



International Journal of Sustainable Transportation

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/ujst20

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To cite this article: Elise Caspersen, Ståle Navrud & Jens Bengtsson (2021): Act locally? Are female online shoppers willing to pay to reduce the carbon footprint of last mile deliveries?, International Journal of Sustainable Transportation, DOI: 10.1080/15568318.2021.1975326

To link to this article: https://doi.org/10.1080/15568318.2021.1975326

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Published online: 20 Sep 2021.

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# Act locally? Are female online shoppers willing to pay to reduce the carbon footprint of last mile deliveries?

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#### ABSTRACT

E-commerce results in more last mile deliveries, increased freight traffic and potentially also higher CO2- emissions. This paper is a novel contribution to the literature in terms of investigating consumers' willingness to pay (WTP) for climate-friendly last mile deliveries through reduced or no CO<sub>2</sub>-emissions from the delivery. 460 females between 18 and 70 years of age responded to an internet panel survey about their stated preferences for last mile delivery options for online clothing rentals. A discrete choice experiment (DCE) was performed and the data analyzed using both multinomial logit (MNL) and mixed multinomial logit (MMNL) models. The results show that females are willing to pay for CO2-mitigation, and that their WTP increases with consumer income, employment, willingness to change habits to solve the environmental challenges of today, and preferences for sustainable online shopping and delivery alternatives, but decreases with the frequency of online shopping. The WTP for  $1 \text{ kg CO}_2$  exceeds the WTP for any other aspects of the last mile delivery; i.e. delivery time, delays and information services (notification of departure and arrival). The results indicate that freight operators (carriers) and online retailers can transfer (some of) the costs of climate-friendly last mile delivery to their customers. This is important knowledge for urban planners as it provides support for CO<sub>2</sub>-mitigating measures aimed at last mile delivery services in order to achieve more environmentally sustainable urban freight transport.

#### **ARTICLE HISTORY**

Received 13 January 2021 Revised 22 August 2021 Accepted 25 August 2021

#### **KEYWORDS**

Climate-friendly; discrete choice experiment; female consumer preferences; last mile delivery; online shopping

#### Introduction

#### Background and aim

The European Green Deal aims for Europe to become the world's first climate-neutral continent (European Commission, 2019a). One of its brave goals is zero net emissions of greenhouse gases by 2050 (European Commission, 2019b). In order to achieve this, transport as a large contributor to overall emissions must reduce its emissions by 90% (European Commission, 2019c). Internalizing climate change externalities to reduce emissions is not enough to reach the goal (as carbon pricing is too weak an instrument and the social cost of carbon (SCC) is too low) and should be combined with other measures like subsidies and regulations (Santos, 2017). Some relevant measures for freight transport in cities are the use of electricity as an alternative power source to diesel (Schulte & Ny, 2018; Teoh et al., 2018), alternative delivery locations like automated delivery stations (de Oliveira et al., 2017), crowdshipping services (Gatta et al., 2018; 2019), and collaboration and cooperation activities for a better use of freight delivery resources (Ranieri et al., 2018).

The targeted emission reduction coincides with the growth in online shopping and shipments from businesses to consumers (B2C) observed the last decade, and thus several of the above-mentioned measures imply involving end consumers in the last mile delivery solution. However, little is known about consumers' preferences for environmentally friendly last mile deliveries, although freight operators are starting to notice an increased consumer interest in sustainable deliveries. For instance, Postnord (2020) found that sustainable deliveries are preferred by 25% of online shoppers, while 35% are willing to pay for climate-compensated deliveries. Further, the environmental aspect of home deliveries is becoming increasingly important, as online shopping grows at an increased pace during the ongoing Covid-19 pandemic (Postnord, 2020). This paper addresses consumers' willingness-to-pay (WTP) for low or no CO<sub>2</sub>-emissions from last mile deliveries in a Discrete Choice Experiment (DCE). More specifically, it aims to answer the following three questions: i) How much are female consumers willing to pay for a reduction in CO<sub>2</sub> -emissions from last mile deliveries versus other attributes of the transport, ii) What consumer characteristics determine their WTP to reduce CO2-emissions from transport, and iii) How can this

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This is an Open Access article distributed under the terms of the Creative Commons Attribution-NonCommercial-NoDerivatives License (http://creativecommons.org/licenses/by-nc-nd/ 4.0/), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited, and is not altered, transformed, or built upon in any way. knowledge support the environmental transformation of last mile transport?

