Investigating the behavioural impact of a price-differentiated kilometer charge

By

Tom Savalle

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A discrete choice model on the Dutch citizen

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Preface

In February 2021 I started my thesis at Rebel Living Mobility. I contacted Rebel with an open application because I was very interested in their projects and heard good stories about them. After initial first conversations where we expressed mutual interests, I came up with a research proposal where I would perform a Stated Choice experiment on the new Fixed Kilometer Charge (FKC). Stated Choice experiments and Discrete Choice Modelling have caught my attention ever since the *Statistical Analysis of Choice behaviour* course. Right in the middle of discussing potential topics, the government announced to implementation of the FKC to avert decreasing tax income. This led to the discussion of how that new charge would change people's choice behaviour and to what effects that could lead to. Combining my preferred method with such an interesting and current topic, led me to believe that I could easily handle this research. After ignoring some warnings, I found setting up, conceptualizing and scoping down the research far more challenging than I thought. With the right guidance and the desired amount of freedom from both the TU Delft and Rebel, I managed to conquer those challenges.

In general, I am everybody thankful that I have been guided by people that have consistently trusted me and have given me the freedom to add my own spices to the project. I was very lucky to design and conduct such a cool experiment myself whilst being surrounded by intelligent, helpful people. Rebel really allowed me to be free in my choices which was key in getting this research to this level. In specific, I would like to thank the following people:

- **Bert van Wee**, your wisdom on the topic of road pricing has been really beneficial to this project. Your initial advice to look at how the models were structured was key to the setup of this entire research.
- **Eric Molin**, I want to thank you for your extensive guidance throughout this project. I learned a lot about Choice Modelling from you. On top of that, you always found time to go through my progress thoroughly and identified all the mistakes that I made. It felt good to know that you put in such an effort every time to help me. Your feedback was sometimes critical but it kept me focused and always helped me in the right direction and I would not have wanted it any other way. It was a shame to hear you didn't get your camper trip in Iceland but I'm sure you will catch up on that in the future. Once you do, have fun!
- **Oded Cats**, it was a pleasure to get to know you and I really appreciated your belief in the by supporting it with a research panel. This really gave value to this study that I couldn't have generated otherwise. Many thanks!
- **Luuc van Tiel**, I want to start by thanking you for the opportunity to perform this research. Next to that, I enjoyed all our late afternoons discussing the project and brainstorming the possibilities. Wrapping up those discussions with a beer at the end of the day was really nice. Finally, the freedom that you gave me to explore the opportunities and to make my own decisions really motivated me to do well and ultimately also added to the quality of this research.

Next to my graduation committee there are a few other people that I would like to express my gratitude. These people have been there from the start of the thesis process and helped me weekly with keeping the spirit going:

- **JW Floor**, I would like to thank you for all the hours that you put in to help me get this research to the level it is now. Without you, my knowledge on this topic would not have been as good. Our endless phone calls provided me with valuable information, tips and insights.
- **TILtrici**, I would like to thank my special TIL study group (Daan, Joost & Joost). The past study years would not have been as much fun as they were without you. Not only did we have fun, but we also helped each other reach a higher educational level. I could ask for help on a Sunday evening at 10 PM and I'd get it on the same night. The coffees and endless discussions on our thesis or other educational-related subjects made my study days. I can't wait to drink one final beer in the TB-café.

Thank you all for making this a memorable and, above all, very learning full end to a chapter in my life. It was a challenging but rewarding experience!

Tom Savalle
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Executive summary

The emergence of cars has immensely impacted life as we know it today. A world without access to a car is unimaginable for many people, and their lives even depend on this. In the Netherlands, fixed costs of owning a car partly consist of the motor vehicle tax, in Dutch: 'Motrorrijtuigenbelasting' (MRB). The MRB is a monthly fee that a car owner pays per car as financial support to the Dutch government for operating and maintaining the road infrastructure. One of the new plans made by the Dutch government is the implementation of the '*Pay according to Use*', or in Dutch: *'Betalen naar Gebruik'* system, also referred to as road pricing (Coalitieakkoord, 2021). This measure indicates that car use will be priced according to usage. Road pricing is an umbrella term that can be implemented in multiple forms. The Dutch government now opts for a Fixed Kilometer Charge (FKC), a new system that has not yet been implemented anywhere. An FKC is a form of road pricing where all road users pay a standardised or differentiated price for every kilometer they drive, no matter the time or place.

Change in people's travel behaviour resulting from this new form of road pricing could impact the characteristics of the national car fleet (car fuel-type choice behaviour) and overall car-use (mode choice behaviour) (Wegener, 2004; Weis et al., 2010). Therefore, the FKC could potentially stimulate a modal shift to greener fuel groups and alternative modes, positively contributing to climate change (Gibson and Carnovale, 2015). The literature considered in this thesis has focused on different road pricing systems and what methods/models were used to derive these estimated effects. Additionally, the review focused on the structure and designs of currently existing models and the types of effects that were measured in the consulted literature. This information was needed to build a theoretical framework that could describe how the experiments were structured.

The coalition agreement states that sustaining sufficient tax income is the primary goal due to decreasing fuel taxes. A secondary goal is the positive effect on car emissions such as CO_2, NO_x and PM_{10} that the kilometer charge is expected to have. At this moment, the government has presented its plan to implement the FKC, but it is yet unknown how the system will be designed in terms of differentiation among users. This design is decisive for its final effects as different implementations are expected to have other effects on different people. Hence, based on the choice for an FKC and the societal relevance and impact of such a policy, it is necessary to understand how these new policies, and their implementation, will affect society and car mobility. One implementation-related decision yet to be made is the choice of a uniform or emission-based differentiated charge. The examined literature includes no study on the effects of this form of price differentiation on a kilometer charge. Consulted literature on other types of road pricing did include this aspect, but for the FKC, relatively limited information was available. Another problem with new policies is the absence of empirical data to measure the impact policies will have. Dutch research institutions now use modelling techniques that include Revealed Preference (RP) data which rely on vehicle selling data. The choices of available fuel-type have become more complex, causing a problem with the validity of that data. The current data primarily consists of choices for conventional vehicles such as gasoline or diesel. On top of that, RP data contains multicollinearity issues, and measuring the attribute parameter estimation of the alternatives present in that decision remains challenging. In the literature, no study addressed these problems and/or using other data types, whilst the review also showed that other data types are suitable.

Two research objectives are set based on the aforementioned issues. One, this research aims to enhance the validity of forecasting policy effects. Two, this research aims to increase knowledge on the impact of a differentiated pricing scheme of the FKC. Based on these two research objectives, the following research - and sub-question has been defined:

Main research question: *To what extent does the level of price-differentiation of a kilometer charge influence people's stated behaviour towards mode choice and car fuel-type choice and what are the resulting effects?*

Sub-question: *What is the difference between groups, based on socio-demographics, in car fuel-type and mode choice behaviour that results from different pricing schemes of a kilometer charge?*

To achieve the research objective set in the previous paragraph, people's Stated Preferences (SP) for different pricing designs were obtained. People's choices in hypothetical situations can be obtained through an SP experiment. The SP data gathered in this experiment can then be modelled using Discrete Choice Modelling (DCM). DCM can estimate the effect, or weight, of pre-defined attributes of the alternatives provided in the choice situation. Two such experiments were performed; one for **car fuel-type choice behaviour** and one for **mode choice behaviour**. The obtained results from these models were then integrated into a model capable of measuring the effect of several differentiated FKC schemes. With this approach, both research objectives could be tackled, and the research questions can be answered.

Research set-up and - methodology
This research aims to use a single approach to reach both objections. The literary review provided insights into currently used models, and elements were extracted from those models to structure the set-up of the new experiment. For the SP experiment, respondents were provided with multiple choice sets in which they had to choose one of the alternatives based on varying attribute levels. In the car fuel-type experiment, the respondent had four alternatives to choose from, a gasoline vehicle (GV), diesel vehicle (DV), plug-in hybrid electric vehicle (PHEV) and battery electric vehicle (BEV). The varying attributes were *purchase price*, *range* and the *fixed kilometer charge*. The attribute levels for range and purchase price were given as a percentage of the base case, where the base case consisted of typical values for every segment. This way, the respondent was given a relevant choice set for their current car segment to obtain the most relevant answers. For mode choice, the respondent could choose one of two alternatives; 1) bike/train, dependent on the distance and 2) the car. The choice situations were varied in terms of *travel cost* and *travel time*. The literature concluded that the choice for an alternative interrelates with the distance; hence, four sub-experiments were performed, one for each distance category (5km, 25km, 75km, 200km) (Scheiner, 2010; Limtanakool et al., 2006). After having answered to their preferences for every choice situation, questions regarding their background, including socio-demographics and car - and travel characteristics, were included in the survey.

The data for these experiments was collected using an online survey and was distributed through an independent panel that could set quotas for gender, age and education to get the most representative sample size. 505 valid answers were obtained. After the data was collected, the data was cleaned and coded into a data set applicable for further modelling. This study uses a technique known as discrete choice modelling (DCM). DCM is a modelling technique that models theoretical or empirical choices made by people among a set of alternatives allowing it to explain or predict future choices. This study explores the use of DCM to gather insights into the important parameters behind choices for what transport mode to use and what car fuel-type to buy based on alternative-specific attributes. Discrete choice models are able to predict the weights that people attach to these attributes. Additionally, DCM can statistically relate choices to background characteristics to evaluate heterogeneity of these weights in the population.

DCM was applied in both the car fuel-type and mode choice experiments. Within DCM, there are several choice model options. The widest used model is the Multinomial Logit (MNL) model, used in both experiments. The main advantage of the MNL model is its simplicity, robustness, and ease of being computable and interpretable. For estimating the utility of car fuel-types, a Mixed Logit (ML) model was estimated to capture nesting effects within alternatives and to incorporate heterogeneity in the population. In the final models, interaction effects were added to the model to better understand how the policy affects different social groups. These effects indicate heterogeneity, or the degree of distinctiveness in choice behaviour and are able to examine which background characteristics cause heterogeneity. This knowledge was necessary to answer the sub question. The interaction parameters to be included were selected using mobility expert interviews. Subsequently, these parameters were translated into binomial values to define two groups for every characteristic.

In the last phase, the outcomes of both estimated choice models were integrated into a new model capable of predicting the effect of different combinations of the FKC per fuel-type on specific criteria. The criteria set were *tax income,* CO_2 *-,* NO_x *-,* PM_{10} *emissions, bike use, train use, EV market share* and *high car segment share*. A base scenario is defined to explain the marginal effects of differentiation towards a uniform charge. In the base scenario, a uniform charge of 6.2 eurocents is used, which is the most reasonable charge at the moment. The exact inputs per scenario can be found in Table 9.2. Scenario 2 includes a low -, medium - and high differentiated tariff for only fuel-type. These scenario's reward the early pioneers of EV use and try to enable a faster EV transition by discouraging ICEVs. Scenario 3 takes it one step further and also differentiates according to the car segment, where cars in a higher segment pay more due to their weight. This way the polluter and space occupant pays. High segment cars occupy significantly more space and emit more emissions. With this strategy, small car owners are rewarded and high segment car owners are discouraged. All results for 2030, 2040 and 2050 are displayed in Table 9.5.

The key findings of this research are split up into three parts. First, the key observations from the choice models and distributed survey are presented. This includes takeaways on the included main parameters and background parameters in both the mode choice experiment and the car fuel-type experiment. Additionally, the public acceptance of the new policy is highlighted. Second, the final results of the marginal effects of emission-based differentiation are given in Table 9.5 and additional key conclusions are drawn. Lastly, wider implications on the potential of using SP data and optimising the pricing schemes are given.

Key findings discrete choice models
From the first experiment, which focused on car fuel-type choice the key findings observed are:

- When the range, purchase price and the FKC are the same for all fuel types, the majority of the Dutch population would purchase a GV, followed by the PHEV and the BEV and lastly the DV. Presumably, the unobserved preference for a GV over an EV and a GV is due to the unreliability and inflexibility of charging EVs and serious health effects that are caused by diesel exhaust.
- The purchase price is, relatively, the most important attribute in people's decisions followed by the FKC and the vehiclet's range.
- The Willingness-to-pay (WtP) for a €0.01 decrease of FKC is €301. Higher income groups are willing to pay €58 more than lower income groups. This poses as an answer to the surprising result that higher income groups are more sensitive to the kilometer charge.
- Frequent car users, business car users and higher educated groups are also more sensitive to the FKC implying that they too have a higher purchasing WtP for a decrease in FKC.

The first key finding shows that, regardless of the stated interest in EV, people still choose a GV over an EV, indicating that even if purchase prices and ranges were to level that of an ICEV, a GV would still gain the highest market share. Second, the relative importance is highest for the purchase price when choosing a fuel-type. The variable FKC costs follows and the importance for range is the lowest. On average, the Willingness-to-pay (WtP) for a €0.01 decrease of FKC is €301, implying a point of return at a mileage of 30,100 kilometer. This 'payback period' is shorter than expected average mileages per car owner, but not all people are willing to make such an investment. The FKC and purchase price might both be monetary attributes but they are very different and appeal differently to specific people. Initially, the higher price-sensitivity for high income groups was surprising. In hindsight, this effect proves explainable because the effect resulted in a higher WtP (€327 vs €279) for a €0.01 decrease of FKC for people with higher incomes. A slight correlation between car use and income is likely to cause this difference. As expected, frequent car users are more price-sensitive because they are likely to have a high mileage and thus high total costs. Therefore, this group is more likely to switch to modes with cheaper variable costs. Another explanation for this higher WtP is that wealthier people are more financially equipped to make an investment (the higher purchase price) that will be earned back years later. If emission-based differentiation only allows people with more income to switch because they have the financial means, lower income classes pay more for road use than higher income classes. This widens the inequality gap.

From the second experiment, focused on mode choice at different trip lengths the key observed findings are:

- The Value of Travel Time Savings (VoTTS) differed substantially between the varying trip lengths. The average VoTTS for bike and car found for short (urban) trips is €6.86. The average VoTTS with car and train as choice options ranges from €4.44 for medium distances (25km) to €14.00 for long distances (200km). An interrelation between distance and the impact of the FKC thus exists.
- 6.2 eurocent fixed kilometer charge led to a car market share of 89%. A modal shift to alternative modes enabling a car market share of 75% requires an FKC of €0.17. A split market share (50% car use) of the car requires a uniform charge of €0.27 per kilometer.
- Those who use the car to commute or live far from the train station are less sensitive to price because no alternative is available. These factors contained a high level of heterogeneity. Less heterogeneity is present for income, implying that variation in choices between low and high income groups is limited.

- High educated and/or public transport card holders are more sensitive to the height of the FKC. Frequent car users are less sensitive for short distances but become more sensitive than occasional car users for long trip distances.

In addition to the inconvenience of taking the train, the preference for the car over the train might also be due to the dependency on people's commuting situations and their distance to the train station. Insensitivity to price for rural people with bad access to train stations or commuters with bad egress from stations could imply a particular car dependency where a high tariff is required to enable a serious modal shift. However, people with bad access to train stations are as good as unable to switch to an alternative, unintentionally creating a system where rural people are heavily disadvantaged compared to urban citizens. The original hypotheses proved correct for all included characteristics but couldn't be confirmed for all distances due to high p-values, which indicate that the found effect can not be generalized to the population. The findings resulted in a conclusion on the risk of disadvantaging groups that do not have an alternative. These groups include frequent car users, commuters and people that live further away from the train station. It looks like these groups are more dependent on the car, and because they might not have an alternative, emission-based differentiation does not result in the modal shift that might be desired with this strategy.
Regarding the acceptance of this new policy and potential implementation, the following can be concluded:

- 74% of people support the new form of road pricing. From all the ways that the kilometer charge can be differentiated (time, place, emission), varying the tariff for emissions proved to have the most national support (82%).
- Emission-based differentiation is, as expected, most supported by EV owners. There is a negligible difference in support amongst different car segment owners. Surprisingly, high car segment owners are generally more supportive.

Key findings application of choice model results
These scenarios that were used as input, all delivered varying absolute results, and these results were compared with the base case of a uniform FKC tariff. The differences were then converted into marginal changes, which are the final outcomes of the model and the answer to the main research question.

Table 1: Results of differentiation scenarios

2030	*base level* 1. Fixed charge - no differentiation	*Effect of various differentiation levels towards base level* 2a. Fuel-type - low	2b. Fuel-type - medium	2. Fuel-type - high	3a. Fuel type & car segment- low	3b. Fuel type & car segment- high
Tax income (mld euro)	8.94	14.3%	28.2%	41.5%	7.9%	33.7%
CO2 emissions (mln kg)	14.31	-0.9%	-1.9%	-3.1%	-0.6%	-2.6%
NOx emissions (tonnes)	3.86	-0.8%	-1.7%	-3.1%	-0.6%	-2.2%
PM10 emissions (tonnes)	17.50	-0.8%	-1.9%	-2.6%	-0.6%	-2.5%
Bike use (mld km)	17.95	0.1%	0.2%	0.3%	0.1%	0.3%
Train use (mld km)	24.10	4.7%	9.9%	15.9%	3.0%	13.1%
EV use (mld km)	18.78	0.8%	1.6%	2.4%	1.0%	2.4%
High car segment (mld km)	18.64	-0.7%	-1.5%	-2.4%	-1.1%	-2.6%

2040	*base level* 1. Fixed charge - no differentiation	*Effect of various differentiation levels towards base level* 2a. Fuel-type - low	2b. Fuel-type - medium	2. Fuel-type - high	3a. Fuel type & car segment- low	3b. Fuel type & car segment- high
Tax income (mld euro)	8.94	10.9%	21.0%	30.3%	4.7%	23.2%
CO2 emissions (mln kg)	14.31	-1.4%	-3.1%	-4.9%	-1.3%	-4.5%
NOx emissions (tonnes)	3.86	-0.2%	-1.9%	-3.1%	-0.1%	-2.2%
PM10 emissions (tonnes)	17.50	-1.1%	-2.0%	-2.6%	-0.9%	-3.3%
Bike use (mld km)	17.95	0.1%	0.2%	0.3%	0.0%	0.2%
Train use (mld km)	24.10	3.9%	8.4%	13.6%	2.3%	11.0%
EV use (mld km)	18.78	2.4%	4.9%	7.3%	2.5%	7.1%
High car segment (mld km)	18.64	-0.5%	-1.1%	-1.8%	-6.8%	-7.9%

2050	*base level* 1. Fixed charge - no differentiation	*Effect of various differentiation levels towards base level* 2a. Fuel-type - low	2b. Fuel-type - medium	2. Fuel-type - high	3a. Fuel type & car segment- low	3b. Fuel type & car segment- high
Tax income (mld euro)	8.94	6.6%	12.1%	16.4%	0.5%	10.0%
CO2 emissions (mln kg)	14.31	-2.6%	-6.0%	-9.5%	-2.9%	-9.4%
NOx emissions (tonnes)	3.86	1.5%	-1.3%	-3.5%	1.1%	-2.5%
PM10 emissions (tonnes)	17.50	-1.5%	-2.4%	-4.3%	-1.2%	-4.1%
Bike use (mld km)	17.95	0.1%	0.1%	0.2%	0.0%	0.1%
Train use (mld km)	24.10	3.0%	6.4%	10.2%	1.5%	8.0%
EV use (mld km)	18.78	2.9%	5.9%	8.8%	3.0%	8.5%
High car segment (mld km)	18.64	-0.3%	-0.6%	-1.0%	-13.1%	7.2%

Table 9.5 provides the answers to the main research question and thus has investigated the effects that various pricing schemes for a kilometer charge would have on several criteria. A brief overview of the key takeaways that can be derived from the table are:

- A higher level of differentiation results in more tax income and reduced emissions. Although this general effect is according to expectation, the table indicates the extent of this.
- Over the years, due to a faster transition to EVs, the emission savings will increase further, and the tax income will decrease (although it is still higher than with a uniform charge). The results show that a higher tax income is possible whilst stimulating EV and greener transport modes like the train.
- Train and EV demand cannot increase too fast due to infrastructural issues. However, the increase in demand for trains and EVs is not problematic and is considered acceptable. The extra tax income that will be collected by the stimulation of greener modes can be used to finance the necessary growth. The argument that EVs have higher purchase prices than ICEVs will weaken over the following years as EVs are expected to become competitive with ICEVs.
- In case the kilometer charge is also differentiated to car segment on emission basis, roughly 10% of high car segment users will switch to a lower segment.

Wider implications of this thesis

One of the two aims of this research was to investigate to what extent the validity of forecasting policy effects could be enhanced. This research has proved SP data worthy of including in decision-making processes. It gives a unique view of how people value specific attributes that are not available in case of new policies and how the policy-makers can use that knowledge to their advantage. However, SP data clearly has reliability issues. Respondents can be quick and careless when answering a survey, which deteriorates reliability, which was also encountered in this study. Based on pre-set criteria, we could remove some answers, but that gives no insurance that the other responses were reliable. Moreover, decision variables and the context for these choices exceed the handful of variables added to this model. This corresponds with the criticism that consumers react differently to hypothetical choice tasks in real life. Hence, SP data should not replace RP data but can function as additional knowledge to support particular decisions. On top of that, SP experiments that will be used to support such vital decisions should require more responses and cater to careless respondents to increase the reliability of the outcomes.

Furthermore, this thesis contributes to the knowledge of the effects of differentiating the FKC and to what extent SP data can be used for (additional) policy forecasting. Other insights this thesis brings consider the chronological order in which decision-makers make decisions. Where the report by MuConsult and Ministerie van Financien (2020) only evaluated a single differentiated pricing scheme, this thesis calculates the effect of 5 pricing schemes. However, both approaches fail to give the optimal strategy. This research has shown that there is a substantial difference in effect between different pricing schemes. This indicates that an optimal scheme can maximise one or multiple criteria. Not all criteria must be maximised, but some are limited to a hard constraint. For example, minimum tax income, a maximum modal shift, a maximum shift to EV and a ceiling rate that cannot be exceeded. Whilst satisfying these constraints, there is still the opportunity to maximise emission reductions. Whilst it is understandable that the government wants to be careful with differentiating too much to protect the more affected people, the majority of the respondents of this survey have indicated being supportive of the decision to let polluters pay more, even the people who get affected the most.

The study concludes with recommendations that further emphasise the benefits of applying and implementing a kilometer charge. It is advised to use SP discrete choice data to get more explanation for the choices people make and how technological development will affect future decisions. In addition, a specific recommendation is not to replace RP data as a whole due to SP data's unreliability. Lastly, a discussion is spurred on the fact that differentiating the kilometer charge might cause potential risks for disadvantaging groups that are highly dependent on car use or do not have the financial means to purchase more expensive cars that are greener and have lower variable tariffs.

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Nomenclature

Abbreviations

Abbreviation	*Definition*
BEV	Battery Electical Vehicle
CO2	Carbon Dioxide
CC	Cordon Charge
CPB	Centraal Planbureau
DCM	Discrete Choice Modelling
EV	Electrical Vehicles
FKC	Fixed Kilometer Charge
HEV	Hybrid Electrical Vehicle
HOT	High Occupency Toll road
ICEV	Internal Combustion Engine Vehicle
IIA	Independence of irrelevant alternatives
MNL	Multinomial Logit
MRB	Motorrijtuigenbelasting/Driving tax
NL	Nested Logit
NOX	Nitrogen
LC	Latent Class
LMS	Landelijk Model Systeem
PBL	PlanBureau Leefomgeving
PC	Peak Charge
PHEV	Plug-in Hybrid Electrical Vehicle
PM	Particular Matter
PT	Public Transport
RP	Revealed Preference
SP	Stated Preference
VoTTS	Value of Travel Time Savings
WtP	Willingness to Pay

Symbols

Symbol	*Meaning*
CO_2	Carbon Dioxide
χ^2	Chi-square
υ	Error component (Upsilon)
ρ^2	Model fit (Rho-square)
NO_x	Nitrogen
PM_{10}	Particular Matter
σ	Standard deviation (Sigma)
β	Taste parameter (Beta)

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1
Introduction

1.1. Background

The emergence of the car has made an immense impact on life as we know it today. A world without access to a car is, for many people, unimaginable, and their lives even depend on it. This rooted societal dependence on car use leads to a decreasing sensitivity to price. Increasing fuel prices, fuel taxes, insurance and motor vehicle taxes have all increased costs for car use over the past decades. Nevertheless, car use in the Netherlands is still growing. The Ukraine-Russian war has shown the impact of rising fuel prices, not only on the costs of car use but also on how these fuel costs echo through into global inflation. In the Netherlands, the fixed costs of owning a car partly consist of the motor vehicle tax, in Dutch: 'Motrorrijtuigenbelasting' (MRB). A car owner pays a monthly fee per car as financial support to the Dutch road system. In December 2021, the new Dutch formation presented the coalition agreement showing the plans to be executed under the Rutte IV cabinet. One of the new plans is the implementation of the '*Pay according to Use*', or in Dutch: *'Betalen naar Gebruik'* system, also referred to as road pricing (Coalitieakkoord, 2021). This definition means that car use will be priced according to usage. Road pricing comes in many forms, such as Cordon Charges (CC), Peak Charges (PC) and High Occupancy Toll (HOT) roads, and these systems have already been implemented somewhere around the world (Burris and Pendyala, 2002; Leape, 2006; Percoco, 2013). However, the Dutch government now opts for a Fixed Kilometer Charge (FKC), a new system that has not yet been implemented anywhere. An FKC is a form of road pricing where all road users pay a standardized or differentiated price for every kilometer they drive, no matter the time or place. It is called the 'MRB Plus' variant, where the original MRB will be repealed. The agreement states that these plans are only meant for private- and business cars and delivery vans (<3500kg) (MuConsult and Ministerie van Financien, 2020).

Road pricing has been an issue of discussion since the early 90s, and now, more than 30 years later, it ultimately looks like the government wants to make preparations, in the form of legislation and designs, to implement in 2030. In the literature and the media, many positive effects on society are mentioned as reasons for this decision. Changes in travel behaviour can occur due to price stimulation which impacts the characteristics of the national car fleet (car fuel-type choice behaviour) and widespread car use (mode choice behaviour) (Wegener, 2004; Weis et al., 2010). Therefore, an FKC would affect the climate because of a modal shift to greener modes and/or alternative modes (Gibson and Carnovale, 2015). In addition, this modal shift also reduces congestion due to less activity on the road network, which is beneficial for overall car accessibility (Xie, 2013; Olszewski and Xie, 2002).

However, the coalition agreement states that the main reason for implementing an FKC is to counter-effect the decreasing tax income (Coalitieakkoord, 2021). This decreasing tax income is due to an upcoming electrical vehicle (EV) fleet, which is, until 2024, excluded from the current MRB. Subsequently, this results in less tax income from the current MRB, even more so because EVs also pay little tax on electricity (ANWB, 2021c; Rijksoverheid, 2021; Nijland et al., 2016). As such, this policy resulted in more EVs but also more tax erosion. The government now faces a difficult trade-off between keeping the tax income stable and stimulating the electrification of the Dutch car fleet. An FKC differentiated to time- and/or place was rejected, while studies show that those systems would, with the proper implementation, have a higher effect on accessibility and emissions

(Centraal PlanBureau and PlanBureau Leefomgeving, 2015). The government prefers the FKC to increase overall tax income and remain a manageable project (Coalitieakkoord, 2021). The choice of the MRB Plus system is considered a 'missed opportunity for real change in behaviour by mobility experts, where the MRB could opt as a tool to impact environment and accessibility. Once the implementation of this FKC is successful, it is difficult to change back to another system, such as a levy based on time and place (Kraan, 2022; Geerlings and van Grieken, 2020).

The agreement states that tax income is the main goal, but the system is expected to affect emissions and accessibility. At this moment, the government has presented its plan to implement the FKC, but it is yet unknown how the system will be designed in terms of differentiation among users. This design is decisive for the final effects as different implementations are expected to have other effects. Hence, based on the choice for an FKC and the societal relevance and impact of such a policy, a good understanding of how such new policies and their implementation will affect society is necessary.

1.2. Literature Overview

The previous section described the relevance of the fixed charge policy and that such implementations require the best estimations possible to enhance decision-making. This section will give an overview of the available literature regarding this subject. Previous studies have looked primarily into the effects of road pricing policies on *mode-choice behaviour* and *car fuel-type choice behaviour*. Additionally, these explanatory variables are used to explain effects in a more tangible output such as income or emissions. There is also a variety in the methods that are used. Widely studied road-pricing types found are Cordon Charging (CC), Peak Charging (PC), Fixed kilometer Charging (FKC) & High Occupancy Toll Charging (HOT). Many studies (Gibson and Carnovale (2015); Xie (2013); Burris and Pendyala (2002); Percoco (2013, 2014); Levinson (2010); Krabbenborg et al. (2021); Olszewski and Xie (2002); Geurs and Van den Brink (2005); Olszewski and Xie (2005); Yamamoto et al. (2000); Leape (2006); Toye (2007) focus on CC, PC & HOT roads because these systems have already been implemented and measuring those effects is relevant. For the FKC, only the government reports Centraal PlanBureau and PlanBureau Leefomgeving (2015); MuConsult and Ministerie van Financien (2020); Tillema et al. (2018) and the other studies by Ubbels et al. (2008); Van Wee (2010); Geurs and Meurs (2010) focus on the FKC. Most studies estimated the impact on emission, tax income, accessibility and road safety or a combination of those.

The estimated effects on society result from behavioural effects of car-users that occur with pricing policies. A change in behaviour occurs because the prices changes but the Willingness-to-pay (WTP) for a type of car, or whether to use the car, in principle remains the same. The WTP includes the monetary value that one attaches to a certain product or service (Chorus, 2021). The literature primarily mentions behavioral effects in terms of mode choice & car fuel-type choice. Car fuel-type choice behaviour represents people's preferences for the fuel group of their car, given certain attributes of the fuel type alternatives. Mode choice behaviour represents people's preferences, given certain attributes of all mode alternatives, for a specific transport mode to take a trip. Many papers, such as Tillema et al. (2018); Geurs and Van den Brink (2005); MuConsult and Ministerie van Financien (2020); Centraal PlanBureau and PlanBureau Leefomgeving (2015); Geurs and Meurs (2010) also address the importance of price-differentiation and how pricing schemes can lead to different effects, which could opt as an additional tool to create the desired effects. Pricing schemes can stimulate/discourage the behaviour by pricing specific alternatives, or particular groups, differently. There are several ways to apply such a pricing scheme. Differentiating between time and/or place is a very well-known tool and is used in respectively the Peak - Cordon charge form (Krabbenborg et al., 2021; Leape, 2006; Percoco, 2013, 2014). As the Dutch government has excluded these options, one other relevant option remains; a pricing scheme based on car emissions. This pricing scheme is also already applied in the MRB (ANWB, 2021c; Ministerie van Financien, b). Cars pay a different variable price for road use depending on the fuel group and fuel economy. Fuel economy is a complex measure; therefore, the MRB divides weight groups to capture the environmental effects. The pricing scheme tool can influence both car fuel-type choice and mode choice. With this type of differentiation, the polluting road users can be targeted. This will not only lead to more tax income but also speeds up electrification Cavallaro et al. (2018).

Dutch governmental organizations, The Netherlands Bureau for Economic Policy Analysis (CPB) and the Netherlands Environmental Assessment Agency (PBL) use standard models (Revnext, 2019; MuConsult and Ministerie van Financien, 2020; Tillema et al., 2018; Centraal PlanBureau and PlanBureau Leefomgeving, 2015) to compute the expected societal effects resulting from policies . Three models, Landelijk Model Systeem (LMS), Carbontax and DYNAMO, were used in the latest report by MuConsult and Ministerie van Financien (2020). For estimating the composition of the Dutch car fleet, the Carbontax model and DYNAMO model are used. These models use vehicle selling data and a Total Costs of Ownership (TCO) analysis to determine price elasticities that are then used to compute the new composition of the car fleet. Recently, the Electrical Vehicle (EV), categorized in the Battery Electrical Vehicle (BEV) and its Plug-in Hybrid (PHEV) version, are upcoming, and its business model is getting more attractive (Liao et al., 2018). The 2020 share of EVs increased by 36% relative to the previous year (Centraal Bureau voor de Statistiek, 2021). According to the Carbontax model, available selling data on EVs is limited, and the selling data mostly consists of diesel (DV) and gasoline (GV) fueled cars which fall under Internal Combustion Engine Vehicles (ICEV). This complicates the estimation of the composition of the Dutch car fleet because there are more car types to choose from and these options all have different characteristics and effects on society. Next, the LMS model by Rijkswaterstaat is used to estimate how pricing policies affect car use. This model uses demographic and socio-economical data to compute the effects (Rijkswaterstaat). Both models use data that is sufficient for estimating car fuel type and mode choice when the car fleet only consists of conventional vehicles. With the rising EV market share, the question arises whether these models, and the data they use, are not getting outdated.

1.2.1. Knowledge Gaps and contribution to the literature

The literary overview gives a good overview of what research is out there and what is already known. This chapter summarizes the gaps that can be tackled in this research to get a better understanding of the available knowledge on this subject. Due to a limitation in the completeness of the data, a serious validation issue arises in estimating the effects of pricing policies. These effect estimations are crucial for decision-making and must therefore be as reliable as possible. Furthermore, we see that pricing schemes are used in the models, but no model or literature gives background information as to how (different) pricing schemes affect people's preferences. Additionally, the models assume that the effect of pricing schemes is uniform to the whole population, while the literature shows that heterogeneity exists among the population.

1. Validity of estimating behavioural and societal effects with historic selling data

The current models, LMS, DYNAMO & Carbontax, that are used to estimate the effects of pricing policies are all limited in forecasting EV purchases (Revnext, 2019; MuConsult and Ministerie van Financien, 2020). Selling records and socio-demographic information is used as input data. The recent increase in - and relevance of - EVs complicate the validation of the models. Using these types of data is a serious shortcoming in evaluating non-existing policies like the FKC. Additionally, the models are used to assess the influences of different pricing mechanisms like price differentiation. Apart from Ubbels et al. (2008), those who used choice data, there are no estimations for FKC effects that are not based on these data typesUbbels et al. (2008) using Stated Preference (SP) data. Still, his analysis completely ignores the existence of EVs, and its results have become invalid. A method must be sought that does not use selling data as the primary or only data type for estimating the effects of price policies of a non-existing system.

2. Effects of different pricing designs on mode choice behaviour

The second knowledge gap in the literature is the limited information on how pricing schemes can be applied to the FKC. MuConsult and Ministerie van Financien (2020) uses minimal differentiation strategies and does not show the underlying effect of different schemes. It also shows no elaboration on why that specific pricing scheme is chosen and how that relates to others. Furthermore, no paper touches upon varying population groups and if there are utility differences between these groups and whether or not some groups are more affected than others. To study the feasibility of these charges, more research must be done into how (different) people respond to various pricing schemes. With the help of these parameters, policy effect forecasting studies could be performed more efficiently.

This research contributes to scientific knowledge and society as a whole. For one, another method is sought to evaluate the effects of a (price-differentiated) FKC on car fuel-type choice and mode choice. This method must increase the validity with respect to the current models (Carbontax, LMS, DYNAMO) used. Insight into whether mathematical transportation models can make use of other data collection methods when applied for forecasting change in behaviour aids governmental decision-making. This way, the government, or governmental organizations, have an extra tool to assess the policy. Additionally, it brings policy-makers a set of options for implementation with estimated effects. Two, this study can contribute to scientific knowledge by adding the taste parameter of the FKC tariff and how this parameter varies among different population groups. When identifying this parameter and how this differs between groups, the policy effects can be estimated more efficiently elsewhere.

1.3. Research Objectives

The aim of this research that flows from the gaps described earlier is twofold. The first research objective is to enhance the validity of estimating behavioural and societal effects of the FKC. The second research objective is to evaluate the impact of differentiation, on mode choice and car fuel-type choice, for the Dutch citizen in general and more specific socio-demographic groups.

1. Enhance the validity of estimating the behavioural of a fixed kilometer charge

This research aims to enhance the validity of the estimation of behavioural effects from pricing policies. The societal effects that flow from this behavioural change are the effects on emissions (CO_2, PM_{10}, NO_x) and tax income and will also be estimated. The research aims to find and use a different method that is suitable to determine these effects. Using a different approach, the car-selling data that is being used now, which holds only limited records from EV, is no longer needed. This is desired as the limited EV records cause a validity issue in the current forecasting models. When making policy decisions of this magnitude, the effect estimations must be as reliable as possible.

2. Increase information on the effect of pricing schemes of a fixed kilometer charge

The literature and model outputs give limited information on the impact of (different) pricing schemes. Societal effects are mentioned but the underlying taste parameters are absent. This complicates future decision making, especially for countries where limited research has been done on the FKC. By increasing the information on what specific effect pricing schemes have, decision-making can be enhanced. When identifying the taste parameters and how this differs between groups, the policy effects can be estimated more easily elsewhere.

The data that is used to estimate the price elasticities is based on data that is called Revealed Preference (RP) data. The data itself is reliable, therefore but it changes when applying this kind of data to a non-existing system (Molin, 2019). Using RP data for systems and alternatives that do not (yet) exist is challenging. According to Molin (2019); Toye (2007); Schaubroeck (2005) it is possible to repeal this issue by engaging people's opinions and their Stated Preferences (SP). The question arises, which also the literature fails to answer, to what extent people say they would take the car and/or change their car fuel-type choice as a response to pricing policies. To achieve the research objectives set in the previous paragraph, people's stated preferences on different pricing designs can be obtained. The research questions that arise from these objectives show what new knowledge must be obtained in order to reach objective 1. To formulate the research question that rises:

To what extent does the level of price-differentiation of a fixed kilometer charge influence peoples stated behaviour towards mode choice and car fuel-type choice and what are the resulting effects?

To add to this research question, additional knowledge is desired about how different people respond to the new FKC policy. Therefore an additional question are formulated:

What is the difference between groups, based on background characteristics, in car fuel-type choice - and mode choice behaviour that result from different pricing schemes of a fixed kilometer charge?

1.4. Research approach and Outline

This study contains several components and requires a systematic approach. The research questions can answer to the lacking information found in the knowledge gaps. Mode choice and car fuel-type choice are the two dependent variables in this research, that are necessary to determine the height of the effect. As these dependent variables are interdependent, it is difficult to estimate their effects in the same experiment. Therefore, two separate experiments are conducted in the form of a stated survey. Both experiments will include the impact of different pricing schemes to fill the second knowledge gap. The outcomes of the stated survey will then be analyzed with the help of Discrete Choice Modelling (DCM). Ultimately the estimated effects will be applied to generate actual results in terms of emissions and tax income Rijkswaterstaat; Revnext (2019); MuConsult and Ministerie van Financien (2020).

1.4.1. Research outline

This research is outlined as follows. It has begun with an introduction to the area of study and, more specifically, the introduction of the FKC as a tool to influence car fuel-type choice and mode choice. A small overview of the present literature is given where after the knowledge gaps could have been defined. As a result of these gaps, the aim and questions of this research were determined. This chapter is finished with a small section where the methods needed to answer these questions are introduced. The next chapter, Chapter 2, reviews the knowledge that is already available in more depth. This knowledge is used to build a theoretical framework that structures the experiments in Chapter 3. Additionally, a section on the methodology is presented in Chapter 4. It consists of more information on how the literature studies and discrete choice models are conducted. Subsequently, the model and survey that will help us collect the data are designed in Chapter 5. The raw survey data that is then collected is cleaned and prepared to be used for DCM in Chapter 6. The set up and outcomes of both the car fuel-type - and mode choice experiments are given in respectively Chapter 7 and Chapter 8. The results of those experiments are then combined into one integrated model that forecasts the future impact of several differentiated pricing schemes. The set up of this model and the outcomes are given in Chapter 9. This study ends in Chapter 10 with a conclusion and discussion on the outcomes followed by actual policy recommendations. The outline is visualised in Figure 1.1.

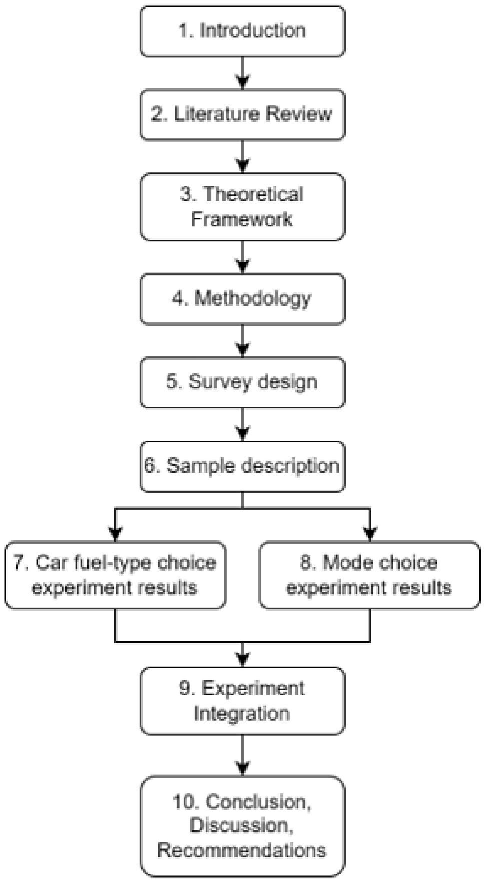

Figure 1.1: Research outline

2
Literature Review

As a result of the research questions, new knowledge has to be obtained. First, however, it is necessary to become acquainted with the theory. This systematic literature review seeks to find and evaluate literature on the effects of implementing different road-pricing strategies. This way, the contribution of the reviewed papers to understanding the problem becomes more clear which is necessary to reach the main goal. The main goal of the literature review is to reveal any existing knowledge gaps. Subsequently, this opens the opportunity to locate this research within the context of existing literature. The theory will then be used to build the theoretical framework to help visualise the new required knowledge. That means that elements from the literature are used to set up the experiment.

The study will provide an overview of various aspects of this new development in terms of the type of road pricing systems, what kind of data was used to estimate choice behaviour, what societal effects were measured as a result of this behaviour and finally, if a governmental organisation wrote the paper/report. Multiple pricing policies are taken into account to seek other methods of estimating the results. It is expected that a lot can be learned from previous studies on how to compute the effects of other road-pricing variants. The chapter kicks off with the methodology that is used to do the literature study. It defines different concept groups, keywords and their corresponding truncation. Hereafter, a detailed review is presented of all relevant information in the literature concerning various aspects.

2.1. Literature review methodology

The concept groups are divided into *Road pricing* and *Effects*. For both concept groups, a few keywords are defined to narrow the search results. Different truncation can narrow the search results when searching for relevant results. This is done by combining the concept groups and/or keywords by means of using AND or OR between those. The following concept groups and keywords were defined:

Table 2.1: Concept groups and keywords

Concept groups	Keywords
Road Pricing	Fixed kilometer charge Peak charge Cordon charge HOT charge
Effects	Emission Tax income Accessibility

2.1.1. Search strategy & Truncation

The search strategy in Google Scholar, TU Delft Library & Scopus uses truncation, which combines multiple keywords. Because not all keywords must be found back in the literature, OR is used. Also, criteria were added to the search.

Table 2.2: Search strategy

Truncation	Road pricing AND Effects - 616.000 results (Fixed kilometer charge OR Peak charge OR Cordon charge OR HOT charge) AND (Emission OR Tax income OR Accessibility) - 503.000 results
Criteria	Papers must be scientific, peer reviewed and cited The findings to include originate from the abstract, results, discussion or conclusion

As this concerns a Dutch study, the same search strategy was also used with the translation to Dutch. Papers of the same interest mentioned in found papers using the search strategy could also be reviewed.

2.2. Review results

This section aims to review and assess the topics discussed in the literature. For the type of road pricing system and the measured societal effects, the concept groups are used to identify what is present. It must be noted that not all papers directly calculate behavioural effects but incorporate the impact on dependent variables such as travel costs, volumes and modal splits, which are also effects as a result of a change in people's behaviour. The table below displays an overview of the literature discussed and what elements were present in that article/report. During the review, other literature was found, explored and outlined in the results too.

Table 2.3: Analysis of Articles published for Related sustainable freight transport problem

		Type					Societal Effects			
Reference	Focus	CC	PC	FC	HOT	Data	EM	TI	AC	GO
Gibson and Carnovale (2015)	Effects of road pricing on pollution	√				R	√	√		
Xie (2013)	Dynamic pricing for entering toll land		√			SP			√	
Burris and Pendyala (2002)	Discrete choice models for variable road pricing		√		√	SP	√		√	
MuConsult and Ministerie van Financien (2020)	Effects variants road pricing	√	√	√		R	√	√	√	√
Centraal PlanBureau and PlanBureau Leefomgeving (2015)	CBA of variants road pricing	√	√	√	√	R	√	√	√	√
Percoco (2013)	Effectiveness of road pricing for pollution	√				SP	√		√	
Levinson (2010)	Equity effects of road pricing	√				Q	√		√	
Krabbenborg et al. (2021)	Public support for tradable peak credits		√			SP			√	
Olszewski and Xie (2005)	Effects of road pricing variants	√	√		√	SP			√	
Verhoef et al. (2004)	Efficiency and acceptability on price policies	√	√		√	Q			√	
Olszewski and Xie (2002)	Elasticity of traffic demand	√				R			√	
Geurs and Van den Brink (2005)	Environmental implications variants road pricing	√				R	√			√
Leape (2006)	London congestion charge evaluation	√	√			Q	√			
Yamamoto et al. (2000)	Choice Behavior Under Congestion Pricing	√	√			SP				
Ubbels et al. (2008)	Effect price policies on car ownership			√		SP				
Toye (2007)	Economic analysis of road pricing	√	√		√	Q		√	√	
Percoco (2014)	Congestion pricing effects on pollution in Milan	√	√		√	Q		√	√	
Van Wee (2010)	kilometer charge as new road pricing system			√		Q	√	√	√	
Tillema et al. (2018)	Effects of pricing policies in the Netherlands			√		Q	√	√	√	√
Geurs and Meurs (2010)	Effects of kilometer charge on the environment			√		R	√			
Leefomgeving (2020)	(Pricing) Policy analysis on accessibility and emission effects	√	√			R	√		√	√

Type: Cordon Charge (CC), Peak Charge (PC), Fixed kilometer charge (FL), High Occupancy Toll lanes (HOT)
Data: Revealed Data (R), Stated Preference Data (SP), Qualitative Data (Q)
Societal Effects: Emissions (EM), Tax Income (TI), Accessibility (AC)

2.2.1. A tool for change in travel behaviour: road-pricing policies

Apart from the purchase price, the Carbontax model names five additional pricing policies that influence car (fuel)-type choice behaviour; the BPM, MRB, Electricity tax, fuel tax and subsidies (Revnext, 2019). Pricing policies for road use can come in many forms. In general, it means that the extent of usage is being charged, the variable costs of vehicle use. These charges work because they trigger a change in people's behaviour (Verhoef et al., 2004). Car users make choices about whether to make a trip and with what mode they prefer to make this trip. The trip - and mode choice decisions are, amongst convenience and comfort, mainly affected by the trade-off between time and costs (Wegener, 2004). Verhoef et al. (2004) wrote a paper where they highlighted how pricing policies also affects other behaviour. Within the area of transportation, people have many choices to make. For instance, the car they own, how many and the car's character (Ubbels et al., 2008). The policies can be applied to private- and business users and freight transportation. Except for the FKC, all road pricing systems, the CC, PC and HOT, have successfully been implemented worldwide Burris and Pendyala (2002); Verhoef et al. (2004). This section reviews these four road-pricing types and how mode- and car fuel-type choice behaviour from (potential) car-owners is impacted by them.

Cordon charge
The Cordon Charge (CC) is a charge paid to enter a certain cordon, often the city's centre, which is operational in big cities like London, Milan and Singapore (Leape, 2006; Olszewski and Xie, 2005; Percoco, 2014). Leape (2006) explains how London was taunted by congestion and how the original vehicle tax (Dutch MRB) had no impact on travel behaviour. The difficulties of an earlier network congestion charge differentiated to time and place turned out to be very expensive and demanded a high level of enforcement. After these unsuccessful attempts, a pilot study with a single, one-time toll when entering the cordon proved to be highly efficient in reducing the congestion in the city centre. According to Olszewski and Xie (2005); Menon (2000), the traffic volumes of Singapore, after introducing a CC, the Singapore Electronic Road Pricing system (ERP), reduced by 15% in the first year. The effect of the charge was higher on the expressways than on the restricted zones because expressway drivers have more re-routing alternatives. The studies by Leape (2006); Olszewski and Xie (2005) show the significant effects of these charges. Another example of a proven efficient introduction of the CC is the Ecopass in Milan (Percoco, 2013, 2014). The morning peak hour traffic volumes were decreased by 25% and led to an overall benefit of €9.3 million.

Peak Charge
The Singapore ERP also added a time-differentiated pricing scheme to the cordon charge where travelling during the daily peak hours is charged more (Olszewski and Xie, 2005). This type of charge is called a Peak Charge (PC). Burris and Pendyala (2002) found the traffic sensitivity during peak hours is substantially higher. They evaluated multiple peak charging systems, under which the Singapore ERP for this conclusion. The peak hour charge is often applied during high traffic volume hours. This excludes weekend days and is usually applicable for hours to and from work (07:0009:15 and 16:0018:15). The charge is meant to distribute traffic volumes over other moments of the day. The level of congestion reduction and traffic distribution is very dependent on the height of the charge (Krabbenborg et al., 2021; Wegener, 2004).

High Occupancy Toll roads
A High Occupancy Toll Road (HOT) is a high occupied piece of infrastructure that is used a lot and is often sensitive to overuse Centraal PlanBureau and PlanBureau Leefomgeving (2015); Burris and Pendyala (2002). In the Netherlands, we know 4 HOT roads, 2 of which are called 'shadow toll roads'. These toll roads are operated by a third party, and the 'toll' for every passenger is paid by the government. It is (yet) the only form of road pricing that the Dutch road network knows. HOT roads are enforced by toll houses or automatic registration in the form of a vignette or Automatic Vehicle Plate Recognition (AVPR). Toye (2007) proposes to add a time-differentiated pricing scheme but concluded that this is contradictory because the necessary toll houses form a bottleneck themselves. Insights by Verhoef et al. (2004) conclude that HOT roads are only worth considering when the primary goal of the pricing policy is to (partly) finance the infrastructure and maintenance. Next to creating a bottleneck on the road itself, it can also cause issues elsewhere, e.g. road networks that are used to avoid the toll.

Fixed Kilometer Charge
The Fixed Kilometer Charge (FKC) is a new proposed system where all drivers pay for their road use, and the original vehicle tax, the Dutch MRB, is repealed. High frequent road-users are thereby disadvantaged whilst people with limited car use are advantaged. The system has not yet been implemented anywhere, but extensive research, mostly by Dutch governmental institutions, has been done. Ubbels et al. (2008) conducted an SP experiment to define car ownership. This research stems from 2008 and does not incorporate electrification which enables people to choose different types of cars. Most reports found that addressed or evaluated the effects of an FKC are reports by governmental institutions (Centraal PlanBureau and PlanBureau Leefomgeving, 2015; MuConsult and Ministerie van Financien, 2020; Tillema et al., 2018; Leefomgeving, 2020). The reports by these institutions were unanimous about the outcomes. An FKC will have a significant impact on car fuel-type choice and mode choice, but the level of differentiation and the height of the tariffs is crucial to determine the final effects. These reports used multiple models to estimate the results, which will be explained further in the next section.

2.2.2. The effect of an individuals' background character

Socio-demographic factors and people's values are fundamental when decision-making. Many papers, regardless the type of road pricing, touch upon this effect or take it into account. When there is a difference in preferences between various consumer groups, it is referred to as heterogeneous preference. Price et al. describes this heterogeneity as the extent to which individual preferences and tastes for a product or service varies between different groups. The value of a bigger car or the value of taking the car instead of the train is different for everybody. Burris and Pendyala (2002); Krabbenborg et al. (2021) included socio-demographic factors like household size, age, gender and income. These factors, especially income, play a substantial role in people's Willingness To Pay (WTP) for more convenience/comfort or a faster travel time (Levinson, 2010). These factors are tangible and can be measured easily. The perception of people is much harder to measure but can not be ignored. If comfort is important to somebody, one is likely to either take a more comfortable car or avoid using Public Transport (Chorus, 2021). Achtnicht (2012) concluded that the value of sustainability plays a significant role when deciding on a car fuel-type choice.

