INTRODUCING SUSTAINABILITY IN PARCEL DELIVERY

An analysis into consumer preferences for delivery choice factors and the impact on sustainable parcel delivery performance

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INTRODUCING SUSTAINABILITY IN APPAREL PARCEL DELIVERY: AN ANALYSIS INTO CONSUMER PREFERENCES FOR DELIVERY CHOICE FACTORS AND THE IMPACT ON SUSTAINABLE PARCEL DELIVERY PERFORMANCE

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Anne-Fleur Nathalie Florence Tjon Joe Gin
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LIST OF ABBREVIATIONS

CPR	Collective Participation Rate
CPD	Context Profile Dependent
DCM	Discrete Choice Modeling
EFA	Exploratory Factor Analysis
SP	Stated Preference
LRS	Likelihood Ratio Statistic
LL	Log Likelihood
LSP	Logistics Service Provider
MNL	Multinomial Logit
RUM	Random Utility Maximization
RRM	Random Regret Minimization
SDCVRP	Site-Dependent Capacitated Vehicle Routing Problem
VRP	Vehicle Routing Problem
WTP	Willingness To Pay

1 INTRODUCTION

The development of the Internet and related technologies has led to an exceptional increase in e-commerce over the past few years. It enables retailers to engage in retail without being restricted by store hours or geographical marketing areas. The e-commerce retail increase is expected to continue at a fast pace, even at times of economic decline Agatz et al. [2016]. The fast fashion industry plays a significant role in the increase in e-commerce, and it is predicted that the widely available inexpensive garments will account for 36% of the total fashion retail by 2022 Meena [2018].

The increasing accessibility of e-commerce retail due to application development and easy access to the internet causes consumers to place orders more frequently. Also, extended delivery options have been introduced by e-retailers (online retailers) to differentiate themselves from the competition: one day (express) delivery options are becoming increasingly common and consumers are expecting these options as part of the e-commerce experience Laghaei et al. [2016].

As a result of the increase in order frequency, online order sizes have reduced Schöder et al. [2016]. The smaller order size, higher frequency and increasing pressure of shorter delivery times pose a great challenge for the last mile delivery for Logistics Service Providers (LSP) who aim at improving parcel delivery to reduce costs for delivery vehicle routing Cattaruzza et al. [2017]; Golden et al. [2008]. The increasing order frequency and demand for faster deliveries result in sub-optimal and costly delivery vehicle routing, causing a significant increase in vehicle kilometers and number of vehicles in city centers Seidel et al. [2014];Nijland et al. [2012]. The increase in delivery vehicles and vehicle kilometers has a significant effect on emission-, pollution- and congestion levels in city centers, and combined with the prospect that over 90% of people will be living in cities by 2050, this will pose a problem for the livability in cities European Commission [2018]; Basbas [2006]. In the light of this forecast, the European Commission has set a first goal of reaching CO2-free city logistics by 2030 in large urban areas Agatz et al. [2016].

To mitigate the negative effects of the increase in e-commerce deliveries in urban areas and the resulting sub-optimality in delivery vehicle routing, alternative strategies have been proposed by researchers for LSPs to minimize the emission and pollution levels of delivery routing to increase the livability in urban areas. For example, eco-routing (green routing) strategies that minimize the overall energy consumption costs, and social routing strategies that explore possibilities of off-peak deliveries to avoid (causing) congestion have been proposed by researchers Bektaş et al. [2015a];Houshmand and Cassandras [2018].

Besides alternative routing strategies, measures are developed to mitigate the effect of increasing e-commerce deliveries as well. One of these measures concerns the development of alternative ways of parcel delivery by means of innovative solutions. For example, the advantages and disadvantages of parcel lockers, drone delivery, and self driving parcel lockers have been researched. The main disadvantage of these innovations as compared to current parcel delivery vehicles is that they do not compete on range and capacity Dorling et al. [2017];Vikingson and Bengtsson [2015]. Another development in the recent years is the partially (hybrid) or fully electric delivery vehicle as an alternative for the currently used diesel delivery vehicles. The use of alternative fuel vehicles decreases the emission and pollution levels in urban areas significantly, both in terms of carbon dioxide and noise Hawkins et al. [2012].

Another proposed measure is cooperation between different logistics providers (LSPs) to increase the efficiency of parcel delivery by collaborative consolidation of parcels. Improving collaboration between LSPs could increase the last mile routing optimization, increase the delivery van load factors and decrease the number of vehicles in city centers Tseng et al. [2019]. An alternative way of parcel consolidation is proposed by providing consumers with a choice for pick-up point delivery instead of visiting each consumer separately as a measure to improve vehicle routing both in terms of costs, emission and pollution levels.

1.1 THE PARADOX OF SUSTAINABILITY CONCERN AND BEHAVIOR

Besides from a delivery supply side perspective to improve the efficiency and sustainability of last mile parcel delivery, a rising consumer concern of sustainability in products and services can be observed as well MVO [2017];Thijssen [2018];MVO [2018]. The increase in willingness to pay for biological (more sustainable) food, and the transformation towards a 'sharing economy' taking place on a small scale reflect this revolution Vecchio and Annunziata [2015];Hawlitschek et al. [2018]. What has been researched however is that the concern for sustainability in products and services might come from certain consumer types and not from the entire Dutch population: in previous research, sustainable minded consumers have been distinguished based on personal characteristics such as gender, age, education, income and household composition Gilg et al. [2005].

The current consumer choice behavior of more frequent ordering and demand for faster deliveries resulting in less sustainable parcel delivery for LSPs seems to contradict with the increasing importance consumers attach to sustainability. Question arises whether this is the result of behavior of a specific consumer group that does not value sustainability in products and services: while some highly value the parcel delivery speed, other consumers might value the sustainability of the delivery more significantly. Another possible explanation might be that while choosing for an online delivery method, consumers do not take into account the effect of their delivery choice on routing costs and emission levels: that they are not aware of the impact of their choice in terms of delivery sustainability Macdiarmid et al. [2016]. In previous research, it was concluded that consumers need assistance to make more sustainable decisions MVO [2017]. To research and distinguish consumer preferences, it has previously been proposed to include the effect of the consumer choices on emission levels in Co2-grams Gaker and Walker [2013]. However for most consumers, this figure is researched to be difficult to translate into a tangible understanding and consumers need more information to encourage more sustainable decisions Gaker et al. [2011]; Schuttelaar [2010].

Therefore, it is proposed in this research to include factors that directly reflect a facet of the sustainability of parcel delivery and to identify the effect of including these factors on consumer parcel delivery preferences. This is proposed to determine the effect and valuation of including these factors and to determine what types of consumers value different aspects of parcel delivery in urban areas. Choice behavior concerning buying sustainable products by including sustainability reflecting factors has been researched Al Mamun et al. [2018]. However, research on choice behavior regarding the addition of sustainability reflecting factors of parcel delivery is still lacking.

1.2 STIMULATING SUSTAINABLE CONSUMER BEHAVIOR

Achieving more sustainability in urban areas in general, could require a level of collective decision making for the common good of livability in cities as well Gray and Milne [2012]. Therefore, it could be argued that, to make the parcel delivery in urban areas more sustainable, collective decision making in the form of cooperative consumer choices for parcel delivery might influence consumer preferences towards different aspects of parcel delivery. Cooperation (collective decision making) is the process of groups working or acting together for common, mutual, or underlying benefit, contrary to working in competition for the own benefit Lindenfors [2017]. The common underlying benefit in the e-commerce parcel delivery is then achieving livability in urban areas.

A consumer's individual choice not to prefer sustainability in delivery options can be explained by the feeling of a minimal individual effect on parcel delivery sustainability, while the feeling of a collective effect of a large share of consumers choosing for more sustainability in delivery services may improve the overall sustainability of parcel delivery routing significantly. To introduce a feeling of collective decision making to benefit the common good of better livability in cities, boosters have been proposed in literature in the form of nudges. A Nudge is a change in choice architecture, or a different design of environment to steer consumers in a more desired (sustainable) direction Goldstein [2008].

An alternative approach to stimulate, or more strict, require collective decision making is to introduce a governmental policy that ensures the collective participation of consumer choices and the collective effect on delivery vehicle routing sustainability. The introduction of a policy requires all consumers to make choices in the same prescribed way, which will assure that other consumers participate in enhancing the common good of livability in cities Mouter et al. [2017]. By introducing a policy that requires consumers to choose a specific set up of a delivery option, possible free-riding effects are eliminated, which most commonly cause consumers not to prefer choices that are less beneficial for their own good as compared to the common good Alphonce et al. [2014]. In researching a citizen perspective as an alternative approach to a consumer choice situation, differences in preferences for different aspects in parcel delivery might be observed.

In order to be prone to nudges that are aimed to steer in collective sustainable decision making, or respond to the cooperation that results from the introduction of a governmental policy, an individual might have to consider cooperation as being morally justified. In this light, Curry et al. Curry et al. [2019] introduced that cooperation can be considered moral behavior, and consists of seven distinct moral domains. They conclude that moral behavior is based on different types of cooperative behavior recurrent in human social life: helping family, helping group, reciprocity, bravery, respect, fairness and property rights. It might be, that consumers that value cooperative behavior highly, value the delivery choice characteristics differently than consumers that do not highly value these types of cooperative behavior.

1.3 RESEARCH OBJECTIVE AND QUESTIONS

In this research, a contribution is made to literature by examining the consumer preference for parcel delivery factors by including sustainability reflecting factors and to determine if heterogeneity in preferences exists between different types of consumers. Researchers focus on the choice behavior regarding green *products*, but the preference for sustainability in parcel delivery *services* (in the fast fashion industry) has not been researched yet.

The contribution of this kind of research will provide insight into consumer preferences and whether steering consumers into a sustainable direction will give a desired effect of choosing for more sustainable delivery. With the insights in consumer preferences and possible differences between consumers for these preferences, more sustainable delivery options that are preferred by consumers can be developed. To research consumer preferences for parcel delivery factors, the research question proposed for this research is:

To what extent do Dutch urban e-consumers value (sustainable) delivery choice factors in the fast fashion industry?

With the following sub-questions to answer the main research question:

1. How do consumers trade-off different delivery choice factors in general?
2. Can differences in preferences for delivery choice factors be observed for different consumers?
3. Can consumers be steered into more sustainable choices for parcel delivery by means of a nudge?
4. Does governmental policy regarding consumer parcel delivery options have an effect on preferences for delivery choice factors?
5. What is the effect of consumer preferences for different delivery policy scenarios on the sustainable parcel delivery performance in urban areas?

Based on these research questions to identify consumer preferences for parcel delivery choice factors, a number of hypotheses are drafted in chapter 4. The last sub-question is included to evaluate the effect of parcel delivery policies based on consumer preferences on sustainable parcel delivery performance. This is done to develop more sustainable parcel delivery policies. The consumer preferences can be translated into consumer delivery choices to evaluate the effect of these choices on the sustainable delivery performance in terms of number of vehicle kilometers and the emission levels resulting from the parcel delivery process.

1.4 RESEARCH APPROACH

The ultimate goal of this research is to contribute to the development of more sustainable parcel delivery policies that are preferred by consumers. Therefore, research into consumer preferences and differences in preferences between consumers for delivery choice factors is suggested. Consumers can be distinguished by age, gender, income or other demographic characteristics, but will also be classified based on whether they morally value cooperative behavior. It is also proposed to research whether preferences for sustainable factors in parcel delivery can be stimulated by means of nudging, or by introducing new governmental policy to serve a common good of a more sustainable livability in cities. The study will only take into account the last-mile of the delivery process in urban areas since this is the main routing challenge of the increasing e-commerce delivery orders Gevaers et al. [2009]. In this research, only consumers are included that live in urban areas and frequently buy apparel online.

In order to research this, a stated preference experiment will be performed. In this choice experiment consumers will choose between different delivery options for their fast fashion apparel parcel delivery. The options proposed to the respondents will differ in terms of delivery service characteristics. The outcome of the consumer preferences of different delivery option characteristics will be evaluated so that a possible implication of parcel delivery performance can be determined for a simplified network of a LSPs delivery service.

In this research, the emphasis lies on the analysis and evaluation of consumer preferences in delivery choice characteristics. Additionally, in the final part of this research it is also indicated how consumer preferences for parcel delivery can be used to evaluate the effect of different delivery policy set ups to consumers. The latter is proposed in the context of a simplified parcel delivery case with a simplified last-mile delivery model based on a vehicle routing problem. The aim of this evaluation is not to determine a generic result but to illustrate a possible proof of concept of delivery policy set ups, consumer choice predictions and the effect on sustainable parcel delivery performance. In most vehicle research, assumptions are made regarding the vehicle routing input in terms of consumer choices. In this research however, the additional contribution is that the consumer choices have been extensively researched and the vehicle routing consumer choice input is rooted in real consumer preferences rather than assumptions.

1.5 THESIS ROAD MAP

figure 1.1 indicates an overview of this thesis research. The conclusions of this research should add up to the existing literature and therefore a feedback loop has been drawn from the choice prediction models towards the literature.

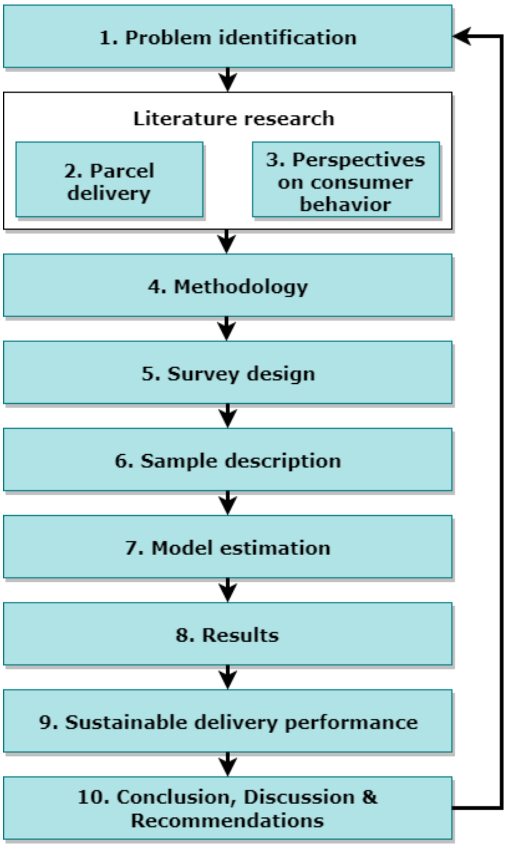


Figure 1.1: Research methodology overview

In chapter 2, the consumer delivery choice process and the resulting delivery routing process is explained. In this chapter, the factors that can currently be considered while choosing a delivery service and factors that directly indicate sustainability are discussed as well. In chapter 3, the different choice perspectives are discussed to assess whether differences in preferences can be distinguished. Chapter 2 and 3 combined serve as input for the stated preference survey design. Chapter 4 proposes the methodology to answer the research questions by proposing a conceptual model, data analysis framework and analysis steps for this research. In chapter 4, based on the preceding chapters, hypothesis are drafted for this research that are linked to the proposed research questions. In chapter 5, the pilot survey, survey improvements and the different sections that are included in the final survey are proposed. In chapter 6, a description of the sample is provided and in chapter 7 the model estimation procedure is discussed. In chapter 8, the results of the model estimations are presented and discussed extensively. In chapter 9, the results of consumer preferences are converted into consumer choices for different parcel delivery policy scenarios to evaluate the effect these choices on sustainable parcel delivery performance. In chapter 10, the answers to the research questions are indicated and conclusions on this research are drawn. In this chapter policy recommendations for different stakeholders are presented, a discussion on the research is included and recommendations for further research are given.

2 PARCEL DELIVERY IN URBAN AREAS

In this chapter, the relevant aspects of last-mile parcel delivery are discussed. In order to provide an overview of the concept of parcel delivery in city centers, first it is explained what the last-mile parcel delivery entails process-wise and stakeholder-wise. Then, different strategies are discussed to optimize last-mile delivery process for Logistics Service Providers. Furthermore, the consumer demand side of parcel delivery is explained and possible factors that could be of interest while choosing for a certain delivery option are discussed. Then, it is explained what sustainability entails as this notion is a widely adopted understanding in several industries. Finally, factors that will be used to research the valuation of sustainability that might reflect the sustainability notion in this research are discussed. Based on all information in this chapter, a conclusion is drawn on factors to include in this research towards the valuation of delivery choice aspects.

As the main objective of this research is to determine consumer preferences of different delivery choice factors by means of discrete choice modelling, this chapter defines the model input partially: the conclusions in this chapter and the conclusions of the following chapter will be used as input for the survey design in chapter 5.

2.1 LAST-MILE PARCEL DELIVERY

The apparel parcel delivery process starts with the order placed by the consumer. Once the online retailer receives the order placement, the piece(s) of apparel is picked and packed in the online retailers' warehouse. Most online retailers cooperate with third party logistic service providers (LSP) to take care of the last-mile parcel delivery due to high costs to perform the delivery themselves Vos and Tahtali [2016]. Just a few online retailers perform the last mile parcel delivery in-house. The LSP consolidates the parcels, and aims at determining its own most efficient parcel delivery route to minimize costs for delivery. This consolidation provides for a decrease in operational delivery costs, but it requires a lot of planning and route optimization effort. Currently, the aim of the optimization of delivery services from an operator view is to minimize the last-mile delivery costs, since this is already the most expensive part of the supply chain Gevaers et al. [2009]. Figure 2.1 illustrates the entire parcel delivery process. Within the fast fashion industry, the delivery to three different destinations is possible: home delivery, pick-up point delivery and in-store delivery where pick-up is needed as well.

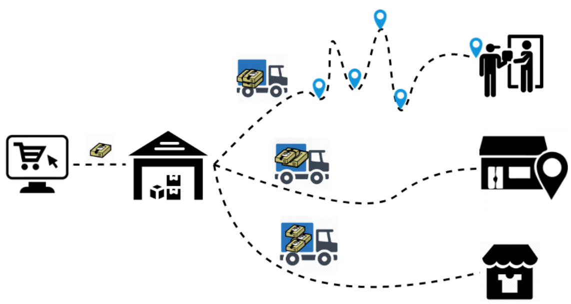


Figure 2.1: Parcel delivery process

In the parcel delivery and ordering process, three parties are involved: the online retailer, the third party logistics provider and the consumer. The relationship between all actors involved is triangular: the consumers places an order at the web store of the online retailer, and the online retailer is under contract with a LSP to perform last-mile delivery. In this research however, focus is on the relationship between the third party logistics provider (which supplies for delivery) and the consumer, who expects to receive the online order (demands delivery).

2.2 LAST-MILE DELIVERY OPTIMIZATION

The increasing demand and need for flexibility from a consumer perspective (for example next-day delivery) for parcel delivery in urban areas results in high inefficiency, and a polluting operation. Besides before mentioned innovative ways to deliver parcels, more strategic measures have been proposed to improve the efficiency, emission, and pollution levels in last-mile delivery. To optimize the last-mile parcel delivery, numerous studies have been performed on vehicle routing strategies. These strategies are based on a standard vehicle routing problem, which was first developed by Dantzig & Ramser 1959 and which are one of the most investigated combinatorial optimization problems in operational research because of their complexity and potential impact on real-world application in last-mile logistics Pillay and Rong [2018]. The basic vehicle routing problem developed by Dantzig & Ramser consists of:

- A depot, from which the delivery starts;
- A set of customers that need to be visited;
- The distance between each of the customers including the depot;
- The amount of vehicles that can be used to perform the delivery;

Based on the above-mentioned information, the optimal routes are determined to deliver parcels, at minimal costs for the LSP. In the years after the development of the first vehicle routing problems, numerous alternatives have been performed by researchers with distinct objectives of research: some aim at minimizing the total distance driven, others aim at developing routing strategies that minimize the total driving costs. An alternative strategy which received a lot of attention in research in the past few years is a focus on minimizing the amount of pollution emitted by the parcel delivery routing: the pollution routing problem and its variants Bektaş and Laporte [2011];Bektaş et al. [2015b];Figliozzi [2010]. The real world application of all VRP adds significantly to the increasing complexity of these problems: variations of the VRP have been studied in research integrating common features ranging from time windows to alternative (cleaner) vehicles, capacitated vehicles, a heterogeneous fleet and customer site-dependent restrictions in urban areas due to for example narrow or one way streets, and environmental zones Mostafa and Eltawil [2017];Kek et al. [2008];Zare-Reisabadi and Hamid Mirmohammadi [2015];Goeke and Schneider [2015].

As previously mentioned, different alternative delivery options have been proposed to consumers to minimize the effort for parcel delivery from a LSP supply side, with the aim of minimizing costs. An example of one of these options is pick-up point delivery, to which multiple packages for several consumers are delivered to a store, supermarket or parcel locker, instead of delivering every parcel to each customer's home individually.

2.3 CONSUMER DEMAND

From the consumer demand side of parcel delivery, several factors can be considered in the fast fashion industry. Therefore, first the check out process is discussed. Consumers place an order at an online store and enters into the 'online check-out-process'. This process is as follows: first, the consumer proceeds to fill in personal information which mostly requires name, address and phone number. Then, the consumer is asked to choose a delivery option. In order to make this choice, the consumer can weigh up multiple factors. Figure 2.2 shows an example of the consumer choice task in the fast fashion check out process.

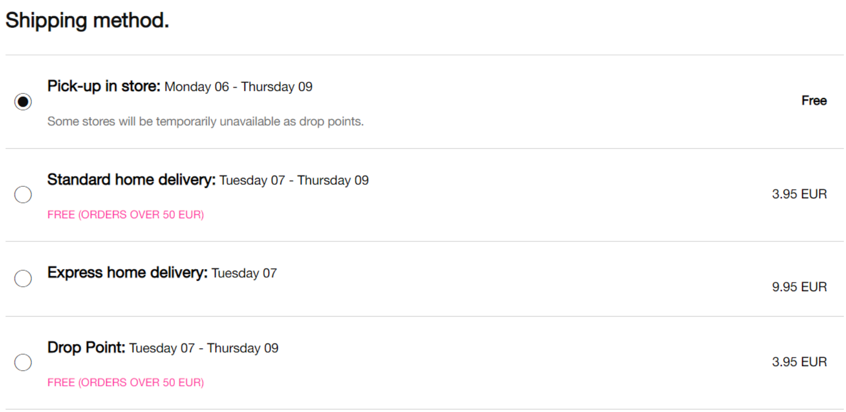


Figure 2.2: Delivery choice characteristics and lay out Zara [2019]

As indicated in figure 2.2, consumers can take into account *delivery speed*, *delivery price*, and *delivery location* while choosing a delivery option in the fast fashion industry Zara [2019]. In other industries it might be offered to weigh up time windows of the delivery (evening delivery or next hour delivery is possible), the accessibility of the pick-up points or the delivery interaction with being a human or a machine.

Delivery speed
In most (online) product categories, delivery speed is of great importance for consumers Marino et al. [2018];Lim and Winkenbach [2019]. Short delivery times can be of influence on consumers' choice for a specific e-tailer and is therefore a factor companies compete over Laghaei et al. [2016]. In the fast fashion industry the shortest delivery time is currently next-day delivery. Next-day delivery puts pressure on the logistics planning and results in inefficient deliveries due to sub-optimal delivery vehicle routing.

Delivery price
The factor *price* of the delivery method has been researched to be an important factor in the choice to order or not to order at a specific webshop van den Burg [2018]. Companies have been offering free deliveries as a part of their service in the last years. However, this has proven not to be a feasible business model. Therefore, several companies are on their return regarding free delivery. Apart from the issue of company profitability, charging a delivery price could facilitate the transition to more sustainable delivery by investing the delivery fee paid into development of sustainable delivery methods.

Delivery Location
First, home delivery was only offered by e-tailers, since warehouses management for the offline and online market were not integrated. Then, pick-up point deliveries emerged as a more efficient delivery location as a response to the increasing number of failed deliveries, but also to increase efficiency and decrease the costs of delivery Edwards et al. [2010]. Recently, in-store deliveries (e-tailers brick and mortar store) have been proposed to consumers to integrate online and offline logistics channels. The choice for delivery pick-up points and in-store deliveries eliminates the possibility of failed home deliveries and decreases the number of vehicle movements in city centers. The proximity of a collection point is determined to be of crucial importance for the choice for pick-up or in-store delivery points Weltevreden [2008]. However, since in this

research only urban residents are researched, it can be assumed that the nearest collection point is close by.

Time window

The time window of the delivery is of interest for most consumers. The failed delivery due to not being able to be at home at the designated time frame is a frustrating event which occurs at a quarter of all parcel deliveries van Oosterhout [2015]. In other industries than fast fashion e-commerce, time windows are communicated with consumers before choosing a delivery option. For example larger electronic stores, or book and toys offer the time windows for the delivery. Within the fast-fashion industry, this time window is not shares with the consumer until after the payment and delivery choice.

Accessibility of pick-up point

The accessibility of the pick-up point or in-store delivery is important information to take into account while choosing a delivery option. While some stores are only open for short periods of time, others have wide opening hours. This opening hours in terms of accessibility can be considered to be of interest while choosing for a delivery option. In this research however, only urban e-consumers are taken into account for their preference towards pick-up point delivery. Therefore, it is assumed that the choice for pick-up point delivery or in-store delivered, implicitly indicates that the consumer knows the accessibility of the pick-up point or store.

2.4 SUSTAINABILITY

Sustainability is an extensive term which is used for various aspects in research and in practice. The interpretation of sustainability can therefore differ from industry to industry. In general, sustainability and sustainable development is "development which meets the needs of the present, without compromising the ability of future generations to meet their own needs" CBS [2019b]. In this research of the analysis of last-mile parcel delivery, the results that might compromise the ability of future generations is the livability in cities in terms of Co2 emission and noise pollution. Therefore, a more sustainable last-mile parcel delivery is obtained when these levels decrease significantly. In order to improve the sustainability of parcel delivery, measures have been proposed. Besides innovative ways of parcel delivery by either drones or self moving parcel lockers that do not compete over range and capacity, alternative fuel vehicles have been proposed to perform delivery Schliwa et al. [2015]. The use of alternative vehicles decreases the Co2 emission levels significantly and therefore contributes to the sustainability of parcel delivery. An alternative approach to minimize the unsustainable effect of parcel delivery in city centers is, besides delivery to parcel pick-up points, also to stimulate cooperation between different LSPs Ploos van Amstel [2015]. The cooperation between different LSPs to deliver parcels in city centers, could reduce the amount of vehicles and vehicle kilometers in city centers, and will therefore also contribute to a more sustainable parcel delivery process.

2.5 MEASURES TO INCREASE SUSTAINABILITY

For this research it is proposed to include delivery choice factors that directly reflect a part of the delivery sustainability of parcel delivery. As mentioned in the introduction of this research, it is possible that consumers do not fully understand the impact of their choices on the sustainability of parcel delivery. To increase this understanding, it is proposed to include effects that directly indicate the effect of the delivery option on parcel delivery sustainability.

Alternative fuel vehicles

One of the measures proposed in research for sustainable improvement of parcel delivery is the introduction of diesel-hybrid and electric battery power vehicles Stanisław et al. [2014]. Currently, of all delivery vehicles in the Netherlands, 96% run on diesel fuel and less than 0,1% run on electric battery power Connekt [2017]. Electric freight vehicles (EFV) perform well in terms of reduction in emissions, low fuel costs and noise pollution but characteristics such as a limited range, relatively long charging times and the necessity to adapt charging infrastructure for the electric fleet pose a barrier for the implementation of electric vehicles Quak et al. [2016] & Lebeau et al. [2015]. However, attitude towards EFVs is changing and in general companies adopt and expand the number of EFV Granovskii et al. [2006].

Hybrid vehicles are powered by two different energy sources: a combination of a petrol and an electric power motor Hawkins et al. [2012]. They are beneficial in terms of air quality in city centers (since part of the energy is obtained from the electric power motor instead of the petrol motor). Hybrids are especially interesting in cities since the battery of the hybrid vehicle is charged upon pressing the brake and a lot of 'stop-and-go' traffic is present in cities due to congestion. This makes hybrid delivery vehicles an interesting interim solution for an increase in sustainability of parcel delivery in urban areas if they can drive on electricity in urban areas, whereas the diesel engine is used for rural areas. However, besides advantages, disadvantages are proposed in literature as compared to the conventional vehicle. Table 2.1 gives an overview of additional strengths and weaknesses of each of the different alternative fuel vehicles. Besides this overview, an indication on the amount of Co2 emissions per driven kilometers in urban areas is indicated in tab;e 2.2.

Table 2.1: Strengths and weaknesses of different vehicle fuel types

	Conventional	**Plug-in hybrid**	**Electric**
Strengths	Range is sufficient Fleet is available	Sufficient range Less emission Battery recharge in city centers because of stop-and-go congestion	No emissions No noise pollution
Weaknesses	High emission High noise pollution	Noise pollution	Battery range limited but sufficient in urban areas High investment costs

Table 2.2: Emission of vehicle types in urban areas

	Emission Co2 [gram/km]
Diesel	214
Hybrid	161
Electric	0

Besides the strengths and weaknesses presented in table 2.1, more factors are of influence on the use of electric and hybrid vehicles for parcel delivery in urban areas. These factors concern for example driving behavior of the driver, extreme temperatures and very heavy loads Vaicaityte et al. [2014];Enclose [2014]. The charging infrastructure for electric delivery vehicles is one of the important issues considered with the use of electric vehicles.

For this research, it is proposed to include a factor within the consumer choice for parcel delivery that indicates what kind of fuel (or what type of vehicle) is used to deliver the ordered parcel. This is proposed because it directly expresses whether or not the chosen fuel type contributes to the sustainability of the parcel delivery.

Delivery vehicle load factor
The load factor of the delivery van determines the share of the total available volume of the delivery van that is filled with parcels. If the entire vehicle is filled with parcels, a Full Truck Load (FTL) is obtained. In the current situation of parcel delivery, most urban delivery vehicles daily are loaded with less than 50% of their total volume Nijland et al. [2012]. This is called a Less than TruckLoad (LTL) and is typical for parcel delivery, especially if next-day delivery is requested by consumers Quak et al. [2016]. This causes more LTL delivery vehicles and and increase in vehicle kilometers in city centers, resulting in a less sustainable parcel delivery performance. The inefficiency and resulting unsustainable parcel delivery are caused by the competitive market and the very low profit margins remaining from this competition make it hard to stay in business for online companies Gansterer et al. [2013]

Increasing the delivery vehicle load factor is not straightforward and requires a lot of coordination within the vehicle routing optimization or between different Logistics Service Providers. Better fleet management has been proposed to address the issue of low load factors Benjelloun and Crainic [2009], and the consolidation of loads of different shippers and carriers requires extensive coordination between LSPs that compete with each other. To fully use the delivery vehicle capacity, it is also proposed to include return logistics in the same vehicle movement.