To address these questions, a sample of Norwegian female internet panelists (18-70 years old) who had received a DCE presenting different alternatives for last mile delivery of clothes rented online was used. The survey was developed in collaboration with a Norwegian online platform for female clothing rentals (FJONG); the aim was to investigate preferences for sustainable last mile deliveries among their customer base under the hypothesis that consumers renting clothes have a particular interest in sustainability. However, a pretest showed very low response rate from FJONG's customer base. Thus, instead a random sample of female respondents was drawn from an internet panel representing the general Norwegian population. The resulting sample therefore represents both those women who are familiar with FJONG and their concept of clothing rentals (15% of the sample) and those who are not (85% of the sample). As the sharing economy covers shared consumption of goods and services on online platforms (Hamari et al., 2016), online clothing rentals can be viewed as a branch of e-commerce. As we included only respondents who agree that their answers to the DCE could also work for other online purchases than clothing rentals, the data was perceived to be suitable for analyzing last mile delivery from e-commerce in general. However, the sample is all-female and as women tend to be more positive toward sustainable consumer behavior than men (White et al., 2019), one should be careful not to generalize the observed WTP for CO<sub>2</sub>-mitigation to the overall population.

The contributions made by this paper includes i) New estimates of female consumers' WTP for  $CO_2$ -mitigation in last mile delivery from an activity resembling online shopping, a topic that is still little researched (cf. the literature review in section 1.2), ii) An emphasis on consumer preference heterogeneity, providing broader knowledge of consumers'  $CO_2$ -mitigation preferences for use by urban planners, online retailers and freight operators to pinpoint  $CO_2$ -mitigation measures targeting consumers, iii) Support of a positive willingness to pay for  $CO_2$ -mitigation from last mile deliveries, which may improve public policy makers' confidence in pushing for more sustainable last mile delivery services, and iv) An all-female sample to counteract use of male dominant sample in consumer preference for emission reduction (as in Achtnicht, 2012; Costa et al., 2019).

The paper is organized as follows: the introduction (Section 1) ends with a review of consumer preference for sustainable last mile deliveries and stated preference literature on people's WTP to reduce  $CO_2$ -emissions from transport. The objective is to identify consumer characteristics expected to influence the WTP for reduced  $CO_2$ -emissions, as stated in the research question. Section 2 presents the methodological framework for DCE, while section 3 describes the survey and data collection. Results are presented in Section 4, including descriptions of the collected data, estimates, discussions and potential implications. Section 5 concludes.

#### **Consumer preferences for climate-friendly transport**

While there is a vast amount of studies on consumer environmental preferences and passenger transport, research on consumer environmental preferences and last mile delivery from internet shopping is currently scarce but gaining increased interest in the literature. Collins (2015) mapped customers' preferences for last mile attributes (using a DCE) when choosing between home delivery or pick-up point and transport mode, with environmental benefits resulting from mode choice. Agatz et al. (2020), also using a DCE, identified the effect of green labels on delivery time slot choices from online grocery shopping. Buldeo Rai et al. (2019), Janjevic et al. (2019) and Nguyen et al. (2019) used a choice-based conjoint analysis to analyze the tradeoffs between last mile delivery attributes, like delivery price, terms of reception, and return possibilities. Janjevic et al. (2019) show that delivery time window, lead time, delivery cost, and delivery safety are (commonly) most relevant when consumers choose last mile delivery services. Buldeo Rai et al. (2019) and Nguyen et al. (2019) show that consumers can switch to more sustainable last mile delivery options (like increased delivery time, sustainable time slots or delivery locations) if the right incentives are provided (like free delivery or green labels). Information about the environmental and social impacts of last mile delivery solutions also seems like a promising approach to influence consumers to choose more sustainable last mile deliveries (Buldeo Rai et al., 2021; Ignat & Chankov, 2020).