2.2.3. Travel behaviour

All researched papers focus on how road pricing policies lead to a change in travel behaviour. What is travel behaviour, and which types of travel behaviour are incorporated in the papers? Travel behaviour is broad and includes observed choices in terms of the number of trips people make, the destination, the travel mode, the purpose of the trip, the timing, the route and the travel company. All these aspects fall under travel behaviour and are attributes of a trip made by a person. Wegener (2004) included a couple of the essential travel characteristics into the transportation land-use model, inspired by Lowry (1964), where one can find the relations between these attributes:

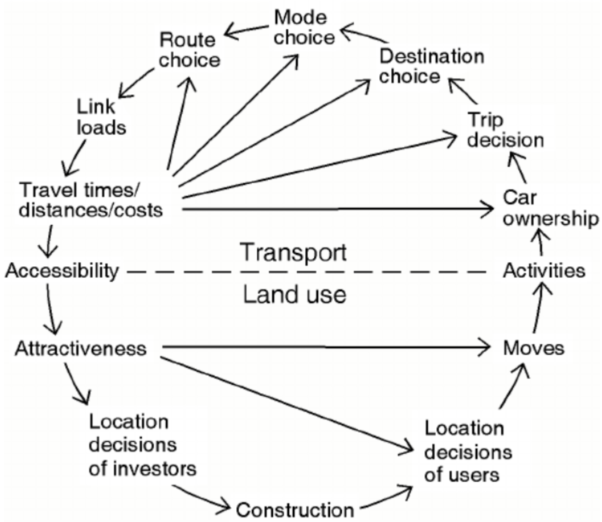

Figure 2.1: Transportation land use feedback loop (Wegener, 2004)

The transport feedback loop shows how different forms of travel behaviour are interrelated with many other factors. The road pricing policy affects the travel costs, which can either be positive or negative, depending on the height of the charge. As can be derived from the figure, transport costs impact the mode choice, and this aspect is relevant for this research. Mode choice behaviour describes the observed choices for a mode one takes when going on a trip. This could be the choice for train, car, air, bus, metro or an active mode like bike or foot. The change of mode choice that occurs as a result of e.g. a change in price is called a modal shift. Such a modal shift can have several effects, such as a reduction in CO_2 emissions (Kim et al., 2010). Within all transport modes, additional, more specific decisions can be made on the type of transport mode. For car travel, one must make additional choices on the kind of propulsion technology they buy (Ewing and Sarigöllü, 1998). The behaviour for choices considering the propulsion technology, we call car fuel-type choice behaviour. Price differentiation to emission can be done based on the propulsion technology. The papers that were analysed all focused on the modal shift (or mode choice behaviour) or car fuel-type choice behaviour. Geurs and Van den Brink (2005) analysed price differentiation in road pricing systems and stated that, when differentiating based on fuel-type (emissions), the two kinds of behaviour are interdependent. The price of the FKC will affect car fuel-type choice and the distribution of the fuel groups in the car fleet, in combination with the associated tariff of that fuel group, is then necessary for measuring the modal shift.

2.2.4. Modelling and data for forecasting the impact of road-pricing

The reports that study the effects of an FKC mostly use the same models for this prediction. The models used are the Carbontax model Revnext (2019), the Landelijk Model Systeem by Rijkswaterstaat and the DYNAMO model by Rijkswaterstaat (2006). To enhance the validity of these predictions, the type of data used in these models must first be thoroughly reviewed. Therefore, in this review, a distinction is made between the data types used to analyse the effects of the different systems. Stated preference (SP), Revealed Preference (RP), and Qualitative (Q) data were used to make that distinction. This is important because the type of data that is collected and used for modelling is crucial for its outcomes and its validity. Therefore this section aims to analyse the data types that were used. For measuring the actual effects in a quantitative way, the literature suggests that both RP data and SP data are possible. Revealed Preference data, for example, being used in the report written by MuConsult and Ministerie van Financien (2020), is used in the form of selling data delivered by the Dienst Wegverkeer (RDW). The report mentions it uses all three models to calculate the final societal effects of policies. A review of these three models is necessary to better understand how current forecast modelling is done and which factors play an important role.

Carbontax Model

The Carbontax model is a model made by Revnext and frequently used by the PBL and CPB to estimate policy effects. It is specifically built for the car industry and determines the car fleet size and its character in terms of segments, fuel-types, market segments and more. It is a widely known model that can configure different policy inputs into specific behavioural outputs. In essence, the model estimates car ownership and car fuel-type choice behaviour to react to these inputs. According to Revnext (2019), the market segments, that divides private - and business use of cars, are very different which are therefore separately modelled. The inputs regarding pricing are vehicle purchase tax (BPM), vehicle road tax (MRB), fuel tax, energy tax, subsidies, excise duties and surcharges. With these inputs, an indirect price-elasticity model is applied to measure the change in human behaviour in terms of car ownership and car fuel-type choice.

For the specific data to converge the policy inputs into behavioural change, historic selling data is used. Revnext (2019) describes this as one of the model's limitations, due to the fact that these records primarily consist of ICEV data rather than EV (PHEV & BEV) data. For ICEV, sufficient data was available, but now that the share of EVs is significantly increasing, the impact of the existence of this group can no longer be ignored Leefomgeving (2020); Centraal Bureau voor de Statistiek (2021); Liao et al. (2018); Centraal Bureau voor de Statistiek (2021). The model by Revnext (2019) uses a Total Cost of Ownership (TCO) analysis to determine the total costs, see the Figure 2.2 for the background model. The TCO includes the purchase price and the costs of operation, with an estimated life cycle Ellram (1993). Price elasticities, generated from historic selling data, are applied to the TCO to calculate the future development of the car fleet. A rational comparison is made with the TCO of EVs to calculate the chance of switching to an electricity-powered type of car. Subsequently, Revnext (2019) works with a threshold system to define the groups that actually switch.

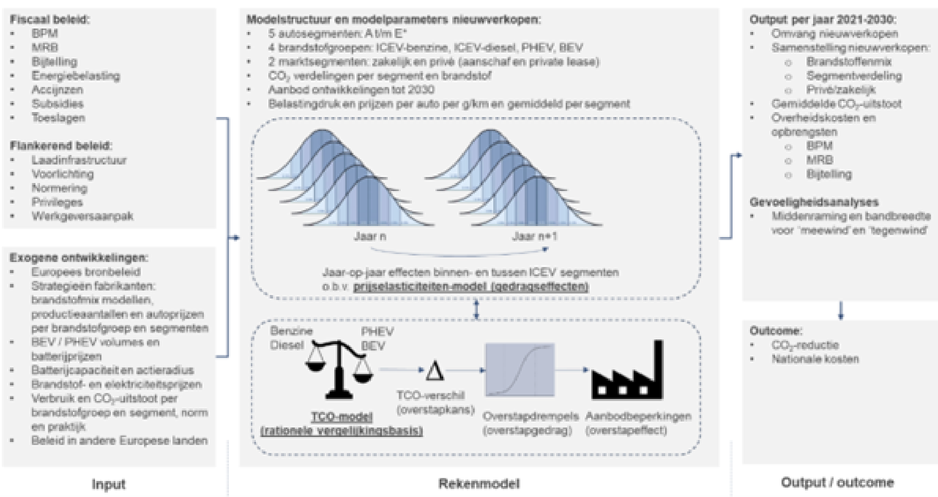

Figure 2.2: Background model of Carbontax model (Revnext, 2019)

DYNAMO Model
The DYNAMO is a somewhat similar model to the Carbontax model and is also used for determining car ownership and car fuel-type choice behaviour. The background model shows a conceptual model, see Figure 2.3. This model approaches car-fleet development from a supply/demand point of view(Rijkswaterstaat). The current car fleet and its characteristics are taken as a reference point, and from there, the effects of changing demand or supply are estimated. Pricing policies are taken into account as external factors, but the price variables do not play a decisive role. This is very different from the Carbontax model. This model is more focused on household development and the demand for car usage. The DYNAMO model, therefore, distinguishes three different trip purposes, where the Carbontax has determined 2. Socio-demographics play a much more meaningful role in this model.

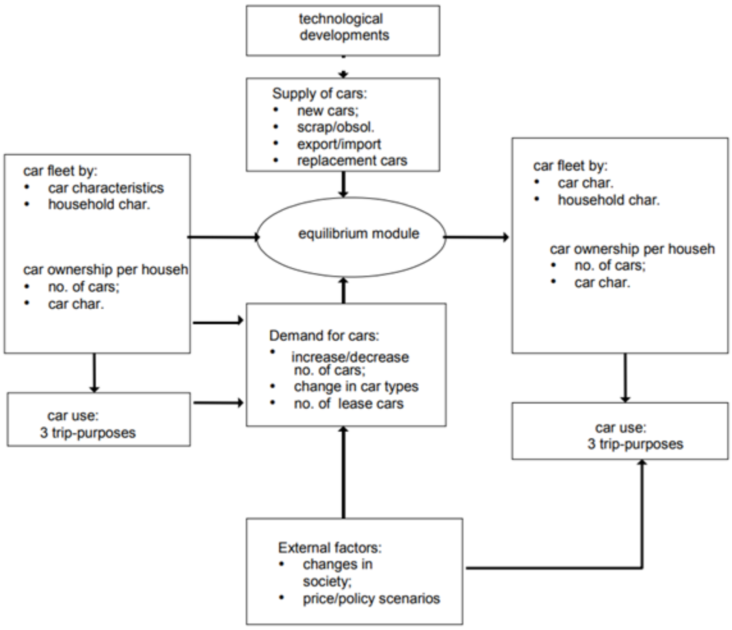

Figure 2.3: Car ownership conceptual model (Rijkswaterstaat, 2006)

Landelijk Model Systeem
The third model that is frequently used is the Landelijk Model System (LMS). The LMS is an internationally known model used and built by Rijkswaterstaat. Rijkswaterstaat uses this model to explore the effects of traffic and transport policy. The main effects estimated are mobility and accessibility (traffic flow). For calculating the effects of the FKC, the LMS is used to determine the impact on mode choice and, ultimately, the societal consequences. It displays the choice behaviour of individuals or households. This choice behaviour can be determined by observed choices or stated choices. The model then structures multiple trip profiles that are connected to specific personal characteristics and socio-demographics. The input thus exists from the existing mobility, socio-demographic data and the current mobility system, including the road/PT network and associated costs. The output of the LMS predicts overall mobility by mode and time of day, traffic flow and PT distribution. There is no extensive model structure available but Figure 2.4 shows that choice behaviour is used in their model.

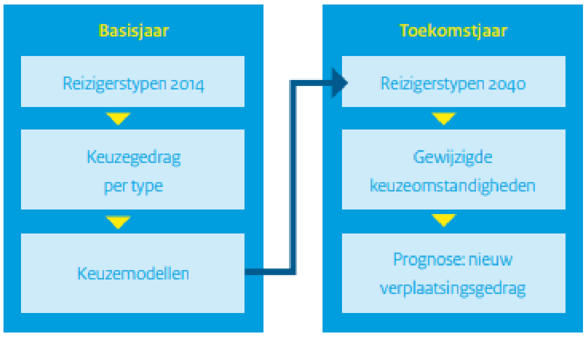

Figure 2.4: LMS model (Rijkswaterstaat)

Summary Section 2.2.4
For the price elasticity generated in the Carbontax model from the selling data (RP data) are key figures that give insight into the effect of a change in price on the demand or usage of a particular product (Geurs and Van Wee, 1997; Toye, 2007; Verhoef et al., 2004). In this case, it displays the change in an individual's behaviour towards car fuel-type choice. Other papers, such as Burris and Pendyala (2002); Xie (2013); Percoco (2013); Krabbenborg et al. (2021); Olszewski and Xie (2005); Yamamoto et al. (2000); Ubbels et al. (2008) use SP data, thus based on the choices individual states to make, to calculate these price elasticities. These papers are all focused on different road-pricing types, but how the data is used is similar to the existing models. The DYNAMO model uses the supply/demand developments and socio-demographic data to use The conclusion can be drawn that SP also suffices to acquire these elasticities.

2.2.5. Relevant model structure elements

A forecasting model consists of more than just the inputs, outputs and data used to configure this input into output. The structure or set-up of the model is an essential element of the model. This section describes important elements that are present in the literature or in one or more of the three reviewed models mentioned in previous section.

Fuel groups
For car fuel-type choice behaviour, the different *fuel groups* that one can choose from must be clear. Two decades ago, the fuel group division was relatively easy; you could choose between a Diesel Vehicle (DV) or a Gasoline Vehicle (GV) (Ubbels et al., 2008). Both types use an internal combustion engine and therefore fall under the Internal Combustion Engine Vehicles (ICEV) category. Additionally, Hybrid electrical vehicles (HEV) are available that combine internal combustion with electricity, creating two power sources (Liao et al., 2018). The Hybrid version collects electricity from internal energy sources like using the brakes. It is therefore not considered as a substantially different fuel-type but as a more efficient ICEV. The ICEV is the biggest fuel category and is therefore present in all research on car fuel-type choice (MuConsult and Ministerie van Financien, 2020; Centraal PlanBureau and PlanBureau Leefomgeving, 2015; Ubbels et al., 2008; Tillema et al., 2018; Leefomgeving, 2020; Liao et al., 2018). With the rise of the Electrical Vehicle (EV), and the electrification of the car fleet, the characteristics of this car fleet are changing rapidly and no longer consist of only ICEVs. An EV is powered by electricity and is charged using an electricity plug-in. The Battery Electrical Vehicle (BEV) is entirely driven by electricity and emits zero carbon. The Plug-in Hybrid Electric Vehicle (PHEV) falls under the EV and is a hybrid version where the electricity is distributed using a plug-in. The availability of electricity is much larger than for an ICEV hybrid, and for daily use, electricity could suffice as the primary energy source. Before 2015, limited papers touched upon Liquid Petroleum Gas (LPG) vehicles, but they only cover a tiny share of all vehicles. Finally, hydrogen is considered a potential new fuel for the car market, but an appropriate Fuel Cell Vehicle (FCV) to generate hydrogen power is not yet widely available.

Car segments
Another characteristic of the car fleet is the *car segment* distribution. The car industry consists of multiple segments. In theory, in the Netherlands, we know 14 segments, from Segment A to Segment N. All segments have different characteristics and small hatchbacks to limousines are included. The red line in all segments is the price category starting with lower prices for segment A and ascending from there. In practice, only segment A to segment E are used. All cars from the other segments are placed into segment E and are therefore denoted with

segment E+ (Revnext, 2019; MuConsult and Ministerie van Financien, 2020). The segment division is important because they have different characteristics in terms of weight, price, tax income, range and pollution (ANWB, 2021d). The segments are the same for all fuel-types. The car characteristics are important when deciding on buying a new car. Some people have more budget and are therefore used to more luxury (Ewing and Sarigöllü, 1998). In the literature, there are few papers that define and apply different car segments to their estimation. The only report by MuConsult and Ministerie van Financien (2020) includes this aspect as it makes use of the Carbontax model. In the other models, the LMS and DYNAMO, no car segment distribution is used.

Trip purpose
All three models make a distinction on the market segment or the purpose of the trip. The trip purpose refers to the type of trip made, the trip purpose. The purpose of the trip can include a distinction between a private trip and a business trip (Washbrook et al., 2006). Additionally, shopping trips and leisure/holiday trips could be added to increase validity (Meixell and Norbis, 2008; Hergesell and Dickinger, 2013). Weis et al. (2010) even distinguished business trips and commuting. The three models also use multiple trip purposes Rijkswaterstaat; Revnext (2019); Rijkswaterstaat (2006).

Price-differentiation
All literature and models for both mode choice and car fuel-type choice take into account the variable of price. Not all do incorporate the effect of different prices. When post-evaluating effects, the prices are known. When forecasting, various pricing schemes could be used to estimate the other effects. Ubbels et al. (2008) showed how different prices lead to a different change in behaviour and ultimately different societal effects. MuConsult and Ministerie van Financien (2020) also added pricing schemes to their estimation. They split it into three variants; no differentiation, a system based on carbon emissions and a scheme based on all car emissions, including CO_2, NO_x and PM_{10}. However, this report only included one pricing scheme and gave no justification for the choice of this tariff.

Electric Vehicle Development
The EV development that is expected over the coming years is starting to play a crucial role in the validity of the models. The increasing pressure for electrification to limit transport emissions leads to constantly changing legislation. The legislation surrounding EV stimulation and ICEV discouragement will affect people's mode choices and car fuel-type choices (Liao et al., 2018). Not only legislative developments, but also technological developments will have a serious effect. The technological developments for ICEV have stagnated whilst EV battery capacity is increasing and construction costs are decreasing (Weldon et al., 2018). With the EV getting more competitive with the ICEV in terms of price and range, it is good to account for this factor. All three models account for these developments (Rijkswaterstaat; Revnext, 2019; Rijkswaterstaat, 2006). It is also visible in Figure 2.3.

Timeline
The developments mentioned in the previous section are affected by the timeline that is looked at. The expected developments are often estimated over a couple of years. The LMS - and DYNAMO models are capable of estimating effects until 2040 (Rijkswaterstaat, 2006). The Carbontax model only estimates until 2030. The literary papers Ewing and Sarigöllü (1998); Weis et al. (2010); Ubbels et al. (2008); Olszewski and Xie (2005) are static and do not forecast for multiple time periods. This is because there was yet no EV development and only ICEVs were available.

Car-emissions
With the growing issues around climate change, car emissions have become a relevant topic in the transportation sector. For both car fuel-type choice and mode choice, car emissions can have a substantial effect on people's behaviour. The environmental impact of driving a (high polluting) car is under more pressure. This leads to people searching for alternatives. Liao et al. (2018) highlights the growing business model of EVs and thereby demonstrates that more people are willing to pay extra (in terms of costs and time) for non-polluting vehicles. This group is still limited and varies between different social groups. For mode choice, the environmental impact plays a role in one's utility (Schoenau and Mueller, 2017). Schoenau and Mueller (2017) also mentions the fact that when income increases, this effect reduces. The psychological influence of car use attributes, such as comfort, flexibility and independence remains important. Inherently, this negatively affects the choice of greener modes such as PT (Steg, 2005).

2.2.6. Societal effects of road-pricing policies

The literature presents numerous effects that flow from these pricing policies. At first, it is good to understand how the pricing policies can lead to the specific impacts. Policy pricing is mentioned as an instrument for emission reduction, congestion regulation and tax income (Coalitieakkoord, 2021; Percoco, 2013, 2014). The search strategy was defined in a way that certain effects were measured. The relationship between policy measures and societal effects are the dependent variables. These dependent variables form the steps in-between, and their understanding must be crystal clear in order to build up the research. In the traditional transportation feedback cycle, a clear framework is presented of how the effects between costs, car ownership, car-characteristic, trip generation, mode choice and more are related (Wegener, 2004). The impact of price policies thus affects multiple variables that independently also influence one another.

To illustrate an example, one that was also drawn by Geurs and Van den Brink (2005): pricing schemes for fixed charges like the FKC have an effect on car fuel-type choice. Inherently, car fuel-type choice is connected to mode choice. As the type of car one owns now has an influence on the cost, mode choice is dependent on the extent of the differentiation. If the differentiation is relatively 'flat', meaning there is little differentiation, the FKC could even lead to more conventional car fuel-type choices with negative effects on society. The effects on society that are found in the literature vary between accessibility, tax income, emissions and even traffic safety is mentioned. Traffic safety and accessibility are factors that are impacted directly by the traffic volume and is indifferent to the characters of the cars (Olszewski and Xie, 2002; Rijkswaterstaat; MuConsult and Ministerie van Financien, 2020; Leefomgeving, 2020). Pricing policies, therefore, have no direct influence on those societal effects whereas emissions and tax income are directly related to this policy tool (Tillema et al., 2018; Geurs and Meurs, 2010; Geurs and Van Wee, 1997; Gibson and Carnovale, 2015). The main emissions emitted by cars that were found focused on Nitrogen (NO_x), Particular Matter (PM_{10}) and Carbon dioxide (CO_2) and were measured in tonnes. Tax income is measured in million euros.

2.3. Summary

To summarise, the Dutch government is looking at implementing an FKC. To compensate for the extra costs, the additional car-ownership tax in the form of the MRB will be repealed (Centraal PlanBureau and PlanBureau Leefomgeving, 2015). Geurs and Van Wee (1997); Weis et al. (2010) judge that pricing policies in the form of fuel tax have two main effects. One, it stimulates to use the car less, either by choosing another mode or by not making the trip at all. Two, the tax stimulates to buying a more eco-friendly car. The tax on fuel and its effects are pretty similar to the impact of an FKC. As a result of the FKC, people will change their behaviour in terms of mode choice and car fuel-type choice. Both directly affect polluting emissions and tax income. The extent of this effect can be impacted by price differentiation, an effect whose impact is not measured in parameter form. For calculating the effects and the development of pricing policy measures, the Dutch governmental organisations primarily use three models; Carbontax, LMS and DYNAMO. These three models either use outdated vehicle selling data or socio-demographic data for forecasting policy effects. Finally, there was an even distribution in papers that used SP data and ones that used RP data to measure the impact. Although SP data is plagued by reliability issues, it is capable of getting more information on people's preferences which is valueble information in case of implementing a new non-existing policy. Although for the FKC, no SP experiment has been estimated to measure the effects, there are papers available on other road pricing systems that show that this is a valid technique. Lastly, Steg (2005); Schoenau and Mueller (2017) did mention an important factor to keep into account when deciding on these type of policies; the effect on different social groups.

The knowledge obtained in this literature review is used for two purposes. One is to identify the present knowledge gaps, further outlined below. Two, to set up and design the choice experiment in terms of structure, attributes and alternatives, which is done in Chapter 3.

Knowledge Gap 1

There is a lack of SP data concerning the effects of the new FKC. All effect estimations are based on historical - or RP data. The market disruption due to the increasing interest and relevance of EVs makes policy estimation more complex than ever before. There is no longer a uniform market where every car is either a petrol or diesel car, which also has almost the same characteristics. This change asks for more relevant academic knowledge on how specific policies affect society as historical - or revealed preference data is losing its validity.

Knowledge Gap 2

A second knowledge gap that flows from the literature is the lack of academic knowledge on to what extent price-differentiation of the FKC can be applied and what the taste parameter is of this aspect. MuConsult and Ministerie van Financien (2020) has studied the effect of multiple price-differentiation variants but has not concluded anything on the beta (), or taste parameter, of this effect. Additionally, one pricing scheme is researched, but price differentiation can come in many forms and combinations that can have different effects. From the literature, it is not yet clear what schemes are possible and to what kind of result that lead. Lastly, this parameter differs among the population and can not be generalised. More research must be done into the effect of different charges and how varying charges affect specific groups.

3
Theoretical Framework

The knowledge gaps defined a weakness in the type of data used to forecast the effects of pricing policies on behavioural - and societal impact. The change in behaviour due to a pricing policy like the FKC leads to changes in traffic volumes and car-fleet characteristics. To estimate these outputs, we will need to gather data about *car fuel-type* and *mode choice behaviour*. Geurs and Van den Brink (2005) defined these two types of behaviour as interdependent; therefore, two separate experiments must be conducted. Weis et al. (2010) acknowledged this and conducted the two experiments separately also. The frameworks that are presented in this section represent a part of the feedback loop by Wegener (2004). Wegener introduced the relationship between mode choice and car-ownership and how travel time, distances and costs impact the both of them. Therefore, these factors are included in two separate frameworks. The other factors mentioned in Wegener (2004) are neglected. First, more elaboration on the structure and extract elements from the literature review are presented. Then, both experiments are shown in the form of a theoretical framework where these elements come back and where a decision is made on what attributes and background characteristics to include. This goal of this framework is to visualise the research elements and variables to be included.

A theoretical framework shows the different elements and attributes to be included in the experiment. The relations and factors that are chosen stem from the literature review that was done in Chapter 2. Such a framework helps with structuring the survey and determining the right questions. The black arrows represent the main effects on utility. Utility is satisfaction received from consuming a good or a service; in this case, it means the choice for such a good or service (Molin, 2019). The dashed lines represent the effects of interactions on the utility of the different alternatives. The red lines indicate the effect of the socio-demographics, current car characteristics and a person's perceptions, for which a direct result is expected, on utility. There are two choice experiments, in this case, each having its framework.

3.1. Experiment 1. car fuel-type choice

The first experiment is focused on retrieving the preferences for car fuel-type choice. With the choice for the fuel-type of a new car being wider than ever, this is quite a complex but relevant experiment. The data that can be generated from this experiment is needed to investigate how people react to differences between FKC tariffs that can vary among these fuel-types. This section starts with the model structure and - design in which the alternatives, attributes and context variables are determined. It ends with the theoretical framework.

3.1.1. Model structure and - Design

Before designing a theoretical framework, the set-up and structure of the stated choice model must be defined. From the literature it could be concluded that defining the attributes is not enough in such a complex system with many alternatives. In practice, people have immense alternative opportunities. Within every segment, there are different brands with various shapes, colours, additional features and propulsion techniques. This research will limit itself to the propulsion techniques, but it acknowledges and incorporates the various segments. These segments are included in the experiment in a way that all respondents will receive a choice set that is relevant to their current car segment. This provides a more realistic choice set and therefore gives more valid answers; more on that is to be found in Section 3.1.1. Apart from the segments it is a must to define if and to what extent model elements are incorporated into context variables. The most crucial model elements found in Chapter 2 are discussed.

Car segments

The *car segments* can be set up in many ways. The LMS and DYNAMO models make no use of such a division, but the Carbontax model does (Rijkswaterstaat, 2006; Revnext, 2019). The car segments help with identifying revealed data on car fuel-type choice. For non- car-owners, a question can be asked about what type of car they would prefer if they could buy one. The car segments are linked to a price segment and could indicate the value one attaches to the type of car one owns. Not all 14 car segments, only the standard A, B, C, D, E+, are included (ANWB, 2021d; OSW, 2021). E+ segment represents all the other categories as these categories often have special cars, e.g. limousines. Cabriolets are often seen as middle class and are therefore added to the C category. The segments are as follows and will be provided with example vehicles and a general image for people who don't know in which category their car falls:

Car segments	**Car model examples**
Segment A - *Submini's*	Volkswagen Up, Opel Karl, Hyundai i10, Citroën C1,Peugeots 206, Toyota Aygo, Fiat 500, Opel Adam, Renault Zoë, Toyota Yaris, Renault Twingo
Segment B – *Small cars*	Toyota Prius, Opel Corsa, Fiat Punto, Ford Fiesta, Renault Clio en Volkswagen Polo
Segment C – *Small-middle class*	Renault Mégane, Peugeot 308, Opel Astra, Ford Focus, Kia Ceed, Audi A3, BMW 1-serie, Volkswagen Golf en Mercedes A-klasse. + Cabriolets
Segment D – *Middle class*	Volkswagen Passat, Opel Insignia, Ford Mondeo, Renault Talisman, Peugeot 508, BMW 3- 0f 4-serie, Mercedes C-klasse, Lexus IS of Audi A4/A5
Segment E+ - *Higher middle class – High Class*	Mercedes E-klasse, BMW 5-serie en Audi A6. Maar ook de Volvo V70, Mercedes CLS, Audi TT, Mazda MX-5 of Mercedez-Benz SLC, Volvo SC60, Hyundai Tucson, BMW XS, Audi Q7, Tesla Models and Polestar + SUV's, Jeep's en sport cars.

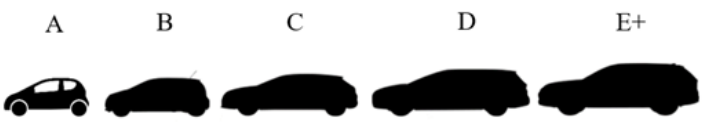

Figure 3.1: Car segments

Alternatives: fuel-types

The fuel-types, or fuel groups, represent the alternatives of this experiment. Therefore, these have to be chosen carefully and not all fuel groups can be taken into account to prevent the complexity of the choice set. According to Liao et al. (2018), the largest share of vehicles still belongs to the Internal Combustion Engine Vehicle (ICEV) category. Although this category could be taken as a whole, it will be interesting to see if there are differences between gasoline vehicles (GV) and diesel vehicles (DV). Therefore the ICEV is split into those two. On the other hand, Liao et al. (2018); MuConsult and Ministerie van Financien (2020); Leefomgeving (2020); Revnext (2019); Centraal Bureau voor de Statistiek (2021); Daziano and Chiew (2012); Daina et al. (2017) see a strong increase in EVs. Both the Plug-in version (PHEV) and the Battery (BEV) are increasing. These categories are therefore chosen as additional alternatives. Fuel cell EVs are not yet operational and LPG vehicles have a meager car-fleet share. These two groups are therefore excluded from this model. Hybrid versions (HEV) are considered efficient ICEV's and are thus not included (Ewing and Sarigöllü, 1998; Rijksdienst voor Ondernemen and Revnext, 2018).

Attributes

In choice modelling, attributes are characteristics of the alternative included in the choice set. An attribute can be fixed or varying per choice set. Generally, to measure the 'importance' of an attribute, attributes get varied into several levels. The attributes and their t'importancet' get combined in a alternative specific utility function. The total utility then defines the probability for choosing that alternative. In this section, the attributes included in this experiment are presented together with a quick elaboration on why they have been chosen.

The utility of this experiment describes how car users pick their type of car and if they would choose differently for varying pricing policies or the implementation of those (Ben-Akiva and Bierlaire, 1999; Chorus, 2021). As a result, the composition of the car fleet can be deducted from this data MuConsult and Ministerie van Financien (2020); Revnext (2019); Tillema et al. (2018); Leefomgeving (2020). The attributes are chosen based on their relevance and appearance in a car fuel-type choice experiment by Ewing and Sarigöllü (1998). Ewing and Sarigöllü (1998) used toll as a variable pricing attribute and distinguished fuel and toll costs. In this experiment, the FKC is relevant as this is the policy measure that this research investigates. The purchase price and range are also attributes and relevant factors due to the current EV development. With the technological and economic development of electric vehicles, ranges are increasing, and prices are decreasing. This learning curve is translated into attributes that can vary so that multiple future scenarios can be modelled.

Purchase price: The purchase price of cars is one of the two main determinants of car fuel-type choice. This is also because the purchase price strongly depends on weight and propulsion technology. For many people, buying a car is an investment; therefore, the purchase price is an important factor when making a car fuel-type decision. Not all people can afford all car types or value cars in such a way that they are worth that investment. Higher car purchase prices are expected to cause disutility and the parameter sign is thus expected to be negative.

Range: Another interesting element that has been added to car fuel-type choice sets is the range of the vehicle. With the increasing amount of EVs, the range has suddenly become a choice attribute because EV range significantly differs from conventional vehicles (Beggs et al., 1981; Liao et al., 2018). It is also taken up in the stated survey experiment done by Ewing and Sarigöllü (1998). Higher ranges are expected to cause disutility and the parameter sign is thus expected to be negative.

Fixed Kilometer Charge: Apart from the purchase price and range, the variable kilometer price is essential in ones choice. It was explicitly included in Ewing and Sarigöllü (1998). The varying price/km covers all costs that depend on the length of your trip. This includes fuel costs and, when implemented, also the fixed kilometer charge. However, fuel costs are not a direct attribute. Fuel costs of a certain trip are very dependent on the weight, age and fuel economy of the car. In real life, the height of these costs are not displayed. To mirror reality as best as possible, fuel costs are not included as a separate attribute. This variable price/km will thus only consist of the FKC and will change among choice sets as this research tries to observe its effect on the responsible variable: car fuel-type choice. Higher variable travel costs are expected to cause disutility and the parameter sign is thus expected to be negative.

In Chapter 5, more research is done on these attributes, and the levels that will be used in the choice set are defined.

Context variables

Context variables are added to the choice task but are fixed and, unlike the attributes, will not change per choice set. Context variables are created to give more context to the choice task so people can make a more deliberate choice. For the car type experiment, three context variables are added, EV (fast) charging time, CO_2 emission and fuel costs.

EV (fast) charging time: The shortened range and long charging times are considered to make the EV, foremost the BEV, less flexible than ICEV. Fast charging times are, however, rapidly increasing, and it is good to make people aware of the actual charging times to let them make a deliberate choice. PHEVs are not entirely reliable on electricity and are therefore considered to have the same refuel time as ICEVs. A context variable 'BEV charging time' is consequently added to the choice task to contextualise the extra time it costs BEVs to fully charge their battery.

CO_2 emissions: Schoenau and Mueller (2017); Ewing and Sarigöllü (1998); Hergesell and Dickinger (2013) highlighted the effect of carbon (CO2) emissions on car fuel-type fuel choice. There is a growing demand for cleaner vehicles, and people are willing to pay more for that. To incorporate this vehicle performance attribute, the alternatives should be provided with information on their level of car emissions. Dominant factors in car emissions are the fuel-type and the car's weight. The weight of the vehicle is strongly related to fuel economy (Transport and Environment, 2018). This research assumes tank-to-wheel emissions, and thus BEVs emit no CO2. PHEVs emissions are in-between BEV and ICEV. Furthermore, it uses relative quantification. Using absolute numbers for CO_2 emission per car fuel-type is difficult for two reasons. For one, the weight varies a lot between the car segments and thus also the fuel economy and the CO_2 emissions. Every fuel group within every

car segment has a different average. However, as we assume a linear growth in weight/fuel economy, we can also assume this linearity in CO_2 emissions. A relative difference is then applicable for all segments. Two, it is generally difficult to interpret an absolute CO_2 value; relative percentages are easier to understand.

Fuel costs: As the FKC costs per km is a fixed price, people will know their FKC costs. For fuel costs, this is different because the exact fuel price per km is unknown. It is unknown because the fuel price is given in price per liter and the fuel economy then is decisive in the final costs per km. To imitate reality as good as possible, the fuel costs are not incorporated in the choice set and must be determined by the people themselves. As the experiment is about fuel-type choice, the relative difference between the four alternatives is given, like for the average car CO_2 emissions. Furthermore, fuel costs are based on oil and electricity prices and fluctuate. As the most significant car share is from the ICEV, the ICEV is again the reference category. Diesel and Gasoline prices are relatively close to each other; the only difference is that Diesel is usually a little bit cheaper, but these users pay an extra fee in their monthly road use tax to compensate for additional PM_{10} emissions (MuConsult and Ministerie van Financien, 2020; Ministerie van Financiën, 2020).

3.1.2. Theoretical framework

The black arrows represent the main effects on utility. The dashed lines represent the effects of interactions on the utility of the different alternatives. The red lines indicate the effect of the socio-demographics, current car characteristics and a person's perceptions, for which a direct result is expected, on utility.

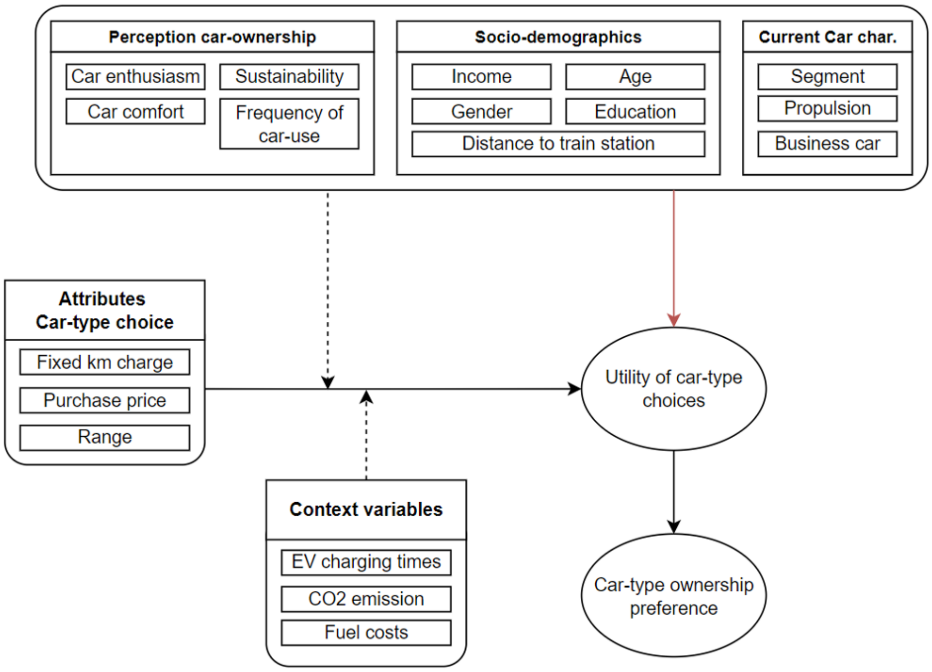

Figure 3.2: Conceptual model car fuel-type choice

Every individual disposes of different characteristics and attitudes towards specific values. These differences echo through in the choices they make. To account for heterogeneity, socio-demographic factors like age, income, gender and education are added to the model. These factors represent different groups in society and are expected to have an impact on decisions, see Section 2.2.2. Additionally, the distance to the nearest train station is an important metric to decide whether you as an individual need a car. Quality and taste in car type choice are difficult to measure. There are many variables that people value differently. This variety in the value of choosing a specific car can not be generalised. On top of that, the characteristics of one's current vehicle are included to gather RP data concerning buying a car. RP data can help us better understand people's value when choosing a car.

Ultimately, the height of the FKC, the the purchase price and the range will be the main effect on the utility of the car type and its specific characters. This main effect is, however, interacted by the socio-demographics of an individual. The impact of these socio-demographics has been studied in Levinson (2010); Burris and Pendyala (2002). They concluded that there was a significant effect between those variables. These socio-demographics will also directly impact the utility; this effect is marked with the red line. Individuals with a higher income might be less sensitive to the height of costs or the environmental impact (Schoenau and Mueller, 2017). Because it is unfair to generalise this effect, it is good to gain more knowledge on how people value this. Therefore perception questions must be asked to better understand different types of individuals. This is the same approach as in the LMS model, where several profiles are sketched to forecast the behaviour of different kinds of people. For this experiment, car comfort, sustainability, flexibility and car enthusiasm are picked. Finally, context variables were added to sketch the context of the research. These fixed variables differ per alternative and are added to give more information when people buy a car. The context variables are fuel/electricity costs, CO_2 emissions and the time it takes for EVs to charge.

3.1.3. Expectations

This section provide the hypothesis on the expected signs of the parameters. For the main parameters this indicates whether these parameters have a positive or negative effect on the total utility. For the interaction parameters, a positive signs indicates a low sensitivity and a negative sign indicates a high sensitivity.

3.1.4. Main parameter expectations

The main parameters, the FKC, purchase price and range have different impacts on utility. The FKC is a cost attribute and generally it is expected that higher costs lead to a lower utility. This indicates a negative effect between utility and the FKC and therefore a negative sign is expected. Purchase price is also a cost attribute indicating that a negative sign is expected. The higher the range, the 'better' the car and therefore a positive sign is expected. Higher ranges lead to higher utilities of that car fuel-type.

3.2. Experiment 2. Mode choice

In the second experiment, mode choice behaviour is observed. As for experiment 1, first, the alternatives must be defined, and the context must be sketched. This section starts with the model structure and - design where these alternatives, attributes and context variables are determined. It ends with the theoretical framework.

3.2.1. Model structure and - Design

Sub-experiments based on distance

This experiment will be sub-divided into four smaller experiments. This is because the FKC is expected to have other effects for different distances. When looking at longer distances within the Netherlands, the train is the only mode that can compete. To do this experiment, we assume that there is a train station in both the departing as well as the arriving nodes. The mode choice models will be estimated using distance-dependent nonlinear utility functions and separately for the various trip purposes and relevant for all other trip characteristics (Washbrook et al., 2006). Scheiner (2010) acknowledged the fact that trip distances are of influence on mode choice. There is no linear effect with respect to distance on mode choice behaviour. In that study, multiple distances are used to examine the different behaviour and thresholds when an individual chooses differently. This experiment uses four distance categories to analyse the results based on different distances. The selected distances are: 5km (mini), 25km (small), 75km (medium) and 200km (long).

Alternatives: the transport modes

The second experiment is much less fuel-type orientated. However, the fuel-type one uses can still impact one's choice. To get the best understanding of when people will use a car, only people who have or have access to a vehicle are selected. This way, this group can answer the questions whilst keeping the car they have access to in mind. No specific fuel groups or car segments are therefore given in this experiment. The vehicle will be compared to two other modes. A trip distance of 5km is seldom taken by train, and the bicycle is the primary competitive mode Centraal Bureau voor Statistiek (2019). Therefore, for the 5km option, the bike is used as a travel mode alternative. For the other distances, the train and car share the modal split as studies show that an increase in the absolute travel time by private cars increases the propensity to travel by train (Limtanakool et al., 2006; Centraal Bureau voor Statistiek, 2019). Limtanakool et al. (2006) defined 50km as the threshold for medium-long distance trips. You can reach most parts of the Netherlands within 200km, therefore, the medium and long-distance trips were respectively set as 75km and 200km. These distances are also considered as different context variables. The interpretation of the other context variables is given in the next section.

Attributes
As explained earlier, attributes are characteristics of the alternative included in the choice sets. They can vary per choice set to measure an individual's sensitivity to variation in these attributes.

Travel costs: The travel cost attribute is one of the main determinants in the choice for mode-use. Meixell and Norbis (2008) describes it as the primary criteria, together with travel time. Multiple studies (Washbrook et al., 2006; Ewing and Sarigöllü, 1998; Dobruszkes et al., 2014; Behrens and Pels, 2012) endorse this. Generally, it is expected that once the price increases, utility and thus demand decreases. In this mode choice experiment, the travel costs in the choice task will consist of solely the FKC. As explained in the Section 3.1.1, the fuel costs are context variables and are not varied nor included in the choice task experiment. Higher travel costs are expected to cause disutility and the parameter sign is thus expected to be negative.

Travel time: Meixell and Norbis (2008) thus also acknowledged travel time as a primary attribute for mode-choice. This has to do with the Value of Travel Time Savings (VoTTS) principle in which people are willing to pay more for lower travel times. In this experiment, we assume that everyone has different access to their modes, especially the train. This is very different for different people in the population, in significantly different areas in terms of density. This is an important factor when deriving peoples preferences towards mode choice Washbrook et al. (2006); Weis et al. (2010). However, to keep the experiment simple and remain the focus on the effect of the FKC, the access time to the mode is individual for everyone and will therefore indirectly be taken into account, but not as a separate attribute. Longer travel times are expected to cause disutility and the parameter sign is thus expected to be negative.

Context variables
Trip purpose: The literature review concludes that multiple market segments, or trip purposes, are possible. The trip purpose is an essential variable in the choice task. Kennisinstituut Mobiliteit (2008) describes a that there is a difference in utility for different types of trips. Kim et al. (2010); MuConsult and Ministerie van Financien (2020) also included different purposes in their trips. On top of that, the three models, LMS, DYNAMO and Carbontax do, too specify a distinction in trips made.

Travel company: One of the context variables in such a mode choice experiment is the number of people you travel with. The decision between car-use or train-use is strongly dependent on this. Travelling with company is cheaper for car use, as the costs can be shared amongst all travellers, this does not count for, e.g., the train or other PT modes. Additionally, travelling by car with more people is more convenient.

Fuel costs: Travel costs can consist of several elements, think of fuel and parking costs Revnext (2019). As egress transport is not taken into account for the train and it does not apply to the bike, parking costs are also excluded. This keeps the choice task simple, and the impact of different FKC heights can be measured as best as possible. Fuel costs play a significant role in the **total** travel costs for car use.

3.2.2. Theoretical framework
The black arrows represent the main effects on utility. The dashed lines represent the effects of interactions on the utility of the different alternatives. The red lines indicate the effect of the socio-demographics, current car characteristics and a person's perceptions, for which a direct result is expected, on utility.

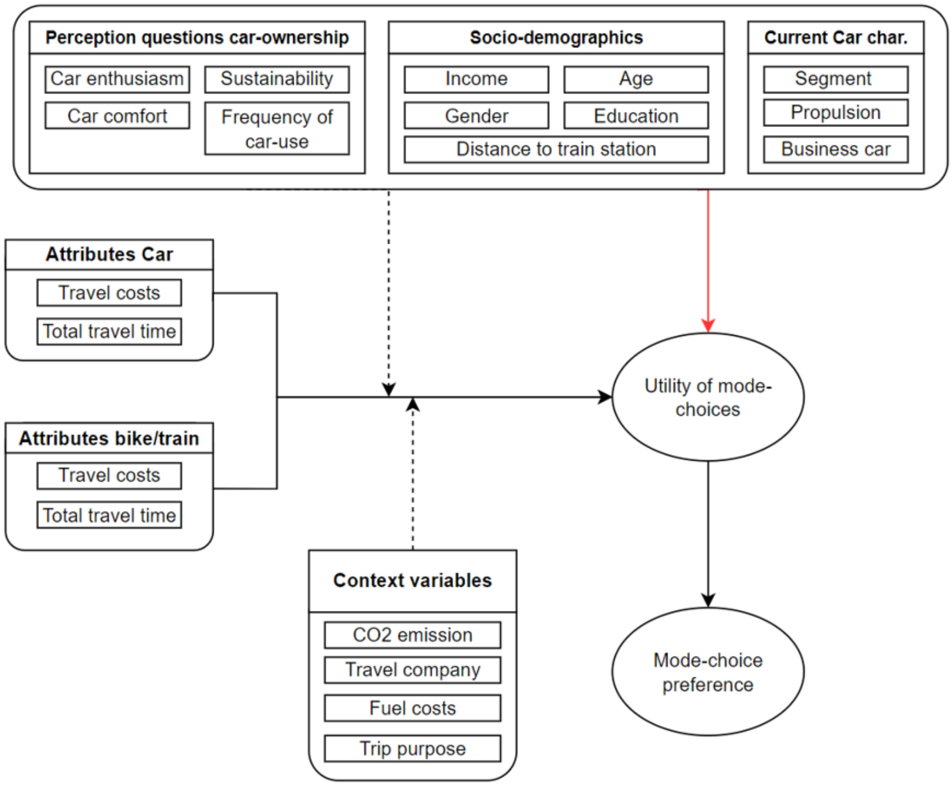

Figure 3.3: Conceptual model mode choice

For the second experiment, we are looking at the utility of car use or mode choice. This experiment seeks to determine to what extent the FKC impacts people's preferences for mode choice. The lines have the same function as in Experiment 1. The framework of this experiment can be found in Figure 3.3.

The utility of car use is primarily based on car attributes and the attributes of the other transport modes. The alternative transport modes that have been defined and also used by the are the Rijkswaterstaat train and bike. Other PT modes such as bus, metro or tram are considered as alternatives too but only represent a minimal share (<3%) of the modal split (Centraal Bureau voor Statistiek, 2019). Train and bike both dispose of close to 10% of the Dutch modal share. The main effect on the utility is represented by the car's attributes and the competing mode. The attributes of both alternatives consist of travel costs and travel times. This study aims to measure the impact of the FKC, which is represented by the travel costs. Due to the VoTTS principle, the time one spends during the trip cannot be neglected.

Additionally, the same socio-demographic, perception questions and current car characteristics are included. These factors are expected to both have an interaction effect with the attributes and a direct effect on the utility (Burris and Pendyala, 2002; Levinson, 2010). These interaction effects modify the effect between attributes and utility, resulting in different coefficients for different groups. The same perception questions can be asked to review a person's value towards car use. The context differs with respect to trip purpose and travel company, i.e. the context variables, which are expected to interact with the attribute estimates. When travelling and choosing a mode, one cannot neglect the effect of the activity. Therefore the trip purpose must be included Rijkswaterstaat; Leefomgeving (2020). Also, the travel company, or the amount of people you are travelling with, is highly decisive for the final costs, and thus also the effect of the FKC Kennisinstituut Mobiliteit (2008). Therefore, these two variables are included in the context.

3.3. Summary

In this chapter, the structure and framework of the two experiments are set up based on findings in the literature review. The first key takeaway from this chapter is the segment division for the car fuel-type experiment. The big difference in car segments proved difficult to incorporate into a single generic choice set. For that reason, five different choice sets, one for each segment, were created to present all respondents with a relevant, realistic set of attribute levels. In Chapter 5, more information on the specific interpretation of the attribute levels can be found. Second is the inclusion of different distances for the mode choice experiment. In the literature, an interrelation was found between mode choice utilities and distance. Transport modes are valued differently amongst different distances. For a 5 km trip, the modal split was dominated by car and bike. Therefore, *bike* and *car* were chosen as alternatives. For the 25 km - 200 km trips, the modal split was dominated by the *car* and the *train*, thus, these were selected as alternatives in the remaining experiments.

The theoretical frameworks show how the alternative attributes, context variables and background characteristics relate to - and impact the utility of mode choice and car-fuel-type choice. These defined variables are further used in designing the survey and the included choice sets, given in Chapter 5.

4 Methodology

The knowledge gap defined a particular weakness in the type of data that is used to forecast the effects of pricing policies on behavioural - and societal impact. The change in behaviour as a result of a pricing policy like the FKC leads to changes in traffic volumes and car-fleet characteristics. To estimate these outputs, we will need to gather data about car-type and mode choice behaviour. Geurs and Van den Brink (2005) defined these two types of behaviour as interdependent; therefore, two separate experiments must be conducted. Before data can be collected, a stated choice survey is designed. This survey includes choice task experiments, socio-demographic and perception questions. This chapter gives a conceptualisation of how the survey is designed and structured. The completion is given in Chapter 5. Once this data is gathered, Discrete Choice Modeling (DCM) is applied to model this raw data into tangible results, more specifics on that can be found in Section 4.2. Subsequently, the behavioural effects that the policy measures will create will then be estimated.

4.1. Data collection

4.1.1. Data collection method

To model the effects of different scenario's on behaviour, data must be collected. The data will be gathered through SP experiments in the form of an online survey. As the SP data will be used to model the effects, this section will provide a bit more background on how this data is collected. The literature already distinguished two forms of data collection, Stated Preference & Revealed Preference. RP data is collected by choices between alternatives that were already made. The fact that these choices are already made leads to a high validity. RP data, however, also has drawbacks. Non-existing alternatives can not be included. The alternatives for individuals in this case consider mode choice and car fuel-type choice. One of the alternatives is buying and using EVs, but as EVs are relatively new to our society, there is little data on them. This relates to the limitation mentioned by Revnext (2019) where the limited EV selling data was a problem. By using SP data, this problem is resolved. Second, in RP data, there is only information about the chosen alternative, not the ones that weren't chosen. Third, multicollinearity might appear, which complicates estimating an individual's trade-offs when making a decision. SP data can resolve these RP data issues (Molin, 2019).

A conclusion was made that for the FKC, there was yet no representative study towards behavioural and societal effects using SP data. Prior to making the survey, the specific logit model must be chosen to ask the right questions Rijkswaterstaat. For generating the survey and the envisaged fractional design, NGene software can be used (NGene, 2018). NGene is the leading software in terms of choice-experiments and therefore opts as a good tool. One of the main limitations of SP experiments is the occurrence of 'strategic behaviour' (Ge and Godager, 2021). This behaviour, where respondents strategically choose their answers for their utility, may lead to biased experiment results. To cope with these biased results, literature studies and expert interviews are conducted to minimise the risk and its impact. More information on how the literature and expert interviews are performed is found in Chapter 2.

Online surveys are a frequently used tool to obtain stated preferences by individuals. The survey can be designed so that people can be profiled, enabling them to make more detailed conclusions. Surveys offer the possibility of prescribing choice tasks where the respondent can choose the best alternative that fits the person's preferences.

Subsequently, socio-demographic and perception questions can be asked to understand better how people differ and how these differences lead to other choices. Qualtrics software is used. Qualtrics offers high-quality surveys and enables a detailed survey flow to optimise the answers.

4.1.2. Data gathering and Target group

Before setting out the survey, the target group must clearly be defined. Also, the way the data will be gathered is essential to ensure that the sample represents the population as best as possible.

Target population

The target population is Dutch citizens above 18 with a driver's license. This is the population that this research wants to conclude on. However, not all experiments will be suitable for everyone. The car fuel-type choice experiment is meant for all people who own a car or are interested in ever buying one. If both are not applicable, the respondent will not do the choice tasks but will answer the socio-demographic and perception questions to gather data about this group. For attending the mode choice experiment, the requirement is that you, or your partner, own a car or have access to it at least a couple of times per year.

Data collection tool

For gathering the respondents, a paid panel is used. To get the best-represented sample, the panel must be given clear instructions on the type of respondents that are desired. The paid panel used is PanelClix, ensuring only people above 18 can attend the survey. Respondents that do not own a car or do not wish to have one are not excluded, as it is still interesting to see what characterises this group. PanelClix's respondent base is large enough to cover the needed respondents, and they can offer a suitable variety of people in terms of age, gender and education. This way, the sample size spread can be guaranteed to mirror the actual population.

4.1.3. Literature studies

The literature researchChapter 2 gave a good overview of existing papers and models that estimate the effects of road pricing policies. Additional studies will be conducted to increase knowledge on the potential implementation of the FKC, the current car market, and its characteristics. Before setting up the survey, defining the context and determining the different levels of attributes is necessary. For setting up the attribute levels, additional research must be done into the government's plans and the possible differentiation strategies. Although this level doesn't have to mirror the same tariffs, an indication is good so that the parameters can be estimated. This differentiation will be based on different car characters. Subsequently, research must be done into the other attributes, their levels and future development. Future development is an essential factor to take into account because it helps with determining the effects when specific attributes change over time, especially with the current EV development and the increasing ICEV legislation. A car consists of many characteristics that one can base its decision on. These characteristics increase the utility when buying a specific vehicle.

4.2. Discrete Choice Modelling

For analysing the data, Discrete Choice Modelling (DCM) is used. The SP data from both experiments are then used to analyse to what extent car drivers choose a fuel-type or mode. Then it is examined to what extent car drivers switch their choices between the four alternatives based on the price-differentiation for the different car characters. DCM is a statistical method that can be applied to gain insights into people's choices and trade-offs when choosing between a finite set of alternatives. The alternatives included together form the choice set, and each alternative is characterised by different attributes. These attributes can be alternative-specific or general for all alternatives included in the choice set. For each attribute, attribute levels are defined (Molin, 2019; Chorus, 2021). Choices can be predicted for all values within the included attribute range (Ben-Akiva et al., 1985). Estimating the choice model gives us different values of parameters that represent the weight people attach to that specific parameter (Chorus, 2021).