Consolidation resulting in increasing vehicle load factors for the individual LSP is proposed with providing consumers with a pick-up point delivery option: choosing for pick-up point delivery will result in higher load factors of vehicles, less vehicles needed to perform delivery, and therefore save costs for delivery for the LSP Gansterer et al. [2013].
While an increase in the delivery vehicle load factor is a complicated optimization process which requires a lot of coordination on the supply side of the parcel delivery, an ex ante communication of load factors towards consumers on the demand side for delivery is proposed for this research. The ex ante communication of the load factor, can directly indicate an aspect of the sustainability of parcel delivery, as this directly indicates the empty percentage of the total vehicle capacity. For the inclusion of this factor in this research, it does not matter whether this load factor which is displayed is a true number or a fictitious number to communicate this sustainability of parcel delivery: it is interesting to research whether consumers value the presence of this type of information and choose differently if low load factors are presented.

2.6 CONCLUSION

This chapter indicated the building blocks on which the attribute and attribute level selection of the choice tasks in the stated preference survey will be based. The chapter included the 1) parcel delivery process in section 2.1, 2) developed strategies to optimize the last-mile delivery for different objectives, 3) the factors that might be considered by consumers when choosing for a delivery option in the online fast fashion webshop, 4) The explanation of what is considered to be sustainable delivery in this research and 5) proposed measures to improve this parcel delivery sustainability which can be include in the research for the trade-off between consumers' choices for parcel delivery are discussed.

The order-and-delivery process consists of consecutive steps. The actors involved in this process are the e-retailer, LSP and the consumer. First, the check-out flow requires a choice for delivery on the currently to consider factors *delivery speed*, *delivery price* and *delivery location*. Then, the order is shipped from the e-retailers warehouse to the LSPs distribution center. Then, the parcel will be delivered to either the consumer's home, a pick-up point or an in-store pick-up point with vehicles within the fleet of the LSP.

Factors that are included in the remainder of this research to evaluate the preferences of consumers are the current factors that can be considered while buying online apparel: delivery location, delivery speed and delivery price. The factor *time window* is not included in the research because in real life, for online apparel webshops, it is not included as well and the time window of each of the delivery locations conflicts with one another, which makes the research towards this attribute in this research somewhat complicated. Additionally to the exclusion of time windows for the choice for delivery, the accessibility of the pick-up point and in-store delivery point are not taken into account in this research as well, as it is presumed that a preference for pick-up or in-store delivery implicitly indicates experience with this type of delivery location for urban consumers.

To include factors in a consumers' choice for a delivery option that reflect an improvement in parcel delivery sustainability, the factors *fuel type* and *load factor* are included in the remainder of the research. The fuel type is dependent on the type of car: diesel, hybrid or fully electrical. While an increase in load factor is complicated and requires a lot of optimization and coordination for the LSP, the preference towards an ex ante prognosis of the load factor of the delivery van while choosing a specific delivery option is included in this research. This might measure the importance consumers attach to the amount of delivery vehicles in city centers. The factor included in this research are indicated in Figure 2.3.

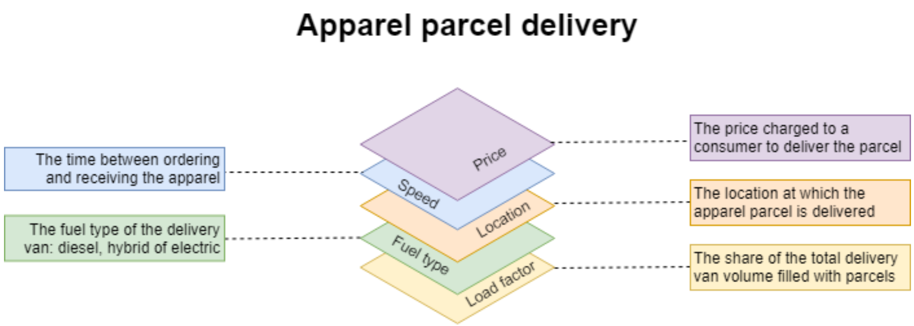


Figure 2.3: Factors included in this research

3 SUSTAINABLE CONSUMER BEHAVIOR

In this chapter, different strategies are discussed to determine whether consumers can be steered into a desired sustainable direction, and whether consumers differ from citizens in preferences for the parcel delivery characteristics discussed in chapter 2. First, the introduction of nudging and possible nudging types are discussed. Subsequently, the approach to require behavior for all citizens by proposing policy is proposed. Finally, the assessment of consumers' moral believes concerning cooperation is discussed to determine whether preferences differ for consumers that value morality in cooperation highly. The conclusion of this chapter will be used as input for context variables in the survey and possible differences in moral values concerning cooperation to identify different preferences for different consumer types.

3.1 NUDGING SUSTAINABLE BEHAVIOR

Strategies are increasingly being implemented that could steer individuals into making more sustainable decisions. The question is whether it is possible to steer individuals in making desired decisions for themselves or society by overcoming limitations of human intellectual capacity and behavioral preferences Lehner et al. [2016]. As indicated, value attached to sustainability has increased in recent years, but intention and preferences are not often translated into action. For example, research on renewable energy has proven that consumers favour energy from sustainable energy sources, but these preferences are not translated into actually ordering more sustainable energy sources Momsen and Stoerk [2014].

This is where nudges are introduced: a small purposefull change in information provided to respondents when making a choice to influence peoples' behavior. Nudges are proposed in many forms, especially in the digital environment Weinmann et al. [2016]. A nudge however is not a material incentive: subsidies and taxes are not considered as nudges: it is important that a nudge must preserve choice freedom for the respondent Sunstein [2015]. Relevant forms of nudging are:

- **Priming**: According to Kahneman and Frederick 2005, people mostly do not use all information available while making a decision but rely on what comes to mind. Priming influences 'what comes to mind' by providing information directly before the choice situation Momsen and Stoerk [2014].
- **Framing**: Framing is the way a choice situation is presented. Framing is the conscious way of information phrasing to activate particular values and attitudes of the individual Lehner et al. [2016].
- **Decoy**: Decoy is used to help the consumer trade-off information. It is mostly implemented as a third alternative (a decoy) that is dominated by one of the two alternatives to influence the decision process Momsen and Stoerk [2014].
- **Social norms**: This form of nudging relies on the tendency to "follow the herd". This following behavior is occasionally the result of a conscious choice but most of the time following a social norm is unconscious Ölander and Thøgersen [2014].
- **Default**: This type of nudging is commonly used in digital environments, where the preferred choice becomes the default choice, since the default choice is the "path of least

resistance". Research has proven that this leads people to select the default option Thaler and Sunstein [2008]

Since a choice experiment is proposed to research the valuation of different characteristics in the delivery alternatives, in a way, a combination of nudges is already included in this research. Priming is implemented because the stated choice experiments include assumptions that are read directly before making a choice and framing is included due to use of a specific layout of the choice experiments. These nudges come along with the set up of a state choice experiment. To steer consumers towards more desired sustainable behavior, the social norm nudge is proposed for this research. The nudge in the form of a social norm is decided to use due to the reflective nature of this nudge: it indicates that others behave in a certain way, and might therefore manipulate respondents to behave likewise (due to some sort of passive peer pressure). An example of this social norm is set in the hotel towel reuse research from Bohner & Schlütter, 2014, who concluded that when hotel guests received a social norm indicating sign that said '75% of guests reuse their towels', the towel reuse increased with 75%. Likewise, this nudge will be implemented in this research.

3.2 PREFERENCES IN POLICY PERSPECTIVE

When an individual decides to choose for a more sustainable delivery option, the benefit of this choice cannot solely be captured by the individual, which could create a feeling of other consumers' free-riding on the benefits paid for by the individual Batley et al. [2001]. Therefore, the consumer-citizen approach is set to research whether eliminating this free-riding effect will indicate different preferences for parcel delivery characteristics.

If sustainability of last-mile parcel delivery in city centers is achieved, this will eventually result in a better quality of life in cities: no urban greenhouse gas emission, low traffic noise, less vehicles and less vehicle kilometers in urban areas Manerba et al. [2018]. Achieving this goal is beneficial for all individuals living in urban areas and choosing for sustainable delivery will therefore not only be for their own good.

On this matter, there has been an ongoing debate in literature regarding environmental economics Ajzen et al. [1996]; Nyborg [2000] in which it is argued that individuals acting as a consumer pursue their own goals, whereas an individual as a voting citizen is also concerned about what is right or beneficial for its community Sagoff [2007]. The so called consumer-citizen duality. When individuals respond as citizens when making choices, they tend to place greater emphasis on public value than when they respond as a consumer Alphonce et al. [2014]. Some of the possible reasons for the duality between citizen and consumer preferences include trust, before mentioned free-riding, and the relative emphasis on prices in different contexts Alphonce et al. [2014]. Mouter & Chorus 2016 adopt an alternative view on this duality that underpins the difference between 'to what extent an individual trades-off different attributes' and the 'individuals' belief on how the government should trade-off these attributes when evaluating transport policies'. In order to research whether preferences for parcel delivery characteristics vary in the different situations, questions arise as to whether there exists a duality in preference as a consumer or citizen for parcel delivery characteristics in urban areas.

3.3 MORALITY IN COOPERATION

Many of the choices we make daily are assumed to have a 'moral dimension'. This moral dimension determines the extent to which decision makers decide whether something is 'right or 'wrong' Chorus [2015]. Sometimes, this decision of right or wrong seems obvious: to choose (not) to defend a classmate to a bully, choosing (not) to declare all relevant incomes to the tax man or choosing (not) to cheat on one's partner. In other situations the moral dimension of the choice is more implicit; latent.

Each time individuals make a choice that affects other human or non-human stakeholders, this is implicitly a moral choice. Weighing up various delivery choice factors to arrive at a delivery choice can be seen as a moral choice as well: the emission, congestion, and nuisance levels in city centers due to parcel delivery can do harm to citizens in terms of mental as well as physical health. The question is, if currently this moral dimension plays a role in the choice for parcel delivery. In order to determine whether this plays a role, different questionnaires have been developed in the past.

Curry 2018 developed the Morality as Cooperation questionnaire (MAC), in which morality is explained as a collection of biological and cultural solutions to cooperation recurrent in social human life. MAC builds on the Moral Foundations Theory (MFT) developed by Graham et al. 2012. By use of the theory of nonzero sum games, in which cooperative behavior can result in win-win situations, the MAC aims to identify seven distinct types of cooperation and to predict that each cooperation type distinguishes different moral domains. It thereby generates a deductive framework in which to make sense of morality Curry et al. [2019].

Seven moral domains are distinguished (as compared to the five moral domains in the MFT):

- **Obligations to family**: Is based on the theory of evolution. It suggests that under certain circumstances, people will help if this will bring benefit to their family. This will realize a mutual benefit, and will therefore be considered morally good. The MAC includes statements that try to predict this family altruism.
- **Group loyalty**: this type of cooperative behavior is also called 'coordination to mutual advantage'. With the MAC, it is predicted that because the solutions to coordination problems are aimed to realize mutual benefits, they will be regarded as morally good.
- **Reciprocity**: This domain indicates conditional cooperation for social dilemmas as a response to free-riders: the ones who receive benefit but do not share the costs.
- **Bravery & respect**: indicates that cooperation by competing in less mutually destructive ways. These types of cooperative behavior are assumed to be considered morally good
- **Fairness**: This domain constitutes from the evolutionary process of reciprocal altruism. It generates ideas of rights, justice, and autonomy.
- **Property rights**: indicate that resource conflicts can be overcome by recognizing prior possession.

In the case of weighing up different delivery choice aspects, domains of *obligations to family*, *group loyalty*, and *reciprocity* are of most interest. Due to their nature of realizing mutual benefit for their family or groups, and the free-riding concern in the reciprocity domain, it might be expected that this is the closest to the concern of preferring sustainability in delivery choices. Therefore, it might be expected that if consumers score highly on these domains, then they might also have a greater preference for sustainability factors in the delivery choice.

3.4 CONCLUSION

This chapter indicated the building blocks on which different contexts for the choice experiment survey are based. The chapter included 1) Nudges that are proposed and their contribution to steer into desired sustainable preferences, 2) policy possibilities to include a the collective decision making and the impact on preferences for parcel delivery, and 3) the different moral domains that aim at distinguishing consumers that value cooperation differently.

To nudge consumers into more desired sustainable preferences for delivery, including a social norm is most suitable to communicate cooperation. This type of nudging does not manipulate the consumer (in a way that autonomy has been affected) but indicates that others behave in a certain way and aims at achieving a certain feeling of peer pressure to value parcel delivery characteristics differently. The nudging types *framing* and *priming* are both passively implemented by using a stated choice experimental survey: priming concerns the inclusion of assumptions that are read directly before the choice task and framing is included due to use of a specific layout of the choice experiments.

In order to take away the feeling of free-riding to identify whether differences in delivery choice characteristics exist, research into the inclusion of a context in which policies are introduced that require *all* consumers to choose similarly is proposed. The so-called consumer-citizen approach reflects this concept in which, instead of asking a consumer to choose a delivery option, a respondents is asked as a consumer to choose a policy regarding delivery options that will be implemented for all consumers.

The morality concerned with cooperation is researched by Curry et al Curry et al. [2019] and determines that morality is explained by cooperative behavior recurrent in social human life. A questionnaire is developed by the researchers that aims to assess the seven distinct moral domains of cooperation: obligations to family, group loyalty, reciprocity, bravery, respect and fairness. It might be expected that consumers that value the domains family, group and reciprocity highly, might also value the delivery choice aspects differently.

4 METHODOLOGY

In this chapter, the methodology to research the preferences for parcel delivery characteristics and to evaluate possible impact of these preferences on sustainable parcel delivery is discussed. First, the proposed parcel delivery choice trade-off is discussed. Then, discrete choice modeling (DCM) approach is explained to estimate the consumer trade-off of delivery characteristics. In this section, the use of stated preference data as compared to the use of revealed preference data and the assumed decision rule are discussed as well. Subsequently, the choice task is provided which is proposed for the survey, together with additional information on the experimental survey setup. Then, the approach to determine the impact of different survey context settings and consumer group differences on the delivery choice characteristics is discussed and the data analysis framework is determined. In addition to this section, hypotheses based on previous chapters are proposed. And finally, the conceptual framework to determine the impact of consumer preferences for parcel delivery policies and choices on sustainable parcel delivery performance is discussed. Along with this conceptual framework, Key Performance Indicators to measure performance and questions for policy development are proposed.

4.1 THE SUSTAINABILITY TRADE-OFF

The first four research questions will be answered by estimating the framework in figure 4.1. This framework indicates that choices are based on attributes (and attribute levels) that determine the utility of a delivery choice alternative. The arrows that interact with the attributes that determine the utility of an alternative indicate the proposed research into heterogeneity in preferences for different consumer characteristics and the impact of different task contexts on the preferences for the delivery characteristics. First, the generic preferences will be estimated to determine the trade-off between the different parcel delivery method attributes. Second, the approach to determine the impact of different context settings on the trade-off is determined by varying the included context variables sufficient times (section 4.4). Third, measured moral norms & values, (sustainable) buying behavior, and socio-demographic variables will be incorporated to determine whether taste heterogeneity can be distinguished between different consumer types (section 4.3).

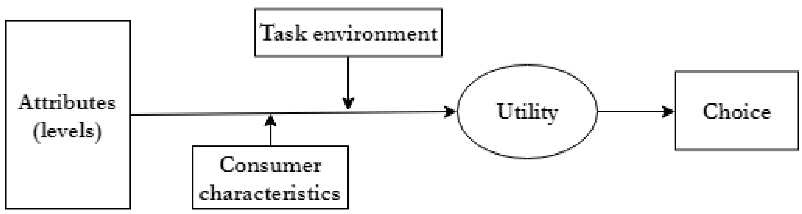


Figure 4.1: Conceptual Model Sustainability Trade-off

4.2 DISCRETE CHOICE MODELING

To research the trade-off in consumer delivery choices, discrete choice models are estimated. Section 4.2.1 underpins the difference in use of Revealed Preference and Stated Preference (SP) data and the decision rule proposed for this research is discussed.

Discrete choice modelling (DCM) considers an economic and quantitative approach with the assumption that each choice made is the outcome of a rational choice process. With DCM, a researcher is able to describe, explain and predict respondents' choices between two or more alternatives in this research considered to be the parcel delivery choices Araghi et al. [2014]. The discrete choice experiments have one additional feature which makes them particularly promising for the evaluation of (moral) choice behavior: DCM is designed for the analysis of the decision makers' trade-off valuation between several attributes at the same time Chorus [2015]; Araghi et al. [2014]. One important note to general discrete choice models concerns that every individual is assumed to have the same preferences, elasticity, and substitution pattern for different alternatives, while in real life this assumption is not completely realistic van Cranenburgh [2017]. However, in this research it is not expected that individuals have the same preferences, but differ in preferences as an interaction with personal characteristics. Therefore, interactions are estimated to determine these preference differences. To estimate the delivery trade-off in discrete choice models, stated preference (SP) experiments are conducted by means of surveys.

4.2.1 Stated Preference data as compared to Revealed Preference data

Revealed Preference (RP) data consists of real-market alternatives, and focuses on what people actually did. The use of this kind of data results in high model validity and is suitable for forecasting choice alternatives if market conditions do not change much Molin [2018]. However, RP data also has downside in the research field: no new alternatives or attribute(-level)s can be included in the research, since these cannot be empirically observed. As indicated in appendix A, the sustainability of the delivery has not yet been included in the currently considered delivery options. Therefore, real behavior regarding this attribute cannot be observed and it is impossible to disentangle utility of the sustainability of the delivery method from the other attributes. Another limitation of the use of this type of data is that the choice set is unknown: if a consumer chooses a delivery alternative, it is not known which other alternatives were considered.

On the contrary, SP data can be obtained from an experiment by means of surveys. The main advantage of the use of this type of data is that it allows for the inclusion of non-existing alternatives, attributes and attribute levels. It is important to keep in mind that the use of SP data could cause hypothetical bias: would people really choose the option in real life? This bias is mainly caused by the fact that the consequences of choices are not felt and the respondent has perfect information on the choice while in real life this is mostly not the case Molin [2018].

4.2.2 Random Utility Maximization

The construction of a Stated Preference experiment is performed for estimation of a specific model or range of models. Therefore, before creating the experimental design, the underlying to be estimated model needs to be determined. One of the most widely adopted models is the Random Utility Maximization (RUM) model developed by McFadden 1973. In this RUM model it is assumed that each decision maker chooses the alternative from which they experience the highest utility. An alternative approach of Random Regret Minimization (RRM) is proposed by Chorus et al. 2008. This approach allows for the possibility that choices between alternatives could be caused by the avoidance of negative emotions, rather than the maximization of utility. In this research, model estimations are done based on the RUM decision rule.

The assumption underlying RUM models is that the decision maker derives a specific utility for each of the attributes of an alternative: the part-worth utility. Based on the sum of all part-worth utilities, the overall utility of an alternative can be determined. For this research, this means that consumers choose for the delivery options that provides them with the highest utility. The overall utility of an alternative is determined by both systematic and random utility: systematic utility can be predicted by the included parameters in the model, while random utility is considered 'noise' and cannot be predicted by the model. The random utility represents variability in the total utility of a specific alternative *i*. The total utility of an alternative is indicated by the linear additive utility function:

$$U_i = V_i + \epsilon_i = \sum_m \beta_m x_{im} + \epsilon_i \tag{4.1}$$

Where,
U_i is the utility from alternative i
V_i is the structural utility, which can be predicted by the model
ϵ_i is the random utility, this cannot be predicted by the model
β_m denotes the attribute weight m, the parameter estimate for attribute m
x_{im} indicates the attribute levels of attribute m for alternative i
i represents an alternative i
m represents an attribute m

By assuming the error term ϵ_i is independently and identically distributed according to the Extreme Value Type 1 distribution, the choice probabilities for a specific alternative is denoted by the Multinomial Logit (MNL) formula indicated in formula 4.2.

$$p_{(i)} = \frac{e^{(V_i)}}{\sum_{j=1...j} e^{(V_j)}} \tag{4.2}$$

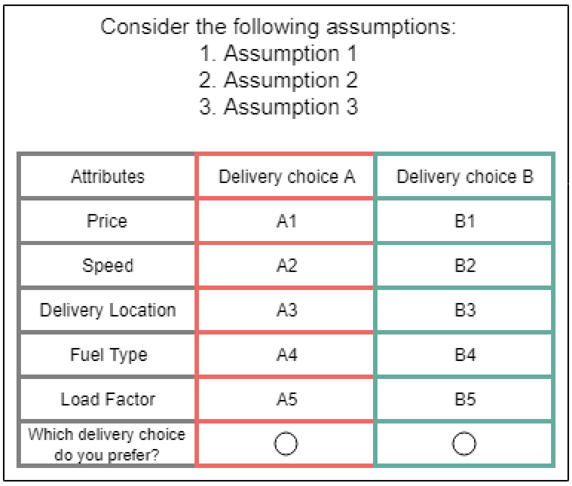
Where,
p_i is the probability that alternative i is chosen among the set of j alternatives
e is the base of the natural logarithm
V_i denotes the utility of alternative i
j denotes the set of alternatives in the choice set

Parameter estimates are determined based on the principle of Maximum Likelihood estimation: the set of parameters that make the *data* most likely Chorus [2018].

4.2.3 Choice tasks

In order to evaluate the importance of the different attributes while a delivery option, choice tasks with varying values for different attributes are included in the research. Each choice task that is proposed to the respondent consists of different components: attributes and attribute levels, alternatives, the choice question and specific assumptions that have to be made while making a choice. The attributes are the characteristics of the delivery method, alternatives are different delivery methods that consist of a combination of these attributes. The respondent needs to decide between *two* alternatives along with some assumptions (these assumptions vary per respondent, see section 4.4). The respondent is then asked to indicate the preferred alternative. A plain example of such a choice task is illustrated in 4.2.

To establish useful combinations of different delivery attributes in each choice alternative, an experimental choice set design needs to be created. This is done to create enough variation in the different choice situations so that the envisioned utility functions can be estimated and the parameter estimates have small standard errors (higher parameter accuracy). It is also very important that the choice tasks (and corresponding survey) do not exhaust the respondent since this can lead to unreliable parameter estimation and increase standard errors Molin [2018].


Consider the following assumptions:
1. Assumption 1
2. Assumption 2
3. Assumption 3

Attributes	Delivery choice A	Delivery choice B
Price	A1	B1
Speed	A2	B2
Delivery Location	A3	B3
Fuel Type	A4	B4
Load Factor	A5	B5
Which delivery choice do you prefer?	○	○

Figure 4.2: Plain choice task example

To achieve this, it is proposed to construct an *efficient design*. This type of design increases the amount of information retrieved from each choice set, obtains higher reliability with the same number of respondents, and allows for utility balance of the alternatives in each choice set (i.e. no dominant alternatives in the choice sets that reveal no information on the consumer trade-offs) Molin [2018]. In order to construct efficient designs a pilot study must be conducted to obtain priors (if priors cannot be retrieved from literature). Priors are best guesses of parameters and since no literature exists on the set of parameters to be estimated in the proposed scope, a small pilot study ($N \geq 30$) is proposed to obtain them. Based on the priors that result from the pilot study, efficient designs can be created and implemented as choice tasks in the final survey to examine the first research question of the research.

4.3 CONSUMER GROUP DECISION VARIABLES

To answer the second research question, the approach to include explanatory variables to determine whether they have mediating effects on consumer delivery choice preferences is discussed. In this light, questions regarding socio-demographics, (sustainable) buying behavior, and morality need to be included in the questionnaire.

As determined in previous research, it was concluded that factors age, income, gender, education level and household composition differ in the sustainable concern of consumers. For this research, this needs to be verified as well. It might be expected that consumers that are younger, are more sensitive for time, as in this changing world of increasing efficiency, speed is of crucial importance. Whereas elder consumers, who have not grown up in this high speed environment, might be less sensitive to longer delivery times. It might also be expected that higher incomes are less sensitive for delivery prices, as this is a smaller part of their disposable income. Similarly, it is expected that respondents that have obtained a higher educational degree, are less sensitive for delivery prices, as they mostly earn more more. For the delivery price, it is also expected that younger consumers are more sensitive for delivery prices, as they mostly do not earn a lot of money.

The highly educated consumers are expected to have a better understanding of the meaning of load factor increase, and a preference of this delivery choice characteristic might be expected. It is also expected that younger consumers have more preference towards higher load factors, as younger consumers are expected to be more environmentally oriented. Based on the research into different sustainable consumer types, it was concluded that in general, females are more sustainable oriented than men. In this light, it might be expected that female consumers value the alternative fuel vehicles more than men. Similarly, it is expected that females like in-store and pick-up point delivery more highly. This might be result of either their more sustainable mindedness, or that they like shopping better in general, resulting in a shopping trip along with the pick-up of the parcel. The consumer's demographic variable of household size might have an effect on the delivery location: due to tight schedules and high occupancy rates of consumers that have children, it might be expected that these type of consumers prefer home delivery more than delivery which needs additional movements to and from a parcel pick-up point or store.

The (sustainable) buying behavior of consumers might also have an effect on the valuation of different delivery choice characteristics. It is therefore interesting to include questions on these factor to determine whether differences in preferences exist. Buying behavior and especially sustainable buying behavior is of interest since it is expected that consumers that already show sustainable behavior and pay extra for sustainable products in real life have a greater preference towards sustainability reflecting delivery choice factors. The online buying behavior however could point out different preferences for delivery choice characteristics between frequent and non-frequent online buyers. It might be expected that consumers that buy frequently, are more sensitive to delivery prices, as they have to pay these prices more frequently. Consumers that spend a lot on the internet might be less sensitive to delivery price changes, as this is a small(er) share of the total amount spend on online shopping. In the same light, these consumers might be more sensitive to delivery speeds, as a high amount of money spent on clothing is expected lead to increased importance attached to faster delivery.

It is preferred to make an individual's 'morality' measurable with as least as possible factors, but morality is a combination of an individual's ideas. Therefore, morality cannot be measured in a single construct. It is proposed to include the Morality as Cooperation Questionnaire from Curry 2019 into the survey. For the Morality questions, seven moral domains are distinguished: obligations to family, group loyalty, reciprocity, bravery, respect, fairness, and property rights Curry et al. [2019]. A scale is used to test whether these types of cooperative behavior are considered morally relevant, and also whether they represent distinct groups. The MAC-questionnaire consists of 42 questions concerning the different morality domains and are divided into 21 Relevance questions and 21 Judgement questions. The judgement questions were originally developed to overcome a limitation of the *relevance*-scale: that it might determine 'second-order' views about how an individual makes moral judgements, instead of the 'first-order' moral judgements Curry and Van Lissa [2018].

It is expected that in the view of 'not-exhausting-the-respondent', 42 relevance and judgement propositions next to the other sections in the survey are too exhausting. Therefore, it is proposed to arrange a small focus group to determine the most controversial questions in both Relevance and Judgement questions. This is proposed because it might be more evident to distinguish different types of individuals and their taste parameters based on the scores for the different moral domains in the questionnaire. The remaining questions, preferably at most 2 for each moral domain, will be included in the final questionnaire. The scores in the different moral domains will be included in the DCM estimation as if they are types of personal characteristics: whether or not they value the different moral domains highly. As previously mentioned, it is expected that the moral domains *family*, *group* and reciprocity are of most interest in this research, and therefore it is expected that consumers who value these cooperation types highly, also value the sustainability reflecting characteristics of parcel delivery more.

The resulting hypotheses that concern the effect of demographics on preferences for different delivery choice characteristics and the hypotheses that consider the effect of (sustainable) buying behavior on the preferences are indicated in table 4.1. These hypotheses relate to the second research question of determining whether differences in preferences for delivery choice factors are to be extinguished between consumers with varying personal characteristics.

Table 4.1: Hypotheses to research consumer preference differences

	Demographics
H1	Consumers with a low income are more sensitive to delivery prices
H2	Young consumers are more sensitive to delivery prices
H3	Highly educated consumers are less sensitive for delivery prices
H4	Young consumers are more sensitive to delivery speeds
H5	Higher educated consumers increase preference for delivery vehicle load factors
H6	Young consumers prefer higher delivery vehicle load factors
H7	Having children decreases the preference towards in-store and pick-up point delivery
H8	Females have more preference towards in-store and pick-up point delivery
H9	Young consumers prefer pick-up and in-store delivery
H10	Females have more preference for alternative fuel vehicles than men
H11	Young consumers have more preference towards alternative fuel vehicles
H12	Highly educated consumers have more preference towards alternative fuel vehicles
	(Sustainable) buying behavior
H13	Consumers that buy bio products, are less sensitive to price changes
H14	Consumers that buy bio products, have an increased preference towards alternative fuel vehicles
H15	Consumers that buy bio products increase preference for in-store and pick-up point delivery
H16	Consumers that spend a lot of money on clothing online, are more sensitive to delivery speed
H17	Consumers that spend a lot of money on clothing online, are more sensitive to delivery price
H18	Consumers that frequently shop online, are more sensitive to delivery speed
H19	Consumers that frequently shop online, are more sensitive to delivery prices
	Morality
H20	Consumers that highly value the cooperation domains, value alternative fuel vehicles more highly
H21	Consumers that highly value the cooperation domains, value load factors more highly
H22	Consumers that highly value the cooperation domains, are less sensitive to price changes

4.4 THE IMPACT OF CONTEXT ON PREFERENCES

The third and fourth research question proposed for this research in section 1.3 indicate research into a consumer-citizen duality and to determine the effect of including a social norm to steer towards more sustainable consumer behavior. Therefore, it is proposed to define context variables and to construct context profiles to apply to the choice sets. Therefore, not only the attributes of the choice alternatives are varied across the choice sets, but also the context variables. By applying different contexts to a respondent, it is possible to observe differences in choice behavior for a specific respondent. In certain context situations however, it is not possible (or desired) to change the context of the experiment within the same respondent: once the application of a nudge or context specific assumptions regarding the role of the consumer are presented, it is assumed that they cannot be 'unseen'. Therefore, in this research, the effect of different contexts on one individual's choice behavior is not observed, only the difference between individuals. These context variables need to be estimated as interactions with the attribute coefficients in the analysis phase Molin [2010].

4.4.1 Consumer or citizen

In order to incorporate and be able to evaluate whether differences in preferences exist between a consumer-perspective and a citizen-perspective as formulated in section 3.2, both perspectives are proposed to be included as different contexts in this research. In one context (consumer), respondents are asked to choose as a consumer of an online clothing order between delivery options which differ in delivery speed, price, delivery location, fuel type and load factor of the delivery van (figure 4.2). Secondly, other individuals are asked to choose between different policy proposals for parcel delivery in city centers. This partly resembles the approach Mouter & Chorus 2016 proposed for determining consumer-and citizens' value of time. This research however adopts a governmental policy view as compared to the governmental investment view which is adopted in Mouter & Chorus' 2016 article. Based on this consumer-citizen duality, it is expected that because of free-riding effects are eliminated in the citizen context, respondents that needs to make choices while acting as a citizen, are less sensitive to price changes than respondents that need to act as a consumer. This also counts for the sustainability reflecting factors: consumers appreciate alternative fuel vehicles and higher load factors less than citizens.

