netherlands is 25%. Lower rates, however, apply to low emission vehicles (see also Chapter 4). A 14% company car tax rate is levied on cars with CO_2 emissions below a lower cut-off point, while a 20% rate applies to cars with emissions between that lower cut-off value and an upper cut-off point.

Figure 5.1 provides a summary of the changes in taxation of low emission company cars (excluding cars with emissions up to 50 gCO_2/km) in the period 2010-2014. For all fuel types except diesel, the cut-off points rendering cars eligible for a 14% company car tax rate coincide with the ones granting exemptions from the BPM. For diesel cars, the cut-off values used for a 14% company car tax rate are also used to determine substantial reductions of the BPM. In summary, there is a double benefit for company cars with very low type-approval CO_2 emissions; both the company car tax rate and the list price taken

[83] In 2016, the exemption from MRB is only in place for full electric cars. Drivers of cars with type-approval emissions from 1 to 50 gCO_2 pay only 50% of the MRB of a comparable petrol or diesel car.

into account for the calculation of the fringe benefit are significantly lower for vehicles with CO_2 emissions below the (14% company car tax rate) cut-off point.[84]

In the period 2010-2013, the private use of full electric cars (zero tailpipe emission vehicles) was not taxed, as the company car tax rate for FEVs was 0%, applicable for a 5-year period. In 2012 and 2013, that rate also applied to cars with 1-50 gCO_2/km, i.e. the majority of plug-in hybrids. In 2014, the rates were increased to 4% for zero tailpipe-emission vehicles and 7% for cars emitting 1-50 gCO_2/km. Changes for the period from mid-2012 onwards were also announced in June 2011.

5.3. Data and analysis of time trends

5.3.1. Data

We use a database of all passenger cars registered in the Netherlands on 1 August 2014. The database is compiled by RDW (Rijksdienst voor het Wegverkeer), the official vehicle registration authority of the Netherlands. It contains microdata on each vehicle registration, including vehicle's plate number, which remains intact along the lifespan of the vehicle, the date of first registration, as well as the list price of the vehicle and the amount of payable registration tax (BPM).[85] Subtracting BPM and VAT from the list price of each vehicle, we calculate its pre-tax recommended retail price.[86] For each registration, a number of vehicle characteristics are also provided in the database, i.e. make and model name, fuel type, number of cylinders and seats, weight, engine capacity and power, and type-approval CO_2 emissions.

The records of this database are matched with the records of a vehicle ownership database, which was purchased from RDW. The vehicle ownership database provides basic information about the identity of the registrar of each vehicle, i.e. whether it is a natural person or a firm. However, the database does not contain any information about the

[84] In 2013, for example, the addition to an employee's annual taxable income due to the private use of a petrol car with 96 gCO_2/km and a pre-tax price of €25,000 would be €6074. If the same vehicle emitted 1 gCO_2/km less, the annual addition to employee's taxable income would be €1839 lower. Using the most common income tax rate in the Netherlands, i.e. 42%, this implies that this 1 gCO_2/km difference results in a €773 annual tax benefit for the employee. Provided that most company cars stay with the same driver for about 4 years, the aggregate benefit is about €3000 over this 4-year period.

[85] The list price of the vehicle is equivalent to the recommended (or manufacturer's suggested) retail price. It includes the price of all accessories and the applicable purchase taxes (BPM and VAT). This is the price taken under consideration by the tax authorities for the calculation of the company car tax.

[86] VAT amounted to 19% of the pre-tax price of the vehicle until October 2012, when it was increased to 21%. In our calculations of pre-tax prices, we assume that the applicable VAT amounts to 19% for all registrations made prior to 1 October 2012, and 21% from that date onwards.

(intended) use of the car and, therefore, does not distinguish between cars used solely for business purposes and company cars (which are mainly used for private travel). In summary, this database is of limited use when it comes to identifying registrations subject to company car taxation.

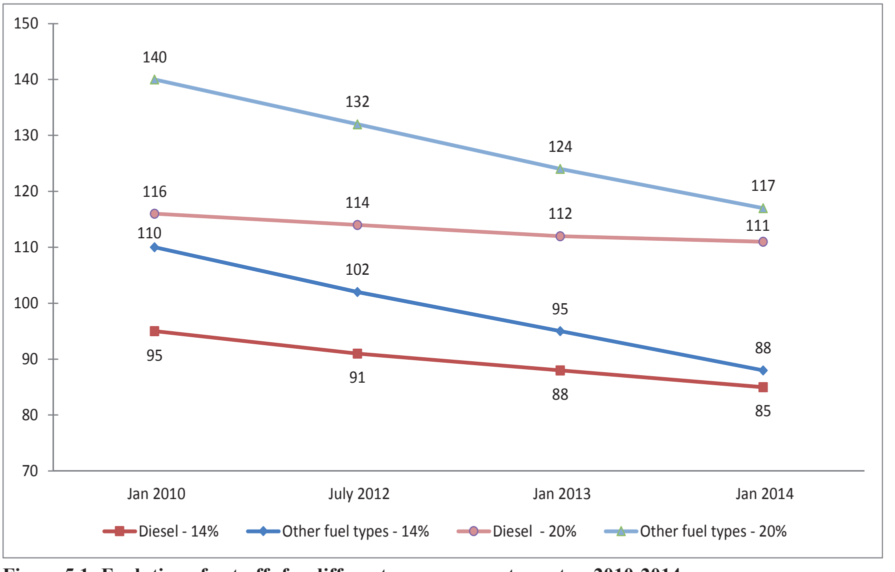


Figure 5.1: Evolution of cut-offs for different company car tax rates: 2010-2014.

Note: Figures are in type-approval grams of CO_2 per km, according to NEDC cycle. Lower company car tax rates apply to cars emitting less than 50 gCO_2/km.
Source: Adapted from Kok et al., 2014.

The publication of list prices is mandatory for all new cars registered from 1 January 2010 onwards and, thus, we restrict our population to these vehicles. We also exclude all vehicles which were initially registered in another country and then registered in the Netherlands (ca. 340,400 vehicles), to ensure that their purchase would not be governed by tax policies of other jurisdictions. Furthermore, we do not consider 343 vehicles for which the records of the vehicle registration database could not be matched with the records of the vehicle ownership database.[87] Our population is further reduced by 724 vehicles for which information about CO_2 emissions is unavailable and 378 vehicles with suspiciously low pre-tax prices (below €5000). Following these adjustments, the population used in our analysis encompasses slightly more than 2,112,800 passenger cars.

[87] We sought for a full matching of the records in the two databases, i.e. for an exact matching of both the plate number and the registration date.

5.3.2. Analysis of time trends

We now turn to analysing the evolution of CO_2 emissions and pre-tax prices of new passenger cars in the examined period. Figure 5.2 illustrates the evolution of average type-approval CO_2 emissions of new passenger cars in the period January 2010 – July 2014. The solid line depicts the evolution of emissions for all passenger cars, whereas the dashed-dotted one illustrates the evolution of emissions when registrations of plug-in electric vehicles (PEVs) are not considered. The figure shows a decreasing trend in average CO_2 emissions from 143 gCO_2/km in January 2010 to 109 gCO_2/km in July 2014, a reduction of about 24%. It further reveals that registrations of lower emission cars are concentrated at the end of the year, probably a reflection of consumer attempts to reap tax benefits vanishing from the beginning of the following year. In this context, we observe a striking downward spike in December 2013, primarily induced by the abolishment of the exemption of plug-in electric vehicles from company car taxation as of the beginning of 2014. A comparison of the plot of registrations including PEVs and the one excluding them shows that PEVs have been an important driving force behind the reduction of average type-approval CO_2 emissions from the second half of 2013 onwards.

Perhaps more striking is, however, the effect of PEVs on average pre-tax prices of newly-registered vehicles. Figure 5.3 shows that there is an increasing trend in the (consumer-price deflated) pre-tax prices of passenger cars.[88] They have increased by ca. 29% in the examined period. PEVs have a notable influence on this trend, as they have been driving average car prices substantially higher as of the second half of 2013. Two plug-in hybrid models (Mitsubishi Outlander PHEV and Volvo V60 PHEV) were introduced in the Dutch market in the beginning of this period. These models did not entail the compromises that drivers had to incur with earlier PEV models in terms of inferior driving range, comfort, luggage space and towing capacity. Combining this with the aforementioned generous tax incentives provided for PEVs in the company car market, it comes as no surprise that these cars were extremely successful in rapidly penetrating the car market. Average prices were heavily influenced by the market success of these costly alternatives, as illustrated in Figure 5.3.

[88] Pre-tax prices were deflated using the consumer price index provided by CBS (see also www.cbs.nl).

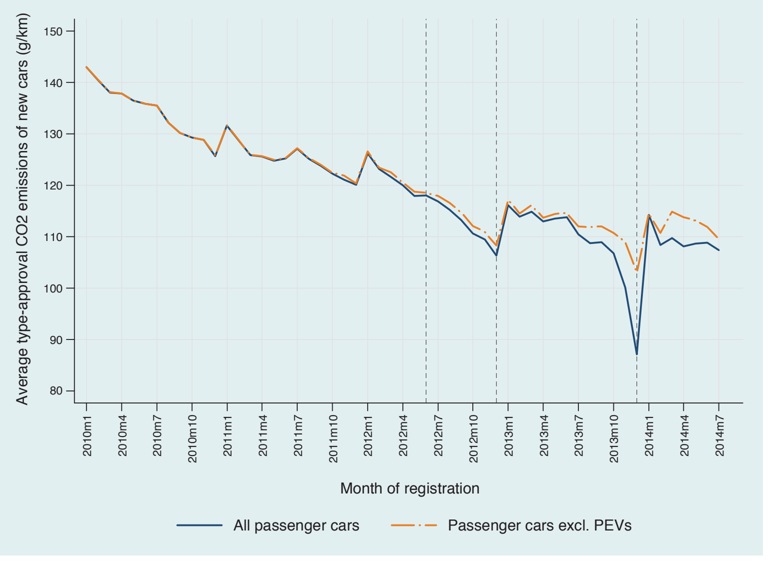


Figure 5.2: Evolution of average CO_2 emissions of new cars, the Netherlands, 01/2010 – 07/2014.

Note: The short-dashed vertical lines indicate the time when a change in notches occurs.

Source: Authors' calculations of RDW official data.

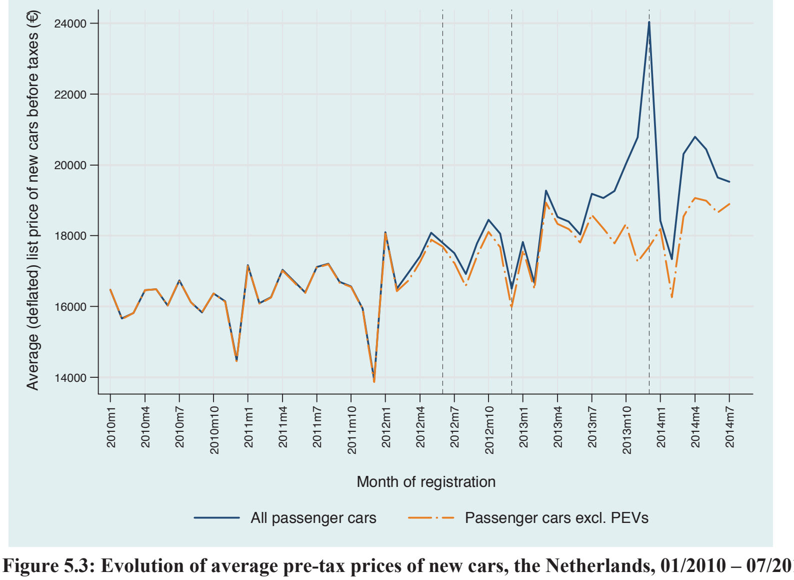


Figure 5.3: Evolution of average pre-tax prices of new cars, the Netherlands, 01/2010 – 07/2014.