Although low delivery price is preferred by most consumers (Buldeo Rai et al. 2019; Nguyen et al. 2019) consumers might be willing to pay to achieve more sustainable last mile deliveries. Polinori et al. (2018) analyzed students' stated WTP for environmentally labeled last mile delivery when purchasing a green t-shirt in a contingent valuation (CV) survey. Schniederjans and Starkey (2014) used the theory of planned behavior to assess the impact of attitude, perceived behavioral control and peer pressure on consumers' intention to buy a green transportation t-shirt, and a method resembling CV to capture their WTP for the green transportation. Punel and Stathopoulos (2017) analyzed WTP for delivery time savings when using crowdshipping services. Vakulenko et al. (2019) did not analyze WTP per se, but found that customers seek the same benefits from the shopping and the delivery service. This implies that consumers seeking low-price products will not be interested in costly transportation, while time sensitive consumers might accept paying for a quick delivery. However, no measure of consumer WTP for CO<sub>2</sub>-reduction was found in the papers referenced above.

/Identified studies that report consumers' WTP for CO<sub>2</sub>reductions from transport are not focused on the last mile delivery. Achtnicht (2012) investigated if the stated level of CO<sub>2</sub>-emissions influences car purchase decisions, and if it does, how much different consumer types are willing to pay to reduce it. He found that median WTP for the reference group ranges from  $\notin$ 90 to  $\notin$ 257 per ton CO<sub>2</sub> (tCO<sub>2</sub>), although differing with travel distance and consumer type (Achtnicht, 2012). Achtnicht employs a mixed-logit model based on discrete choice experiment data where CO<sub>2</sub>-emissions is one of several attributes, and has greatly inspired this paper. Costa et al. (2019) estimated a (conditional) multinomial logit model using data from a DCE including levels of CO<sub>2</sub>-emission and found a WTP of €88 for a CO<sub>2</sub>-reduction of 1 g/km for Italian consumers. Mabit and Fosgerau (2011), Tanaka et al. (2014), Hidrue et al. (2011), Hackbarth and Madlener (2013), and Hackbarth and Madlener (2016) revealed that the WTP depends on the emission reduction in question, and on consumer segments (Hackbarth & Madlener, 2016). For the abatement of 1% of vehicle CO<sub>2</sub>-emissions, the WTP ranges are €5-65 (Tanaka et al., 2014), €20-90 (Hackbarth & Madlener, 2013) and €2–52 (Hackbarth & Madlener, 2016). Alberini et al. (2018) utilized DCE survey data in both multinomial logit and mixed logit models to estimate consumer preferences for different policies to reduce CO2-emissions in Italy and the Czech Republic. They found that the WTP to reduce CO2emissions by one ton was €133 in Italy and €94 in the Czech Republic.

Schniederjans and Starkey (2014) and Achtnicht (2012) both found that females and young adults (up to 44 years) had a higher WTP for green transportation than their counterparts. While Schniederjans and Starkey (2014) did not find any significant impact of education, location and income on WTP, Achtnicht (2012) found a significant, but marginally higher WTP for highly educated individuals. Alberini et al. (2018) showed that people with higher household income are more likely to have environmental knowledge, awareness, and higher marginal utility of emission reductions: the larger the CO<sub>2</sub>-emission reduction, the more people are willing to pay. The rural population has a lower willingness to pay for the environment than urban residents (Lera-López et al., 2014; Tianyu & Meng, 2020). WTP for eco-labeled urban freight transport (among students) increases with income, pro-environmental behavior and attitude, knowledge about sustainability issues, interest in and attention to labels (Polinori et al., 2018). Schniederjans and Starkey (2014) also found that a positive attitude toward environmentally friendly consumption increased intentions to choose green transportation. This is consistent with several studies of consumer attitude and behavior, showing that people who are concerned about the environment and the potential damage humans are causing are more likely to be positive toward environmental behavior (Gadenne et al., 2011).