4.4.2 Nudging the decision

In order to determine whether respondents value the delivery factors differently if they are steered into a desired sustainable direction, it is proposed to include a collective participation rate (social norm) of people who have chosen 'sustainable delivery' Araghi et al. [2014]. The research towards the incorporation of a social norm is interesting because it has been researched that people are mostly only willing to contribute to a common good such as sustainability if other do as well Egerton et al. [2009]. It is expected that the inclusion of a social norm in the context of the respondent's choice task, decreases the sensitivity for price changes and increases the preference for alternative fuel vehicles and load factors in delivery vehicles, as it is indicated in the social norm, that other consumers do as well.

The resulting hypotheses that concern the impact of contexts on the preferences for different delivery choice attributes is indicated in table 4.2. The hypotheses drafted in this table relate to the third and fourth research question that aim to research the effect of including a nudge to steer towards more sustainable behavior and the effect of varying choice perspectives to determine whether a consumer-citizen duality exists for preferences.

Table 4.2: Hypotheses for the impact of context on consumer preferences

	Context
H23	Consumers are more sensitive to price changes than citizens
H24	Citizens value alternative fuel types higher than consumers
H25	Consumers value home delivery more than citizens
H26	Citizens value the average load factor of the delivery van more than consumers
H27	The inclusion of a social norm increases the preference for alternative fuel types
H28	The inclusion of a social norm decreases the sensitivity for delivery prices
H29	The inclusion of a social norm increases the preference for higher load factors

4.5 DATA ANALYSIS FRAMEWORK

Once the survey data has been collected, the general discrete choice models and the discrete choice models with different interactions will be estimated by means of PythonBiogeme. This software consists of a Python package which is specifically designed for estimation of parameters of discrete choice models by use of maximum likelihood estimation as described in section 4.2.2: the parameter estimations that make the *data* most likely Chorus [2018]; Bierlaire [2018]. Figure 4.3 illustrates the detailed framework proposed for this research.

First, a RUM-MNL model needs be estimated to determine parameter values that make the data most likely. Then, the different contexts are included in the model, in order to determine

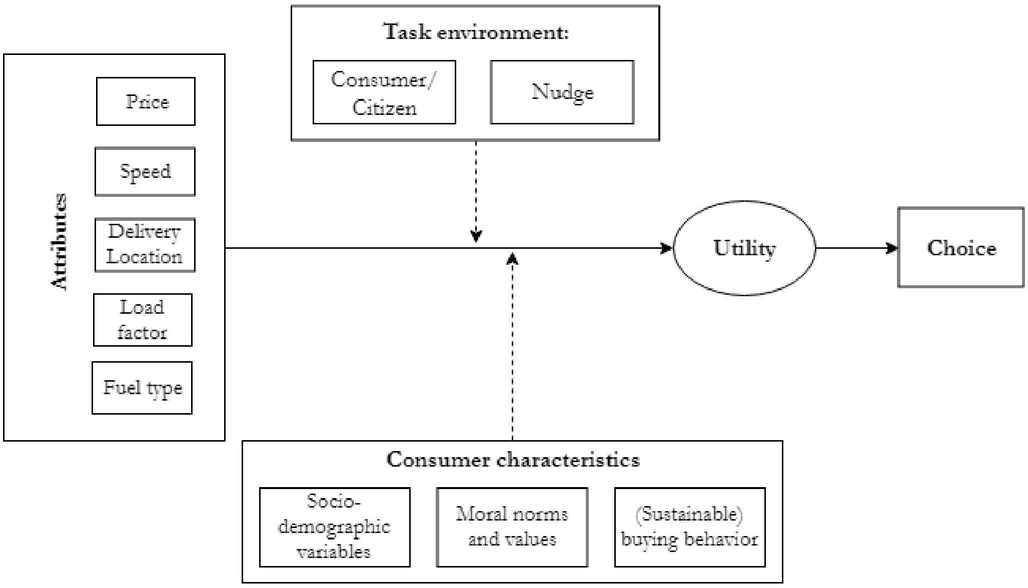


Figure 4.3: Data analysis framework

whether differences in context have an impact on the delivery preferences. Subsequently, a DCM with interactions is estimated to determine whether the hypothesized consumer characteristics explain differences in preferences between different consumer demographics, (sustainable) shopping behavior and moral believes. For the model with the interaction of context as well as the model which includes consumer characteristics, the impact of different interactions will first be estimated individually, and finally all significant interactions are included in one model to determine the remaining significant factors Molin [2010]. Based on the determined consumer references, a model can be constructed that predicts the consumer choices with different apparel parcel delivery policy settings based on the choice probability function indicated in equation 4.2.

4.6 THE EFFECT OF CONSUMER PREFERENCES ON SUSTAINABLE PARCEL DELIVERY PERFORMANCE

To evaluate the impact of consumer preferences on sustainable parcel delivery performance, different delivery policy scenarios are constructed. The choice prediction model resulting from the consumer preferences is then used to predict the consumer choice shares for each of the constructed scenarios. The consumer choice shares can then be used as input for the sustainable delivery policy analysis as indicated in figure 4.4.

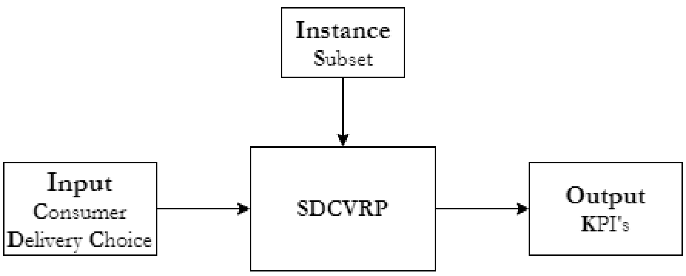


Figure 4.4: Conceptual model sustainable parcel delivery performance assessment

Once the consumer choices for different scenarios are determined, a vehicle routing (VRP) needs to be formulated to process the input into output that indicates the sustainable parcel delivery performance. For the VRP, a configuration must be developed that incorporates the choices consumers can make in the delivery choice that are compatible with a static vehicle routing problem: delivery location, vehicle load factor and vehicle fuel type. As a static model is proposed for this research, the delivery speed will remain constant in the determination of consumer preferences for different policies, and it will not be included in the VRP. Whereas the delivery costs can be considered in the development of delivery policies, they will not be implemented in the configuration of the VRP. In this light, a Site-Dependent Capacitated VRP (SDCVRP) is proposed for this research which is mainly based on the approach proposed by Zare-Reisabadi & Mirmohammadi 2015. With this model it is aimed to find optimal routes given a specific objective function, while considering several relevant constraints. The use of SDCVRP is also indicated in figure 4.4 in which the consumer choices combined with a small network (instance) are used as input to generate output in the form of Key Performance Indicators (KPI).

The term instance denotes a (small) network with one or multiple depots from which the parcels are delivered. It also contains a set of consumers that have to be served with corresponding locations and for each a specific demand. For this research a subset of 10 consumers of the well-known Solomon instance C108 is proposed Solomon [1987]. The general Solomon instance subset needs to be altered according to the predicted consumer choice shares for delivery options in different scenarios.

4.6.1 Delivery performance KPI's

As research into the effect of consumer choices on sustainable parcel delivery is proposed, it is important to determine what is considered to be the *effect* for this research (denoted as the output in figure 4.4). Therefore, different KPI's are determined that indicate the performance of each of the scenarios, based on a comparison of each of the KPI's for each of the scenarios, the performance can be evaluated and recommendations can be set.

In previous chapters, it is determined that the livability in cities is partially affected by parcel delivery in terms of the increasing number of vehicles and vehicle kilometers and increasing Co2 emission levels. The number of vehicles combined with the number of vehicle kilometers indicate the level of congestion or obstruction that delivery vehicles cause in city centers. This has a negative effect on the sustainability of parcel delivery and results in a decrease in the livability in urban areas. The Co2 emission levels are result from both the number of kilometers driven in urban areas and the different types of vehicles used with different levels of Co2 emissions per kilometre in urban areas. In order to minimize the number of vehicles used in urban areas, a third effect that is measured for the different scenarios is the average load factor of the delivery vehicles. Therefore, as a result, the KPI's that are included to measure and compare the effect of different delivery policies are indicated in table 4.3

Table 4.3: Key performance indicators for sustainable parcel delivery performance

KPI	Explanation	Unit
Total distance	The total number of delivery vehicle kilometers in urban areas	km
Total amount of Co2 emissions	The total kilograms Co2 emitted by the parcel delivery in urban areas	kg
Average load factor of the delivery vehicles	The average percentage of the total vehicle capacity which is filled with parcels	%

As indicated, the KPI's are the result of a combination of different model output values, which are indicated in table 4.4.

Table 4.4: Model output to arrive at KPI's

Model result	Relationship with KPI	Unit
Number of vehicles used	The number of vehicles used to deliver all demand to the consumers	vehicles
Clean vehicle kilometers	Number of kilometers driven with electric vehicles	km
Vehicle loads	The share of the total volume of the delivery vehicle filled with parcels for each vehicle	%

4.6.2 Research question for delivery option policies

To set up policy scenarios that are of interest to increase sustainability in parcel delivery, research questions are constructed. The research questions relate to a standard delivery policy, in which home delivery with diesel vehicles is assumed. For this part of the research, the following research questions have been proposed:

- What is the effect of including pick-up point delivery in the delivery policy set up on sustainable parcel delivery performance?
- What is the effect of adding an electric vehicle delivery service to the currently considered diesel delivery on sustainable parcel delivery performance?
- What is the effect of offering free pick-up point delivery and paid home delivery to the consumers on parcel delivery performance?
- What is the effect of offering electric pick-up point delivery to the consumer on sustainable parcel delivery performance?
- What is the effect of offering free diesel home delivery, as compared to paid electric home delivery to the consumer on sustainable parcel delivery performance?

4.7 CONCLUSION

To answer the research questions and to point out policy recommendations for the improvement of sustainability in parcel delivery which is preferred by consumers, the methodology proposed for this research is two-folded: a stated preference discrete choice experiment is proposed to determine consumer preferences and a Site-Dependent VRP is proposed to determine the effect of consumer preferences on the sustainability in parcel delivery.

First, it is proposed to determine the trade-off between the different delivery choice factors by means of a survey for a discrete choice model approach based on a RUM-MNL model. Once the consumer trade-off of the delivery factors is determined for the general population, it will be determined whether certain consumer characteristics can explain differences in preferences for delivery choice factors. The inclusion of different survey contexts is proposed to determine whether consumers differ in preferences as compared to voting citizens (consumer-citizen duality). It is also proposed to include the social norm in the contexts, to determine whether these social norms have an effect on the preferences for delivery choice factors. Based on the identified consumer preferences, it is proposed to set up a choice prediction model, in which the consumer choice shares of different parcel delivery set ups can be determined.

Second, it is proposed to determine the choice shares for different scenarios of parcel delivery set ups. These choice shares are used as input for the proposed Site-Dependent VRP to determine the effect of the different scenarios on sustainable parcel delivery performance. The choice shares are applied to an instance which is a small network representation of a depot and consumers with corresponding locations, demand and site-dependencies. The effect of the input of consumer preferences and choices on the sustainable parcel delivery performance is indicated and evaluated in terms of total kilometres driven in urban areas, which results in congestion and obstruction of roads, and the amount of CO_2 emitted by the delivery operation. In addition, the average load factor is indicated.

5 SUSTAINABLE DELIVERY SURVEY DESIGN

In this chapter, the construction of the SP survey and the included attributes, attribute levels, context variables, socio-demographics, consumer buying behavior and moral questions are discussed. First, the different attributes and attribute levels included in the SP choice experiments are introduced. Then, the choice set for the pilot survey, to obtain best guesses on parameter values (priors), is constructed. Based on the prior parameter values for the different attributes, the final survey choice sets are determined by means of Ngene efficient designs in section 5.3. In section 5.4, the context variables are constructed into context profiles, the distinct sections included in the final survey are described, and the required number of respondents is determined.

5.1 ATTRIBUTES AND LEVEL SELECTION

To set up the SP survey, attributes and attribute levels are determined. Attribute selection is based on the conclusions in chapter 2 on characteristics of the available online delivery methods. From the currently available delivery methods for fashion orders, the attributes *delivery price*, *delivery location* and *delivery speed* are considered. For the fashion consumer, *delivery prices* increase when *delivery speed* increases (the delivery time decreases). The attribute *delivery location* differs per company: most companies offer home delivery and pick-up point delivery, but some companies begin to, or have already, offer in-store delivery (appendix A).

The incorporation of sustainability factors of delivery and to test the preference of consumers towards these factors, two attributes are included in the choice experiment. The first considered factor is the *fuel type* of the delivery van, since this underpins the difference between conventional vehicles as compared to more sustainable modes in terms of fuel use and emissions (both in terms of Co2 and noise pollution) Granovskii et al. [2006]. The second attribute that is included is the delivery vehicle *Load Factor*. This attribute is selected to research whether an ex-ante prognosis on the load factor of the delivery van is of interest for the e-consumers. Figure 5.1 indicates the different attributes and different attribute levels included in this research.

Attributes	Level 0	Level 1	Level 2
Price	€0	€3,95	€6,95
Speed	1 day	3 days	4 days
Delivery Location	In-store	Pick-up Point	Home Delivery
Fuel Type	Electric	Plugin Hybrid	Diesel
Load Factor	25%	50%	75%

Figure 5.1: Attributes & levels

5.1.1 Alternatives & choice set construction

For the construction of the choice set based on the different attributes and attribute levels, it is determined to provide the consumer with 2 alternatives per choice set. This is the commonly used number of alternatives per choice set. By choosing alternative A, the respondent indicates that (s)he prefers alternative A over alternative B. The considered alternatives are unlabeled since only generic attributes are included (the same attributes and levels apply to all alternatives). As a consequence, the alternatives remain unlabeled, and are defined as 'delivery option A' and 'delivery option B'. Since unlabeled alternatives are considered in this experiment, choice sets are sequentially constructed Molin [2018].

5.2 PILOT SURVEY TO OBTAIN PRIOR VALUES

In order to obtain priors (best guesses on parameter values needed to balance utilities of the choice alternatives) for the final efficient survey design a pilot survey has been set up. The attributes and attribute-levels determined in the previous section are used for this pilot survey.

5.2.1 Alternative & choice set construction

To obtain prior values, an orthogonal design (appendix B) is used to determine the different configurations of the alternatives. A sequential construction method is used for the construction of the choice sets: each subsequent choice set is determined by *sequentially* drawing different sets from two vases.

Fractional factorial design

Basic plans are used to determine the smallest design that is able to accommodate all selected attributes that establish orthogonality (uncorrelated attributes) and that preferably secure attribute level balance (each level appears an equal number of times across the choice sets). For the amount of attributes and levels considered in this research (figure 5.1), basic plan 3 is appropriate to apply for choice set construction of the pilot study. This basic plan results in 16 choice sets.

The use of the specific orthogonal design results 16 choice sets per respondent. However, 5 out of the 16 constructed choice sets resulted in one of the alternatives being dominant over the other (at least better on one attribute, not worse on all others). Dominant alternatives do not provide any information about the respondent's trade-off. Therefore, based on the conclusion of Walker et al. 2016 that the removal of dominant alternatives can improve the efficiency of the design where a small sample is used to generate priors, the 5 dominant alternatives are removed from the choice set. Details on the generated choice sets can be found in Appendix B. An example of a choice set is illustrated in table 5.1.

Table 5.1: Example of a choice set

Attribute	**Delivery choice 1**	**Delivery choice 2**
Delivery speed	4 days	1 day
Delivery location	Home delivery	Pick-up point
Fuel type of van	Electric	Diesel
Load factor	50%	50%
Price	€3,95	€3,95

5.2.2 Prior parameter estimation

In order to estimate the prior parameters for the different attributes, a PythonBiogeme script has been written and is illustrated in appendix B. Besides numerical/continuous attributes (price, delivery speed, load factor), also categorical attributes have been included in this research. It is expected that the utility contribution (parameter value) of the different levels of the categorical attributes (fuel type & delivery location) is not linear, and therefore it is needed to re-code these variables into dummy variables. This is done according to a fixed dummy coding scheme used by Ngene which determines that the third-mentioned level of the attribute becomes the reference level. The dummy coding applied and the corresponding to be estimated parameters are indicated in table 5.2.

Table 5.2: Dummy coding categorical variables

Attribute	Level	V1	V2	Indicator	Parameter
Fuel type	Electric	1	0	Electric	B_FEL
	Hybrid	0	1	Hybrid	B_FHY
	Diesel	0	0	-	-
Delivery location	In-store	1	0	Store	B_DL1
	Pick-up point	0	1	Pick-up	B_DL2
	Home delivery	0	0	-	-

5.2.3 Results

For the pilot study, in total 37 respondents commenced the survey but only 30 respondents completely finished it. The respondents for this pilot study are the researcher's acquaintances. Only a finished survey is taken into consideration for parameter estimation and therefore N=30. Based on the data retrieved from the 30 respondents for the pilot study, prior values are determined for each RUM parameter. This is done by means of PythonBiogeme. The prior parameter estimations can be found in table 5.3. The full overview for the model fit and a report on the parameter estimation can be found in appendix B. Insignificant parameters in table 5.3 are not problematic at this stage, as this is a result of the pilot survey on a relatively small number of respondents. The prior values seem plausible to use for an efficient design, as all variables have the expected sign. Even the dummy parameter estimates have the expected sign. It has been noticed that the indicator for the hybrid fuel type is higher than the parameter estimate for the electric fuel type. This is a well-known phenomenon: people prefer something that is familiar to them Coupey et al. [1998].

Table 5.3: Prior parameter estimates

Name	Value	Std err	t-test
Delivery location (ind. B_DL1)	-.843	.427	-1.98
Delivery location (ind. B_DL2)	-.471	.334	-1.41
Fuel type (ind. B_FEL	.673	.268	2.52
Fuel type (ind. B_FHY)	1.12	.297	3.78
Load factor	.0354	.00771	4.59
Delivery price	-.393	.0561	-6.99
Delivery speed	-.117	.118	-0.99

5.2.4 Conclusion pilot survey

Next to the small remarks (appendix B) in terms of phrasing and the way in which the questions are presented, for the final survey only the number of choice sets need to be determined based on the efficient design approach.

5.3 FINAL SURVEY DESIGN

The different parts of the final survey are set forth in this section. First the new efficient choice sets are constructed by means of a Ngene efficient design script (appendix C). The attributes and attribute levels do not change as compared to the pilot survey. Then, the proposed context profiles are constructed. Context-dependent SP experiments request respondents to choose between choice alternatives while assuming a certain context. Therefore, two experiment need to be constructed: the regular choice experiment and a context experiment that varies the considered context variables. Then, an overview is given on the remaining sections in the survey. These sections have been included in order to possibly determine differences in preferences for different delivery choice characteristics as hypothesized in chapter 4 section 4.3. These sections are based on demographics, (sustainable) buying behavior and morality.

5.3.1 Efficient design choice set construction

An efficient design is introduced when too much dominant alternatives are present in the orthogonal choice set design: it helps to avoid dominance Molin [2018]. The efficient design provides for more reliable parameters as opposed to the orthogonal design, with the same number of respondents. D-efficient designs are proposed for this research, which seek to minimize the standard errors of all parameters Rose and Bliemer M.C.J. [2009]. The efficient design requires a smaller number of choice sets, since it is not required to be orthogonal. However, by constructing efficient designs, the *prior values* obtained by the pilot study could have the risk of being the wrong prior, which could lead to less efficient and biased parameters.

5.3.2 Number of required choice sets

In the efficient design, 8 choice sets are required. This is because the number of parameters to be estimated is seven: three single-parameters for *price*, *delivery speed*, and *load factor*, and two dummy-parameters for *delivery location* and *fuel type of the delivery van* (4 parameters) as these attributes are categorical variables (appendix B). Since in each choice set 2 alternatives are proposed, the trade-off between alternative A and B can be determined: this adds 1 degree of freedom Molin [2018]. The minimum amount for this design with 7 parameters therefore results in 8 (7+1) choice sets. The complete approach and evaluation to construct the efficient design can be found in appendix C.

5.4 SURVEY CONTEXT

After the construction of the choice experiments, the context experiments are constructed. *Context* is the physical, socio-emotional setting in which behavior takes place Molin [2010]. The context defines the 'playing field' of the consumer: what the respondents need to assume while making choices. Consumers could have different taste values (for parameters) in different context situations as mentioned in chapter 3. Therefore, the included cooperation context variables in this research are *whether someone needs to act as a consumer or as a citizen* (duality) and the *collective participation rate* (social norm). The context variables and levels are constructed in context profiles indicated in table 5.4. The efficient choice sets in the choice experiment are nested under context profiles with each a specific context description.

Table 5.4: Context variables & levels

Context Effect	Level
Duality	Consumer
	Citizen
Social Norm	0 (no social norm)
	75%

The consumer-citizen duality considers two levels: making a choice while acting as a citizen and making a choice while being a consumer Alphonce et al. [2014];Mouter et al. [2017]. In the citizen context, respondents might reveal different preferences because free-riding effect are eliminated due to policy implementation. The levels of the context variable *social norm* are chosen based on previous research by Bohner & Schlüter 2014 and Araghi et al Araghi et al. [2014]. In Bohner & Schluter's research it was concluded that a 75% social norm for towel reuse in hotel bathrooms contributed significantly to more sustainable. Araghi et al. 2014 concluded that as opposed to the researchers' expectations, the relationship between a collective participation rate (CPR) and choosing for carbon offsetting (for airplane carbon-dioxide emission) does not take on a linear form: high collective participation rates increase the utility of carbon offsetting but a CPR of 50% had a negative influence on consumers' willingness to contribute. Therefore, it is proposed for this research to include a high and a low (no) collective participation rate as context attribute level (table 5.5). With 2 context variables consisting of two levels the number of context profiles is 4. This means that 4 different contexts are considered for this research.

Table 5.5: Context profiles

Context profile/ Context variable	1	2	3	4
Consumer/Citizen	Co	Ci	Co	Ci
Social Norm	no norm	75%	75%	no norm

The 8 choice sets previously determined need to be nested under the context profiles in a balanced way. Hence, if all choice situations are combined with all context profiles, the total number of context-choice sets is equal to the number of choice situations multiplied by the number of context descriptions Molin [2010]. This gives a total number of 32 (4*8) context-choice sets.

5.4.1 Context dependent assumptions

In the choice set section of the survey, each respondent will be assigned to one experimental context profile. This profile will not differ across all choices. Along with this context a set of (context-) specific assumptions is developed and provided to the respondent. Respondents will be requested to imagine that this context applies when choosing a delivery option. The assumptions that specifically account for the consumer-context are illustrated in table 5.6. The assumptions that specifically account for the citizen-context are illustrated in table 5.7. The social norm-context will be added either with no social norm (nothing is added to the context) or by adding the sentence "75% of all consumers choose a sustainable option". If applied to a respondent the nudging social norm will be repeated on top of every choice situation.

Table 5.6: Consumer context description

When choosing a delivery option, the following situation applies:
You place an order at one of the aforementioned webshops and are asked to choose a delivery options
The following assumptions have to be made:
You place an order on the internet and you have to choose between two delivery options; You only order for yourself; A load factor of 25% means that the delivery van is 75% empty

Table 5.7: Citizen context description

The following situation applies:
In order to improve the quality of life in city centres, the government is considering to adopt a new policy on parcel delivery. Different types of government policy are considered, with different effects on price, load factor, delivery time, fuel type of vans and delivery location.
The following assumptions have to be made:
The values for the characteristics of the proposed policy apply to all citizens who place orders online. A load factor of 25% means that the delivery van is 75% empty

5.5 MORALITY

The third section of the survey concerns the inclusion of innate morality questions. The final selection of the original Morality-As-Cooperation survey is included Curry and Van Lissa [2018]. The survey is reduced from 42 theses to 14 theses in order to keep the respondent's attention. The approach to this reduction can be found in appendix D. First, the respondents need to rate how relevance related statements are evaluated when a respondent decides whether something is right or wrong. The scale of this importance is pointed out in a 6-point Likert-scale ranging from "not at all relevant" to "extremely relevant". Then, the respondents need to determine to what extend he/she agrees with the seven statements on a 5-point Likert-scale, ranging from "strongly disagree" to "strongly agree".

5.6 SOCIO-DEMOGRAPHICS AND BUYING BEHAVIOR

In the final part of the survey, socio-demographic factors are included. The answer to these questions will be used to map the respondent group and to (later on) be able to determine whether substantial differences in preferences (taste parameters) between different types of consumers exist. The questions related to socio-demographics and possible answering possibilities are indicated in table 5.8.

The questions concerning buying behavior are two-folded: on the one hand questions relate to sustainable consumer buying behavior in order to determine whether respondents have paid more for the sustainable version of a product in real life. An example of this question is *"Do you buy organic meat?"*. On the other hand buying behavior questions relate to the frequency and expense patterns, (table 5.9. An overview of the entire survey can be found in appendix C.

Table 5.8: Socio-demographic questions

Year of birth?	Gender?	Average annual net income? (x1000 euro)	Highest level of education?	Household composition?
Year of birth	Woman Man Transsexual Prefer not to say	0-10 10-20 20-30 30-40 40-50 50-60 60-100 >100	High school HAVO VWO MBO HBO WO	Single Partner Partner with children Single with children

Table 5.9: Buying behavior questions

Average expense per month?	Online order frequency?
Less than €50	Once a year
Between €50 and €100	Once every half year
Between €100 and €250	Once a month
Between €250 and €500	Once every two weeks
Between €500 and €750	Every week
More than €750	

5.7 SURVEY ROUTING

The survey consists of four parts for each respondent. In order to filter whether respondents fit in the intended target group of *online apparel consumers* and *living in urban areas*, two filter questions are included.

1. Respondents are asked whether they shop online for apparel at fast fashion online retailers;

2. Respondents are asked to fill in the numerical part of their zip code to determine whether they live in an urban area

The respondent is excluded from the remainder of the experiment if either the answer to the first question is 'never' or the answer to the zip code question corresponds to a (predetermined CBS [2018]) non-urban area. Secondly, a context profile with the choice sets is randomly assigned to the respondent the minute they start to fill in the survey. This means that the respondent either receives a consumer or citizen context and in 50% of the cases a social norm is added to the context description. Respondents are then asked to complete the 8 choice situations after reading the introductory text and corresponding assumptions that have to be made. The introductory text and corresponding assumptions are of great importance for this research, therefore this text will be repeatedly presented in all choice situations. Then, respondents need to fill in the demographics questions and questions are asked concerning consumer (sustainable) buying behavior. Finally, respondents are asked to fill in the morality statements.

5.7.1 Required number of respondents

Based on the estimated prior values for each parameter in the pilot study, the number of respondents for this research can be determined. Therefore, the corresponding t-value must be $|t| > 1.96$ to assure statistically significant parameters (keep in mind that $t = \beta/SE$ and $|\beta| > 1.96 * SE$) Molin [2018]. Normally, the $S.E.$ is only known if you have obtained a large dataset. However, assuming the determined prior is correct, the $S.E.$ can be calculated for N=1 for a given experimental design. Based on the efficient design determined by Ngene, the number of required respondents to assure parameters to be statistically significant, (SP estimates) are determined and indicated in table 5.10. Speed has the highest Sp estimate of 41 respondents. However, SP values are estimated on the assumption that all priors are exactly correct and no uncertainty is assumed. Therefore, to leave some room for uncertainty in prior values, more respondents are preferred. The SP estimate however indicates that if a large number of respondents is not achieved, this will not be extremely problematic.

Table 5.10: Number of respondents to achieve statistical significance on each parameter

Prior	**b_Price**	**b_Speed**	**b_lf**	**b_fuel(d0)**	**b_fuel(d1)**	**b_dl(d0)**	**b_dl(d1)**
Fixed prior value	-0.393	-0.117	0.0354	0.673	1.12	0.843	-0.471
Sp estimates	4.952	40.542	6.658	22.055	13.074	11.491	25.478

5.8 CONCLUSION

The survey that is proposed for this research consists of different sections. First, 8 choice tasks are presented to the respondents which asks them to choose between two different delivery options with varying delivery prices, delivery speeds, delivery locations, delivery vehicle fuel types and delivery vehicle load factors. The choice tasks are set up following an efficient design. To determine the efficient design, first a pilot survey is conducted to arrive at prior values for the parameters (best guesses). Second, questions regarding socio-demographic variables and (sustainable) buying behavior are introduced to determine whether differences in preferences can be observed for different consumer characteristics.

Third, the shortened morality in cooperation questionnaire is proposed to the respondents to determine whether valuation of morality in cooperation has an influence on consumer preferences towards delivery choice factors. Finally, different context settings are proposed to determine whether consumers differ from citizens and whether the inclusion of a social norm provides a change in preferences for the different choice characteristics of parcel delivery. Four different context settings are determined based on the included context variables, the different context settings include context-dependent assumptions which are proposed to the respondents. Each respondent only gets to answer one of the four survey contexts.

To remain in the scope of this research, the survey can only be filled in by respondents that live in urban areas and that have experience with shopping online. Therefore, two filter questions that are related to both the respondent requirements will be asked at the start of the survey.

6 SAMPLE DESCRIPTION

In this chapter, the survey data collection and preparation procedure is discussed in section 6.1. In section 6.2, an evaluation is given on the respondents that filled in the survey, and a discussion is provided on the representativeness of the sample. This section also discusses an overview of the (sustainable) buying behavior of the consumers within the sample and the retrieved factor that is used for estimation is discussed. In section 6.3, the conclusion of a factor analysis to arrive at less but more reliable factors is discussed and the resulting distribution of answer indication of some morality statements is provided.In section 6.4 the (binomial) variables are indicated that are used for the model estimation to determine whether differences in preferences exist between consumers.

6.1 DATA COLLECTION AND PREPARATION

The data collection is done by means of SurveyGizmo survey software which was recommended by the TU Delft. The data collection started April 17th 2019. All respondents can fill in the survey, as no prerequisites where required. Because no budget was available to collect data, respondents were recruited by means of a snowballing method in which the researcher asked family and friends that shop online and to distribute these among their friends and family who shop online. A second way of respondent recruitment was through the online university broadcast channels, as these involve a lot respondents that and of dissemination through the university broadcast channels. Since no monetary incentive has been provided to respondents, the risk of respondents rushing through the survey just to earn money is decreased. However, by applying aforementioned methods to collect data, a risk exists that data from an undifferentiated group of respondents will be obtained. The descriptive statistics of the sample are provided in the next section, and will give clarity concerning this matter.

For this research, respondents were selected based on the criteria: experience with online fast fashion shopping and living in an urban area according to the classification of CBS 2018. Therefore, respondents are excluded from the sample based on the following characteristics:

- If the respondent had never bought any apparel online before at the top fashion retailers in the Netherlands. Based on this characteristic, 11 respondents are removed from the data set.
- After indication of the numerical part of the respondent's postal code, this is converted to the degree of urbanity based on the CBS urbanity classification CBS [2018]. Based on this characteristic, 14 additional respondents where excluded from the data set.

After removal of respondents that met one or both of the aforementioned characteristics, 156 out of 181 respondents are left for further analysis. Table 6.1 indicates the the allocation of the remaining total number of respondents to the different survey contexts.