Note: Pre-tax prices are consumer-price deflated. The short-dashed vertical lines indicate the time when a change in notches occurs.

Source: Authors' calculations of RDW official data.

Differences in average CO_2 emissions and pre-tax prices between petrol and diesel cars are explored in Figures 5.4 and 5.5 respectively. The two categories also include the hybrid-electric variants of the two fuel types. With the exception of the beginning of the examined period, average CO_2 emissions per kilometre of diesel cars are substantially lower than the ones of petrol cars. Changes in cut-off points result in spikes in CO_2 emissions of both fuel types, but their impact on diesel cars is much more pronounced. Noticeably, the gap between average emissions of petrol and diesel cars narrows considerably on the month following the change of cut-off points.

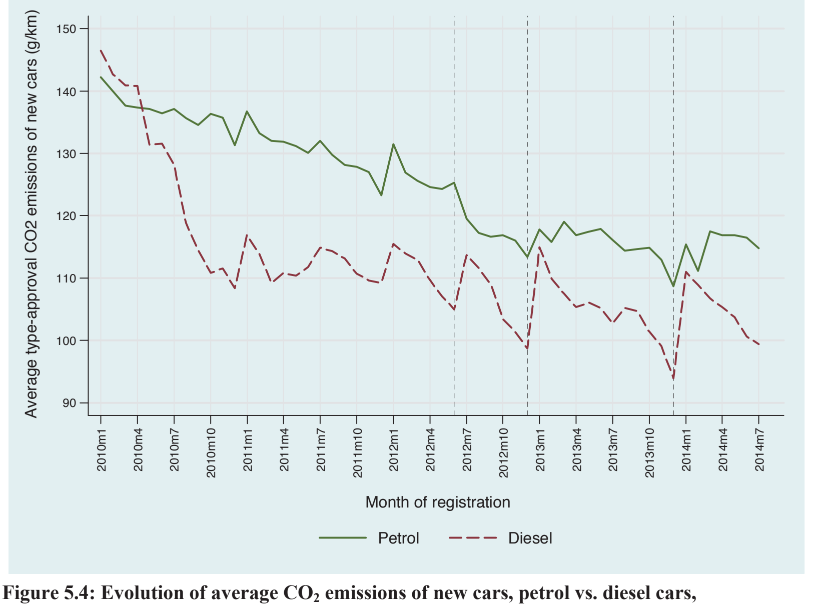


Figure 5.4: Evolution of average CO_2 emissions of new cars, petrol vs. diesel cars, the Netherlands, 01/2010 – 07/2014.

Note: Registrations of hybrid-electric variants of the two fuel types are also taken into account. The short-dashed vertical lines indicate the time when a change in notches occurs.

Source: Authors' calculations of RDW official data.

Figure 5.5 presents the evolution of pre-tax prices for the two fuel types. Diesel cars are on average about 50% more expensive than petrol cars. This could be attributed to a number of factors. First, diesel cars are on average heavier, larger and more powerful in our data. Second, diesel cars are traditionally more expensive than their petrol-fuelled counterparts, due to higher marginal costs of production. Third, it has been suggested that higher mark-ups are charged by car manufacturers on diesel cars (for details, see Verboven, 2002). Volatility in average prices of diesel cars is also much higher than volatility in the prices of petrol cars. Diesel car prices saw a noteworthy drop in the second half of 2010, before starting to increase back to their early 2010 levels.

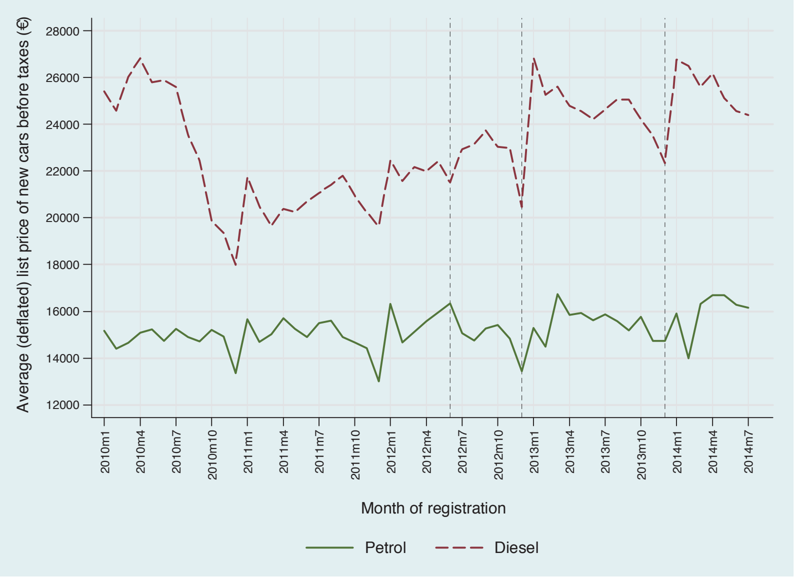
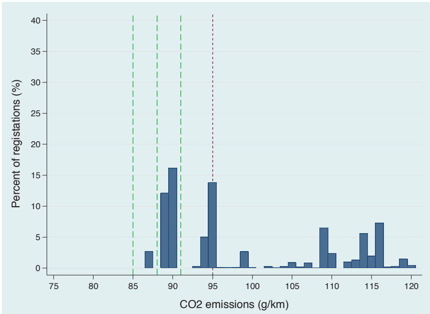


Figure 5.5: Evolution of average pre-tax prices of new cars, petrol vs. diesel cars, the Netherlands, 01/2010 – 07/2014.

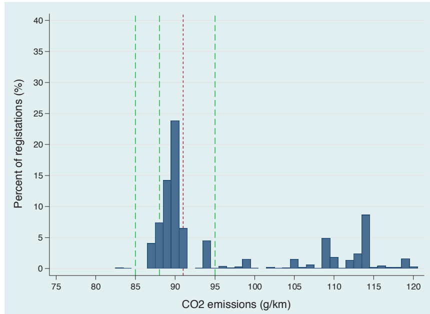
Note: Pre-tax prices are consumer-price deflated. Registrations of hybrid-electric variants of the two fuel types are also taken into account. The short-dashed vertical lines indicate the time when a change in notches occurs.
Source: Authors' calculations of RDW official data.

5.4. Notches and consumer demand

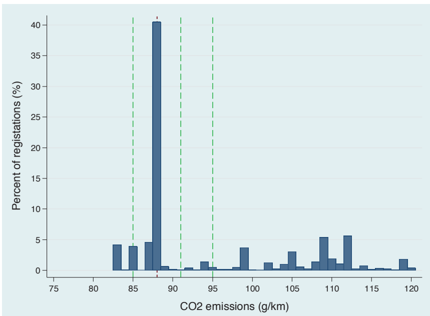
This section provides graphical evidence of the salient impact of tax notches on consumer demand for petrol and diesel cars. In particular, we illustrate that there is remarkable bunching of vehicle registrations occurring on the tax favourable side of the notches. Figure 5.6 presents a series of graphs showing the distribution of registrations of diesel cars and their hybrid-electric variants over CO_2 emissions. Graphs illustrate only the part of the distribution between 75 and 120 gCO_2/km to facilitate the exposition of demand reactions to notches. In each graph, the short-dashed red line denotes the cut-off point used to determine low emission diesel cars which are eligible for substantial reductions in the registration tax and a significantly lower company car tax rate (14%) in the examined period. The long-dashed yellow lines indicate the cut-off points used in the following or preceding periods. Registrations made within the first two months after the change of the cut-off point are excluded from the analysis, as an important number of registrations recorded during this period are subject to the cut-off points employed in the previous period.[89]



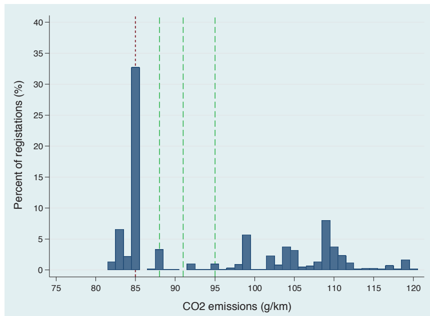
(a) Diesel cars: 1st half of 2012



(b) Diesel cars: 2nd half of 2012



(c) Diesel cars: 2013



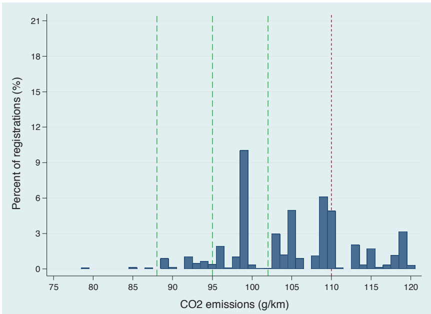
(d) Diesel cars: 2014

Figure 5.6: Distribution of diesel car registrations over type-approval CO_2 emissions.

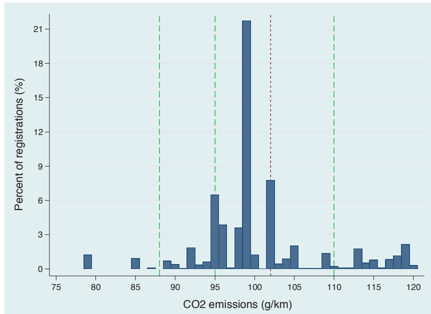
Note: Short-dashed lines indicate cut-off points determining eligibility for a lower company car tax rate (14%) and sharp reductions of the registration tax. Long-dashed lines indicate cut-off points in previous and following periods. Figures show only the part of the distribution between 75 and 120 grams CO_2/km, but percentages are calculated taking into account the full range of CO_2 emissions for diesel cars. We exclude the first 2 months following the change of cut-off points. Data cover the period until the end of July 2014.

Source: Authors' calculations of RDW official data.

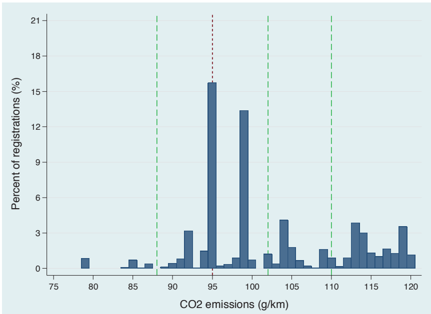
[89] There is a difference between the date on which payable BPM is determined and the one on which the company car tax rate is determined. The company car tax rate is determined on the date that the vehicle is registered under the name of the registrar. On the contrary, BPM is determined on the date that the importer or dealer of the vehicle requests the plate number from RDW (see also Leaseplan, 2012). This date may be a couple of months before the date that the vehicle is registered, implying, for example, that the BPM applicable in June 2012 might have applied to a car registered in August 2012. Our data confirm this suggestion, as we find a non-negligible number of registrations where the BPM of previous months applies to the vehicle, instead of the BPM of the month of registration. Typically, this effect starts vanishing two months after the BPM change. Nevertheless, the findings drawn from the graphical analysis do not qualitatively change if the first two months after the change are also included in the analysis.