The decision rules, or how decision-makers score the attributes included in the choice set, consist of two main types; Random Utility Maximization (RUM) & Random Regret Maximization (RRM) (McFadden, 1986; Chorus, 2021, 2012). Both strive to get the highest net utility but have different approaches. Where RUM strives for maximisation of utility, RRM strives for minimising disutility or regret. RUM is chosen for this choice model as RRM needs generic alternatives, and that does not apply to the experiments that will be conducted.

4.2.1. Random Utility Maximization

RUM models are the most popular and most accessible choice models. To obtain the highest utility Ben-Akiva and Bierlaire (1999) formulated, a mathematical representation of this phenomenon. It includes the system utility (or observed utility), which flows from attributes and their weights (β), and unobserved utility. Unobserved utility symbolises all the utility that is not incorporated in the selected attributes. The equation is as follows:

$$U_i = V_i + \varepsilon_i = \sum \beta_m + x_m + \varepsilon_i \tag{4.1}$$

where:
U_i = the utility of alternative i
V_i = the systematic part of utility of alternative i
ε_i = error term or unobserved utility of alternative i
β_m = Taste parameter of attribute m
X_m = Attribute level of attribute m

4.2.2. Choice models

There are multiple choice models in the form of Logit models that one can use for this analysis. It could also be a combination of models. The Multinomial Logit Model (MNL) is the most widely used structure for modelling discrete choices in travel behaviour (Ben-Akiva et al., 1985; Cirillo and Xu, 2011). The MNL model has gained several derivatives that all let go of more assumptions (Mianková and Kliestik, 2017). Where the MNL model is straightforward with a lot of assumptions, other models like the Mixed Logit (ML), Nested Logit (NL), Latent Class (LC) & Panel Mixed Logit (PML) are more complex models. They let go of more assumptions and aim to be able to retrieve more specific information about people's choices. Apollo, a software package that relies on R, will be used as a modelling programme as it is free, easy to use, customisable and discrete and continuous (Hess and Palma, 2019). Next to the MNL model, this research also estimated a ML model.

MNL model

The most widely used type of discrete choice model is the MNL model. This is mainly due to the closed form of the function determining the choice probabilities in MNL models, making the choice probabilities easy to compute (McFadden and Train, 2000). The choice probabilities can be calculated using the following formula (Chorus, 2021):

$$P_{in} = \frac{e^{V_{in}}}{\sum_{j=1,J} e^{V_{nj}}} \tag{4.2}$$

Where:
P_in = the probability that alternative i is chosen by the decision-maker n
V_in = the systematic utility that decision-maker n gives to alternative i
$V_n j$ = the sum of the systematic utility of all alternatives in choice set J given by decision-maker n

For the car fuel-type experiment, an MNL is a good start. Ewing and Sarigöllü (1998) also used this model and proved applicable. Ewing and Sarigöllü (1998) however did not incorporate the different segments and earlier displayed preferences. Therefore, an LC approach might be suited. Next to that, an MNL model can not capture correlations between the alternatives. As the ICEV alternatives are very closely related, they are expected to correlate high. This issue could be resolved with an ML model, as ML adds an extra error component to those alternatives that have something in common.

The mode choice experiment is modelled in a value of travel time savings (VTTS) space. This phenomenon means that time and costs are weighed to see the utility of faster travel (or the dis-utility of slower travel). As this space only requires costs and time, a simple MNL model would suffice (Weis et al., 2010). However, as MNL models can not capture taste heterogeneity and panel effects, ML models might provide a better fit to answer the research sub-questions regarding the influence of socio-demographics on choice behaviour. On top of that, ML models offer to capture panel effects allowing to observe correlations between choices resulting from individual tastes and preferences.

Mixed Logit
An ML model has three main advantages. One, the ML model can capture nesting effects between alternatives. This means that market shares will not be proportionally distributed over the available alternatives. Instead, alternatives that are assumed to correlate receive an additional error component to represent the correlation between these alternatives. This way, the IIA property can correctly be exhibited and solves one of the problems associated with the MNL model Chorus (2012). Two, the ML offers the opportunity of incorporating heterogeneity among individual choices. This is a model in which the parameters of attributes (tastes) and alternatives (preferences) are assumed to be affected by the personal taste that echoes through in all choices made (Chorus, 2021; Klem, 2000; Molin and Maat, 2015). Three, the ML is able to account for panel effects. The MNL model assumes all choice observations as one independent choice. However, choices made by the same respondent correlate and therefore MNL underestimates the standard error. This causes the MNL model to overestimate the amount of information in each choice. In reality, following choices carry less information than earlier observed choices (Chorus, 2021).

ML models are not closed form, meaning that the outcomes can not be computed with a fixed number of operations to the arguments. Halton draws are necessary up till the point that the outcome hardly changes (Train, 2000).

4.2.3. Model fitness

Model fitness is assumed to be an important metric to check how the estimated model fits with the data presented. To express this model fitness into an assessable parameter, Log-Likelihood (LL) is used. According to Chorus (2021), the higher the LL of the final model, the better the model fit. As the Log-Likelihood can not exceed zero, the closer the LL to zero, the better. There are two types of LL, zero LL and final LL. Zero LL represents the LL when all Beta's (parameter estimates) are set to zero. When estimating the model with the Beta's being non-zero, it presents the LL of the final estimated model. In 1974, McFadden introduced the rho-square (ρ^2). The higher the rho-square, the 'better' the model fit. The rho square indicates the relative fit of the model, and the formula is as follows:

$$\rho^2 = 1 - \frac{LL_F}{LL_0} \tag{4.3}$$

where:
ρ^2 = McFaddens rho-square parameter
LL_F = Likelihood of final model
LL_O = Likelihood of model without parameters

A rho-square of 0 would mean the model estimates no better than 'throwing a dice', whereas a rho-square of 1 represents a perfect model which does not exist. Guidelines have been set that define what model fit is reasonable. A value above 0.5 is considered an 'excellent' model, whereas a value below 0.1 is considered as 'limited'. Between 0.1 and 0.3 is 'reasonable', and between 0.3 and 0.5 is 'good' (Chorus, 2021). Model fitness is used in a relative sense, meaning that models can be compared to each other to determine the best model estimates and can give the most information. When setting up the model, the model fit can assist in the extra information brought by adding parameters such as alternative specific parameters (ASP). This is tested using the Likelihood Ratio Statistic (LRS). Adding a parameter also requires one extra degree of freedom as added parameters eat away information of other parameters; therefore, maximising the number of parameters is not per definition desired. This is because an extra degree of freedom also asks for bigger sample size; else, it 'spends' information that can not be spent on other parameters. The area in the tails of the t-distribution decreases while the area near the centre increases, the degrees of freedom thus affect the t-value and thus also the p-value. The LRS is calculated by the formula below, and according to this theory, a parameter can be added if the LRS is higher than the corresponding value in the chi-square table, based on the desired confidence interval.

$$LRS = -2 * (LL_A - LL_B) \geq \chi^2 \tag{4.4}$$

where:
LRS = Likelihood ratio statistic
LL_A = Likelihood model A
LL_B = Likelihood model B

χ^2 = Chi-square value

4.2.4. Parameter estimates

The parameter estimates that are present in the utility function are computed by means of using the R program. R is able to estimate the coefficients of every attribute parameter by means of the maximum likelihood principle. Each estimation of an attribute resembles the weight of the attribute. However, these weights cannot be compared directly due to differences in attribute levels. The attribute levels for the FKC are in euros while other attributes are in % or min. As soon as the parameter estimations are multiplied by the corresponding attribute levels, it shows the actual utility contribution of the parameters which can then be compared with each other. For every estimation, the model will also provide the parameter significance; this value indicates whether or not the coefficient can be generalized to the entire population. The parameter significance can be evaluated using two metrics; the t-value and p-value. We can speak of a statistically significant parameter when the p-value is below 5% (0.05) or the t-value is above 1.96. If the parameter does not meet these requirements, the null-hypothesis is accepted and the parameter can not be generalized to the population. However, statistically insignificant does not per definition mean that there is no effect (Amrhein et al., 2019).
The utility contributions enable us to standardize the value people attaches to attributes with different units. To be able to directly compare the attribute contributions, the values can be expressed in a monetary value; the Willingness to Pay (WTP). This is only possible if there is a monetary parameter present among the attributes. The formula to compute this WTP is as follows:

$$WTP_m = \beta_m / \beta_n \tag{4.5}$$

where:
WTP_m = The willingness to pay for one unit increase of attribute m
β_m = Taste parameter of attribute m
β_n = Taste parameter of monetary attribute n

4.2.5. Market share determination

Ultimately, market shares are needed for the model application and the experiment integration phase. To translate the utility functions of previous section into market shares, the total utility V per alternative i must be determined. For the MNL, this procedure is quite easy. For the ML model, this is a bit more complicated. Adding the error component provides a σ (sigma). Using a randomised function in Excel, the σ_{ICEV} and σ_{charge} were randomly distributed, using a normal distribution, over all respondents. A synthetic data set, a multiplication of the original data set, was used. The market shares are determined by computing the logit choice probability function, which is determined using the following formula:

$$P_{in} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}} \tag{4.6}$$

where:
P_{in} = Probability that decision-maker n choses alternative i
V_{ni} = Utility of alternative i for decision-maker n
V_{nj} = Total utility of j alternatives for decision-maker n

For the MNL models, the value for the interaction variables is set to the sample size average. This way, the utility contribution of those variables is generic. For the ML model, an Excel data sheet is used with all individual-specific background characteristics. However, with an ML model, a randomised error component based on the estimated standard deviation is added to the utility function of the alternatives that have been given such an error component. The ML model includes heterogeneity of the population in the probability function. The utilities are no longer generic but are respondent specific.

Additionally, there are two ways to compute the market share when using an ML model. One is a market share based on the average probability of the respondent choosing the alternatives. Or two, a market share based on the highest probability. The right approach for further application is decided on at a later stage.

4.3. Estimation of interaction parameters

Apart from the main investigation towards the impact of differentiation, this study also aims to investigate how people with different backgrounds respond to the FKC. In the survey, the respondents will be asked questions on three categories; socio-demographics, car characteristics and travel characteristics. These variables will then be added to the model as interaction effects (Molin and Timmermans, 2010). Interaction effects can be added to examine to what extent the coefficient for the FKC varies among specific (social) groups. This information can help identify what groups are more sensitive to the FKC and are more impactec by it. Once the data is gathered, the particular groups are defined by allocating binomial values to the characteristics included in the survey. Not all generated personal data are used for this examination. Small expert interviews are held to select the most relevant ones.

These interactions are added to test if there are differences in sensitivity towards the FKC between different social groups. As described in Chapter 6, a couple of interaction factors are included in the model based on held expert interviews. An interaction factor is included in the utility function for alternative i by the following addition:

$$(\beta_{FKC} + \beta_{FKC_{age}} * Age) * FKC_i \tag{4.7}$$

The sign of the interaction parameters will determine the sensitivity. If the sensitivity of a parameter is positive, this indicates that the 'higher' group is more sensitive. If the sensitivity of a parameter is positive, this indicates that the 'lower' group is less sensitive. Whether a group is high or low can be determined by the absolute value such as age or income or the distinction between two binomial groups, 0 being 'low' and 1 being 'high'.

4.4. Application of DCM results

The DCM used to estimate behavioural effects does not automatically generate societal effects. The road pricing policy is expected to affect societal aspects. The literature provided valuable insights into how society is impacted by the FKC and its implementation strategy. A conclusion was made that of all found societal effects, only car emissions(or pollution) and tax income are directly impacted and do not require additional modelling. Thus, car emissions and tax income are the societal effects to be accounted for in this study. Both EVs and conventional cars are polluting. Although EVs have no combustion emissions due to the absence of engine exhaust and thus no emission, they tend to weigh much more because of their high battery weight. This additional weight causes more and faster tyre degradation, which causes PM_{10} pollution. When the SP experiments are conducted and the DCM analysis is done, the effects on traffic volumes, resulting from the mode choice experiment, and on the character of the car fleet, resulting from the car fuel-type choice experiment, are known (Timmers and Achten, 2016).

The application of a pricing scheme is likely to result in different emissions and tax income. Furthermore, a modal shift between car use and other modes is expected. The main emissions emitted by cars that this research focuses on are NO_x, PM_{10} & CO_2 (Natuur en Milieu, 2017; Verbeek et al., 2014; Londo et al., 2015). Additionally, more research will go into the existing Carbontax model and the parameters it uses to see if a comparison between both approaches, using SP or RP data, can be made. The estimation of the effects that stem from traffic volume and the characteristics of the car fleet, done by Revnext and/or PBL, is likely to be based on more variables. This final estimation part is to be more reliable than the estimation that can be done in this research. It would therefore upgrade the quality of the results if the same approach for estimating the societal effects could be used. Additional study is done on the relationship between behavioural change and societal impact to obtain the key numbers and generalise the results from the experiment to society.

4.5. Summary

In this chapter, the methodology of this research is outlined. The chapter starts by stating how the data for the SP experiment is going to be collected. The validity of the data used for Discrete Choice Modelling is essential for the outcomes. This is followed by a more elaborate explanation of the available discrete choice models and which ones could be applied to these types of experiments. The section ends with a proposition on how to apply and integrate the outcomes of both experiments to answer the research question. In the next section, more information is given on the type of respondent that the research requires and the best tool for collecting the best data.

The MNL model is the most simple and robust model with the most assumptions. This model will be used in both experiments. The ML model seems a good fit for both experiments. For the mode choice experiment, the ML model can capture panel effects. For the car fuel-type choice experiment, the ML can capture nesting effects within alternatives.

What makes a model a 'good' model? This is an important question when using choice modelling to estimate choice behaviour. Hauser (1978) also questions the relevance and importance of certain model quality tests. The same goes for the usability of parameters in case of insignificance (at a 95% confidence interval). Amrhein et al. (2019) showed that about half of the papers tested misinterpreted statistical insignificance and did not use the found parameters for further application. Amrhein et al. states that although the parameters are not significant at a 95% confidence interval, the effect is still present. It is thus essential to note that model fitness and statistical significance are relevant metrics to consider when setting up the model. As these models will be applied and integrated, parameters cannot be left out because of statistical insignificance or not meeting the LRS requirement. Therefore, the relevance of parameters for conclusions and further application were prioritised rather than statistical insignificance or LRS tests. Less critical parameters such as alternative specific parameters were tested on model fitness addition.

This chapter formed the basis of the model estimations and how these are set up. Next to that, this chapter gives insights on how to asses the models and to what extent extra parameters can help improve it. Chapter 7Chapter 8 show the results of the final models of respectively car fuel-type choice and mode choice, and interprets the outcomes. Specifying what models will be applied is crucial for the outcomes

5
Survey Design

In this chapter, the survey is designed. This survey is primarily based on the theoretical framework built in Chapter 3 and all discussed elements will return. The survey will consist of two experiments to define the two dependent variables: m*ode choice* and *car fuel-type choice* behaviour. These dependent variables are impacted by the FKC policy and, subsequently, have societal effects. This section will elaborate on the introduction of the experiment, the perception questions, the acceptance questions and the socio-demographic questions. These elements will be present for everyone who opens the survey. Based on certain car-ownership-related conditions, either one or two choice experiments are presented. Both choice task experiments and their model specification, experimental design and survey construction are consecutively presented. The introduction of the SP experiment strives to inform respondents about the research topic and the different alternatives that are included in a neutral, short way using simple language. Only information that would have been accessible to respondents in the real-life choice situation should be included. The key challenge in writing the introduction of the SP experiment is informing respondents sufficiently and in a neutral way that is not seen as a clue for the desired answer on the one hand but keeping the introduction short on the other hand.

Based on the guidelines by NGene (2018), the choice task was constructed. A distinction between the three steps is made. The first step is the model specification, in which the included alternatives and the accompanying attributes are defined. In the second step, the experimental design of the choice task is generated by determining the included attribute level for the different attributes and alternatives. After that, in step three, the questionnaire, or choice situation, is constructed. The chapter concludes with a short summary and a survey flow of how the questionnaire is structured.

5.1. Choice task experiment 1. Choice task set-up

The survey is designed to get the stated choice observations of car-owners or potential car-owners on the fuel-type of car they would buy given the specific attributes of that choice situation.

5.1.1. Model specification

In this step, we elaborate more on the alternatives and the attributes that must be included to estimate the preferences. Both experiments have different alternatives and thus also different attributes and attribute levels. The attributes were defined based on new literature research and the earlier design of differentiation levels, see chapter 4.

For car fuel-type choice, four labelled alternatives are distinguished in terms of propulsion technology. We first ask what segment (A, B, C, D, E+) their current car is in. This tells us what kind of car they initially preferred and the price category they are in. The choice set will then be based on the alternatives within that segment. This allows us to measure the car fuel-type choice more within a persons value of cars. The attributes that are used to define these alternatives are explained below. These attributes were also used in studies on car fuel-type choices for different vehicles (Ewing and Sarigöllü, 1998; Daina et al., 2017; Daziano and Chiew, 2012). The attributes are the **FKC, Purchase price** and **Range**, which were defined in Chapter 3, based on conducted literature research. Their attribute levels are defined in Section 5.1.2.

Specification of context variables
Additionally, the context variables need to be quantified, so they are generic for every segment. For that reason, it was decided to display these context variables in relative differences with respect to a base case; the ICEV category.

BEV charging times: The charging times for BEVs are based on reports by (ANWB, 2021b; ANWB). BEV fast charging times ranged from 18 to 45 minutes with an average of 29 minutes, seeAppendix A. This was rounded to 30 minutes and textually included for every segment category.

CO_2 emissions: The CO_2 emissions of DV and GV (ICEV) were assumed the same and were set as a reference. Based on thorough research using the report by Transport and Environment (2018); Hao et al. (2016), the CO_2 emissions per fuel group were determined. Fully EV's emit 100% less than the ICEV. For the PHEV, a 50/50 approach is used where a PHEV is considered 50% EV and 50% ICEV (Liao et al., 2018). Therefore, the PHEV is assumed to emit 50% less than the ICEV. Apart from CO_2 emissions, cars do also emit NO_x and PM_{10}. As not everybody is acquainted with these pollution types, the focus is solely on CO2.

Fuel costs: The average fuel costs were conducted using average fuel economies per segment and fuel/electricity prices. For the ICEV and the PHEV, the gasoline/diesel costs were determined using the fuel price of mid-2021 (Centraal Bureau voor Statistiek, 2022). For the other part of PHEV and the BEV, the price for charging was used with a 60-30-10 approach (ANWB, 2021a). This approach means that 60% is charged at home, 30% is charged at public charging stations and 10% is charged at fast-charging stations. This approach led to 60% fewer fuel costs for BEV and 40% for PHEV relative to the ICEV. See Appendix A for more information.

5.1.2. Generation of the experimental design

Defining the attribute levels in such a complex system with many variables and alternatives is time-consuming. It also requires many respondents and will result in a long survey. To simplify the experiment, the number of questions and the desired sample size, all respondents will receive choice sets based on the segment of their current car (or car they intend to buy).

Purchase price: The purchase prices of vehicles differ significantly. The cheapest cars start at €10,000 and can reach very high amounts. For this research, we look at the most used cars and leave eccentric purchase prices out of scope. The purchase prices differ among the vehicle segments and the fuel groups. EVs are generally still more expensive, although according to the ANWB (2021b) study by the ANWB, the gap is closing. They ANWB (2021d) developed a couple of pricing segments for EVs that can directly be linked to the earlier-defined five car classes. For the ICEV, average selling prices were taken for the weight classes as defined by OSW (2021).

Table 5.1: ICEV characteristics for the base case

ICEV characteristics		Purchase price	Range (km)
Weight class	Segment A	€12.500	400
	Segment B	€17.500	500
	Segment C	€27.500	600
	Segment D	€35.000	600
	Segment E+	€50.000	600

The ICEV category functions as a reference category, and its characteristics (price and range) are shown above. The current market prices of BEVs show that average BEV prices could still be at least 75% higher regarding the ICEV category. For PHEV, this is a maximum of 20%. To incorporate EV development, several relative price differences are considered as attribute levels. The relative prices for BEV are 0% - +25% - +50% - +75%. The attribute levels for PHEV are +0% - +10% - +20%. To incorporate potential ICEV discouragement and stimulate the electrification, the attribute levels for both ICEV categories, are +0% - +10% - +20%.

Range: The range can be treated as a categorical value as the alternatives have different values. Between the conventional GV and DV, there are no significant differences between the various segments. Smaller cars often have a smaller tank and range; the results are displayed in Table 5.1 (ANWB, 2021a). These results for the range are fixed and are not expected to change over time. For EVs, the ranges are different among the segments. The higher the segment, the better the battery and the longer the range. For the smaller segments, this battery is often less. Again, the PHEV value is constructed using 50% of the BEV value and 50% of the ICEV values. The BEV ranges were constructed using the ANWB (2021d) overview of all available EV segments and their specifications. However, technological development will increase the battery capacity, thus the range, over the coming decades. Therefore, several relative range attribute levels are taken into account. The relative ranges for BEV are -50% - -25% - 0%. The attribute levels for PHEV are -25% - 0%. The ICEV ranges are fixed and therefore have no varying attribute levels.

Fixed Kilometer Charge: For estimating the effect of the FKC, a range of potential charges is defined. This is done by the use of the MuConsult and Ministerie van Financien (2020) study and information provided by the government (Coalitieakkoord, 2021; Ministerie van Financien, a; Ministerie van Financiën, 2020). This study looks into different strategies to price-differentiate the FKC. The Dutch government has stated not to implement an FKC differentiated to time or place. However, a differentiation to emissions/pollution is still possible. The height of this differentiation is crucial for the effects. Additional research has been done on the options for differentiation. Three types were found: 1) no differentiation, 2) differentiation to CO_2 emission, 3) differentiation to CO_2, PM_{10}, and NO_x emissions. Extensive research on the height of those charges for different fuel groups and car segments provided the right information on the boundaries of the charge. More information can be found in Appendix A. The data excluded from the literature ranges from 4.1 cents/km to 19.1 cents/km. The following attribute levels are used: €0.05 - €0.10 - €0.15 - €0.20 - €0.25. One extra level (€0.25) is added as extra safe margin to ensure all potential levels are covered.

The following table gives an overview of the attributes, alternatives and their levels:

Table 5.2: Attribute levels car fuel-fuel-type experiment

Attribute	Alternatives	Attribute levels				
Purchase Price	GV	0%	+10%	+20%		
(€)	DV	0%	+10%	+20%		
	PHEV	0%	+10%	+20%		
	BEV	0%	+25%	+50%	+75%	
Range	GV	0%				
(km)	DV	0%				
	PHEV	0%	-25%			
	BEV	0%	-25%	-50%		
Fixed Kilometer Charge	GV	€0.05	€0.10	€0.15	€0.20	€0.25
(€/km)	DV	€0.05	€0.10	€0.15	€0.20	€0.25
	PHEV	€0.05	€0.10	€0.15	€0.20	€0.25
	BEV	€0.05	€0.10	€0.15	€0.20	€0.25

Now that the alternatives, attributes and the attribute levels have been defined, the experimental design can be generated. For this, Ngene software is used (NGene, 2018). Ngene asks for a syntax in which all utility functions become apparent and the desired design. The syntaxes for both experiments can be found in Appendix B. The experiment includes labelled alternatives with alternative specific attributes. Only the DV and GV attributes are similar. The FKC attribute is generic for all four alternatives, but the purchase price and range are different. There are two fixed attribute levels: the range for DV and GV. The experiment makes use of a fractional factorial design. Due to the high number of attribute levels, a full factorial design was impossible as the number of choice sets would get too high. An efficient design is not possible as there are no priors used. Finally, this design does not comply full orthogonality as there is no attribute level balance. As this experiment contains linear attributes and no dummy variables, there is no specific need for this.

Ngene was asked to conduct 20 rows of choice sets, and blocking was applied. It was instructed to block the rows into four choice sets each; therefore, five blocks needed to be used.

5.1.3. Choice situations

The choice task includes the choice set, the explanation and the context variables. The explanation and context variables can be found in Appendix B. The choice set given to the respondent is reworked to the base category, the ICEV category, shown in Table 5.1. This was done based on the experimental design generated by Ngene, see the previous section. Displaying percentages to the respondent can lead to confusion and misunderstandings. The absolute values are displayed, and an example of the C segment choice set is shown below. Choice set examples for the other segments can be found in Appendix A.

Segment C	**GV**	**DV**	**PHEV**	**BEV**
Purchase Price (€)	€27,500	€33,000	€27,500	€48,125
Range (km)	600	600	600	300
Fixed Kilometer Charge (€ per km)	€0.25	€0.25	€0.20	€0.15

Figure 5.1: Choice set example segment C

The above choice situation was given to the respondent four times to generate multiple answers. All choice situations, as shown in the Qualtrics survey, can be found in Appendix C.

5.2. Choice task experiment 2: Mode choice

The choice task construction, as outlined by NGene (2018), follows the same approach as in the first experiment.

5.2.1. Model specification

In the model specification, the attributes of the alternatives are specified. Each experiment is created explicitly for estimating a specific model, and it must be clear what parameters will be estimated. When this step is completed, the experimental design can be created. The attributes of this mode choice experiment were already defined in Chapter 3. This experiment will consist of two attributes in the choice set; travel costs (the FKC for the car) and travel time.

Defining the context variables

Again, the context variables must be defined to be generic for all distances. To keep it simple, it was chosen to keep the variables in units that can be generalised, such as CO_2 per km.

CO_2 emission: The CO_2 emission was taken up as a context variable in both experiments. The same approach is used in experiment 1, where the difference in CO_2 between alternatives was displayed in a percentage difference. The train is estimated to be emitting 50% less CO_2 per passenger kilometer than the car.

Trip purpose: This research will examine two markets; business-related activities and non-business-related activities. According to the Kennisinstituut Mobiliteit (2008), the non-business related trips share includes 49% of all driven kilometers, see Figure 5.2.

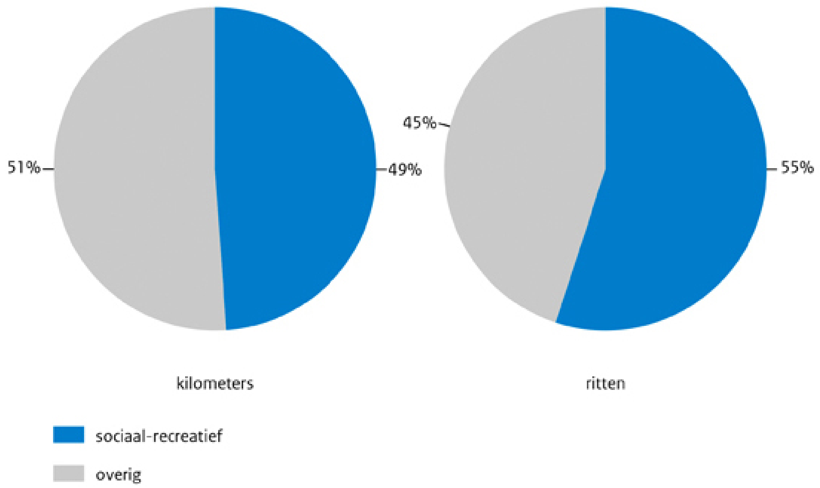

Figure 5.2: Social-recreational trips versus other (Kennisinstituut Mobiliteit, 2008)

The other trips are all business-related activities, including commuting, business trips and trips to school/study. All social-recreational-related trips are the rest of the trips you make with your car. This can include shopping, leisure, holidays or any other trip. Business and non-business-related trips are distinguished in many papers on mode choice, and therefore this distinction is chosen (Kennisinstituut Mobiliteit, 2008; Weis et al., 2010; Washbrook et al., 2006).

Travel company: According t the Kennisinstituut Mobiliteit (2008), the average car occupancy is 1.43. This experiment is kept simple and only includes trips with a single traveller. This means that the found market shares only account for all single trips.

Fuel costs: The fuel costs will not expressly be incorporated in the choice task, just like in experiment 1, but the variable must be accounted for by the respondent. To get the respondent thinking of the costs one spends on fuel, a trigger question is asked about how much they believe fuel costs are for 100 km. In the choice task explanation, it is mentioned that they must not forget about this cost type.

5.2.2. Generation of the experimental design

As explained in Section 3.1.1, this experiment is set out over four different distances. The four distances are used on four different edges. The 5km edge is based on a max speed of 60km/h, 30km/h and 20km/h. The attribute levels for 5km trips are often not accessible on the highway and include different possible speed limits. The 25km edge is based on a trip between Rotterdam and The Hague. The 75km trip is based on a trip between Rotterdam and Amsterdam. The 200km trip is based on a trip between Rotterdam and Enschede.

Travel costs: The travel costs for mode choice consist of solely the new FKC. The total price per km beholds the same range as was used the car-type choice experiment, €0.05 - €0.10 - €0.15 - €0.20 - €0.25, see Section 5.1.2 for more information. The total FKC costs are multiplied by the specific distance to generate the different attribute levels. The costs for the alternative mode (bike or train) are defined as follows: Biking is free, and the research assumes all Dutch citizens can take the bike. For the train, a fixed price is used. For the 25km train trip, 5€is charged, for 75km it is 15€and for 200km it is 28€. This is based on tariffs that the NS maintains; see NS.nl for more information.

Travel time: The travel times of the train are conducted using 9292, the Dutch train scheduling site. The travel times to the different cities of the corresponding distances are found to be 00:25 00:35 for 25km, 00:45 01:00 for 75km and 02:15 02:45 for 200km. This was based on an intercity train and a sprinter train. For biking 5km, an average of 15km/h was used, thus a 20 min travel time. For the car, Google maps was used to conduct all travel times between the centre of city nodes. Additional time was added to account for travelling during peak hours. All attribute levels of travel time and costs are displayed in Table 5.3.

Table 5.3: Attribute level overview mode choice experiment

Distance: 5 km		
Attribute	**Alternatives**	**Attribute levels**
Travel time (hh:mm)	Bike	00:20
	Car	00:05 - 00:10 - 00:15
Travel cost (euro)	Bike	€0.00
	Car	€0.25 - €0.50 - €0.75 - €1 - €1.25

Distance: 25 km		
Attribute	**Alternatives**	**Attribute levels**
Travel time (hh:mm)	Train	00:25 - 00:35
	Car	00:20 - 00:25 - 00:30
Travel cost (euro)	Train	€5.00
	Car	€1.25 - €2.50 - 3.75€- €5 - €6.25

Distance: 75 km		
Attribute	**Alternatives**	**Attribute levels**
Travel cost (euro)	Train	00:45 - 01:00
	Car	01:00 - 01:10
Travel cost (euro)	Train	€15.00
	Car	€3.75 - €7.50 - €11.25 - €15 - €18.75

Distance: 200 km		
Attribute	**Alternatives**	**Attribute levels**
Travel time (hh:mm)	Train	02:15 - 02:45
	Car	02:15 - 02:45
Travel cost (euro)	Train	€28.00
	Car	€10 - €20 - €30 - €40 - €50

As for experiment 1, Ngene is also used for experiment 2. The same experimental design, a fractional factorial design, is used for the same reasons. Priors are not incorporated, and attribute level balance is unnecessary as there will be no need for dummy coding. Therefore efficient designs are not required, and a factorial design suffices. Because every person must answer to all four distances, not too many choice sets per distance can be distributed. Subsequently, the design is now fractional factorial. Eight rows were chosen in blocks of 4, resulting in 2 choice sets per distance. As there are eight rows and the attributes, consist of 2,3,4 and 5 levels, full orthogonality, by satisfying attribute level balance, is not achieved. As all attributes are linear values, this is no problem.

5.2.3. Choice situations

The choice situations were derived from the experimental design. This was done based on the experimental design generated by Ngene (NGene, 2018), see the previous section. In total, 8 choice tasks were constructed and split into four blocks of 2 choice tasks. Each respondent was randomly assigned to one of the four blocks. Figure 5.3 shows an example of a choice task..

5 kilometer	Car	Bike
Travel time (hh:mm)	00:05	00:20
Travel cost (euro)	€1.25	€0.00

25 kilometer	Car	Train
Travel time (hh:mm)	00:30	00:25
Travel cost (euro)	€2.50	€5.00

75 kilometer	Car	Train
Travel time (hh:mm)	01:10	01:00
Travel cost (€)	€3.75	€15.00

200 kilometer	Car	Train
Travel time (hh:mm)	02:15	02:45
Travel cost (euro)	€20.00	€28.00

Figure 5.3: Choice set examples experiment 2

The different choice situations for the different distances and how they are presented in the Qualtrics survey can be found in Appendix C.

5.3. General survey set-up

This section provides more insights on other questions that are asked in the survey and how the survey was tested in a pilot. This chapter ends with a survey flow where the different survey sections are displayed and how to skip and display logic were used to let the eligible respondents answer the experiments.

5.3.1. Background characteristics

Background characteristics such as socio-demographics, car- and travel characteristics are included in this survey to distinguish specific social and travel groups. This way, the behaviour must not only be generalised to the whole population but can also represent such a group. This explains potential heterogeneity in preferences between the respondents, which is needed to answer the sub-question. On top of that, more available data on respondents increases the information of the data found in the choice sets. Adding such effects to your chosen model will likely improve the model fit Ben-Akiva and Bierlaire (1999). The questions include gender, age, education, income, household level and distance to the train station. This data will help us profile the respondents. Subsequently, the one sub-question of this study can be answered.

Additionally, current car - and travel characteristics are asked. This allows us not only to sketch a person on a socio-demographic level but also on the type of traveller or car user. Information on car ownership, car segment, fuel group, the mode used for work, frequency of car use and the payer of travel expenses is asked. This information can help justify the choices made by car users - and traveller profiles.

Next to a person's characteristics, a person's value is also interesting to model to see if there are specific connections between these perceptions and the choices made in the choice task experiments. Sustainability is one of the themes presented in the survey. In both experiments, the varying CO_2 emissions are mentioned. This aspect can not be modelled, but it might trigger sustainable-minded persons to choose differently as (Centraal Bureau voor de Statistiek, 2021) found the main reason to switch to EV is for sustainability reasons. To see if one is sustainably-minded, we ask to what extent people care for the environment and how they let day-to-day decisions be impacted by this. Furthermore, we can look at how people value cars by asking how much they love having a car and using it. Subsequently, one's value towards flexibility and comfort can be derived.

5.3.2. Survey piloting

The survey was set out under 20-30 people to get tested. The people varied in age, gender and education. The survey was tested on clarity, response time and general impressions. The fastest response time was 7 minutes, and the slowest was 15. On average, it took the respondent 12 minutes to fill in the survey. A couple of issues were raised on clarity, and the feedback was processed. Especially textual changes on the choice task explanations. Furthermore, some relevant feedback was given on the socio-demographic and travel data of those not owning a car nor ever wanting one. At first, this group had to leave the survey. Now they still receive questions adding data about this group.

5.4. Summary: Survey flow

In this chapter, the complete choice task, including the context variables, is sketched. Both experiments were covered in this chapter and followed the same procedure. It started with the model specification where the attributes and context variables were defined. In the experimental design phase, multiple levels were attached to the alternative attributes, varying across the choice sets. These choice sets (or situations) were designed in the third phase using the NGene program. This survey consists of 6 different sections. The survey flow is displayed in Figure 5.4. Experiment 1 contains four choice situations; experiment 2 contains eight choice situations. Five perception questions are asked, and a schematic overview of the survey:

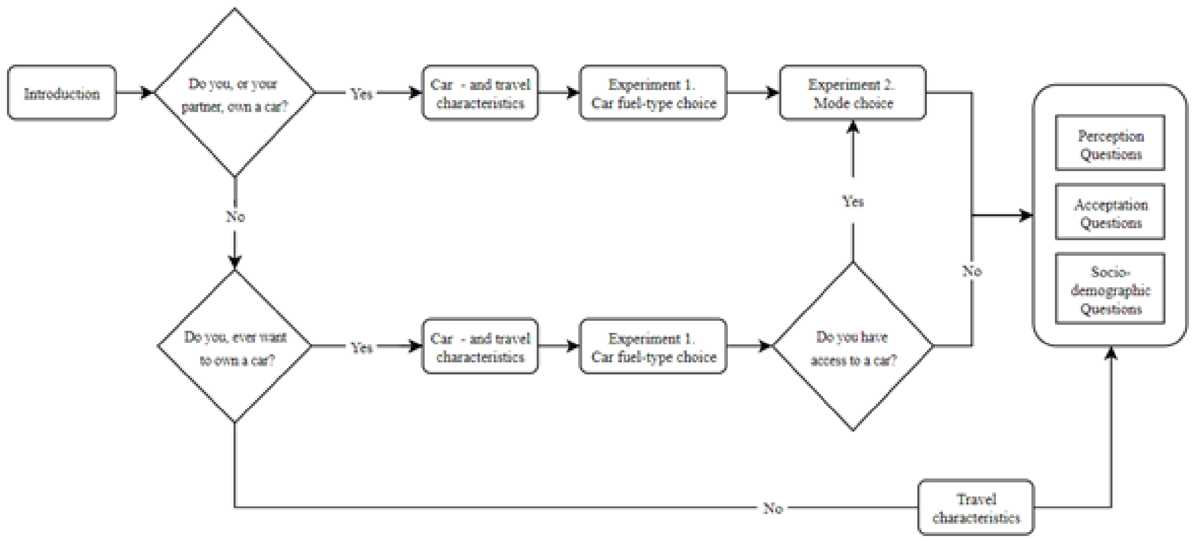

Figure 5.4: Survey Flow

The next chapter describes the sample to evaluate the kind of respondents that have filled in the survey. The way questions and choice sets are presented in a survey is very important for the reliability and validity of the collected data. The presentation of the choice sets and the context is essential for people to understand what is asked. If people misunderstand what is asked, the answers are not valid. Therefore, this chapter on survey design is a crucial element in data collection and the quality of the ultimate findings.

6 Sample Description

In this chapter, Section 6.1 discusses the survey data collection. This section is followed by an elaboration on how the data was prepared. In Section 6.2, an evaluation is given on the respondents that filled in the survey, and a discussion is provided on the sample's representativeness. This section also presents an overview of the car characteristics of car-owners and people's acceptance of differentiating the FKC. In Section 6.3, the (binomial) variables are indicated that are used for the model estimation to determine whether different groups in society behave differently. The last section, Section 6.4 presents the choice distribution of both choice experiments.

6.1. Survey data collection and preparation

For collecting the survey data, PanelClix, a research panel, was recruited. The TU Delft advised this collection organisation. Qualtrics was used as survey software to generate the questions. Data collection started on the 29th of April 2022 and finished on the 3rd of May 2022. A representative sample of the Dutch population could be guaranteed with the panel. As this experiment collects data on car fuel-type choice and mode choice with the car as an alternative, the respondent needed to have a driving license. This was the only screen-out question that was asked. For entering the choice task, car ownership or interest in car ownership was necessary. Furthermore, 550 respondents were recruited for this experiment to increase the chance of having 500 valid and reliable answers. Short answering times or identifying a response pattern were criteria set to accomplish this.

In the end, 527 respondents completed the survey. We set the criteria for short answers to 150 seconds. The average response time was 617 seconds, with outliers between 90 and 9000 seconds. When removing the outliers, the average response time was 450 seconds (7.5 minutes). 21 responses were deleted because of short responding times, therefore, we ended up with 505 final completes.

Before the data can be used for modelling, the survey data must be translated into a data set suitable for choice modelling. To do that, the original choices need to be linked to the numerical alternatives. The alternatives for the car fuel-type experiment were set as; GV=1, DV=2, PHEV=3, and BEV=4. The alternatives for the mode choice experiment were set as Bike/Train=1 and Car=2. The choices were then linked to the given choice sets based on the block they were put in. At last, the final background characteristics were added to the data set. An example of what the choice data sets looked like in the appendix is given.

6.2. Survey evaluation and respondent characteristics

The responses were successfully collected, and this section reviews the distribution of the respondents, including the extent of representativeness to the population. This section is divided into three parts, the socio-demographics, car characteristics and travel characteristics.

6.2.1. Socio-demographics

Five socio-demographic questions were asked to the respondent; *age, gender, income, education and number of household members*. The results are displayed in the following table:

Table 6.1: Socio demographics sample

Demographic	Category	Respondents
Age	18-30 years	14.3%
	30-40 years	19.2%
	40-50 years	23.4%
	50-60 years	16.1%
	60+ years	27.1%
Gender	Female	49.7%
	Male	50.3%
Income	< 10.000	4.3%
	10.000 - 20.000	11.4%
	20.000 - 30.000	18.1%
	30.000 - 40.000	24.6%
	40.000 - 60.000	25.5%
	60.000 - 80.000	11.0%
	80.000 - 100.000	3.1%
	>100.000	2.0%
Education	No high education	56.8%
	With high education	43.6%
Household level	1	17.3%
	2	38.3%
	3	20.8%
	4+	23.7%
Average distance to station	Less than 5 min	9.1%
	Less than 10 min	19.4%
	Less than 15 min	17.2%
	Less than 20 min	13.1%
	Less than 25 min	16.4%
	More than 25 min	24.8%

Age, gender and education were set as criteria for the panel institution to guarantee a representative sample in terms of those three attributes. Gender is close to 50/50, and age and education represent the current Dutch distribution. Although multiple educational levels were asked in the questionnaire, they were divided into two final classes: High education (HBO, WO(+master)) and No high education (Primary school, MAVO, MBO). The distribution is similar to the distribution found in Liao et al. (2018). The average distance to the train station was fairly distributed with 15 minutes as average.

6.2.2. Car-characteristics

For the car fuel-type choice experiment, the first and most important question is about (the interest in) car ownership. The other characteristics involve segment, fuel group and how the car is paid.

Table 6.2: Car characteristics sample

Car characteristics	Category	Respondents
Car ownership	Yes	93.5%
	No, but interested in one	6.2%
	No, not interested	0.4%
Car segment	A	19.6%
	B	32.9%
	C	28.8%
	D	13.8%
	E+	4.8%
Fuel group	GV	84.4%
	DV	8.9%
	PHEV	4.6%
	BEV	2.1%
Business (lease) car	Employer pays car and fuel + private use	6.4%
	Employer pays car and fuel	3.5%
	Private lease	5.6%
	Own car	84.5%
Interest in EV	Yes (or has one)	53.5%
	No (or doesn't know)	46.5%

This figure proves the dependency on cars of the Dutch citizens. Well over 90% own a car and, apart from 2 respondents, all non-car-owners are interested in buying one. This shows the affinity to cars and how vital car ownership is in this country. The car segment distribution shows a Normal distribution, but the number of E+ segment owners is relatively low. The fuel group division offers a good representation of the population (Liao et al., 2018; Transport and Environment, 2018). GV's are still the widest used vehicles, and EV's still own a low share. BEV share was expected to be between 2% and 3%, and the found results thus satisfy that expectation. Presumably, due to high purchase prices, 78% of all EV owners have a high income. Of the ICEV car-owners, 11.3% indicated driving a hybrid ICEV; however, they are not included in the car fuel-type choice experiment. Looking at the 2020 car fleet report published by the ministry in cooperation with Revnext, the sample size represents the current car segment division sufficient. Segments B and C have the largest market share, followed by A, D and E+ with a meager share (Rijksdienst voor Ondernemen and Revnext, 2018). Furthermore, according to this report, the number of business owners is 9,9%, the same share as in the sample size.

6.2.3. Travel characteristics

For the mode-choice experiment, additional travel characteristics were sought to understand better why someone prefers a particular mode.

Table 6.3: Travel characteristics sample

Travel characteristics	Category	Respondents
Car use	1x/month or less	5.2%
	1x/week or less	6.3%
	2x/week	18.9%
	3-4x/week	26.8%
	5-6x/week	22.3%
	Daily	20.5%
Commuting travel mode	Car	66.7%
	PT	8.4%
	Bike	19.6%
	Foot	5.2%
PT Card	Unlimited*	3.3%
	Discount**	10.8%
	Unlimited paid by employer	5.1%
	Discount paid by employer	1.6%
	Student card	3.1%
	None	76.1%

*Always, Weekend, Route, Peak or Off-peak subscription
**Always, Weekend, Route, Peak or Off-peak discount

6.2.4. Acceptance towards differentiation

When reviewing the effects of new policies, it is also good to test people's acceptance of this new policy. Policy-makers in specific governmental organisations are benefited from supported decision-making. The different policies, including the FKC in general, were tested to see how accepting people were of these implementations. It turned out that the FKC, in general, was supported by almost 3/4 of the people. The policy for differentiating to emissions received the highest acceptance, 82%.

Table 6.4: Acceptance of FKC policies

Acceptance	Accepting %
Paying per use, i.e. the FKC	74%
Differentiation to time	72%
Differentiation to emission	82%
Differentiation to place	52%

ICEV vehicles are the most polluting, and PHEV is assumed to be right between ICEV and BEV. Pollution is also dependent on the weight, and thus segment, of the car. In the table below, an overview is given on the distribution of people that were either neutral or more than accepting of a policy where the polluter pays. It is distributed among the type of car people have (or prefer in the future)

Table 6.5: Acceptance of emission differentiation

Acceptance to emission based differentiation	Accepting	Total	%
Segment A	61	88	69%
Segment B	117	160	73%
Segment C	109	148	74%
Segment D	54	69	78%
Segment E+	21	24	88%
GV	283	395	72%
DV	35	45	78%
PHEV	19	22	86%
BEV	9	10	90%

The table shows a logical distribution in terms of acceptance among different fuel-type owners. The most polluting vehicles, GV and DV, have the lowest approval, as they understand that this will evidently result in higher charges for them. Interestingly, for the segments, it is the other way around, and people with more expensive and polluting cars are more open to a system where the polluters pay. People with a higher income purchase higher segments, and this group is expected to be less sensitive to price changes and thus more accepting.

6.3. Binomial variables for estimating interaction effects

To measure how certain variables impact the utility as an interaction effect, they must first be re-coded into usable metrics. An option is to re-code all variables to binomial variables with 0's and 1's. All variables were coded into binomial levels except age to translate the non-numeric values into numeric binary ones. As age is a linear variable, most information can be retrieved when this is held continuous. These explanatory variables will then be added to the data set with choices and choice sets so specific background characteristics can be linked to choices made. This way, it can be tested whether particular groups, based on those characteristics, within the Dutch society, choose differently.

Table 6.6: Binomial values of background characteristics

Binomial values	Value 0	Value 1	Value 0	Value 1
Distance to nearest train station	Close	Far	<15 min	=>15 min
Income	Low	High	<40,000	=>40,000
*Age**	-	-	-	-
Gender	Female	Male	Female	Male
Education	Low	High	MBO, MAVO, HAVO, VWO	HBO, WO
Car ownership	No	Yes	No	Yes
Car segment	Low	High	A,B	C,D,E+
Current fuel-type	ICEV	EV	GV,DV	PHEV,BEV
Business cars	No	Yes	Own car	Paid (partly)
Car use	Occassional	Often	< 3days/week	=>3 days/week
Public Transport (discount) card	No	Yes	No card	Card (discount)
Trip purpose	Private	Business	Private	Business
Commuting mode	No car	Car	Train, walk, bike	Car
Sustainability	Not sustainable	Sustainable	Not sustainable	Sustainable
Car affinity	No car affinity	Car affinity	No car affinity	Car affinity

* Age is measured as a continuous variable and is not categorized in a binomial group

6.3.1. Binomial variables used for testing heterogeneity

Not all variables were taken up in the model. This is because not every additional parameter also leads to extra information and an increase in the Log-Likelihood. This thesis seeks to only include relevant background characteristics in the model that will be used for further analysis and conclusions. Expert interviews were held to determine the variables that will be used for further testing of heterogeneity in the population. The questions were based on the relevance of the characters and their hypothesis on how this characteristic would interact with the parameter of the FKC. All results can be found in Section E.2. The following figure shows the chosen characteristics and the general hypothesis provided by the experts.

Table 6.7: Hypotheses interaction effects of selected background characteristics

Car fuel-type choice experiment	
Background characteristic	*Hypothesis*
Income	People with a higher income are less sensitive to the height of the kilometer charge
Education	People with a higher education are more sensitive to the height of the kilometer charge
Car use	People with high frequent car use are more sensitive to the height of the kilometer charge
Business Car	People with a business car are less sensitive to the height of the kilometer charge
Mode choice experiment	
Background characteristic	*Hypothesis*
Income	People with a higher income are less sensitive to the height of the kilometer charge
Education	People that own a business car are less sensitive to the height of the kilometer charge
Car use	People with a higher education are more sensitive to the height of the kilometer charge
Business Car	People with high frequent car use are more sensitive to the height of the kilometer charge
Public Transport card	People that own a PT card are more sensitive to the height of the kilometer charge
Commuting mode	People with the car as commuting mode are less sensitive to the height of the kilometer charge
Age	People that are older are less sensitive to the height of the kilometer charge
Distance to train station	People that live close to a train station are more sensitive to the height of the kilometer charge

Age: Age is included in the model as the FKC can pose as it would be interesting how price sensitivity varies among younger and older people. The hypothesis here is that older people are less sensitive to the costs as they are not used to the inflexibility of train travelling.

Income: The general hypothesis on sensitivity for different income groups is that people with higher income are less sensitive to mode choice and car fuel-type choice. Aydin (2012) argues that people with higher income are generally less sensitive to price, which is the most prominent assumption found in the literature. The flexibility and comfort of a car are prominent attributes that people with higher incomes are more willing to spend money on. The experts also mention that a higher sensitivity of higher-income groups could occur because wealthier people are more careful when spending money.

Distance to train: The hypothesis on the *Distance to the train station* is that people that live closer to the train station are more sensitive to the FKC because they have an alternative in terms of mode choice.

Business car: The hypothesis for business car owners is that they are more sensitive to switching fuel-type choices as, in many cases, the private kilometers are still paid by the employee. However, when another fuel-type is cheaper but, for instance, has a higher purchase price, the sensitivity for the FKC is higher as the employer purchases the car. For the mode choice, business car drivers are expected to be less sensitive because they own a car that is, in some cases, fully paid for by the employer.

Public Transport card: This variable is only taken up in the mode choice experiment. People with a public transport card are assumed to be more sensitive to the height of the FKC because they have a good and cheaper alternative.

Commuting mode: The commuting mode interaction effect is only included in the mode choice experiments. For this experiment, the hypothesis differed among the experts. On the one hand, you could expect that people that drive a car to work (value 1) use the car more often and are therefore more sensitive to higher costs. On the other hand, people are path-dependent, meaning they are not very likely to easily switch transport modes if they have been using the car for many years.

Education: The hypothesis on education is debatable for both experiments as education is often correlated with income. Higher educated people are expected to be more sensitive towards the FKC. Meyer (2015) found higher educated people to make more environmental friendly decisions. Applying this theory to these experiments would mean that higher educated people must be more sensitive. They are more open to environmental friendly alternatives such as EV or the train. Hackbarth and Madlener (2013) found well-educated consumers to be more sensitive to price.

Car use: The FKC is a variable cost indicating that frequent car users might start using their car less as total costs would increase. On the other hand, frequent car users might be the ones that commute to work by car. That means they are more dependent on the car and might not have a relevant mode choice alternative; the same goes for people living further from train stations. On the other side, you could argue that, as the FKC is a variable cost, frequent car users would start using their car less as total costs would increase. Both are therefore possible, and there is not one general set hypothesis. Both are therefore possible, and there is not one general set hypothesis. For car fuel-type choice, frequent car users are expected to be more sensitive to the FKC. This is because variable costs increase and having an alternative with lower FKC is therefore more attractive for people that use the car often.

6.4. Overview of selected choices

This section briefly visualises the choices made per alternative and specified to the specific choice set. This provides more insight into the distribution of the choices people make and which alternatives are the most popular. As the variation in attribute levels was not completely random and specifically based for each alternative, the overall choice distribution should be able to resemble realistic market shares.

Car fuel-type experiment

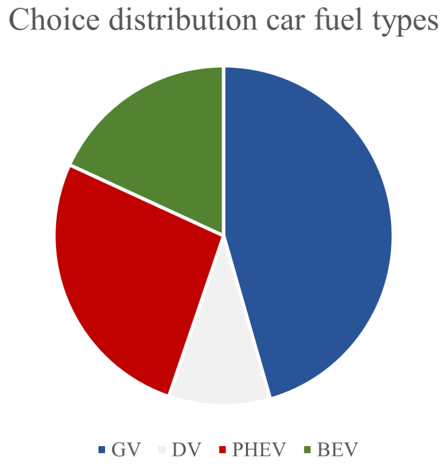

Figure 6.1: Choice distribution of car fuel-types

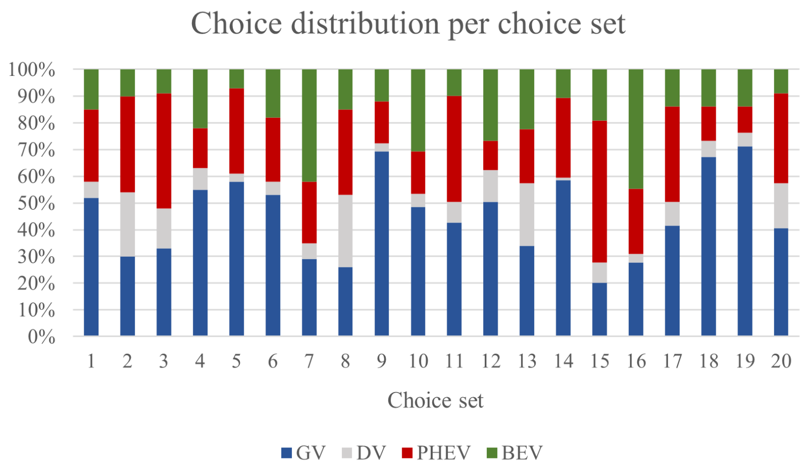

Figure 6.2: Choices car type per choice set

The graphs above show a high dominance of the GV, which was expected. The GV is still the most prominent car; therefore, it is no surprise that the biggest market share of newly bought vehicles is for GV. Based on the car fleet report by Rijksdienst voor Ondernemen and Revnext (2018), we can conclude that the choice distribution of vehicles is in line with the expectation. We also see a quite substantial share going to the EV segment. The observed choices for EV are slightly lower than the respondent share that considers buying an electric car. This has to do with the ongoing electrification of the Dutch car fleet and the price stimulants that the government uses to attract these early adopters. The market share of newly sold vehicles was 24% in 2020, and that share has only increased. The distribution, completely dependent on the attribute levels presented, shows similarities. Only the PHEV share is much higher than revealed data has shown over the years. At first, the PHEV was not expected to take such a significant market share. This bigger share resembles that people are willing to switch to other fuel-types but, maybe due to charging inflexibility, not all of them would like to go fully electric. Another reason BEV purchases have been much higher over the past years is that the BEV received a significant tax decrease over the last years, and the PHEV did not. This car tax is annually increasing (see Section A.0.3), and therefore, early adapters were stimulated to purchase BEV. This tax advancement is not incorporated in the choice task and therefore outcomes might mismatch with the revealed data. Since the decrease in tax advancement for BEVs, the PHEVs have become more popular again.