6.2 RESPONDENT CHARACTERISTICS

This section indicates the consumer characteristics and the distribution of characteristics across the sample group. First, the demographic variables that appear across the sample group are

Table 6.1: Distribution of 156 respondents over context profiles

Survey context	Respondents	Percentage
Consumer	46	29,5
Citizen	38	24,4
Consumer & Nudge	39	25,0
Citizen & Nudge	33	21,2

indicated and discussed. Then, the indication of actual showed sustainable behavior from the respondents is discussed and finally, the shopping frequency and expense pattern distribution across the respondents are indicated.

Table 6.2: Distribution of demographics across the sample

Demographic	**Category**	**Respondents**
Age	<25 years	25,6%
	25-30 years	52,6%
	30-35 years	11,5%
	35-40 years	5,8%
	40+ years	4,5%
		Respondents
Gender	Female	51,9%
	Male	48,1%
Income	<10.000	41,7%
	10.000-20.000	14,1%
	20.000-30.000	12,2%
	30.000-40.000	7,7%
	40.000-50.000	9,6%
	50.000-60.000	5,1%
	60.000-100.000	6,4%
	>100.000	3,2%
Education	MBO	7,9%
	HBO	17,9%
	WO	79,5%
Household composition	Single	71,8%
	Partner	19,9%
	Partner with children	8,3%

6.2.1 Representativeness

Table 6.2 indicates the distribution of the respondents in the sample in terms of demographic characteristics. To conclude whether the collected sample is representative and parameter estimates can be trusted, it must first be determined whether no selectivity emerged. Because if selectivity is present, this gives a biased view on the parameter estimates. It is concluded that no selectivity is present in the sample, because the sample is randomly retrieved, without any monetary incentive and therefore, the parameter estimates are considered not to be biased. Now, it is determined whether the distribution of the sample resembles the same pattern as in the real population. As the real population of consumers that live in urban areas and shop online is unknown, educates guesses can be made on the distribution of the population. Based on few figures that are available on the population of online apparel shoppers from CBS some conclusions on the representativeness of the sample can be drawn CBS [2019a]. Other conclusions are based on logic.

Focusing on the age distribution, it can be seen that a large share of the respondents in the sample is between 25 and 30 years old, and with increasing age, this percentage decreases extensively. This is in line with the CBS figures, which indicate a decreasing percentage of online consumers with increasing age. In the sample, males and females are almost equally represented which matches the CBS figures. In terms of income, no figures are present that indicate the income of online shoppers. However, as the age distribution resembles the figures, it can be concluded that the corresponding high percentage of lower incomes results from the younger respondents that are either students or have a part time job. The relatively large share could indicate a slightly biased parameter for delivery prices, as prices might be more important to consumers that have lower incomes. The share of online shoppers with education levels is in compliance with the CBS figures, as increasing levels of education results in higher shares of consumers buying online. Finally, fast fashion industry attracts a lot of young consumers, from which it could be plausible that most of them are single, and don't have kids yet.

In conclusion, it is likely that no selectivity has emerged in data collection and that the sample distribution resembles the distribution in the population to the best of knowledge.

6.2.2 Sustainable buying behavior

To determine the impact of interaction variables of sustainable buying behavior with the delivery choice parameters, a factor analysis has been performed on the answers to all sustainable behavior questions to arrive at less, but more reliable factors that determine the sustainable behavior of the respondent. Based on this analysis (the analysis can be found in appendix D), two factors are determined: the first indicates sustainable buying behavior which is a combination of all biological product categories, and the latter only consists of the waste separation question. A sum score is determined for the first factor: the maximum value of the first factor is 4 indicating that the consumer buys all biological product types, whilst the minimum value is 0, indicating that the consumer does not buy any of the sustainable products which were mentioned. Table 6.3 indicates the distribution of the consumers over the factor score. As it is hypothesized that sustainable buying behavior has an effect on the preference for the sustainable characteristics as well as for prices, the effect of this factor on the delivery choice parameters will be discussed in the next chapters 7 and 8.

Table 6.3: Factor values sustainable buying behavior

Sustainable Factor value	Respondent percentage
0	26.9
1	21.8
2	23.7
3	13.5
4	14.1

6.2.3 Shopping behavior

The division allocation of shopping frequency and expense pattern indicates four different types of consumers: 1) the frequent online shopper that spends a high amount of money, 2) the frequent shopper that spends little money, 3) the rare online shopper that spends a lot of money and 4) the rare online shopper that spend little money (table 6.4). The online shoppers that order often represent 28,2% of the consumer group, while in general, most people shop online rarely and spend little money. An extensive overview of all frequencies regarding shopping behavior are indicated in table E.3.

Table 6.4: Categorized shopping behavior respondent

	High expenses (> €100 per month)	Low expenses (≤ €100 per month)
Often (≥ once a month)	17,3 (1) %	28,2 (2)%
Rarely (< once a month)	7,7 (3) %	46,8% (4)

6.3 MORAL COOPERATION DOMAINS

In order to determine whether the statements measure the same construct, for this section, a factor analysis is performed as well. This is done to arrive at fewer, but more reliable factors to indicate a consumer's morality in cooperation (the analysis can be found in appendix D). Unfortunately, no trustworthy factors could be retrieved from the statements and therefore, no factors are used to estimate the moral effect on choice parameters.

However, it was hypothesized that the factors *family*, *group loyalty* and *reciprocity* are plausible moral domains that could be of effect on the parameters. Therefore, one statement of each of these three domains is used to estimate whether an effect exists on the parameters. The questions that are researched whether they have an effect on the preferences of delivery choice characteristics are:

- **Family:** An individual must always be loyal to family;
- **Group:** It is important to play an active role in your community;
- **Reciprocity:** You should always make amends for the things you have done wrong.

The distribution of values indicated for these three statements is indicated in table 6.5.

Table 6.5: Score distribution of three selected statements

	Family	Group	Reciprocity
1	6,4%	3,2%	1,3%
2	19,9%	10,3%	11,5%
3	27,6%	32,7%	23,7%
4	37,8%	49,4%	56,4%
5	8,3%	4,5%	7,1%
Mean	3,2	3,4	3,6
Median	3	4	4

6.4 EXPLANATORY VARIABLES FOR PREFERENCE HETEROGENEITY

To determine whether differences in preferences can be distinguished based on consumer characteristics, some ordinal and categorical explanatory factors are transformed into binomial levels for ease of modeling. Table 6.6 indicates the classification of the factors into binomial variables. The explanatory variable such as age is still estimated as a continuous variable, to retrieve as much information from this explanatory variable as possible. The distinction of men and women is taken into account to determine the difference in gender for delivery choice characteristics. The different categories concerning sustainable behavior might reveal whether consumers that indicate to pay more for a sustainable product, will value the delivery choice characteristics differently (especially the ones concerning sustainability improving). Shopping behavior in general is included as explanatory variable in the model as buying frequency could influence the sensitivity for speed and prices. The parameters in table 6.6 are either 0 or 1. As an example for the *income* explanatory (categorical) variable, this value indicates 0 if the respondent's income is below €10.000 per year and 1 if income is above €10.000 per year.

As indicated in section 6.5, the mean and median of the scores on the three moral statements lie around the value 3.5. The next integer value would then be 4, which will be the threshold for the binomial variable. Therefore, the binomial factor indicates 1 if a high valuation of the statement is observed.

Table 6.6: Binomial variables for model estimation

Variable	Variable is one if respondent	% of respondents
Female	The gender is woman	51,9%
Low income	Income is below €10.000 per year	41,7%
WO education	Has obtained high educational degree	79,5%
Parent	Has children	8,3%
Frequent shopper	Shops online once a month or more often	45,5%
High spender	Spends more than €100 per month on online shopping	25%
Family	Scores above 4 on the family domain	46,2%
Group	Scores above 4 on the group domain	53,8%
Reciprocity	Scores above 3 on the reciprocity domain	63,5%

7 DISCRETE CHOICE MODEL ESTIMATION

In this chapter, the general MNL model estimation procedure is discussed. First, it is indicated how to define the model fit and how to interpret these results. In this section, it is also indicated how to determine whether a model with additional parameters fits better not due to coincidence. Then, the estimation procedure for the general MNL parameters is discussed along with additional parameter interpretation information, Then the set up to estimate whether the inclusion of context interaction variables gives a better model fit is discussed. Finally, the estimation of interaction of explanatory consumer characteristics with the general delivery choice parameters (table 6.6) is discussed.

7.1 MODEL FIT

Based on the chosen efficient design in chapter 5, the general delivery choice parameters *Price*, *Speed* and *load factor* can only be estimated linearly. Due to the categorical nature of *delivery location* and *fuel type*, these parameters are estimated with two dummy-parameters.
For each estimated model proposed in chapter 8, performance indicators are presented that indicate the model fit. The model fit is determined by the Log Likelihood (LL) and the Rho-square (ρ^2). The higher the LL (closer to zero), the better the model fit. The ρ^2 parameter indicates whether the specific estimated model fits better than a model that considers all parameters to be zero. The relative model fit (ρ^2) is denoted in the model estimation report from PythonBiogeme, but can be determined with the formula in equation 7.1 as well. The formula is accompanied by the model fit interpretation of the ρ^2: this indicator value is between zero and one, indicating a limited to good model fit respectively.

Rho-square value	Model fit
$\rho^2 \leq 0.1$	Limited
$0.1 \leq \rho^2 \leq 0.3$	Reasonable
$0.3 \leq \rho^2 \leq 0.5$	Reasonably good
$\rho^2 \geq 0.5$	Good

$$\rho^2 = 1 - \frac{LL_{model}}{LL_{zero}} \tag{7.1}$$

In chapter 8 different models are presented. Based on the model fit parameters, the models can be compared. Based on the likelihood ratio statistic (LRS), it can be determined whether a model with more parameters is a significantly better model. The LRS is calculated by formula 7.2. Whereas model A is the model with the least estimated parameters. As a rule of thumb, it is suggested that each additional parameter must add a two-point improvement in Loglikelihood, whereas the exact value depends on a value that is determined in the chi-square table based on the chosen significance level (which is 9.210 for a significance level set at 99%). If the value of the LRS is higher than the threshold value indicated in the table, it can be determined that the model with additional parameters fits better, and that this better model fit is not due to coincidence.

$$LRS = -2 * (LL_A - LL_B) \tag{7.2}$$

Where,
LL_A is the final LL of the model with the least parameters
LL_B is the final LL of the model with q additional parameters

7.2 MNL PARAMETER ESTIMATES

From the respondents' observed choices, discrete choice models are estimated to indicate to what extend delivery price (Price), speed (Speed), location (DL), vehicle load factor (LF) and fuel type (Fuel) have an effect on the utility of a delivery choice alternative, and as such on consumer choices. To estimate the MNL attribute parameters, the setup discussed in section 7.1 is used in Python by means of the maximum likelihood principle Bierlaire [2018]. Equation 7.3 indicates the utility function for the estimation of the general parameters.

$$V_{DeliveryChoice(n)} = \beta_{Price} * Price_n + \beta_{speed} * Speed_n + \beta_{LF} * LF_n + \\ \beta_{fel} * Fuel_{n1} + \beta_{fhy} * Fuel_{n2} + \beta_{DL1} * DL_{DL1n} + \beta_{DL2} * DL_{DL2n} \tag{7.3}$$

For each of the parcel delivery choice characteristics, the following terms are discussed:

- **Parameter value and the utility of the attributes**: the value of each parameter estimate resembles the weight of the attribute. Once this weight is multiplied by each of the considered attribute levels, it determines the positive or negative utility contribution of the specific attribute level to the utility function.
- **Parameter significance**: this value indicates whether the parameter weight can be generalized to the population (the respondent characteristics of the research sample). The significance is indicated with a $p - value$ and a t-value. Once the p-value is below 0.05 or the t-value is equal or more than 1.96, the parameter is considered to be significant on a pre-determined 95% significance level. If on this determined significance level the p-value of a parameter is not below 0.05, a parameter is not statistically significant: this means that the value only applies to the sample in the research. Then, the null-hypothesis is accepted (parameter value = 0 for the population) and the parameter does not need to be described further.
- **Curve characteristics of the attribute**: the curve characteristics visualize the utilities of different attribute levels. It is checked as well if the curve has the expected characteristics
- **Utility range**: this is determined by the difference between the highest utility and the lowest utility of each attribute level. The range indicates the impact the attribute can have on the overall utility of an alternative.
- **Interpretation**: the interpretation of the parameters is indicated for the significant parameters (which describe the population).

In table 8.1, the general MNL parameter estimates for the included apparel parcel delivery attributes are indicated. The parameter estimates indicate the direction and magnitude of the specific delivery choice attributes to the delivery choice alternative. The willingness to pay for an increase in an attribute value is indicated an evaluated as well, to determine the willingness to pay for a level of increase of each attributes, equation 7.4 is used.

$$WTP = \frac{\beta_{attribute}}{\beta_{Price}} \tag{7.4}$$

7.3 ESTIMATION OF EFFECT OF CONTEXTS

To consider whether the different survey contexts have an effect on (one of) the parameters in delivery choice, the context variables are added to the model as interaction effects. The coding scheme for each of both context variables is indicated in table 7.1. This table indicates that if a significant interaction effect is found for (one of) the context variables, the parameter for *ConCit* will be multiplied by 1 for a consumer context, and multiplied by -1 for a citizen context. Likewise, the effect of including a nudge is estimated. The results of the significant interactions of context and delivery choice attributes are discussed. Then, it is determined whether this model fits better than the model without inclusion of the context variables.

Table 7.1: Context estimation effect coding scheme

Label	Effect coding
Duality	
Consumer	1
Citizen	-1
Social norm	
Yes	1
No	-1

7.4 ESTIMATION OF CONSUMER PREFERENCE HETEROGENEITY

To research to what extent specific consumer characteristics such as *age* or *income* mediate the effect of the different delivery choice attributes, discrete choice models are estimated that include interaction effects of the significant parameter interactions with consumer characteristics. In order to research which consumer characteristics have significant interactions with the delivery choice attributes, one interaction effect is included at a time.

For example, an interaction effect of an income category with the price attribute for delivery choice is denoted by $\beta_{income_{price}}$. To estimate whether the interaction effect of income and price is significant, the utility function in equation 7.3 is extended. For the price parameter, this results in $(\beta_{price} + \beta_{price}^{income} * income) \cdot Price$.

By estimating different interactions, it is determined which of the consumer characteristics have statistically significant effects on the preference for a delivery choice attribute. The model estimation is performed based on the hypotheses formulated in the methodology section (chapter 4). The same 'rule' is applied to the general delivery choice attribute parameters: an interaction parameter is considered statistically significant (on a 95% confidence level) if the t-value exceeds 1.96.

When established which explanatory variables significantly interact with the delivery choice attributes, all are added in the same model estimation simultaneously. This estimation might result in some interaction effects becoming insignificant. Then, one factor at a time, insignificant interaction effects are removed. The resulting significant parameters and interactions are indicated in table 8.4 in chapter 8.

7.5 CONCLUSION

The general estimated model for the delivery choice alternatives is a model in which *delivery speed*, *delivery price*, and delivery van *load factor* are considered to be of linear nature. The utility contributions of the delivery van *fuel type* and the *delivery location* are considered to be of a non-linear categorical nature. This means that each of the included levels differ from each other in a nonlinear trend.

To determine the effect of the context variables on preferences for delivery choice characteristics, interaction are estimated. The significant interaction effects are reported in the next chapter. To determine the preferences for different delivery choice attributes and the effect of different consumer (behavioral) characteristics, an MNL model will be estimated including these characteristics.

First, the results of a general MNL model will be discussed in the results chapter. This is followed by the results of the effect of including different contexts. Finally, a model is presented with parameters that indicate the mediating effect of consumer characteristics on the preference for delivery choice attributes.

8 RESULTS

As discussed in chapter 4, the focus of this research is on the analysis of consumer preferences regarding the included delivery choice attributes. Furthermore, a focus of this research is to determine whether respondent characteristics have mediating effects on the choice for a specific parcel delivery alternative. An additional objective of this research is to research to what extend social norms (in the form of social norms) steer consumers into more desired (sustainable) behavior and whether a consumer citizen duality between preferences for delivery choice attributes exists.

In section 8.1, the parameters are proposed that indicate the average preference of consumers for delivery choice attributes in general. In this section, the parameter interpretation terms as indicated in section 7.2, the (general) relative importance and the utility contribution of the delivery choice attributes are discussed in detail. In section 8.3, the results of the model estimation including context effects are discussed. Subsequently in section 8.4, the results of the mediating effects of respondent characteristics on delivery choice preferences are presented and finally, the results are used to set up an MNL choice prediction model to be able to predict consumer choices on parcel delivery in different contexts.

8.1 GENERAL MNL PARAMETER INTERPRETATION

Table 8.1 indicates the MNL parameters that have been estimated by means of PythonBiogeme. The discussion of each of the general parameters is presented below. In appendix F, the expectation for each of the general parameters is provided. The corresponding model fit parameters for this estimated model are 1) final LL = -726,885 2) Rho-square = 0,146.

Table 8.1: MNL parameter estimates apparel parcel delivery

Name	Value	Rob Std err	p-value	Significant?	Expected sign?
Price	-.416	.0407	.00	Yes	Yes
Speed	-.320	.0334	.00	Yes	Yes
In-store delivery	-.811	.128	.00	Yes	Yes
Pick-up point delivery	-.319	.0955	.00	Yes	Yes
Load factor	.0214	.00388	.00	Yes	Yes
Electric fuel	1.18	.132	.00	Yes	Yes
Hybrid fuel	1.17	.164	.00	Yes	Yes

Delivery Price
The parcel delivery price is a choice characteristic which is negatively valued: a higher delivery price results in lower utility of the alternative (ceteris paribus). In the light of previous research, the sign of this parameter is expected. The parameter is significant and it can therefore be concluded that the value of the price attribute in the delivery choice is different from zero. Figure 8.1 indicates the utility course of the price attribute given the attribute levels. The utility

is considered to be linear and the graph indicates that with higher delivery prices consumers in general less favor a delivery option (if all other characteristics are held constant).

Figure 8.1: Utility course of price attribute

Delivery Speed
The speed in which the parcel is delivered, is in general negatively valued by respondents. The levels of the attribute have a negative linear relationship with utility: the longer the wait, the less utility is retrieved in general. As compared to the delivery price attribute, this aversion is however slightly smaller. The parameter is significant as well, indicating that the parameter is different from zero in the population and that consumers are less fond of longer delivery times. Figure 8.2 indicates the utility course of the speed attribute.

Figure 8.2: Utility course of speed attribute

It was expected that the speed attribute is an important factor. As the experimental efficient design used for this research does not allow for testing non-linearity of the speed attribute, it is considered to be linear.

Delivery location
The delivery location of the parcel is estimated with two different parameters which are both significant, indicating a differently utility for each of the delivery locations as compared to home delivery. The in-store delivery, in which the apparel parcel is brought to the company's store, is valued negatively. This indicates that in general respondents do not value this type of delivery location over home delivery. The same applies to pick-up point delivery. However, this delivery

location is valued less negative and the utility gain (or loose in this case) is less large. It can therefore be concluded that as compared to home delivery, the respondents value the in-store delivery most negative followed by the pick-up point delivery.

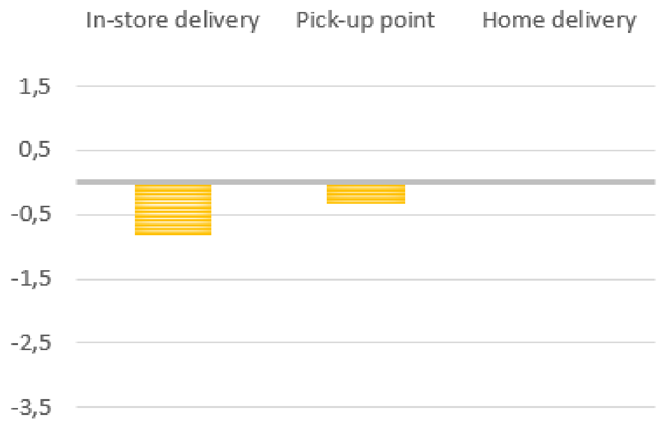


Figure 8.3: Utility course of delivery location attribute

For the delivery location attribute, which is a categorical attribute, a non-linear relationship with utility was expected. Figure 8.3 indicates the utility contribution of both pick-up and in-store delivery as compared to the reference of home delivery.

Delivery Vehicle Load factor
The delivery vehicle load factor indicates a positive parameter, indicating that respondents value a higher delivery vehicle load factor in general. This effect is assumed to be linear: indicating that the utility of this attributes increases with .0214 with every percentage of load factor increase. Figure 8.4 indicates the utility course of the load factor parameter.

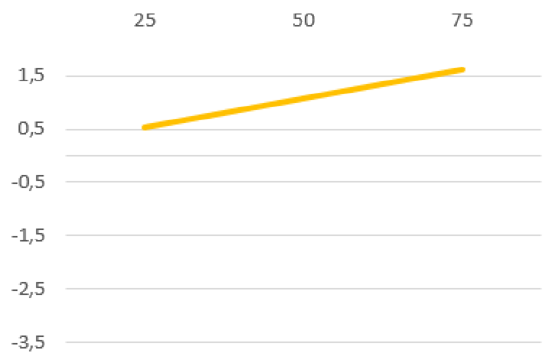


Figure 8.4: Utility course of load factor attribute

The load factor expresses the share of the total volume of the delivery vehicle. Less than 100% load factor is therefore considered an sub-optimal load factor. An ex ante prognosis, communicated to the consumer as performed in this research, is therefore of interest to consumers in general.

Delivery vehicle Fuel Type
Both alternative fuel vehicle types are, as compared to the diesel delivery vehicle, valued more positively by consumers in general. This indicates that consumers favor both electric and hybrid fuel vehicles over diesel powered fuel vehicles. What stands out in the parameter values for this delivery choice characteristic, is that the utility contribution of the electric fuel and hybrid fuel

vehicles is (almost) similar: indicating that consumers are indifferent for the type of sustainable fuel used, as long as it is a sustainable alternative to diesel delivery vehicles. Figure 8.5 indicates the utility contribution of the hybrid and electric vehicle as compared to diesel.

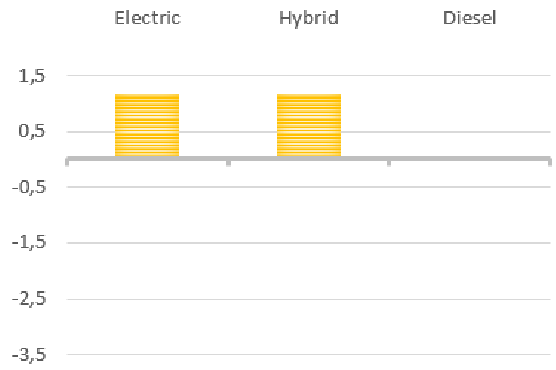


Figure 8.5: Utility course of fuel type attribute

8.2 RELATIVE IMPORTANCE AND UTILITY CONTRIBUTION

Next to the parameter values indicated in table 8.1, more detailed information on the parameter estimates is discussed. The utility contribution of each of the attribute levels is determined as well in table 8.2.

Table 8.2: Detailed information on parameter contribution

Attribute	Parameter	Levels	Utility contribution	Utility range	WTP/unit	Value difference	Price range	Relative importance
Price	.416	0	0	2.891	€1.00	6.95	€6.95	41.8%
		3.95	-1.643					
		6.95	-2.891					
Speed	.320	1	-.320	.960	€0.77	3	€2.31	13.9%
		3	-.960					
		4	-1.28					
Load Factor	.021	25	.535	1.07	€0.05	50	€2.57	15.5%
		50	.1.07					
		75	1.605					
Fuel Electric	1.18	1	1.18	1	€2.84	1	€2.84	17.1%
Fuel Hybrid	1.17	1	1.17	1	€2.81	1	€2.81	
In-store delivery	-.811	1	-.811	1	€-1.95	1	€-1.95	11.7%
Pick-up point delivery	-.319	1	-.319	1	€-.77	1	€-0.77	

Per attribute the three included levels are indicated in table 8.2. Based on the utility change per unit, the willingness to pay for a unit increase in each of the parameter is indicated. For example, in general, consumers indicate that they are willing to pay €2,80 for electric delivery. The relative importance indicates the impact of each individual characteristic on the consumer's choice for a delivery method. Insight into this relative importance can serve as a foundation for the focus on the different characteristics in the marketing proposition. Important to note is that the relative importance of each of the attributes is completely dependent on the chosen attribute levels of the considered attribute and the levels of the remaining attributes.

For apparel parcel delivery choice, price is the most important attribute as compared to all other considered attributes (41,8%). All factors are concluded to be of significant influence, this indicates that companies should focus on all factors while proposing delivery methods. In decreasing order of delivery choice characteristic importance: 1) cheaper 2) more electric and hybrid vehicles 3) higher load factors in delivery vehicles 4) faster and 5) delivery at home are preferred by consumers in general.

8.3 THE EFFECT OF DIFFERENT CONTEXTS

In order to determine whether the inclusion of the different contexts have had an effect on the delivery choice factor preferences, in appendix section F.4 four different models (for each of the contexts) have been estimated. Based on the estimation results of these four models, it was concluded that differences exist for all parameters in each of the different contexts. To estimate whether these differences in preferences are statistically different, the model is estimated according to the effect coding model estimation procedure posed in section 7.3. The resulting parameter that significantly interacts with the context variables is the *delivery price* parameter. Table 8.3 indicates the parameter values with the inclusion of the context variables that interact with price.

Table 8.3: MNL estimates including contexts

Parameter	Est.	St. error	t-value
Price	-.416	.040	-10.46
Speed	-.321	.034	-9.64
Load Factor (LF)	.022	.004	5.46
In-store (DL1)	-.817	.126	-6.49
Pick-up point (DL2)	-.320	.096	-3.34
Electric Fuel (FEL	1.20	.131	9.12
Hybrid Fuel (FHY)	1.17	.168	6.97
Consumer*Price	-.040	.015	-2.65
social norm included*Price	.031	.015	2.05
0-LL		-859.503	
Final-LL		-721.245	
Rho-square		0.150	

As can be concluded from table 8.3, the social norm and the consumer-citizen context significantly influence the sensitivity for delivery price changes. This can also be seen in figure 8.6, in which the utility of the price parameter is drawn for each context individually. Respondents in the consumer context are most sensitive for price changes as compared to citizens. This might mean that if everyone should pay the same delivery price due to (governmental) policy, respondents have less aversion to the delivery price attribute.

The inclusion of a social norm decreases the sensitivity for price changes for both consumers and citizens, whereas the citizen environment including a social norm results in the least price sensitive. With the conclusion of both context variables having a significant interaction with price, the hypothesis of the consumer being more sensitive to price changes can be accepted, as well as the hypothesized decreased sensitivity for price if a social norm is included.

Besides the context variables having an effect on price, it was also hypothesized that respondents acting as a voting citizen would favour aspects that enhance sustainability more than the consumers would. This was suggested because free-riding effects of choosing for sustainability while others don't would be eliminated in the citizen context, and it would increase the value attached to sustainable alternatives such as alternative fuel vehicles, higher load factors and de-

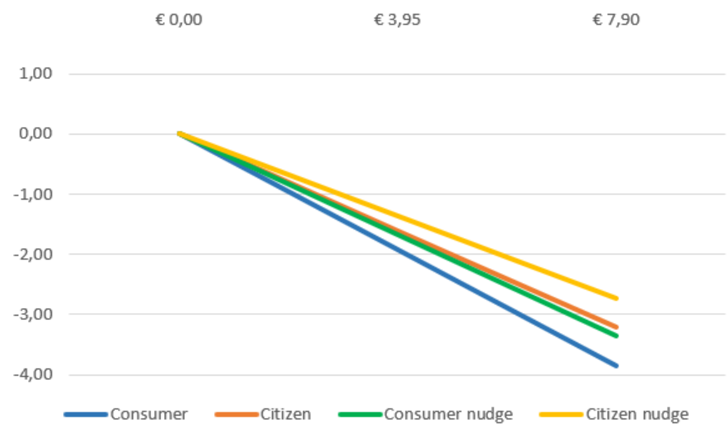


Figure 8.6: Utility course of price in different contexts

livery to parcel pick-up points to decrease the effect on the livability in city centers. However, this effect of citizens being more willing to choose for more sustainability (in terms of alternative fuel vehicles, load factors and delivery locations) was not found in this research and the conclusion is drawn that while in general these factors are valued significantly, no consumer-citizen duality can be observed in the preference for more sustainable aspects in parcel delivery.

One of the research questions indicated to research whether respondents can be steered into choosing for more sustainability in parcel delivery. Therefore, hypotheses concerning the effect of this social norm context suggested that this would increase the preference for alternative fuel vehicles and higher load factors. This was suggested since the social norm indicates a type of peer pressure, which was hypothesized to steer respondents into more desired sustainable behavior. However, the effect of the social norm on both sustainability reflecting factors has not been found in this research, and it can therefore be concluded that, while in general respondents attach (positive) value to these factors, no differences in preferences can be observed with the inclusion of a social norm.

The model with the included context variables (and two additional parameters for these context variables) is compared with the general MNL model in terms of model fit. The LL is lower as compared to the general MNL model (table 8.3). The LRS is 11,28 which indicates that the model including the context variables is indeed the better model (equation 8.1) as this LRS value exceeds the threshold value of 9,21 with a predetermined significance level of 99%. Based on this fact, it can be concluded that the inclusion of the context variables has had an effect on the model fit.

$$LRS = -2 * (-726,885 - -721,245) = 11,28 \tag{8.1}$$

8.4 HETEROGENEITY IN PREFERENCES BETWEEN CONSUMERS

The result of the estimated MNL model of consumer characteristics and the effect on preference parameters for the delivery choice factors is indicated in table 8.4. In this model, it is explained to what extend heterogeneity in preferences is explained by the interaction effects of the attributes with consumer characteristics. The resulting significant parameters are proposed based on the approach discussed in chapter 7. What can be observed from the results of this model is indicated per choice factor.

Table 8.4: DCM estimation with interaction factors

Parameters	Est.	S.E.	t-value
Price	-.594	.093	-6.42
Speed	-.332	.040	-8.30
Load Factor	.013	.005	2.55
In-store (DL1)	-1.19	.199	-5.96
Pick-up point (DL2)	-.476	.135	-3.54
Electric Fuel	.583	.215	2.71
Hybrid Fuel	.640	.255	2.51
Price*Age	.006	.002	2.29
Price*WO education	-.147	.032	-3.81
Price*Family	.083	.032	2.60
Price*Group	.084	.033	2.52
Speed*High spender	-.151	.065	-2.33
LF*Bio	.006	.002	3.10
DL1*Bio	.186	.075	2.47
DL1*Parent	-1.35	.435	-3.11
DL2*Female	.474	.160	2.96
DL2*Parent	-1.48	.433	-3.43
FEL*Bio	.399	.094	4.23
FHY*Bio	.329	.105	3.14
0-LL		-859.503	
Final-LL		-667.827	
Rho-square		0.201	

Delivery price
As indicated in table 8.4, most significant interaction parameters are estimated for the choice factor *delivery price*. As the age parameter is continuous and the value for the interaction parameter is positive, with increasing age, consumers are less sensitive to delivery prices. With regard to higher educated consumers, it cannot be concluded that these consumers are less sensitive for delivery prices. As the value for this parameter is negative, it can be concluded that the contrary of the hypotheses can be assumed which indicates that highly educated consumers are *more* sensitive for delivery prices. No significant interaction effect of delivery price and income has been estimated and therefore it can be concluded that for this research, consumers with different income levels do not vary in preferences for delivery prices.