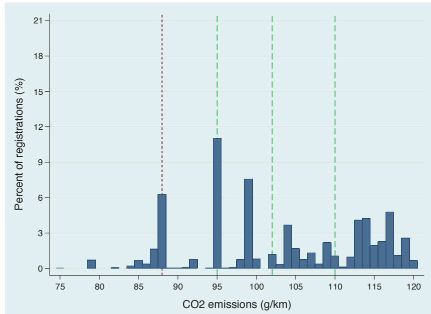
(a) Petrol cars: 1st half of 2012



(b) Petrol cars: 2nd half of 2012



(c) Petrol cars: 2013



(d) Petrol cars: 2014

Figure 5.7: Distribution of petrol car registrations over type-approval CO_2 emissions.

Note: Short-dashed lines indicate cut-off points determining eligibility for a lower company car tax rate (14%) and exemptions from the registration tax. Long-dashed lines indicate cut-off points in previous and following periods. Figures show only the part of the distribution between 75 and 120 grams CO_2/km, but percentages are calculated taking into account the full range of CO_2 emissions for petrol cars. We exclude the first 2 months following the change of cut-off points. Data cover the period until the end of July 2014.

Source: Authors' calculations of RDW official data.

In all cases, registrations bunch on the tax-favoured side of the notches, whereas only a tiny share of registrations takes place on their disfavoured side.[90] Perhaps the most striking example of bunching is that more than 40% of *all* diesel cars sold in the Dutch market in 2013 were located exactly at the cut-off point of 88 gCO_2/km. At the same time, about 33% of all diesel cars registered between March and July 2014 were emitting 85 gCO_2/km, i.e. the 2014 cut-off point. Similar patterns are also observed in 2012, even though they are not equally pronounced. In the period September-December 2012, for instance, around 30% of registrations occur within 1 gram below the cut-off point, while

[90] Appendix 5.A presents the distributions of model specifications over CO_2 emissions for each period and fuel technology. A model specification is defined here as a unique combination of make, model, weight and CO_2 emissions (e.g. Ford Focus, 1250kg, 115 gCO_2/km). We show that the number of model specifications sold in the market is also affected by tax notches. However, this is not the main driver of the demand response presented in this section.

more than 51% of registrations are located within 3 grams below it. On the other hand, only a very small share of the registered vehicles has emissions right above the cut-off points.

A qualitatively similar situation is also observed for petrol cars and their hybrid-electric variants. The sequence of graphs presented in Figure 5.7 shows that petrol car registrations also bunch around the tax favoured side of the notch.[91] In 2013, for instance, about 16% of all petrol car registrations concerned cars with 95 gCO_2/km, while in the second half of 2012, more than 30% of the registrations occurred within 3 gCO_2/km below the notch. However, the degree of bunching is noticeably lower than the one observed for diesel cars. We believe that the differences in bunching between the two technologies result from the fact that diesel cars are primarily company cars, while petrol cars are usually under private ownership. In our data, 79% of diesel cars are registered by a firm; in contrast, the relevant percentage of petrol cars is only 43%. This implies that notches in company car taxation have a much stronger effect on diesel cars than on petrol ones.[92]

5.5. Manufacturers' strategic responses to tax notches

We saw that tax notches induce salient changes in consumer behaviour. This section shows that they also induce strategic responses from car manufacturers. We start with a short graphical analysis, which, however, does not provide conclusive evidence of manufacturer responses. We rely, thus, on a quasi-experimental econometric approach to examine whether manufacturers respond to notches by offering more specifications with CO_2 emissions right below the notch. The approach is conceptually similar to a difference-in-differences strategy.

5.5.1. Graphical analysis

We focus on model specifications with type-approval CO_2 emissions within a 4 g/km interval from each cut-off point, i.e. between 1 g/km below and 2 g/km above it. Models with type-approval CO_2 emissions 1 g/km below the cut-off point and exactly on it are on

[91] It is important to note here that the cut-off points presented in the graphs for petrol cars determine *full exemptions* from the registration tax. This is in contrast to the situation for diesel cars, where the cut-off points shown in panels (b) – (d) of Figure 5.6 only make a car eligible for a substantial reduction in the registration tax.

[92] We do not have information about the use of business cars and, thus, we cannot distinguish between cars used purely for business purposes and cars which are also privately used (company cars). Our argument holds, however, as long as the share of company cars in business registrations of diesel vehicles is not significantly lower than the share of company cars in business registrations of petrol vehicles; an assumption which seems reasonable.

the favourable side of the notch, whereas model specifications with emissions 1 or 2 g/km above the cut-off point are on the unfavourable side. For each quarterly period, we compute the share of specifications (i.e. unique combinations of make, model and weight) on the favourable side of the notch in the total number of specifications within the examined interval (cf. Klier and Linn, 2015).[93] Figure 5.8 shows a series of graphs plotting the evolution of this share over time for the cut-off points for diesel and hybrid diesel-electric cars, while the series of graphs presented in Figure 5.9 illustrates the evolution of this share for petrol and hybrid petrol-electric cars.

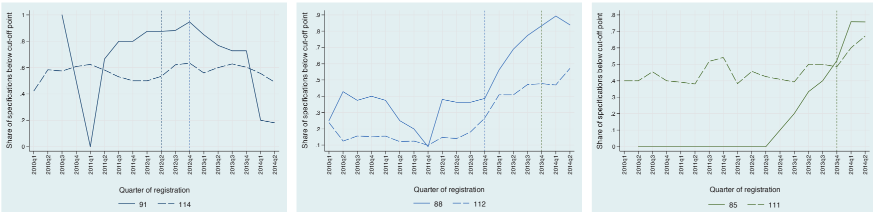
Figure 5.8 indicates that the share of diesel specifications on the favourable side of the notch has increased in the affected period in the case of the 2013 change and, to a lesser extent, in the case of the mid-2012 and 2014 change. Figure 5.9 suggests that manufacturers may have responded strategically to the notches which entered into force for petrol cars in mid-2012 and, especially, in 2014. It is slightly less revealing of a response to the 2013 notches. Even though it provides some insights into the possible reactions of car manufacturers to notches, this graphical analysis does not provide adequate empirical evidence to let us argue for or against a strategic response. To this end, we rely on the econometric approach described in the subsection that follows.

5.5.2. Empirical strategy

The empirical approach builds on the work of Klier and Linn (2015) for France, but extends it in various ways. First, our analysis looks into variation within each unique combination of car model and weight, thereby enabling us to provide more accurate estimates of manufacturer responses. This approach not only allows a more rigorous distinction between supply and demand effects, but also better reveals manufacturer fine-tuning of *existing* car model specifications. Second, we are able to exploit the fuel-type-based differentiation of notches to investigate whether manufacturers react differently to notches for different fuel types. Different reactions may be triggered by differences in marginal costs to reduce CO_2 emissions of existing or new specifications, or differences in the expected impact of a response on consumer demand. Manufacturers may, for instance, decide to have a firmer response to notches on diesel cars, because they are more popular among company car drivers, who are more heavily affected by the notches (notches influence both the list price of the cars and the company car tax rates applied to them).

[93] The data allow us to consider only car model specifications which have been sold at least once in the examined period. It is certainly possible that some specifications may have not sold a single car in the examined quarter.

Third, changes in notches in the Dutch car taxation policy allow us to analyse car manufacturers' behaviour in different points in time and provide consistent evidence of strategic responses to notches.

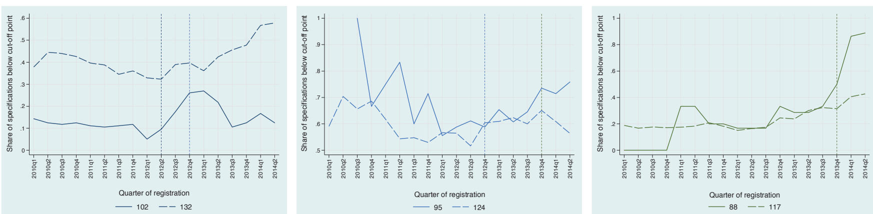


(a) July 2012 (b) 2013 (c) 2014

Figure 5.8: Share of specifications on the favourable side of the notch: diesel and hybrid diesel-electric cars.

Note: The series of graphs draws on specifications sold in the Dutch market. It shows the share of specifications on the favourable side of the notch in the total number of specifications with CO_2 emissions between 1 g/km below and 2 g/km above the cut-off point. Graphs draw on the cut-off points introduced in (a) July 2012, (b) January 2013, and (c) January 2014. Type-approval emission levels in the legends are in gCO_2/km. Solid lines indicate cut-off points determining eligibility for higher tax advantages (exemption from registration tax and 14% company car tax rate), while long-dashed lines for lower tax advantages (20% company car tax rate). Short-dashed reference lines show the time of the policy change for specifications with affected emission levels. Each set of notches is in effect for the period delimited by the two reference lines (2014 cut-off points are into force until the end of the period). Data cover the period January 2010 – June 2014.

Source: Authors' calculations of RDW official data.



(a) July 2012 (b) 2013 (c) 2014

Figure 5.9: Share of specifications on the favourable side of the notch: petrol and hybrid petrol-electric cars.

Note: The series of graphs draws on specifications sold in the Dutch market. The series of graphs shows the share of specifications on the favourable side of the notch in the total number of specifications with CO_2 emissions between 1 g/km below and 2 g/km above the cut-off point. Graphs draw on the cut-off points introduced in (a) July 2012, (b) January 2013, and (c) January 2014. Type-approval emission levels in the legend are in gCO_2/km. Solid lines indicate cut-off points determining eligibility for higher tax advantages (exemption from registration tax and 14% company car tax rate), while long-dashed lines for lower tax advantages (20% company car tax rate). Short-dashed reference lines show the time of the policy change for specifications with affected emission levels. Each set of notches is in effect for the period delimited by the two reference lines (2014 cut-off points are into force until the end of the period). Data cover the period January 2010 – June 2014.

Source: Authors' calculations of RDW official data.

We start with an econometric model which follows rather closely the work of Klier and Linn (2015). We then build on their work to show that strategic responses of manufacturers vary significantly with fuel type and that they are identifiable even at a very narrow definition of model specification. It is worth noting that the analysis presented in this section does not consider the mid-2012, 2013 and 2014 changes in notches separately. Econometric results by policy change are presented and discussed in Appendix 5.B.