Mode choice experiment

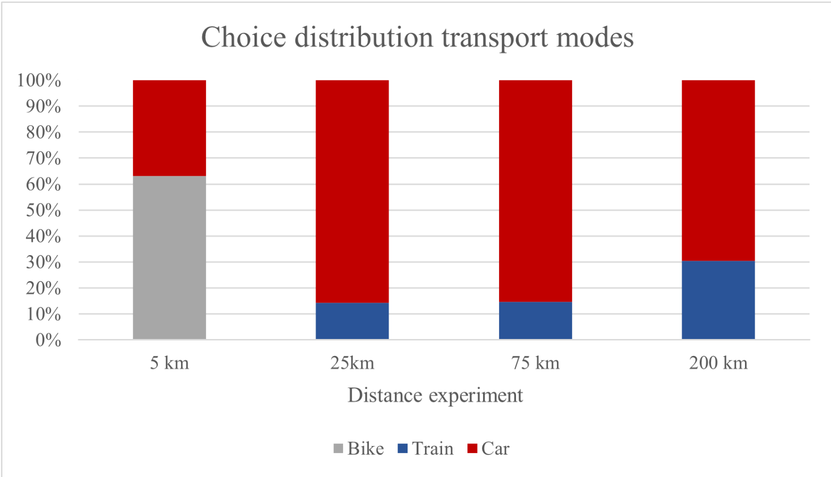

Figure 6.3: Choice distribution of car fuel-types

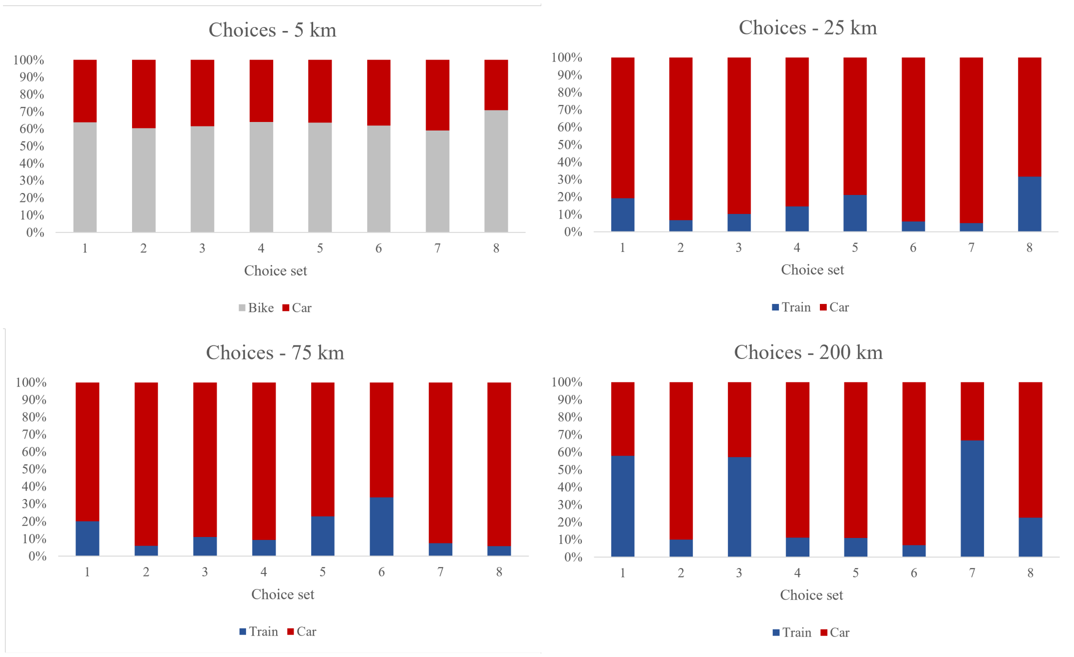

Figure 6.4: Choices car type per choice set

The choice distribution shows that the car is the preferred alternative for medium to longer distances for the mode choice experiments. When comparing the train to the car, the car is much more flexible than the train. The train has a fixed schedule, including access/egress times and sometimes waiting times and transfers. Additionally, the train is often not even (much) cheaper than the variable costs of car use. These are the main reasons people still prefer the car over the train. For the shorter distance, the results show that the bike is picked. This probably has to do with the flexibility of cycling whereas cars must find a parking spot. Seeing as these travel times are relatively short, the car inflexibility has a higher impact than when compared to the train for longer distances.

6.5. Summary

In this chapter, the sample is evaluated. The sample characteristics are essential for the relevance and for generalising the effects to the Dutch citizens. It can be concluded that out of the 550 recruited respondents, 505 completed the survey and were found to be qualified to include in the data set. Overall, it can be concluded that the sample size represents the Dutch citizen well. Apart from the set respondent quotas for age, gender and education, car- and travel characteristics were also quite similar. For example, the distribution in car segments was close to the distribution found in Rijksdienst voor Ondernemen and Revnext (2018). The choices distribution showed the highest market share for GV and the lowest for DV. This was according to expectations as people predominantly have a GV fuel-type, and DVs market share has been declining for years due to its high emissions and pollution. The choices for PHEV turned out substantially higher than the past years showed. For the distribution between the train-bike and the car, the car had a strong dominance in the mid - to long-distance trips (>25km), while the bike got slightly preferred on the short distance trips (5 km). Furthermore, the acceptance outcomes showed that, overall, people are well supportive of the FKC in general and differentiating the tariffs to emission. The respondents proved to be more supportive of this policy rather than differentiating based on time or based on place. Lastly, all background characteristics were converted into binomial values (except for age), and a decision, supported by expert interviews, was made on which characteristics to include further. *Age, Income, Distance to train, Car use, Business car, Public transport card, Commuting mode & Education* were chosen.

A sample description is an essential element in a SP choice experiment because of expected heterogeneity in peoples answers. Populations are assumed to consist of several groups that each are heterogeneous in decision-making. For a sample to represent the Dutch populations, the nature and distribution of the respondents must be presented and evaluated. This knowledge contributes to the quality of the collected data and the ultimate findings. Additionally, extra information can be gathered about specific groups in order to evaluate the heterogeneity.

7

Results of car fuel-type experiment

In this chapter, the outcomes of the final choice model for the car fuel-type experiment are displayed, interpreted and discussed. These results flow from the choice model that is set up in Section 7.1 using the collected data from the survey design which was presented in Chapter 6. The chapter starts by showing how the choice model was set up and the results that flow of the final choice model, a Mixed Logit (ML) model. The ML model was chosen over the MNL model for further analysis and application based on the model fitness and the suspected nesting effects within the alternatives. The MNL choice model and outcomes can be found in Appendix F. As the contribution to utility depends on the attribute levels, the next section is dedicated to introducing to what absolute extent the parameters contribute to utility. Subsequently, the added interaction effects and their coefficients are presented in combination with the model fit of the final model. The chapter ends with a summary.

7.1. Set up of ML choice model

In this section, a justification is given for adding extra constants and parameters. Subsequently, the estimation procedure for the general parameters is discussed, along with additional parameter interpretation information. Finally, the estimation of the interaction of explanatory driver characteristics with the FKC is discussed and whether or not they lead to extra information and how that can increase model fitness.

7.1.1. Car segment experiments

Multiple segments were distinguished in the research and design phase. For the size of the survey and sample size requirements, the different segments were taken into account but were used in the same experiment. Based on the current car segment or the desired future car segment, the respondents received different purchase prices. However, the attribute levels of the purchase prices varied with the same marginal changes for all segments. This was done to maintain 1 experiment but still make the attribute levels generic for all segments. The marginal changes were relative to the base scenario for ICEVs. In the choice task itself, the respondents received absolute values so that it would be easier to relate. One choice model is estimated for all segments. The parameters that are found are based on the percentage increase. This can therefore not be directly translated into a WtP. To do that, the found parameters must be converted from percentages to euro's.

7.1.2. Alternative specific constants and parameters

Alternative specific constants (ASC) are usually added to MNL choice models to account for the generic (dis)utility (V) of a particular alternative compared to each other. ASCs represent the total (average) utility associated with factors other than observed attributes taken up in the experiment. The signs indicate whether one alternative is preferred over the other. However, the ASCs are dependent on the coding of the variables and interpreting the value of the ASC as a separate parameter is therefore difficult. Alternatives might have additional attributes or characteristics that are not included in the choice set but must be accounted for. In the case of the car fuel-type choice, these characteristics could include the CO_2 emissions, costs of fuel/electricity, fueling/charging time or the limited (public) charging places. To account for these characteristics of a fuel-type, ASCs are added. This experiment contains four alternatives, meaning three alternatives are given an ASC parameter relative to the other alternative (BEV) that is fixed to zero.

Attribute parameters can be added to the model as a generic parameter or an alternative specific parameter (ASP). A model with four alternatives would result in four extra degrees of freedom per attribute. Using the LRS test, adding these ASPs is not adding the required amount of extra model information. On top of that, and regardless the LRS test, it does not contain extra information that is needed to answer the research questions. The LRS test is thus not taken as a hard requirement but more as a guideline.

7.1.3. Mixed Logit model

For the car fuel-type experiment, an additional Mixed Logit (ML) model is estimated. This is because it is expected that heterogeneity exists in the population. The MNL error terms assume independent draws with the same variance across alternatives. That means the MNL overestimates the probabilities of individual alternatives that have something in common. It ignores correlation within 'nests of alternatives' (Chorus, 2021). On top of that, the MNL ignores the correlation between choices made by the same respondent. This taste varies across individuals but should be similar per observation per individual. To account for these biased outcomes, a Mixed Logit model with additional error components can be estimated. This model suits this experiment as there is an expected correlation between some alternatives. The ML model includes error components υ that eat away from the i.i.d. (independent identically distribution) error terms variance. It does so by reallocating part of the unobserved heterogeneity (Brownstone et al., 2000). Because of normalisation issues, the error term is fixed. An extra term (error component) must be added to the utility function for which this heterogeneity is expected.

In the literature, GVs and DVs are placed in the ICEV category. As they are pretty similar fuel-types and have no electric element like the other two alternatives, an error component υ_{ICEV} is added. Although BEV and PHEV are considered EVs, there is a big difference in charging reliability. As an EV is no hybrid, it is very dependent on charging infrastructure. This is considered one of the main limitations in EV adoption (Liao et al., 2018). Therefore an error component υ_{charge} is added to all three alternatives that are not dependent on available charging infrastructure.

ML basic utility functions

$$V(GV) = ASC_{GV} + \beta_{PP} * PP_{GV} + \beta_{FKC} * FKC_{GV} + \upsilon_{ICEV} + \upsilon_{charge} \tag{7.1}$$

$$V(DV) = ASC_{DV} + \beta_{PP} * PP_{DV} + \beta_{FKC} * FKC_{DV} + \upsilon_{ICEV} + \upsilon_{charge} \tag{7.2}$$

$$V(PHEV) = ASC_{PHEV} + \beta_{PP} * PP_{PHEV} + \beta_{FKC} * FKC_{PHEV} + \beta_{Range} * Range_{PHEV} + \upsilon_{charge} \tag{7.3}$$

$$V(BEV) = \beta_{PP} * PP_{BEV} + \beta_{FKC} * FKC_{BEV} + \beta_{Range} * Range_{BEV} \tag{7.4}$$

7.1.4. Background interactions with the FKC

The basic utility functions are now extended with the interaction effects. These interaction effects represent the sensitivity of background characteristics with *Income, Education, Car use* and *Business Car* are added to the utility function of car fuel-type choice. These characteristics were chosen based on three expert interviews. The expectations that flowed from these interviews were concluded in Section 6.3.1. The final utility functions to determine the utility for alternative i that were estimated with the interaction effects added are as follows:

$$\begin{aligned} V(i) = ASC_i + \beta_{PP} * PP_i + \beta_{FKC} * FKC_i + \beta_{Range} * Range_i + (\beta_{FKC} + \beta_{FKC_{Income}} * Income) * FKC_i \\ + (\beta_{FKC} + \beta_{FKC_{Education}} * Education) * FKC_i + (\beta_{FKC} + \beta_{FKC_{Businesscar}} * Businesscar) * FKC_i \\ + (\beta_{FKC} + \beta_{FKC_{CarUse}} * CarUse) * FKC_i + \upsilon_{ICEV_i} + \upsilon_{Charge_i} \end{aligned} \tag{7.5}$$

7.2. Model estimation results

This section aims to provide the outcomes of the ML model given the utility functions provided in previous section. The ML model was chosen as final model because the assumption that the MNL model might overestimate the parameter coefficients. The MNL model accounts every choice observation as a separate choice while earlier choices impact other choices. More information on the differences between the ML and MNL can be found in Chapter 4.

7.2.1. Parameter estimations

The results of the ML model are displayed in Table 7.1. These outcomes show the main attribute parameters, the constants & the sigmas. 250 Halton draws were used to compute these outcomes. The converged parameters did not significantly differ from 500 draws. The columns represent the estimated coefficient of the parameter. These numbers are going to be used in the integrated model in Chapter 9. The standard error (s.e.) resembles the reliability of the parameter. The parameter significance is given by the p-value.

Table 7.1: Car fuel-type ML model outcomes

Parameters	Est.	s.e.	p-value	Significant?	Expected sign?
ASC GV	0.97	0.12	0.00	Yes	Yes
ASC DV	-0.93	0.12	0.00	Yes	Yes
ASC PHEV	0.48	0.08	0.00	Yes	No
β Purchase price	-0.03	0.00	0.00	Yes	Yes
β FKC	-1.18	0.10	0.00	Yes	Yes
β Range	0.01	0.00	0.00	Yes	Yes
β FKC*Income	-2.04	0.53	0.00	Yes	No
β FKC*Business car	-2.10	0.83	0.02	Yes	No
β FKC*Car use	-1.42	0.51	0.01	Yes	Yes
β FKC*Education	-1.05	0.69	0.17*	No	Yes
σ Charge	1.21	0.10	0.00	Yes	-
σ ICEV	-2.67	0.10	0.00	Yes	-
Model fit					
LL(0)		2750.4			
LL(C)		-2472.4			
LL(final)		-2021.6			
Rho-square		0.265			

Model fit of the final model

Considering the model fit, there is a substantial increase in model fit for the ML model ($\rho^2 = 0.265$) with respect to the MNL model ($\rho^2 = 0.1559$). Both model fits are, however, considered *reasonable* to *good*. Therefore, we can conclude that the ML model is also the better model based on the model fitness. The overestimation of the MNL model can explain the difference in LL and ρ^2.

7.2.2. Main parameters

The first thing to look at is the signs of the main parameters (ASCs, FKC, Purchase price, Range). This is the first check to see if your model estimates are according to expectations. The expectations for the signs of these main parameters were sketched in Chapter 3. In this case, the FKC and Purchase Price are both costs and costs are assumed to have a negative parameter; the higher the costs, the less utility. Both parameters are harmful to utility and, therefore, according to expectation. For Range, we expected a positive sign; a higher range should contribute to utility, or better, a low range should contribute less to utility. The sigmas of the error components are statistically significant, meaning there is no high correlation between estimated sigma's (Chorus, 2021). A higher sigma (or standard deviation) shows that the data is widely spread, which means that the data is less reliable and a low standard deviation shows that the data are clustered closely around the mean. It represents variation (across individuals and their choices) of the utility of the common unobserved factors. The error component υ_{ICEV} is higher and choices are more spread between GV and DV. The error component for υ_{Charge}, that is only excluded in the utility function for BEV, is much smaller indicating that this error component is more reliable. It shows that ICEVs relatively have less in common than the alternatives that included υ_{Charge} (GV, DV and PHEV). The interaction effects and their interpretation are discussed later on in Section 7.2.3.

For the ASCs, we can conclude that the values are sensible. A positive ASC means that the unobserved preference for that alternative is higher than the base alternative (BEV). A negative ASC means that the unobserved preference for that alternative is lower than the base alternative (BEV). The BEV value is set to zero and is the reference level. The GV is still the most prominent and broadest used fuel-type in the Netherlands. Unlike the

EV, where there is inflexibility in terms of charging, the GV is much more reliable. However, due to increasing diesel prices (relative to gasoline prices) and high PM_{10} and NO_x emissions, which are harmful to the human body, diesel's reputation is shrinking. Rijksdienst voor Ondernemen and Revnext (2018) confirmed this by identifying a significant shrink in new diesel vehicle sales. It was expected that the ASC for DV is the lowest. In Chapter 6, this was confirmed by the low share of overall choices for DV. The higher ASC for PHEV over BEV was initially not expected. The past years, the BEV has had a higher market share for newly bought vehicles than the PHEV. The PHEV is a hybrid where people have the option to switch to gasoline when the battery is empty, which might be the reason for people preferring a PHEV over a BEV.

Finally, the statistical (in)significance is an important metric to see to what extent the parameter estimates can be generalised to the entire population and if the actual hypetheses can be confirmed. In the ML model, all parameters, including the standard deviations of the error components, meet the 95% confidence level. That means the found coefficients can be generalised to the population. For the standard deviations (υ), statistically significance means that there is a found correlation between the alternatives that include that (υ). υ_{ICEV} seperating EV and ICEV has the highest st. dev which indicates a higher correlation.

7.2.3. Interaction parameters

This section elaborates more on the added interaction effects and their outcomes. The sign and height of the interaction parameters show to what extent the characterised groups are sensitive to the FKC. As they are interaction effects and not direct effects, the formula indicated in Section 4.3, is applied. In Table 7.1, it is found that the parameters of all four included interaction effects have the same negative sign and are pretty close to one another. Except for the education parameter, all interaction effects are also significant. A negative sign indicates that the people belonging to the group with value 1 are more sensitive to the FKC. The distinction in groups can be found in Section 6.3.

Income

For income, the outcomes show that people with *higher income* are more sensitive to the FKC. This is surprising and is not according to the original hypothesis that people with higher income have more money to spend, thus have a higher WTP and should be less sensitive. The hypothesis can therefore not be confirmed. A potential explanation could be that people with higher incomes are more easily able, and thus willing, to buy another fuel-type that might be more expensive. This indicates a higher WtP in terms of fixed purchase price in exchange for €0.01 of FKC. People with a lower income might not be in the financial position to make an extra investment into a car with a lower FKC. In Section 7.3, more elaboration on the utility contributions and the found WtP is given. An additional explanation for this higher WtP could be the correlation between people with higher income and car use. Table F.1 show a slight correlation with car use and income. The found responses show that 65% of higher income groups use the car frequently whereas that value is only 58% for lower income groups.

Business cars

Business car users tend to switch more easily to another fuel-type if the FKC increases. Again, this is surprising and not according to the initial expectation. This higher sensitivity could be explained by the fact that business cars are often bought or leased by the employer. The FKC is a variable cost that, although not in all cases, must be paid for by the user. This means that switching to another fuel-type because of a lower FKC is more accessible when the car is purchased or leased by the employer. It must be noted that the group 'business cars' exists of all people that have their vehicle (partly) paid for by their employer. However, there are also differences in whether the private kilometres are also reimbursed. If that is the case there is a smaller stimulant to switch cars for FKC reasons.

Car use

People that *frequently use their car* were expected to be more sensitive to the height of the FKC. This hypothesis can be confirmed as the sign is, indeed, negative and the parameter found is statistically significant. The FKC is a variable cost; thus, people who drive more often are expected to be more sensitive to those costs.

Education

Finally, higher educated people were expected to be more sensitive. Outcomes of the model proved that this expectation was correct since a negative effect was found. However, education correlates heavily with income (>0.4), therefore it remains the question if the effect that was found is not due to that correlation. This is the most expected correlation as higher educated people have more income (Wolla and Sullivan, 2017). On the other hand, consulted literature show that higher educated people make more environmental friendly decisions (Meyer, 2015). Choosing an EV over an ICEV is considered as such a decision. Since the 95% confidence interval is not met, this hypothesis can not be confirmed.

The following table shows the percentage of both groups within one of the selected background characteristics, that chose an EV (PHEV & BEV). In other words, 43% of the low income group chose an EV. The table shows that higher income groups and education, which are correlated (>0.4), are more fond of buying (partially) electric. This correlation means that the effect of the education interaction might be overestimated due to the fact that the effect found is partly explained by to the groups' income. The other parameters have very low correlations. Another finding is that people that own a business car or use the car very often are less interested in buying electric, potentially due to the lower flexibility of EVs.

Table 7.2: Percentage in background groups choosing EV

Income		Business car		Car use		Education	
Low	High	No	Yes	Low	High	Low	High
43%	46%	45%	40%	45%	44%	37%	52%

7.3. Utility contribution of main parameters

It is incorrect to directly compare the estimated parameters to each other because other attribute level ranges were used. To find the correct contributions to utility for all specific parameters, the parameters need to be multiplied with this range. These ranges are the absolute differences between the maximum and minimum range. The attribute level range of the FKC is therefore much smaller (between €0.05 and €0.25) than the purchase price range (between 0% and 75%), thus the absolute parameter for FKC is much higher. The utility contributions given in Table 7.3 translate the found estimates into comparable figures. The estimate for FKC differs from the estimate shown in Table 7.1. Only the main paramters are taken account in this table and the interaction effects carry part of the FKC estimate. Excluding the interaction effects thus result in a higher parameter. In the model outcomes, the estimates are dependent on the height, and the difference, between attribute levels. Multiplying the estimate with the incorporated range gives the actual contribution to utility of that factor.

Table 7.3: Utility contribution car fuel-type choice

Attribute	**Estimate**	**Min. Level**	**Max. level**	**Utility contribution**	**Relative importance**
Purchase price	-0.03	0	75	-1.91	60%
FKC	-3.40	0.05	0.25	-0.68	21%
Range	0.01	-50	0	0.59	19%

The utility contributions seem sensible. The attribute levels of the purchase price and range are measured in percentages, and thus they can directly be compared. The results show that the contribution for utility, among these two attributes, is highest for the purchase price and lowest for the range. That means that people still value both attributes, but an extra percentage increase/decrease in purchase price weighs much higher than an additional increase/decrease in range. The utility contribution and the relative importance allow us to calculate how much extra Purchase Price we are willing to pay in exchange for €0.01 of FKC. As purchase prices vary per segment, the results are given per segment. Note that the found parameters are assumed to be the same for every segment. In theory, the parameters for the varying segments can differ.

Table 7.4: WtP for \texteuro0.01 of FKC per car segment

Car segment	***WtP purchase price for 0.01 of FKC***	
	Low income	*High income*
Segment A	€151	€183
Segment B	€212	€256
Segment C	€333	€403
Segment D	€424	€512
Segment E+	€606	€732
average	*€273*	*€329*

Table 7.4 shows the WtP for Purchase price for people, separated in low and high income groups, to decrease the variable FKC with 1 eurocent. The average, based on the distribution of car segment shares, is €301.10. The 'payback-period' of this trade-off thus lies at 30,100 kilometer which means that after 30,100 km one has 'earned' back its original investment. People with a higher income are more willing to make such an extra investment as they are more likely to have the financial means. Because frequent car users also tend to be more sensitive for the FKC, this indicates that frequent car users are willing to pay a higher purchase price in result for a lower FKC, than regular car users. Frequent car users are more likely to reach the break even point of return.

7.4. Car fuel-type choice model interpretation and key observations

This section elaborates on the outcomes of the model to provide insight into what these outcomes mean and the key takeaways.

The first key finding shows that, regardless of the stated interest in EV, people still choose a GV over EV, indicating that even if purchase prices and ranges were to level that of ICEV, GV would still gain the highest market share. Second, the relative importance is highest for purchase price when choosing a fuel-type. The variable FKC costs follows and the value of range is the lowest. Presumably, the unobserved preference for GV over EV and DV is due to the unreliability and inflexibility of charging EVs and serious health effects that are caused by diesel exhaust.

Surprisingly, the theory that people with higher incomes are less sensitive to price could not be confirmed in this experiment. This experiment included two types of costs, the variable FKC costs and the cars' purchase price. The current car market causes a trade-off between lower fuel costs and higher purchase prices for EVs. For every €0.01 decrease of FKC, people with more income are willing to pay a more for purchasing (€329) than people with a low income (€273). Arguably, this found effect can be explained by the difference in financial means or by the slight correlation between car use and income. In essence, the trade-off between a higher purchase price (the investment) and lower variable costs (the return) is a common dilemma. However, not all people have the choice for such trade-offs as not everyone is capable of making such investments. An overall take out from the other included interaction effects show that car use is crucial in the price sensitivity towards buying a new vehicle. This effect is logical because lower variable costs directly impact the total costs of car use. However, this impact is much larger for people that drive their car more often than for people that don't. The found effect can be generalized to the population and the hypothesis can be confirmed.

Key observations

- The unobserved preference for GV is still the highest. It is followed by PHEV, BEV and DV. DV has gained a bad reputation over the years in terms of causing health problems. The preference for a fully electric car is still lower than the hybrid version. Charging inflexibility is expected to be the cause of that. The unobserved preference for PHEV is much higher than expected.
- Correlations were present between the alternatives included in the *ICEV* nest and *Charge* nest. The correlation between ICEVs and BEVs was the highest.
- Utility contribution is highest for purchase price, this means that people still value purchase price more than the FKC.
- For a decrease of 1 eurocent (€0.01) of the FKC, low income people people are willing to pay €273 for a car. High income people people are willing to pay more, €329 for a car in exchange for a €0.01 decrease.
- People with a higher income are willing to pay more for a lower FKC. Arguably, this is because higher income groups have more financial means to spend money that they can earn back later. On top of that, there is a relationship present between car users and high income people.

- Frequent car users are more likely to earn back their extra car investment if a more expensive car has a lower FKC. Therefore they are more sensitive to the FKC.
- High educated people are more sensitive than low educated people. Possibly, this is due to the high correlation with income.

7.5. Summary

In this chapter, the results of the estimated choice model were presented, and in this summary, we will briefly discuss them. The chapter started with an overview of the primary parameter estimations and a quick review of the quality of those results. The estimations were then translated into utility contributions Section 7.3 for comparison. In the last section, Section 7.2.3, the selected interaction effects were added to the model, and their estimates were evaluated and interpreted. This final chapter provides the weights of the included attributes that are needed to determine the final market shares. The results of this chapter present how policies affect car fuel-type choice behaviour of people. Additionally, it also gives information on the present heterogeneity that is in the population. This information allows this study to answer the sub question on how background characteristics impact the sensitivity to an FKC.

Overall, the quality of the results was good with the correct signs, low p-values and a reasonable model fit. An MNL and ML model was estimated, and the ML was chosen for further application and interpretation. The ML model led to a higher model fit and was also able to capture taste heterogeneity and panel effects which is relevant in this experiment. The model added two error components to include heterogeneity for ICEV fuel-types (GV, DV) and fuel-types with high charging reliability (GV, DV, PHEV). The error components were found to be statistically significant and were included in an Excel simulation.

The utility contributions showed that Purchase price still has the highest absolute contribution to utility, which means it is still the most decisive and essential criteria. The relationship between a purchase price investment and the variable FKC was presented by means of a willingness to pay for a 0.01€decrease of FKC.The FKC is the 2nd most important criteria, and the Range attribute was the least contributing. In a situation with set parameter values that resemble the current market, the resulting market shares resembled a dominant preference for GV, followed by PHEV, BEV and DV. In the ML model, there are two approaches for determining this market share; highest probability or average probability. This research used the average probability approach for further result application. A summary of the set hypothesis is found in the table below where the hypothesis is only confirmed if the hypothesis is correct as well as statistically significant.

Table 7.5: Hypotheses car fuel type experiment

Car fuel-type choice experiment			
Background characteristic	*Hypothesis*	*Expected sign?*	*Confirmation*
Income	People with a *higher income* are **less** sensitive to the height of the kilometer charge	No	No
Education	People with a *higher education* are **more** sensitive to the height of the kilometer charge	Yes	No
Car use	People with *high frequent car* use are **more** sensitive to the height of the kilometer charge	Yes	Yes
Business Car	People *with a business car* are **less** sensitive to the height of the kilometer charge	No	No

Based on this experiment, the only hypotheses that could be confirmed is the hypothesis that people that frequently use their car are more sensitive to the FKC. The hypothesis that more educated people are more sensitive to the FKC. However, the results where high income groups and people owning a business car are more sensitive is surprising and not according to the original theory of high income groups being less sensitive than low income groups. The answer was found in this same chapter where it turned out that people with more income are willing to pay a higher purchase price for a decrease in variable costs.

8

Results mode choice experiment

In this chapter, the outcomes of the final choice model for the car fuel-type experiment are displayed, interpreted and discussed. These results flow from the choice model that is set up in Section 8.1 using the collected data from the survey design which was presented in Chapter 6. For the mode choice experiment, only an MNL was estimated. Four different experiments were held, and it was chosen to keep this estimation process simple and robust. Furthermore, it must be noted that this research aims to investigate the effects of the FKC, and therefore the focus lies on the impact of the travel costs parameter. First, the outcome of the estimated model is presented. The effects of the main attributes are interpreted and converted into utility contributions. Subsequently, the interaction effects needed to answer the sub-question are added to the model, analysed and discussed.

8.1. Set up of choice model

An MNL model has proven to be a good fit for simple mode choice experiments like these. More elaboration on an MNL setup is given in Chapter 4. As four different models must be estimated, one for each distance is chosen to keep it simple and robust. First, this section looks at if ASCs and/or ASPs are added to the utility function. Subsequently, the basic utility functions are given.

8.1.1. Multinomial Logit model

Alternative specific constants and - parameters

As for the car fuel-type choice estimation model, ASCs could be added to the utility function to include the fact that there is an overall difference in utility between alternatives. In this case, this difference is, e.g. based on unobservable factors like being able to work, waiting time, transfers, and access/egress times. The ASC parameter is added to the utility function of the train alternative, and the ASC for the car is set to zero.

Unlike the model estimation of the other experiment, this model did try to incorporate alternative specific parameters. We assumed that travel costs are generic and are not valued more or less between the two alternatives; it is different for travel time. This is because, on the train, other activities could be performed whilst driving the car; the focus must be solely on the road. It is expected that time increases/decreases are much more valuable for train travellers than for car travellers. However, making the parameters, alternative-specific did not increase the Final LL; therefore, the LRS test did not suffice. As the alternative specific parameters are not essential for the further development of this research, it is chosen not to include any alternative specific parameters. The travel time for using the bike is fixed and does not need an additional parameter.

Final utility functions MNL model

To translate the decisions made considering the ASCs, ASPs and included interaction effects, the following utility functions are determined:

$$V(Train/Bike) = ASC_{Train/Bike} + \beta_{TC} * TC_{Train/Bike} + \beta_{TT} * TT_{Train/Bike} \tag{8.1}$$

$$V(Car) = \beta_{TC} * TC_{Car} + \beta_{TT} * TT_{Car} \tag{8.2}$$

8.2. Model estimation outcomes

This section reviews the outcomes of the model estimation. The estimate (Est.) is the parameter coefficient, the s.e. is the standard error and the p-value is the statistical significance of the parameter. The model parameters include the ASCs, the main paramters and the interaction effects. These interaction effects are only added to the utility function for car. Hence, the background effects are only interacted with the travel costs for car; the FKC. Below the parameter results, the model fit for each experiment is shown. The results, per distance experiment, are found below:

Parameters	5 km			25 km			75 km			200 km		
	Est.	s.e.	p-value	Est.	s.e.	p-value	Est.	s.e.	p-value	Est.	s.e.	p-value
ASC Bike	0.60	0.26	0.01	-	-	-	-	-	-	-	-	-
ASC Train	-	-	-	-3.80	0.36	0.00	-3.86	0.41	0.00	-2.54	0.10	0.00
β Travel Costs	-0.16	0.19	0.01	-0.08	0.01	0.00	-0.02	0.01	0.00	-0.01	0.01	0.00
β Travel Time	-0.03	0.02	0.03	-0.03	0.02	0.00	-0.03	0.01	0.00	-0.02	0.00	0.00
β FKC*Dist. to train	0.46	0.18	0.03	0.06	0.04	0.26*	0.03	0.02	0.11*	0.02	0.00	0.04
β FKC*Income	0.02	0.18	0.39*	0.00	0.04	0.46*	0.01	0.02	0.31*	0.01	0.00	0.04
β FKC*PT card	-0.30	0.24	0.22*	-0.17	0.04	0.00	-0.08	0.02	0.00	-0.01	0.01	0.01
β FKC*Business car	0.79	0.27	0.01	0.05	0.06	0.24*	0.04	0.02	0.07*	0.01	0.01	0.06*
β FKC*Education	-0.05	0.13	0.32*	-0.13	0.02	0.01	-0.06	0.01	0.00	-0.02	0.00	0.00
β FKC*Commute	1.29	0.22	0.00	0.16	0.04	0.00	0.02	0.02	0.02	0.01	0.00	0.01
β FKC*Age	-0.01	0.01	0.09*	0.00	0.00	0.08	0.00	0.00	0.27*	0.00	0.00	0.03
β FKC*Car use	0.73	0.24	0.01	0.06	0.05	0.14*	0.05	0.02	0.01	-0.01	0.01	0.14*
Model fit												
LL(0)	-651.56			-651.56			-651.56			-651.56		
LL(C)	-616.25			-388.57			-392.10			-578.39		
LL(final)	-569.83			-333.42			-328.73			-424.46		
ρ^2	0.13			0.49			0.50			0.35		

* Not significant at a 95% confidence interval

Table 8.1: Mode choice model outcomes

Model fit of the final model

The table below shows the increase in LL and the ρ^2 value. Seven parameters were added to the model, and according to the chi-square table, the LRS statistic must be higher than 14.07 to speak of a 'better' model. For all four experiments, the LRS statistic was well over that threshold value. Overall, the model fit of all experiments is considered 'reasonable to good', except for the 5 km experiment, which is considered 'limited to reasonable'.

8.2.1. Main parameters

The first thing to review is the signs of the main parameters. For the ASCs, a negative value was expected for the train. This is due to additional unobservable factors like access/egress time and transfers. These values were negative for the distances, including the train alternative (25, 75, and 200 km). For the longest distance, 200km, the ASC is the least negative. This could be explained by the fact that people don't like long car drives or that when having a long travel time, train travel becomes, relative to the other distances, more convenient. Relatively, egress/access times, e.g. become less important. For the bike as travel mode in the 5km experiment, the estimate is positive, and we can conclude that, generally, short distances are preferred to be done by bike rather than the car. A possible explanation is that the bike is much more flexible than the car in terms of parking and people prefer being outside and exercising. .

For the attribute parameters, Travel time (TT) and Travel costs (TC), both are negative and statistically significant. The TC parameter represents the train ticket costs for the train alternative and the total FKC costs for the car alternative. As four different experiments were conducted, it was chosen to keep the model simple. No additional attribute-specific parameters were added. The LRS was not significant, and including these parameters does not lead to the additional value of this research. The parameters for costs are visualised below, and apart from the short-distance (5km) experiment, the parameters decline with longer distances. This is because the attribute level ranges are higher. In the next section, the utility contributions will be outlined to compare the effects of different attributes and distances.

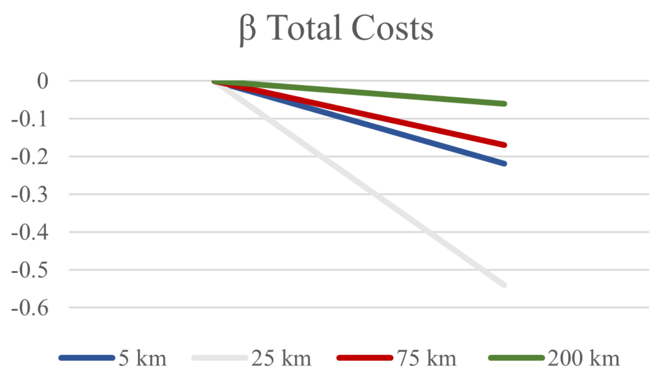

Figure 8.1: Total costs parameter mode choice experiment

8.2.2. Interaction parameters

In this section, the added interaction effects are reviewed, see Table 8.1. Unfortunately, none of the estimated interaction effects is statistically significant for all four experiments. This is probably due to the limited amount of choice observations per experiment. As the experiments and the found data are not integrated, and the experiments are separately modelled, the choice data collected per single experiment proved insufficient to generalise the found effects for all distances. Nevertheless, it must be noted that, although the confidence interval is not always met, the effect is still there it can not be generalised (Amrhein et al., 2019). Therefore, there is no reason to exclude this variable for further application. We can conclude that the interaction effects found have the same sign for every distance, except for Car use. This means that the effects seen are consistent among the different experiments.

Distance to train station

The interactions show that people that live *close to a train station* are more sensitive to the FKC. This was according to the expectation as people with easier access to an alternative are more sensitive to price changes. The high parameter parameter for the experiment including the bike alternative compared to train can be explained by the fact that people that live close to the train station often live in more dense areas. These dense areas can increase travel times making it more likely for people to be less affected by the price. The hypothesis can be confirmed for the 5 km and 200 km experiments.

Income

People with a *higher income* are less sensitive to the FKC. The effect is not big, but it does support the theory that people with more income have more money to spend and are therefore less sensitive to switching transport modes. Unfortunately, the hypothesis can only be confirmed in the 200km experiment.

Public transport (discount) card

Public transport card subscriptions - or discount holders are more sensitive. This was according to the original expectation. The alternative for train is more attractive for PT card holders. When one has multiple alternatives, one becomes more sensitive to the price of the other.

Education

The *education* parameter estimate shows that more educated people are more sensitive to switching, and the same effect was found in the car fuel-type experiment. It must be noted that there is correlation (>0.4) between education and income, see Table G.5. Still, the results between education and income differ in the way that higher educated people are more sensitive and people with high income are not. One explanation, consulted by Meyer (2015) is that higher educated people make more environmental friendly decisions. The train alternative is considered as a more environmental friendly choice.

Car use

Frequent car users are not sensitive to the FKC on the short to medium distances, but on the very long distance, this switches. This is an interesting finding and it means that frequent drivers are not sensitive to costs on small distances. Although there is strong correlation between car use and commuting, commuting are more forced trips with certain expected arrival times, whilst car use is more free of choice and if there is a good alternative when it gets really expensive, people choose that. Low car users might see long trips as very occasional and are less impacted by the costs of that trip.

Commuting mode
The hypothesis for commuting mode type was that car commuters would be less sensitive to the FKC. This is because car commuters are more likely to have a working location that is not reachable by train or bike. Car availability rather than accessibility to PT or the possibility of using an active commuting mode. People with the car as a commuting mode are less sensitive than other users.

Business car use
Business car owners are, as expected, less sensitive to the travel costs. This was expected because business car owners are not, or only partially, paying these costs themselves. When the costs don't directly hit your own budget, you are likely to care less on the costs and choose the alternative that fits your preferences best.

Age
The parameters for *age* do look small, but that is because this is the only variable with continuous rather than binomial data. Example given, the disutility (25 km experiment) for a 20-year old is lower (0.04) than that of a 75-year old (0.16). Older people are more fond of the bike The effects are primarily positive, meaning that older people are less sensitive to the height of the FKC, probably because of the inflexibility and social discomfort of train travel.

When introducing interaction effects, it is interesting to see how specific interactions correlate. The correlations are presented in Appendix F. The correlations showed a maximum correlation of 0.26 for all four experiments. It is therefore concluded that the interactions are not correlated.To conclude, all effects were as expected. The effects for *car use*, the *commuting mode* and the car payer (*business or non-business*), all car characteristics, were positive and had the most impact in all four experiments. It must be noted, to generalise these findings to the entire population, more choices must be observed to reach statistical significance for every interaction parameter.

8.2.3. Parameter significance

What makes a model a 'good' model? This is an important question when using choice modelling to estimate choice behaviour. Hauser (1978) also questions the relevance and importance of certain model quality tests. The same goes for the usability of parameters in case of insignificance (at a 95% confidence interval). Amrhein et al. (2019) showed that about half of the papers tested misinterpreted statistical insignificance and did not use the found parameters for further application. Amrhein et al. states that although the parameters are not significant at a 95% confidence interval, the effect is still present. It is thus essential to note that model fitness and statistical significance are relevant metrics to consider when setting up the model. As these models will be applied and integrated, parameters cannot be left out because of statistical insignificance or not meeting the LRS requirement. Therefore, the relevance of parameters for conclusions and further application were prioritised rather than statistical insignificance or LRS tests. Less critical parameters such as alternative specific parameters were tested on model fitness addition.

8.3. Utility contribution of main model parameters

For obtaining the utility contributions, the same approach can be used as in the previous chapter, which was outlined in Chapter 4. Note that the main estimates differ from those found in Table 8.1. In Table 8.1, the included interaction effects capture part of the FKC beta. Estimating a model without interaction effects shows the effect purely caused by the two main parameters. These outcomes are shown in Table G.2. The table is extended with the Value of Travel Time Savings (VoTTS) and the relative importance of the attribute. The VoTTS represents the average 'willingness to pay' for one hour of travel time decrease. With the VoTTS it is easier to compare the found relations between travel time and travel costs for the different experiments. The tables below give the results, followed by a summary in the form of a graph.

Table 8.2: Utility contribution and value of travel time savings of main parameters

Distance	Parameter	Estimate	Min. level	Max. level	Utility contribution	VoTTS
5 km	Travel costs	-0.21	0	1.25	-0.26	€6.86
	Travel time	-0.02	5	20	-0.36	
25 km	Travel costs	-0.54	1.25	6.25	-2.70	€4.44
	Travel time	-0.04	25	35	-0.40	
75 km	Travel costs	-0.17	3.75	18.75	-2.55	€10.59
	Travel time	-0.03	45	70	-0.75	
200 km	Travel costs	-0.06	10	50	-2.40	€14.00
	Travel time	-0.01	135	165	-0.42	

VoTTS= Value of Travel Time Savings

The utility contributions of the four experiments, displayed in the table above, show a unanimous dominance of the travel costs. The utility contributions of the travel costs are much higher than the travel times. This indicates that an extra minute of travel time is worth less than an extra euro of travel costs. For the experiment including the car and bike as alternatives, the average VoTTS found was €6.86. For the experiments including the train alternative (25 km - 200 km), the VoTTS ranged from €4.44 - €14.00 increasing with trip length. Note that modes usually have different VoTTS values and as this study computed the average of both alternatives included, the VoTTS found for the experiment including bike cannot be directly compared to that of the train. To check the validity, they are compared to a study on the VoTTS for different modes and trips by Wardman (2004); Van Wee (2010). His findings can be found in Appendix A. When comparing his findings to this research, it can be concluded that, except for the 25km experiment, the found VoT's are valid. Wardman made an extinction in urban and inter-urban trips and found that the VoTTS must be significantly higher in the inter-urban trips. This is also the case in this research and the values are comparable. Notably, Wardman did include *mode valued variation*, meaning that he acknowledged differences in VoTTS for different modes. The displayed VoTTS in this research are the combined average of both modes included in the respective experiment. VoTTS found in this research are the mean of all mode alternatives included in the experiment.

The experiment was set up over four experiments for different distances. This was done because Scheiner (2010) showed interrelations present between a modal shift and the distance. Figure 8.2 shows the effect on a modal shift of linear increasing FKC tariffs at different distances. Short-distance trips (5km) are less sensitive than longer-distance trips. This has to do with the fact that the total travel costs are still meager and that the FKC will not make that much of a difference in deciding whether to take the bike or the car. A weather context variable or trip purpose would probably make more of a difference in this decision (Liu et al., 2015). The function in Figure 8.2 looks linear but because the effect is so marginal, the logistic curve can not be observed from this graph. The same logistic distribution is found for every distance in the medium to long-distance trips. The graph shows that longer trips including the train alternative consist of a flatter function which indicates that a smaller price increase has a higher effect on longer distances. This is sensible as the absolute costs for longer trips become much higher. From this graph we can conclude that an interrelation does exist between the distance and the sensitivity towards a uniform price of the FKC.

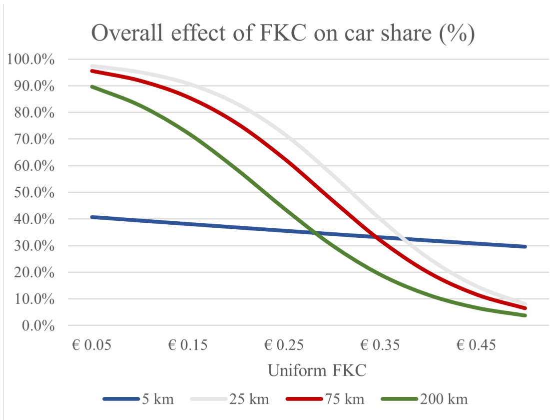

Figure 8.2: Car share of FKC for different distances

8.4. Mode choice model interpretation and key observations

This section elaborates on the outcomes of the model to provide insight into what these outcomes mean and the key takeaways. In general, the model showed to be performing to expectation. The main parameters of Travel costs and Travel time proved to have estimations according to the expectations. This means that both costs and time had a negative impact on the utility of the alternatives. Secondly, The constants (ASCs), representing the unobserved factors, showed, if the attribute levels are generic for all alternatives, that there is a preference for bike over car on short distances. Presumably, this is due to health benefits, high flexibility and high accessibility (Börjesson and Eliasson, 2012). In the remaining three experiments, a clear preference for the car over train was found. Unobserved preferences imply the preference for an alternative whilst not incorporating the included attributes. As such, the preference for car over train is likely to be due to flexibility issues, uncomfortable travel and additional access/egress times of the train (Eluru et al., 2012). The unobserved disutility for car fuel costs is still marginal compared to the disutility of the aforementioned factors.

The outcomes of the mode choice models for the different distances showed results that were expected. Time and costs were negative coefficients meaning that the more time or costs, the less utility the traveller experiences from that alternative. The VoTTS were found sensible and, apart from the 25km distance, are comparable to the VoTTS outcomes from studies done by Wardman and van Ginkel. The outcomes show that long distance trips (>75km) have a higher VoTTS than smaller distance trips. For many people, especially the ones living far from the train station or car commuters, the train is not considered as an alternative. For frequent car users, annual costs will rise significantly and they will start looking for alternatives. People that don't use their car much might only use the car in specific occasions. For this occasion, they are more likely to accept higher overall costs because annual total costs are still smaller. The preference for car over train is still substantial and incorporating a high FKC is not enough to enable a substantial modal shift.

Another part of the model included the interaction effects where background characteristics were tested on their sensitivity to price. All estimations turned out to be according to expectation. Not all interactions proved to be significant in every experiment. People close to the train station are more sensitive to the price of car use which is logical as they have easier access to an alternative; the train.

Key observations

In this section the key observations found in this experiment are listed and briefly summarized:

- The constants (ASCs), representing the unobserved factors, showed, if the attribute levels are generic for all alternatives, that there is a preference for bike over car on short distances. For medium to long distances (25, 75, 200 km), the car is preferred over the train. For long distances, the preference for car is substantially smaller. This means the train increases in popularity for longer distances.
- There is an interrelation between distance and the sensitivity to price. Four different distance experiments were performed. Although they were set up the same, it resulted into different VoTTS. The VoTTS found in the 25 km experiment is somewhat lower than expected which also implies that the policy won't have much effect on trips with this distance. Short urban mode choices between the bike and the car are less impacted by the FKC than in other trips. Long distance trips have a higher Value of Travel Time Savings and are more impacted by the policy. These differences show that an interrelation between the sensitivity to price and distance is present.
- Frequent car users are less sensitive for short trips, but for long distance trips they become more sensitive. Larger distances cause higher total costs.
- Income does not play a significant role on the short distance and its utility contribution increases slightly with larger distances. Overall the contribution of income is limited. See Table G.1 for the average contributions of all interaction effects. Those who use the car to commute or live far from the train station are less sensitive to price because no alternative is available. These factors contained a high level of heterogeneity.
- PT card ownership, age and commuting contribute the most to overall utility implying higher overall heterogeneity. Higher utility contribution implies that more heterogeneity is present within these groups. PT card owners show a high sensitivity to the FKC indicating that they consider the train as an alternative. Stimulating PT cards could pose as an opportunity to enable a larger modal shift to the train.
- The hypotheses can not be confirmed for every experiment due to high p-values. It does not mean that the effects are not present but the hypotheses can not yet be confirmed for the entire population. For that to happen, more choice observations per person are needed to be collected.

8.5. Summary

This chapter presents the results of the estimated choice model for modelling mode choice preferences for four different distances. In this section, they will briefly be discussed. The chapter started with an overview of the main parameter estimations and a quick review of the quality of those results in terms of signs, p-values and model fitness. The estimations were then translated into utility contributions Section 7.3 for comparison. In the last section, Section 7.2.3, the selected interaction effects were added to the model, and their estimates were evaluated and interpreted. This final chapter provides the weights of the included attributes that are needed to determine the final market shares in Chapter 9. The results of this chapter present how policies affect mode choice behaviour of people. Additionally, it also gives information on the present heterogeneity that is in the population. This information allows this study to answer the sub question on how background characteristics impact the sensitivity to an FKC.

The main parameter estimations seem sensible, and the signs are correct, the p-values are low, and, apart from the 5 km experiment, the model fitness of all models is high. When looking at the utility contributions, we see that one euro of travel costs still weighs much more than 1 minute of travel time. The WtP values showed significant differences in the WtP between the four distances, indicating that an interrelation between distance and the VoTTS exists.

In the third section, the interaction parameters selected in Chapter 6, are added to the model. For every distance experiment, the model fit increased, and the LRS requirement was met. From the estimated interaction parameter results, we can conclude that *high-income, business cars, cars as commuting mode* and *frequent car users* are less sensitive to the height of the FKC. Although most of the parameters across all four experiments were found to be statistically significant, unfortunately, there was not a single parameter that was significant for every distance. This has to do with the limited number of choice observations per person which is essential because we are investigating the effect of background characteristics. More choice observations with the same background characteristics are needed to increase the ability to generalise to the population. A summary of the set hypothesis is found in the table below where the hypothesis is only confirmed if the hypothesis is correct as well as statistically significant. As not one generic experiment was performed, the table shows for which distances the hypothesis can be confirmed:

Table 8.3: Hypotheses mode choice experiment

Car fuel-type choice experiment			
Background characteristic	*Hypothesis*	*Expected sign?*	*Confirmed?*
Income	People that live close to a train station are more sensitive to the height of the kilometer charge	Yes	5, 200
Education	People with a higher income are less sensitive to the height of the kilometer charge	Yes	200
Car use	People that own a PT card are more sensitive to the height of the kilometer charge	Yes	25, 75, 200
Business Car	People that own a business car are less sensitive to the height of the kilometer charge	Yes	5, 200
Public Transport card	People with a higher education are more sensitive to the height of the kilometer charge	Yes	25, 75, 200
Commuting mode	People with the car as commuting mode are less sensitive to the height of the kilometer charge	Yes	5, 25, 75, 200
Age	People that are older are less sensitive to the height of the kilometer charge	Yes	200
Distance to train station	People with high frequent car use are more sensitive to the height of the kilometer charge	Yes	5, 75

9 Application and integration of experiment outcomes

In this chapter, both experiments' results are integrated and applied. Combining the experiments in model form leads to more interpretable results on the effect of various pricing schemes. This way, the policy-makers can be given more tangible recommendations. This chapter will evaluate numerous scenarios and test them on criteria such as tax income, emissions and the impact on modal shift. The chapter kicks off with an elaboration on the approach. This section is followed up by different pricing scheme designs. Those designs will be applied as possible scenarios. An FKC distributed equally over all vehicle fuel types and - segments is set as a base scenario. This fixed option is also evaluated to see the outcomes if all tariffs were to be the same for all fuel types and fixed to 6.2 eurocents, which is the most recent indication of the tariff given by the Dutch government. Ultimately, the effects of different designs, with respect to that base scenario, are presented.