With regard to the morality hypothesis on price, it was suggested that consumers that highly value all suggested cooperation domains that were included (Helping Family, Group Loyalty and Reciprocity), would be less sensitive to delivery prices. The significant interaction effects that have been estimated for the delivery price are helping family and being loyal to your group. High scores on both of these loyal domains indicate less sensitivity for delivery prices.

With regard to the bio consumers, it was expected that these types of consumers were less sensitive for delivery prices as they indicate to pay more for more sustainable products. However, no significant interaction effect has been estimated for the bio consumers and delivery prices. Therefore, it can be concluded that no decrease in sensitivity for delivery prices is observed for bio consumers.

Figure 8.7 indicates the differences of the price utility course between different significant consumer characteristics. As can be seen, high educations value delivery prices more negatively as

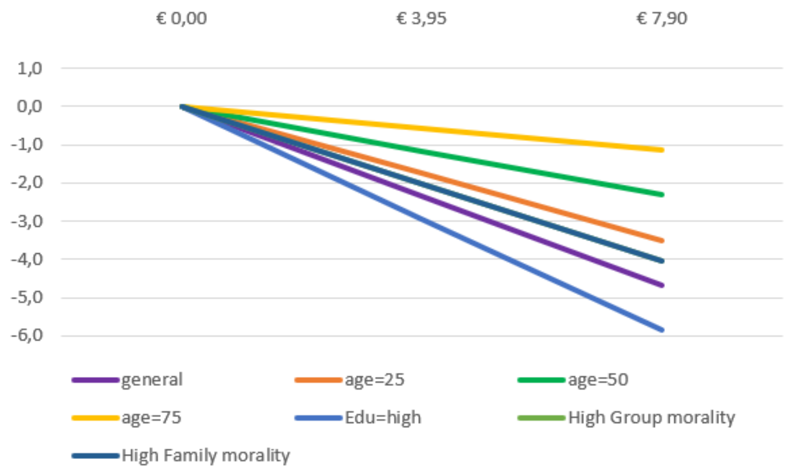


Figure 8.7: Utility course of consumer characteristics interactions with price

compared to the general price parameter, whereas all other consumer characteristics result in less negative values for the price parameter.

Speed

Only one of the consumer characteristics interacts with delivery speed: the consumer that spends over €100 per month on online shopping for apparel. Meaning that consumers that spend more on shopping for clothing online, are more sensitive for the delivery speed of the delivery alternative. The interaction of age and speed was not found to be significant, and therefore the hypothesis that people who are younger are more sensitive to delivery speed changes can be rejected. Figure 8.8 indicates the difference between the utility course of the general parameter and the preferences of consumers that spend a lot of money online.

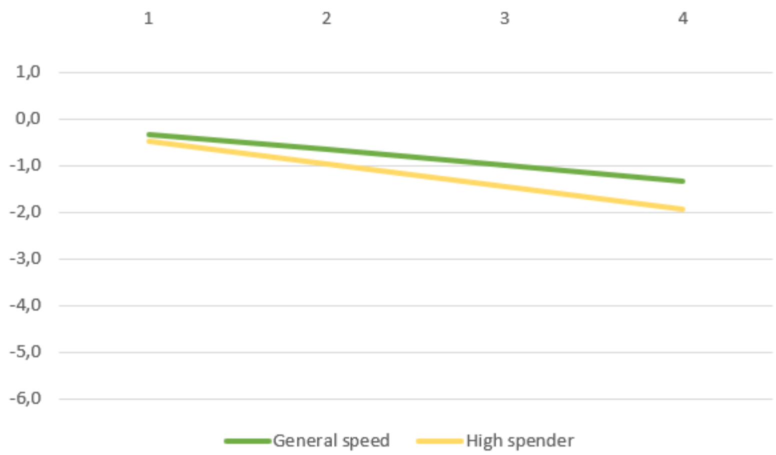


Figure 8.8: Utility course of consumer characteristics interaction with delivery speed

Delivery vehicle Load Factor

For the delivery vehicle load factor, it was expected that the demographics *age* and *higher education* would have an interaction effect with load factors, as it was expected that these consumers are more concerned with and familiar to sustainability. However, these demographics were not found to be significant and it can therefore be concluded for this research, that these consumer types do not change preferences towards delivery vehicle load factors. As expected are consumers that are already concerned with buying biological products (that are more sustainable) value a higher load factor more highly than consumers who do not buy these biological products. The moral domains do not have any effect on the preferences for delivery vehicle load factor. Since no interaction effect is found between the explanatory variables and the load factor parameter, the hypothesis can be rejected. Figure 8.9 indicates the difference between the general load factor utility course and the one from bio consumers. It can be seen that the valuation of load factor increase is slightly higher for bio consumers.

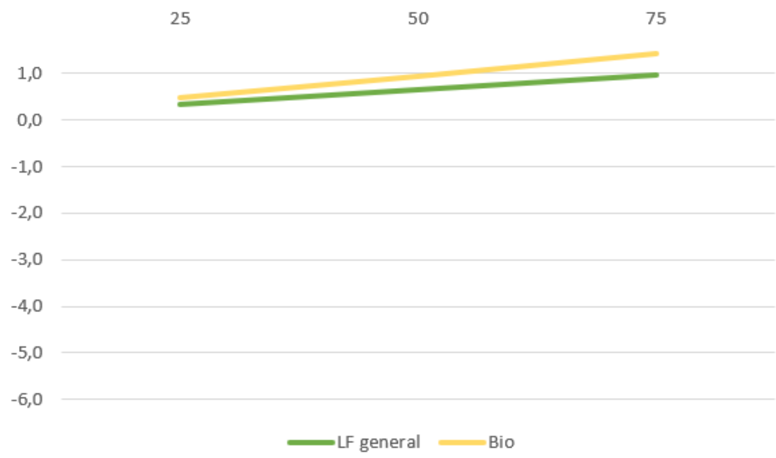


Figure 8.9: Utility course of consumer characteristics interaction with load factor

Delivery Location

For the preference towards delivery locations, differences in preferences can be observed for different consumer characteristics. For example, consumers that have children extremely detest both pick-up locations, while females are less sensitive to pick-up point delivery as compared to home delivery. Both of these findings were hypothesized and can therefore be accepted. Again, consumer that buy biological products and are assumed to be more sustainable oriented, are less sensitive to the alternative delivery location of the in-store delivery option. However, no effect was found on the valuation of the pick-up point delivery for these bio consumers. It was also hypothesized that young consumers are less sensitive for alternative delivery locations as pick-up point and in-store delivery as they are more flexible and more concerned with sustainability. However, this effect is not found to be significant in this research. Figure 8.10 indicates the different utilities for the consumer characteristics for the in-store and pick-up point delivery as compared to the home delivery for each of the consumer characteristics individually.

Delivery vehicle Fuel Type

While considering the delivery vehicle fuel type, in the general MNL parameter estimates it was noted that both vehicle fuel types were valued equally positive as compared to the diesel delivery vehicles. In this interaction model, the bio factor explains some of the heterogeneity of this preferences as the interaction of this consumer characteristic is significant for both alternative fuel parameters. Therefore, it can be concluded that consumers that buy biological products value alternative fuel vehicles that are cleaner more significantly. It was also hypothesized that females would have more preferences towards alternative fuel types, as they are in general more concerned with sustainability. However, this effect has not been found in this research and it can therefore not be stated that females have more preferences towards alternative fuel vehicles than men. As it is expected that younger consumers are more concerned with sustainability, the interaction effect of age and fuel type was expected to be significant. However, no interaction effect has been found and therefore this effect cannot be concluded. The hypothesis that highly educated consumers are more fond of alternative fuel vehicles due to a greater understanding of the effects of this implementation can also not be confirmed as not significant interaction effect

Figure 8.10: Utility course of consumer characteristics interactions with delivery location

is estimated. The hypothesis that consumers that value the cooperative moral domains highly, also value the alternative fuel vehicles more highly, can be rejected as well as no significant interactions are found. Figure 8.11 indicates the differences in preferences for alternative fuel vehicles for bio consumers, as this is the only interaction of a consumer characteristics that is significant with alternative fuel type vehicles.

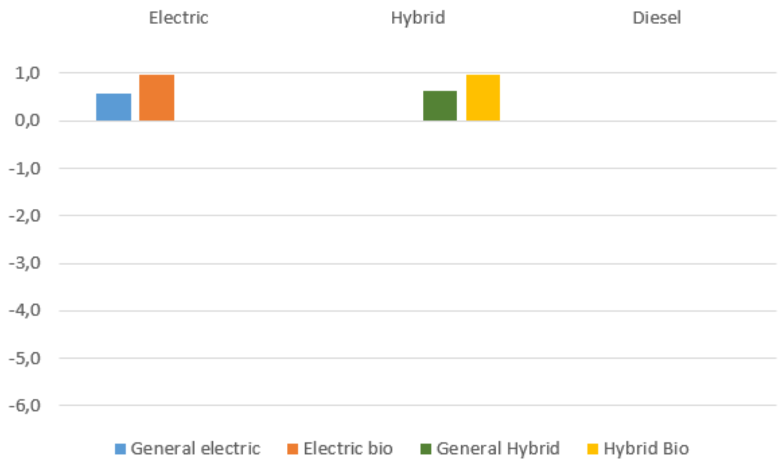


Figure 8.11: Utility course of consumer characteristics interactions with delivery vehicle fuel type

8.5 DELIVERY CHOICE PREDICTION MODEL

An important feature of the estimated MNL model is the ability to predict consumer choices. The estimated parameters multiplied by the delivery attribute set up defines the utility contribution of a delivery choice characteristic. The sum of all individual attribute utility contributions equals the total structural utility of the delivery choice alternative. The attributes in this research are the *price*, *speed*, *load factor*, *fuel type*, and the *delivery location* of parcel delivery. The parameter weights (as indicated in previous sections) and the parameter levels underpin the relative importance of the attributes based on the data retrieved from the survey.

To identify the percentage of consumers that choose for a certain delivery option (set up) relative to another delivery option set up, the MNL choice probability function (equation 8.2) is calculated.

$$p_i = \frac{e^{(V_i)}}{\sum_{j=1...j} e^{(V_j)}} \tag{8.2}$$

To predict consumer choice shares with the choice prediction model, different delivery option policy scenarios can be constructed. For example, in figure 8.12, two delivery choice set ups are indicated along with the resulting choice shares. Within this model, unlabeled choices are used similar to the ones used in the survey: the delivery options are denoted by 'option 1' and 'option 2'. In appendix F.6, a comparison is made between choice shares for the same delivery policy for different contexts. As concluded in this chapter, respondents are more sensitive to price changes in the consumer context than in the citizen context. Therefore, policies that include price changes result in higher choice shares towards the lower price delivery option. With a social norm included respondents are less sensitive for delivery prices. Therefore, the inclusion of a social norm in a policy with varying delivery prices increases the choice towards the cheaper option less significantly.

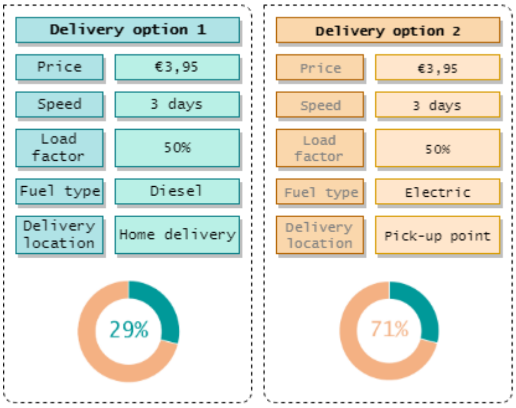


Figure 8.12: MNL choice prediction consumer apparel delivery choice example

8.6 CONCLUSION

In this chapter, the results of the conducted survey and estimated parameter values are presented and discussed. The implications for delivery choice attribute increases and choice predictions are mentioned as well. In section 7.2, the parameter estimates of the key attributes are discussed and interpreted in terms of WTP, relative importance and utility contribution. In section 8.3 significant interaction effects of the consumer-citizen environment and the inclusion of a social norm with the delivery price parameter are discussed. Then, the 12 significant interaction effects with delivery choice factors and consumer characteristics are presented and evaluated. Based on the drafted hypotheses in chapter 4, it is indicated whether the hypotheses are confirmed or rejected in table 8.5. Finally, in section 8.5, the choice prediction model is introduced that will be used to determine choice shares for different delivery policy settings to evaluate sustainable parcel delivery performance in the next chapter.

Key attributes apparel parcel delivery and relative importance
Within the apparel delivery choice parameter estimations, all parameters are found the be significant and proposed in descending order of relative importance: delivery *price* (41,8%), the *fuel type* of the delivery vehicle (17,1%), the delivery vehicle *load factor* (15,5%), *delivery speed* (13,9%)

and the *delivery location* (11,7%).

The impact of context

Context variables that have been varied between respondents were the delivery choice assumptions concerning 1) a consumer environment in which a delivery choice for an order is proposed a 2) a citizen environment in which choice for policy for parcel delivery is proposed, 3) a consumer environment including a social norm and 4) a citizen environment including a social norm. The consumer and citizen environment interact significantly with the price parameter which indicates that citizens are less sensitive for increasing delivery prices as compared to consumers. With the social norm included, respondents are even less sensitive for price changes as well.

Consumer characteristic interactions

Within the delivery choice for apparel parcel delivery, the elder the consumers are, the less sensitive they are for price changes. A higher education level however indicated more aversion against the price parameter. While consumers who show bio behavior are not considered to be sensitive for price changes, they do value higher load factors, in-store delivery and alternative fuel vehicles more significantly. Pick-up points and in-store delivery are heavily detested by consumers that have children, which was expected as the home delivery allows for more convenience. The delivery speed of the parcel is more negatively valued by consumers that spend high amounts of money on online clothing.

Delivery choice prediction model

With this MNL choice prediction model, consumer choice shares predicted for different delivery policy set ups. For this model, the parameter estimates from the MNL with context interactions is used. With the model, the considered parcel delivery policies can be constructed, and the output of the model indicates the percentage of consumers choosing a specific delivery option. The output of the choice shares will be used as input for the proof of concept of sustainable parcel delivery performance, which is discussed and performed in the next section. In chapter 4 a set of hypothesis has been drafted. An overview of these hypotheses is indicated in table 8.5, along with the last column indicating whether the hypothesis is confirmed or not.

Table 8.5: Confirmation or rejection of hypotheses

	Demographics	Confirmed?
H1	Consumers with a low income are more sensitive to delivery prices	No
H2	Young consumers are more sensitive to delivery prices	Yes
H3	Highly educated consumers are less sensitive for delivery prices	No
H4	Young consumers are more sensitive to delivery speeds	No
H5	Higher educated consumers increase preference for delivery vehicle load factors	No
H6	Young consumers prefer higher delivery vehicle load factors	No
H7	Having children decreases the preference towards in-store and pick-up point delivery	Yes
H8	Females have more preference towards in-store and pick-up point delivery	Yes, pick-up
H9	Young consumers prefer pick-up and in-store delivery	No
H10	Females have more preference for alternative fuel vehicles than men	No
H11	Young consumers have more preference towards alternative fuel vehicles	No
H12	Highly educated consumers have more preference towards alternative fuel vehicles	No
	(Sustainable) buying behavior	
H13	Consumers that buy bio products, are less sensitive to price changes	No
H14	Consumers that buy bio products, have an increased preference towards alternative fuel vehicles	Yes
H15	Consumers that buy bio products increase preference for in-store and pick-up point delivery	Yes, in-store
H16	Consumers that spend a lot of money on clothing online, are more sensitive to delivery speed	Yes
H17	Consumers that spend a lot of money on clothing online, are more sensitive to delivery price	No
H18	Consumers that frequently shop online, are more sensitive to delivery speed	No
H19	Consumers that frequently shop online, are more sensitive to delivery prices	No
	Morality	
H20	Consumers that highly value the cooperation domains, value alternative fuel vehicles more highly	No
H21	Consumers that highly value the cooperation domains, value load factors more highly	No
H22	Consumers that highly value the cooperation domains, are less sensitive to price changes	Yes, except for reciprocity
	Context	
H23	Consumers are more sensitive to price changes than citizens	Yes
H24	Citizens value alternative fuel types higher than consumers	No
H25	Consumers value home delivery more than citizens	No
H26	Citizens value the average load factor of the delivery van more than consumers	No
H27	The inclusion of a social norm increases the preference for alternative fuel types	No
H28	The inclusion of a social norm decreases the sensitivity for delivery prices	Yes
H29	The inclusion of a social norm increases the preference for higher load factors	No

9 IMPACT OF CONSUMER PREFERENCES ON PARCEL DELIVERY PERFORMANCE

In this research, besides an in-depth discrete choice experiment to identify consumer preferences regarding parcel delivery, a vehicle routing experiment has been performed as well. In most vehicle routing research, assumptions are made regarding the VRP input in terms of consumer choices. In this research however, these consumer choices have been extensively researched and can therefore be empirically anchored. As a result, the input of the sustainable parcel delivery vehicle routing problem is rooted in real consumer preferences and as such, the results of the SDCVRP indicate results based on real consumer choices rather than assumptions.

The inclusion of the empirically measured consumer choices is done by estimating a logit model for each of the delivery choice scenarios. These choice shares are multiplied by the total number of consumers in the vehicle routing case to determine how many consumers choose for the more sustainable delivery option in each scenario. Based on this demand for the sustainable option per scenario, the optimal parcel delivery performance is derived.

To determine the effect of different parcel delivery policies on the sustainable parcel delivery performance, the conceptual model proposed in chapter 4 is carried out in this chapter (figure 9.1). In this conceptual model, for constructed delivery policy scenarios, the predicted consumer choice shares for each of the policy scenarios is used as input to modify the delivery network configuration. The approach to this modification can be found in section 9.2. A site-dependent capacitated vehicle routing model (SDCVRP) is used to process this input into interpretive output in terms of the indicated Key Performance Indicators *Total kilometers*, *Co2 emissions* and *Average load factor of the delivery vehicles* for the total parcel delivery process (figure 9.1).

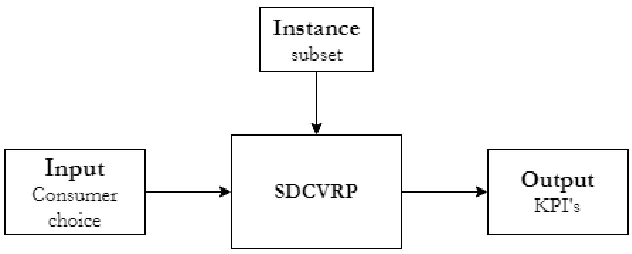


Figure 9.1: Conceptual model routing performance assessment

Section 9.1 proposes different delivery choice policy scenarios based on the research questions determined in chapter 4. Based on the different delivery policy scenarios, consumer choice prediction are identified. Section 9.2 illustrates the approach on how to translate the consumer choice shares into changes in the delivery network configuration for parcel delivery. This section indicates the requirements for the SDCVRP model configuration as well. To estimate the KPI's, the mathematical model of the SDCVRP is proposed. This model is mainly based on the model proposed by Zare-Reisabadi & Mirmohammadi 2015 and will further be discussed in section 9.3. In section 9.4 the resulting output is discussed and the KPI's are evaluated to compare the sustainable parcel delivery policy performance between the scenarios.

9.1 DELIVERY POLICY SCENARIOS

In the first part of this research, the discrete choice experiment is conducted to arrive at empirically measured consumer preferences for the delivery choice factors while choosing for an online delivery method. In this section, different parcel delivery policy scenarios are constructed based on partially increasing the sustainability of one of the delivery choice options in one scenario, while the other options is held constant. The first delivery option, which is held constant because only differences in utility matter for the choice prediction model, is set forth in table 9.1.

Table 9.1: Delivery option 1 with scenario dependent delivery option 2

Factor	Delivery option 1	Delivery option 2
Price	€3,95	Scenario dependent
Speed	1 day	
DL	Home	
LF	50%	
Fuel	Diesel	

In order to construct scenarios that determine the impact of consumers choices on the sustainability of parcel delivery, it is suggested to determine the differences in effect of different sustainability enhancing factors for parcel delivery. Therefore, some scenarios include pick-up point delivery which enables the possibility of consolidation of parcels. Additionally, it is suggested to vary the use of electric vehicles in the scenarios, since this is proposed to decrease the Co2 emissions and pollution of the parcel delivery process. As numerous delivery option policies are possible to research, it is proposed to research the five scenarios based on the research questions that were indicated for the sustainable delivery performance evaluation in chapter 4. This results in the following scenarios:

- **One delivery option (Base)**:
  All parcels are delivered at home, no pick-up points are present and the delivery will only be performed with diesel vehicles (table 9.1).
- **Central Pick-up point (CP)**:
  The second delivery choice option is pick-up point delivery for the same price, speed, LF and fuel type.
- **Electric delivery (ED)**:
  The second delivery option is home delivery with electric vehicles for the same price, speed, LF and fuel type.
- **Free pick-up point (FP)**:
  The second delivery choice option is free pick-up point delivery for the same speed, LF and fuel type.
- **Electric Pick-up point Delivery (EPD)**:
  The second delivery option is pick-up point delivery performed by electric vehicles, for the same price, speed, LF and fuel type.
- **Paid Electric Delivery (PED)**:
  In this scenario, *both* the delivery options are adjusted: only home delivery is proposed in both options. Home delivery with diesel vehicles is for free, while the home delivery with electric vehicles requires payment.

Choice prediction for each of the proposed scenarios are determined in table 9.2. The resulting choice shares are used as input to determine the effect of these choices on sustainable parcel delivery performance (figure 9.1).

Table 9.2: Choice shares for different delivery policy scenarios

Scenario	Concerns	Option 1	Option 2
Base	Both diesel, 1 day. €3,95	50%	50%
CP	Central Pick-up point option	58%	42%
ED	Electric home delivery	23%	77%
FP	Pickup point delivery is free	17%	83%
EPD	To pick-up point with electric	29%	71%
PED	Free home delivery for diesel, paid for electric	77%	33%

9.2 EMPIRICALLY MEASURED CHOICE SHARES AS MODEL INPUT CONFIGURATION

In order to use these empirically measured and predicted choices in a vehicle routing performance experiment, the consumer choices for the five delivery policy scenarios are converted into model configurations. Therefore, a standard toy network of 10 consumers and 1 depot is used and adapted according to the choice shares in each of the scenarios. The standard toy network is called an instance and in this research this is a subset retrieved from the well-known Solomon 25 consumer instance C108 Solomon [1987]. This small network representation of 10 consumers and 1 depot is illustrated in figure 9.2.

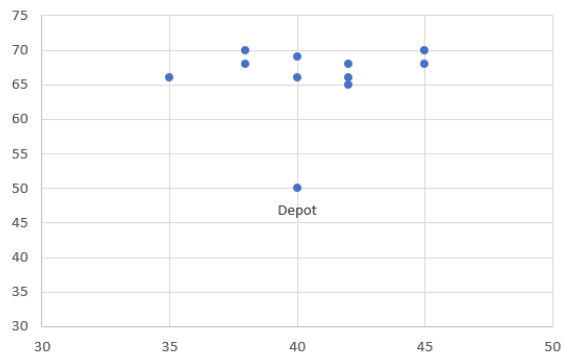


Figure 9.2: Location of consumers and depot in proposed instance subset

Besides a location indicated for each consumer, the demand per consumer is provided in this instance as well, along with the vehicle capacity for all vehicles. As the vehicle capacity indicated for the 25 consumers was 200, the capacity for vehicles that serve 10 out of 25 consumers is set to 80 in this research (10/25th of 200). The characteristics of the instance along with the locations is indicated in table 9.3.

Table 9.3: Instance characteristics subset of Solomon instance C108

Instance	Value
Number of consumers [N]	10
Total demand [q]	150
Vehicle capacity [Q]	80

In order to convert the empirically measured consumer choices for delivery policy scenarios into an adjusted network representation, first the instance is extended with consumer site-dependency: indicating what types of vehicles can deliver demand to consumers (Diesel, Electric or both). This means that besides a given consumer location and demand, the allowable vehicles types for each consumer are included in the delivery network. Based on the predicted choice shares for the policy scenarios, the proposed Solomon instances are altered to meet the different policy scenarios. Only diesel and electric vehicles are included in this research, as it was concluded that consumers valued both hybrid en electric vehicles equally. In terms of improving overall sustainability, the use of electric vehicles is therefore preferred to use in this research.

The approach to the modification of the instance is indicated in 9.3: the logit model output based on consumer preferences is multiplied by the total number of consumers (N=10) to arrive at the number of consumers choosing a specific delivery option. This specific delivery option can indicate one of the changes or both at the same time:

1. A change in allowable vehicle types for the consumer ('Allowable vehicle' in figure 9.3)
2. A change in total number of consumers ('consumer' in figure 9.3)

Consumer	X-coord	Y-coord	Demand	Allowable vehicle
0	40	50	0	Electric, Diesel
1	45	68	30	Diesel
2	45	70	20	Diesel
3	42	66	10	Diesel
4	42	68	10	Diesel
5	42	65	20	Diesel
6	40	69	10	Diesel
7	40	66	10	Diesel
8	38	68	10	Diesel
9	38	70	10	Diesel
10	35	66	20	Diesel

Consumer	X-coord	Y-coord	Demand	Allowable vehicle
0	40	50	0	Electric, Diesel
1	45	68	10	Diesel
2	45	70	30	Diesel
3	42	66	10	Diesel
4	42	65	10	Diesel
5	40	66	60	Diesel
6	38	68	20	Diesel
7	38	70	10	Diesel

Figure 9.3: Delivery network modification based on predicted consumer choice consumer 0 is depot

For example, the modification in figure 9.3 is based on policy scenario 'Central Pick-up Point', where 42% of consumers choose for pick-up point delivery and 58% chooses for home delivery. The number of consumers are integers and 42% of 10 consumers results in 4,2 consumer choosing for the central pick-up point. In the instance in figure 9.3, this is implemented in a way that 4 out of 10 consumers choose for pick-up point delivery and the remaining 6 choose for home delivery. This results in 7 (6 consumer homes and 1 pick-up point) delivery locations in this scenario. To arrive at integer values of the number of consumers choosing for a delivery option, in this research the choice shares are rounded off to increments of 10%. This results in the following rounded choice shares for each of the proposed scenarios in table 9.4

Table 9.4: Choice shares delivery policy scenarios

Scenario for choice option 2	**Choice option 1**	**Choice option 2**
CP: The option to choose pick-up point delivery is included	60%	40%
ED: The option to choose for electric delivery is included	20%	80%
FP: The option to choose for free pick-up point delivery is included	20%	80%
EPD: The option to choose for pick-up point electric delivery is included	30%	70%
PED: The option to choose for free diesel delivery, as compared to paid electric delivery is included	70%	30%

For each of the policy scenarios, different model configurations are determined. The model configurations for each of the research questions and corresponding scenarios are:

- **Base configuration**:
  All parcels are delivered at home to all 10 consumers, no pick-up points are present and the delivery will only be performed with diesel vehicles;
- **Configuration Central Pick-up Point (CP)**:
  A pick-up point is opened, to which 4 out of 10 consumers decide to have their order delivered. Only diesel vehicles are used;

- **Configuration Electric Home Delivery (ED)**:
  Demand is only delivered to consumers homes, 8 out of 10 consumers will have their order delivered by electric vehicles;
- **Configuration Free Pick-up Point (FP)**:
  A pick-up point is opened to which 8 out of 10 consumers will have their order delivered to a pick-up point;
- **Electric pick-up point Delivery (EPD)**:
  A pick-up point is opened, which will be served by an electric vehicle. 7 out of 10 consumers decide to have their order delivered to this pick-up point. The pick-up point will be served by electric vehicles.
- **Free diesel, Paid Electric Delivery (PED)**:
  All demand is delivered to the consumers' homes, 3 out of 10 consumers decide to choose for delivery by electric vehicles.

9.3 MATHEMATICAL MODEL SDCVRP

To convert the input of consumer choices into output on sustainable parcel delivery performance, a site-dependent capacitated vehicle routing problem (SDCVRP) is proposed for this research. The SDCVRP considers an extension in the configuration of the basic VRP of compatibility issues exist between consumers (sites) and vehicles Golden et al. [2008]. This resembles the consumer's choice for electric or diesel vehicles. As such, every consumer is associated with allowable vehicle types as indicated in figure 9.3. To match the consumer choices from the discrete choice experiment, the configuration of this SDCVRP therefore needs to involve:

- Site-dependencies which allow for a dependency between the consumer and an (alternative fuel) vehicle type that can serve the consumer
- A mixed fleet configuration
- A minimal load factor indication for vehicles to be allowed to drive a route
- A vehicle capacity parameter, which cannot be exceeded

The objective of this model is to minimize the total distance traveled by the vehicle fleet and all constraints for the basic VRP as well as the site-dependency constraints must be satisfied Zare-Reisabadi and Hamid Mirmohammadi [2015]. The constraints in this model relate to the choice characteristics of the delivery method: what kind of delivery van fuel types can be used, what the considered delivery location are and what the minimum load factor should be. The price of the delivery choices is taken into account while predicting the choice shares in the *free pick-up point* and *free diesel as compared to paid electric delivery*, but cannot be varied in the model set up, as this is not taken into account in the vehicle routing model.

9.3.1 Problem formulation

For this mathematical model problem formulation, a new notation is proposed as compared to the discrete choice experiments. Some characters may match the characters of the discrete choice formulas. However, this is a completely different notation. To stay with the convention of mathematical vehicle routing problems, the notation that is most frequently used for vehicle routing problems is maintained in this research as well.

The SDCVRP suggested in this research partially resembles the approach from Zare-Reisabadi & Mirmohammadi 2015. However, an additional load factor constraint is added to this proposed model: indicating that vehicles with relatively low carrying load cannot perform parcel delivery as this results in an unnecessary increase in vehicles in city centers. The mathematical model that underpins the SDCVRP optimization uses an undirected graph with n consumers where node 0 and all consumers n are indicated by nodes V in figure 9.2. Node 0 represents the LSPs parcel depot and A is the set of edges that determine the travel possibility between the different consumers and the depot. K is the set of available heterogeneous vehicles (diesel = K_d and electric = K_e). Each consumer has a demand q_i which should be met by only the vehicle types that are appropriate for the consumer (N_d & N_e).