As in the graphical analysis above, we focus on model specifications with type-approval CO_2 emissions between 1 gram below and 2 grams above each cut-off point.[94] The following fixed-effects binary logit model can then be formulated (see also Chamberlain, 1980; Greene, 2012, pp. 761-764):

$$\mathrm{Prob}(below_{ijsq} = 1 \mid treatment_{sq}, \mathbf{X}_{ijsq}) = \frac{\exp(\alpha treatment_{sq} + \boldsymbol{\gamma}'\mathbf{X}_{ijsq} + \delta_j)}{1 + \exp(\alpha treatment_{sq} + \boldsymbol{\gamma}'\mathbf{X}_{ijsq} + \delta_j)}, \quad (5.1)$$

where i denotes a model specification, j indicates a unique combination of make and model (e.g. Ford Focus), s is the set of cut-off points in effect for a specific time period, and q is the quarter of registration (e.g. Q2 2012). The dummy variable *below* takes the value of unity for specifications whose CO_2 emissions are lower than or equal to the cut-off point.[95] The *treatment* dummy is the main variable of interest, as its coefficient, α, reveals whether manufacturers respond strategically. The variable takes the value of one when the specification belongs to the set of cut-off points s which makes a car eligible for tax advantages in a specific time period. For example, for the set of cut-off points being in effect in 2013, *treatment* will take the value of 1 for specifications registered in 2013 and the value of zero otherwise. The expected sign of *treatment* is positive, as manufacturers are anticipated to release more specifications right below the cut-off point within the treatment period. In other words, the conditional – on specification's CO_2 emissions being within the examined 4-gram interval – probability that a specification is below the cut-off point is expected to increase in the treatment period.

The vector of control variables, **X**, consists of: (i) time-period fixed effects (i.e. dummies for the second half of 2012, 2013 and 2014); (ii) set of cut-off-point fixed effects to control for time-invariant differences between sets of cut-off points; (iii) quarter fixed effects to control for seasonal variation; (iv) a dummy indicating whether the cut-off point grants higher tax advantages (14% company car tax and exemptions from registration tax)

[94] Note that we use a very conservative range of emissions. Klier and Linn (2015) consider specifications with CO_2 emissions within 2 grams below and 2 grams above each cut-off point in their analysis. We opted for a more balanced quasi-experimental design.

[95] In 2014, for example, the CO_2 emission cut-off point granting exemptions from the BPM and a 14% company car tax rate for diesel cars was 85 g/km, whereas the cut-off point making a diesel car eligible for a 20% company car tax rate was 111 g/km. In this case, *below* takes the value of one for specifications with 84, 85, 110 and 111 g/km.

or lower ones (20% company car tax), to control for differences between the two types of cut-off points; (v) a linear time trend, (vi) interactions between the time trend and (ii) to control for differences in trends between sets of cut-off points; (vii) an interaction between the time trend and (iv) to control for differences in trends between less and more advantageous cut-offs; and (vii) interactions between the trend and make of the car to control for differences in emission trends between makes.[96] The vector of parameters $\boldsymbol{\gamma}$ is to be estimated. Model fixed effects, δ, control for model characteristics which are constant across specifications and over time.

The econometric analysis is conducted both for each fuel type separately and for all fuel types pooled together. Our hypothesis is that manufacturer responses will be more acute for diesel cars, mainly due to two reasons. First, the majority of diesel cars in the Netherlands are registered by companies (79% in our data), and the demand for different specifications is largely driven by company car taxation. A manufacturer's response to a change in notches may, thus, prove critical for the future of some diesel specifications in the Dutch market. This is especially important for models whose production relies to a relatively large extent on sales in the Netherlands. Second, diesel cars are on average more expensive than their petrol-fuelled counterparts, which implies that a reduced company car tax rate (e.g. from 20% to 14%) will result in a larger tax advantage for them. Therefore, manufacturers have stronger incentives to respond to notches in diesel car tax schedules than to notches in petrol car ones.

The econometric model formulated above allows for three possible strategic responses of car manufacturers. Manufacturers can adjust the CO_2 emissions of existing specifications, introduce new specifications with lower CO_2 emissions, or discontinue more polluting ones (Klier and Linn, 2015). A caveat of the econometric model above is that it might be capturing to some extent extreme demand responses instead of manufacturer strategies. For example, if a specification located right above the cut-off point does not sell a single car after the change in the notch, it will be deemed as discontinued by the econometric models. In other words, the model of Equation (5.1) is not able to distinguish a manufacturer's choice to remove a more polluting specification from consumers' choice sets from consumers' universal rejection of an alternative (which is, yet, available in their choice sets).

[96] Car makes are grouped together if they belong to the same corporate group of companies or to a car manufacturer alliance.

We are especially interested in isolating the effect of changes in notches on the CO_2 emissions of existing specifications. Apart from addressing the econometric caveat discussed above, an identifiable effect on existing specifications would provide stronger support to Sallee and Slemrod's (2012) argument that manufacturers can fine-tune the environmental performance of vehicles by making minor modifications at the very last stage of production. To isolate the effect on existing specifications, we focus on variation within combinations of make, model and finely defined vehicle weight (at the kilogram level). The fixed-effects econometric model of Equation (5.1) can then be adapted as follows:

$$\text{Prob}(below_{iksq} = 1 \,|\, treatment_{sq}, \mathbf{X}_{iksq}) = \frac{\exp(\beta treatment_{sq} + \boldsymbol{\lambda}'\mathbf{X}_{iksq} + \xi_k)}{1 + \exp(\beta treatment_{sq} + \boldsymbol{\lambda}'\mathbf{X}_{iksq} + \xi_k)}, \quad (5.2)$$

where k indicates a unique combination of make, model and vehicle weight (e.g. Toyota Auris 1195 kg), β is the parameter of interest, $\boldsymbol{\lambda}$ is a vector of parameters to be estimated, and ξ are make-model-weight fixed effects.

5.5.3. Estimation results

5.5.3.1. Make-model fixed effects

Table 5.2 presents the estimation results of logit and linear probability models with make-model fixed effects. Linear probability models are presented for comparison purposes and for providing insights in case logit models do not converge. The table shows the estimates of the coefficient of *treatment* (α) in Equation (5.1), as well as the marginal effect of the variable. The marginal effects for the logit models are calculated assuming that the fixed-effects are equal to zero. We find that the conditional probability of a vehicle specification falling right below or exactly on the cut-off point increases, on average, by around 17 percentage points in the treatment period (see columns labelled "All" in Table 5.2). These estimates point to a much more pronounced average effect – about 5 times larger – than the one identified by Klier and Linn (2015) for the French market.

We suspect that the divergence between our estimates and the ones of Klier and Linn can be explained by the much larger average tax advantage provided by the Dutch system in comparison with the French one. Provided than an average company car has a list price of around €35,000, the difference of 6 percentage points in the company car tax rate implies an average advantage of at least €880 per year, not taking into account the benefit from reduced registration tax. A typical company car stays with the same driver for about 4 years, thus the advantage for the 4-year period totals about €3500. This is seven times larger than the most common tax advantage in France in the period analysed by Klier and Linn (2015). It is, therefore, very likely that this difference in the fiscal benefits between the two countries is responsible for the divergence in the estimated magnitude of the effect of the policy between our study and the study of Klier and Linn.

Table 5.2: Fixed-effects model results – make-model fixed effects.

	All				Petrol				Diesel [a]	
	Fixed-effects Logit		Fixed-effects Linear		Fixed-effects Logit		Fixed-effects Linear		Fixed-effects Linear	
	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error
Treatment (α)	1.051***	(0.133)	0.159***	(0.023)	0.352**	(0.141)	0.054***	(0.019)	0.185***	(0.032)
2nd half 2012	-0.236	(0.149)	-0.028	(0.027)	-0.078	(0.177)	-0.007	(0.023)	-0.037	(0.049)
2013	0.142	(0.264)	0.025	(0.044)	0.582*	(0.305)	0.076**	(0.038)	-0.019	(0.060)
1st half 2014	0.672*	(0.403)	0.084	(0.067)	1.722***	(0.485)	0.220***	(0.059)	-0.037	(0.084)
Marginal effect of treatment	*0.165****	*(0.030)*	*0.159****	*(0.023)*	*0.039***	*(0.019)*	*0.054****	*(0.019)*	*0.185****	*(0.032)*
Observations		5,988		5,988		3,723		3,723		2,265
R-squared		-		0.385		-		0.466		0.597
Adjusted R-squared		-		0.361		-		0.440		0.569
McFadden R-squared		0.145		-		0.226		-		-
LL (convergence)		-2449		-		-1265		-		-

Note: In addition, all models include make-model fixed effects, quarter fixed effects, set of cut-off-point fixed effects, a dummy distinguishing cut-off points granting higher tax advantages from cut-off points granting lower ones, a linear time trend and interactions between the trend and: (a) the sets of cut-off points, (b) the lower advantage cut-off, and (c) car makes. Estimates of these variables are not shown here due to space limitations. The column labelled "All" shows estimates for all fuel types considered in the analyses. The column labelled "Petrol" shows estimates for petrol cars and hybrid petrol-electric ones, whereas the one labelled "Diesel" for diesel and hybrid diesel-electric cars. Data cover the period January 2010 – June 2014.

[a] Convergence problems did not allow the estimation of a fixed-effects logit model for diesel cars.

Data source: RDW.

A comparison between the marginal effects in the columns labelled "Petrol" and the column labelled "Diesel" in Table 5.2 confirms that manufacturer responses are considerably more pronounced for cars driving on diesel. In particular, the response for diesel cars is more than 3 times stronger than the one for petrol cars. However, in the event that extreme demand responses (i.e. failures of specifications to sell a single car in the market after the change in the notch) are more frequent for diesel than for petrol cars, the identified differences may be reflecting differences in consumer responses rather than in manufacturer ones.[97] The results presented in the next section reveal, however, that

[97] This might be likely, as extreme demand responses may be more prevalent in the company car market, where incentives to opt for cars right below the notch are stronger and bulk deliveries of specific model specifications are not uncommon.

extreme demand responses are only responsible to a limited extent for the identified differences.

5.5.3.2. Make-model-weight fixed effects

We now turn to the estimation results of logit and linear probability models with make-model-weight fixed effects. Table 5.3 presents estimates of parameter β of Equation (5.2), as well as the corresponding marginal effects. The estimates reveal that manufacturers responded to changes in notches by fine-tuning the CO_2 emissions of some specifications, so that the latter could shift to the favourable side of the new notch. Our most conservative estimate is that the conditional probability of a specification falling below (or exactly on) the cut-off point increases by ca. 6.5 percentage points in the treatment period. This is economically significant when contrasted to an average 45% conditional probability of being below the cut-off point in 2010-2011, i.e. before any of the examined cut-off points came into effect.

The identification of a relatively large effect of notches at such a high level of detail and a conservative range of CO_2 emissions is remarkable, as it implies that manufacturers may only need to make marginal changes to a car – changes that even leave its weight almost intact – to enable it to qualify for important tax advantages. This is a rather problematic finding for policymakers, as it suggests that CO_2 emissions ratings can often be rather easily manipulated by manufacturers, allowing them to secure relatively high sales of their models at the expense of social welfare and public finance.

Table 5.3: Fixed-effects model results – make-model-weight fixed effects.