9.1. Integration phase approach

The integration section uses the market shares to investigate the development of the modal split and the fuel distribution of the car fleet. These market shares are determined by defining the attribute levels first. Since, the goal of this study is to measure the impact of the FKC, this is the only attribute that will be varied in the scenarios. For the mode-choice experiment, the average of the included travel times were used. The total costs for train was already fixed and remains the same. For defining the purchase price and range attributes of the car-fuel type experiment, a more comprehensive approach is needed. EVs are still not fully competitive with ICEV, but that is expected to change over the coming decades (Liao et al., 2018; Wolfram and Lutsey, 2016). The technological development of EVs is essential in the electrification of the car fleet; this was shown by the significant utility contributions of range and purchase price. The future car fleet distribution cannot be based on current prices and ranges, Section 9.1.1 elaborates more on this development.

For this integration phase, the expected development of modal shifts and car fleet characteristics are laid out over four moments in time; 2022, 2030, 2040 and 2050. This is done to incorporate the development of purchase prices and EV ranges, further elaborated in the next section. Furthermore, this timeline is included to account for slow EV adoption. People can not and will not switch cars straight away. Many people don't have the financial means to purchase a new EV, and as the market share of EVs is very low, the number of available occasions (second-hand cars) is also limited. It can therefore take a couple of years before people switch. Average yearly car inflows (new vehicle sales), based on estimated market shares, and annual car outflows (demolition) are used to determine the perennial fuel characteristics of the car fleet up to 2050. This approach only accounts for new sales and destruction. It thus excludes import, export and occasion sales. Import and export have shown to equal out whereas occasion sales will not impact the fuel distribution of the car fleet (Rijksdienst voor Ondernemen and Revnext, 2018).

9.1.1. Setting the attribute levels: price and range development ICEVs and EVs

The previous paragraphs outlined why the development of EVs over the coming decades can not be ignored. The business model is getting more attractive, and the ranges are still increasing. The expectations are based on earlier research conducted to set up the attribute levels and a report by Wolfram and Lutsey (2016) about the price - and range development of BEVs and PHEVs. The experiment uses percentages relative to the current ICEV levels which were set as reference alternative. For all absolute values per segment category, see Section H.3 in the Appendix.

Table 9.1: Expected development of car fuel-types

Expected development (% of base case)	***2022***	***2030***	***2040***	***2050***
Purchase Price GV	0	0	0	+20%
Purchase Price DV	0	0	0	+20%
Purchase Price PHEV	+30%	+15%	0	0
Purchase Price BEV	+50%	+25%	0	0
Range PHEV	-25%	0	0	0
Range BEV	-50%	-25%	0	0

As can be concluded from Table 9.1, it is expected to take up to 2040 for the development of the EVs to have matched that of the ICEVs. The future of the ICEVs is hard to predict. This table assumes that purchasing an ICEV, if at all still possible, will be discouraged by increasing taxation on purchasing. The utility contribution, shown in Chapter 7, shows that the range and purchase price attributes play a substantial role in buying a car. This development, therefore, leads to changes in the car fleet, regardless of the implementation of the FKC and the height of this charge.

This scenario includes no emission-based differentiation and beholds a conservative technological development. Due to the dominance of GV over DV in terms of ASC and the fact that their utility function includes the same σ's, the DV will never be picked when using the highest probability approach. Looking at the car fleet report Rijksdienst voor Ondernemen and Revnext (2018), the average market share approach is closest to the average market shares of the past years, seeFigure A.2. Therefore, the decision was made to imply the average probability approach, as this market share is the best resemblance of the current vehicle selling market shares.

9.1.2. Passenger kilometers

The market shares that flow from the attribute level inputs give us an understanding of how people would behave under these circumstances. However, the passenger kilometers must be defined to translate the distribution of car types and the corresponding mode choice of multiple distances. The passenger kilometers per mode and fuel type will provide the necessary information to answer the research question. There are more trips of shorter distances, but as the distance is shorter, the overall passenger kilometers are still relatively low. Centraal Bureau voor Statistiek (2019) provided insight into the number of trips for certain distances, and the groups were subdivided under the 5,25,75 and 200 km distances. Centraal Bureau voor Statistiek found over 6 billion passenger kilometers for 5 km trips and well over 30 billion passenger kilometers for the other distances, resulting in a total of 100 billion passenger kilometers. It must be noted that for this calculation, that the total passenger kilometers is assumed to stay the same over the years. The final results will be compared on a relative level; thus, incorporating a decrease - or increase in this level is unnecessary. The experiments are based on a single trip of one passenger. Centraal Bureau voor Statistiek (2019) also provides insight into different modes used per distance; only bicycle, train and one passenger car kilometers are used for the distribution. Finally, the one passenger car kilometers were divided among the four fuel types.

The one passenger car kilometers are further divided into passenger kilometers per fuel group. The outcomes of the car fuel type experiment were used, and the results are based on the differentiation of the FKC between those groups and the technological development. As vehicle purchases do not go overnight and people don't switch cars regularly, the total car fleet fuel distribution is calculated by the in- and outflow of vehicles. The inflow represents the newly bought vehicles and is based on the found car fuel type market shares. The outflow is based on the yearly demolition and only consists of ICEV for the next ten years.

9.1.3. Pricing scheme designs

The pricing scheme designs are the scenarios that will function as input for the model. The following scenarios have been defined, and their specific pricing scheme has been added. In these scenario's the attribute levels of the other attributes, purchase price and range, which were defined in Section 9.1.1, remain the same in every scenario. The scenarios distinguishes two types of differentiation: differentiation to *fuel type* and differentiation to *fuel type + car segment*.

Table 9.2: Pricing scheme designs

Scenario's (eurocent)	GV	DV	PHEV	BEV
1. No differentiation (base): price equality	6.2	9.4	6.2	6.2
2a. Emission based pricing scheme: small	7.4	10.6	6.4	5.3
2b. Emission based pricing scheme: medium	8.7	11.9	6.5	4.3
2c. Emission based pricing scheme: high	9.9	13.1	6.7	3.4
3a. Fuel type differentiation & segment differentiation: low				
Segment A	*6.0*	*9.2*	*5.1*	*4.2*
Segment B	*6.7*	*9.9*	*5.7*	*4.7*
Segment C	*7.4*	*10.6*	*6.4*	*5.3*
Segment D	*8.2*	*11.4*	*7.0*	*5.8*
Segment E+	*8.9*	*12.1*	*7.6*	*6.3*
3b. Fuel type differentiation & segment differentiation: high				
Segment A	*7.9*	*11.1*	*5.3*	*2.7*
Segment B	*8.9*	*12.1*	*6.0*	*3.1*
Segment C	*9.9*	*13.1*	*6.7*	*3.4*
Segment D	*10.9*	*14.1*	*7.3*	*3.8*
Segment E+	*11.9*	*15.1*	*8.0*	*4.1*

1. No differentiation: Price equality
This scenario is used as a base case. This research focuses on the impact of pricing designs compared to an FKC without differentiation, scenario 1. For setting up the prices, the report by MuConsult and Ministerie van Financien (2020) is used. This report is the most relevant and was attached to the coalition agreement. This report gives the best estimation of the FKC that will be implemented. MuConsult and Ministerie van Financien define a standard charge for all car types of 6.2 eurocents. On top of that, Diesel cars receive a diesel-specific surcharge of 3.2 eurocents. The results of this scenario are given in Section 9.2.

2. Emission-based pricing schemes: The polluter pays
In this design, the polluter pays. People who use a polluting fuel group pay more than the flat charge. This can work as a price stimulant for people to switch to EVs. On the other hand, the early adaptors of EVs get rewarded with a lower charge. This scenario makes a distinction in low (ICEV +20%, EV -15%), medium (ICEV +40%, EV -30%) and high (ICEV +60%, EV -45%) differentiation. Again, for PHEV, the 50/50 approach is applied. The estimated weights that flow from Chapter 7 8 are used to compute the market shares for fuel-types and modal split. The market shares of all scenarios are displayed in Section H.5. The more tangible effects of these market shares are shown in Section 9.2.2.

3. Fuel type - & segment differentiation: The polluter and space occupant pays
This scenario goes one step further and also distinguishes different car segments in their pricing scheme. Generally, cars of a higher segment have a lower fuel economy and emit more CO2. Not only do they emit more emissions, but they also occupy more space which can lead to an increase in spatial quality and a reduction in congestion. These positive side opportunities will not be quantified in this research but are worth mentioning. Based on the average weights of the five different car segments, a $\tilde{2}0\%$ increase in CO_2 emissions was found between the middle segment C and the high segment E+, see Table A.5 in the Appendix. Segments A, B and D respectively get a 20% decrease, 10% decrease and 10% increase. These differences were applied to the low - and high-pricing designs defined in scenario 2.

9.2. Results base case - a fixed kilometer charge

In this section, the results from the model application are shown. First, the passenger-kilometer distribution indicates how the model is set up. The passenger kilometers are then linked to several criteria. The criteria chosen are tax income, emissions and pollution (CO2, PM_{10} & NO_x), the modal shift (to train and bike) and the development of EVs and high segment cars. It must be noted that all emissions are based on a tank-to-wheel approach where only the direct emissions and pollution from the vehicle are taken into account. The tire abrasion, causing non-exhaust PM_{10} to be released into the air, is also included. Thus, it excludes all electricity generation, vehicle production, and transport emissions. The found shares of passenger kilometers are based on the shares found in the choice models with the FKC set to a uniform charge of 6.2 eurocents.

9.2.1. Passenger kilometers

Passenger kilometers are an essential variable to measure the impact of pricing schemes. As explained earlier, the experiments estimate one person trips. Table 9.3 shows how, in the base scenario, the passenger kilometer are distributed over transport mode (bike/train vs car) and within car fuel type (GV vs DV vs PHEV vs BEV). The forecasted values of the remaining attributes were determined in Section 9.1.1. The empirical changes in this table are due to the development of the remaining attributes as the FKC remains the same.

Table 9.3: Passenger kilometer distribution of 1p trips base scenario

km	mld kilometer	2022	2030	2040	2050
5	**Total km**	**6.33**	**6.33**	**6.33**	**6.33**
	Total bike	3.91	3.91	3.91	3.91
	Total car (1p)	2.4	2.4	2.4	2.4
	GV	*2.1*	*1.9*	*1.5*	*1.1*
	DV	*0.3*	*0.2*	*0.2*	*0.1*
	PHEV	*0.0*	*0.1*	*0.4*	*0.6*
	BEV	*0.1*	*0.2*	*0.4*	*0.5*
25	**Total km**	**31.20**	**31.20**	**31.20**	**31.20**
	Total train	1.22	1.20	1.19	1.17
	Total car (1p)	30.0	30.0	30.0	30.0
	GV	*25.5*	*23.3*	*19.1*	*14.3*
	DV	*3.4*	*2.6*	*2.0*	*1.2*
	PHEV	*0.4*	*1.1*	*4.4*	*7.8*
	BEV	*0.7*	*3.0*	*4.5*	*6.8*
75	**Total km**	**37.91**	**37.91**	**37.91**	**37.91**
	Total train	2.20	2.18	2.16	2.70
	Total car (1p)	35.7	35.7	35.8	35.2
	GV	*30.4*	*27.8*	*22.8*	*17.0*
	DV	*4.0*	*3.1*	*2.3*	*1.5*
	PHEV	*0.5*	*1.3*	*5.3*	*9.2*
	BEV	*0.8*	*3.5*	*5.3*	*7.5*
200	**Total km**	**35.38**	**35.38**	**35.38**	**35.38**
	Total train	4.50	4.46	4.42	4.38
	Total car (1p)	30.9	30.9	31.0	31.0
	GV	*26.4*	*24.1*	*19.8*	*14.8*
	DV	*3.4*	*2.6*	*2.0*	*1.2*
	PHEV	*0.4*	*1.1*	*4.6*	*8.0*
	BEV	*0.7*	*3.1*	*4.6*	*7.0*

Several conclusions can be drawn from this table. For one, it can be concluded that the modal split remains more or less the same over the first 20 years. This makes sense as a uniform tariff, except the extra DV charge, would not cause a modal shift because the model assumes that current car and train prices remain the same. Furthermore, this model assumes that the total km per distance category stays the same over the coming decades. Another observation is that the share of EV cars eats away market shares from that of the ICEV s. Even without differentiating the FKC to emission, the technological development of EVs is expected to increase over the following years resulting in lower purchase prices and higher ranges. This would make these fuel types more competitive with ICEV. The share of vehicle kilometers per fuel type accounts for the average time to purchase a new vehicle. The market share of new vehicles sold is not the same as that of the entire car fleet at that time.

9.2.2. Final results base case

The passenger kilometer distribution is then translated into the criteria. The experiments and the found market shares are focused on **1 person travels**. The 2+ person passenger kilometers (car, bike, train) are added to measure the real impact of the differentiated charge. The relative impact measured in the experiments is, therefore, a bit lower. For the specific emission per fuel type kilometer, see Appendix A. The results for the base case are as follows:

Table 9.4: Base scenario results - fixed uniform charge

1. base scenario - a uniform charge	2030	2040	2050
Tax income (euro)	8.94	8.81	8.64
CO2 emissions (mln kg)	14.31	12.47	8.35
PM10 emissions (tonnes)	3.86	3.72	3.52
NOx emissions (tonnes)	17.50	14.68	11.52
Bike use (mld km)	17.95	17.95	17.95
Train use (mld km)	24.10	24.02	23.91
EV use (mld km)	18.78	41.34	66.95
High car segment use (mld km)	18.64	18.65	18.59

The base case, where a uniform charge is applied of 6.2 cents, consists of important metrics. These results will form the base case to which the scenario outcomes can be compared. The outcomes of this model will shortly be validated by comparing these outcomes with the outcomes stated in the report by MuConsult and Ministerie van Financien (2020). This research has no insight in key numbers used by MuConsult and Ministerie van Financien, therefore these numbers will vary but it is still good to test the model. The difference in tax income was slightly different (<10%). The effects on emissions differed more (20%), but that has to do with the chosen number for emission/km. This varies in the literature. The number of kilometers travelled by bike or train is not given and can not be compared With this uniform charge, as concluded already in Table 9.3, we will see a change in modal shift, but not the fuel characteristics of the car fleet.

9.2.3. The effect of a uniform tariff

It is hard to test the model's sensitivity by evaluating one fixed uniform tariff. Therefore, the effect of the height of the uniform tariff, i.e. the curve characteristic, is displayed. Increasing the height of this tariff will not directly lead to a difference in fuel-type distributions, but it will affect mode choice. The price of travelling by car, in general, gets more expensive while train - and bike costs remain the same. To see the influence of the height of the FKC is Figure 9.1 computed, which shows the modal shift in car use (%). The figure shows a logistic distribution of car use for higher charges. With the current base tariff of 6.2 euro cents, the market share for car use remains high. A modal shift to alternative modes enabling a car market share of 75% requires an FKC of €0.17. A split market share (50% car use) of the car requires a uniform charge of €0.27 per kilometer. For more information on how to tax income and CO_2 emissions are affected by higher tariffs, see Appendix H.

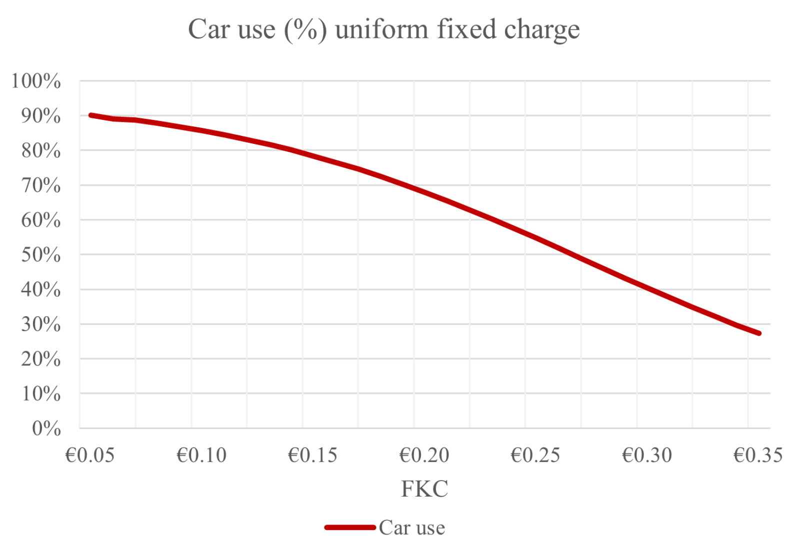

Figure 9.1: Car use uniform charge

The next figure displays the development of the car characteristics for a uniform charge. Because the charge is uniform and thus is the same for all fuel-types, the height of the FKC is of no influence to the car fleet distribution. The car fleet distribution is based on in - and outflows that are presented in Appendix H. The figure shows that, based on the expected development of prices and ranges of all fuel-types (see Table 9.1), the ICEV shares will decrease to less than 50% over the next 3 decades. It must be noted that SP data observes current preferences for certain modes or fuel-types. Future preferences are also very dependent on the external, unobserved, factors such as fuel and electricity prices, CO2-emission development and charging infrastructure which are expected to change also but cannot be incorporated in this forecast.

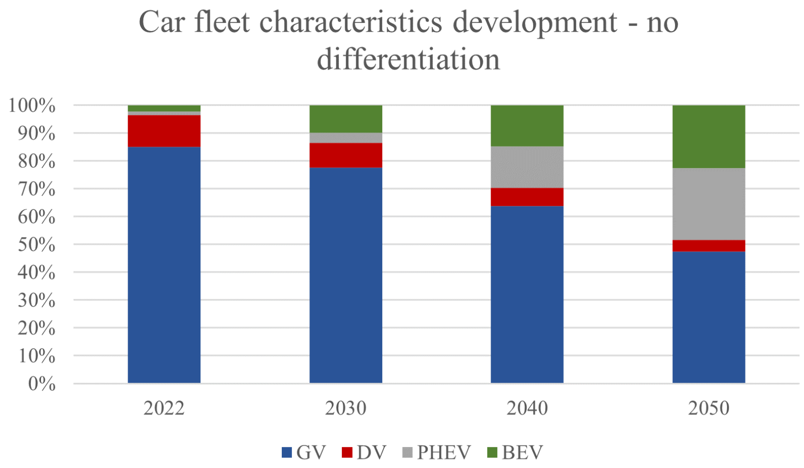

Figure 9.2: Expected car fleet development per fuel-type

9.3. Scenario Results

Now that the base case has been defined, the actual impact of differentiated tariffs can be determined. The same strategy is used, but different tariffs are used as input. A modal shift happens immediately, but it takes more time to see the impact on the car fleet development. The total passenger kilometers are held the same, but the distribution of those kilometers changes; see Section 9.3 for the extensive results. For car fuel choice, exchanging cars does not go overnight and requires a serious investment. In the technological development scenario, we assumed that it still will take a while before an EV would be on the same price/range level as an ICEV. The results are therefore very dependent on the year in time. Three moments in time, 2030, 2040 and 2050, are shown. The relative - or marginal changes are annual and relative to the base scenario.

Table 9.5: Results of differentiation scenarios

2030	*base level* 1. Fixed charge - no differentiation	*Effect of various differentiation levels towards base level* 2a. Fuel-type - low	2b. Fuel-type - medium	2. Fuel-type - high	3a. Fuel type & car segment- low	3b. Fuel type & car segment- high
Tax income (mld euro)	8.94	14.3%	28.2%	41.5%	7.9%	33.7%
CO2 emissions (mln kg)	14.31	-0.9%	-1.9%	-3.1%	-0.6%	-2.6%
NOx emissions (tonnes)	3.86	-0.8%	-1.7%	-3.1%	-0.6%	-2.2%
PM10 emissions (tonnes)	17.50	-0.8%	-1.9%	-2.6%	-0.6%	-2.5%
Bike use (mld km)	17.95	0.1%	0.2%	0.3%	0.1%	0.3%
Train use (mld km)	24.10	4.7%	9.9%	15.9%	3.0%	13.1%
EV use (mld km)	18.78	0.8%	1.6%	2.4%	1.0%	2.4%
High car segment (mld km)	18.64	-0.7%	-1.5%	-2.4%	-1.1%	-2.6%

2040	*base level* 1. Fixed charge - no differentiation	*Effect of various differentiation levels towards base level* 2a. Fuel-type - low	2b. Fuel-type - medium	2. Fuel-type - high	3a. Fuel type & car segment- low	3b. Fuel type & car segment- high
Tax income (mld euro)	8.94	10.9%	21.0%	30.3%	4.7%	23.2%
CO2 emissions (mln kg)	14.31	-1.4%	-3.1%	-4.9%	-1.3%	-4.5%
NOx emissions (tonnes)	3.86	-0.2%	-1.9%	-3.1%	-0.1%	-2.2%
PM10 emissions (tonnes)	17.50	-1.1%	-2.0%	-2.6%	-0.9%	-3.3%
Bike use (mld km)	17.95	0.1%	0.2%	0.3%	0.0%	0.2%
Train use (mld km)	24.10	3.9%	8.4%	13.6%	2.3%	11.0%
EV use (mld km)	18.78	2.4%	4.9%	7.3%	2.5%	7.1%
High car segment (mld km)	18.64	-0.5%	-1.1%	-1.8%	-6.8%	-7.9%

2050	*base level* 1. Fixed charge - no differentiation	*Effect of various differentiation levels towards base level* 2a. Fuel-type - low	2b. Fuel-type - medium	2. Fuel-type - high	3a. Fuel type & car segment- low	3b. Fuel type & car segment- high
Tax income (mld euro)	8.94	6.6%	12.1%	16.4%	0.5%	10.0%
CO2 emissions (mln kg)	14.31	-2.6%	-6.0%	-9.5%	-2.9%	-9.4%
NOx emissions (tonnes)	3.86	1.5%	-1.3%	-3.5%	1.1%	-2.5%
PM10 emissions (tonnes)	17.50	-1.5%	-2.4%	-4.3%	-1.2%	-4.1%
Bike use (mld km)	17.95	0.1%	0.1%	0.2%	0.0%	0.1%
Train use (mld km)	24.10	3.0%	6.4%	10.2%	1.5%	8.0%
EV use (mld km)	18.78	2.9%	5.9%	8.8%	3.0%	8.5%
High car segment (mld km)	18.64	-0.3%	-0.6%	-1.0%	-13.1%	7.2%

9.4. Integration model interpretation and key observations

This section will review the outcomes based on the criteria defined. The coalition agreement states that tax erosion due to EV is the main reason for the FKC. The results show that including a pricing scheme will, per definition, lead to increased tax income. The ICEV share is much higher than the EV share. Higher charges for this larger group will thus lead to increased income. Over the years, we see a shrink in the increase in income. This stagnation is due to the transition to EV. The bigger the differentiation to fuel, the higher the tax income. The addition of differentiating based on car segment does not lead to the same tax income increase. The market share of smaller segments (A & B) is higher and thus leads, relatively, to less increase in tax.

For the impact on the emissions, all pricing schemes have a positive effect. The higher levels of both scenarios lead to higher emission savings. Again, the emission savings are higher if the pricing scheme is more differentiated. This is directly related to the modal shift to train and bike and thus the reduction in car use (Kim et al., 2010). Due to a pre-defined fixed period for exchanging cars, it takes a while for the effects to be visible; therefore, the effects are higher in 2040 and 2050. The relative impact of a pricing scheme on CO_2 emissions is the highest, which can be explained by the fact that BEVs do not emit CO_2 but still cause PM_{10} emissions. Notably, the emissions savings do not incorporate emissions emitted by a substituting mode such as the train.

The emission savings are a direct effect of a shift towards a substituting transport mode. The modal shift is an important variable to measure to see if that network is built for such a change in passengers. As derived from the tables, the impact on passenger kilometers travelled by bike is minimal. Compared to the longer distances with train as substituting alternative, short trips are less sensitive to the travel costs, see Table 9.4. The minimal impact on bike travellers is no reason for any infrastructural concerns. Train travel is more affected by the implementation of pricing schemes. A more differentiated scheme leads to more train use, but the increase stagnates over the years due to a more electrified car fleet, which is a result of a lower FKC and EV development. The outcomes also support that a lower FKC for EVs increases their market share. The EV market share grows significantly but will not result in too much extra demand. Too much demand is not desired as the current

charging infrastructure is not capable of handling that. The additional annual tax income resulting from the pricing scheme can be used to finance the increased infrastructure needed to service the early adapters.
In the third scenario, the pricing schemes are also differentiated to the car segment. As derived from the table, this differentiation strategy does not lead to additional tax income or emission savings. It will affect the higher car segment which has more benefits than emission reduction and/or tax income. Differentiating based on segments has as advantage that people with lower incomes, who are more likely to have a lower segment car, don't get affected as much as people with big polluting cars. This way of differentiating will therefore be more 'fair'. Tackling the higher car segment could also lead to more livable and spacious city's. Impacts on livability and spaciousness fall out of the scope of this study but it is good to notice this.

Key observations
The table provides the answers to the main research question and thus has investigated the effects that various pricing schemes for a kilometer charge would have on several criteria. A brief overview of the key takeaways that can be derived from the table are the following:

- **Optimal tax income & emission savings**: A higher level of differentiation results in more tax income and reduced emissions. Although this general effect is according to expectation, the table indicates the extent of this.
- **Increase in EV use**: Over the years, due to a faster transition to EVs, the emission savings will increase further, and the tax income will decrease (although it is still higher than with a uniform charge). The results show that a higher tax income is possible whilst stimulating EV and greener transport modes like the train.
- **Modal shift effects**: Train and EV demand cannot increase too fast due to infrastructural issues. However, the increase in demand for trains and EVs is not problematic and is considered acceptable. The extra tax income that will be collected by the stimulation of greener modes can be used to finance the necessary growth. The argument that EVs have higher purchase prices than ICEVs will weaken over the following years as EVs are expected to become competitive with ICEVs.
- **Car segment-based differentiation**: In case the kilometer charge is differentiated to fuel-type and car segment, roughly 10% of high car segment users will switch to a lower segment

9.5. Summary

In this chapter, the behavioural effects found in the experiments, see Chapter 8 Chapter 7 and Chapter 8, are integrated to obtain the ultimate impact of differentiating the FKC. First, an extensive approach is outlined where the assumed technological development is defined, and the role of passenger kilometers is explained. The last subsection gives an overview of the selected scenarios that would be used as input for the final results. The final results are shown as a marginal difference from the base case scenario; no differentiation. Therefore, first, the absolute results of the base case are calculated. This is done by translating the passenger kilometers into the chosen criteria: *tax income, CO_2 -, NO_x -, PM_{10} emissions, bike use, train use, EV market share* and *high car segment share*. The chapter ends with the final results shown in a table over three moments in time (2030, 2040 and 2050).

The base case results are considered sensible, and the expected tax income comes close to that of the tax income calculated by MuConsult and Ministerie van Financien (2020). It can be concluded that although these absolute results are sensible, the goal of this study is not yet achieved. The objective of this study was to investigate if and to what extent differentiation would lead to other effects. These marginal changes are the final results, shown in Section 9.3 and interpreted in Section 9.4. The outcomes of these final results show that differentiation does lead to a faster transition to EV. As the market share for ICEV is still dominant, the annual tax income will significantly increase over the first few decades. However, due to a faster changing car fleet, the total increase in tax income becomes less every year. Although, compared to scenario 2, including differentiation to segment (scenario 3) results in less tax income increase and less emission reduction, the total share of high segment cars decreases, positively affecting spaciousness and accessibility. While tax income increases, emissions are reduced by the accelerating transition to EVs and a small to medium increase in bike - and train use. Differentiating the FKC seems only to have positive effects. It must be noted that increasing the price is not always desired as it can lead to serious disadvantaging of certain groups.

This final chapter provides an answer to the research question on the effects of an emission-based differentiation of a kilometer charge towards a fixed kilometer charge. It shows how different implementations and the behavioural changes found in Chapter 7 and Chapter 8 impacts the criteria.

10
Conclusion, discussion and recommendations

In this research, the goal was to contribute knowledge to the decision-making process of implementing the fixed kilometer charge (FKC). The ultimate aim was twofold; 1) enhancing the validity of people's behaviour by using Stated Preference (SP) data and 2) increasing knowledge on how and to what extent differentiated price schemes affect travel behaviour and can be used as a tool to meet specific criteria. The final research question was formulated as follows: *"To what extent does the level of price-differentiation of a fixed kilometer charge influence people's stated behaviour towards mode choice and car fuel-type choice, and what are the effects?"*. The behavioural effects were measured but translated into tangible results such as tax income, emissions, modal shift and EV development. Traditional models for measuring these policy effects, the LMS, DYNAMO and Carbontax, use Revealed Preference (RP) data but deal with a more complex supply of different fuel-types than ever before. This research evaluates the collection and application of another data type, SP data, on such policies. Two SP experiments are performed, one on mode choice (for four distances) and one on car fuel-type choice. To collect this data, a survey was set up and distributed among panel members representing the current Dutch population regarding gender, age and education. The collected data was then used as input for discrete choice models that were performed to unravel traveller preferences. The found stated preferences of both experiments were then integrated to determine the effect of multiple differentiated pricing schemes.

Along with the impact of the FKC, two other main factors for car purchasing, the purchase price and range, have been researched. They are included to forecast purchasing behaviour and how EVs' technological - and political development influence the transition towards an electrified car fleet. For estimating mode choice behaviour, the survey included travel times and costs for cars and alternative modes (bike and train) to learn how these attributes impact the choice of a transport mode.

Based on the utility contribution of the FKC for car purchase - or mode choice, interaction effects were added, and it has been researched whether preferences differ between groups with varying personal characteristics. These interaction effects help us answer the sub-question about how these background characteristics impact the sensitivity to the height of the FKC. Interviews with mobility experts were held to select several groups based on relevance. Studying these social differences is beneficial for strategy purposes, as this evaluation allows us to see risks for disadvantaging certain groups in society and opportunities to enable a faster EV transition whilst providing all groups in society with fair options. The sensitivity says something about whether a group can adjust easily or can not/will not adjust. Varying the kilometer charge to greener cars might disadvantage certain groups in society, and this research aims to point out what groups must be carefully handled. Contrary, opportunities may also arise to steer towards more/less.

10.1. Conclusion

The key findings of this research are split up into two parts. First, the key observations from the choice models and distributed survey are presented. This includes takeaways on the included main and background parameters in both the mode choice experiment and the car fuel-type experiment. Additionally, the public acceptance of the new policy is highlighted. Second, the final results of the marginal effects of emission-based differentiation are given, and additional key conclusions are drawn.

Choice model outcomes
The choice model for car fuel-type choice shows that, regardless of the stated interest in EV, people still choose a GV over EV, indicating that even if purchase prices and ranges were to level that of ICEV, GV would still gain the highest market share. Presumably, the unobserved preference for GV over EV and GV is due to the unreliability and inflexibility of charging EVs and severe health effects caused by diesel exhaust.Second, the relative importance is highest for purchase price when choosing a fuel-type. The variable FKC costs follows, and the value of the range is the lowest. To compare the utility contribution for the purchase price to that of the kilometer charge, a Willingness-to-Pay (WtP) for a higher purchase price in exchange for a reduction in variable costs (FKC) was computed. For a reduction of 1 Eurocent (€0.01) of the FKC, people are willing to pay €301 for a car.

When travel costs and travel (in-vehicle) time are the same for all mode alternatives, the Dutch citizen chooses the bike over the car for short trips (5km), presumably because of health benefits, flexibility and accessibility. For medium to long distances (25km - 200km), the car is strongly preferred over the train but gives in market share when distance increases. The unobserved preference for car over train is likely due to the train's low flexibility, social discomfort and access/egress times. The Value of Travel Time Savings (VoTTS) that was computed differed substantially between the different distances. The average VoTTS for bike and car found for short (urban) trips is €6.86. The average VoTTS with car and train as choice options, ranges from €4.44 for medium distances (25km) to €14.00 for long distances (200km). An interrelation between distance and the impact of the FKC thus exists. A modal shift to alternative modes enabling a car market share of 75% requires an FKC of €0.17. A split market share (50% car use) of the car requires a uniform charge of €0.27 per kilometer. The required tariffs to enable a modal shift are quite substantial and are due to the aforementioned preference for car over train and people's car dependency.

The effect of the FKC on different groups
In this paragraph, we will answer to our one sub-question; "*What is the difference between groups, based on socio-demographics, in car fuel-type choice - and mode choice behaviour that result from different implementations of a kilometer charge*". The original hypothesis was that variable taxation of road use would have a different impact on different groups. To evaluate the effect of the FKC on different groups, groups were first defined, then selected based on relevance and finally incorporated as interaction effect in the model. This was done to measure the impact of a background characteristic on the sensitivity of the price, or price elasticity. On car fuel-type choice, *higher-income* and *well-educated* groups that either *frequently use their car* or have own a *business car* case are more sensitive to the FKC. A high price sensitivity for the choice of fuel-type was surprising due to the general theory that higher income groups have more to spend and, as such have a higher WtP. More thorough research into the relationship between variable costs (FKC) and the investment (purchase price) led to the conclusion that, in exchange for a €0.01 decrease in FKC costs, higher-income groups are willing to spend more (€329) on car purchasing than lower income groups (€271).

For mode choice, unfortunately, too few choices were observed to generalise all found effects to the population. Nevertheless, for at least the sample size, we found that *older* people, people that live *far from the train station* and people with higher *incomes* are less sensitive to the height of the FKC. Car use characteristics, such as the car as *commuting mode*, the car paid for by the *business* and *frequent car use*, are less sensitive to the FKC. *Public transport card holders* and *higher educated* are more sensitive than others. A higher sensitivity generally means that there is an easy alternative or that people attach more value to the luxury of car use. To evaluate the differences in various trip lengths, the Value of Travel Time Savings (VoTTS) were computed which indicates the monetary value one is willing to spend to reduce the travel time. For the experiment including the car and bike as alternatives, the average VoTTS found was €6.86. For the experiments including the train alternative (25 km - 200 km), the VoTTS ranged from €4.44 - €14.00 increasing with trip length.

This research identified two main risks for disadvantaging groups in the population, as a result of implementing a differentiated pricing scheme, thus increasing the price for ICEV owners. The first risk has to do with location. People who live close to the train station have easier access to an alternative, and therefore people living in rural, less densely populated areas are disadvantaged. Second, frequent car users (up to 75 km) and car commuters are less sensitive because they are potentially mandated to use the car to get to work and also do not have the train as a serious alternative. In both cases, a higher FKC only leads to higher costs for this group and does not result in a modal shift, which is ultimately the goal of including differentiation. These groups get disadvantaged, which could be a risk for the support of this policy. Furthermore, stimulating PT card use is considered as an opportunity to enable a faster modal shift.

Price differentiation as a tool for speeding up the electrification
Looking at the results of the integrated choice model experiments, it can be concluded that differentiating the FKC in such a way that the polluter pays will lead to positive effects in terms of tax income and emissions. The Dutch government has stated tax erosion to be the main reason for the FKC to be implemented in the first place, but the question was if the FKC could not also result in fewer car emissions (CO_2, NO_x, PM_{10}). The results show that differentiating the price according to the vehicle's pollution will not only lead to higher tax incomes over the next decades but will also result in fewer emissions. The more differentiation comes in place, the more emissions will be saved and the faster the electrification of the Dutch car fleet will go. This is because, although the average tariffs weigh out, the share of high polluting vehicles (ICEV) is much higher than the share of cleaner vehicles (EV). A higher level of differentiation leads to a significant faster transition towards EV use, and therefore the increase in tax income becomes less over time. Next to the level of differentiation, a differentiated price scheme for car segments was also evaluated. The results show that, because the market share of smaller vehicles is higher, this strategy does not lead to more emission gains or a higher tax income. However, it does result in less high segment cars which has additional benefits considering spaciousness and city livability.

Policy support
For these types of policies, where some people pay more than others for, in principle, the same service/good, there must also be support from the Dutch citizen. This research concludes that, although some people are affected more than others, the vast majority supports a differentiated pricing scheme based on emission. This policy is supported by over 74% of Dutch citizens. More specifically, over 70% of ICEV users and over 78% of high segment users support the policy. 87% of frequent car users support the policy. Even the majority of the people in the more affected groups support this policy.

10.2. Discussion

This discussion reflects on the contribution of this study and reflects to the initial research aims:

The effects of emission-based differentiation
Differentiating the pricing scheme of a kilometer charge has shown to be an effective tool to meet criteria like a minimal tax income whilst maximising emission gains. This tool can play a viable part in reaching the necessary goals and, at the same time, optimising side opportunities. In this research, 5 (sub)-scenarios were defined, and the effects of those were quantified. The model created to calculate the impact is not an optimisation model, but it looks like the problem that decision-makers are dealing with is an optimisation problem. The pre-defined scenarios sketch a good outline of the available input parameters, but it does not yet show the 'best' inputs. In the end, tax income is a requirement that must be met to keep the road network intact. Additionally, due to infrastructural limits, other requirements such as a maximum increase in EV - and train share must also be considered. The FKC could be set to a maximum to keep car use affordable. Instead of first determining a pricing scheme and investigating its effects, a pricing scheme can be sought that meets all requirements and still maximises emission gains. This research shows that the FKC can function as a way to retain tax income but that, with the inclusion of differentiation, the FKC can also be used to have a (maximum) positive effect on other factors.

Second, the included interaction parameters for relevant background characteristics allowed us to draw conclusions on the heterogeneity in the population with regards to price sensitivity. These unique insights bring up a discussion as to how an (emission-based) kilometer charge might affect different groups in society and that some of those groups, such as car commuters, people living far from the train station, frequent car users and lower incomes are disadvantaged by the policy and its implementation.

SP data as data for measuring policy effects
As to whether SP data can function as an alternative/replacement for RP data, this study concludes that it can serve as an addition but, in this form, not as a replacement. Forecasting the effects of policies remains complex and dependent on many factors we do not influence on. Unlike the other models, this research uses SP data to enhance its validity. SP data has the advantage that the effects of new non-existing policies like the FKC can

be measured. The other models use historic or revealed preference data but can not take the current complexity of, e.g. car fuel-types, into account as there is very limited historic/revealed data available. The choice for other modes such as BEV or PHEV is higher than ever and will only increase over the following decades. Looking at the estimates of the parameters found during this research, it can be concluded that an SP forecasting research method can deliver solid forecasts. The outcomes seemed realistic and, in many cases, matched the results of the other models. It is difficult to define the 'better' model as the approaches are substantially different. Defining the 'better' model is not necessary, though. Using multiple models can help increase the reliability and plausibility of forecasting estimations which adds to decision-making. Therefore a model run on SP data does not necessarily have to replace the other RP models but could function as an addition. Hence, SP data might not work as the most plausible datatype; for non-existing policies, it can be critical to obtain information on specific attribute contributions which can not be found in RP data.

10.2.1. Limitations & future research

In this section, we'll elaborate more on this researchs insights. This includes the limitations of the study and future research possibilities.

Foremost, this research acknowledged and encountered the downsides of SP data as it found some of the data to be unreliable. One of the main limitations of SP data is that it is unpredictable whether people would actually do what they state they would do. Usage of SP data might increase the validity, but in terms of reliability, it is much weaker than RP data. RP data, or empirical data, is, in fact, 100% reliable. Looking at the stated choices and answers, we saw unreliable answers in the form of dominant choice sets. Some respondents stated they would switch modes whilst the attribute parameters would stay the same or improve (fewer travel costs/time). Subsequently, this leads to biased results as these choices weaken the actual effect. On top of that, a substantial amount of people kept their choices on default. In combination with the low survey duration, this data is not very reliable. A secondary issue with SP data is that preferences for specific modes or fuel-types are also very dependent on external, unobserved factors such as fuel and electricity prices, CO2 emission development and charging infrastructure. The unreliability of SP choice experiments makes this method debatable in the application for calculating market shares. The insights in the weights of variables is essential information that could be used for policy-making. Determining the market shares is possible but RP data is a more suitable datatype for this. For example, the difference found between revealed and stated market shares for PHEV was substantial and therefore the found stated share is unreliable.

Second, no model or method is perfect to assess future effects of policies like these. Comparing the absolute outcomes of this model to another is therefore unnecessary as there is no knowledge on all assumptions made. Assumptions such as CO_2 emission in g/km have a crucial impact on the final total effect on emission. Compared to the earlier discussed models (LMS, DYNAMO, Carbontax), the model used to compute the final effects in this research is less complete. It does not include the same level of depth and input - or context variables. Nevertheless, this research still shows relevant insights that are independent of many underlying assumptions. The final effects of the different pricing schemes show a marginal change relative to the base case (no differentiation). It does, therefore, not matter if not all absolute effects are perfectly estimated. All scenarios make use of the same application model and the same underlying behavioural effects. The marginal or relative changes found will still apply to different absolute values. The model is not built to provide the best estimations for the FKC as a whole; it is instead used to see what relations exist within multiple pricing scheme designs (the scenarios).

Third, the different scenarios have varying final effects and give a good insight into the influence of the extent of this differentiation. These scenarios are first defined, and the corresponding results follow. Differentiating the pricing scheme to emission has proved to be an effective tool to reduce adverse effects and increase positive effects. From this research, a discussion can be introduced on the chronological order of making policy. Policy-making includes hard requirements and objectives. Requirements are fixed and non-negotiable, whereas objectives are sought to be maximised. Ultimately, the FKC and the differentiation tool can be described as an optimisation problem. Requirements must first be set to retrieve the pricing scheme range that is possible. From there, the best combination can be derived to achieve maximum tax income, emission savings or a transition to EV, depending on the ultimate goal of the policy and the policy-maker, which is touched upon more in Section 10.3.

Fourth, rather than using Revealed Preference (RP) data in the form of limited vehicle selling data, this research shows that it is possible to use and apply SP data to increase the validity of the outcomes. However, it must be noted that, although SP data enhances the validity, it has to give in on reliability. The quality of the choice observations is very dependent on the respondents' size and effort. Small samples and careless respondents can quickly lead to biased results. This makes the data sensitive and insecure; therefore, relying entirely on SP data is not advised. When evaluating new policies like these, it is good to include an SP experiment for extra decision-making support. An increase in sample size and more explicit instructions on the importance of 'good' answers will maximise the reliability, though it will never reach the reliability level of RP data. It is thus proposed to increase the number of respondents to enhance the reliability of the found parameter estimations. To increase the statistical significance of the interaction parameters, more choice observations per person must be generated. Another option would be to try and integrate or pool the various distance experiments to combine the information.

Fifth, the methods and models that were used in this research, including the survey, choice models and integration, were not comprehensive. The choice sets and models were kept simple and robust, which is suitable for evaluating the application of the model and extracting the marginal changes of different strategies. To increase the completeness of the SP data, other modes such as the bus, metro, tram and foot can be added to the choice sets for mode choice. The most important alternative ignored in this research is the null alternative, i.e. *not taking the trip*. The integrated model assumes all passenger kilometers are being kept the same. However, with the rise of hybrid working, **not** going to work has become a serious alternative. If commuting becomes too expensive, people will be more urged to stay - and work from home. This is a very important alternative that is neglected in this experiment. Another shortcoming of this model is the limited use of alternative specific parameters. In the utility functions no such parameters were accounted for. According to the literature, the estimations for the time - and cost parameters could vary per alternative (Schmid et al., 2016). Spending more time on a train is considered to have a lower negative utility contribution than time spent in a car. For travel costs, this research assumes the travel costs to be the costs for the travel, i.e. a train ticket for the train and the FKC as a ticket for road use. However, for train, these costs are the total travel costs whilst for car travel, it is only part of the total costs of ownership. The cost parameter completely ignores fuel/electricity costs and purchase - and maintenance costs. Incorporating relevant alternatives and including alternative specific parameters will lead to more reliable market shares. This mode valued variation is then capable of computing more reliable VoTTS as they can vary significantly between modes (Wardman, 2004). Lastly, the integrated model that computes the final effects of the scenario's does not take emissions of substituting transport modes into account. A substantial switch to train might require more operational trains causing additional emissions. For completeness, it would be good also take these into account next time.

Sixth, setting up the choice context is difficult but can significantly impact the observed choices. Whether or not to include fuel/electricity costs as an additional attribute remains an interesting discussion. It is hard to draw any conclusions on whether, or to what extent, the fuel costs were taken into account by the respondent as they were not included as a separate main attribute but as a context variable. Initially, this was done because, in real life, people don't get directly confronted with the fuel/electricity costs of a trip. Although it was textually included in the survey, the question remains if people really read the text and took this into account as much as they should. This has a severe impact on people's choices. Future research into this topic could show what the effect is of including this cost type versus leaving it as a context variable. Another context variable that is a crucial element in ones mode choice is the access/egress time. This variable was not included as only conclusions could then be drawn for that context. Additional experiments could be done with multiple access/egress scenarios. The absence of this variable might cause invalid answers as people don't know whether to take it into account or not. Some might do it unintentionally; others might not.

Seventh, in scenario 3, the pricing scheme was differentiated to fuel-type and segment. This scenario's set-up did not result in more tax income or more emission reduction. However, it did have a much higher impact on the high car segment (D & E+) share. It must be noted that this effect was calculated using elasticities determined by Revnext (2019), see Appendix H. Unlike the other effects, this effect was not calculated using SP data. It is proposed to add a third experiment in the form of a car segment choice experiment. The experiments in this research did take the car segments into account but assumed that people would not switch to another car segment. Because different pricing applies to other segments, you could expect these segment switches. Thus, a similar experiment like the car fuel-type choice experiment could be performed for segment choice with attributes like the specific FKC, purchase price, range, car size, max. speed, acceleration and fuel economy.

Eight, the performed experiments are based on preferences at the moment. Three moments in time (2030, 2040 and 2050) were picked as measuring moments to see the effects. This is a unique insight that is not given by any other report. However, these estimated preferences will change over the years. The lower probability for choosing EV over GV is caused by unobserved factors like the inflexibility of charging and long on-the-road charging times. With the initiated transition to EV, these unobserved factors will also change, and people might look different towards EV use in the following decades than they do now. Therefore, regardless of attribute levels, generic preferences for alternatives might change over the years. An SP choice experiment is not capable of forecasting how these preferences will change. Frequently doing such an experiment provides more insight into how relative preferences for specific alternatives change over time. Another option is to include more attributes in the choice set or to create unlabeled alternatives. The impact of fuel prices is another unobserved factor in this experiment. As discussed, it remains unknown if this gives the highest reliability. Fuel prices are an important factor that can rise to unexpected heights in a short time, with the Ukraine-Russian war as empirical evidence. Although included as unobserved factor, the height of fuel prices can be decisive in estimating preferences for both mode choice and car-fuel-type choice. In this choice experiment, the individuals assumed current fuel prices, and the estimations will become outdated when these prices rise.

Nine, car use is measured in the frequency of people using the car. However, people can take a car every day and still not drive many kilometers. These answers do not provide us with data on an individuals' yearly mileage. Mileage might be a more valid metric to determine car use. In a following experiment, one should take the mileage into account. It should be set up in big categories because respondents might have difficulty determining their mileage in an open question. Incorporating mileage results in a more complete view of how car use interacts with the FKC. This research shows that mileage impacts both explanatory variables, *car fuel-type choice* and *mode choice*.

Lastly, in the mode choice experiment, a simple and robust MNL model was used. This model treats every choice independently. In theory, this is incorrect because choices correlate with earlier choices made. If you choose the train alternative in the first option, you are, compared to the first choice, more likely to choose the train in the second choice. The MNL model ignores earlier choices; therefore, following choice situations carry less information. As a result, the parameters' standard errors (SE) are underestimated. Unlike the MNL model, the ML model can capture these so-called panel effects. In combination with the earlier notion of increasing the choice sets per respondent, it is advised to estimate an ML model to capture these panel effects. Additionally, if extra PT modes such as metro, tram and bus are included, an error component 'Public transport' can be added to the functions. Both an MNL and ML were estimated to capture heterogeneity within alternatives for the car fuel-type choice experiment. For the car fuel-type experiment, the choice of EV over ICEV can be considered a moral choice because the EV is not yet competitive with the ICEV. The sole purpose of choosing an EV over an ICEV is to reduce emissions and increase sustainability and livability. The group that wants to 'pioneer' toward an electric car fleet is hard to determine. (Centraal Bureau voor de Statistiek, 2021) found several reasons for switching to EV. These reasons can not directly be linked to a specific social group such as high income or the distance to the nearest train station. Adding *latent classes* to the traditional RUM model could opt as a solution to define the characteristics of this group, such a model is called a Hybrid Choice model (Ben-Akiva et al., 2002). To study these effects, the attitude questions that were asked in the survey could be used for this purpose.

This section acknowledges numerous limitations of this study. These limitations, and more specific the recommendations that follow, are in order to enhance the reliability and validity of the study. Nevertheless, these limitations do not alter the drawn conclusions. The conclusions remain, although the reliability of specific key findings could be improved by addressing the limitations in further research. On top of that, further research can generate even more information from the collected data.

10.3. Policy recommendations

This section will provide tailor-made and non-methodological recommendations for the policy-makers, in this case, the Dutch government. Differentiating the pricing scheme has proven to have positive effects on society. A modal shift to other, less polluting transport modes (e.g. train or EV) is triggered when including a higher charge for more polluting cars. Additionally, more tax income can be generated with this system. This enables the government to open up an extra budget for the additional investment that is necessary to accommodate the growing demand for trains and EVs. Although there is still an intrinsic preference for ICEV cars over EVs and trains, increasing the costs functions as an excellent tool to shorten the gap. Moreover, the research has also shown that, generally, people support this policy and that for ICEV users in specific, 74% is supportive. Emission-based differentiation is the most supported form of differentiation if it were to be applied (82%).

For EV adoption, the height of the FKC plays a significant role. Still, the utility contributions and relative importance show that the purchase price is a more crucial factor for the electrified transition. Therefore, it is suggested that whilst considering a differentiated FKC, it does not remain the only option to use pricing policies to speed up electrification. The focus must also remain on bringing EV purchase prices to that of the ICEV level. The ultimate utility of getting EV purchase prices to the same level as ICEV will generate a faster transition than the current discussed differentiation strategies. Given the higher Willingness-to-pay for a decrease in variable costs for high income groups, an additional positive effect is that lowering purchase prices will not enable a larger inequality gap. With lower variable costs for higher-priced cars, wealthier people can more easily invest. The payback period of such investments is generally lower than a car's lifespan. Buying a higher-priced car for lower variable rates and thus retrieving a return on this trade-off, a differentiated pricing scheme is more interesting for financially equipped groups. Therefore, the recommendation is also to explore the costs and benefits of using FKC tax income to lower EV purchase prices. For example, a slightly higher FKC tariff can be implemented so that all income groups are treated the same and and EV purchasing becomes more attractive for both high and low income groups.

We have seen that policy is not only about maximising one effect, whether this is taxable income or car emission savings. Moreover, it is concluded that policies must meet several hard requirements before they can be integrated. In order to meet the requirements but still optimise certain objectives such as emission reduction, it is proposed to apply an optimisation tool to investigate the best emission combination. This way, policy tools like differentiating based on emission can be used as best as possible without overstepping borders or falling short on requirements. This form of policy-making is more active than the manual approach used currently, where certain pricing schemes are determined without justification or knowledge of the best combination. Requirements such as a maximum transition to EV or the train must be included as hard requirements because the FKC may not enable such a transition to both (fuel-type) modes which cannot be handled by the infrastructure yet. Setting up requirements like these in an optimisation model will give the pricing scheme that meets all requirements and still maximises the objective. This way, the pricing scheme can enable the minimum required tax income and still function as a tool to speed up the electrification of the car fleet.

Although applying price differentiation to the pricing scheme seems only to have positive effects, asking for higher prices than others can disadvantage certain groups. Groups affected more heavily than others can, for instance, potentially lead to a larger gap between poor and rich. The average price that is asked may stay the same, but the fact remains that EV purchasing is still more expensive, and not all can afford such a transition as easy as others. Concerning car fuel-type choice, we saw that higher incomes and business users were more sensitive to the price. This is probably because these people can afford a switch. In the end, that would mean that people with more financial means have less operational costs and that 'their' infrastructure is paid for by those with less income who might not be able to afford such a switch. Additionally, some people are more dependent on the car because of their geographical location or commuting location and do not consider the train or other PT modes as an alternative. People with no access to an alternative are presented with higher costs which do not enable the desired decrease in car use. Location-based differentiation could pose as a solution but this option has already been ruled out and, moreover, this form of differentiation is least supported by the population. These inequalities do form a considerable risk and must be taken into careful consideration.

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A

Data

A.0.1. Information FKC attribute levels and context variables

For setting up the attribute levels, and also the context variables, research has been conducted to finding values for purchase price, range, co2 emission, charging times and fuel economy. The following results were found.

Purchase price

Purchase prices were based on ANWB (2021b); OSW (2021).

Table A.1: Purchase prices

Purchase price (euro)		Propulsion type			
		GV	DV	PHEV	BEV
Weight class	Segment A	12.500	12.500	14.625	25.000
	Segment B	17.500	17.500	20.475	35.000
	Segment C	25.000	25.000	29.250	45.000
	Segment D	35.000	35.000	40.950	60.000
	Segment E+	50.000	50.000	58.500	80.000

Range

Ranges were based on OSW (2021); ANWB (2021b,d). The ICEV ranges were based on average car tank of 600km. PHEV was assumed to be in the middle of ICEV and BEV ranges.

Table A.2: Range

Range (km)		Propulsion type			
		GV	DV	PHEV	BEV
Weight class	Segment A	400	600	375	150
	Segment B	600	600	425	250
	Segment C	600	600	475	350
	Segment D	600	600	525	450
	Segment E+	600	600	575	550

Fast charging times

Fast charging times are based on a source by the ANWB (2021d,b,a).