First, the parameters used in this model are discussed. Then, the decision variables are set. Subsequently, the objective function and constraints are indicated to solve the site-dependent vehicle routing problem and to determine the impact of consumer choices on delivery routing performance in terms of *Total kilometers*, *Co2 emissions* and *Average load factor of the delivery vehicles* for the total parcel delivery process.

Parameters

n is the number of consumers
N_e is the set of consumers that can be served by electric vehicles in set K_e
N_d is the set of consumers that can be served by diesel vehicles in set K_d
N is the set of consumers, with $N = N_e \cup N_d$
V is the set of nodes, with $V = \{0\} \cup N$
A is the set of edges, with $A = \left\{(i,j) \in V^2 : i \neq j\right\}$
c_{ij} is the Euclidean travel distance over edge $(i,j) \in A$
q_i is the demand at consumer i, for $i \in N$
K_e is the set of electric vehicles to serve consumer n_e
K_d is the set of diesel vehicles to serve consumer n_d
K is the set of all vehicles, with $K = K_d \cup K_e$
Q_k is the capacity for vehicle k, with $k \in K$
a is the load factor: the minimal percentage of vehicle capacity that has to be filled when leaving the depot

Decision variables

$$x_{ijk} = \begin{Bmatrix} 1 & \text{If arc (i,j) is traversed by vehicle } k \\ 0 & \text{Otherwise} \end{Bmatrix}$$

$$y_k = \begin{Bmatrix} 1 & \text{If vehicle k is used} \\ 0 & \text{Otherwise} \end{Bmatrix}$$

z_{ik} is the cumulative load transported by vehicle k when it reaches consumer node i

Objective function and constraints

$$\min \quad \sum_{i \in V} \sum_{j \in V_j \neq i} \sum_{k \in K} c_{ij} x_{ijk} \tag{9.1}$$

$$
\begin{aligned}
\text{subject to} \quad & \sum_{j\in V}\sum_{k\in K} x_{ijk} = 1 \quad \forall i \in N && (9.2a)\\
& \sum_{i\in V}\sum_{k\in K} x_{ijk} = 1 \quad \forall j \in N && (9.2b)\\
& \sum_{j\in V}\sum_{k\notin K_e} x_{ijk} = 0 \quad \forall i \in N_e && (9.2c)\\
& \sum_{i\in V i\neq j} x_{ijk} - \sum_{i\in V_i\neq j} x_{ijk} = 0, \quad \forall j \in V, k \in K && (9.2d)\\
& z_{0k} = 0 \quad \forall k \in K && (9.2e)\\
& z_{ik} + q_j - z_{jk} \leq (1 - X_{ijk})M \quad \forall \quad i,j \in A : j \neq 0, i \neq 0 \quad \forall k \in K && (9.2f)\\
& q_i \leq z_{ik} \leq Q_k \quad i \in N \quad k \in K && (9.2g)\\
& z_{ik} - a \cdot Q_k \geq (1 - X_{ijk})M \quad \forall i \in N, \quad j = 0, \quad \forall k \in K && (9.2h)\\
& x_{ijk} \in \{0,1\} \quad i,j \in V, \quad k \in K, \quad i \neq j && (9.2i)\\
& y_k \in \{0,1\} \quad k \in K && (9.2j)\\
& z_{ik} \geq 0 \quad \forall i \in N, \quad k \in K && (9.2k)
\end{aligned}
$$

Constraint (9.2a), (9.2b) and (9.2c) force each consumers to be visited only once by an allowable vehicle. Constraints (9.2c) indicate this strictness of an allowable vehicle type for electric vehicles. However, for diesel vehicles this constraint is not set, indicating that consumers that can be served by diesel vehicles, might also be visited by electric vehicles. Flow conservation constraints (9.2d) guarantee that for each vertex that the incoming arcs is equal to the number of outgoing arcs. Constraints (9.2e) ensure that the cumulative load of vehicles is equal to zero when it leaves the depot. Constraints (9.2f) and (9.2g) guarantee that the vehicle capacity is not exceeded on the driven vehicle route. Constraints (9.2h) ensure that the cumulative load of a vehicle up to the latest node in the route satisfies the minimum required load factor. In constraints (9.2i) and (9.2j), the binary decision variables are defined and finally in (9.2k), the cumulative demand variable is set to be non-negative.

9.4 RESULTS ON PARCEL DELIVERY PERFORMANCE

Based on the mathematical model elaborated on in the previous section, a script is developed in operation research optimization software and indicated in appendix G. In order to prevent that the outcome of one of the consumer choice input configurations gives a distorted view on the performance indicators due to coincidence, 10 replications (N=10) are done with each time another share of the 10 consumers is depicted to choose for the more sustainable delivery option in each scenario. In reality, these replications implicate 10 different days in which each day, different consumers choose the more sustainable delivery option. The replication of the experiments also decreases the confidence interval of the output values, which is desired for the optimization model. To test whether the model indicates appropriate output, the model has been verified. This verification can be found in appendix G.

Table 9.5 indicates the results on the key performance indicators for each of the different configurations. The average load factor of the vehicles in each of the policy scenarios was equal to 93,8%. This can be explained because due to the minimum load factor constraint (of 50%) indicated in the model, it is possible to add another vehicle to the model. However since this vehicle has to come from the depot and go back to the depot (which is located outside the city center), it is not beneficial to do so in light of the objective function of minimizing total distance travelled. In the table, the KPI's are presented for each configuration. The Co2 emission in kilograms is based on the estimated Co2 emissions in grams per kilometer indicated in table 2.2 in chapter 2 which is equal to 214 grams Co2 per kilometer. The corresponding confidence intervals of each of the obtained values is indicated in appendix G.5 table G.4.

Table 9.5: Vehicle routing results delivery policy configurations

Policy Configuration	Total distance travelled [km]	Co2 emission [kg]	Average load factor [%]
Base	86.5	18.5	93.8
Central Pick-up point (CP)	82.7	17.7	93.8
Electric home delivery (ED)	86.0	0	93.8
Free pick-up point (FP)	78.9	16.9	93.8
Electric pick-up point (EPD)	82.0	0	93.8
Free diesel, paid electric (PED)	89.0	9.4	93.8

Offering parcel central pick-up point delivery (CP) as a second delivery choice besides home delivery, results in a significant decrease in vehicle kilometers. This might not be directly interpreted from the average value of total distance driven which is just a bit lower than the average for the base configuration, but the box plot in figure 9.4 indicates this significant difference. The significant decrease in vehicle kilometers in urban areas resulting from the policy of introducing a pick-up point therefore also results in a significant decrease of Co2 emitted for the total delivery.

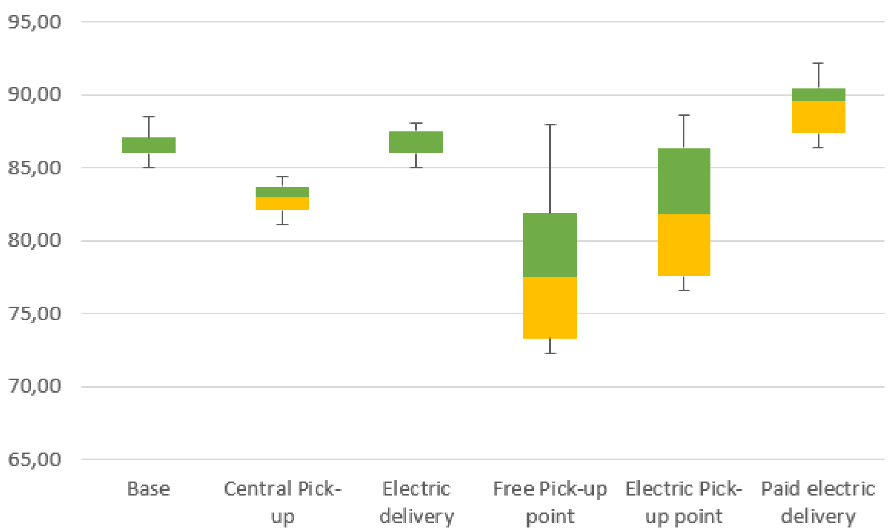


Figure 9.4: Box plot total kilometers in city centers for different configurations

The policy of proposing electric delivery (ED) results in a high share of consumers choosing for the electric delivery option and a lot of parcels have to be delivered by electric vehicles. Therefore, the resulting demand of the consumers that did not choose for electric vehicle delivery, can be delivered by the same vehicle. This does not result in significantly lower vehicle kilometers in city centers, but it does however decrease the emission levels to zero.

If parcel delivery to a pick-up point will be offered for free (FP), a large share of consumers (8 out of 10) will choose for parcel delivery to a pick-up point. Because this results in a demand for this pick-up point that exceeds the vehicle capacity, an additional vehicle is needed to serve the demand in that pick-up point. As one of the two vehicles is used for the parcel delivery to the central pick-up point for this network configuration, the other can serve both the consumers home delivery and the remaining demand for the pick-up point. The free pick-up point policy will not decrease the amount of kilometers driven and does not decrease the emission levels significantly. Mainly due to the use of conventional diesel vehicles and the vehicle capacities. As can be seen in both figures, the outcomes of this alternative extremely depend on the location of the pick-up point: if this pick-up point is relatively close to the depot, an increase in parcel delivery sustainability is observed. Whereas if the pick-up point is relatively far from the depot, this does not result in an increase in parcel delivery sustainability (dispersion of the optimal values is large).

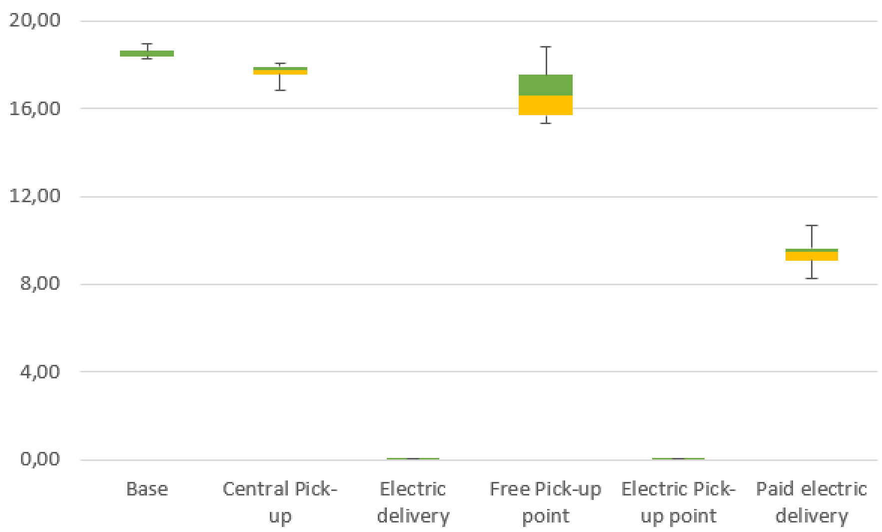


Figure 9.5: Box plot emissions for different configurations

Pick-up point delivery that is indicated to be delivered by electric vehicles is of interest of a large share of consumers. The same holds for this delivery set up as for the increase in the share of consumers choosing for electric pick-up point delivery: while the amount of vehicle kilometers does not significantly decrease by introducing this delivery policy setup, the emission levels decrease to zero due to the remaining demand which did not require to be delivered by electric vehicles, is however delivered by electric vehicles since this vehicle is already set up for a route which requires electric vehicle delivery.

Finally, the choice between free diesel delivery and paid electric delivery results in a third of the consumers choosing for paid electric delivery. While the total amount of kilometers in the city center does not differ significantly from the base policy because still all parcels need to be delivered to the consumers' home addresses, the emission levels however do differ significantly due to a share of the parcels being delivered by electric vehicles: while only 3 out of 10 consumers choose for paid electric delivery, the Co2 emission levels decreased with almost 50%.

9.5 CONCLUSION

While a lot of vehicle routing studies aim to determine optimal routes based on assumptions of consumer choices, the vehicle routing problem in this research converted the empirically measured consumer preferences based on the discrete choice experiment into vehicle routing configurations to determine the impact on the key performance indicators for sustainable parcel delivery in urban areas.

The goal of this implementation and evaluation of consumer choices on the effect of sustainable parcel delivery was not to determine a generic result but to show a proof of concept on how consumer preferences for delivery choice characteristics and different policy scenarios have an effect on sustainable delivery performance. This in terms of the indicated Key Performance Indicators *Total kilometers*, *Co2 emissions* and *Average load factor of the delivery vehicles* for the total parcel delivery process.

To achieve this, the consumer choices predicted with a logit model based on consumer preferences, were used to determine the share of consumers that choose for the specific delivery policy scenarios *central pick-up point delivery*, *electric home delivery*, *free pick-up point delivery*, *electric pick-up point delivery* and *paid electric home delivery* as compared to free diesel home delivery. These choice ratios are multiplied by the number of consumers (N=10 in this research) to arrive at the number of consumers choosing for the more sustainable delivery alternative in each choice scenario.

The proposal of the five delivery option policies results in different possible implications for sustainable parcel delivery performance. Based on the output on the KPI's, policy set ups that include electric delivery for no increase in price, score best. The alternative in which electric delivery is proposed for payment while the alternative diesel delivery is for free, also shows a significant increase in the sustainability of parcel delivery. The average load factor remains the same for each of the policy scenarios, as a minimal load factor of 50% is set, and the addition of another vehicle is not more beneficial to the minimization of total distance driven.

10 CONCLUSION, DISCUSSION & RECOMMENDATIONS

In this research, the goal was to contribute to the development of sustainable delivery policy options that are preferred by urban consumers that buy fast fashion online. Therefore, the main research question of this research was "To what extent do Dutch urban e-consumers value (sustainable) delivery choice factors in the fast fashion industry?". Next to the currently considered delivery choice factors, this research also focused on the preferences towards sustainable aspects of last-mile parcel delivery. In order to develop these policies, first a discrete choice experiment was performed to unravel consumer preferences. These preferences were then converted into vehicle routing input to determine the effect of empirically observed consumer choices on sustainable parcel delivery performance.

Based on the preferences for delivery choice factors in general, it has been researched whether preferences differ between consumers with varying personal characteristics. This is beneficial for marketing purposes, as this evaluation allows for better development of consumer-oriented delivery policies. To conclude whether consumers differ in preferences for delivery choice characteristics from different choice perspectives, surveys with different contexts have been investigated in this research. With the variation of the different contexts, it as been determined whether a consumer-citizen duality exists in preferences for delivery choice characteristics and whether consumers can be steered towards sustainable behavior by including a social norm indicating that 75% of consumers choose for sustainability in delivery services.

The preference for delivery choice factors that have been researched are *delivery price*, *delivery speed*, *delivery location*, delivery vehicle *load factor* and the delivery vehicle *fuel type*. As consumers currently have to trade-off between the first three delivery choice characteristics in real life, the latter two are included to research the extent to which these sustainability reflecting aspects are considered important to a consumer when making a parcel delivery choice (if these factors are included in the choice option).

10.1 CONCLUSION

Based on this research, it can be concluded that the addition of the sustainability factors *load factor* and *alternative fuel types* of the parcel delivery had a positive effect on the overall utility of a delivery option. The *fuel type* delivery choice factor is important to consumers and both alternative fuel vehicle types are considered to be equally valued, indicating that as long as the fuel type in the delivery choice indicates a more sustainable alternative to diesel vehicles, this is preferred by consumers. This means that once the choice for these factors is included, consumers have an increased appreciation of the delivery alternative in general. The fact that bio-consumers result to have greater preference towards both these sustainability factors, is considered to validate the inclusion of these factors with the goal of expressing sustainability. On the other hand, this knowledge of bio consumer preferences can be used for marketing purposes to develop bio consumer-oriented delivery policies. By adding the positively valued choice for alternative fuel vehicles in a delivery choice, this research concluded that this will also lead to an increase in the sustainability of parcel delivery, even if consumers have to pay for the parcel delivery by electric vehicles.

An increase in delivery choice factors such as *delivery price* and *delivery speed* are valued negatively and therefore delivery policy developers need to be careful with the value of these factors. In general consumers attach most importance to delivery prices while choosing a delivery option: as most e-retailers nowadays have to offer free delivery as part of the e-commerce service to compete among other companies, the importance attached to delivery prices in this research was expected. However, it has been concluded that the preference towards delivery prices differs between different consumer types, as well as from different choice perspectives. Elder consumers are less sensitive for delivery prices, whereas consumers with a high level of education are more sensitive to higher delivery prices. This sensitivity also differs between consumer and citizen and therefore indicates a consumer-citizen duality on delivery prices in the parcel delivery choice. The result that consumers are more sensitive for delivery price increases than citizens can indicate an intervention possibility for the Dutch government. The inclusion of a social norm nudge to introduce a form of peer pressure to steer consumers into more sustainable behavior results in consumers as well as citizens to be even less sensitive to price changes. This indicates that the inclusion of the social norm has steered respondents into being less sensitive for price changes. However, the intention of this social norm nudge was originally to steer consumers into more sustainable behavior, i.e. having more preference towards the sustainability reflecting factors. While the inclusion of a social norm does not specifically result in more sustainable behavior, the effect is however interesting for delivery policy development.

In general higher delivery times decrease the attractiveness of the delivery option. However, it is also indicated that this choice factor, is one of the less important factors for consumers. This indicates that the next day delivery that is proposed by a lot of e-retailers to differentiate among the competition, is not necessarily the most important factor to compete on when sustainability reflecting factors are included in the delivery choice option. Consumers that are more sensitive to longer delivery times are consumers that spend a lot of money online per month on apparel. In this light, policies could be developed that indicate that if consumers spend over an amount of money in the webshop, delivery will be faster instead of how it is currently offered: cheaper.

The choice for an alternative *delivery location* is not (yet) positively valued by consumers. However, proposing alternative delivery locations to consumers at the same price of home delivery resulted in an increase in sustainability of parcel delivery, once the alternative delivery location is carefully chosen upon. The delivery location is least important for consumers in general, and home delivery is preferred most as compared to the recently introduced alternative delivery locations. This preference however differs extensively between different consumer types. As the alternative delivery locations are beneficial for LSPs in terms of costs, it is therefore useful to focus on consumers that are less sensitive for alternative delivery locations. Consumers that have children extremely detest the alternative pick-up locations as compared to home delivery and women in general indicate to have less aversion to pick-up point delivery. Also for this delivery choice factor, an increasing importance (or in this case less aversion) can be observed for bio consumers, indicating that these consumers mind it less to having their parcel delivered in an alternative delivery location. As it was concluded for the sustainability factors that bio consumers validated the inclusion of these factors to reflect sustainability improvements, the increased valuation of the alternative delivery locations can also indicate that consumers value this in the light of sustainability improvement. Research into the promotion of the alternative delivery location in by indicating the improvement in sustainability is proposed for this delivery choice factor.

Based on the empirically anchored consumer preferences for delivery choice characteristics, different delivery policy scenarios were developed in this research. The consumer choice shares for each scenario are used as an input for the vehicle routing model to find optimal routes with the objective of minimizing the total distance driven from the parcel depot and all consumers that have to be visited. For this research, the effect of proposing five policy scenarios to consumers has been researched in terms of total kilometers driven (the hindrance and congestion that results from these urban vehicle kilometers), the CO_2 emission levels (which decrease livability) and the average vehicle load factors. Based on the sustainable parcel delivery performance it can be concluded that to increase the sustainable performance of parcel delivery on both total kilometres driven and the level of CO_2 emitted, it is advised to propose a central pick-up point delivery option besides a home delivery option. By introducing this choice to consumers, a significant decrease in total vehicle kilometres in city centers, as well as CO_2 emission levels has been determined. For the delivery policy scenarios that include electric vehicles to deliver parcels, only a significant decrease in CO_2 emission levels is observed. It needs however noticing that the introduction of this delivery policy will require for investment in a new vehicle fleet. A delivery policy that introduces free delivery to pick-up point can result in more sustainable parcel delivery. It should however be mentioned that the increase in sustainability is heavily dependent on the location of the pick-up point and this location should therefore be an informed decision.

10.2 POLICY RECOMMENDATIONS

Based on the outcomes of this research, recommendations are made for stakeholders that are involved or could be involved in the development of more sustainable parcel delivery policy which is preferred by consumers. As indicated in previous chapters, consumers, Logistics Service Providers (LSP) and e-retailers are currently involved in the last-mile delivery process and will be discussed. Additionally, based on the outcomes of this research in terms of the consumer-citizen duality, a recommendation for the role of the Dutch government is indicated as well.

E-retailers
As e-retailers allow for interaction with consumers to choose for a delivery option, the outcome of the research that concerns the interaction between consumer and e-retailer are of interest for e-tailers. As it has been determined that elder consumers are less sensitive to price changes and consumers with a high level of education are more sensitive to price changes, this can be used for marketing purposes by e-tailers that serve elder and/or highly educated consumers. For elder consumer target groups, the delivery prices could be set higher, and for high level educated people, e-tailers should be more careful with delivery prices to retain their consumers. The inclusion of a social norm in the parcel delivery choice resulting in consumers being less sensitive for delivery prices means that if a social norm is provided to consumers during the check-out phase of the online order, they are less sensitive for delivery price increases. It needs noticing that the social norm in this research was set to 75%, which means that this number should be proposed to consumers to achieve the result indicated in this research. The effect of lower or higher percentages has not been tested and could result in different (and even unexpected) outcomes. It is however suggested to perform real life testing of the inclusion of the social norm, before implementing this recommendation.

It is recommended to include the sustainability reflecting factors into the delivery options consumers can choose from, both because it is positively valued by consumers in general and because including electric delivery was researched to decrease CO_2 emission levels significantly. However, it is important that if the factors are included in the delivery choice policy, the sustainability enhancement is also realized in the parcel delivery operation. Therefore, it is proposed to negotiate the possibilities for vehicle fleet expansion and better consolidation with the LSP. With regard to the load factor indication of the delivery vehicle, this can be indicated as an ex ante prognosis to the consumer, and agreements can be made between the LSP and the e-retailer to either set a lower bound for the delivery vehicle load factor or a real time indication of the delivery vehicle load factor. By introducing a policy that considers paid delivery by electric vehicle, and free diesel vehicle delivery, not an elimination but a significant decrease in CO_2 emission levels is observed. Therefore to stimulate negotiations with the LSPs in terms of investments in an electric vehicle fleet, the paid electric delivery could partially allow for a monetary incentive to facilitate this transition.

The promotion of pick-up point delivery as an alternative delivery option policy is also recommended to achieve more sustainability in parcel delivery. As most consumers are very sensitive to price changes, it is recommended to provide this pick-up point delivery for free but to be very cautious with choosing the location of the pick-up point, as this was determined to have a great difference in effect on the sustainability in parcel delivery. It is recommended to focus on women and bio consumers to promote these parcel pick-up points, as these consumers have the least aversion to this type of delivery location.

Logistics Service Providers
Due to the relatively high importance consumers attach to the introduction of electric as well as hybrid delivery vehicles, it is suggested to expand or modify the vehicle fleet towards electric vehicles. As this probably involves a large investment, this might be done together with an increase in delivery prices set within the e-retailer's contract. Therefore, it is recommended to explore the possibilities of paid electric delivery, to increase sustainability and at the same time collect money to realize the fleet changes. Another recommendation for LSPs is, as consumers attach value to the load factor of the delivery vehicle, the optimization and communication of load factors with e-retailers. As recommended for e-retailers to propose the load factor to the consumers this could either be an ex-ante or a real-time estimation. On the optimization side of the parcel delivery process, the inclusion of the load factor for vehicle delivery routing optimization is therefore recommended. However, as this minimum load factor for each vehicle significantly decelerates the speed of the optimization process, it is recommended to use an average load factor for all delivery vehicles to be maintained. Additionally, higher load factors could be established by collaboration between different LSPs and this is therefore recommended.

Dutch government
As it is concluded that a duality between consumers and citizens preferences exists for delivery prices, it could be of interest for the Dutch government to intervene in the last-mile delivery policies. As indicated in the introduction of this research, consumer behavior and increasing (online) retail competition lead to significant increase in vehicle kilometers and a decrease in livability in urban areas. The relatively lower sensitivity for delivery prices in a consumer environment could allow for companies to set delivery prices for parcel delivery and invest the incomes resulting from this delivery price charge in the improvement of parcel delivery sustainability. The introduction of a policy regarding parcel delivery prices could also decrease pressure from the parcel delivery competition market by setting a threshold value for delivery prices for urban parcel delivery. As price sensitivity is indicated to be lower for consumers in a citizen environment: indicating that all consumers pay the same price by default.

10.3 DISCUSSION

In this section, a discussion of this research is provided as well as recommendations for further research are indicated both on the first and main part of the research to identify consumer preferences by means of a discrete choice experiment, and the second part of the research to determine the effect of parcel delivery policies, the resulting consumer choice shares in each policy based on the empirically measured preferences and the results in terms of sustainable parcel delivery performance.

First of all, in the survey to identify consumer preferences an example of the choice set is presented along with the explanation of each of the included attributes in the choice tasks. This might count as priming and might have influenced the parameters because the priming texts indicate the increase in sustainability in a positive way (i.e. higher values for the factors indicate more sustainability). It can be expected that the introductory page results in an overestimation of the sustainability reflecting parameters. In reality however, it is likely that this priming will also be applied in practice as consumers indicate to need help to make more sustainable decisions. This "help" could either be provided in the online order check-out process next to the choice task or as an information button provided along the sustainability reflecting factors in the choice task.

Second, the use of discrete choice experiments to identify consumer preferences results in the limitation that in this research, it is plausible to assume that consumer take more factors into consideration while making a delivery choice. As earlier proposed for the inclusion in this research are the accessibility of the pick-up point and the in-store delivery. As both these delivery options are less preferred as compared to home delivery in this research, the inclusion of accessibility could have had an effect on the valuation for the alternative delivery points. Another attribute that could have an effect on the valuation of alternative delivery locations is the possibility of returning items at the pick-up point. Another limitation of the use of discrete choice experiments is that the choices that are made are *hypothetical* choices and there are no consequences to the choices consumers make. Therefore, the parameters might be overestimated as respondents might be too positive on their valuation of alternative fuel vehicles, or the inclusion of the load factor parameter. It is however expected that the factors that currently have to be considered in real life are less overestimated than the parameters that reflect sustainability, as the consumers included in this research are assumed to have experience with and a preference for these factors. The inclusion of different contexts in this research might also have an effect on the parameter estimations, whereas consumers have to make hypothetical choices in a hypothetical context, this might result in an overestimation of the consumer-citizen duality for delivery price, and the effect of including a social norm in the choice task. Additionally, in real life, it might occur that, due to high online retail competition, consumers decide to buy their product at another online store if they do not prefer the possible delivery options as no "I will buy somewhere else" alternative is included. In this research it was chosen not to include this option, as this might result in the easy way out to avoid complicated trade-offs between delivery choice characteristics. This decision might have an overestimation of the delivery choice characteristics, due to consumers having to make a choice.

Third, from a more technical choice set construction perspective, a few aspects are reflected upon. First, the chosen choice set design for this research is not entirely optimal. Delivery speed could have been considered to be of nonlinear nature. Additionally, the choice for 8 choice sets did not result in attribute level balance, which would have been been more optimal. Finally, for model estimation and interpretation, the equidistance of attribute levels from the attribute price and speed would have been more efficient.

Fourth, to identify differences in consumer preferences based on morality as cooperation and corresponding seven moral domain (factors), the MAC was used. However, the results of the factor analysis did not indicate nor the seven domain factors neither any other reliable factor. It is suspected that this might be the result of the Dutch translation of these statements. Additionally, it is argued that morality might be considered a latent factor in real life as compared to an observed consumer characteristic as used in this research. Therefore, this research could be extended with a hybrid choice model, allowing for the inclusion of the latent variable with the statements ratings as indicators to define an individual's morality in cooperation Ben-Akiva et al. [2002]. To identify consumer differences, the estimation of latent class models could be of interest for the purpose of targeting specific consumer group. Within the latent class models, individuals are divided into groups based on the likelihood of belonging in that group based on various characteristics. This could result in different consumers groups based on demographics or even based on different decision rules. The research towards latent classes based on different decision rules is proposed by Chorus 2015. In this research, this decision rule heterogeneity was distinguished in moral choice situations, of which increasing sustainability in urban areas could be considered a moral situation. As the sustainability and livability might also be seen as a moral choice situation (albeit in the long run), the research towards decision rule heterogeneity for these choices might be interesting as well.

Fifth, as it was concluded that both the sustainability enhancing factors are positively valued once included in the choice environment, further research on the inclusion of sustainability reflecting factors is proposed. In this research only the load factor and the fuel type of the vehicles was taken into account, but research into other factors that directly partially indicate the sustainability of the delivery option is proposed. Likewise, it is proposed to research whether the inclusion of both factors in this research might be valued equally in delivery innovations, as well as in other delivery markets. An example of a delivery innovation is for example the self moving parcel locker or the delivery drone. An example of another delivery market is the quickly emerging grocery delivery market in the Netherlands.

Sixth, to evaluate the consumer choices based on empirically measured preferences, the SDCVRP model was implemented. This model is, as compared to the in-depth research into consumer preferences for delivery choice factors, a simplification of a real world application. As in this research, the intention was to indicate a proof of concept, a small network application was sufficient. The application to a real world situation would require significantly more constraints and will require a solving heuristic instead of searching for an exact solution. Due to the simplification of this model, the SDCVRP results might be an overestimation of the benefits in terms of sustainable parcel delivery performance. However, this proof of concept can be extended in order to add more reality and to increase the value of the integration of real life consumer preferences in the estimated result. For example, the real energy use of electric as well as diesel vehicles in city centers could be added to the model as in this model the energy use is only dependent on the kilometers driven Goeke and Schneider [2015]. As the vehicle energy usage is also dependent on traffic density, it is proposed to add real time or at least accurate traffic information. The emission levels indicated for parcel delivery in this research could also be extended to determine the total effect of fast fashion on emissions. This effect is not solely based on the emissions in city centers, but also on the production and the emission resulting from transport of the parcel outside city centers. Additionally, in this research time windows for delivery are not taken into account. However, since consumers are nowadays mostly on tight schedules, they might expect this from delivery services as well. Research into the consumer preferences for different types of time windows and the effect of including the (choice for) time windows in sustainable parcel delivery performance is proposed. As in this research for each of the configurations 10 experiment replications have been performed to arrive at more reliable estimations, it is suggested that this replication can be done 100 or even 1000 times if time allows. The increase in the number of replications not only decreases the confidence interval, it also allows for determining the consumer choice shares of for example 42% and 52%, instead of the 10% increment in this research. As an increase in significance will be obtained by increasing the number of replications, a sensitivity analysis for the choices in different delivery policies is allowed. By executing this sensitivity analysis, it is determined whether the performance of the delivery policies based on consumer choices are firm and reliable. As in this research the 10% increment was maintained, it was concluded that a sensitivity analysis of consumer choices of 10% was too large to draw conclusions from.

Finally, in order to extend the analysis on sustainable parcel delivery performance in this research to develop more sustainable parcel delivery policies that are preferred by consumers, it is proposed to perform a cost-benefit analysis to determine the cut-off price value for which more sustainability in parcel delivery is introduced. To determine this cut-off price value to which the parcel delivery process significantly increases sustainability, more specific policy set up can be developed in further research.