	All				Petrol				Diesel			
	Fixed-effects Logit		Fixed-effects Linear		Fixed-effects Logit		Fixed-effects Linear		Fixed-effects Logit		Fixed-effects Linear	
	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error	estimate	std. error
Treatment (β)	1.074***	(0.182)	0.081***	(0.018)	0.481**	(0.195)	0.036**	(0.015)	4.622***	(0.877)	0.118***	(0.031)
2nd half 2012	-0.462*	(0.258)	-0.017	(0.020)	0.406*	(0.233)	0.003	(0.017)	-2.757*	(1.459)	-0.033	(0.033)
2013	0.020	(0.356)	0.005	(0.026)	0.834**	(0.390)	0.043*	(0.026)	-0.289	(1.424)	-0.004	(0.036)
1st half 2014	0.980*	(0.512)	0.054	(0.037)	2.046***	(0.728)	0.140***	(0.038)	4.986***	(1.846)	-0.012	(0.050)
Marginal effect of treatment	*0.064****	*(0.023)*	*0.081****	*(0.018)*	*0.032***	*(0.016)*	*0.036***	*(0.015)*	*0.233****	*(0.056)*	*0.118****	*(0.031)*
Observations		5,988		5,988		3,723		3,723		2,265		2,265
R-squared		-		0.741		-		0.755		-		0.784
Adjusted R-squared		-		0.704		-		0.721		-		0.747
McFadden R-squared		0.289		-		0.370		-		0.646		-
LL (convergence)		-794.9		-		-422.0		-		-133.5		-

Note: In addition, all models include make-model fixed effects, quarter fixed effects, set of cut-off-point fixed effects, a dummy distinguishing cut-off points granting higher tax advantages from cut-off points granting lower ones, a linear time trend and interactions between the trend and: (a) the sets of cut-off points, (b) the lower advantage cut-off, and (c) car makes. Estimates of these variables are not shown here due to space limitations. The column labelled “All” shows estimates for all fuel types considered in the analyses. The column labelled “Petrol” shows estimates for petrol cars and

hybrid petrol-electric ones, whereas the one labelled "Diesel" for diesel and hybrid diesel-electric cars. Data cover the period January 2010 – June 2014.
Data source: RDW.

Table 5.3 also confirms that manufacturers are significantly more responsive to notches in the tax schedules of diesel cars than to notches in the schedules of petrol cars. The conditional probability of a petrol-fuelled specification falling below (or exactly on) the cut-off point increases by slightly more than 3 percentage points in the treatment period. In sharp contrast, the estimated increase of the probability for a diesel-fuelled specification is multiple times higher. The 23 percentage-point increase in the conditional probability estimated by the logit model could be compared with a 60% average conditional probability of being below a cut-off point in the period 2010-2011. Therefore, the probability that a diesel car is reported to have CO_2 emissions just below the new cut-off point is about 39% higher than would be expected in the absence of a manipulative response. The company car market is critical for the market success of diesel-fuelled specifications. Hence, manufacturers respond strategically, promptly and much more strongly to changes in the notches of the (company car) tax schedule of diesel cars.

5.6. Conclusions and policy implications

In many countries, taxes on cars have been redesigned in the last decades to target vehicles with higher type-approval tailpipe CO_2 emissions. Despite the fact that environmental externalities are a continuous function of tailpipe emissions, the use of notched schedules of CO_2 emissions has been prevalent in car taxation worldwide. Notches jeopardise the efficiency of car taxation, however, as they entail that marginal changes in the behaviour of economic agents can result in private net benefits or costs which substantially outweigh the external benefits or costs of these behavioural changes. Notches allow manufacturers and consumers to respond strategically to policy, thereby substantially undermining its economic efficiency and environmental effectiveness.

In this chapter, we analyse the effects of the deployment of notched schedules of type-approval CO_2 emissions to determine car registration and company car taxes in the Netherlands. Dutch company car taxation is particularly interesting for the study of notches, as two components of the company car tax liability (the list price of the car and the company car tax rate) are determined on the basis of a notched schedule of CO_2 emissions. The cut-off points determining the notches for reductions in the list price of the car and the company car tax rate in most cases coincide, providing, thus, salient tax advantages to cars falling right below the cut-off points.[98] These notches often imply differences of thousands of euros in tax liability between cars differing only marginally in their type-approval CO_2 emissions. Such tax advantages result in noticeable responses from manufactures and consumers.

Adding to existing literature on the economic efficiency implications of notches in car taxation (Klier and Linn, 2015; Sallee and Slemrod, 2012), we provide graphical and econometric evidence that CO_2 emission-based notches in the Netherlands induce strategic responses from manufacturers and abrupt changes in consumer demand. To this end, we use an official micro-dataset of more than 2 million new cars registered in the period January 2010 – July 2014 across the country. Graphical analysis reveals that there is striking bunching of car registrations around the cut-off points making cars eligible for lower company car tax rates and substantial reductions in the registration tax. Furthermore, bunching of diesel car registrations is much more intense than bunching of petrol car ones. In 2013 only, more than 40% of diesel car registrations occurred exactly on the cut-off point of 88 gCO_2/km, a percentage underscoring the drastic impact of notches on consumer demand.

Our quasi-experimental econometric approach investigates whether car manufacturers fine-tune *existing* car model specifications to enable them to cross to the tax-favourable side of the cut-off. Thus, we focus on model specifications with type-approval CO_2 emissions between 1 gram below and 2 grams above each cut-off point and a very narrow definition of car model specification, i.e. a unique combination of make, model and finely defined weight. Our most conservative estimate is that the conditional probability of a car model specification falling right below a cut-off point increases by about 6.5 percentage points when the cut-off point determines eligibility for tax advantages. This effect is economically significant when compared with an average 45% conditional probability in the period before cut-off points enter into force. We interpret this as evidence that manufacturers do fine-tune type-approval CO_2 emissions of existing specifications to allow them to cross to the tax-favourable side of the notch.

Our econometric analysis also confirms that manufacturer responses mainly concentrate on the supply of diesel cars, most probably because these cars are more heavily influenced by company car taxation (around 79% of diesel cars are sold to companies in our data). Holding vehicle weight constant, the conditional probability of a diesel car

[98] For the importance of salience in the effectiveness of taxation, see e.g. Chetty et al. (2009) and DellaVigna (2009), and on the salience of company car taxation in the Netherlands, see also Kok (2015).

specification falling right below a cut-off point increases by about 39% when the cut-off point is into effect. This is especially unfortunate in light of recent evidence that the divergence between type-approval and real-world CO_2 emissions of diesel company cars in the Netherlands exceeds 50% (Tietge et al., 2015).

Our findings have a number of policy implications. First, current methods of measuring CO_2 emissions of cars in Europe allow manufacturers to manipulate type-approval CO_2 emission levels by making relatively simple adjustments to car models. This underlines the importance of revising vehicle emission testing procedures at the European level so that they provide accurate measurements of CO_2 emissions under real-world conditions. The second policy implication is based on our finding that the current prevalence of notched schedules in car taxation causes strong strategic responses from manufacturers and consumers and, therefore, large distortions in the car market.

A number of steps could be taken towards the reduction of the number of notched schedules in car taxation in the Netherlands. A relatively simple first step would be to remove notches in the company car tax rate. The notched schedule of the company car tax rate is one of the primary causes of market distortion, as the significant local (around cut-off points) incentives it provides cause salient strategic responses from manufacturers and consumers. The findings of this chapter provide further support to the findings of Chapter 4 and suggest that the differentiation of company car tax rates on the basis of vehicles' potential environmental burden is strongly distortionary. The designation of a single company car tax rate, applying to all types of company cars regardless of their environmental impact, would be a simple way to address the unintended effects of company car tax differentiation.

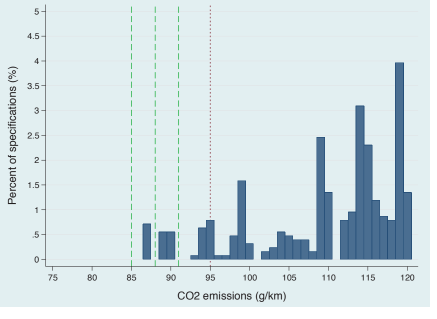
A second step that could be taken to achieve higher economic efficiency in car taxation would be to remove notches from the schedule of the car registration tax. The car registration tax could be redesigned as a continuous schedule of CO_2 emissions, and if possible of emissions of other air pollutants (e.g. NO_X, PM_{10}). Each gram of CO_2/km and accordingly each unit of emissions of other air pollutants, could then be priced at its marginal cost, in order to reflect as accurately as possible the environmental externalities imposed by the use of the car.[99]

[99] A possible complication arising here is that the marginal external costs of air emissions vary across space and over time and depend on a number of factors (e.g. population density, urban structure). These costs could be more accurately reflected in a road pricing scheme, where prices vary across space and over time. In the absence of such a scheme, a second-best option would be to price each unit of air emissions by the national average of its external costs (weighted by e.g. population density).

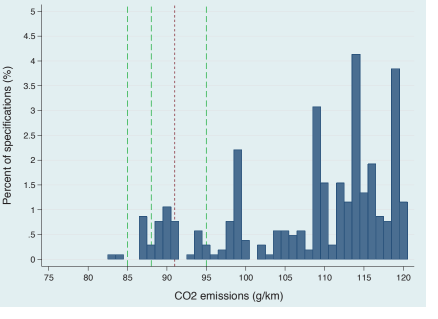
Notches in tax schedules and other corrective policies have recently attracted the interest of economists (e.g. Kleven and Waseem, 2013; Sallee and Slemrod, 2012), but there is still relatively little research conducted in this area. Considering that notched schedules are ubiquitous (see also Sallee and Slemrod, 2012), more research is needed to uncover the welfare implications of their widespread deployment and the gains that could be achieved by replacing them, where possible, with continuous functions of the underlying sources of externalities. It might not always be that notched schedules promote administrative simplicity, and even when they do so, increased simplicity usually comes at the expense of considerable reductions in economic efficiency. In this context, it would also be interesting to investigate the effects of notched schedules on market structure and competition. Intuitively, under specific circumstances, notches may unintendedly grant competitive advantages to firms whose products are located right below cut-off points, thus eventually encouraging less competitive market structures. The empirical investigation of this hypothesis is a promising avenue for future research.

Appendix 5.A: Distribution of car specifications over CO_2 emissions

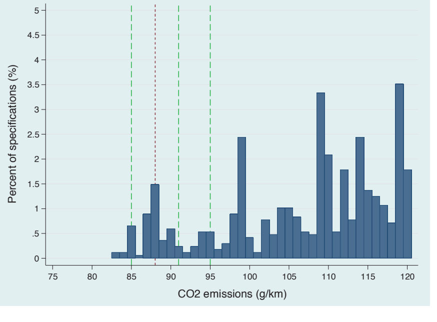
Figures 5A.1 and 5A.2 present the distribution of model specifications for diesel and petrol cars respectively. A model specification is defined as a unique combination of make, model and weight (e.g. Ford Focus 1274kg). Graphs for diesel cars provide evidence of bunching of model specifications on the tax-favoured side of notches in all periods examined here. However, stronger bunching is observed in categories which are not affected by these tax notches. Apparently, bunching primarily occurs at type-approval CO_2 emission levels which end at zero or five g/km or right below them (e.g. 99 g/km, 109 g/km, etc.). As the Dutch car market is relatively small, it is perhaps reasonable to suspect that the bunching around these CO_2 emission levels is the artefact of tax notches occurring in other European car taxation systems.