Table A.3: Charging time

Fast charging time (min)(min)		**Propulsion type**			
		GV	DV	PHEV	BEV
Weight class	Segment A	4	4	4	45
	Segment B	4	4	4	35
	Segment C	4	4	4	25
	Segment D	4	4	4	22
	Segment E+	4	4	4	18

Fuel economy
The fuel economy is based on weight levels.

Table A.4: Fuel economy

Fuel economy		**Propulsion type**			
		GV (L/100)	DV (L/100)	PHEV (L/100)	BEV(KW/km)
Weight class	Segment A	4	4	0	6
	Segment B	5	5	0	10
	Segment C	7	7	0	15
	Segment D	9	9	0	20
	Segment E+	11	11	0	25

Emissions and pollution
These emissions are based on the fuel economy and the fuel type. For the PHEV a 50/50 approach is used, where it is assumed that 50% of the kilometers are using electricity and the other 50% uses gasoline or diesel. For the PM10 and NOx findings, Milieu Centraal is used as source.

Table A.5: CO_2 emissions

CO2 (g/km)	GV	DV	PHEV	BEV
Segment A	0.106	0.102	0.043	0.000
Segment B	0.117	0.112	0.055	0.000
Segment C	0.122	0.117	0.049	0.000
Segment D	0.129	0.123	0.058	0.000
Segment E+	0.143	0.137	0.068	0.000

Table A.6: PM_{10} emissions

PM10 (g/km)	GV	DV	PHEV	BEV
Segment A	0.026	0.019	0.020	0.015
Segment B	0.029	0.022	0.023	0.017
Segment C	0.032	0.024	0.026	0.019
Segment D	0.035	0.026	0.029	0.021
Segment E+	0.038	0.029	0.031	0.023

Table A.7: NO_X emissions

NOx (g/km)	GV	DV	PHEV	BEV
Segment A	0.102	0.286	0.051	0.0
Segment B	0.115	0.321	0.076	0.0
Segment C	0.128	0.357	0.064	0.0
Segment D	0.141	0.393	0.070	0.0
Segment E+	0.154	0.428	0.077	0.0

A.0.2. Choice sets car data

Segment A	Benzine	Diesel	Plug-in Hybrid	Elektrisch
Aanschafprijs (euro)	€12,500	€13,750	€12,500	€21,875
Actieradius (km)	400	400	400	200
Kilometerheffing (euro per km)	€0.25	€0.05	€0.20	€0.15

Segment B	Benzine	Diesel	Plug-in Hybrid	Elektrisch
Aanschafprijs (euro)	€17,500	€19,250	€17,500	€30,625
Actieradius (km)	500	500	500	250
Kilometerheffing (euro per km)	€0.25	€0.05	€0.20	€0.15

Segment C	Benzine	Diesel	Plug-in Hybrid	Elektrisch
Aanschafprijs (euro)	€27,500	€30,250	€27,500	€48,125
Actieradius (km)	600	600	600	300
Kilometerheffing (euro per km)	€0.25	€0.05	€0.20	€0.15

Segment D	Benzine	Diesel	Plug-in Hybrid	Elektrisch
Aanschafprijs (euro)	€35,000	€38,500	€35,000	€61,250
Actieradius (km)	600	600	600	300
Kilometerheffing (euro per km)	€0.25	€0.05	€0.20	€0.15

Segment E+	Benzine	Diesel	Plug-in Hybrid	Elektrisch
Aanschafprijs (euro)	€50,000	€55,000	€50,000	€87,500
Actieradius (km)	600	600	600	300
Kilometerheffing (euro per km)	€0.25	€0.05	€0.20	€0.15

Figure A.1: Choice sets per car segment

A.0.3. Car fleet data

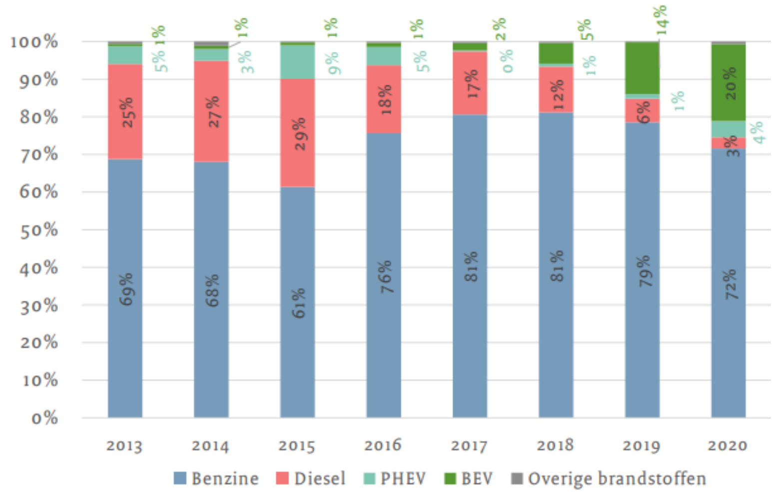


Figure A.2: Car fleet fuel share (Rijksdienst voor Ondernemen and Revnext, 2018)

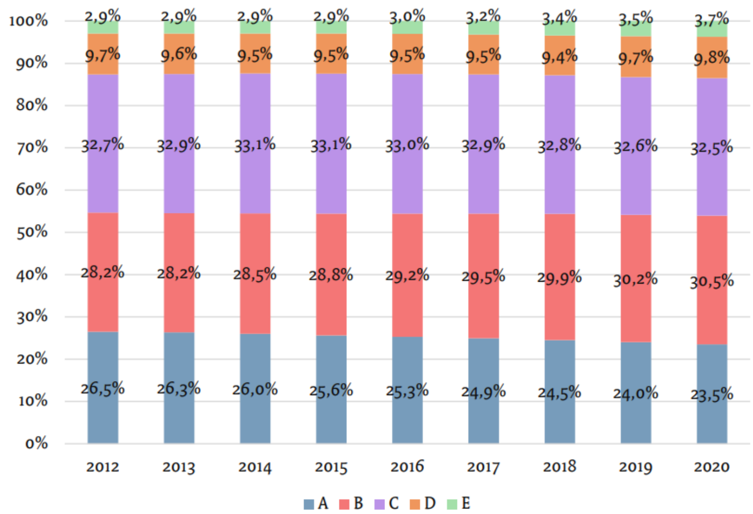


Figure A.3: Segment distribution (Rijksdienst voor Ondernemen and Revnext, 2018)

A.0.4. Reason to drive electric

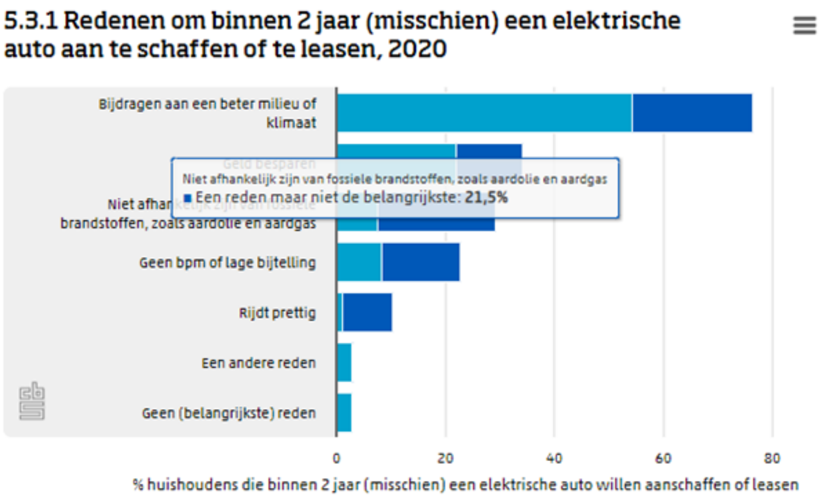


Figure A.4: Reasons to go electric (Centraal Bureau voor de Statistiek, 2021)

A.0.5. Perceived in-vehicle value of time

Table 5: Monetary Values of IVT

		Urban			Inter-Urban		
Purpose	Mode	Mean	SE	n	Mean	SE	n
Commuting	Car	6.0	0.4	64	10.5	1.8	11
	Bus	4.2	1.0	17			
	Rail	7.2	0.9	17	12.6	0.8	21
	UG	9.2	0.9	5			
Leisure	Car	6.5	0.5	73	9.2	1.1	23
	Bus	2.6	0.3	22			
	Rail	6.5	1.0	14	13.3	1.2	44
	UG	7.3	0.7	16			
Business	Car	13.2	3.6	11	18.3	2.6	16
	Bus	3.2	0.3	27			
	Rail&UG	19.2	9.0	8	32.2	3.5	34
	Rail1st				52.3	5.7	17
	Air				90.2	19.3	12

Figure A.5: Perceived in-vehicle value of time (Wardman, 2004)

B
Ngene syntax

In this appendix the Ngene code that was used to generate the choice sets is provided.

B.1. Experiment 1: Car fuel-type choice

```
Design
;alts = GV , DV ,  PHEV , BEV
;rows = 20
;block = 4
;fact
;model:
U(GV) = B_PP_ GV * PP_ICEV[0,10,20] + B_FKC_ GV * FKC_ GV [0.05,0.10,0.15,0.20,0.25]/
U(DV) =  B_PP_ DV * PP_ICEV + B_ FKC _ DV * FKC _ DV [0.05,0.10,0.15,0.20,0.25]/
U(PHEV) = B_PP_ PHEV * PP_ PHEV [0,10,20] + B_ FKC _ PHEV * FKC
_plugin[0.05,0.10,0.15,0.20,0.25] + B_AR_plugin * AR_plugin[0,-25]/
U(BEV) = B_PP_ BEV * PP_ BEV [0,25,50,75] + B_ FKC _ BEV * FKC _ BEV
[0.05,0.10,0.15,0.20,0.25] + B_AR_ BEV * AR_ BEV [0,-25,-50]
$
```

Figure B.1: Ngene syntax Exp 1

B.2. Experiment 2: Mode choice
In this experiment, 4 sub-experiments are conducted for every separate distance.

B.2.1. 5 kilometer

```
Design
;alts = car , bike
;rows = 8
;block = 4
;fact
;model:
U(car) = B_TT_car * TT_car[5,10,15] + B_TC_car * TC_car[0.25,0.5,0.75,1,1.2]/
U(bike) = B_TT_bike * TT_bike[20] + B_TC_bike * TC_bike[0]
$
```

Figure B.2: Ngene syntax Exp 2. 5 kilometer

B.2.2. 25 kilometer

```
Design

;alts = car , train
;rows = 8
;block = 4
;fact
;model:

U(car) = B_TT_car * TT_car[20,25,30] + B_TC_car * TC_car[1.25,2.5,3.75,5,6.25]/

U(train) = B_TT_train * TT_train[25,35] + B_TC_train * TC_train[5]

$
```

Figure B.3: Ngene syntax Exp 2. 25 kilometer

B.2.3. 75 kilometer

```
Design

;alts =  car , train
;rows = 8
;block = 4
;fact
;model:

U(car) = B_TT_car * TT_car[60,70] + B_TC_car * TC_car[3.75,7.5,11.25,15,18.75]/

U(train) = B_TT_train * TT_train[45,60] + B_TC_train * TC_train[15]

$
```

Figure B.4: Ngene syntax Exp 2. 75 kilometer

B.2.4. 200 kilometer

```
Design

;alts = car , train
;rows = 8
;block = 4
;fact
;model:

U(car) = B_TT_car * TT_car[135,165] + B_TC_car * TC_car[10,20,30,40,50]/

U(train) = B_TT_train * TT_train[135,165] + B_TC_train * TC_train[28]

$
```

Figure B.5: Ngene syntax Exp 2. 200 kilometer

C
Survey Overview

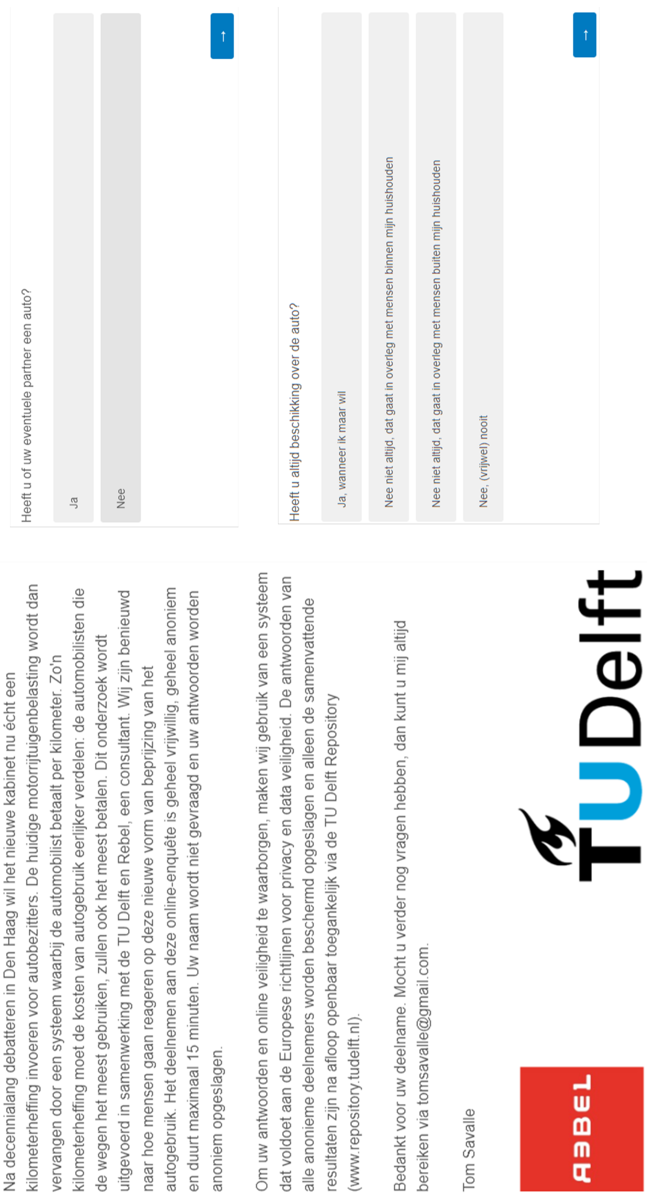
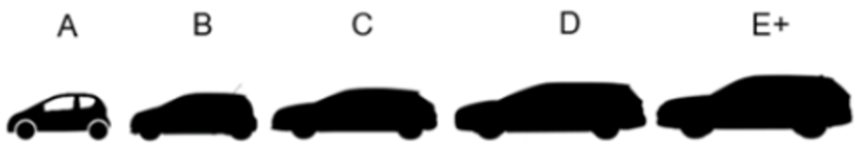


Figure C.1: Survey 1/12

Hieronder staan de verschillende autosegmenten (autoklasses) die Nederland kent, opgedeeld in 5 segmenten: A,B,C,D,E+. Elke auto valt onder één van de segmenten.

Autosegmenten	Voorbeelden automodellen
Segment A - Submini's	Volkswagen Up, Opel Karl, Hyundai i10, Citroën C1,Peugeots 206, Toyota Aygo, Fiat 500 en de Opel Adam. Renault Zoë, Toyota Yaris, Renault Twingo
Segment B – Kleine auto's	Toyota Prius, Opel Corsa, Fiat Punto, Ford Fiesta, Renault Clio en Volkswagen Polo
Segment C – Kleine middenklasse	Renault Mégane, Peugeot 308, Opel Astra, Ford Focus, Kia Ceed, Audi A3, BMW 1-serie, Volkswagen Golf en Mercedes A-klasse. + Cabriolets
Segment D - Middenklasse	Volkswagen Passat, Opel Insignia, Ford Mondeo, Renault Talisman of Peugeot 508, BMW 3- 0f 4-serie, Mercedes C-klasse, Lexus IS of Audi A4/A5
Segment E+ - Hogere middenklasse + Hoge klasse	Mercedes E-klasse, BMW 5-serie en Audi A6. Maar ook de Volvo V70, Mercedes CLS, Audi TT, Mazda MX-5 of Mercedez-Benz SLC en SUV's zoals Volvo SC60, Hyundai Tucson, BMW XS, Audi Q7, Tesla Models and Polestar. + SUV's, Jeep's en sportmodellen.



In welk segment valt de auto die u heeft of in welke u geinteresseerd zou zijn als u gaat kopen? Heeft u meerdere auto's, antwoord dan de auto die u het meest gebruikt. Zit de auto er niet bij en twijfelt u over het segment, kies dan het segment die het meest lijkt op de auto in het plaatje.

Segment A

Segment B

Segment C

Segment D

Segment E+

Figure C.2: Survey 2/12

Wat voor brandstoftype auto heeft u of uw partner nu?

- Benzine auto
- Diesel auto
- Plug-in Hybrid
- Elektrisch
- Anders namelijk:

Rijdt u een (lease) auto, en wordt deze betaald door de zaak?

- Ja, mijn werkgever betaalt de auto plus brandstof voor privégebruik
- Ja, mijn werkgever betaalt de auto (geen privé kilometers)
- Nee, ik rij private lease
- Nee, ik heb de auto zelf gekocht

Hoe reist u naar werk/studie?

- Auto
- Openbaar Vervoer
- Fiets
- Lopend

Heeft u een abonnement of korting op de trein?

- Ja, Onbeperkt reizen (Weekend -, Traject -, Dal - en Altijd Vrij) abbonement - zelf betaald
- Ja, Onbeperkt reizen (Weekend -, Traject -, Dal - en Altijd Vrij) abbonement - betaald door werkgever
- Ja, Kortingsabbonement (Weekend -, Dal - en Altijd Voordeel) - zelf betaald
- Ja, Kortingsabbonement (Weekend -, Dal - en Altijd Voordeel) - betaald door werkgever
- Ja, Studentenreisproduct
- Nee
- Anders namelijk:

Bent u van plan een (nieuwe) auto te kopen en op welke termijn?

- Ja, binnen 1 jaar
- Ja, binnen 1-2 jaar
- Ja, binnen 3-5 jaar
- Ja, binnen 5-10 jaar
- Ja, maar niet binnen 10 jaar
- Nee

Overweegt u, wanneer u een (nieuwe) auto koopt om een elektrische auto aan te schaffen?

- Ik heb er al een
- Ja ik overweeg om bij mijn volgende aankoop voor een elektrische auto te kiezen
- Geen interesse
- Weet ik niet

→

Hoe vaak gebruikt u, zowel zakelijk als privé, de auto (of bent u van plan deze te gaan gebruiken)?

- minder dan 1 dag per jaar
- 1-5 dagen per jaar
- 6-11 dagen per jaar
- 1-3 dagen per maand
- 1-2 dagen per week
- 3-4 dagen per week
- 5-6 dagen per week
- (vrijwel) elke dag

→

Figure C.3: Survey 3/12

Uitleg: De volgende 4 vragen gaan over uw voorkeur voor brandstoftype. De keuze is tussen een benzine, diesel, plug-in hybrid of elektrische auto. In het voorbeeld hieronder zijn 3 verschillende kenmerken van een auto, de aanschafprijs, actieradius en de kilometerheffing. U mag hierbij van het volgende uitgaan:

- De **aanschafprijs** is de totale prijs voor een nieuwe auto.
- De **actieradius** is de afstand die de auto kan afleggen met één volle tank- of laadbeurt. Een snellaadbeurt buitenshuis, dat alleen nodig is voor elektrische auto's, duurt gemiddeld 30 minuten.
- De **kilometerheffing** is de nieuwe belasting die de overheid wil invoeren als vervanging van de huidige maandelijkse wegenbelasting. Deze is dus niet meer vast en maandelijks maar continu per gereden kilometer. **Let op:** deze prijs is voor alleen de kilometerheffing en nog exclusief de brandstofkosten.

Voorbeeld	Benzine	Diesel	Plug-in Hybrid	Elektrisch
Aanschafprijs (euro)	€33,000	€33,000	€27,500	€48,125
Actieradius (km)	600	600	450	600
Kilometerheffing (euro per km)	€0.15	€0.25	€0.25	€0.10

Een *plug-in hybrid* stoot gemiddeld 50% minder CO2 uit en kost gemiddeld 40% minder aan brandstof dan de conventionele benzine - en diesel auto's. Een *elektrische* auto stoot 100% minder CO2 uit en kost gemiddeld 60% minder aan brandstof dan de conventionele benzine - en diesel auto's.

Nu volgen de 4 vragen, met elk verschillende waardes voor de kenmerken. Geef per vraag aan welk brandstoftype auto u zou kiezen.

Keuze 1/4

Segment B	Benzine	Diesel	Plug-in Hybrid	Elektrisch
Aanschafprijs (euro)	€21,000	€21,000	€17,500	€30,625
Actieradius (km)	500	500	375	500
Kilometerheffing (euro per km)	€0.15	€0.25	€0.25	€0.10

A.Welke brandstoftype auto kiest u?

Benzine

Diesel

Plug-in hybrid

Elektrisch

Keuze 2/4

Segment B	Benzine	Diesel	Plug-in Hybrid	Elektrisch
Aanschafprijs (euro)	€17,500	€19,250	€17,500	€30,625
Actieradius (km)	500	500	500	250
Kilometerheffing (euro per km)	€0.25	€0.05	€0.20	€0.15

B. Welke brandstoftype auto kiest u?

Benzine

Diesel

Plug-in hybrid

Elektrisch

Figure C.4: Survey 4/12

Keuze 3/4

Segment B	Benzine	Diesel	Plug-in Hybrid	Elektrisch
Aanschafprijs (euro)	€21,000	€17,500	€20,125	€30,625
Actieradius (km)	500	500	500	250
Kilometerheffing (euro per km)	€0.10	€0.15	€0.10	€0.10

C. Welke brandstoftype auto kiest u?

- Benzine
- Diesel
- Plug-in hybrid
- Elektrisch

Keuze 4/4

Segment B	Benzine	Diesel	Plug-in Hybrid	Elektrisch
Aanschafprijs (euro)	€19,250	€21,000	€22,750	€17,500
Actieradius (km)	500	500	375	250
Kilometerheffing (euro per km)	€0.20	€0.20	€0.25	€0.25

D. Welke brandstoftype auto kiest u?

- Benzine
- Diesel
- Plug-in hybrid
- Elektrisch

→

Figure C.5: Survey 5/12

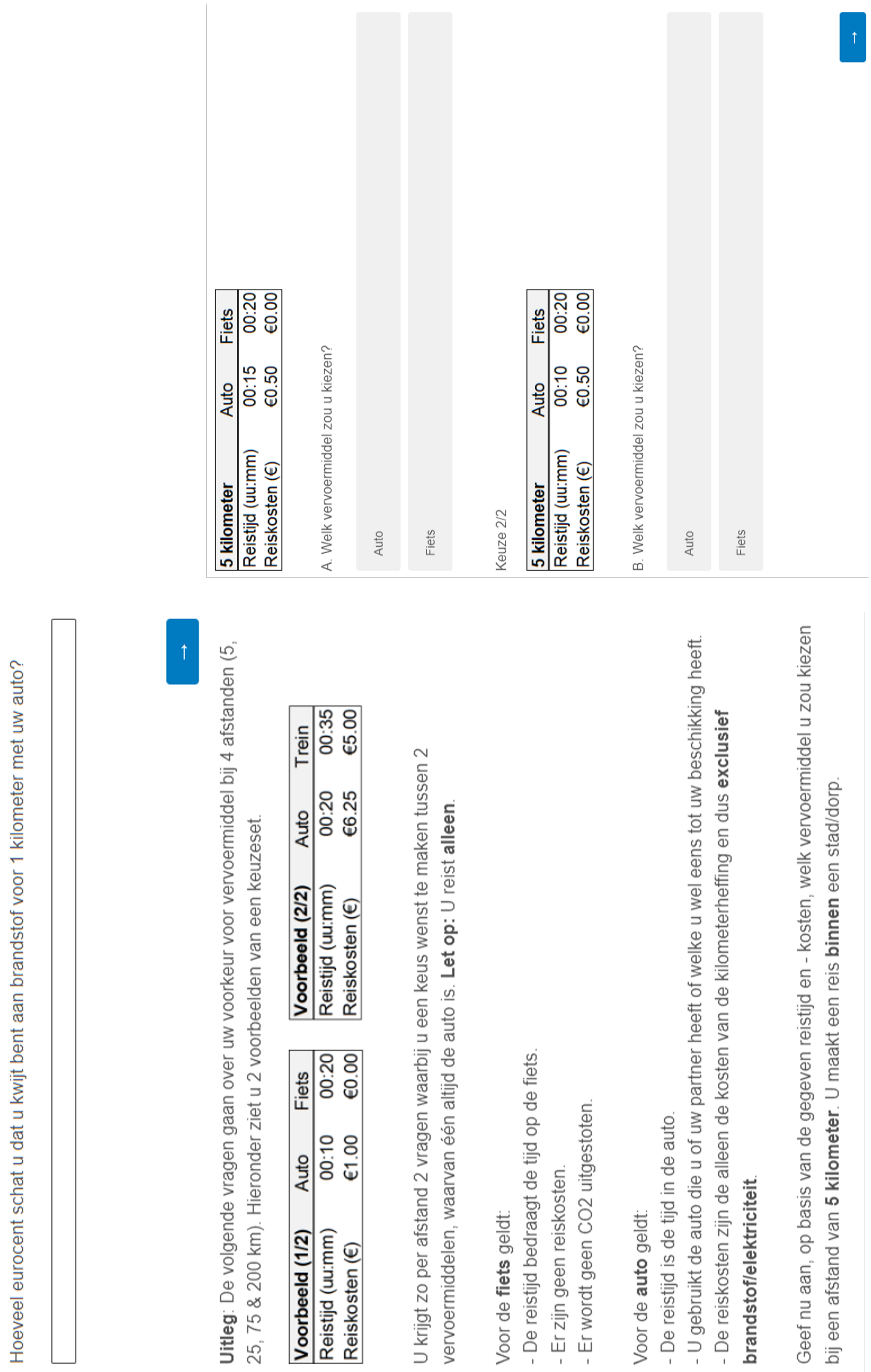
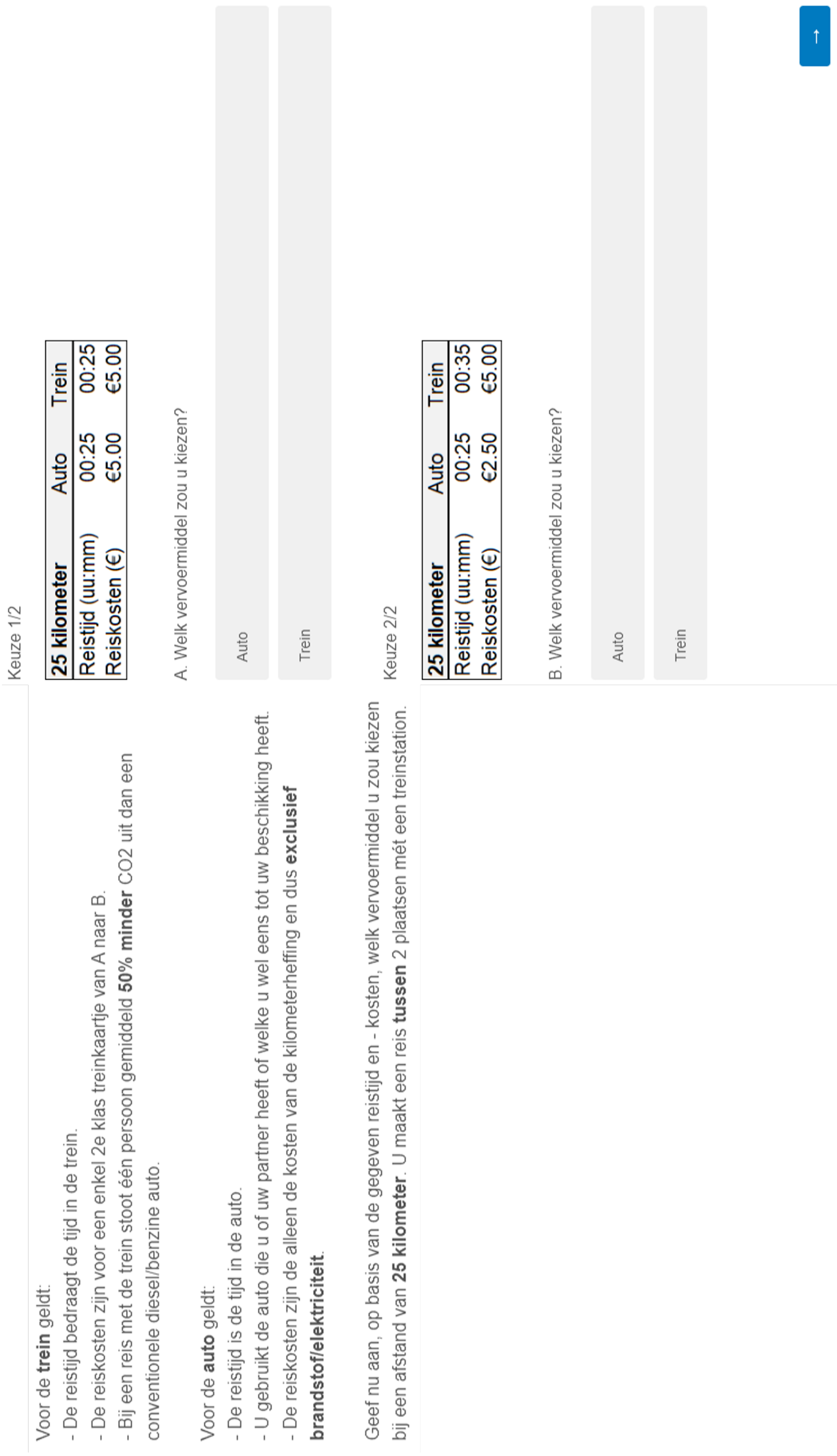


Figure C.6: Survey 6/12



Voor de **trein** geldt:
- De reistijd bedraagt de tijd in de trein.
- De reiskosten zijn voor een enkel 2e klas treinkaartje van A naar B.
- Bij een reis met de trein stoot één persoon gemiddeld **50% minder** CO2 uit dan een conventionele diesel/benzine auto.

Voor de **auto** geldt:
- De reistijd is de tijd in de auto.
- U gebruikt de auto die u of uw partner heeft of welke u wel eens tot uw beschikking heeft.
- De reiskosten zijn de alleen de kosten van de kilometerheffing en dus **exclusief brandstof/elektriciteit**.

Geef nu aan, op basis van de gegeven reistijd en - kosten, welk vervoermiddel u zou kiezen bij een afstand van **25 kilometer**. U maakt een reis **tussen** 2 plaatsen mét een treinstation.

Keuze 1/2

25 kilometer	Auto	Trein
Reistijd (uu:mm)	00:25	00:25
Reiskosten (€)	€5.00	€5.00

A. Welk vervoermiddel zou u kiezen?

Auto

Trein

Keuze 2/2

25 kilometer	Auto	Trein
Reistijd (uu:mm)	00:25	00:35
Reiskosten (€)	€2.50	€5.00

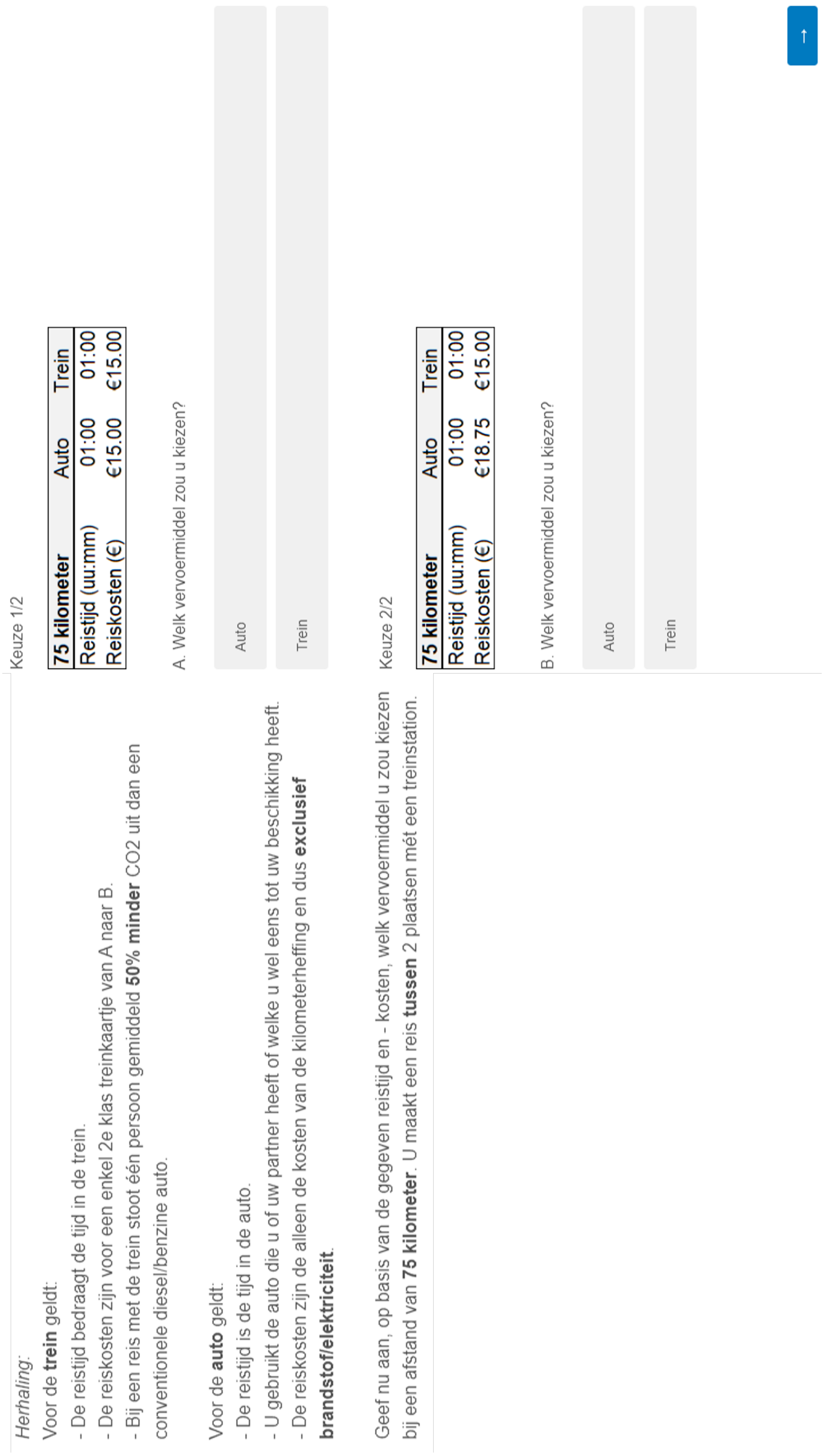
B. Welk vervoermiddel zou u kiezen?

Auto

Trein

→

Figure C.7: Survey 7/12



Herhaling:

Voor de **trein** geldt:

- De reistijd bedraagt de tijd in de trein.
- De reiskosten zijn voor een enkel 2e klas treinkaartje van A naar B.
- Bij een reis met de trein stoot één persoon gemiddeld **50% minder** CO2 uit dan een conventionele diesel/benzine auto.

Voor de **auto** geldt:

- De reistijd is de tijd in de auto.
- U gebruikt de auto die u of uw partner heeft of welke u wel eens tot uw beschikking heeft.
- De reiskosten zijn de alleen de kosten van de kilometerheffing en dus **exclusief brandstof/elektriciteit**.

Geef nu aan, op basis van de gegeven reistijd en - kosten, welk vervoermiddel u zou kiezen bij een afstand van **75 kilometer**. U maakt een reis **tussen** 2 plaatsen mét een treinstation.

Keuze 1/2

75 kilometer	Auto	Trein
Reistijd (uu:mm)	01:00	01:00
Reiskosten (€)	€15.00	€15.00

A. Welk vervoermiddel zou u kiezen?

Auto

Trein

Keuze 2/2

75 kilometer	Auto	Trein
Reistijd (uu:mm)	01:00	01:00
Reiskosten (€)	€18.75	€15.00

B. Welk vervoermiddel zou u kiezen?

Auto

Trein

→

Figure C.8: Survey 8/12

Herhaling:
Voor de **trein** geldt:
- De reistijd bedraagt de tijd in de trein.
- De reiskosten zijn voor een enkel 2e klas treinkaartje van A naar B.
- Bij een reis met de trein stoot één persoon gemiddeld **50% minder** CO2 uit dan een conventionele diesel/benzine auto.

Voor de **auto** geldt:
- De reistijd is de tijd in de auto.
- U gebruikt de auto die u of uw partner heeft of welke u wel eens tot uw beschikking heeft.
- De reiskosten zijn de alleen de kosten van de kilometerheffing en dus **exclusief brandstof/elektriciteit**.

Geef nu aan, op basis van de gegeven reistijd en - kosten, welk vervoermiddel u zou kiezen bij een afstand van **200 kilometer**. U maakt een reis **tussen** 2 plaatsen mét een treinstation.

Keuze 1/2

200 kilometer	Auto	Trein
Reistijd (uu:mm)	02:15	02:15
Reiskosten (€)	€10.00	€28.00

A. Welk vervoermiddel zou u kiezen?

Auto

Trein

Keuze 2/2

200 kilometer	Auto	Trein
Reistijd (uu:mm)	02:15	02:45
Reiskosten (€)	€10.00	€28.00

B. Welk vervoermiddel zou u kiezen?

Auto

Trein

→

Figure C.9: Survey 9/12

Figure C.10: Survey 10/12

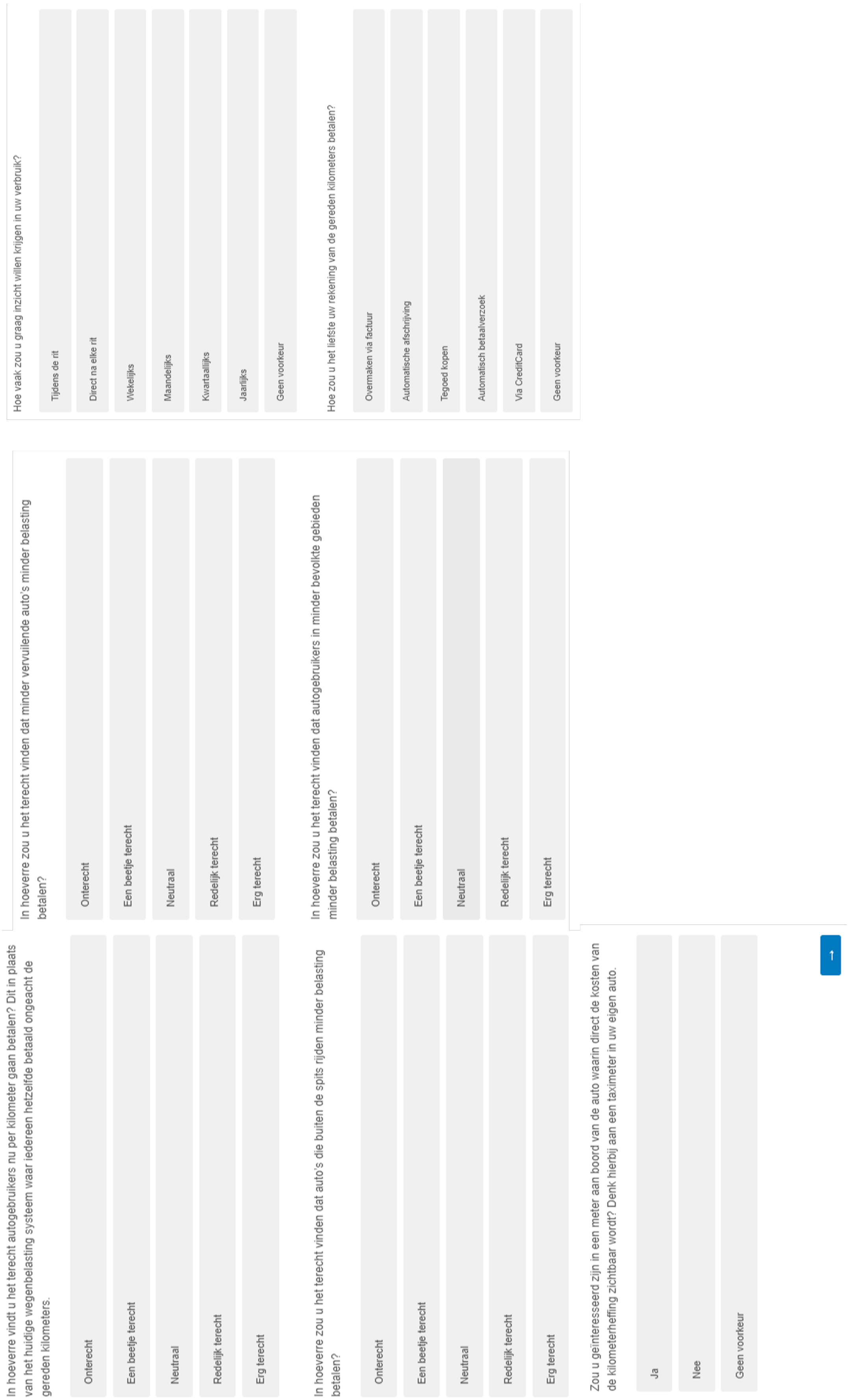


Figure C.11: Survey 11/12

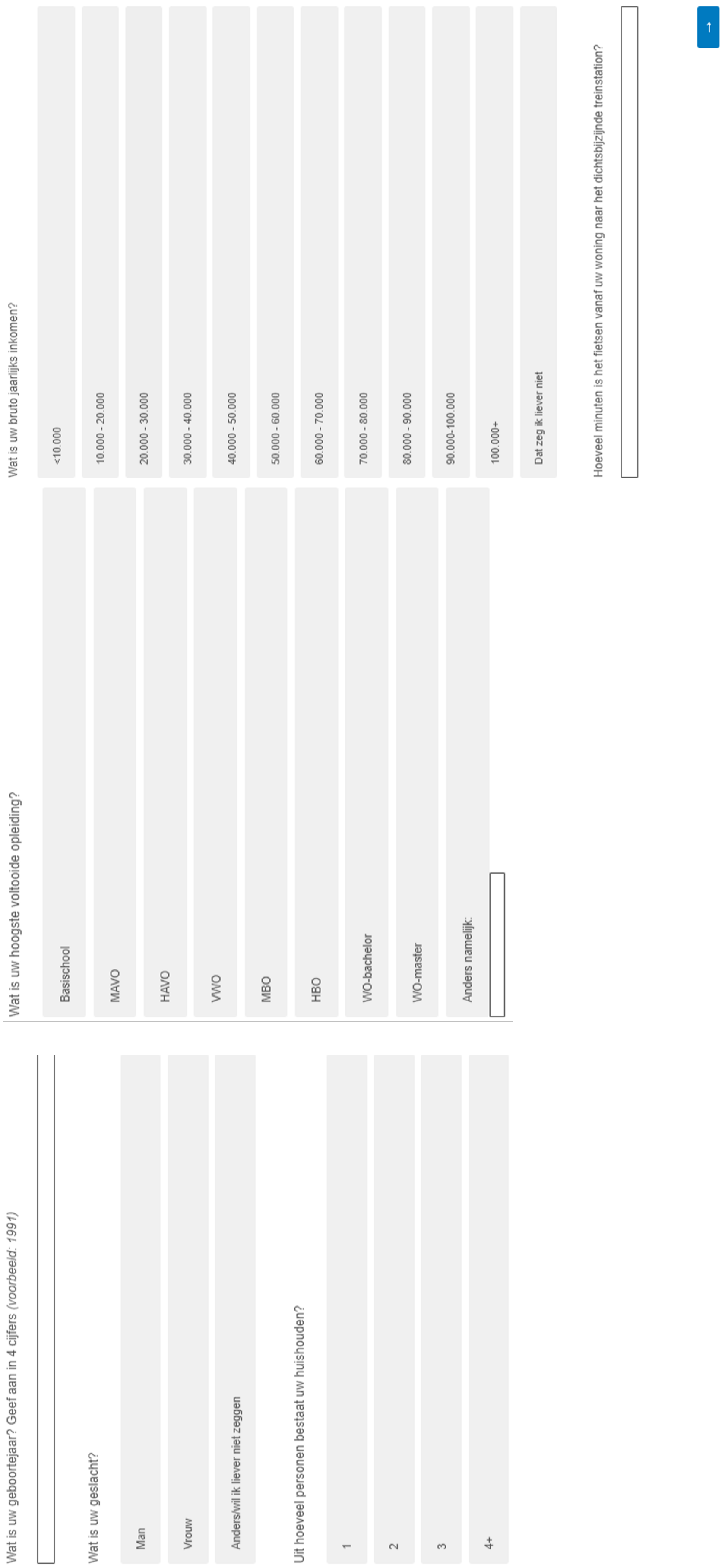


Figure C.12: Survey 12/12

D

Data preparation

D.1. Factor Analysis

Factor analysis can be performed to group or cluster perception questions. In Factor analysis, the variance between the variables is explored. The extent of correlation show how the variables relate to one another and how multiple variables can maybe be grouped into one to reduce the amount of dimensions. SPSS is used as a tool to perform the factor analysis. In the end, one's sustainability and car affinity was not included in the final model. For further research, these variables could be included.

Perceptions	Average	Standard dev.
I am environmentally friendly	3.042	1.021
I make environmental daily choices	2.588	1.055
I value car availability	3.610	1.055
I value car flexibility	3.461	1.071
I value car comfort	3.622	0.959

1 = not true, 5 = true

Acceptation	Average	Standard dev.
Paying per use, i.e. the FKC	3.394	3.155
Differentiation to time	3.155	1.330
Differentiation to emission	3.320	1.279
Differentiation to place	2.408	1.384

1 = non accepting, 5 = very accepting

Figure D.1: Perception - and acceptation results

The factor analysis was performed on the 5 statement questions and was done using SPSS. A Maximum likelihood method was used and rotated using Direct Oblimin. The Maximum likelihood estimation provides a solid method for factor matrices estimation (Tucker and Lewis, 1973). Direct oblimin will rotate the factors in such a way that the statements can correlate with one another. The criteria for an eigenvalue above 1 has been set.

D.1.1. Results Factor analysis

The results that flowed from the analysis with a higher eigenvalue than 1 are displayed below, which were only two:

Factor analysis results	Factor 1	Factor 2
Sustainability	-,031	**,805**
Sustainable activities	-,151	**,786**
Car availability	**,855**	-,092
Car$_{flexibility}$	**,866**	-,127
Car$_{comfort}$	**,629**	-,053

2 factors rolled out of the Factor Analysis, as expected. Factor 1 is named 'Car affinity' and Factor 2 is named 'Sustainable'. All individual values will be scaled per factor and used further in the model estimation for interaction-effects.

D.2. Binomial variables for model estimation

	Value 0	Value 1	Value 0	Value 1
Distance to nearest train station	Close	Far	<15 min	=>15 min
Income	Low	High	<40,000	=>40,000
*Age**	-	-	-	-
Gender	Female	Male	Female	Male
Education	Low	High	MBO, MAVO, HAVO, VWO	HAVO, VWO, HBO, WO
Car ownership	No	Yes	No	Yes
Car segment	Low	High	A,B	C,D,E+
Current fuel type	ICEV	EV	GV,DV	PHEV,BEV
Business cars	No	Yes	Own car	Paid (partly)
Car use	Occassional	Often	< 3days/week	=>3 days/week
Public Transport (discount) card	No	Yes	No card	Card (discount)
Trip purpose	Private	Business	Private	Business
Commuting mode	No car	Car	Train, walk, bike	Car
Sustainability	Not sustainable	Sustainable	Not sustainable	Sustainable
Car affinity	No car affinity	Car affinity	No car affinity	Car affinity

*Age uses non-binary linear values

Figure D.2: Binomial variables for model estimation

E

Interviews

E.1. Interview PlanBureau Leefomgeving

Below you find a brief transcription of the interview with PBL, responsible for calculating the effects of policy measures. The interviewee is modeller at PBL. The questions are regarding the Carbontax model and is meant to give more insight in the different models that are used and how they work.

Waar wordt het Revnext model veelal voor gebruikt?

Bij PBL zelf gebruiken we ook veelal het Dynamo model. De laatste jaren zijn we ook steeds meer het Carbon tax model van Revnext gaan gebruiken. Dit doen we samen met Revnext. En dit gebruiken we o.a. voor de verkiezingsprogrammas waar verschillende varianten van de kilometerheffing uit.

Is ook het systeem van nu, het MRB plus systeem, doorgerekend?

Vormgeving is niet bekend, er staan nog een aantal dingen open. Er komt een heffing ten alle tijden, een heffing voor alle momenten op de dag. Het is nog onduidelijk hoe ze zullen omgaan met tariefdifferentiatie tussen kenmerken van autos. Er zijn wel varianten van het MRB Plus systeem die zijn doorgerekend met beide modellen. De vormgeving maakt uit voor de effecten. Dit is gedaan in de BnG studie van vorig jaar. Voor verschillende partijen zijn verschillende varianten doorgerekend. Kijk ook is naar de MKBA studie uit 2015. Hierin staan de effecten op veel aspecten zoals leefomgeving, emissies etc. Deze MKBA gaat verder dan alleen verkeerseffecten en wagenparksamenstelling. Dit is nu erg anders omdat er veel meer electrificatie plaatsvindt. Het Carbontax model neemt deze electrificatie meer mee dan het Dynamo model en wordt daardoor steeds vaker gebruikt.

Wordt er keuzedata gebruikt in één van deze twee systemen?

Op dit moment nog niet. De modellen maken gebruik van verkoopdata en TCO data. PBL is er zelf ook mee bezig om op dit moment te kijken hoe SP gebruikt kan worden om de beperkingen van het model tegen te gaan. Dit wordt in die zin de concurrent van het Carbontax model.

In die zin zitten er in het Carbontax model vooraf ingestelde elasticiteiten die door verschillende inputs voor verschillende outputs zorgen?

Er wordt geteerd op RDW data dat bestaat uit nieuwverkoopbestanden. Uit deze bestanden haal je inderdaad kostenelasticiteiten. Dit is revealed preference data. Elektrisch rijden is vrij nieuw en er zijn relatief weinig waarnemingen. Daardoor wordt veelal gebruikt gemaakt van TCO analyses. Ik weet niet of je dat een kwetsbaarheid kan noemen. In die zin zou je kunnen zeggen dat het ook op een andere manier kan. Zoals we in dat nieuwe model ook schattingen zullen maken, onder meer op basis van SP onderzoek, dit is een hele andere invalshoek. Er wordt ook wel onderscheid gemaakt tussen 3 verschillende deelmarkten: prive markt, zakelijke markt, private lease. Dat uit zich in het TCO analyses. Voor de niet financiele factoren wordt er rekening gehouden met overstapdrempels zoals nieuwe technologie en actie-radius. Overstapcurves worden hiervoor gebruikt. Er wordt

dus onderscheid gemaakt tussen de financiele TCO analyses en de wat softere eigenschappen. Dat is een beetje in een notendop hoe het model werkt.
Voor de verkiezingsprogrammas is inderdaad gebruik gemaakt van het Carbontax model. Tijdens de doorrekenen van de verkiezingsprogrammas kwamen er net wat andere effecten uit dan uit die BnG studie. Mocht de vlakke heffing zoals deze nu wordt beoogd er inderdaad komen, dan kan je inderdaad forse samenstellingseffecten verwachten. Onder meer een verzwaring van je autopark en dat zwaardere autos er op vooruit gaan. Een gedifferentieerd systeem kan zeer gunstig uitpakken voor elektrische autos, je zal daar een flinke schuif in gaan krijgen.

Hoe worden die indirecte elasticiteiten elk jaar bepaald? Deze worden dus elk jaar opnieuw bepaald op voorgaande verkoopgegevens?

Voor benzine en diesel autos zijn er genoeg verkopen geweest dus die data is goed te gebruiken, maar voor elektrische autos wordt er gebruik gemaakt van de TCO-aanpak, in die zin dus indirecte elasticiteiten. Dat is gefit op actuele data in combinatie met overstapdrempels. Het zijn dus echt indirecte kostenelasticiteiten. Voor elektrische autos zitten geen voorafgeschatte elasticiteiten in die door SP zijn bepaald. Het zou kunnen dat elektrische autos zelf zwaarder worden beprijsd omdat ze nu eenmaal zwaarder zijn maar ook dat hangt af hoe de batterijen e.d. zich gaan ontwikkelen. Het zou ook kunnen dat er gedifferentieerd wordt op basis van CO2-uitstoot. Uit het model komt nu al wel naar voren dat dat grote verschuivingen zal opleveren.

Als laatste notie wil ik je meegeven dat de overheid graag een systeem wilt vormgeven wat ook budgetair neutraal is. Dat is ook iets waar je wel rekening mee moet houden bij het bepalen van prijstarieven. Als je gedifferentieerd gaat beginnen krijg je een afname in autogebruik, dus minder accijnsinkomsten en je krijgt een verschuiving in je wagenpark, dan ga je ook inkomsten verliezen. De overheid wil daar altijd voor corrigeren. Er staat ook in de kleine letters in het regeerakkoord dat ze graag het belastingsniveau op pijl willen houden.

E.2. Results interviews for choice of variables

To choose the variables that were going to be included in the model and thus used for further analysed, expert interviews were done to get an idea of interesting factors. To test these variables, the experts were questioned on their hypothesis. They could choose if they thought the variables had an interaction effect with the FKC attribute. 3 interviews were held. 2 of them are experts on mobility and how pricing policies trigger behaviour. The third is an expert in the FKC specifically. The priority column is stated by the expert to be interesting for including in the model.