A CURRENT DELIVERY PROCESS DETAILS

In this appendix, an overview of different fast fashion e-tailers that offer different delivery options is discussed. Based on the information in table A.1, it can be concluded that all fast fashion e-tailers show similarities in terms of *delivery price*, *delivery location* and *delivery speed*.

A.1 FAST FASHION ONLINE DELIVERY CHARACTERISTICS

Table A.1: Current characteristics of fast fashion delivery options at different e-tailers

Delivery location:	**Home**	**In-store**	**Pickup point**	**Express**	**E-tailer**
Price (€)	2,95	0	2,95	8,95	Mango
Speed (days)	4	4	4	1	
Price (€)	3,95	0	3,95	9,95	Zara
Speed (days)	4	4	4	1	
Price (€)	3,99	3,99	3,99	4,99	H&M
Speed (days)	3	3	3	1	
Price (€)	3,95	0	3,95	9,95	Pull&Bear
Speed (days)	3	4	4	1	
Price (€)	3,95	-	-	9,95	Uniqlo
Speed (days)	3	-	-	1	

B PILOT SURVEY

Based on the conclusion of the literature review, the different attributes to include for the pilot study are constructed into choice sets to include in the survey. First, the choice sets for the pilot survey are constructed. The approach to the choice set construction is indicated in this chapter.

B.1 GENERATION OF EXPERIMENTAL DESIGN

Once the model specification is determined, the experimental design can be constructed. The experimental design indicates which hypothetical choice situations the respondents are faced with in the stated choice experiment.

Should the design be labelled or unlabelled?
The design should be unlabelled, since the alternatives do not have alternative-specific parameters. The different alternatives will be unlabelled and called 'delivery option A, delivery option B'.

Should the design be attribute level balanced?
Attribute level balance means that each attribute level (for each attribute) appears an equal number of time across the experiment. Attribute level balance is generally considered a desirable property in an experiment since this ensures that it is possible to estimate parameters on the whole range of levels as compared to only having data points at a few of the attribute levels.

How many attribute levels are used?
The number of attribute levels to use is dependent on the model specification. Dummy and/or effects coded attributes are included, so the number of levels to use for the attributes 'sustainability' and 'Pick-Up Location' are predetermined. The more levels used, the higher the number of choice situations will be. Also, mixing the number of attribute levels for different attributes may yield a higher number of choice situations (because of attribute level balance). For example, if there are three attributes with 2, 3, and 5 levels, respectively, then the minimum number of choice situations will be 30 (since this is divisible by 2, 3, and 5). On the other hand, if one would use 2, 4, and 6 levels, then only a minimum of 12 choice situations would be enough. Therefore, it is wise not to mix too many different numbers of attribute levels, or at least have all even or all odd numbers of attribute levels.

What are the attribute level ranges?
Table B.1 indicates the overview of the attribute levels and corresponding attribute level ranges.

Table B.1: Attribute levels and range definition

	Level 1	**Level 2**	**Level 3**	**Range**
Price	0	€3,95	€6,95	€6,95
Speed	1	3	4	3
Load Factor	25	50	75	50
Delivery location	In-store	Pick-up point	Home	n.a.
Fuel type van	Electric	Hybrid	Diesel	n.a.

Multicollinearity
This means that very high correlations exist between attributes. Multicollinearity poses a problem with the estimation of parameters: 1) the parameters are not valid (i.e. biased) and 2) the parameters are low in reliability which can cause the parameters to be insignificant. Solution is orthogonal design: zero correlations between attributes which results in low standard errors (i.e. reliable parameters).

What type of design to be used?
Several different design types can be considered for the choice set:

1. **Full factorial design**: this design consists of all possible choice situations and with this design all possible effects (both main and interaction) can be estimated. However, for a practical study the number of choice situations in a full factorial design is too large and time consuming. The number of choice alternatives in a full factorial design is denoted by:

$$Alternatives = L^N \tag{B.1}$$

   In which L are the number of levels and N are the number of attributes. This corresponds with 81 (3^4) choice alternatives.

2. **Fractional factorial design**: a fractional factorial design consists of a subset of choice situations from the full factorial design. However, within the fractional factorial design, interaction effects cannot be estimated. Within the fractional factorial design, different types can be distinguished: orthogonal design - a split of the choice experiment while preserving attribute level balance - and efficient designs, to balance the utility of options in the choice set.

B.2 CHOICE SET CONSTRUCTION

In order to obtain priors, the use of orthogonal designs is proposed. Since 5 attributes (price, speed, delivery location, fuel type, and load factor) are included in this research with each 3 attribute levels, basic plan 3 is proposed which results in 16 choice sets (figure B.1) . After sequential construction of the different alternatives in the 16 choice sets and after repeating this process 3 times, the complete set of choices is illustrated in table B.2. 5 alternatives are determined to be 'dominant': choice set (with alternative) 2(1),4 (1),8(2),13(1) and 16(2).

Table B.2: Basic Plan 3 with 5 dominant alternatives

Choice set	**Alternative 1**	Alternative 2	**Price1**	**Speed1**	**LF1**	**FUEL1**	**DL1**	**Price2**	**Speed2**	**LF2**	**FUEL2**	**DL2**
1	16	12	3,95	3	50	2	0	6,95	3	25	1	1
2	6	16	**3,95**	**3**	**75**	**1**	**0**	3,95	3	50	2	0
3	9	15	6,95	1	75	2	2	3,95	4	75	0	1
4	15	11	**3,95**	**4**	**75**	**0**	**1**	6,95	4	50	1	0
5	8	13	3,95	3	50	0	2	3,95	1	50	1	1
6	3	14	0	4	50	1	2	3,95	3	25	1	2
7	10	1	6,95	3	50	0	1	0	1	25	0	0
8	14	8	3,95	3	25	1	2	**3,95**	**3**	**50**	**0**	**2**
9	7	10	3,95	4	25	2	1	6,95	3	50	0	1
10	4	9	0	3	75	1	1	6,95	1	75	2	2
11	2	6	0	3	50	2	1	3,95	3	75	1	0
12	12	3	6,95	3	25	1	1	0	4	50	1	2
13	13	7	**3,95**	**1**	**50**	**1**	**1**	3,95	4	25	2	1
14	1	5	0	1	25	0	0	3,95	1	50	1	1
15	5	4	3,95	1	50	1	1	0	3	75	1	1
16	11	2	6,95	4	50	1	0	**0**	**3**	**50**	**2**	**1**

BASIC PLAN 3: 4^5; 3^5; 2^{15}; 16 trials

```
 1 2 3 4 5    1 2 3 4  5    0 0 0 0 0 0 0 0 0 1 1 1 1 1 1
 * * * * *    * * * *  *    1 2 3 4 5 6 7 8 9 0 1 2 3 4 5

 0 0 0 0 0    0 0 0 0  0    0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 1 1 2 3    0 1 1 2  1    0 0 0 0 1 1 0 1 1 1 0 1 1 1 0
 0 2 2 3 1    0 2 2 1  1    0 0 0 1 0 1 1 0 1 1 1 0 0 1 1
 0 3 3 1 2    0 1 1 1  2    0 0 0 1 1 0 1 1 0 0 1 1 1 0 1
 1 0 1 1 1    1 0 1 1  1    0 1 1 0 0 0 0 1 1 0 1 1 0 1 1
 1 1 0 3 2    1 1 0 1  2    0 1 1 0 1 1 0 0 0 1 1 0 1 0 1
 1 2 3 2 0    1 2 1 2  0    0 1 1 1 0 1 1 1 0 1 0 1 0 0 0
 1 3 2 0 3    1 1 2 0  1    0 1 1 1 1 0 1 0 1 0 0 0 1 1 0
 2 0 2 2 2    2 0 2 2  2    1 0 1 0 0 0 1 0 1 1 0 1 1 0 1
 2 1 3 0 1    2 1 1 0  1    1 0 1 0 1 1 1 1 0 0 0 0 0 1 1
 2 2 0 1 3    2 2 0 1  1    1 0 1 1 0 1 0 0 0 0 1 1 1 1 0
 2 3 1 3 0    2 1 1 1  0    1 0 1 1 1 0 0 1 1 1 1 0 0 0 0
 3 0 3 3 3    1 0 1 1  1    1 1 0 0 0 0 1 1 0 1 1 0 1 1 0
 3 1 2 1 0    1 1 2 1  0    1 1 0 0 1 1 1 0 1 0 1 1 0 0 0
 3 2 1 0 2    1 2 1 0  2    1 1 0 1 0 1 0 1 1 0 0 0 1 0 1
 3 3 0 2 1    1 1 0 2  1    1 1 0 1 1 0 0 0 0 1 0 1 0 1 1

1-  0 0 0   2-  0 0 0   3-  0 0 0   4- 1 1 1   5- 1 1 1
*-  1 2 3   *-  4 5 6   *-  7 8 9   *- 0 1 2   *- 3 4 5
```

Figure B.1: Basic plan 3

B.3 DATA PROCESSING

In order to determine the best guesses on the parameters after the pilot survey has been filled out by enough respondents ($N \geq 30$), PythonBiogeme software is used Bierlaire [2018]. This a Python package particularly designed to estimate parameters of discrete choice models using maximum likelihood estimation Bierlaire [2018]. This software package requires two inputs: the choice data and a Python estimation script. This script is indicated in figure B.2. Different configurations for the utility functions and the to be estimated parameters have been tested by the researchers, but this configuration of the estimation script (figure B.2) resulted in the best LogLikelihood: the set of parameters that make the *data* most likely Chorus [2018]. In this script, 3 linear parameters and 2 non-linear parameters will be estimated. Section B.3.1 elaborates on (non)-linearity of the parameters.

B.3.1 (non)linearity of parameters

From the attributes included in this research, *delivery location* and *fuel type* of the delivery van are considered to be nonlinear by their categorical nature: it is expected that the utility contribution of the different levels of this attribute are not linear. Therefore, for these variables 'dummy coding' is required: the estimates for both parameters are each coded in $L - 1$ indicator variables. The choice data retrieved from the pilot survey is altered in the way illustrated in table B.3 to estimate the nonlinear parameters *delivery location* and *fuel type*.

Table B.3: Dummy coding scheme nonlinear parameters

Attribute	Level	Dummy 1	Dummy 2
Fuel type	Electric	1	0
	Hybrid	0	1
	Diesel	0	0
Delivery location	In-store	1	0
	Pick-up Point	0	1
	Home delivery	0	0

```
from biogeme import *
from headers import *
from loglikelihood import *
from statistics import *

# Parameters to be estimated
BETA_Price  = Beta('BETA_Price',0,-1000,1000,0)
BETA_Speed  = Beta('BETA_Speed',0,-1000,1000,0)
BETA_LF     = Beta('BETA_LF',0,-1000,1000,0)
BETA_FEL    = Beta('BETA_FEL',0,-1000,1000,0)
BETA_FHY    = Beta('BETA_FHY',0,-1000,1000,0)
BETA_DL1    = Beta('BETA_DL1',0,-1000,1000,0)
BETA_DL2    = Beta('BETA_DL2',0,-1000,1000,0)


V1 = BETA_Price * Price1 + BETA_Speed * Speed1 + BETA_LF * LF1 + BETA_FEL * FEL1A + BETA_FHY * FEL2A + BETA_DL1 * DL1A + BETA_DL2 * DL2A
V2 = BETA_Price * Price2 + BETA_Speed * Speed2 + BETA_LF * LF2 + BETA_FEL * FEL1B + BETA_FHY * FEL2B + BETA_DL1 * DL1B + BETA_DL2 * DL2B

# Associate utility functions with the numbering of alternatives
V = {1: V1,
     2: V2}

AV1 = 1
AV2 = 1

# Associate the availability conditions with the alternatives
av = {1: AV1,
      2: AV2}

# The choice model is a logit, with availability conditions
logprob = bioLogLogit(V,av,CHOICE)

# Defines an itertor on the data
rowIterator('obsIter')

# DEfine the likelihood function for the estimation
BIOGEME_OBJECT.ESTIMATE = Sum(logprob,'obsIter')

# Statistics
```

Figure B.2: PythonBiogeme script to determine parameter estimates

Once the optimization has run, the software indicates the estimation report in figure B.3. With this information, it can be determined how the model fits the data.

```
           Number of estimated parameters: 7
                              Sample size: 330
                   Excluded observations: 0
                     Init log likelihood: -228.739
                    Final log likelihood: -158.509
Likelihood ratio test for the init. model: 140.459
          Rho-square for the init. model: 0.307
      Rho-square-bar for the init. model: 0.276
           Akaike Information Criterion: 331.018
         Bayesian Information Criterion: 357.612
                    Final gradient norm: +2.770e-004
                             Diagnostic: Trust region algorithm with simple bounds (CGT2000): Convergence reached...
                             Iterations: 7
                   Data processing time: 00:00
                               Run time: 00:00
                         Nbr of threads: 2
```

Figure B.3: Estimation report

B.4 PRIOR PARAMETER ESTIMATES

Parameter output for the specific estimation script can be found in table B.4. These parameters are used as priors for the efficient design.

Table B.4: Prior parameter estimates pilot survey

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
BETA_DL1	-0.843	0.427	-1.98	0.05		0.389	-2.17	0.03	
BETA_DL2	-0.471	0.334	-1.41	0.16	*	0.305	-1.54	0.12	*
BETA_FEL	0.673	0.268	2.52	0.01		0.270	2.49	0.01	
BETA_FHY	1.12	0.297	3.78	0.00		0.308	3.65	0.00	
BETA_LF	0.0354	0.00771	4.59	0.00		0.00730	4.85	0.00	
BETA_Price	-0.393	0.0561	-6.99	0.00		0.0538	-7.30	0.00	
BETA_Speed	-0.117	0.118	-0.99	0.32	*	0.119	-0.99	0.32	*

B.5 REMARKS

Apart from some visual improvements regarding font type and style, and phrasing of different sentences, the following comments where made on the pilot survey:

1. The relevance questions where placed directly after the choice situations. Therefore, a lot of respondents where wondering whether the questions related to the delivery choice situations;
2. Only (mostly) woman's stores where included, it is suggested to include man's stores as well;
3. In-store delivery is confused with pick-up point delivery in the Dutch translation, since pick-up point delivery is also in a store. Therefore, it must be explicitly distinguished with the clothing store delivery.

C FINAL SURVEY DESIGN

For the design of the final survey, efficient designs are constructed. The details on the construction, such as the Ngene script, the output for the efficient design choice sets and the corresponding choice probabilities of each of the choice sets is discussed in this section. Finally, the survey which is used to evaluate consumer preferences for delivery choice factors, the impact of context and the differences in preferences between different consumers is provided.

C.1 EFFICIENT DESIGN CONSTRUCTION APPROACH

Figure C.1 indicates the script that is used to arrive at the efficient design choice sets. As can be seen are the parameters that were estimated for the priors included in this script in order to achieve utility balance and to balance the MNL choice probabilities.

```
Design
;alts = alt1, alt2
;rows = 8
;eff = (mnl,d)
;model:
U(alt1) = B_price[-0.393]*Price[0,3.95,6.95] + B_speed[-0.117]*Speed[1,3,4] + B_LF[0.0354]*LF[25,50,75]
          + B_Fuel.dummy[0.673|1.12]*Fuel[0,1,2] +B_DL.dummy[-0.843|-0.471]*DL[0,1,2]/
U(alt2) = B_price*Price + B_speed*Speed + B_LF*LF + B_Fuel*Fuel + B_DL*DL
$
```

Figure C.1: Ngene script to construct efficient design

The Ngene scripts produces several choice set for an efficient design. These choice sets are indicated in table C.1. The table indicates the choice set number, the attributes and attribute levels for the first delivery option and for the second delivery option from left to right.

Table C.1: Ngene choice sets efficient output

Choice set	Price1	Speed1	LF1	Fuel1	DL1		Price2	Speed2	LF2	Fuel2	Dl2
1	3,95	3	75	Diesel	In-store pick up		3,95	3	25	Hybrid	Pick-up point
2	3,95	1	50	Electric	In-store pick up		0	4	25	Diesel	Home delivery
3	3,95	4	50	Electric	Home delivery		3,95	1	50	Diesel	Pick-up point
4	6,95	3	75	Hybrid	Pick-up point		0	3	25	Electric	In-store pick up
5	6,95	3	50	Electric	Pick-up point		3,95	1	50	Hybrid	In-store pick-up
6	0	1	25	Diesel	Pick-up point		6,95	3	50	Hybrid	In-store pick-up
7	0	1	25	Hybrid	Home delivery		0	4	75	Electric	Pick-up point
8	0	4	25	Hybrid	In-store pick up		6,95	1	75	Electric	Home delivery

In table C.2 the expected probability of the different alternatives is indicated. The closer the expected probability is to 1, the more limited the information about trade-offs. Therefore, as a rule of thumb, the probability of an alternative must be ≤ 0.90 to check for utility balance. Table C.2 does not contain any value above 0.82 and therefore it can be concluded that utility balance is checked.

Table C.2: Ngene MNL probabilities to check utility balance

Choice situation	alternative 1	alternative 2
1	0.57	0.43
2	0.38	0.62
3	0.69	0.31
4	0.46	0.54
5	0.18	0.82
6	0.79	0.21
7	0.38	0.62
8	0.54	0.45

C.2 FINAL SURVEY CONTENT

In this section, the final survey content is presented. First the filter questions are presented. Then, one choice set of each of the four different context profiles proposed are presented. In total, 8 choice set will be proposed to one respondent, each having the same context (out of the 4 contexts shown in this survey). Then, the relevance and statement questions regarding morality as cooperation are included. Subsequently, actual sustainable buying behavior questions are included. Finally, questions regarding demographics and shopping behavior are included.

1. Hoe vaak koopt u **online** items bij een van de volgende winkels: H&M/Zara/&Other Stories/Pull&Bear/Bershka/Uniqlo/Forever21/Topshop/Mango/Urban Outfitters/CharlieTemple/Ace&Tate/Zalando/Wehkamp/Asos.com.. of andere winkels die in dit segment vallen *

- ◯ Nooit
- ◯ 1 keer per jaar
- ◯ 1 keer per half jaar
- ◯ 1 keer per maand
- ◯ 1 keer per twee weken
- ◯ 1 keer per week
- ◯ Meer dan 1 keer per week
- ◯ Dagelijks

2. Wat is uw postcode? (U wordt alleen gevraagd om de **cijfers** van uw postcode). Bijvoorbeeld: is uw postcode '1048 FF' dan hoeft u alleen **1048** in te vullen *

3. **Bij het kiezen van een bezorgoptie, is de volgende situatie van toepassing:**

U plaatst een bestelling bij één van de eerdergenoemde webwinkels en u wordt gevraagd een bezorgoptie te kiezen.

Hierbij dient u de volgende aannames te doen:

- U plaatst een bestelling op het internet en u moet de keuze maken tussen **twee bezorgopties**;
- U bestelt alleen voor uzelf;
- Een beladingsgraad van 25% betekent dat de bestelbus voor 75% leeg is.

	BEZORGOPTIE 1	BEZORGOPTIE 2
Levertijd	3 dagen	3 dagen
Leverlocatie	Afhalen in (kleding-)winkel	Afhalen bij een pakketpunt
Brandstoftype auto	Diesel	Hybride
Beladingsgraad	75%	25%
Prijs	3,95	3,95

Welke bezorgoptie kiest u? *

- ◯ Bezorgoptie1
- ◯ Bezorgoptie 2

Bij het kiezen van een bezorgoptie, is de volgende situatie van toepassing:

U plaatst een bestelling bij één van de eerdergenoemde webwinkels en u wordt gevraagd een bezorgoptie te kiezen.

Hierbij dient u de volgende aannames te doen:

- U plaatst een bestelling op het internet en u moet de keuze maken tussen **twee bezorgopties**;
- U bestelt alleen voor uzelf;
- Een beladingsgraad van 25% betekent dat de bestelbus voor 75% leeg is;
- **75% van de consumenten kiest voor een duurzame verzendmethode.**

11. Welke bezorgoptie kiest u?

	BEZORGOPTIE 1	BEZORGOPTIE 2
Levertijd	3 dagen	3 dagen
Leverlocatie	Afhalen in (kleding-)winkel	Afhalen bij een pakketpunt
Brandstoftype auto	Diesel	Hybride
Beladingsgraad	75%	25%
Prijs	3,95	3,95

*

- ◯ Bezorgoptie1
- ◯ Bezorgoptie 2

De volgende situatie is van toepassing:

Om de leefbaarheid van stadscentra te verbeteren, overweegt de overheid om nieuw beleid ten aanzien van pakketbezorging in stadscentra in te voeren.
Verschillende typen overheidsbeleid worden hiervoor overwogen, met verschillende effecten op prijs, beladingsgraad, levertijd, brandstoftype van bestelwagens en afleverlocatie.

Hierbij dient u de volgende aannames te doen:

- De waarden die u ziet voor de karakteristieken van het voorgestelde overheidsbeleid, gelden **voor alle burgers** die online bestellingen plaatsen bij eerder genoemde kleding webwinkels;
- Een beladingsgraad van 25% betekent dat de bestelbus voor 75% leeg is.

	OVERHEIDSBELEID 1	OVERHEIDSBELEID 2
Levertijd	3 dagen	3 dagen
Leverlocatie	Afhalen in (kleding-)winkel	Afhalen bij een pakketpunt
Brandstoftype auto	Diesel	Hybride
Beladingsgraad	75%	25%
Prijs	3,95	3,95

Welk overheidsbeleid heeft uw voorkeur? *

- Overheidsbeleid 1
- Overheidsbeleid 2

De volgende situatie is van toepassing:

Om de leefbaarheid van stadscentra te verbeteren, overweegt de overheid om nieuw beleid ten aanzien van pakketbezorging in stadscentra in te voeren. Verschillende typen overheidsbeleid worden hiervoor overwogen, met verschillende effecten op prijs, beladingsgraad, levertijd, brandstoftype van bestelwagens en afleverlocatie.

Hierbij dient u de volgende aannames te doen:

- De waarden die u ziet voor de karakteristieken van het voorgestelde overheidsbeleid, gelden **voor alle burgers** die online bestellingen plaatsen bij eerder genoemde kleding webwinkels;
- Een beladingsgraad van 25% betekent dat de bestelbus voor 75% leeg is;
- **75% van de burgers kiest voor een duurzaam overheidsbeleid.**

Welk overheidsbeleid heeft uw voorkeur?

	OVERHEIDSBELEID 1	OVERHEIDSBELEID 2
Levertijd	3 dagen	3 dagen
Leverlocatie	Afhalen in (kleding-)winkel	Afhalen bij een pakketpunt
Brandstoftype auto	Diesel	Hybride
Beladingsgraad	75%	25%
Prijs	3,95	3,95

*

- Overheidsbeleid 1
- Overheidsbeleid 2

Het tweede deel van de enquête start met dit onderdeel.
Vanaf dit onderdeel gaat het niet meer over de pakketbezorging, maar dit zijn algemene vragen.

Wanneer u besluit of iets **goed** of **slecht** is: in welke mate zijn de volgende **overwegingen** dan relevant voor uw oordeel?

U kunt uw antwoord aangeven van 'totaal niet relevant' (Deze overweging heeft niets te maken met mijn besluit over goed en slecht) tot 'extreem relevant' (Dit is een van de belangrijkste factoren wanneer ik oordeel over goed en slecht) *

	Totaal niet relevant	Niet relevant	Lichtelijk irrelevant	Enigszins relevant	Relevant	Extreem relevant
Of iemands daden liefde toonden voor zijn familie	○	○	○	○	○	○
Of iemand zich heeft ingezet om een groep te verenigen	○	○	○	○	○	○
Of iemand met zijn/haar daad heeft bewezen dat hij/zij te vertrouwen is	○	○	○	○	○	○
Of iemand moed toonde bij een tegenslag	○	○	○	○	○	○
Of iemand met zijn/haar daad respect heeft getoond voor autoriteiten	○	○	○	○	○	○
Of iemand het beste deel voor zichzelf hield	○	○	○	○	○	○
Of eigendom van een individu beschadigd is	○	○	○	○	○	○

Zou u willen aangeven in hoeverre u het eens bent met de volgende **stellingen**? *

	Helemaal oneens	Oneens	Niet oneens, maar ook niet mee eens	Mee eens	Helemaal mee eens
Een individu moet altijd loyaal zijn aan zijn/haar familie	○	○	○	○	○
Voor individuen is het belangrijk om een actieve rol te spelen in hun gemeenschap	○	○	○	○	○
Dingen die u fout heeft gedaan moet u altijd proberen goed te maken	○	○	○	○	○
Het toppunt van moed is bereid te zijn uw leven te geven voor uw land	○	○	○	○	○
Iedereen moet gelijk worden behandeld	○	○	○	○	○
U moet mensen respecteren die ouder zijn dan u	○	○	○	○	○
Het is gerechtvaardigd om waardevolle items die u vindt te behouden, in plaats van op zoek te gaan naar de rechtmatige eigenaar	○	○	○	○	○

35. In welk jaar bent u geboren? *

36. Wat is uw geslacht?

- Vrouw
- Man
- Transseksueel
- Zeg ik liever niet

37. Wat is gemiddeld uw **netto** jaarinkomen?

- 0-10.000 euro
- 10.000-20.000 euro
- 20.000-30.000 euro
- 30.000-40.000 euro
- 40.000-50.000 euro
- 50.000-60.000 euro
- 60.000-70.000 euro
- 70.000-80.000 euro
- 80.000-90.000 euro
- 90.000-100.000 euro
- meer dan 100.000 euro

38. Wat is uw hoogst genoten opleiding?

- Basisonderwijs
- Lager beroepsonderwijs
- Havo
- VWO
- MBO
- HBO
- WO

39. Wat is de samenstelling van uw huishouden? *

- Alleenstaand (dit geldt ook als u een woningdeler bent)
- Samenwonend met partner
- Samenwonend met partner en kinderen
- Alleenstaand met kinderen

Koopt u biologisch vlees? *

- Ja
- Nee
- Weet ik niet
- Nee, ik ben vegetarisch

Koopt u duurzaam gevangen vis? *

- Ja
- Nee
- Weet ik niet
- Nee, ik ben vegetarisch

Koopt u de biologische varianten van groenten en/of fruit? *

- Ja
- Nee
- Weet ik niet

Koopt u biologische (vrije uitloop) eieren? *

- Ja
- Nee
- Weet ik niet

Hoeveel geeft u gemiddeld uit aan online winkelen per maand? *

- Minder dan 50 euro
- Tussen de 50 en 100 euro
- Tussen de 100 en 250 euro
- Tussen de 250 en 500 euro
- Tussen de 500 en 750 euro
- Meer dan 750 euro

Volgt u de modetrends door de jaren heen? *

- Ja, ik volg ze op de voet
- Ja, ik vind ze interessant maar ik volg ze niet op de voet
- Nee

Vergelijkt u prijzen voor bezorging tussen verschillende aanbieders als u online winkelt? *

- Ja
- Soms, maar niet altijd
- Nee

D MORALITY AS COOPERATION

D.1 APPROACH TO SELECTION OF CONTROVERSIAL STATEMENTS

In order to determine the most controversial relevance questions and agree or disagree statements, a small focus group (N=11). Based on each respondent's answers to the question, a final selection of 7 relevance and 7 judgement statements has been made. Table D.1 indicates the data of the focusgroup, along with the standard deviation of the answers. The statements with the largest standard deviations are included in the final survey.

Table D.1: Focus group data (R) = reverse coded

Moral domain	**RELEVANCE**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**st. dev.**
Family	Whether or not someone acted to protect their family.	4	3	2	4	4	4	4	5	6	5	6	1,19
	Whether or not someone helped a member of their family.	2	3	2	4	3	4	4	4	3	4	6	1,13
	Whether or not someone's action showed love for their family.	3	4	1	2	2	5	3	5	5	3	6	1,57
Group	Whether or not someone acted in a way that helped their community.	1	2	1	2	2	2	2	4	4	4	5	1,36
	Whether or not someone helped a member of their community.	1	2	2	2	2	2	2	5	3	4	5	1,35
	Whether or not someone worked to unite a community.	2	3	3	2	2	4	2	6	4	5	5	1,44
Reciprocity	Whether or not someone did what they had agreed to do.	3	3	5	1	1	5	5	5	4	6	6	1,79
	Whether or not someone kept their promise.	3	4	4	2	2	5	5	5	4	5	6	1,30
	Whether or not someone proved that they could be trusted.	2	5	4	1	1	3	6	6	4	3	5	1,80
Heroism	Whether or not someone acted heroically.	4	4	3	2	1	2	2	3	4	3	4	1,04
	Whether or not someone showed courage in the face of adversity.	2	4	3	3	4	4	3	4	6	5	4	1,08
	Whether or not someone was brave.	3	2	4	3	2	2	3	4	3	5	4	0,98
Deference	Whether or not someone deferred to those in authority.	2	2	3	1	3	3	4	3	2	3	4	0,90
	Whether or not someone disobeyed orders.	3	3	3	3	2	3	5	3	2	5	4	1,01
	Whether or not someone showed respect for authority.	3	5	2	2	2	5	4	4	2	4	4	1,21
Fairness	Whether or not someone kept the best part for themselves.	4	2	2	3	3	6	2	3	2	3	5	1,33
	Whether or not someone showed favouritism.	5	3	5	4	3	3	3	3	2	2	4	1,03
	Whether or not someone took more than others.	4	1	2	2	3	3	2	3	2	4	5	1,17
Property	Whether or not someone vandalised another person's property.	4	5	4	4	5	5	4	5	5	4	6	0,67
	Whether or not someone kept something that didn't belong to them.	4	4	4	5	5	5	4	5	6	4	6	0,79
	Whether or not someone's property was damaged.	2	3	2	4	5	5	3	5	4	4	6	1,30
	JUDGEMENTS	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	
Family	People should be willing to do anything to help a member of their family.	3	2	2	4	2	4	3	4	4	2	4	0,94
	You should always be loyal to your family.	5	2	3	3	3	4	2	5	2	4	4	1,12
	You should always put the interests of your family first.	3	2	2	2	2	2	2	3	1	2	2	0,54
Group	People have an obligation to help members of their community.	1	2	2	2	4	3	3	3	3	4	3	0,90
	It's important for individuals to play an active role in their communities.	2	1	2	2	4	2	4	3	4	3	3	1,01
	You should try to be a useful member of society.	4	2	4	4	5	4	4	4	5	5	4	0,83
Reciprocity	You have an obligation to help those who have helped you.	3	2	2	3	2	4	4	5	1	2	2	1,19
	You should always make amends for the things you have done wrong.	2	1	1	2	4	2	2	5	1	2	2	1,25
	You should always return a favour if you can.	2	3	3	4	2	4	2	5	3	4	3	0,98
Heroism	Courage in the face of adversity is the most admirable trait.	3	4	3	2	3	2	2	3	3	3	2	0,65
	Society should do more to honour its heroes.	2	2	2	3	4	3	3	4	3	3	4	0,77
	To be willing to lay down your life for your country is the height of bravery.	1	1	2	2	1	2	4	2	4	3	1	1,14
Deference	People should always defer to their superiors.	2	2	2	1	1	3	2	3	2	3	1	0,77
	Society would be better if people were more obedient to authority.	2	2	2	1	3	2	2	3	2	3	2	0,60
	You should respect people who are older than you.	4	3	4	2	3	4	4	4	2	3	3	0,79
Fairness	Everyone should be treated the same.	4	2	4	2	4	4	2	3	5	4	5	1,13
	Everyone's rights are equally important.	4	4	4	4	5	4	4	4	5	5	5	0,50
	The current levels of inequality in society are unfair.	4	4	4	4	5	4	3	4	5	3	4	0,63
Property	It's acceptable to steal food if you are starving. (R)	2	3	4	3	3	4	3	4	5	2	4	0,92
	It's ok to keep valuable items that you find, rather than try to locate the rightful owner. (R)	4	1	2	4	2	1	1	1	2	2	2	1,10
	Sometimes you are entitled to take things you need from other people. (R)	2	3	2	3	2	2	4	2	1	4	2	0,93

D.2 EXPLORATORY FACTOR ANALYSIS

To research which indicators cohere to combine as a factor, an exploratory factor analysis (EFA) is performed. An EFA is performed to explore the relationship between indicator variables and to define factors that represent a common denominator. The EFA goal is to obtain a simple and clear structure in the indicator variables and to find factors that represent the simple structure. To determine a simple structure, indicators must load high on one factor (≥ 0.5) and low (≤ 0.3) on all other factors. An indicator that does not apply to this rule is removed. If less than 2 indicator variables load on one factor, the factor is removed from the model. The following steps are constructed to perform the EFA:

1. First, it is determined whether the factors are correlated or uncorrelated. In order to test this, an oblique rotation method is performed in SPSS with all indicators (14 questions in the survey). This rotation method is performed when it is expected that the factors are correlated. The oblique rotation is used to come closest to a simple structure. A sub result of this analysis indicates whether the factors are correlated or uncorrelated. Because all correlations between the factors is less then 0,138, it is concluded that the factors are not correlated. Therefore, the Varimax rotation method is applied (in this rotation, it is assumed that the factors are uncorrelated).