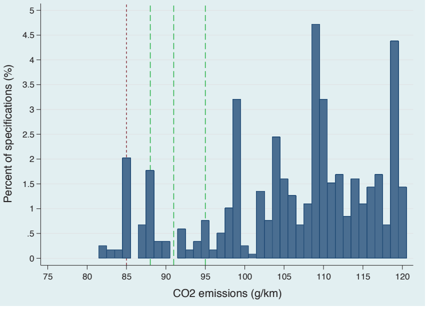
(a) Diesel cars: 1st half of 2012



(b) Diesel cars: 2nd half of 2012



(c) Diesel cars: 2013



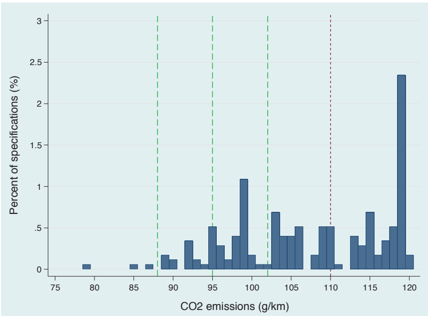
(d) Diesel cars: 2014

Figure 5A.1: Distribution of diesel model specifications over type-approval CO_2 emissions.

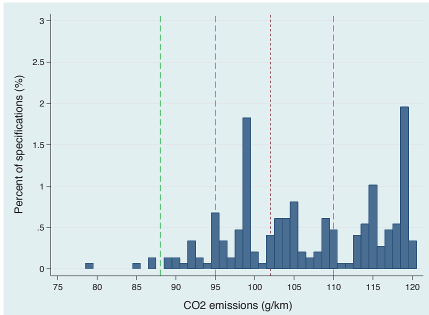
Note: Graphs draw on diesel and hybrid diesel-electric specifications which have sold at least 1 vehicle. Short-dashed lines indicate cut-off points determining eligibility for a lower company car tax rate (14%) and sharp reductions of the registration tax. Long-dashed lines indicate cut-off points in previous and following periods. Figures show only the part of the distribution between 75 and 120 gCO_2/km, but percentages are calculated taking into account the full range of CO_2 emissions for diesel cars. We exclude the first 2 months following the change of cut-off points. Data cover the period until the end of July 2014.

Source: Authors' calculations of RDW official data.

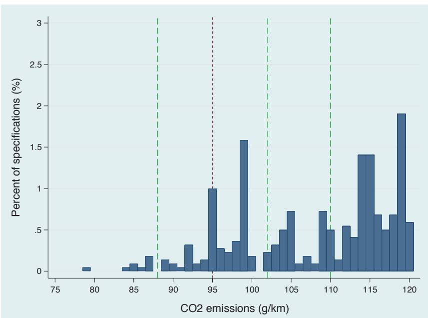
Bunching around tax notches is less evident for petrol cars. We find stronger indications for bunching in 2013 and 2014 than in 2012, but our graphical analysis reveals that more bunching is still concentrated at type-approval CO_2 emission levels ending at zero or five g/km or right below them (especially at 9 g/km). This is consistent with our previous suggestion that a likely driver of car manufacturers' behaviour is the tax notches existing in other European systems, which do not differentiate between diesel and petrol cars.



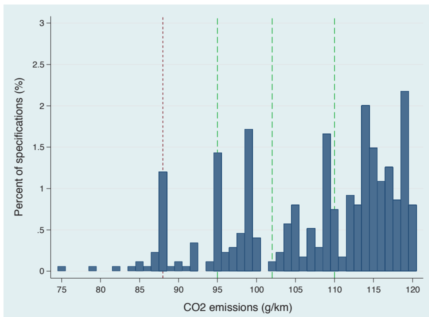
(a) Petrol cars: 1st half of 2012



(b) Petrol cars: 2nd half of 2012



(c) Petrol cars: 2013



(d) Petrol cars: 2014

Figure 5A.2: Distribution of petrol model specifications over type-approval CO_2 emissions.
Note: Graphs draw on petrol and hybrid petrol-electric specifications which have sold at least 1 vehicle. Short-dashed lines indicate cut-off points determining eligibility for a lower company car tax rate (14%) and exemptions from the registration tax. Long-dashed lines indicate cut-off points in previous and following periods. Figures show only the part of the distribution between 75 and 120 gCO_2/km, but percentages are calculated taking into account the full range of CO_2 emissions for petrol cars. We exclude the first 2 months following the change of cut-off points. Data cover the period until the end of July 2014.

Source: Authors' calculations of RDW official data.

Appendix 5.B: Econometric analysis by policy change

5.B.1. Empirical approach

In Section 5.5 we analysed manufacturer responses to changes in notches. To that end, we did not investigate possible differences in manufacturer responses among policy changes. The analysis presented here aims to provide insights into such possible differences. As in Section 5.5, we start by formulating the following fixed-effects logit model for each policy change – and therefore for each set of cut-off points *s*:

$$\mathrm{Prob}(below_{ijq} = 1 \mid treatment_q, \mathbf{Y}_{ijq}) = \frac{\exp(\rho treatment_q + \boldsymbol{\tau}'\mathbf{Y}_{ijq} + \delta_j)}{1 + \exp(\rho treatment_q + \boldsymbol{\tau}'\mathbf{Y}_{ijq} + \delta_j)}, \qquad (5B.1)$$

where the subscripts are defined as in Section 5.5. The variable of interest, *treatment*, takes the value of one when the specification is registered in the period when the set of cut-off points *s* determines whether a specification is eligible for tax advantages. The vector of control variables, **Y**, consists of: (i) a linear time trend; (ii) an interaction between the time trend and a binary variable indicating whether the cut-off point grants higher tax advantages or lower ones; (iii) interactions between the trend and make of the car; and (iv) quarter fixed effects. The coefficient of interest is ρ and the vector of parameters $\boldsymbol{\tau}$ is to be estimated. Car model fixed effects, δ, control for model characteristics which are constant across specifications and over time.

Similar to the econometric model of Equation (5.2), we also focus on responses within make-model-weight combinations. To this end, we use the following fixed-effects model:

$$\mathrm{Prob}(below_{ikq} = 1 \mid treatment_q, \mathbf{Y}_{ikq}) = \frac{\exp(\mu treatment_q + \boldsymbol{\psi}'\mathbf{Y}_{ikq} + \xi_k)}{1 + \exp(\mu treatment_q + \boldsymbol{\psi}'\mathbf{Y}_{ikq} + \xi_k)}, \qquad (5B.2)$$

where μ is the parameter of interest, ψ is a vector of parameters to be estimated, and ξ are make-model-weight fixed effects.

5.B.2. Estimation results

Table 5B.1 presents the parameter estimates for the model of Equation (5B.1). The table shows the estimates of the coefficient of treatment, ρ, as well as the relevant marginal effects when fixed effects are assumed to be equal to zero. Columns labelled "mid-2012" show the results of models estimated on data for the period 2010-2012 and the cut-off points taking effect in July 2012. Likewise, columns labelled “2013” are based on models estimated on data for the period 2010-2013 and the cut-off points introduced in January 2013. The same idea applies to the labelling of the “2014” columns.

The conditional probability of a vehicle specification falling right below or exactly on the cut-off point increases by a value between 7.8 and 16.6 percentage points after the policy change. The response to the policy change of mid-2012 seems to be slightly larger than the responses to the changes of 2013 and 2014. As discussed in Section 5.5, however, make-model fixed effects do not sufficiently disentangle supply from demand responses. We, thus, turn to the results of econometric models using make-model-weight fixed effects.

Table 5B.2 focuses on estimates of μ, the coefficient of treatment in Equation (5B.2), as well as the corresponding marginal effects. The results presented here paint a different picture from the one illustrated in Table 5B.1. In particular, they reveal that the policy change of mid-2012 did not induce significant responses from car manufacturers. On the contrary, the changes of 2013 and 2014 led to an increase in the probability of a specification falling below the cut-off point of 10.6 and 13 percentage points respectively. Once again, we find econometric evidence that manufacturers responded to changes in notches by fine-tuning the CO_2 emissions of some specifications, so that the latter could shift to the favourable side of the new notch. Responses were larger for the changes which provided manufacturers a longer time period to adjust to the new cut-off points, i.e. the changes of 2013 and 2014.

Table 5B.1: Fixed-effects logit model results – make-model fixed effects.

	mid-2012		2013		2014	
	estimate	std. error	estimate	std. error	estimate	std. error
Treatment (ρ)	0.934***	(0.278)	0.509*	(0.269)	0.686**	(0.345)
Marginal effect of treatment	*0.166****	*(0.044)*	*0.078**	*(0.042)*	*0.087***	*(0.043)*
Observations		1754		2153		1969
McFadden's R-squared		0.103		0.119		0.187
LL (convergence)		-502.7		-731.5		-516.4

Note: In addition, all models include make-model fixed effects, quarter fixed effects, a linear time trend, an interaction between the trend and a binary indicator of whether the cut-off point grants higher or lower tax advantages, and interactions between the trend and car makes. Estimates of these variables are not shown here due to space limitations. Models in the column labelled “mid-2012” are estimated on data until the end of 2012; treatment period is 1 July – 31 December 2012. Models in the column labelled “2013” are estimated on data until the end of 2013; treatment period is the year 2013. Models in the column labelled “2014” are estimated on data until 30 June 2014; treatment period is 1 January – 30 June 2014.

Data source: RDW.

Table 5B.2: Fixed-effects logit model results – make-model-weight fixed effects.

	mid-2012		2013		2014	
	estimate	std. error	estimate	std. error	estimate	std. error
Treatment (μ)	0.400	(0.566)	1.096**	(0.519)	1.752***	(0.672)
Marginal effect of treatment	*0.025*	*(0.044)*	*0.106*	*(0.070)*	*0.130***	*(0.066)*
Observations		1754		2153		1969
McFadden's R-squared		0.299		0.251		0.203
LL (convergence)		-97.3		-223.0		-144.8

Note: In addition, all models include make-model-weight fixed effects, quarter fixed effects, a linear time trend, an interaction between the trend and a binary indicator of whether the cut-off point grants higher or lower tax advantages, and interactions between the trend and car makes. Estimates of these variables are not shown here due to space limitations. Models in the column labelled "mid-2012" are estimated on data until the end of 2012; treatment period is 1 July – 31 December 2012. Models in the column labelled "2013" are estimated on data until the end of 2013; treatment period is the year 2013. Models in the column labelled "2014" are estimated on data until 30 June 2014; treatment period is 1 January – 30 June 2014.

Data source: RDW.

Chapter 6

Conclusions

6.1. Summary

Growing concerns over environmental problems and energy security have redirected the attention of policymakers, manufacturers and consumers to plug-in electric vehicles (PEVs). Global demand for PEVs has been increasing, but the pace of their market penetration is in most countries slow when compared with the pace of penetration of other alternative fuel cars. Perhaps more importantly, however, early demand for PEVs has thus far been strongly dependent on generous fiscal incentives. Even though this is a common feature of many technologies at their early stage of adoption, it is important to analyse the factors hampering a greater market penetration of PEVs and evaluate the impact of the provided fiscal incentives on agent behaviour and economic welfare.