Table E.1: Interview results mobility expert 1

Hypotheses of higher sensitivity towards height of the FKC	Transport behaviour expert 1		
	Car fuel-type choice	Mode choice	Priority
Distance to nearest train station	-*	0	x
Income	0	0	x
Age	0	0	
Gender	0	0	
Education	1	1	
Car ownership	0	-*	
Car segment	0	0	
Current fuel type	0	0	
Business cars	1	0	x
Car use	1	1	x
PT (discount) card	0	1	
Trip purpose	0	0	
Commuting mode	1	1	x
Sustainability	0	0	
Car affinity	0	0	

* no significant effect

Table E.2: Interview results mobility expert 2

Hypotheses of higher sensitivity towards height of the FKC	Transport behaviour expert 2		
	Car fuel-type choice	Mode choice	Priority
Distance to nearest train station	-*	0	x
Income	0	0	x
Age	0	0	
Gender	0	0	
Education	1	1	
Car ownership	0	-*	
Car segment	0	0	
Current fuel type	0	0	
Business cars	1	0	x
Car use	1	1	x
PT (discount) card	0	1	
Trip purpose	0	0	
Commuting mode	1	1	x
Sustainability	0	0	
Car affinity	0	0	

* no significant effect

Table E.3: Interview results ministery of I and W

Hypotheses of higher sensitivity towards height of the FKC	Ministery of I and W		
	Car fuel-type choice	Mode choice	Priority
Distance to nearest train station	0	0	x
Income	-	-	x
Age	0	0	
Gender	0	0	
Education	0	0	
Car ownership	0	-*	
Car segment	-*	-*	
Current fuel type	0	0	
Business cars	1	0	
Car use	1	1	x
PT (discount) card	-*	1	
Trip purpose	0	0	
Commuting mode	1	0	
Sustainability	0	0	
Car affinity	0	0	

* no significant effect

F
Car fuel-type choice experiment

F.1. MNL model

MNL basic utility functions

$$V(GV) = ASC_{GV} + \beta_{PP} * PP_{GV} + \beta_{FKC} * FKC_{GV} \tag{F.1}$$

$$V(DV) = ASC_{DV} + \beta_{PP} * PP_{DV} + \beta_{FKC} * FKC_{DV} \tag{F.2}$$

$$V(PHEV) = ASC_{PHEV} + \beta_{PP} * PP_{PHEV} + \beta_{FKC} * FKC_{PHEV} + \beta_{Range} * Range_{PHEV} \tag{F.3}$$

$$V(BEV) = \beta_{PP} * PP_{BEV} + \beta_{FKC} * FKC_{BEV} + \beta_{Range} * Range_{BEV} \tag{F.4}$$

MNL final utility functions

$$\begin{aligned} V(i) = ASC_i + \beta_{PP} * PP_i + \beta_{FKC} * FKC_i + \beta_{Range} * Range_i + (\beta_{FKC} + \beta_{FKC_{Income}} * Income) * FKC_i \\ + (\beta_{FKC} + \beta_{FKC_{Education}} * Education) * FKC_i + (\beta_{FKC} + \beta_{FKC_{Businesscar}} * Businesscar) * FKC_i \\ + (\beta_{FKC} + \beta_{FKC_{CarUse}} * CarUse) * FKC_i \end{aligned} \tag{F.5}$$

F.1.1. MNL model outcomes

Parameter	MNL model			ML model		
	Estimate	s.e.	p-value	Estimate	s.e.	p-value
ASC GV	0.38	0.04	0.00	0.97	0.12	0.00
ASC DV	-1.40	0.05	0.00	-0.93	0.12	0.00
ASC PHEV	-0.18	0.04	0.00	0.48	0.08	0.00
β Purchase price	-0.02	0.00	0.00	-0.03	0.00	0.00
β FKC	-0.99	0.08	0.00	-1.18	0.10	0.00
β Range	0.01	0.00	0.00	0.01	0.00	0.00
β FKC*Income	-1.77	0.46	0.00	-2.04	0.53	0.00
β FKC*Business Car	-2.44	0.79	0.02	-2.10	0.83	0.02
β FKC*Car Use	-0.95	0.44	0.01	-1.42	0.51	0.01
β FKC*Education	-0.56	0.45	0.17*	-1.05	0.69	0.17*
σ Charge				1.21	0.10	0.00
σ ICEV				-2.67	0.10	0.00

Figure F.1: Estimation outcomes MNL & ML model car fuel-type choice experiment

F.2. ML model

This figure represents the outcomes of the basic ML model excluding interaction effects. These factors were used for the application model.

F.2.1. Script ML model

```
### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control = list(
  modelName  ="MLEC_250draw_2",
  modelDescr ="Panel MLEC model Exercise 2",
  indivID    ="ID",
  mixing     = TRUE
)


#### LOAD DATA
database = read.delim("DATA CARTYPE",header=TRUE)

### Vector of parameters, including any that are kept fixed in estimation
apollo_beta=c(ASC_GV = 0,
              ASC_DV = 0,
              ASC_PHEV = 0,
              BETA_FKC = 0,
              BETA_PP = 0,
              BETA_AR = 0,
              BETA_BUSINESS_CAR_FKC = 0,
              BETA_EDUCATION_FKC = 0,
              BETA_INCOME_FKC = 0,
              BETA_CAR_USE_FKC = 0,
              SIGMA_CHARGE = 0,
              SIGMA_ICEV = 0)

### Vector with names (in quotes) of parameters to be kept fixed at their starting value in apollo_beta, use apollo_beta_fixed = c() if none
apollo_fixed = c()

### Set parameters for generating draws
apollo_draws = list(
  interDrawsType = "halton",
  interNDraws    = 250,
  interUnifDraws = c(),
  interNormDraws = c("draws"),
  intraDrawsType = "halton",
  intraNDraws    = 0,
  intraUnifDraws = c(),
  intraNormDraws = c()
)

### Create random parameters
apollo_randCoeff = function(apollo_beta, apollo_inputs){
  randcoeff = list()

  randcoeff[["EC_ICEV_RND"]] =  SIGMA_ICEV * draws
  randcoeff[["EC_CHARGE_RND"]] =  SIGMA_CHARGE * draws


  return(randcoeff)
}


#### GROUP AND VALIDATE INPUTS
apollo_inputs = apollo_validateInputs()


#### DEFINE MODEL AND LIKELIHOOD FUNCTION
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
  V = list()
  V[['GV']]  = ASC_GV + BETA_PP * PP_GV + BETA_FKC * FKC_GV + (BETA_FKC + BETA_INCOME_FKC * INCOME) * FKC_GV + (BETA_FKC + BETA_BUSINESS_CAR_FKC * BUSINESS_CAR)
        * FKC_GV + (BETA_FKC + BETA_CAR_USE_FKC * CAR_USE) * FKC_GV + (BETA_FKC + BETA_EDUCATION_FKC * EDUCATION) * FKC_GV + EC_ICEV_RND + EC_CHARGE_RND
  V[['DV']]  = ASC_DV + BETA_PP * PP_DV + BETA_FKC * FKC_DV + (BETA_FKC + BETA_INCOME_FKC * INCOME) * FKC_DV + (BETA_FKC + BETA_BUSINESS_CAR_FKC * BUSINESS_CAR)
        * FKC_DV + (BETA_FKC + BETA_CAR_USE_FKC * CAR_USE) * FKC_DV + (BETA_FKC + BETA_EDUCATION_FKC * EDUCATION) * FKC_DV + EC_ICEV_RND + EC_CHARGE_RND
  V[['PHEV']]= ASC_PHEV + BETA_PP * PP_PHEV + BETA_FKC * FKC_PHEV + BETA_AR * AR_PHEV + (BETA_FKC + BETA_INCOME_FKC * INCOME) * FKC_PHEV + (BETA_FKC + BETA_BUSINESS_CAR_FKC * BUSINESS_CAR)
        * FKC_PHEV + (BETA_FKC + BETA_CAR_USE_FKC * CAR_USE) * FKC_PHEV + (BETA_FKC + BETA_EDUCATION_FKC * EDUCATION) * FKC_PHEV + EC_CHARGE_RND
  V[['BEV']] = BETA_PP * PP_BEV + BETA_FKC * FKC_BEV + BETA_AR * AR_BEV + (BETA_FKC + BETA_INCOME_FKC * INCOME) * FKC_BEV + (BETA_FKC + BETA_BUSINESS_CAR_FKC * BUSINESS_CAR) * FKC_BEV +
        (BETA_FKC + BETA_CAR_USE_FKC * CAR_USE) * FKC_BEV + (BETA_FKC + BETA_EDUCATION_FKC * EDUCATION) * FKC_BEV + EC_CHARGE_RND

  ### Define settings for MNL model component
  mnl_settings = list(
    alternatives  = c(GV=1, DV=2, PHEV=3, BEV=4),
    avail         = list(GV=1, DV=1, PHEV=1, BEV=1),
    choiceVar     = CHOICE,
    V             = V
  )
```

Figure F.2: Script ML car fuel-type choice experiment

Final ML model outcomes

This figure represents the outcomes of the final ML model including interaction effects.

Parameter	Estimate	s.e.	p-value
ASC GV	0.97	0.12	0.00
ASC DV	-0.93	0.12	0.00
ASC PHEV	0.48	0.08	0.00
β Purchase price	-0.03	0.00	0.00
β FKC	-1.18	0.10	0.00
β Range	0.01	0.00	0.00
β FKC*Income	-2.04	0.53	0.00
β FKC*Business Car	-2.10	0.83	0.02
β FKC*Car Use	-1.42	0.51	0.01
β FKC*Education	-1.05	0.69	0.17*
σ Charge	1.21	0.10	0.00
σ ICEV	-2.67	0.10	0.00

Figure F.3: Outcome ML car fuel-type choice experiment

Correlations between interaction effects
The table only displays relevant correlations that are bigger than 0.15. Note that the correlations found are the correlations for the interaction with a 'negative' FKC. Negative values can therefore be interpreted as a positive correlation. A positive correlation represents the relationship between two variables where if one variable increases, the other included variable increases. A negative correlation shows that if one variable increases, the other decreases.

Table F.1: Correlations (>0.15) car fuel-type experiment

Car fuel-type correlations	Income	Car use	Education	Business car
Income	-	-0.16	-0.49	-
Car use	-0.16	-	0.27	-
Education	-0.49	0.27	-	-
Business car	-	-	-	-

F.2.2. Final model fit of ML vs MNL

The model fit, shown in the form of the Log-Likelihood (0 and Final) and McFadden's rho-square (ρ^2), is given in Table F.2, (for more information, see Section 4.2.3. The model fit for the MNL is also included to display the big difference in the ρ^2 value.

Table F.2: Final Model fit ML & MNL

Model Fit	**ML**	**MNL**
LL(0)	-2750.41	-2750.41
LL(C)	-2472.36	-2472.36
LL(final)	-2021.55	-2468.91
Rho-square	*0.265*	*0.156*

F.2.3. Utility contribution of interaction parameters

Table F.3: Utility contribution car fuel type choice interaction parameters

Attribute	**Est.**	**Min. Level**	**Max. level**	**Utility contribution**
FKC*Income	-2.04	0	1	-0.64
FKC*Business Car	-2.10	0	1	-0.65
FKC*Car Use	-1.42	0	1	-0.52
FKC*Education	-1.05	0	1	-0.45

G
Mode choice experiment

G.1. MNL script

In this section, the script that was used in R is presented.

```
### Load Apollo library
library(apollo)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control = list(
  modelName  ="MNL_1",
  modelDescr ="MNL model Exercise 1",
  indivID    ="ID"
)

#### LOAD DATA
database = read.delim("DATA75",header=TRUE)


### Vector of parameters, including any that are kept fixed in estimation
apollo_beta=c(ASC_TRAIN = 0,
              BETA_TT = 0,
              BETA_TC = 0,
              BETA_TC_INCOME = 0,
              BETA_TC_BUSINESS_CAR = 0,
              BETA_TC_DIST_TRAIN = 0,
              BETA_TC_PT_CARD = 0,
              BETA_TC_AGE = 0,
              BETA_TC_COMMUTE = 0,
              BETA_TC_CAR_USE)

### Vector with names (in quotes) of parameters to be kept fixed at their starting value in apollo_beta, use apollo_beta_fixed = c() if none
apollo_fixed = c()


#### GROUP AND VALIDATE INPUTS
apollo_inputs = apollo_validateInputs()


#### DEFINE MODEL AND LIKELIHOOD FUNCTION

apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
  V = list()
  V[['TRAIN']]  =  ASC_TRAIN + TRAIN_TT * BETA_TT_TRAIN + TRAIN_TC * BETA_TC_TRAIN
  V[['CAR']]    = CAR_TC * BETA_TC + CAR_TT * BETA_TT_CAR + (BETA_TC + BETA_TC_INCOME * INCOME) * CAR_TC +
                (BETA_TC + BETA_TC_AGE * AGE* CAR_TC + (BETA_TC + BETA_TC_CAR_USE * CAR_USE) * CAR_TC +
                (BETA_TC + BETA_TC_BUSINESS_CAR * BUSINESS_CAR) * CAR_TC  + (BETA_TC + BETA_TC_DIST_TRAIN * DIST_TRAIN) * CAR_TC +
                (BETA_TC + BETA_TC_PT_CARD * PT_CARD) * CAR_TC + (BETA_TC + BETA_TC_CAR_COMMUTE * CAR_COMMUTE) * CAR_TC

  ### Define settings for MNL model component
  mnl_settings = list(
    alternatives  = c(TRAIN=1, CAR=2),
    avail         = list(TRAIN=1, CAR=1),
    choiceVar     = CHOICE,
    V             = V
  )
```

Figure G.1: MNL script mode choice experiment

G.1.1. Basic utility functions MNL model

To translate the decisions made considering the ASCs and ASPs, the following utility functions are determined. These utility functions do not include interaction effects.

$$V(Train/Bike) = ASC_{Train/Bike} + \beta_{TC} * TC_{Train/Bike} + \beta_{TT} * TT_{Train/Bike} \quad (G.1)$$

$$V(Car) = \beta_{TC} * TC_{Car} + \beta_{TT} * TT_{Car} \quad (G.2)$$

G.2. Outcomes

This section shows the outcomes of the MNL models for all four distances. It includes the final model with interaction effects and the MNL model outcomes with only the main parameters included.

G.2.1. Final MNL model outcome

Parameters	**5 km**			**25 km**			**75 km**			**200 km**		
	Est.	**s.e.**	**p-value**	**Est.**	**s.e.**	**p-value**	**Est.**	**s.e.**	**p-value**	**Est.**	**s.e.**	**p-value**
ASC Bike	0.60	0.26	0.01	-	-	-	-	-	-	-	-	-
ASC Train	-	-	-	-3.80	0.36	0.00	-3.86	0.41	0.00	-2.54	0.10	0.00
β Travel Costs	-0.16	0.19	0.01	-0.08	0.01	0.00	-0.02	0.01	0.00	-0.01	0.01	0.00
β Travel Time	-0.03	0.02	0.03	-0.03	0.02	0.00	-0.03	0.01	0.00	-0.02	0.00	0.00
β FKC*Dist. to train	0.46	0.18	0.03	0.06	0.04	0.26*	0.03	0.02	0.11*	0.02	0.00	0.04
β FKC*Income	0.02	0.18	0.39*	0.00	0.04	0.46*	0.01	0.02	0.31*	0.01	0.00	0.04
β FKC*PT card	-0.30	0.24	0.22*	-0.17	0.04	0.00	-0.08	0.02	0.00	-0.01	0.01	0.01
β FKC*Business car	0.79	0.27	0.01	0.05	0.06	0.24*	0.04	0.02	0.07*	0.01	0.01	0.06*
β FKC*Education	-0.05	0.13	0.32*	-0.13	0.02	0.01	-0.06	0.01	0.00	-0.02	0.00	0.00
β FKC*Commute	1.29	0.22	0.00	0.16	0.04	0.00	0.02	0.02	0.02	0.01	0.00	0.01
β FKC*Age	-0.01	0.01	0.09*	0.00	0.00	0.08	0.00	0.00	0.27*	0.00	0.00	0.03
β FKC*Car use	0.73	0.24	0.01	0.06	0.05	0.14*	0.05	0.02	0.01	-0.01	0.01	0.14*
Model fit												
LL(0)	-651.56			-651.56			-651.56			-651.56		
LL(C)	-616.25			-388.57			-392.10			-578.39		
LL(final)	-569.83			-333.42			-328.73			-424.46		
ρ^2	0.13			0.49			0.50			0.35		

* Not significant at a 95% confidence interval

Table G.1: tab:Mode choice utility contributions interaction effects

G.2.2. MNL model without interaction effects

Table G.2: MNL model outcomes without interaction effects.

Parameters	**5 km**			**25 km**			**75 km**			**200 km**		
	Est.	**s.e.**	**p-value**	**Est.**	**s.e.**	**p-value**	**Est.**	**s.e.**	**p-value**	**Est.**	**s.e.**	**p-value**
ASC Bike	0.68	0.26	0.00	-	-	-	-	-	-	-	-	-
ASC Train	-	-	-	-1.40	0.13	0.00	-1.37	0.13	0.00	-1.05	0.10	0.00
β Travel Costs	-0.21	0.20	**0.18**	-0.54	0.08	0.00	-0.17	0.03	0.00	-0.06	0.01	0.00
β Travel Time	-0.03	0.02	0.03	-0.04	0.02	0.01	-0.03	0.01	0.01	-0.01	0.00	0.00
LL(0)	-651.56			-651.56			-651.56			-651.56		
LL(C)	-616.25			-388.57			-392.10			-578.39		
LL(final)	-615.29			-361.29			-362.37			-447.03		
Rho-square	0.06			0.45			0.44			0.31		

Table G.4: Utility contribution mode choice interaction parameters

Interaction parameter	Min. Level	Max. level	Utility contribution 5 km	25 km	75 km	200 km
β TC*Distance to train	0	1	0.46	0.30	0.45	0.80
β TC*Income	0	1	0.02	-0.01	0.19	0.27
β TC*Public Transport card	0	1	-0.30	-0.86	-1.26	-0.56
β TC*Business Car	0	1	0.79	0.25	0.60	0.44
β TC*Education	0	1	-0.05	-0.65	-0.90	-0.80
β TC*Commute	0	1	1.29	0.79	0.29	0.40
β TC*Age	19	80	-0.88	0.69	0.40	0.73
β TC*Car Use	0	1	0.73	0.28	0.80	-0.24

G.3. Utility contributions

Table G.3: Utility contributions of interaction effects

	Utility contribution *5 km*	*25 km*	*75 km*	*200 km*	*Average*
Distance to train	10%	9%	9%	19%	*11%*
Income	0%	0%	4%	6%	*3%*
PT card	7%	24%	26%	13%	*17%*
Business Car	18%	7%	12%	10%	*12%*
Eucation	1%	18%	18%	19%	*14%*
Commute	28%	22%	6%	9%	*16%*
Age	20%	20%	8%	17%	*16%*
Car Use	16%	8%	16%	6%	*11%*

Utility contribution interaction effects
A graphical representation of mode choice utility contributions

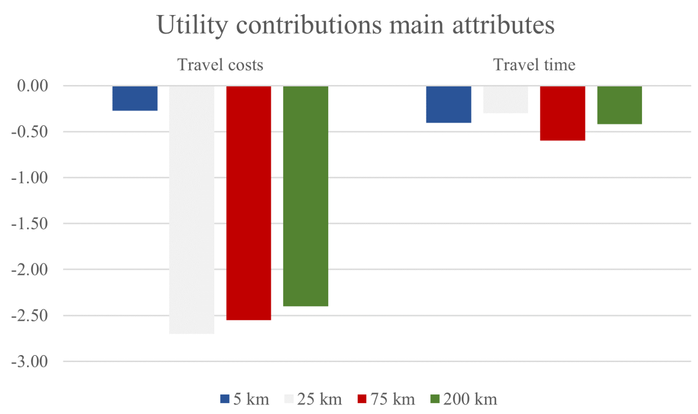


Figure G.2: Utility contribution mode choice attributes

G.4. Correlations between interaction effects

The table below shows the correlations between all interaction effects. The correlations per distance are shown in a chronological order, from 5 km to 200 km. The table only displays relevant correlations that are bigger than 0.15. Note that the correlations found are the correlations for the interaction with a 'negative' FKC. Negative values can therefore be interpreted as a positive correlation. A positive correlation represents the relationship between two variables where if one variable increases, the other included variable increases. A negative correlation shows that if one variable increases, the other decreases.

Table G.5: Correlations (>0.15) mode choice experiment

5 km	Income	Commute	Car use	Education	Business car	PT Card	Age	Dist to train
Income	-	-	-	-	-	-	-	-
Commute	-	-	-0.21	-	-	-	-	-
Car use	-	-0.21	-	0.27	-	-	-	-
Education	-	-	0.27	-	-	-	-	-
Business car	-	-	-	-	-	-	0.16	-
PT Card	-	-	-	-	-	-	-	-
Age	-	-	-	-	0.16	-	-	-
Dist to train	-	-	-	-	-	-	-	-

25 km	Income	Commute	Car use	Education	Business car	PT Card	Age	Dist to train
Income	-	-	-	-	-	-	-	-
Commute	-	-	-0.32	-	-	-	-	-
Car use	-	-0.32	-	-	-	-	-	-
Education	-	-	-	-	-	-	-	-
Business car	-	-	-	-	-	-0.15	0.15	-
PT Card	-	-	-	-	-0.15	-	-	-
Age	-	-	-	-	0.15	-	-	-
Dist to train	-	-	-	-	-	-	-	-

75 km	Income	Commute	Car use	Education	Business car	PT Card	Age	Dist to train
Income	-	-	-	-0.16	-	-	-	-
Commute	-	-	-0.31	-	-	-	0.18	-
Car use	-	-0.31	-	-	-	-	0.17	-
Education	-0.16	-	-	-	-	-	-	-
Business car	-	-	-	-	-	-0.21	-	-
PT Card	-	-	-	-	-0.21	-	-	-
Age	-	0.18	0.17	-	-	-	-	-
Dist to train	-	-	-	-	-	-	-	-

200 km	Income	Commute	Car use	Education	Business car	PT Card	Age	Dist to train
Income	-	-	-	-0.16	-	-	-	-
Commute	-	-	-0.31	-	-	-	0.18	-
Car use	-	-0.36	-	-	-	-	0.17	-
Education	-0.16	-	-	-	-	-	-	-
Business car	-	-	-	-	-	-0.15	0.17	-
PT Card	-	-	-	-	-0.15	-	-	-
Age	-	0.18	0.17	-	0.17	-	-	-
Dist to train	-	-	-	-	-	-	-	-

H

Results integration phase

In this appendix, some more elaboration is given on the found results. The base case, where a uniform charge is applied of 6.2 eurocent, consist of important metrics. In this section we'll review some of the information found in order to evaluate the forecasting quality of SP data.

H.1. Approach integration phase

For the set up of this integration phase, the Rijksdienst voor Ondernemen and Revnext (2018); MuConsult and Ministerie van Financien (2020); Kennisinstituut Mobiliteit (2008); Revnext (2019) were used as inspiration. This is a new model as there is no research yet that combines car fuel type choice and mode choice in this way. The green circled box represents the input of the pricing scheme. The yellow box represent the outcomes that were shown in the tables.

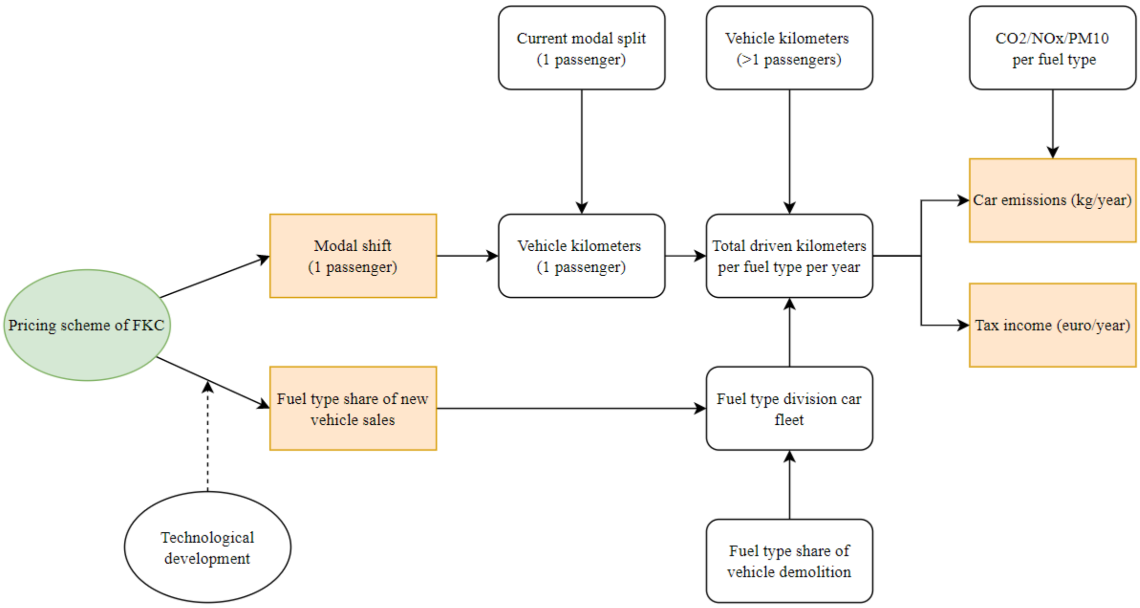


Figure H.1: Set up integration phase

H.2. Outcomes base case - Uniform charge

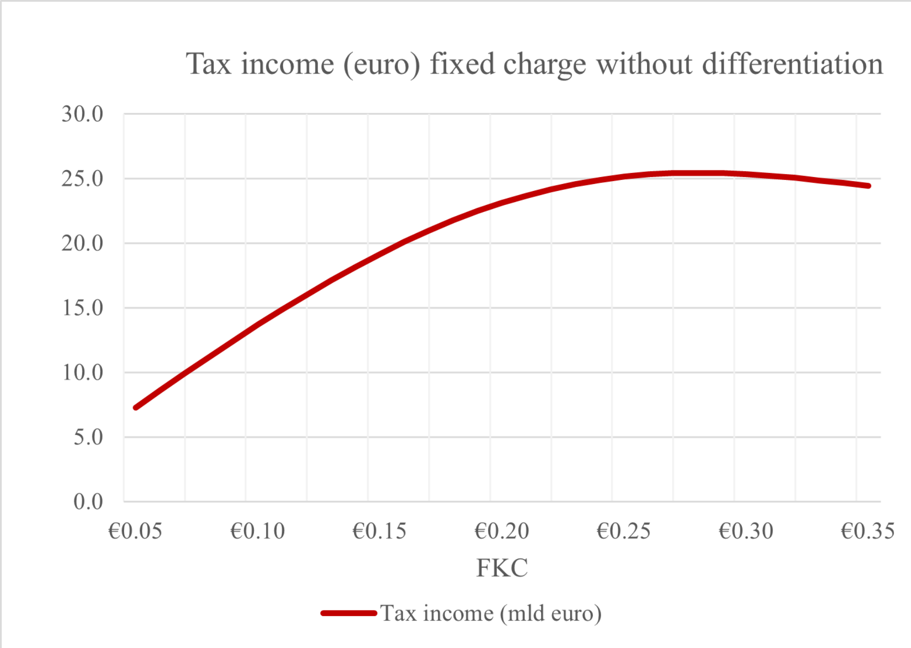


Figure H.2: Tax income uniform charge

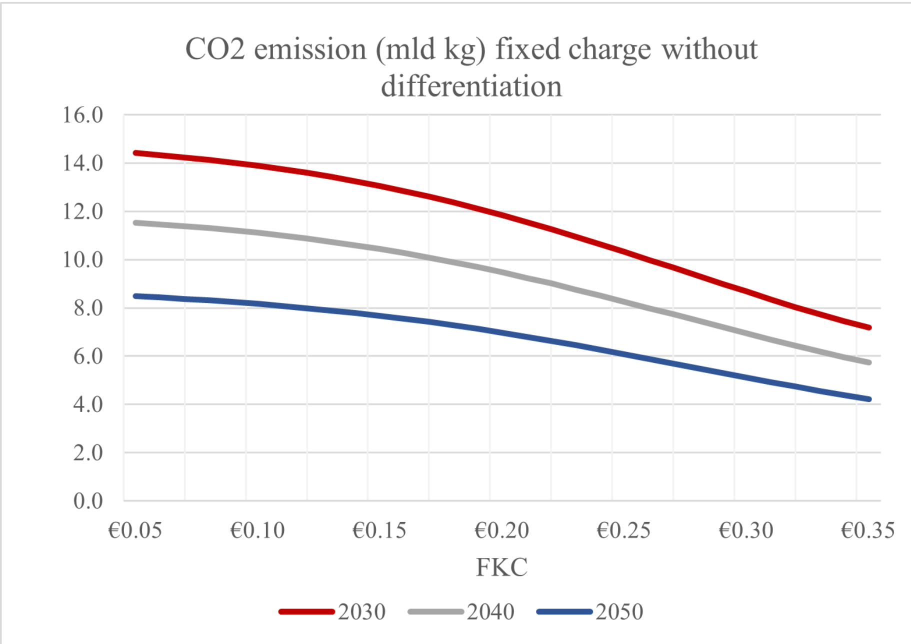


Figure H.3: Tax income uniform charge

H.3. Expected technological development

H.4. In- and outflow car-fleet

The tables below represent the in - and outflows of the cars. It is based on Rijksdienst voor Ondernemen and Revnext (2018). For the ease of modelling the outlfow of EV's, which was unavailable per car fuel type, was set to zero for the first ten years. As the average car life cycle is 18 years and the most EVs have not been operational on the road that long yet (Held et al., 2021).

Table H.1: In- and outflow cars

Inflow					
Year	**Total inflow**	**GV**	**DV**	**PHEV**	**BEV**
2022	350.000	248.500	10.500	14.000	77.000
2023	350.000	248.500	10.500	14.000	77.000
2024	350.000	248.500	10.500	14.000	77.000
2025	350.000	248.500	10.500	14.000	77.000
2026	350.000	248.500	10.500	14.000	77.000
2027	350.000	248.500	10.500	14.000	77.000
2028	350.000	248.500	10.500	14.000	77.000
2029	350.000	248.500	10.500	14.000	77.000
2030	350.000	179.315	20.712	101.253	48.719
2031	350.000	179.315	20.712	101.253	48.719
2032	350.000	179.315	20.712	101.253	48.719
2033	350.000	179.315	20.712	101.253	48.719
2034	350.000	179.315	20.712	101.253	48.719
2035	350.000	179.315	20.712	101.253	48.719
2036	350.000	179.315	20.712	101.253	48.719
2037	350.000	179.315	20.712	101.253	48.719
2038	350.000	179.315	20.712	101.253	48.719
2039	350.000	179.315	20.712	101.253	48.719
2040	350.000	156.668	18.097	100.157	75.078
2041	350.000	156.668	18.097	100.157	75.078
2042	350.000	156.668	18.097	100.157	75.078
2043	350.000	156.668	18.097	100.157	75.078
2044	350.000	156.668	18.097	100.157	75.078
2045	350.000	156.668	18.097	100.157	75.078
2046	350.000	156.668	18.097	100.157	75.078
2047	350.000	156.668	18.097	100.157	75.078
2048	350.000	156.668	18.097	100.157	75.078
2049	350.000	156.668	18.097	100.157	75.078
2050	350.000	156.668	18.097	100.157	75.078

Outflow					
Year	**Total outflow**	**GV**	**DV**	**PHEV**	**BEV**
2022	350.000	315.000	35.000	0	0
2023	350.000	315.000	35.000	0	0
2024	350.000	315.000	35.000	0	0
2025	350.000	315.000	35.000	0	0
2026	350.000	315.000	35.000	0	0
2027	350.000	315.000	35.000	0	0
2028	350.000	315.000	35.000	0	0
2029	350.000	315.000	35.000	0	0
2030	350.000	297.500	39.900	4.550	8.050
2031	350.000	297.500	39.900	4.550	8.050
2032	350.000	297.500	39.900	4.550	8.050
2033	350.000	297.500	39.900	4.550	8.050
2034	350.000	297.500	39.900	4.550	8.050
2035	350.000	297.500	39.900	4.550	8.050
2036	350.000	297.500	39.900	4.550	8.050
2037	350.000	297.500	39.900	4.550	8.050
2038	350.000	297.500	39.900	4.550	8.050
2039	350.000	297.500	39.900	4.550	8.050
2040	350.000	297.500	39.900	4.550	8.050
2041	350.000	297.500	39.900	4.550	8.050
2042	350.000	297.500	39.900	4.550	8.050
2043	350.000	297.500	39.900	4.550	8.050
2044	350.000	297.500	39.900	4.550	8.050
2045	350.000	297.500	39.900	4.550	8.050
2046	350.000	297.500	39.900	4.550	8.050
2047	350.000	297.500	39.900	4.550	8.050
2048	350.000	297.500	39.900	4.550	8.050
2049	350.000	297.500	39.900	4.550	8.050
2050	350.000	297.500	39.900	4.550	8.050

Table H.2: Car fleet compostion development

Car fleet composition				
Year	**GV**	**DV**	**PHEV**	**BEV**
2022	7.328.500	967.300	127.100	277.100
2023	7.262.000	942.800	141.100	354.100
2024	7.195.500	918.300	155.100	431.100
2025	7.129.000	893.800	169.100	508.100
2026	7.062.500	869.300	183.100	585.100
2027	6.996.000	844.800	197.100	662.100
2028	6.929.500	820.300	211.100	739.100
2029	6.863.000	795.800	225.100	816.100
2030	6.744.815	776.612	321.803	856.769
2031	6.626.631	757.424	418.507	897.438
2032	6.508.446	738.236	515.210	938.107
2033	6.390.262	719.048	611.914	978.776
2034	6.272.077	699.860	708.617	1.019.446
2035	6.153.892	680.672	805.321	1.060.115
2036	6.035.708	661.485	902.024	1.100.784
2037	5.917.523	642.297	998.727	1.141.453
2038	5.799.338	623.109	1.095.431	1.182.122
2039	5.681.154	603.921	1.192.134	1.222.791
2040	5.540.321	582.118	1.287.741	1.289.819
2041	5.399.489	560.315	1.383.348	1.356.848
2042	5.258.656	538.513	1.478.955	1.423.876
2043	5.117.824	516.710	1.574.562	1.490.904
2044	4.976.991	494.907	1.670.169	1.557.932
2045	4.836.159	473.104	1.765.776	1.624.960
2046	4.695.326	451.302	1.861.383	1.691.989
2047	4.554.494	429.499	1.956.990	1.759.017
2048	4.413.662	407.696	2.052.597	1.826.045
2049	4.272.829	385.893	2.148.204	1.893.073
2050	4.131.997	364.091	2.243.811	1.960.101

H.5. Scenario results

H.5.1. Scenario 2: Differentiation to fuel type

For the differentiation to fuel type, three schemes were set up: a low, medium and high differentiated schemes. The exact charges can be found in Table 9.2. These charges led to the following passenger kilometers distributions which can be converted into the results displayed in Section 9.3.

Next table shows the modal shift for the low, medium, high scenarios.

Table H.3: Modal shift of scenarios 2a,2b,2c

2a. Modal share 1p trips	**2022**	**2030**	**2040**	**2050**
Car	88%	89%	89%	89%
Bike and train	12%	11%	11%	11%

2b. Modal share 1p trips	**2022**	**2030**	**2040**	**2050**
Car	87%	88%	88%	88%
Bike and train	13%	12%	12%	12%

2c. Modal share 1p trips	**2022**	**2030**	**2040**	**2050**
Car	86%	86%	87%	88%
Bike and train	14%	14%	13%	12%

Next table shows the car fleet characteristics development for the low, medium, high scenarios.

Table H.4: Car fleet shares

2a	GV	DV	PHEV	BEV
2022	85%	11%	1%	2%
2030	77%	9%	4%	10%
2040	63%	7%	15%	15%
2050	46%	4%	26%	24%

2b	GV	DV	PHEV	BEV
2022	85%	11%	1%	2%
2030	77%	9%	4%	10%
2040	63%	7%	15%	16%
2050	45%	4%	26%	25%

2c	GV	DV	PHEV	BEV
2022	85%	11%	1%	2%
2030	77%	9%	4%	10%
2040	62%	6%	15%	17%
2050	44%	4%	26%	26%

Scenario 2a. Low

Table H.5: Passenger kilometers scenario 2a. low

km	**mld kilometer**	**2022**	**2030**	**2040**	**2050**
5	**Total km**	**6.33**	**6.33**	**6.33**	**6.33**
	Total bike	3.93	3.93	3.92	3.92
	Total car (1p)	2.4	2.4	2.4	2.4
	GV	*2.0*	*1.9*	*1.5*	*1.1*
	DV	*0.3*	*0.2*	*0.1*	*0.0*
	PHEV	*0.0*	*0.1*	*0.4*	*0.6*
	BEV	*0.1*	*0.2*	*0.4*	*0.6*
25	**Total km**	**31.20**	**31.20**	**31.20**	**31.20**
	Total train	1.42	1.37	1.31	1.23
	Total car (1p)	29.8	29.8	29.9	30.0
	GV	*25.4*	*23.1*	*18.7*	*13.5*
	DV	*3.3*	*2.6*	*1.6*	*0.6*
	PHEV	*0.4*	*1.1*	*4.6*	*7.9*
	BEV	*0.7*	*3.0*	*5.0*	*8.0*
75	**Total km**	**37.91**	**37.91**	**37.91**	**37.91**
	Total train	2.54	2.46	2.35	2.84
	Total car (1p)	35.4	35.5	35.6	35.1
	GV	*30.2*	*27.5*	*22.2*	*16.0*
	DV	*3.9*	*3.0*	*1.9*	*0.7*
	PHEV	*0.5*	*1.3*	*5.5*	*9.4*
	BEV	*0.8*	*3.6*	*6.0*	*9.0*
200	**Total km**	**35.38**	**35.38**	**35.38**	**35.38**
	Total train	5.08	4.95	4.76	4.54
	Total car (1p)	30.3	30.4	30.6	30.8
	GV	*25.9*	*23.6*	*19.1*	*13.7*
	DV	*3.3*	*2.5*	*1.6*	*0.6*
	PHEV	*0.4*	*1.2*	*4.7*	*8.2*
	BEV	*0.7*	*3.2*	*5.3*	*8.4*

Scenario 2b. Medium

Table H.6: Passenger kilometers scenario 2b. medium

km	mld kilometer	2022	2030	2040	2050
5	**Total km**	**6.33**	**6.33**	**6.33**	**6.33**
	Total bike	3.95	3.94	3.93	3.92
	Total car (1p)	2.4	2.4	2.4	2.4
	GV	*2.0*	*1.8*	*1.4*	*1.0*
	DV	*0.3*	*0.2*	*0.1*	*0.0*
	PHEV	*0.0*	*0.1*	*0.4*	*0.6*
	BEV	*0.1*	*0.3*	*0.5*	*0.8*
25	**Total km**	**31.20**	**31.20**	**31.20**	**31.20**
	Total train	1.65	1.57	1.44	1.29
	Total car (1p)	29.5	29.6	29.8	29.9
	GV	*25.2*	*22.9*	*17.9*	*12.2*
	DV	*3.3*	*2.5*	*1.5*	*0.5*
	PHEV	*0.4*	*1.1*	*4.6*	*7.8*
	BEV	*0.7*	*3.1*	*5.7*	*9.4*
75	**Total km**	**37.91**	**37.91**	**37.91**	**37.91**
	Total train	2.92	2.79	2.57	2.97
	Total car (1p)	35.0	35.1	35.3	34.9
	GV	*29.8*	*27.1*	*21.2*	*14.5*
	DV	*3.9*	*3.0*	*1.8*	*0.6*
	PHEV	*0.5*	*1.3*	*5.5*	*9.3*
	BEV	*0.8*	*3.7*	*6.8*	*10.6*
200	**Total km**	**35.38**	**35.38**	**35.38**	**35.38**
	Total train	5.74	5.50	5.12	4.68
	Total car (1p)	29.6	29.9	30.3	30.7
	GV	*25.3*	*23.0*	*18.0*	*12.3*
	DV	*3.2*	*2.4*	*1.5*	*0.5*
	PHEV	*0.4*	*1.2*	*4.7*	*8.1*
	BEV	*0.7*	*3.2*	*6.0*	*9.9*

Scenario 2c. High

Table H.7: Passenger kilometers scenario 2c. high

km	mld kilometer	2022	2030	2040	2050
5	**Total km**	**6.33**	**6.33**	**6.33**	**6.33**
	Total bike	3.97	3.96	3.94	3.92
	Total car (1p)	2.4	2.4	2.4	2.4
	GV	*2.0*	*1.8*	*1.4*	*0.9*
	DV	*0.3*	*0.2*	*0.1*	*0.0*
	PHEV	*0.0*	*0.1*	*0.4*	*0.6*
	BEV	*0.1*	*0.3*	*0.5*	*0.9*
25	**Total km**	**31.20**	**31.20**	**31.20**	**31.20**
	Total train	1.93	1.80	1.58	1.33
	Total car (1p)	29.3	29.4	29.6	29.9
	GV	*24.9*	*22.6*	*17.2*	*10.9*
	DV	*3.2*	*2.5*	*1.5*	*0.4*
	PHEV	*0.4*	*1.1*	*4.5*	*7.6*
	BEV	*0.7*	*3.2*	*6.4*	*10.9*
75	**Total km**	**37.91**	**37.91**	**37.91**	**37.91**
	Total train	3.36	3.16	2.80	3.07
	Total car (1p)	34.5	34.8	35.1	34.8
	GV	*29.5*	*26.7*	*20.3*	*12.9*
	DV	*3.8*	*2.9*	*1.7*	*0.5*
	PHEV	*0.5*	*1.3*	*5.4*	*9.1*
	BEV	*0.8*	*3.8*	*7.7*	*12.3*
200	**Total km**	**35.38**	**35.38**	**35.38**	**35.38**
	Total train	6.46	6.11	5.49	4.77
	Total car (1p)	28.9	29.3	29.9	30.6
	GV	*24.7*	*22.4*	*17.0*	*10.8*
	DV	*3.1*	*2.4*	*1.4*	*0.4*
	PHEV	*0.4*	*1.2*	*4.7*	*7.9*
	BEV	*0.7*	*3.4*	*6.8*	*11.5*

H.5.2. Scenario 3: High segment market share

This research contained no experiment testing the effect of pricing schemes on different car segments. To get an idea of how the car segments would react, the price elasticities used by Revnext (2019) were used, see figure below. As car use in passenger km decreases due to the implementation FKC, so does the passenger km of the high car segment. On top of that, when applying a car segment price differentiated scheme,scenario 3a and 3b, lead to an extra decrease of 9.8% for the D and E+ segment(10% segment D, 9.4% segment E+). Again, car adoption or exchange does not go overnight and an average car exchange period of 15 years was used.

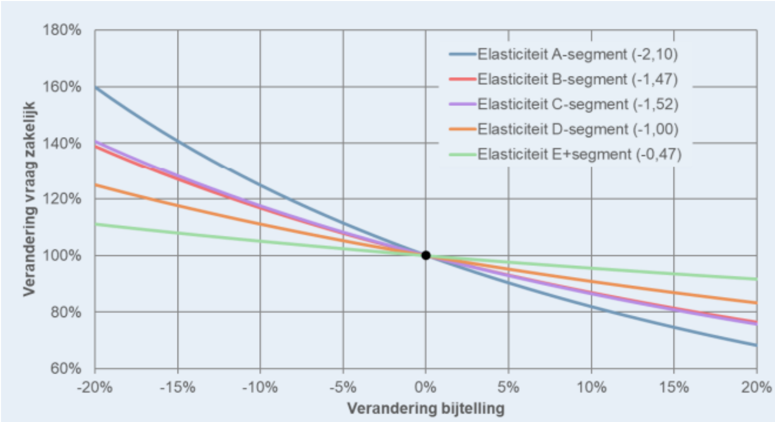


Figure H.4: Elasticities car segments Revnext (2019)

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Contact Data

Table I.1: Graduation committee contacts

Role	Contact	Institution	E-mail
Chairman	Prof.dr. G.P. (Bert) van Wee	TPM	G.P.vanWee@tudelft.nl
1st supervisor	Dr. E.J.E. (Eric) Molin	TPM	E.J.E.Molin@tudelft.nl
2nd supervisor	Dr. O. (Oded) Cats	CITG	o.cats@tudelft.nl
External supervisor	L.(Luuc) van Tiel	Rebel	Luuc.vanTiel@rebelgroup.com

J Report Outline

Figure J.1 shows the planning of this research. The planning consists of 4 body parts; the Literature, survey conduction, discrete choice modelling and quantitative modeling. After the kick-off meeting on the 15th of January, the research beholds exactly 24 weeks(6 months) up until the Final Presentation & Defense.

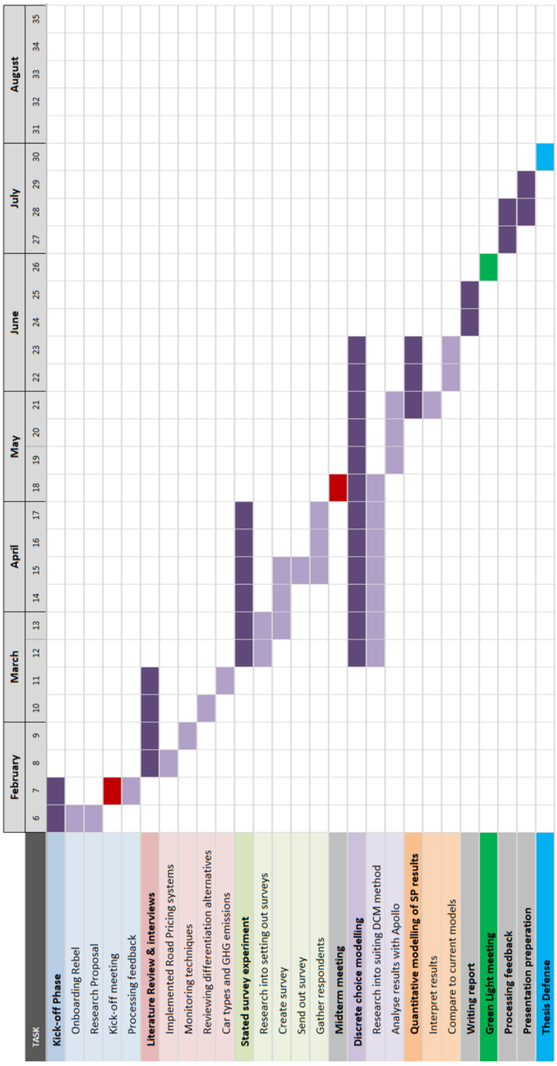

Figure J.1: Planning

Investigating the behavioural impact of a price-differentiated kilometer charge

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Abstract

This paper investigates the kilometer charge and the potential effects of emission-based differentiation, how this policy is supported among Dutch citizens and how it affects different groups. It investigates the behavioural change caused by the new policy using Dutch stated preference discrete choice data. Two stated choice experiments are performed, one exploring the demand for privately used alternative fuel vehicles and one on the modal shift for one-person trips with varying distances. A mixed logit model was applied to determine to what extent specific groups were price-sensitive to the kilometer charge. We find that well-educated,high-income people, who either frequently use their car or own a business car, are more incentivised by the kilometer charge to purchase alternative fuel vehicles. In general, people value purchase prices over the kilometer charge and range. Moreover, it turns out that these groups are willing to purchase a substantially more expensive car in exchange for a lower variable kilometer charge. By applying a multinomial logit model for all distances in the mode choice experiment, we find that the least sensitive group towards the kilometer charge for a modal shift are high-educated, older, commuting car users that live relatively far away from the nearest train station. Furthermore, the larger the travel distance, the higher The value of travel time savings ranges from €4.44 - €14.00 for distances including train and car whilst small city trips with bike and car as mode alternatives have a value of €6.86. The found behavioural effects were used to evaluate the impact of constructed scenarios with varying tariffs for the kilometer charge, ultimately showing that an emission-based differentiation can positively affect tax income and emission savings. Besides that, this implementation form is the most supported by the Dutch population. In addition to these substantial insights, this paper makes a contribution by showing how stated preference discrete choice data can enhance the decision-making of such pricing policies.

Keywords: Road pricing, Kilometer charge, Differentiation, Stated Preference experiment, Mode choice, Car fuel-type choice, Survey, Tax income, Emissions, Modal shift

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1 Background

The emergence of cars has immensely impacted life as we know it today. A world without access to a car is unimaginable for many people, and their lives even depend on this. In the Netherlands, fixed costs of owning a car partly consist of the motor vehicle tax, in Dutch: 'Motorrijtuigenbelasting' (MRB). The MRB is a monthly fee that a car owner pays per car as financial support to the Dutch government for operating and maintaining the road infrastructure. One of the new plans made by the Dutch government is the implementation of the '*Pay according to Use*', or in Dutch: *'Betalen naar Gebruik'* system, also referred to as road pricing (Coalitieakkoord, 2021). This measure indicates that car use will be priced according to usage. Road pricing is an umbrella term that can be implemented in multiple forms. The Dutch government now opts for a Fixed Kilometer Charge (FKC), a new system that has not yet been implemented anywhere. An FKC is a form of road pricing where all road users pay a standardised or differentiated price for every kilometer they drive, no matter the time or place.

Change in people's travel behaviour resulting from this new form of road pricing could impact the characteristics of the national car fleet (car fuel-type choice behaviour) and overall car-use (mode choice behaviour) (Wegener, 2004; Weis et al., 2010). Therefore, the FKC could potentially stimulate a modal shift to greener fuel groups and alternative modes, positively contributing to climate change (Gibson and Carnovale, 2015). The literature considered in this thesis has focused on different road pricing systems and what methods/models were used to derive these estimated effects. Additionally, the review focused on the structure and designs of currently existing models and the types of effects that were measured in the consulted literature. This information was needed to build a theoretical framework that could describe how the experiments were structured.

The coalition agreement states that sustaining sufficient tax income is the primary goal due to decreasing fuel taxes. A secondary goal is the positive effect on car emissions such as CO_2, NO_x and PM_{10} that the kilometer charge is expected to have. At this moment, the government has presented its plan to implement the FKC, but it is yet unknown how the system will be designed in terms of differentiation among users. This design is decisive for its final effects as different implementations are expected to have other effects on different people. Hence, based on the choice for an FKC and the societal relevance and impact of such a policy, it is necessary to understand how these new policies, and their implementation, will affect society and car mobility. One implementation-related decision yet to be made is the choice of a uniform or emission-based differentiated charge. The examined literature includes no study on the effects of this form of price differentiation on the FKC. Consulted literature on other types of road pricing did include this aspect, but for the FKC, relatively limited information was available. Another problem with new policies is the absence of empirical data to measure the impact policies will have. Dutch research institutions now use modelling techniques that include Revealed Preference (RP) data which rely on vehicle selling data. The choices of available fuel-type have become more complex, causing a problem with the validity of that data. The current data primarily consists of choices for conventional vehicles such as gasoline or diesel. On top of that, RP data contains multicollinearity issues, and measuring the attribute parameter estimation of the alternatives present in that decision remains challenging. In the literature, no study addressed these problems and/or using other data types, whilst the review also showed that other data types are suitable.

Two research objectives are set based on the aforementioned issues. One, this research aims to enhance the validity of forecasting policy effects. Two, this research aims to increase knowledge on the impact of a differentiated pricing scheme of the FKC. Based on these two research objectives, the following research - and sub-question has been defined:

Main research question: *To what extent does the level of price-differentiation of a kilometer charge influence people's stated behaviour towards mode choice and car fuel-type choice and what are the resulting effects?*

Sub-question: *What is the difference between groups, based on socio-demographics, in car fuel-type and mode choice behaviour that results from different pricing schemes of a kilometer charge?*

To achieve the research objective set in the previous paragraph, people's Stated Preferences (SP) for different pricing designs were obtained. People's choices in hypothetical situations can be obtained through an SP experiment. The SP data gathered in this experiment can then be modelled using Discrete Choice Modelling (DCM). DCM can estimate the effect, or weight, of pre-defined attributes of the alternatives provided in the choice situation. Two such experiments were performed; one for **car fuel-type choice behaviour** and one for **mode choice behaviour**. The obtained results from these models were then integrated into a model capable of measuring the effect of several differentiated FKC schemes. With this approach, both research objectives could be tackled, and the research questions can be answered.

This article is organized as follows: Section 2 presents the theoretical framework and specification of the models; Section 3 introduces the data collection and survey design; Section 4 presents the estimation results of the models and the key findings; The last section gives the drawn conclusions discusses the limitations.