2. The statements that are removed from the structure because they do not load high on one factor and low on all others are statements number 4, 9 and 10.

3. The rotation is re-estimated with the resulting indicators. The final simple structure of indicators and corresponding 4 factors are indicated in table D.2.

Table D.2: Exploratory factor analysis

	Factor			
Statement	**1**	**2**	**3**	**4**
S2	**0,794**	0,018	0,132	0,179
S1	**0,712**	0,228	0,082	0,216
S3	**0,683**	0,031	0,014	0,144
S13	0,095	**0,745**	0,064	0,173
S8	0,219	**0,694**	0,110	0,005
S11	0,009	**0,504**	0,093	0,293
S7	0,026	0,096	**0,839**	0,114
S5	0,135	0,321	**0,676**	0,220
S14	0,012	0,140	0,186	**0,739**
S12	0,216	0,194	0,251	**0,648**

The interpretation of the underlying factors is not straightforward as this is a combination of different moral domains. The first factor consists of the moral domains group, family and reciprocity. These domains were expected to be of importance for cooperation and achieving the common good. Factor two is a combination of moral domains fairness, family and heroism. This Factor 3 and 4 both contain indicators of the property moral domain and the deference moral domain. These factors represent respect for individuals and property. For each of the constructed factors, the Cronbach's alpha is calculated to indicate the trust-worthiness of the factor: the scale reliability. For each of the four factors, the Cronbach's alpha is calculated and indicated in table D.3. The second and the fourth factor cannot be considered trustworthy due to a very low Cronbach's alpha, while factor 1 and 3 indicate higher Cronbach's alpha scales, however none of the factors is above the 0.7 threshold value of a trusthworthy factor.

Table D.3: Cronbach's alpha factor

	Cronbach's Alpha
Factor 1	0.569
Factor 2	0.414
Factor 3	0.688
Factor 4	0.150

D.3 FACTOR ANALYSIS FOR BIO BUYERS

To reduce the dimension of the answers to the sustainable buying behavior questions in the survey, a factor analysis is performed on these questions as well. Table D.4 indicates the scores of the questions on the factors. Two factors where extracted, where the first factor indicates the sustainable buying behavior and the second only consists of whether or not consumers separate waste. The second is therefore not considered to be a factor, but is included as a binomial variable in the interaction estimation of the consumer characteristics and the delivery choice attributes.

Table D.4: Factor analysis sustainable behavior consumers

Variable	Factor 1	Factor 2
Buy bio meat	**.788**	-.086
Buy bio fish	**.711**	-.031
Buy bio fruit & vegetables	**.689**	-.121
Buy bio eggs	**.668**	.217
Separate waste	-.035	**.973**
Cronbach's alpha	.70	-

E DATA PREPARATION

In this appendix, the approach to prepare the data for Discrete Choice Model estimation is proposed. This ranges from structuring the output data from the SurveyGizmo software to the approach for DCM parameter estimation.

E.1 DESCRIPTIVE STATISTICS

This section describes the sample composition: 1) can outliers be identified, 2) How many respondents are left per constructed context profile and 3) what are the consumer characteristics of the remaining respondents.

E.1.1 Outliers

Outliers are data points that are unreliable due to specific reasons. In most surveys that provide a monetary reward for filling in the survey, speeding occurs that is caused by the incentive to just earn money. In this research, no monetary incentive was proposed to the respondents and speeding does not occur in the data set as the average completion time of the survey was proposed to be 5 minutes, and the shortest completing time of the respondents was 4 minutes and 4 seconds. Two filter questions were added to determine outlier data points that cannot be used for analysis. The first needs to indicate

E.1.2 Frequency distribution

Four different survey contexts have been constructed for the survey and applied with a branching mechanism in the survey software. In order to determine, it is of importance that the distribution of respondents is about even over the different contexts. After deleting the 25 respondents based on the filter questions as described the outlier section, the 156 remaining respondents are distributed over the different contexts as indicated in table E.1

Table E.1: Distribution of 156 respondents over context profiles

	Respondents	Percentage
Consumer	46	29,5
Citizen	38	24,4
Consumer + Nudge	39	25,0
Citizen + Nudge	33	21,2

E.1.3 Demographics

Table E.2 denotes the different demographic characteristics of the respondents. A large share of the sample (80%) has a higher level education. Moreover, 41,7% of the respondents earns less then 10.000 euro per year. This probably means that this percentage of respondents is still studying or might have a part time job. Lastly, a majority of the respondents is single and only 8,3% of the respondents have children.

Table E.2: Demographic characteristics respondent group

		Respondents [%]
Gender	Male	51,9
	Female	48,1
Education	High school	0
	MBO	2,8
	HBO	21,0
	WO	79,5
Income	<10.000	41,7
	10.000-20.000	14,7
	20.000-30.000	12,8
	30.000-40.000	8,3
	40.000-50.000	7,7
	50.000-100.000	11,5
	>100.000	3,2
Household	Single	71,8
	Partner	19,9
	Partner and children	8,3

E.1.4 Shopping behavior

Table E.3 indicates the online shopping behavior of the respondents.

Table E.3: Shopping behavior respondents

		Respondent %
Expenditure (per month)	<€50	37,8
	€50-€100	37,2
	€100-€250	18,6
	>€250	6,4
Fashion trend interest	Fashion pioneer	13,5
	Fashion follower	51,3
	Non-fashion interest	35,3
Comparing delivery prices	Yes	37,8
	Yes, not consistently	41,0
	No	21,2
Shopping frequency	Once a year	9,6
	Once every half year	44,9
	Once a month	34,0
	Once every two weeks	9,6
	Once a week	1,9

Sustainable (buying) behavior
In order to determine if people that *have* shown sustainable behavior, *will* show more preference towards sustainability factors in parcel delivery, general sustainable behavior questions have been proposed. Table E.4 shows the sustainable behavior of the respondent group. It has been decided to include the 'I don't know' answering option and the 'I don't eat ..' within the 'no' indication for estimation purposes. It is argued that respondents who indicate not to know whether they buy biological meat or not, do not buy biological food as they would have known this due to significantly higher prices for products than the regular type of the product. In addition, the share of respondents that indicate these answers is relatively small so that most probably no significant effect will be obtained if estimated individually.

Table E.4: Sustainable behavior in real life

Sustainable product category	Answer	Respondents %
Bio meat	Yes	51.9
	No	37.8
	I don't know	3.8
	I don't eat meat (vega)	6.4
Bio fish	Yes	33.3
	No	46.8
	I don't know	17.9
	I don't eat fish (pesco)	1.9
Bio fruits and vegetables	Yes	66.6
	No	27.0
	I don't know	6.4
Bio eggs	Yes	60.9
	No	34.6
	I don't know	4.5
Separate trash	Yes	60.9
	No	39.1

E.1.5 Data preparation

From the SurveyGizmo software an excel file with all the response data is retrieved. This data file contains a lot of noise: information that will not be used for analysis. Therefore, the data must be altered to meet the format for the parameter estimation software PythonBiogeme Bierlaire [2018].

The steps that are taken to complete the data preparation are:

1. Filter the choice data until a matrix remains that consists of 'respondent ID' and the choices made by this individual. The choices that a indicated categorically are adapted into integer values. For example: sustainability or delivery location are translated to 1,2,3;

2. Construct a matrix that consists of all parameters, indicator variables and parameter values for each choice set;

3. Merge both matrices into one file. This file contains each respondent's choices and the characteristics of the corresponding choice set;

4. Convert the Excel data file into a tab delimited data file (with an .dat extension)

The resulting data file provides information on the respondent's choice for each specific choice set as determined with efficient designs. It also contains demographic data, relevance and statement data and (sustainable) consumer behavior data. Table E.5 shows an example of the constructed data set for parameter estimation.

E.2 CHOICE FREQUENCIES

In this section, the choice frequencies for the choice sets are illustrated. As illustrated in figure E.1, alternative 1 is not clearly chosen more often than alternative 2 in the choice sets. In choice set 6, dominance occurs with alternative 1 having a 88,5% choice share as compared to a 11,5% choice share for alternative 2.

Table E.5: Example choice data file

ID	SET	CHOICE	Price1	Speed1	LF1	FEL1	DL1	Price2	Speed2	LF2	FEL2	DL2
1	1	1	3,95	3	75	3	1	3,95	3	25	2	2
1	2	2	3,95	1	50	1	1	0	4	25	3	3
1	3	1	3,95	4	50	1	3	3,95	1	50	3	2
1	4	2	6,95	3	75	2	2	0	3	25	1	1
2	1	1	3,95	3	75	3	1	3,95	3	25	2	2
2	2	2	3,95	1	50	1	1	0	4	25	3	3
2	3	1	3,95	4	50	1	3	3,95	1	50	3	2
2	4	2	6,95	3	75	2	2	0	3	25	1	1
3	1	2	3,95	3	75	3	1	3,95	3	25	2	2
3	2	1	3,95	1	50	1	1	0	4	25	3	3
3	3	2	3,95	4	50	1	3	3,95	1	50	3	2
3	4	2	6,95	3	75	2	2	0	3	25	1	1

Figure E.1: Frequency distribution of general choices in survey

Figure E.2 indicates the choice frequencies for each choice set divided over the four different context settings. As can be observed, different choice frequencies are obtained for each context setting in all choice sets. The sixth choice set remains a dominant alternative for each of the context settings, while for the consumer context setting, this dominance is the largest

Figure E.2: Choice frequencies per context [Con=Consumer, Cit=Citizen, CoN=Consumer with Nudge & CiN=Citizen with Nudge]

E.3 BINOMIAL VARIABLES FOR MODEL ESTIMATION

The approach to construct binomial variables for ease of model estimation is explained in this section. First, based on the frequency of respondent characteristics, it is determined where a useful binomial separation can be made. Then, it it is determined which of the two binomial variables receives values 1 and zero.

By viewing the respondent characteristics in the sample group, it can be observed that the genders are equally represented in the sample. Therefore, a distinction needs to be made between men and women. Then, most of the respondents have an university degree, and therefore the distinction between having an university degree and *not* having an university degree is interesting for modeling purposes. Based on income, almost half of the respondents earn equal or less than €10.000 per year, which indicates part time or student incomes. A distinction between the student incomes and working incomes is included as a binomial variable. A lot of respondents indicate to be single or have a partner, but having children represents less than 10% of the respondent group. However, this distinction is interesting to make.

Besides demographic consumer characteristics, the shopping frequency, sustainable buying behavior and the valuation of the moral domains are also considered as binomial variables to estimate the model. Table E.6 indicates the characteristic included as binomial variable, along with a short indication of the meaning of both binomial variable levels.

Table E.6: Value indication binomial variables

Binomial category	Value 1	Value 0
Gender	Female	Male
Income	Low income (student or part time)	High income
Education level	University degree	HBO or MBO degree
Household composition	Children	Partner or single
Sustainable buying behavior	Buys a lot of biological products	Buys a few or no Biological products
Trash	Separates trash	Does not separate trash
Shopping frequency	Shops online often	Shops online rarely
Shopping expenses	Spends over €100 per month on online shopping	Spends under €100 per month on online shopping
6 moral domains	Highly values the first 6 moral domains	Values the first 6 moral domains low

F MODEL ESTIMATION AND INTERPRETATION

In this appendix, a detailed description of the different analyses is proposed. First, methodological steps that define the best model estimation are proposed. Second, the resulting parameters are discussed and matched with the expectations of the parameter sign and utility course. Then, the analysis steps to determine whether consumer characteristics and context settings have significant mediating effects on preferences for attributes is discussed.

F.1 MODEL ESTIMATION

In order to estimate model parameters, two files are required as input for PythonBiogeme software: a data set and a model specification. The first is previously discussed in appendix E table E.5, the latter needs to contain the model type, prior values, utility functions, and parameter properties. The general utility function for the delivery choice option is indicated in equation F.1. As can be seen, are the categorical variables effect coded. This is according to the coding scheme in table F.1.

Table F.1: Coding scheme for categorical variables

	Levels	Dummy 1	Dummy 2
		β_{fel}	β_{fhy}
Fuel type	Electric	1	0
	Hybrid	0	1
	Diesel	0	0
		β_{DL1}	β_{DL2}
Delivery location	In-store	1	0
	Pick-up point	0	1
	Home delivery	0	0

The corresponding utility function from the model is illustrated in equation F.1.

$$V_{DeliveryChoice(n)} = \beta_{Price} * Price_n + \beta_{speed} * Speed_n + \beta_{LF} * LF_n + \beta_{fel} * Fuel_{n1} + \beta_{fhy} * Fuel_{n2} + \beta_{DL1} * DL_{DL1n} + \beta_{DL2} * DL_{DL2n} \tag{F.1}$$

F.2 PARAMETER EXPECTATIONS

As can be seen in table F.2, five different parcel delivery choice characteristics are included in 7 parameters: delivery price (price), delivery speed (speed), In-store delivery (DL1), Pick-up point delivery (DL2), electric fuel type (FEL), hybrid fuel type (FHY) of the delivery van (FUEL) and the load factor of the delivery van (LF). For the proposed alternatives in the choice sets, all attributes were generic.

The price parameter is expected to be negative, since higher prices for delivery are expected to result in lower utility for an alternative. It is also expected that this attribute is significant, since price is generally considered to be a (very) important attribute for consumers.

It is expected that the speed attribute is an important factor. It is also expected that the levels of the attribute have a negative linear relationship with utility: the longer the wait, the less utility is retrieved in general.

For the delivery location attribute, which is a categorical attribute, a non-linear relationship with utility is expected. As retrieved from the pilot study, home delivery is expected to be most preferred and as compared to this attribute level, in-store delivery and pick-up point delivery are expected to have a negative relationship with utility. This is probably the result of the consumer having to leave their home to collect the package. However an alternative approach, since urban consumers are taken into account, could be that pick-up point and in-store pick-up are preferred since it does not require for the consumer to be home for the delivery and it leaves more flexibility for package pick-up for the consumer.

The fuel type is a categorical variable as well and it is therefore expected that the utility contribution of each of the attribute levels is not linear but categorical. By introducing this attribute, it is expected that diesel fueled delivery vans are the less preferred attribute level, hybrid in the middle and fully electric is the most preferred attribute level. Based on the pilot study, the utility contributions (and signs) are positive as compared to the reference level 'diesel fuel type'. In the pilot study however, more utility was retrieved from the hybrid fuel type. This was explained by the phenomenon of 'preferring the known alternative'.

The load factor expresses the share of the total volume of the delivery van. Less than 100% load factor is therefore considered an sub-optimal load factor. An ex ante prognosis, communicated to the consumer, was indicate to determine whether the inclusion has an effect on the choice for a specific delivery alternative. The load factor attribute is expected to be linear, and to have a positive sign: the higher the load factor, the higher the utility contribution of this attribute. Equidistance was maintained for this attribute, and the utility course of the attribute shown in figure 8.4 shows the utility contribution of each of the determined attribute levels to be positive as expected.

F.3 GENERAL MNL MODEL ESTIMATION RESULTS

In this section, an analysis is provided based on the general MNL parameter estimations resulting from the estimation based on equation F.1. Table F.2 indicates the outcomes for the parameter values. The resulting utility function for the delivery choice in this research is indicated in table F.2.

Table F.2: MNL parameter estimates apparel parcel delivery

Name	Value	Rob Std err	p-value	Significant?	Expected sign?
Price	-.416	.0407	.00	Yes	Yes
Speed	-.320	.0334	.00	Yes	Yes
In-store delivery	-.811	.128	.00	Yes	Yes
Pick-up point delivery	-.319	.0955	.00	Yes	Yes
Load factor	.0214	.00388	.00	Yes	Yes
Electric fuel	1.18	.132	.00	Yes	Yes
Hybrid fuel	1.17	.164	.00	Yes	Yes

By considering the parameter estimates indicated in table 8.1, the resulting utility function for delivery choice is indicated in equation F.2.

$$U_{deliverychoice} = -0,416 \cdot Price - 0,320 \cdot Speed + 0,0214 \cdot LF + 1,18 \cdot Fuel_{FEL} + 1,17 \cdot Fuel_{HYB} \\ -0,811 \cdot DL_{DL1} - 0,319 \cdot DL_{DL2} \tag{F.2}$$

F.4 THE EFFECT OF DIFFERENT CONTEXTS

For each of the four different contexts, a separate model is estimated. The results on the parameter values are indicated in table F.3. Based on these parameter estimations, it can be seen with the naked eye that differences exist in preferences for all of the delivery choice factors.

Table F.3: Parameter estimations of four different contexts

Parameters	Consumer	Citizen	Consumer Nudge	Citizen Nudge
Price	-.604	-.365	-.390	-.355
Speed	-.417	-.258	-.408	-.262
Load Factor	.031	.017	.025	.017
In-store	-1.13	-.768	-1.08	-.435
Pick-up point	-.299	-.325	-.578	-.151
Electric	1.43	1.21	1.19	1.02
Hybrid	1.53	.954	1.45	.889
0-LL	-249.533	-210.717	-182.991	-216.262
Final-LL	-192.256	-181.270	-153.871	-187.318
Rho-square	.201	.107	.121	.101

Therefore, with effect coding, the effect of the four different contexts on each of the parameters has been estimated statistically. This resulted in the only significant context-parameter interaction of both the consumer-citizen and the nudge environment with the price parameter. The effect coding of the context variables is indicated in table F.4

Table F.4: Dummy coding estimation of context effects

Context label	Ind1
Duality	
Consumer	1
Citizen	-1
Social norm	
Yes	1
No	-1

F.5 THE MEDIATING EFFECT OF EXPLANATORY BINOMIAL VARIABLES TO EXPLAIN HETEROGENEITY

To determine whether the predefined binomial variables have mediating impact on the preferences of consumers, the variables are estimated as interaction effects with all delivery choice parameters. Significant parameters are stored until all interactions have been estimated with the parameters. Table F.5 indicates whether (or not) the binomial variables and the interaction effects are significant (when estimated separately). The empty cells with a minus in the table indicate a non-significant interaction effect, while the significant interaction effects are indicated with text in the table.

Table F.5: Significant individual interactions tested based on hypotheses

	Price	Speed	Location	Fuel type	Load Factor
Age	Sig.	-	-	-	-
Gender	-	-	DL2 sig.	-	-
Income	Sig.	-	-	-	-
Edu	Sig.	Sig.	DL1 sig.	-	-
HH	Sig.		DL1 & DL2 sig.	-	-
Bio	Sig.	-	DL1 sig.	FEL & FHY sig.	Sig.
Freq	Sig.	-	-	-	-
Exp	Sig.	Sig.	-	-	-
Family	Sig.	-	-	-	-
Group	Sig.	-	-	-	-
Reciprocity	-	-	-	-	-

The binomial interaction effects are estimated as follows: the interaction effect of the nudging context for β_{price} is denoted by $\beta_{priceNUDGE}$ and the interaction effect of the consumer/citizen context for the same parameter is denoted by $\beta_{priceCONCIT}$. In order to determine the utility of each attribute with context included is $\beta_{price} * Price_n + \beta_{priceNUDGE} * Nudge + \beta_{priceCONCIT} * ConCit$.
Once the significant interaction effects with the parameters have been determined, all of these effects are estimated simultaneously in one model. This results in interaction variables becoming insignificant. These interaction variables are then eliminated from the estimation model, starting with the largest insignificant interaction parameter. In this way, 7 out of 19 interaction parameters are step-wise deleted from the model, until a model remains with only significant main as well as interaction parameters.
In the main text, the resulting interaction effects and parameters are indicated in table 8.4 and discussed in chapter 8. The resulting utility function with interaction effects is given by equation F.3.

$$\begin{aligned} V_{(i)} = (\beta_{price} + \beta_{priceEdu} * Edu + \beta_{pricebio} * Bio) + \beta_{family} * Fam + \beta_{group} * Group) * Price_{(i)} \\ +(\beta_{speed} + \beta_{speedExp}) * Speed_{(i)} \\ +(\beta_{LF} + \beta_{LFBio} * Bio) * LF_{(i)} \\ +(\beta_{FEL} + \beta_{FELBio} * Bio) * FEL_{(i)} \\ +(\beta_{FHY} + \beta_{FHYBio} * Bio) * FHY(i) \\ +(\beta_{DL1} + \beta_{DL1HH} * HH + \beta_{DL1Bio} * Bio) * DL1_{(i)} \\ +(\beta_{DL2} + \beta_{DL2Gen} * Gender + \beta_{DL2HH} * HH) * DL2_{(i)} \end{aligned} \tag{F.3}$$

F.6 CONTEXT IMPACT ON DELIVERY POLICY CHOICE SHARES

As different context variables indicated different sensitivities for the price parameter in delivery choices, delivery policies that include price changes vary in choice predictions between contexts. Table F.6 indicates scenarios that include price differences between the delivery options, as well as the percentage of respondents choosing the described alternative.

Table F.6: Comparison of context impact on delivery policy choice shares

Context dependent delivery policies	Consumer	Citizen	Consumer with social norm	Citizen with social norm
Free pick-up point delivery compared to paid home delivery	83%	78%	80%	74%
Paid Electric Delivery compared to Free Diesel Delivery	33%	40%	38%	46%

G CHOICE MODEL IMPACT ON ROUTING

In this appendix section, details are provided on the delivery policy set ups and resulting choice shares. The DOcplex model script with Python API is proposed in section G.2 and the verification of this model is proposed in section G.3. Finally, the results with confidence intervals are indicated in section G.5.

G.1 DELIVERY POLICY SET UPS AND PREDICTED CHOICE SHARES

Table G.1 indicates the set-ups of the different attributes for both delivery options in each scenario. The resulting choice shares are indicated in the most right corner.

Table G.1: Different delivery policy set-ups and choice shares

Scenario	Delivery option 1					Delivery option 2					Choice	
	Price	*Speed*	*Delivery location*	*Load factor*	*Fuel type*	*Price*	*Speed*	*Delivery location*	*Load factor*	*Fuel type*	*Option 1*	*Option 2*
1	€3,95	1	Home	50	Diesel	€3,95	1	Pick-up	50	Diesel	58%	42%
2	€3,95	1	Home	50	Diesel	€3,95	1	Home	50	Electric	23%	77%
3	€3,95	1	Home	50	Diesel	Free	1	Pick-up	50	Diesel	17%	83%
4	€3,95	1	Home	50	Diesel	€3,95	1	Pick-up	50	Electric	29%	71%
5	Free	1	Home	50	Diesel	€3,95	1	Home	50	Electric	67%	33%

G.2 OPTIMIZATION SCRIPT

In figure G.1, the SDCVRP optimization script is proposed.

```
Q = 80 # voor instances met 10 customers
N = list(df.customer[1:])
V = [0] + N
k = 15
# aantal vehicles
K = range(1,k+1)
# alle vehicles definieren zoals 1:[1,2]
vehicle_types = {1:[1],2:[1],3:[1],4:[1],5:[1],6:[2],7:[2],8:[2],9:[2],10:[2],
                11:[0],12:[0],13:[0],14:[0],15:[0]}
# vehicle_types = {1:'1',2:'1',3:'1',4:'1',5:'1',6:'2',7:'2',8:'2',9:'2',10:'2',11:'0',12:'0',13:'0',14:'0',15:'0'
lf = 0.5
R = range(1,11)

# Creat arcs and costs
A = [(i,j,k) for i in V for j in V for k in K if i!=j]
Y = [(k) for k in K]
c = {(i,j):np.hypot(df.loc_x[i]-df.loc_x[j], df.loc_y[i]-df.loc_y[j]) for i,j,k in A}

mdl = Model('SDCVRP')

# u = z in mathematical model
x = mdl.binary_var_dict(A, name = 'x')
u = mdl.continuous_var_dict(df.customer, ub = Q, name = 'u')
y = mdl.binary_var_dict(Y, name = 'y')

# objective function
mdl.minimize(mdl.sum(c[i,j]*x[i,j,k] for i,j,k in A))

### CONSTRAINTS SECTION ---> BELOW ###
# Depot constraint: each vehicle only leaves the depot 1 time
mdl.add_constraints(mdl.sum(x[0,j,k] for j in N) <= 1 for k in K)

#constraint 1 each node may be exited once
mdl.add_constraints(mdl.sum(x[i,j,k] for k in K for j in V if j != i
                            and vehicle_types[k][0] in df.req_vehicle[j]) == 1 for i in N)
# contraint 2 each node may be visited once
mdl.add_constraints(mdl.sum(x[i,j,k] for k in K for i in V if i != j
                            and vehicle_types[k][0] in df.req_vehicle[j]) == 1 for j in N)

#constraint 3 -- Flow constraint
mdl.add_constraints((mdl.sum(x[i, j, k] for j in V if j != i)  -
                     mdl.sum(x[j, i, k] for j in V if i != j)) == 0 for i in N for k in K)

#constraint 4 -- Cumulative load
mdl.add_indicator_constraints([mdl.indicator_constraint(x[i,j,k],u[j]==u[i]+df.demand[j]) for i,j,k in A if j!=0])

# constraint 5
mdl.add_indicator_constraints([mdl.indicator_constraint(x[i,j,k],y[k] == 1) for i,j,k in A if i!=0 and j!=0])

# cconstraint 6 cumulative load is 0 in start
mdl.add_constraint(u[0] == 0)

#constraint 7 - load factor constraint
mdl.add_indicator_constraints([mdl.indicator_constraint(x[j,0,k],u[j]>=lf*Q) for j in N for k in K if j != 0])

#Constraint 8 - number of vehicles included may not exceed the number of vehicles assigned to arcs
mdl.add_constraints(y[k] <= mdl.sum(x[0,j,k] for j in N) for k in K)

### CONSTRAINTS SECTION ---> ABOVE ####

# mdl.parameters.timelimit = 50
mdl.parameters.mip.tolerances.mipgap = .05
solution = mdl.solve(log_output=True)
print(solution)
```

Figure G.1: SDCVRP script

G.3 MODEL VERIFICATION

Since the instances used to determine the impact of consumers choices on vehicle routing are adjusted to serve the determined model in this evaluation, a verification is done by hand. For this verification 2 customers and a depot are inserted in the model with the following characteristics indicated in table G.2.

To verify whether the model gives the desired and intended output, several modifications to the data set in table G.2 have been tested. These modifications are indicated in table G.3. Based

Table G.2: Model verification input

Consumer	Loc_x	Loc_y	Demand	Vehicle
0	40	50	0	0,1,2
1	45	68	10	0
2	45	70	30	0

on these verification steps which are applied on variations in demand, and locations, it can be concluded that the model works the way it was meant to and the model is therefore verified.

Table G.3: Model verification input and output

	Verification content	Output	Intended output?
1	Demand of the node exceeds the vehicle capacity	The model indicates non-feasibility	Yes, because split deliveries are not allowed and the addition of a second vehicle will result in too low load factor
2	One of the consumers can only be visited with an electric vehicle	1 electric vehicles is used to deliver both parcels to both consumers	Yes, as one of the consumers can ONLY be served with an electric vehicle, it is logical that the other is also served with an electric vehicle because the depot increases the total distance driven significantly
3	An unknown vehicle is indicated to serve one of the consumers	Error	Yes, unknown vehicles which are not present in the fleet cannot deliver parcels to consumers
4	Negative coordinates for the locations	General output	Yes, this does not differ because the Euclidean distance is based on squares
5	Depot cannot be served by diesel vehicles, while consumers are served by diesel vehicles	Error	Yes, as the vehicle cannot return to the depot, the route cannot be finished and therefore not assigned.
6	The vehicle capacity is set to 200, which is larger than the total demand	Only one vehicle is used deliver the total demand	Yes, hence the VRP becomes a traveling salesman problem, in which the shortest route for one vehicle is determined

G.4 CONFIDENCE INTERVALS

To determine the confidence interval of the objective function in each of the configurations, the following approach is used:

1. The degrees of freedom is determined, which is the sample size minus 1;
2. The desired confidence level is subtracted from 1 and then divided by two;
3. From the t-distribution table, a threshold value is retrieved based on the degrees of freedom and the desired confidence level of 95%, this value is 2.776;
4. The standard deviation of the sample is divided by the square root of the sample size;
5. The latter is multiplied by the t-distribution threshold value;
6. The confidence interval is determined: the sample mean minus the obtained value in 5 is the *lower bound* and the sample mean plus the obtained value in 5 is the *upper bound*.

G.5 RESULTS

In table G.4, the amount of kilometres driven and kg emission per scenario is determined along with the confidence intervals.

Table G.4: Results and confidence intervals lb = lower bound and ub = upperbound

Policy configuration	Mean routing [km]	CI lb	CI ub	Co2 emission [kg]	CI lb	CI ub
Base	86.45	86.34	86.57	18.50	18.48	18.53
1	82.66	82.49	82.84	17.70	17.65	17.73
2	86.00	85.93	86.12	0	0	0
3	78.90	78.24	79.55	16.90	16.74	17.02
4	81.99	81.50	82.48	0	0	0
5	88.98	88.77	89.20	9.35	9.30	9.43

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