This thesis has a two-fold objective. First, it aims to identify the main barriers to consumer early adoption of PEVs and other low emission vehicles and estimate the impact of these barriers on demand for these technologies. Its second objective is to analyse the effects of recent fiscal policies to stimulate demand for low emission vehicles in the Netherlands on consumer and manufacturer behaviour and economic welfare. To this end, it mainly focuses on policies implemented in the company car market, which has served as the main channel for the penetration of low emission vehicles in the Netherlands and other European countries. Chapters 2 and 3 of this thesis aimed at achieving the first objective, whereas Chapter 5 focused on reaching the second one. Chapter 4 addressed both objectives of the thesis.

Chapter 2 presented a meta-analysis of 33 studies investigating consumer preferences for PEVs and other alternative fuel vehicles to provide insights into the way driving range is traded off for capital costs. Based on 129 WTP estimates, the meta-analysis revealed that consumers are willing to pay, on average, about 67 US$ (PPP-adjusted 2005 prices) for a 1-mile increase in driving range. Consumer willingness to pay for additional range diminishes as the driving range of the vehicle increases. Ceteris paribus, cars with a range of 100 miles (ca. 161 km) have to be priced around 17,000 US$ less than their petrol-fuelled counterparts to be competitive. The variation in WTP estimates across examined studies can be attributed to differences in the levels of driving range considered, other elements of study design and the country of study. The findings of Chapter 2 confirm that short driving range has been a major limitation to the large-scale adoption of PEVs and that technological developments permitting longer driving ranges will, to some extent, facilitate their market penetration.

Chapters 3 and 4 have been based on the results of new large-scale surveys among Dutch company and private car drivers. Both surveys used choice experiments to elicit driver preferences for PEVs and internal combustion engine vehicles. Chapter 3 drew on the stated choices of more than 1500 drivers of private cars to examine the influence of environmental concerns on preferences for different types of plug-in electric vehicles (PEVs). Environmental concerns were elicited through Likert-type questions. Latent class and hybrid latent class models were used to study preference heterogeneity and its link to drivers' socio-demographic background and environmental concerns. Chapter 3 showed that environmental concerns are an important predictor of class membership and that highly concerned drivers tend to cluster in classes with stronger preferences for PEVs. Environmental concerns are higher among older and more educated drivers, and lower among drivers with high household income.

More than 15 million cars are provided as fringe benefits by employers in Europe. The company car market is the driving force of changes in European car fleets and one of the main channels for the penetration of PEVs and other low emission vehicles. Chapter 4 developed an approach to estimate the immediate welfare effects of policies using reduced company car tax rates to promote the adoption of PEVs. The approach was built on stated preference data from the survey of company car drivers and a panel latent class model. Even though reductions in company car tax rates are effective in stimulating early demand for PEVs, our estimates revealed that they also lead to important welfare losses, which even outweigh the foregone tax revenues. The result holds even if it is assumed that there are substantial future benefits from the adoption of electric company cars, e.g. in terms of positive network externalities, technological innovation and concomitant environmental benefits. Depending on the assumption made for the magnitude of external benefits provided by PEVs, the annual welfare losses are estimated to be between 42 and 95 million Euros. Welfare losses are mainly caused by tax advantages for plug-in hybrids, whose resemblance to conventional cars justifies much less generosity than the one implied by the provided tax incentives.

Chapter 5 focused on a wider range of low emission vehicles and analysed the impact of tax policies using notched schedules of type-approval CO_2 emissions on the behaviour of car manufacturers and consumers. Using data on new car registrations for the period 2010-2014 in the Netherlands, we demonstrated that notches not only cause salient changes in consumer demand, but also induce strong responses from car manufacturers. Consumer response to notches is manifested in the notable bunching of car registrations on the tax favourable side of the notch. Bunching is much more dramatic for diesel cars than for petrol ones.

Automakers' response was analysed through a quasi-experimental econometric approach. We showed that manufacturers strongly respond to reductions in cut-off points for diesel cars by reducing the type-approval emission levels of specific models just below the new cut-off points, while even leaving car weight unchanged. The probability that a diesel car is reported to have CO_2 emissions just below the new cut-off point is about 39 percent higher than what would be expected in the absence of a manipulative response. Automakers' response to reductions in cut-off points for petrol cars is much weaker. Provided that the company car share of new diesel cars in the Netherlands is around 70 percent, the findings of Chapter 5 suggest that car manufacturer and consumer reactions are primarily induced by notches in company car taxation.

A number of general conclusions can be drawn from this thesis. First, most full electric vehicles are still far from attractive for the majority of consumers, who seek for PEV alternatives whose attributes resemble the ones of internal combustion engine vehicles. To this end, plug-in hybrid and extended-range electric vehicles have considerable potential to mitigate drivers' current concerns over short driving range and long charging time. Second, early adopters of PEVs are likely to be relatively young workers with high environmental concerns and relatively low driving needs. High income households do not appear more likely to be early PEV adopters neither among company car drivers nor among private car ones. Third, the role of fiscal incentives has been critical for the early adoption of PEVs and other low emission vehicles in the Netherlands. Especially incentives provided in the company car market have been particularly effective in stimulating demand for these technologies. However, the generosity of these incentives, their dependence on car purchase prices, and the use of notched schedules for registration and company car taxes, have led to significant distortions in the car market, the foregoing of substantial amounts of tax revenue and important deadweight losses.

6.2. Policy implications

The rate of adoption of novel technologies, such as modern PEVs and other alternative fuel vehicles, depends to a large extent on the early stages of the adoption process (Rogers, 2010). As these technologies hold considerable promise for making future road transport more environmentally sustainable, it is important that potential barriers to their adoption are well understood and that policies which can help overcome these barriers are put in place. The findings of this thesis lead to a number of policy implications for the treatment of PEVs and other low emission vehicles.

Plug-in hybrids vs. full electric cars

Regardless of whether discussion revolves around barriers to PEV adoption or policies to overcome them, the distinction between plug-in hybrids and full electric cars is crucial. Plug-in hybrids can drive on both electricity and conventional fuel and are, thus, much closer substitutes to petrol and diesel cars than full electrics. Driving limitations related to short range, long charging times and limited charging infrastructure are of minor concern to drivers of plug-in hybrids, as they can readily shift to driving on conventional fuel. This has a number of implications for policy. First, plug-in hybrids can play a key role in the transition to electric mobility, as they can serve as intermediate alternatives that consumers can readily switch to and start getting accustomed with the special features of electric driving (e.g. vehicle charging, battery monitoring, silent driving at low speeds and rapid acceleration). However, it is also important to acknowledge that the environmental and energy security benefits of a switch to plug-in hybrids will be much lower and more uncertain, as individuals are likely to keep driving, at least to some extent, on conventional fuel.

Second, as plug-in hybrids face lower barriers to adoption and have lower expected environmental and energy security benefits than full electric cars, fiscal support for their adoption should be noticeably lower than the one provided for full electrics. When such support is provided in the company car market and employers pay for fuel, extra caution should be exercised by policymakers. Drivers who choose plug-in hybrids generally have very low incentives to opt for electric driving (as they are not the ones eventually reaping the benefits of reduced fuel costs) and thus fiscal incentives may prove too generous for the environmental benefits achieved in the medium run. To avoid this pitfall, fiscal incentives provided for plug-in hybrids in the company car market should be linked to the share of kilometres driven on electricity in the total distance travelled by the car.

Main barriers to consumer adoption of full electric cars

PEVs face concerns over reliability, high purchase prices, and uncertainty about future performance and resale values; barriers which usually hamper the adoption of innovative technologies. These barriers are common for all types of PEVs, regardless of whether they drive only on electricity (full electric cars) or also on conventional fuel (plug-in hybrids and their variants). On top of these challenges, however, *full electric cars* face consumer concerns over short driving range, long charging time and an inadequate coverage of charging (or battery-swapping) infrastructure. Chapters 2 to 4 provided empirical evidence that these concerns translate in high willingness to pay to avoid these barriers. Consumers have particularly strong preferences for significant increases of driving range – especially from levels in the area of 150 km, like the ones offered by most commercially available full electric cars – and a wider coverage of fast-charging infrastructure.

Breakthroughs in electric vehicle battery and charging technology allowing significant reductions in PEV acquisition costs and the achievement of substantially higher driving ranges and lower charging times will be necessary to ensure a sustainable future for full electric cars in the mainstream market. Otherwise, full electric cars will mainly be serving niche markets, such as the ones for sports or luxury cars, or specific travel purposes, such as the ones served by car-sharing schemes. It is, thus, important that policy stimulates R&D investment in developing new battery technologies, leading to cost reductions and increases of driving range, and advanced fast-charging systems resulting in lower charging times. At the early stage of adoption, developments in the supply side could be substantially assisted by policies aiming at raising drivers' awareness of their range needs and training them to use the range resources in their possession more efficiently (see also Franke and Krems, 2013).

The rate of development of fast-charging infrastructure is key for the transition to electric mobility.[100] Drivers value proximity to fast-charging stations considerably and (public and private) investments in such infrastructure can reduce the need to resort to generous fiscal incentives to stimulate PEV adoption. Furthermore, a dense network of fast-charging stations can induce drivers of plug-in hybrids to drive more frequently on electricity, something which has thus far proven difficult for fiscal policy to achieve. A wide coverage of fast-charging infrastructure is necessary to sustain interest in PEVs and reduce the dependence of their adoption on fiscal incentives.

[100] Despite its benefits in terms of very low refuelling times and a capital-operating cost ratio more similar to the one of conventional cars, the future of battery-swapping still looks uncertain. Battery-swapping stations require large capital investments, which are justified only when a large scale of PEV adoption has been reached. At the same time, the success of battery-swapping is strongly dependent on manufacturers' willingness to standardise the design of batteries and their positioning in the vehicle. Provided the high competition in developing new battery technologies with better performance and lower costs, standardisation does not seem to be a current priority for battery and vehicle manufacturers.

Consumer segments likely to be more receptive to policies promoting early adoption of PEVs

When designing policies to accelerate the adoption of a new technology, it is important to know which individuals are likely to be more receptive to it. Early adopters of new technologies usually exhibit different characteristics from individuals adopting the technology at a later stage (Rogers, 2010). Policies can then be targeted to the population groups who are the most likely early adopters of the new technology and, thus, be more effective in achieving their goal. The stated preference studies presented in Chapters 3 and 4 identify the profiles of private and company car drivers who are most likely to be early adopters of PEVs. In the company car market, early adopters of PEVs are more likely to be found among drivers with lower driving needs and a preference for smaller cars. They are also not likely to belong to the highest income percentiles of company car owning households. In the private car market, early adopters of PEVs are more likely to be females and have high environmental concerns.

Policies and communication strategies built around the environmental benefits of PEVs can attract highly concerned drivers' attention and stimulate their interest in PEVs. Women, highly educated and older drivers are more likely to have high environmental concerns, and are thus more likely to be attracted by the aforementioned means, while individuals belonging to households with relatively high income are less likely to do so. In general, when controlling for private or company car ownership, high income households appear less likely to become early adopters of PEVs.