1.1 Literature overview

The previous section described the relevance of the fixed charge policy and that such implementations require the best estimations possible to enhance decision-making. This section will give an overview of the available literature regarding this subject. Previous studies have looked primarily into the effects of road pricing policies on *mode-choice behaviour* and *car fuel-type choice behaviour*. Additionally, these explanatory variables are used to explain effects in a more tangible output such as income or emissions. There is also a variety in the methods that are used. Widely studied road-pricing types found are Cordon Charging (CC), Peak Charging (PC), Fixed kilometer Charging (FKC) & High Occupancy Toll Charging (HOT). Many studies (Gibson and Carnovale (2015); Xie (2013); Burris and Pendyala (2002); Percoco (2013, 2014); Levinson (2010); Krabbenborg et al. (2021); Olszewski and Xie (2002); Geurs and Van den Brink (2005); Olszewski and Xie (2005); Yamamoto et al. (2000); Leape (2006); Toye (2007) focus on CC, PC & HOT roads because these systems have already been implemented and measuring those effects is relevant. For the FKC, only the government reports Centraal PlanBureau and PlanBureau Leefomgeving (2015); MuConsult and Ministerie van Financien (2020); Tillema et al. (2018) and the other studies by Ubbels et al. (2008); Van Wee (2010); Geurs and Meurs (2010) focus on the FKC. Most studies estimated the impact on emission, tax income, accessibility and road safety or a combination of those.

The estimated effects on society result from behavioural effects of car-users that occur with pricing policies. A change in behaviour occurs because the prices changes but the Willingness-to-pay (WTP) for a type of car, or whether to use the car, in principle remains the same. The WTP includes the monetary value that one attaches to a certain product or service (Chorus, 2021). The literature primarily mentions behavioral effects in terms of mode choice & car fuel-type choice. Car fuel-type choice behaviour represents people's preferences for the fuel group of their car, given certain attributes of the fuel type alternatives. Mode choice behaviour represents people's preferences, given certain attributes of all mode alternatives, for a specific transport mode to take a trip. Many papers, such as Tillema et al. (2018); Geurs and Van den Brink (2005); MuConsult and Ministerie van Financien (2020); Centraal PlanBureau and PlanBureau Leefomgeving (2015); Geurs and Meurs (2010) also address the importance of price-differentiation and how pricing schemes can lead to different effects, which could opt as an additional tool to create the desired effects. Pricing schemes can stimulate/discourage the behaviour by pricing specific alternatives, or particular groups, differently. There are several ways to apply such a pricing scheme. Differentiating between time and/or place is a very well-known tool and is used in respectively the Peak - Cordon charge form (Krabbenborg et al., 2021; Leape, 2006; Percoco, 2013, 2014). As the Dutch government has excluded these options, one other relevant option remains; a pricing scheme based on car emissions. This pricing scheme is also already applied in the MRB (ANWB, 2021; Ministerie van Financien). Cars pay a different variable price for road use depending on the fuel group and fuel economy. Fuel economy is a complex measure; therefore, the MRB divides weight groups to capture the environmental effects. The pricing scheme tool can influence both car fuel-type choice and mode choice. With this type of differentiation, the polluting road users can be targeted. This will not only lead to more tax income but also speeds up electrification Cavallaro et al. (2018).

Dutch governmental organizations, The Netherlands Bureau for Economic Policy Analysis (CPB) and the Netherlands Environmental Assessment Agency (PBL) use standard models (Revnext, 2019; MuConsult and Ministerie van Financien, 2020; Tillema et al., 2018; Centraal PlanBureau and PlanBureau Leefomgeving, 2015) to compute the expected societal effects resulting from policies . Three models, Landelijk Model Systeem (LMS), Carbontax and DYNAMO, were used in the latest report by MuConsult and Ministerie van Financien (2020). For estimating the composition of the Dutch car fleet, the Carbontax model and DYNAMO model are used. These models use vehicle selling data and a Total Costs of Ownership (TCO) analysis to determine price elasticities that are then used to compute the new composition of the car fleet. Recently, the Electrical Vehicle (EV), categorized in the Battery Electrical Vehicle (BEV) and its Plug-in Hybrid (PHEV) version, are upcoming, and its business model is getting more attractive (Liao et al., 2018). The 2020 share of EVs increased by 36% relative to the previous year (Centraal Bureau voor de Statistiek, 2021). According to the Carbontax model, available selling data on EVs is limited, and the selling data mostly consists of diesel (DV) and gasoline (GV) fueled cars which fall under Internal Combustion Engine Vehicles (ICEV). This complicates the estimation of the composition of the Dutch car fleet because there are more car types to choose from and these options all have different characteristics and effects on society. Next, the LMS model by Rijkswaterstaat is used to estimate how pricing policies affect car use. This model uses demographic and socio-economical data to compute the effects (Rijkswaterstaat). Both models use data that is sufficient for estimating car fuel type and mode choice when the car fleet only consists of conventional vehicles. With the rising EV market share, the question arises whether these models, and the data they use, are not getting outdated.

2 Modeling framework

The consulted literature presented several studies, which aim to investigate the behavioral change induced by policies or strategies (Percoco, 2013, 2014; Olszewski and Xie, 2002; Liao et al., 2018; Xie, 2013; Burris and Pendyala, 2002; Ubbels et al., 2008). Many of them collected data using stated choice experiments and use the framework of discrete choice models to pre-evaluate policy measures that either change the characteristics of a particular alternative or change the preferences of individuals. Discrete choice modelling (DCM) is a modelling technique that models theoretical or empirical choices made by people among a set of alternatives allowing it to explain or predict future choices. This study explores the use of DCM to gather insights into the important parameters behind choices for what transport mode to use and what car fuel-type to buy. Additionally, DCM can statistically relate choices to background characteristics to evaluate heterogeneity in the population. Solely Ubbels et al. (2008) has attempted to use Stated Preference data as data collection method but this study ignores the current complexity of the car market with upcoming affordable EVs. With the help of SP data, the policy can be represented as a change in one or more attributes and the magnitude of the policy impact can be deduced from the corresponding parameter (Hackbarth and Madlener, 2013).

The knowledge gaps defined a weakness in the type of data used to forecast the effects of pricing policies on behavioural - and societal impact. The change in behaviour due to a pricing policy like the FKC leads to changes in traffic volumes and car-fleet characteristics. To estimate these outputs, we will need to gather data about *car fuel-type* and *mode choice behaviour*. Geurs and Van den Brink (2005) defined these two types of behaviour as interdependent; therefore, two separate experiments must be conducted. Weis et al. (2010) acknowledged this and conducted the two experiments separately also. First, more elaboration on the structure and extract elements from the literature review are presented. Then, both experiments are shown in the form of a theoretical framework where these elements come back and where a decision is made on what attributes and background characteristics to include. This goal of this framework is to visualise the research elements and variables to be included.

A theoretical framework shows the different elements and attributes to be included in the experiment. The relations and factors that are chosen stem from consulted literature. Such a framework helps with structuring the survey and determining the right questions. The black arrows represent the main effects on utility. Utility is satisfaction received from consuming a good or a service; in this case, it means the choice for such a good or service (Molin, 2019). The dashed lines represent the effects of interactions on the utility of the different alternatives. The red lines indicate the effect of the socio-demographics, current car characteristics and a person's perceptions, for which a direct result is expected, on utility. There are two choice experiments, in this case, each having its framework.

2.1 Experiment 1: Car fuel-type choice

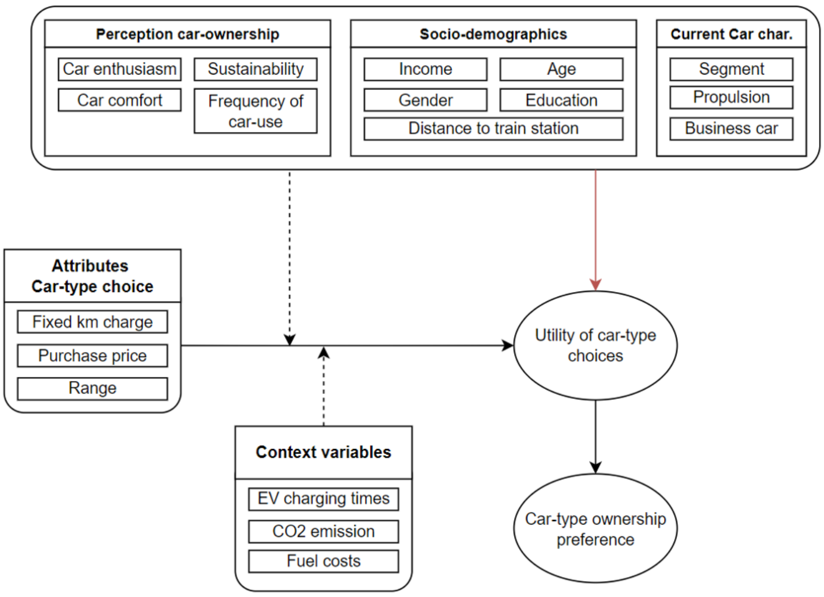

Figure 1: Theoretical framework car fuel-type choice

According to Liao et al. (2018), the largest share of vehicles still belongs to the Internal Combustion Engine Vehicle (ICEV) category. Although this category could be taken as a whole, it will be interesting to see if there are differences between gasoline vehicles (GV) and diesel vehicles (DV). Therefore the ICEV is split into those two. On the other hand, Liao et al. (2018); MuConsult and Ministerie van Financien (2020); Leefomgeving (2020); Revnext (2019); Centraal Bureau voor de Statistiek (2021); Daziano and Chiew (2012); Daina et al. (2017) see a strong increase in EVs. Both the Plug-in version (PHEV) and the Battery (BEV) are increasing. These categories are therefore chosen as additional alternatives. Fuel cell EVs are not yet operational and LPG vehicles have a meager car-fleet share. These two groups are therefore excluded from this model. Hybrid versions (HEV) are considered efficient ICEV's and are thus not included (Ewing and Sarigöllü, 1998; Rijksdienst voor Ondernemen and Revnext, 2018).

The utility of this experiment describes how car users pick their type of car and if they would choose differently for varying pricing policies or the implementation of those (Ben-Akiva and Bierlaire, 1999; Chorus, 2021). As a result, the composition of the car fleet can be deducted from this data MuConsult and Ministerie van Financien (2020); Revnext (2019); Tillema et al. (2018); Leefomgeving (2020). The attributes are chosen based on their relevance and appearance in a car fuel-type choice experiment by Ewing and Sarigöllü (1998). Ewing and Sarigöllü (1998) used toll as a variable pricing attribute and distinguished fuel and toll costs. In this experiment, the FKC is relevant as this is the policy measure that this research investigates. The purchase price and range are also attributes and relevant factors due to the current EV development. With the technological and economic development of electric vehicles, ranges are increasing, and prices are decreasing. This learning curve is translated into attributes that can vary so that multiple future scenarios can be modelled.

2.1.1 Heterogeneous impact on price sensitivity

A second aim of this research focuses on the heterogeneity of consumer preferences and their behavioral change. The entire population is assumed to consist of several groups; preferences for fuel types and other car attributes are homogeneous within each group and heterogeneous across different groups. Therefore, this impact on the price sensitivity is captured by interaction effects that represent how various background characteristics interact with the sensitivity to the FKC. By means of interviews with mobility experts, several background characteristics were selected for further modeling and converted into binomial groups(0 & 1). Adding these in the form of an interaction effect to the basic utility function gives the following utility for alternative i:

$$\begin{aligned} V(i) = ASC_i + \beta_{PP} * PP_i + \beta_{FKC} * FKC_i + \beta_{Range} * Range_i + (\beta_{FKC} + \beta_{FKC_{Income}} * Income) * FKC_i \\ + (\beta_{FKC} + \beta_{FKC_{Education}} * Education) * FKC_i + (\beta_{FKC} + \beta_{FKC_{Businesscar}} * Businesscar) * FKC_i \\ + (\beta_{FKC} + \beta_{FKC_{CarUse}} * CarUse) * FKC_i + \upsilon_{ICEV_i} + \upsilon_{Charge_i} \end{aligned} \tag{1}$$

2.2 Experiment 2: Mode choice

This experiment is sub-divided into four smaller experiments. This is because the FKC is expected to have other effects for different distances. When looking at longer distances within the Netherlands, the train is the only mode that can compete. To do this experiment, we assume that there is a train station in both the departing as well as the arriving nodes. The mode choice models are estimated using distance-dependent nonlinear utility functions and separately for the various trip purposes and relevant for all other trip characteristics (Washbrook et al., 2006). The literature concluded that the choice for an alternative interrelates with the distance; hence, four sub-experiments were performed, one for each distance category (5km, 25km, 75km, 200km) (Scheiner, 2010; Limtanakool et al., 2006).

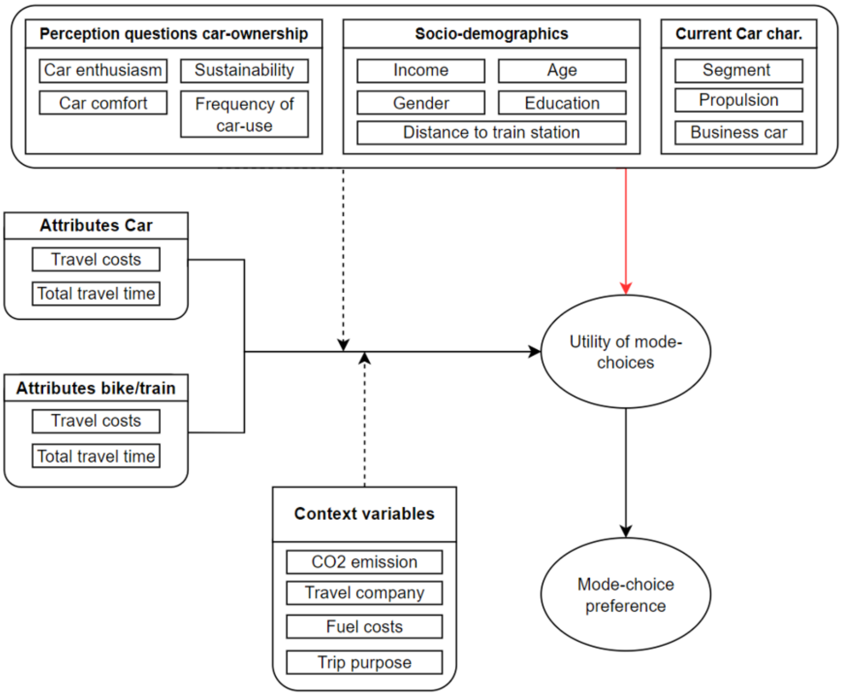

Figure 2: Theoretical framework mode choice

The travel cost attribute is one of the main determinants in the choice for mode-use. Meixell and Norbis (2008) describes it as the primary criteria, together with travel time. Multiple studies (Washbrook et al., 2006; Ewing and Sarigöllü, 1998; Dobruszkes et al., 2014; Behrens and Pels, 2012; Wegener, 2004) endorse this. Generally, it is expected that once the price increases, utility and thus demand decreases. In this mode choice experiment, the travel costs in the choice task will consist of solely the FKC. The fuel costs are context variables and are not varied nor included in the choice task experiment.

Meixell and Norbis (2008); Wegener (2004) also acknowledged travel time as a primary attribute for mode-choice. This has to do with the Value of Travel Time Savings (VoTTS) principle in which people are willing to pay more for lower travel times. In this experiment, we assume that everyone has different access to their modes, especially the train. Access times vary for people in the population, in significantly different areas in terms of density. This is an important factor when deriving people's preferences towards mode choice Washbrook et al. (2006); Weis et al. (2010). However, to keep the experiment simple and remain the focus on the effect of the FKC, the access time to the mode is individual for everyone and will therefore indirectly be taken into account, but not as a separate attribute. Longer travel times are expected to cause disutility and the parameter sign is thus expected to be negative.

2.2.1 Heterogeneous impact on price sensitivity

A second aim of this research focuses on the heterogeneity of consumer preferences and their behavioral change. The entire population is assumed to consist of several groups; preferences for fuel types and other car attributes are homogeneous within each group and heterogeneous across different groups. By means of expert interviews, it was decided to include the following background characteristics: Age, Income, Education, Business car, Car use, Commuting mode, PT card availability, Distance to train station. Except for Age, all factors were converted into binomial groups(0 & 1). Adding these in the form of an interaction effect to the basic utility function gives the following utility for alternative i:

$$
\begin{aligned}
V(i) = ASC_i + \beta_{TC} * TC_i + \beta_{TT} * TT_i + (\beta_{TC} + \beta_{TC_{Age}} * Age) * TC_i + (\beta_{TC} + \beta_{TC_{Income}} * Income) * TC_i \\
+ (\beta_{TC} + \beta_{TC_{Education}} * Education) * TC_i + (\beta_{TC} + \beta_{TC_{Businesscar}} * Businesscar) * TC_i \\
+ (\beta_{TC} + \beta_{TC_{CarUse}} * CarUse) * TC_i + (\beta_{TC} + \beta_{TC_{Commute}} * Commute) * TC_i \\
+ (\beta_{TC} + \beta_{TC_{PT-card}} * PT - card) * TC_i + (\beta_{TC} + \beta_{TC_{TrainDist}} * TrainDist) * TC_i
\end{aligned} \tag{2}
$$

3 Data collection

The data for these experiments was collected in May 2022 using an online survey and was distributed through an independent panel (PanelClix) that could set quotas for gender, age and education to get the most representative sample size. 505 valid answers were obtained. After the data was collected, the data was cleaned and coded into a data set applicable for further modelling. Apart from the choice experiment which is introduced in the following section, the online survey also included questions regarding the respondents' socio-demographics, current travel - and car characteristics. Table 1 presented the socio-demographics and basic characteristics included:

3.1 Survey design and sample statistics

Table 1: Sample description

Demographic	**Category**	**Respondents**
Age	18-30 years	14.3%
	30-40 years	19.2%
	40-50 years	23.4%
	50-60 years	16.1%
	60+ years	27.1%
Gender	Female	49.7%
	Male	50.3%
Income	Low income	4.3%
	High income	11.4%
	€20.000 - €30.000	18.1%
	€30.000 - €40.000	24.6%
	€40.000 - €60.000	25.5%
	€60.000 - €80.000	11.0%
	€80.000 - €100.000	3.1%
	>€100.000	2.0%
Education	No high education	56.8%
	With high education	43.6%
Household level	1	17.3%
	2	38.3%
	3	20.8%
	4+	23.7%
Average distance to station	Less than 5 min	9.1%
	Less than 10 min	19.4%
	Less than 15 min	17.2%
	Less than 20 min	13.1%
	Less than 25 min	16.4%
	More than 25 min	24.8%
Car characteristics	**Category**	**Respondents**
Car ownership	Yes	93.5%
	No, but interested in one	6.2%
	No, not interested	0.4%
Car segment	A	19.6%
	B	32.9%
	C	28.8%
	D	13.8%
	E+	4.8%
Fuel group	GV	84.4%
	DV	8.9%
	PHEV	4.6%
	BEV	2.1%
Business (lease) car	Employer pays car and fuel + private use	6.4%
	Employer pays car and fuel	3.5%
	Private lease	5.6%
	Own car	84.5%
Travel characteristics	**Category**	**Respondents**
Car use	1x/month or less	5.2%
	1x/week or less	6.3%
	2x/week	18.9%
	3-4x/week	26.8%
	5-6x/week	22.3%
	Daily	20.5%
Commuting travel mode	Car	66.7%
	PT	8.4%
	Bike	19.6%
	Foot	5.2%
PT Card	Unlimited*	3.3%
	Discount**	10.8%
	Unlimited paid by employer	5.1%
	Discount paid by employer	1.6%
	Student card	3.1%
	None	76.1%

3.1.1 Policy support

For these types of policies, where some people pay more than others for, in principle, the same service/good, there must also be support from the Dutch citizen. This research concludes that, although some people are affected more than others, the vast majority supports a differentiated pricing scheme based on emission. This policy is supported by over 74% of Dutch citizens. More specifically, over 70% of ICEV users and over 78% of high segment users support the policy. 87% of frequent car users support the policy. Even the majority of the people in the more affected groups support this policy.

3.2 Choice experiment design: car fuel-type choice experiment 1

The choice experiment assumes a context situation in which respondents are buying their next car. Respondents have to assume that three versions of the same car are available which only differ in propulsion technologies, namely a gasoline car (GV), a diesel car (DV), a plugin hybrid electric vehicle (PHEV)or a full battery electric vehicle (BEV). The attribute levels for GV and DV (ICEV category) are the same and are taken as reference alternative, the values are given in Table 2. The experiment is made respondent-specific to increase the realism of the choice experiment: the value of its purchase price and are taken from the car segment the respondent stated to currently own or is planning on owning.

Each alternative consists of levels earlier described in the modelling framework; purchase price, FKC cost and driving range. Energy/fuel costs are left out to observe the pure effect of the FKC and because fuel/electricity prices differ significantly among different car types. Fast charging times, CO2 emissions and average fuel/electricity prices are context variables and mentioned in a relative sense to the ICEV reference alternatives. The specific attribute levels are given in Table 3.

Table 2: ICEV characteristics for the base case

ICEV characteristics		Purchase price	Range (km)
Weight class	Segment A	€12.500	400
	Segment B	€17.500	500
	Segment C	€27.500	600
	Segment D	€35.000	600
	Segment E+	€50.000	600

Table 3: Attribute levels car fuel-fuel-type experiment

Attribute	Alternatives	Attribute levels				
Purchase Price	GV	0%	+10%	+20%		
(€)	DV	0%	+10%	+20%		
	PHEV	0%	+10%	+20%		
	BEV	0%	+25%	+50%	+75%	
Range	GV	0%				
(km)	DV	0%				
	PHEV	0%	-25%			
	BEV	0%	-25%	-50%		
Fixed Kilometer Charge	GV	€0.05	€0.10	€0.15	€0.20	€0.25
(€/km)	DV	€0.05	€0.10	€0.15	€0.20	€0.25
	PHEV	€0.05	€0.10	€0.15	€0.20	€0.25
	BEV	€0.05	€0.10	€0.15	€0.20	€0.25

Now that the alternatives, attributes and the attribute levels have been defined, the experimental design can be generated. For this, Ngene software is used (NGene, 2018). The experiment includes labelled alternatives with alternative specific attributes. Only the DV and GV attributes are similar. The FKC attribute is generic for all four alternatives, but the purchase price and range are different. There are two fixed attribute levels: the range for DV and GV. 5 blocks of four choice tasks each were constructed and each person randomly received one block. An example of the choice set is found below:

Segment C	GV	DV	PHEV	BEV
Purchase Price (€)	€27,500	€33,000	€27,500	€48,125
Range (km)	600	600	600	300
Fixed Kilometer Charge (€ per km)	€0.25	€0.25	€0.20	€0.15

Figure 3: Choice set example segment C

3.3 Choice experiment design: mode choice experiment 2

This experiment uses four distance categories to analyse the results based on different distances because Scheiner (2010) acknowledged the fact that trip distances are of influence on mode choice. The selected distances are: 5km (mini), 25km (small), 75km (medium) and 200km (long). The vehicle will be compared to two other modes. A trip distance of 5km is seldom taken by train, and the bicycle is the primary competitive mode Centraal Bureau voor Statistiek (2019). Therefore, for the 5km option, the bike is used as a travel mode alternative. For other distances, the train and car share the modal split as studies show that an increase in the absolute travel time by private cars increases the propensity to travel by train (Limtanakool et al., 2006; Centraal Bureau voor Statistiek, 2019). Limtanakool et al. (2006) defined 50km as the threshold for medium-long distance trips. You can reach most parts of the Netherlands within 200km, therefore, the medium and long-distance trips were respectively set as 75km and 200km. These distances are also considered as different context variables. The interpretation of the other context variables is given in the next section.

Each alternative consists of levels earlier described in the modelling framework; travel costs (FKC for car) and travel time. Energy/fuel costs are left out to observe the pure effect of the FKC and because fuel/electricity prices are, in reality, not directly observed by the car driver. Travel purpose, CO2 per mode, travel company and fuel/electricity prices are included as context variables. The specific attribute levels are given in Table 4.

Table 4: Attribute level overview mode choice experiment

Distance: 5 km		
Attribute	**Alternatives**	**Attribute levels**
Travel time (hh:mm)	Bike	00:20
	Car	00:05 - 00:10 - 00:15
Travel cost (euro)	Bike	€0.00
	Car	€0.25 - €0.50 - €0.75 - €1 - €1.25

Distance: 25 km		
Attribute	**Alternatives**	**Attribute levels**
Travel time (hh:mm)	Train	00:25 - 00:35
	Car	00:20 - 00:25 - 00:30
Travel cost (euro)	Train	€5.00
	Car	€1.25 - €2.50 - 3.75€- €5 - €6.25

Distance: 75 km		
Attribute	**Alternatives**	**Attribute levels**
Travel cost (euro)	Train	00:45 - 01:00
	Car	01:00 - 01:10
Travel cost (euro)	Train	€15.00
	Car	€3.75 - €7.50 - €11.25 - €15 - €18.75

Distance: 200 km		
Attribute	**Alternatives**	**Attribute levels**
Travel time (hh:mm)	Train	02:15 - 02:45
	Car	02:15 - 02:45
Travel cost (euro)	Train	€28.00
	Car	€10 - €20 - €30 - €40 - €50

Choice situations were derived from the experimental design. This was done based on the experimental design generated by Ngene (NGene, 2018), see the previous section. In total, 8 choice tasks were constructed and split into four blocks of 2 choice tasks. Each respondent was randomly assigned to one of the four blocks. Figure 4 shows an example of a choice task.

5 kilometer	Car	Bike
Travel time (hh:mm)	00:05	00:20
Travel cost (euro)	€1.25	€0.00

25 kilometer	Car	Train
Travel time (hh:mm)	00:30	00:25
Travel cost (euro)	€2.50	€5.00

75 kilometer	Car	Train
Travel time (hh:mm)	01:10	01:00
Travel cost (€)	€3.75	€15.00

200 kilometer	Car	Train
Travel time (hh:mm)	02:15	02:45
Travel cost (euro)	€20.00	€28.00

Figure 4: Choice set examples experiment 2

4 Results

4.1 The average impact of a fixed kilometer charge: car fuel-type choice

We estimate two models, the first model examines the weights of the attributes for car fuel-type choice using a Mixed Logit model. 250 Halton draws were used for estimation. The interaction parameters were added one by one and the ASC was set to the BEV alternative. The ML model includes error components υ that eat away from the i.i.d. (independent identically distribution) error term's variance. It does so by reallocating part of the unobserved heterogeneity (Brownstone et al., 2000). GVs and DVs are placed in the ICEV category as they are pretty similar fuel-types and have no electric element like the other two alternatives, an error component υ_{ICEV} is added. Although BEV and PHEV are considered EVs, there is a big difference in charging reliability. As an EV is no hybrid, it is very dependent on charging infrastructure. This is considered one of the main limitations in EV adoption (Liao et al., 2018). Therefore an error component υ_{charge} is added to all three alternatives that are not dependent on available charging infrastructure.

Table 5: Car fuel-type ML model outcomes

Parameters	**Est.**	**s.e.**	**p-value**	**Significant?**	**Expected sign?**
ASC GV	0.97	0.12	0.00	Yes	Yes
ASC DV	-0.93	0.12	0.00	Yes	Yes
ASC PHEV	0.48	0.08	0.00	Yes	No
β Purchase price	-0.03	0.00	0.00	Yes	Yes
β FKC	-1.18	0.10	0.00	Yes	Yes
β Range	0.01	0.00	0.00	Yes	Yes
β FKC*Income	-2.04	0.53	0.00	Yes	No
β FKC*Business car	-2.10	0.83	0.02	Yes	No
β FKC*Car use	-1.42	0.51	0.01	Yes	Yes
β FKC*Education	-1.05	0.69	0.17*	No	Yes
σ Charge	1.21	0.10	0.00	Yes	-
σ ICEV	-2.67	0.10	0.00	Yes	-
Model fit					
LL(0)		2750.4			
LL(C)		-2472.4			
LL(final)		-2021.6			
Rho-square		0.265			

The first thing to look at is the signs of the main parameters (ASCs, FKC, Purchase price, Range). This is the first check to see if your model estimates are according to expectations. The expectations for the signs of these main parameters were sketched in section 2. In this case, the FKC and Purchase Price are both costs and costs are assumed to have a negative parameter; the higher the costs, the less utility. For Range, we expected a positive sign; a higher range should contribute to utility, or better, a low range should contribute less to utility. The sigmas of the error components are statistically significant, meaning there is no high correlation between estimated sigma's (Chorus, 2021). A higher sigma (or standard deviation) shows that the data is widely spread, which means that the data is less reliable and a low standard deviation shows that the data are clustered closely around the mean. It represents variation (across individuals and their choices) of the utility of the common unobserved factors. The error component υ_{ICEV} is higher and choices are more spread between GV and DV. The error component for υ_{Charge}, that is only excluded in the utility function for BEV, is much smaller indicating that this error component is more reliable. It shows that ICEVs relatively have less in common than the alternatives that included υ_{Charge} (GV, DV and PHEV).

For the ASCs, we can conclude that the values are sensible. A positive ASC means that the unobserved preference for that alternative is higher than the base alternative (BEV). A negative ASC means that the unobserved preference for that alternative is lower than the base alternative (BEV). The BEV value is set to zero and is the reference level. The GV is still the most prominent and broadest used fuel-type in the Netherlands. Unlike the EV, where there is inflexibility in terms of charging, the GV is much more reliable. However, due to increasing diesel prices (relative to gasoline prices) and high PM_{10} and NO_x emissions, which are harmful to the human body, diesel's reputation is shrinking. Rijksdienst voor Ondernemen and Revnext (2018) confirmed this by identifying a significant shrink in new diesel vehicle sales. It was expected that the ASC for DV is the lowest. In section 3, this was confirmed by the low share of overall choices for DV. The higher ASC for PHEV over BEV was initially not expected. The past years, the BEV has had a higher market share for newly bought vehicles than the PHEV. The PHEV is a hybrid where people have the option to switch to gasoline when the battery is empty, which might be the reason for people preferring a PHEV over a BEV.

Finally, the statistical (in)significance is an important metric to see to what extent the parameter estimates can be generalised to the entire population and if the actual hypetheses can be confirmed. In the ML model, all parameters, including the standard deviations of the error components, meet the 95% confidence level. That means the found coefficients can be generalised to the population. For the standard deviations (υ), statistically significance means that there is a found correlation between the alternatives that include that (υ). υ_{ICEV} separating EV and ICEV has the highest st. dev which indicates a higher correlation.

4.1.1 Interpretation of car fuel-type experiment results

From the first experiment, which focused on car fuel-type choice the following key findings were observed:

- When the range, purchase price and the FKC are the same for all fuel types, the Dutch citizen chooses GV first, followed by the PHEV and BEV and lastly the DV. Presumably, the unobserved preference for GV over EV and DV is due to the unreliability and inflexibility of charging EVs and serious health effects that are caused by diesel exhaust.

- The purchase price is, relatively, the most important attribute in people's decisions followed by the FKC and the range.

- The Willingness-to-pay (WtP) for a €0.01 decrease of FKC is €301. Higher income groups are willing to pay €58 more than lower income groups. This poses as an answer to the surprising result that higher income groups are more sensitive to the kilometer charge.

- Frequent car users, business car users and higher educated groups are also more sensitive to the FKC implying that they, like high-income groups, have a higher purchasing WtP for a decrease in FKC.

The choice model estimations for car fuel-type choice shows that, regardless of the stated interest in EV, people still choose a GV over EV, indicating that even if purchase prices and ranges were to level that of ICEV, GV would still gain the highest market share. Presumably, the unobserved preference for GV over EV and GV is due to the unreliability and inflexibility of charging EVs and severe health effects caused by diesel exhaust. Second, the relative importance is highest for purchase price when choosing a fuel-type. The variable FKC costs follows and the importance for range is the lowest. On average, the Willingness-to-pay (WtP) for a €0.01 decrease of FKC is €301, implying a point of return at a mileage of 30,100 kilometer. This 'payback period' is shorter than expected average mileages per car owner, but not all people are willing to make such an investment. The FKC and purchase price might both be monetary attributes but they are very different and appeal differently to specific people. Initially, the higher price-sensitivity for high income groups was surprising. In hindsight, this effect proves explainable because the effect resulted in a higher WtP (€327 vs €279) for a €0.01 decrease of FKC for people with higher incomes. A slight correlation between car use and income is likely to cause this difference. As expected, frequent car users are more price-sensitive because they are likely to have a high mileage and thus high total costs. Therefore, this group is more likely to switch to modes with cheaper variable costs. Another explanation for this higher WtP is that wealthier people are more financially equipped to make an investment (the higher purchase price) that will be earned back years later. If emission-based differentiation only allows people with more income to switch because they have the financial means, lower income classes pay more for road use than higher income classes. This widens the inequality gap.

The choice model estimations for car fuel-type choice shows that, regardless of the stated interest in EV, people still choose a GV over EV, indicating that even if purchase prices and ranges were to level that of ICEV, GV would still gain the highest market share. Presumably, the unobserved preference for GV over EV and GV is due to the unreliability and inflexibility of charging EVs and severe health effects caused by diesel exhaust. Second, the relative importance is highest for purchase price when choosing a fuel-type. The variable FKC costs is second important followed by the range. To compare the utility contribution for the purchase price to that of the kilometer charge, a Willingness-to-Pay (WtP) for a higher purchase price in exchange for a reduction in variable costs (FKC) was computed. For a reduction of 1 Eurocent (€0.01) of the FKC, people are willing to pay €301 for a car.

4.2 The average impact of a fixed kilometer charge: mode choice

Parameters	**5 km**			**25 km**			**75 km**			**200 km**		
	Est.	**s.e.**	**p-value**	**Est.**	**s.e.**	**p-value**	**Est.**	**s.e.**	**p-value**	**Est.**	**s.e.**	**p-value**
ASC Bike	0.60	0.26	0.01	-	-	-	-	-	-	-	-	-
ASC Train	-	-	-	-3.80	0.36	0.00	-3.86	0.41	0.00	-2.54	0.10	0.00
β Travel Costs	-0.16	0.19	0.01	-0.08	0.01	0.00	-0.02	0.01	0.00	-0.01	0.01	0.00
β Travel Time	-0.03	0.02	0.03	-0.03	0.02	0.00	-0.03	0.01	0.00	-0.02	0.00	0.00
β FKC*Dist. to train	0.46	0.18	0.03	0.06	0.04	0.26*	0.03	0.02	0.11*	0.02	0.00	0.04
β FKC*Income	0.02	0.18	0.39*	0.00	0.04	0.46*	0.01	0.02	0.31*	0.01	0.00	0.04
β FKC*PT card	-0.30	0.24	0.22*	-0.17	0.04	0.00	-0.08	0.02	0.00	-0.01	0.01	0.01
β FKC*Business car	0.79	0.27	0.01	0.05	0.06	0.24*	0.04	0.02	0.07*	0.01	0.01	0.06*
β FKC*Education	-0.05	0.13	0.32*	-0.13	0.02	0.01	-0.06	0.01	0.00	-0.02	0.00	0.00
β FKC*Commute	1.29	0.22	0.00	0.16	0.04	0.00	0.02	0.02	0.02	0.01	0.00	0.01
β FKC*Age	-0.01	0.01	0.09*	0.00	0.00	0.08	0.00	0.00	0.27*	0.00	0.00	0.03
β FKC*Car use	0.73	0.24	0.01	0.06	0.05	0.14*	0.05	0.02	0.01	-0.01	0.01	0.14*
Model fit												
LL(0)	-651.56			-651.56			-651.56			-651.56		
LL(C)	-616.25			-388.57			-392.10			-578.39		
LL(final)	-569.83			-333.42			-328.73			-424.46		
ρ^2	0.13			0.49			0.50			0.35		

* Not significant at a 95% confidence interval

Table 6: Mode choice model outcomes

The first thing to review is the signs of the main parameters. For the ASCs, a negative value was expected for the train. This is due to additional unobservable factors like access/egress time and transfers. These values were negative for the distances, including the train alternative (25, 75, and 200 km). For the longest distance, 200km, the ASC is the least negative. This could be explained by the fact that people don't like long car drives or that when having a long travel time, train travel becomes, relative to the other distances, more convenient. Relatively, egress/access times, e.g. become less important. For the bike as travel mode in the 5km experiment, the estimate is positive, and we can conclude that, generally, short distances are preferred to be done by bike rather than the car. A possible explanation is that the bike is much more flexible than the car in terms of parking and people prefer being outside and exercising.

For the attribute parameters, Travel time (TT) and Travel costs (TC), both are negative and statistically significant. The TC parameter represents the train ticket costs for the train alternative and the total FKC costs for the car alternative. As four different experiments were conducted, it was chosen to keep the model simple. No additional attribute-specific parameters were added. The LRS was not significant, and including these parameters does not lead to the additional value of this research.

4.2.1 Interpretation of mode choice experiment results

From the second experiment, focused on mode choice at different trip lengths the following key findings were observed:

- The Value of Travel Time Savings (VoTTS) differed substantially between the different distances. The average VoTTS for bike and car found for short (urban) trips is €6.86. The average VoTTS with car and train as choice options ranges from €4.44 for medium distances (25km) to €14.00 for long distances (200km). An interrelation between distance and the impact of the FKC thus exists.

- A modal shift to alternative modes enabling a car market share of 75% requires an FKC of €0.17. A split market share (50% car use) of the car requires a uniform charge of €0.27 per kilometer.
- Those who use the car to commute or live far from the train station are less sensitive to price because no alternative is available. These factors contained a high level of heterogeneity. Less heterogeneity is present for income, implying that variation in choices between low and high income groups is limited.
- High educated and/or public transport card holders are more sensitive to the height of the FKC. Frequent car users are less sensitive for short distances but become more sensitive than occasional car users for long trip distances.

We found that *older* people, people that live *far from the train station* and people with higher *incomes* are less sensitive to the height of the FKC. Car use characteristics, such as the car as *commuting mode*, the car paid for by the *business* and *frequent car use*, are less sensitive to the FKC. *Public transport card holders* and *higher educated* are more sensitive than others. A higher sensitivity generally means that there is an easy alternative or that people attach more value to the luxury of car use. To evaluate the differences in various trip lengths, the Value of Travel Time Savings (VoTTS) were computed which indicates the monetary value one is willing to spend to reduce the travel time. For the experiment including the car and bike as alternatives, the average VoTTS found was €6.86. For the experiments including the train alternative (25 km - 200 km), the VoTTS ranged from €4.44 - €14.00 increasing with trip length.

In addition to the inconvenience of taking the train, the preference for the car over the train might also be due to the dependency on people's commuting situations and their distance to the train station. Insensitivity to price for rural people with bad access to train stations or commuters with bad egress from stations could imply a particular car dependency where a high tariff is required to enable a serious modal shift. However, people with bad access to train stations are as good as unable to switch to an alternative, unintentionally creating a system where rural people are heavily disadvantaged compared to urban citizens. The original hypotheses proved correct for all included characteristics but couldn't be confirmed for all distances due to high p-values.

4.3 Key findings application of choice model results

In the last phase, the outcomes of both estimated choice models were integrated into a new model capable of predicting the effect of different combinations of the FKC per fuel-type on specific criteria. The criteria set were *tax income, CO_2 -, NO_x -, PM_{10} emissions, bike use, train use, EV market share* and *high car segment share*. A base scenario is defined to explain the marginal effects of differentiation towards a uniform charge. In the base scenario, a uniform charge of 6.2 eurocents is used, which is the most reasonable charge at the moment. The exact inputs per scenario can be found in Table 7. Scenario 2 includes a low -, medium - and high differentiated tariff for only fuel-type. Scenario 3 takes it one step further and also differentiates according to the car segment, where cars in a higher segment pay more due to their weight. All results for 2030, 2040 and 2050 are displayed in Table 8.

4.3.1 Pricing scheme designs

The pricing scheme designs are the scenarios that will function as input for the model. The following scenarios have been defined, and their specific pricing scheme has been added. In these scenario's the attribute levels of the other attributes, purchase price and range, which were determined according to technological development based on Wolfram and Lutsey (2016), remain the same in every scenario. The scenarios distinguishes two types of differentiation: differentiation to *fuel type* and differentiation to *fuel type + car segment*.

Table 7: Pricing scheme designs

Scenario's (eurocent)	GV	DV	PHEV	BEV
1. No differentiation (base): price equality	6.2	9.4	6.2	6.2
2a. Emission based pricing scheme: small	7.4	10.6	6.4	5.3
2b. Emission based pricing scheme: medium	8.7	11.9	6.5	4.3
2c. Emission based pricing scheme: high	9.9	13.1	6.7	3.4
3a. Fuel type differentiation & segment differentiation: low				
Segment A	*6.0*	*9.2*	*5.1*	*4.2*
Segment B	*6.7*	*9.9*	*5.7*	*4.7*
Segment C	*7.4*	*10.6*	*6.4*	*5.3*
Segment D	*8.2*	*11.4*	*7.0*	*5.8*
Segment E+	*8.9*	*12.1*	*7.6*	*6.3*
3b. Fuel type differentiation & segment differentiation: high				
Segment A	*7.9*	*11.1*	*5.3*	*2.7*
Segment B	*8.9*	*12.1*	*6.0*	*3.1*
Segment C	*9.9*	*13.1*	*6.7*	*3.4*
Segment D	*10.9*	*14.1*	*7.3*	*3.8*
Segment E+	*11.9*	*15.1*	*8.0*	*4.1*

4.3.2 Experiment integration results

These scenarios that were used as input, all delivered varying absolute results, and these results were compared with the base case of a uniform FKC tariff. The differences were then converted into marginal changes, which are the final outcomes of the model and the answer to the main research question.

Table 8: Results

	base level	*Effect of various differentiation levels towards base level*				
2030	**1. Fixed charge - no differentiation**	**2a. Fuel-type - low**	**2b. Fuel-type - medium**	**2. Fuel-type - high**	**3a. Fuel type & car segment- low**	**3b. Fuel type & car segment- high**
Tax income	-	14.3%	28.2%	41.5%	7.9%	33.7%
CO_2 emissions	-	-0.9%	-1.9%	-3.1%	-0.6%	-2.6%
NO_x emissions	-	-0.8%	-1.7%	-3.1%	-0.6%	-2.2%
PM_{10} emissions	-	-0.8%	-1.9%	-2.6%	-0.6%	-2.5%
Bike use	-	0.1%	0.2%	0.3%	0.1%	0.3%
Train use	-	4.7%	9.9%	15.9%	3.0%	13.1%
EV market share	-	0.8%	1.6%	2.4%	1.0%	2.4%
High car segment	-	-0.7%	-1.5%	-2.4%	-1.1%	-2.6%

	base level	*Effect of various differentiation levels towards base level*				
2040	**1. Fixed charge - no differentiation**	**2a. Fuel-type - low**	**2b. Fuel-type - medium**	**2. Fuel-type - high**	**3a. Fuel type & car segment- low**	**3b. Fuel type & car segment- high**
Tax income	-	10.9%	21.0%	30.3%	4.7%	23.2%
CO2 emissions	-	-1.4%	-3.1%	-4.9%	-1.3%	-4.5%
NOx emissions	-	-0.2%	-1.9%	-3.1%	-0.1%	-2.2%
PM10 emissions	-	-1.1%	-2.0%	-2.6%	-0.9%	-3.3%
Bike use	-	0.1%	0.2%	0.3%	0.0%	0.2%
Train use	-	3.9%	8.4%	13.6%	2.3%	11.0%
EV market share	-	2.4%	4.9%	7.3%	2.5%	7.1%
High car segment	-	-0.5%	-1.1%	-1.8%	-6.8%	-7.9%

	base level	*Effect of various differentiation levels towards base level*				
2050	**1. Fixed charge - no differentiation**	**2a. Fuel-type - low**	**2b. Fuel-type - medium**	**2. Fuel-type - high**	**3a. Fuel type & car segment- low**	**3b. Fuel type & car segment- high**
Tax income	-	6.6%	12.1%	16.4%	0.5%	10.0%
CO2 emissions	-	-2.6%	-6.0%	-9.5%	-2.9%	-9.4%
NOx emissions	-	1.5%	-1.3%	-3.5%	1.1%	-2.5%
PM10 emissions	-	-1.5%	-2.4%	-4.3%	-1.2%	-4.1%
Bike use	-	0.1%	0.1%	0.2%	0.0%	0.1%
Train use	-	3.0%	6.4%	10.2%	1.5%	8.0%
EV market share	-	2.9%	5.9%	8.8%	3.0%	8.5%
High car segment	-	-0.3%	-0.6%	-1.0%	-13.1%	7.2%

The table provides the answers to the main research question and thus has investigated the effects that various pricing schemes for a kilometer charge would have on several criteria. A brief overview of the key takeaways that can be derived from the table are the following:

- **Optimal tax income & emission savings**: A higher level of differentiation results in more tax income and reduced emissions. Although this general effect is according to expectation, the table indicates the extent of this.

- **Increase in EV use**: Over the years, due to a faster transition to EVs, the emission savings will increase further, and the tax income will decrease (although it is still higher than with a uniform charge). The results show that a higher tax income is possible whilst stimulating EV and greener transport modes like the train.

- **Modal shift effects**: Train and EV demand cannot increase too fast due to infrastructural issues. However, the increase in demand for trains and EVs is not problematic and is considered acceptable. The extra tax income that will be collected by the stimulation of greener modes can be used to finance the necessary growth. The argument that EVs have higher purchase prices than ICEVs will weaken over the following years as EVs are expected to become competitive with ICEVs.

- **Car segment-based differentiation**: In case the kilometer charge is differentiated to fuel-type and car segment, roughly 10% of high car segment users will switch to a lower segment

Looking at the results of the integrated choice model experiments, it can be concluded that differentiating the FKC in such a way that the polluter pays will lead to positive effects in terms of tax income and emissions. The Dutch government has stated tax erosion to be the main reason for the FKC to be implemented in the first place, but the question was if the FKC could not also result in fewer car emissions (CO_2, NO_x, PM_{10}). The results show that differentiating the price according to the vehicle's pollution will not only lead to higher tax incomes over the next decades but will also result in fewer emissions. The more differentiation comes in place, the more emissions will be saved and the faster the electrification of the Dutch car fleet will go. This is because, although the average tariffs weigh out, the share of high polluting vehicles (ICEV) is much higher than the share of cleaner vehicles (EV). A higher level of differentiation leads to a significant faster transition towards EV use, and therefore the increase in tax income becomes less over time. Next to the level of differentiation, a differentiated price scheme for car segments was also evaluated. The results show that, because the market share of smaller vehicles is higher, this strategy does not lead to more emission gains or a higher tax income. However, it does result in less high segment cars which has additional benefits considering spaciousness and city livability.

5 Conclusion and discussion

We find that well-educated,high-income people, who either frequently use their car or own a business car, are more incentivised by the kilometer charge to purchase alternative fuel vehicles. In general, people value purchase prices over the kilometer charge and range. Moreover, it turns out that these groups are willing to purchase a substantially more expensive car in exchange for a lower variable kilometer charge. By applying a multinomial logit model for all distances in the mode choice experiment, we find that the least sensitive group towards the kilometer charge for a modal shift are high-educated, older, commuting car users that live relatively far away from the nearest train station. Furthermore, the larger the travel distance, the higher the value of travel time savings. The ultimate found behavioural effects were used to evaluate the impact of constructed scenarios with varying tariffs for the kilometer charge, showing that an emission-based differentiation can positively affect tax income and emission savings. Besides that, this implementation form is the most supported under the Dutch population. In addition to these substantial insights, this paper makes a contribution by showing how stated preference discrete choice data can enhance decision-making of such pricing policies.

One of the two aims of this research was to investigate to what extent the validity of forecasting policy effects could be enhanced. This research has proved SP data worthy of being included in decision-making processes. It gives a unique view of how people value specific attributes that are not available in case of new policies and how the policy-makers can use that knowledge to their advantage. However, SP data clearly has reliability issues. Respondents can be quick and careless when answering a survey, which deteriorates reliability, something that was also encountered in this study. Based on pre-set criteria, we could remove some answers, but that gives no insurance that the other responses were reliable. Moreover, decision variables and the context for these choices exceed the handful of variables added to this model. This corresponds with the criticism that consumers react differently to hypothetical choice tasks in real life. Hence, SP data should not replace RP data but can function as additional knowledge to support particular decisions. On top of that, SP experiments that will be used to support such vital decisions should require more responses and cater to careless respondents to increase the reliability of the outcomes.

Furthermore, this thesis contributes to the knowledge of the effects of differentiating the FKC and to what extent SP data can be used for (additional) policy forecasting. Other insights this thesis brings consider the chronological order in which decision-makers make decisions. Where the report by MuConsult and Ministerie van Financien (2020) only evaluated a single differentiated pricing scheme, this thesis calculates the effect of 5 pricing schemes. However, both approaches fail to give the optimal strategy. This research has shown that there is a substantial difference in effect between different pricing schemes. This indicates that an optimal scheme can maximise one or multiple criteria. Not all criteria must be maximised, but some are limited to a hard constraint. Think of a minimum tax income, a maximum modal shift, a maximum shift to EV and a ceiling rate that cannot be exceeded. Whilst satisfying these constraints, there is still the opportunity to maximise emission reductions. Whilst it is understandable that the government wants to be careful with differentiating too much to protect the more affected people, the majority of the respondents of this survey have indicated being supportive of the decision to let polluters pay more, even the people who get affected the most.

5.1 Limitations and further research

Foremost, this research acknowledged and encountered the downsides of SP data as it found some of the data to be unreliable. One of the main limitations of SP data is that it is unpredictable whether people would actually do what they state they would do. Usage of SP data might increase the validity, but in terms of reliability, it is much weaker than RP data. RP data, or empirical data, is, in fact, 100% reliable. A secondary issue with SP data is that preferences for specific modes or fuel-types are also very dependent on external, unobserved factors such as fuel and electricity prices, CO2 emission development and charging infrastructure. The insights in the weights of variables is essential information that could be used for policy-making. Determining the market shares is possible but RP data is a more suitable datatype for this.

Second, the methods and models that were used in this research, including the survey, choice models and integration, were not comprehensive. The choice sets and models were kept simple and robust, which is suitable for evaluating the application of the model and extracting the marginal changes of different strategies. To increase the completeness of the SP data, other modes such as the bus, metro, tram and foot can be added to the choice sets for mode choice. The most important alternative ignored in this research is the null alternative, i.e. *not taking the trip*. The integrated model assumes all passenger kilometers are being kept the same. However, with the rise of hybrid working, **not** going to work has become a serious alternative. If commuting becomes too expensive, people will be more urged to stay - and work from home. This is a very important alternative that is neglected in this experiment. Another shortcoming of this model is the limited use of alternative specific parameters. In the utility functions no such parameters were accounted for. According to the literature, the estimations for the time - and cost parameters could vary per alternative (Schmid et al., 2016).

Third, no model or method is perfect to assess future effects of policies like these. Comparing the absolute outcomes of this model to another is therefore unnecessary as there is no knowledge on all assumptions made. Assumptions such as CO_2 emission in g/km have a crucial impact on the final total effect on emission. Compared to the earlier discussed models (LMS, DYNAMO, Carbontax), the model used to compute the final effects in this research is less complete.

Fourth, setting up the choice context is difficult but can significantly impact the observed choices. Whether or not to include fuel/electricity costs as an additional attribute remains an interesting discussion. It is hard to draw any conclusions on whether, or to what extent, the fuel costs were taken into account by the respondent as they were not included as a separate main attribute but as a context variable. Future research into this topic could show what the effect is of including this cost type versus leaving it as a context variable. Another context variable that is a crucial element in ones mode choice is the access/egress time. This variable was not included as only conclusions could then be drawn for that context. Additional experiments could be done with multiple access/egress scenarios.

Fifth, in scenario 3, the pricing scheme was differentiated to fuel-type and segment. This scenario's set-up did not result in more tax income or more emission reduction. However, it did have a much higher impact on the high car segment (D & E+) share. A similar experiment like the car fuel-type choice experiment could be performed for segment choice with attributes like the specific FKC, purchase price, range, car size, max. speed, acceleration and fuel economy.

Sixth, car use is measured in the frequency of people using the car. However, people can take a car every day and still not drive many kilometers. These answers do not provide us with data on an individuals' yearly mileage. Mileage might be a more valid metric to determine car use.

Lastly, in the mode choice experiment, a simple and robust MNL model was used. This model treats every choice independently. In theory, this is incorrect because choices correlate with earlier choices made. If you choose the train alternative in the first option, you are, compared to the first choice, more likely to choose the train in the second choice. The MNL model ignores earlier choices; therefore, following choice situations carry less information. It is advised to estimate an ML model to capture these panel effects.For the car fuel-type experiment, the choice of EV over ICEV can be considered a moral choice because the EV is not yet competitive with the ICEV. The sole purpose of choosing an EV over an ICEV is to reduce emissions and increase sustainability and livability. The group that wants to 'pioneer' toward an electric car fleet is hard to determine. (Centraal Bureau voor de Statistiek, 2021) found several reasons for switching to EV. These reasons can not directly be linked to a specific social group such as high income or the distance to the nearest train station. Adding *latent classes* to the traditional RUM model could opt as a solution to define the characteristics of this group, such a model is called a Hybrid Choice model (Ben-Akiva et al., 2002).

5.1.1 Policy recommendations

The study concludes with policy recommendations that further emphasise the benefits of applying and implementing a kilometer charge. On top of that, it tells how more insight can be generated by using SP data into how people make choices and how technological change affects that. Furthermore, a specific recommendation is not to replace RP data as a whole due to SP data's unreliability. Lastly, a discussion is spurred on the fact that differentiating the kilometer charge might cause potential risks for disadvantaging groups that are highly dependent on car use or do not have the financial means to purchase more expensive cars that are greener and have lower variable tariffs.

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