What sort of fiscal incentives (not) to use to stimulate demand for PEVs and other low emission vehicles in the company car market?

At the end of 2015, the Netherlands had the largest PEV fleet in Europe and the 4th largest in the world with more than 87,000 PEVs sold across the country (RVO, 2016). The vast majority of these PEVs were company cars leased for a period of 5 years or less. The company car market can play a critical role in the early adoption of PEVs, as drivers of company cars face much lower barriers than drivers of private ones. Company car drivers do not have to incur the high upfront costs of PEVs and the uncertainty about vehicle's resale price and operating costs is shifted from the driver to the employer or the car leasing firm. Fiscal incentives for the adoption of company PEVs can be very effective in stimulating early demand, and the experience of the Netherlands and other European countries shows that they have succeeded in doing so. However, effectiveness does not necessarily imply policy success. Policies are successful when they achieve their goals at the minimum social cost. The findings of Chapter 4 reveal that the fiscal incentives provided in the Dutch company car market promoted PEV adoption at costs much higher than the socially desirable ones.

Fiscal incentives for PEVs and other low emission cars should not take the form of *reduced company car tax rates* as they have done in the Netherlands, the United Kingdom and other European countries. Such fiscal incentives would only be meaningful if the environmental benefits provided by low emission vehicles had a one-to-one relationship with car prices. However, no such relationship is observed in reality. An unintended consequence of this sort of fiscal incentives is that company car drivers are likely to opt for more expensive vehicles than they would do if fiscal incentives for PEVs reflected their actual external benefits. This results in welfare losses, as the marginal social costs of adopting these vehicles are higher than their marginal social benefits.

Instead, fiscal incentives for the adoption of PEVs could take the form of *deductions in the PEV list prices* considered when calculating the addition to taxable income due to the private use of the company car. The deducted amounts would be *solely determined on the basis of PEVs' external benefits* – including current environmental benefits, and benefits related to positive network externalities, technological innovation and concomitant future environmental benefits. This implies, for instance, that the deducted amount would be the same for all *full* electric cars, regardless of their market price.[101] The deducted amount for plug-in hybrids should be lower than the one for full electric cars, as their expected external benefits are lower. For the former, the deducted amount could be determined by the battery capacity of the car and the typical use of the electric driving mode. A feebate scheme which penalises driving on conventional fuel and rewards driving on electricity can then be envisaged. Such a feebate would not only be economically efficient, but also incentivise company car users to drive on electricity.

Which fiscal incentive designs are less likely to induce strategic responses from car manufacturers and consumers?

Fiscal policy in Europe and elsewhere increasingly relies on notched schedules of type-approval CO_2 emissions to stimulate demand for low emission vehicles. In Chapter 5, we saw that this prevalence of notched schedules in car taxation causes strong strategic

[101] Alternative schemes where deductions vary with full electric vehicle's' performance characteristics (e.g. driving range) are also worth considering, despite their higher administrative complexity.

responses from manufacturers and consumers and, therefore, large distortions in the car market. Distortions are especially pronounced in countries where more than one types of fiscal policy instruments are based on notched schedules, like the Netherlands.

Car tax policy in the Netherlands could benefit from a redesign along two lines. First, the use of a single *company car tax rate*, applying to all types of company cars regardless of their environmental impact, would be a relatively simple way to address the unintended effects of company car tax differentiation. The notched schedule of the company car tax rate has been particularly distortionary, as the salient local incentives it provides have stimulated strong strategic responses from manufacturers and consumers.

Second, the *car registration tax* could be based on a continuous schedule of type-approval CO_2 emissions, and if possible of emissions of air pollutants (e.g. NO_X, PM).[102] Each gram of CO_2/km and accordingly each unit of emissions of air pollutants could then be priced at its marginal cost to reflect as accurately as possible the environmental externalities of car use.[103] As diesel cars produce significantly fewer emissions of CO_2 per kilometre than their petrol counterparts, but are substantially more polluting, it is important that the car registration tax also takes into account emissions of air pollutants. Policies based solely on schedules of CO_2 emissions not only provide an unjustified comparative advantage to diesel cars, but also have important unintended consequences on human health and economic welfare.

6.3. Suggestions for future research

This thesis contributes to the ongoing debate on how to efficiently reduce emissions from road transport and increase energy security. In doing so, it mainly focuses on the early adoption process of PEVs and other low emission vehicles. However, a long-term transition to electric road transport requires much more than a successful early adoption process. Future research should aim to shed light on the challenges expected to be faced in

[102] A prerequisite for the environmental effectiveness and economic efficiency of any policy instrument is that the type-approval values of emissions are as representative as possible of the real-world emissions of cars under typical driving conditions. As we saw in Chapter 5, current official procedures to measure vehicle emissions do not adequately reflect real-world driving conditions and allow manufacturers to manipulate approved emission levels. It is, thus, of utmost importance that vehicle emission testing procedures are revised in order to provide accurate measurements of emissions under real-world conditions.

[103] It is important to consider, however, that the marginal external costs of air emissions vary across space and over time and depend on a number of factors (e.g. microclimate, geomorphology, population density, urban structure). These costs could be more directly internalised by space- and time-variant distance-based taxes. In the absence of such taxes, a second-best option would be to price each unit of air emissions by the national average of its external costs (weighted by e.g. population density).

this transition, the welfare implications of these challenges, and what policy responses are likely to be required to effectively address them. A list of possible topics for future research in this area is presented below. The proposed list is not intended to be exhaustive; instead, it focuses on a small number of issues which could, however, be expected to play a key role in the transition to electric road transport.

The effects of non-competitive market structures on consumer demand for low emission vehicles and economic welfare have not been considered in this thesis. This is mainly because the thesis focuses to a large extent on the Dutch car market, which can loosely be assumed to be competitive. It would be interesting, however, to analyse the welfare effects of tax incentives provided for the adoption of PEVs and other low emission vehicles in a setting where car manufacturers engage in price competition with differentiated products (see e.g. Beresteanu and Li, 2011; Berry et al., 1995; Goldberg, 1995; Petrin, 2002). To this end, researchers could use microdata on new car registrations which are becoming publicly available in an increasing number of countries.

Plug-in electric vehicles do not only compete with low emission internal combustion engine cars, but also with hydrogen fuel cell vehicles. Fuel cell cars are also propelled by electric motors and have already started becoming commercially available. Despite not facing important barriers related to driving range or charging time, fuel cell cars face high production costs and challenges related to the infrastructure required to produce, store and transport hydrogen. They are also much less energy efficient than PEVs and their environmental impact is strongly dependent on the energy source and chemical process used to produce hydrogen.

In the past few years, a number of stated preference studies investigated consumer preferences for PEVs, hydrogen fuel cell cars and other alternative fuel vehicles, generally showing that most consumers prefer hydrogen cars to full electric vehicles even when performance characteristics and coverage of refuelling infrastructure are largely similar (e.g. Hackbarth and Madlener, 2013; Hoen and Koetse, 2014; Koetse and Hoen, 2014). As electric vehicle technology rapidly advances, more research could be conducted to provide an up-to-date assessment of consumer preferences for alternative electric vehicle technologies. Such research efforts could also evaluate the market prospects of these technologies under alternative scenarios of the evolution of production costs, driving range and density of (fast-) refuelling infrastructure. Welfare analyses of potential policy interventions to support the market uptake of these technologies would then be based on updated information about consumer preferences, vehicle characteristics, infrastructure costs and *well-to-wheel* environmental benefits.

A long-term transition to electric road transport implies that full electric and hydrogen fuel cell cars will be able to cover virtually all travel needs currently covered by cars driving on internal combustion engines. An international widespread coverage of fast-charging and hydrogen filling stations is key to achieve this goal. Policies to encourage the adoption of electric cars and the development of the necessary refuelling infrastructure have thus far mainly relied on national or regional initiatives. However, stronger international policy coordination would be justified in this area, provided that consumers frequently take into account the coverage of refuelling infrastructure in neighbouring countries when making vehicle choices and that electric cars are seen as one of the most promising technologies to reduce CO_2 emissions from road transport (see also Vollebergh and van der Werf, 2014). Therefore, more research is needed to estimate the welfare effects of the lack of international policy coordination in facilitating the expansion of the network of fast-charging and hydrogen filling stations, as well as the potential welfare gains from multilateral policy actions in this area.

Plug-in hybrids will play an important role in the transition to electric road transport. Their contribution to achieving expected environmental benefits is, however, much more ambiguous, as it depends on the extent to which they drive on electricity. Policy needs to incentivise plug-in hybrid users to drive on electricity, but policymakers do not have clear guidance on what sort of incentives can be used to this end. The previous subsection proposed such an incentive scheme for company plug-in hybrids, but, in general, there is a surprising lack of research efforts towards this direction. Researchers could, for example, focus on the evaluation of the impact of changes in charging time and density of charging infrastructure on the amount of kilometres driven on electricity or on the estimation of the welfare effects of alternative policy instruments based on car use (e.g. a distance-based feebate or tax which rewards kilometres driven on electricity and penalises kilometres driven on conventional fuel).

This thesis has paid particular attention to the company car market and in particular to the design of fiscal policy to stimulate demand for low emission vehicles from company car drivers. In doing so, the thesis has implicitly assumed that company car drivers are free to choose the car they want. In reality, however, company car drivers' choice set is frequently restricted by their employers. Employers may, for example, require that the employee opts for a model of a specific make or fuel type. At the same time, the degree to which employees' choices are restricted, as well as the vehicle attributes on which such restrictions are based, vary significantly across employers and are rarely known to the researcher.

Alternative approaches to discrete choice modelling can be particularly useful in this framework. A seemingly suitable approach is to model company car choice as a two-stage decision making process. In the first stage, the individual uses a *non-compensatory* rule to screen out alternatives whose attributes are not allowed by the employer (e.g. alternatives of certain makes or fuel types) and formulate *consideration sets*. In the second stage, the individual uses a *compensatory* rule to choose her preferred alternative from the consideration set. As the non-compensatory rule employed by the individual in the first stage is unobserved by the researcher and can vary across employees, different approaches are proposed for the generation of the consideration set (see e.g. Ben-Akiva and Boccara, 1995; Gilbride and Allenby, 2004; Hauser et al., 2010; Jedidi and Kohli, 2005; Kaplan et al., 2012). To the best of my knowledge, such an empirical framework has not been used for the analysis of company car driver choices. As such models can provide more realistic representations of company car drivers' decision-making processes, their application to company car choice modelling is a promising avenue for further research.

Notches feature prominently in various applications of fiscal and regulatory policy, but there is yet relatively little research analysing their consequences on policy effectiveness and economic welfare (see e.g. Ito and Sallee, 2014; Kleven and Waseem, 2013; Sallee and Slemrod, 2012). More research efforts could, therefore, be directed to identifying the implications of the widespread use of notches and estimating the welfare gains that could be achieved by replacing notched schedules, where possible, with continuous functions of targeted outputs (e.g. emissions). Another interesting avenue for further research is to investigate the potential effects of notched schedules on competition. For example, notches may unintentionally result in competitive advantages for firms whose products are located right below the notch or can be shifted there at relatively low cost. Future research could empirically test this hypothesis and evaluate the impact of notched schedules on market competition.

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