The literature review indicates that characteristics like income, education, age, urban or rural residency and environmental attitude could help explain the variation in people's WTP for  $CO_2$ -reductions. Thus, we expect women's WTP for climate-friendly last mile delivery to be higher for i) women with high personal income, ii) highly educated women, iii) younger women (Generation Z or Millennials born 1981 or later), iv) women living in urban areas, and v) women with a pro-environmental attitude.

#### **Discrete choice modeling**

To identify consumer preferences and WTP for climatefriendly last mile deliveries, a good that is not yet in the market, stated preference methods, more specifically discrete choice experiments (DCE), are used to collect data. As several choice tasks are collected from the same individual (panel data) and consumer attitudes and intentions are important but difficult to capture the random parameter logit/mixed multinomial logit model (MMNL), as suggested by Revelt and Train (1998), McFadden and Train (2000) and others, is chosen for estimation. This is also consistent with other studies on WTP for CO<sub>2</sub>-emissions (Achtnicht, 2012; Alberini et al., 2018). The multinomial logit model (MNL) is estimated as a benchmark model. Following the methodology by Hess and Rose (2009), which builds on the framework by Revelt and Train (1998), as well as Sarrias and Daziano (2017) (for consistency with the "gmnl" R software (R Core Team, 2019) package used for estimation), the framework is described below.

#### The mixed multinomial logit model (MMNL)

An individual n answers t choice tasks, and is assumed to choose the alternative *i*, out of *J* options, that provides the highest utility, U. The utility is explained by observable attributes and sociodemographic variables, x, but also by other factors,  $\varepsilon$ , that are unobservable (random) to the researcher. When assuming a linear relationship between attributes and taste, the utility can be written as follows, denoted the random utility model (RUM):  $U_{i,n,t} = V_{i,n,t} +$  $\varepsilon_{i,n,t} = \beta_{n,t} x_{i,n,t} + \varepsilon_{i,n,t}$ , where  $\beta_{n,t}$  is a vector of taste coefficients that can differ between individuals and choice sets. It is assumed that  $\varepsilon$  follows an independent and identically type I extreme value (Gumbel) distribution. The variable specification depends on the assumptions made about  $\beta_{n,t}$ . For the standard MNL, it is assumed that the taste variation is fixed between individuals and choice situations  $(\beta_{n,t} = \beta)$ , and the probability that individual *n* chooses alternative *i* becomes:

$$P_n(i \,|\, \beta) = \frac{e^{\beta x_{i,n,t}}}{\sum_{j=1}^{J} e^{\beta x_{j,n,t}}}$$
(1)

This model presented in Equation (1) relies on the assumption of independence of irrelevant alternatives (IIA), does not allow for unobserved taste heterogeneity, nor correlation between repeated choice tasks by the same respondent (Achtnicht, 2012). The mixed logit model (MMNL) however allows taste to vary between individuals ( $\beta_{n,t} = \beta_n$ ) by following a random (unknown) distribution  $\beta_n \sim f(\beta\Omega)$ . Here  $\Omega$  is parameters explaining the distribution of  $\beta$  (mean and standard deviation, but also individual-specific covariates, for instance  $\Omega = \Pi z_n + L\eta$ , where z is a set of characteristics that influences the mean of the preference parameter,  $\pi$  is its corresponding vector of parameters,  $\eta$  denotes random parameter distribution, and L is the lower-triangular Cholesky factor of  $\sum$  such that  $LL^T = VAR(\beta_i) = \sum$  (Sarrias & Daziano, 2017)). In this case the probability function becomes:

$$P_n = \int_{\beta_n} \left( \prod_{t=1}^{T_n} \frac{e^{\beta_n x_{i,n,t}}}{\sum_{j=1}^J e^{\beta_n x_{i,n,t}}} \right) f(\beta_n \mid \Omega) d\beta_n$$
(2)

Taking the log-likelihood of Equation (2) and summarizing over all individuals provides the log-likelihood function

 Table 1. Characteristics of the experimental design: attribute description and levels.

| Attribute                    | Description and levels   |  |  |
|------------------------------|--|--|--|
| 1. Delivery time             | Number of days the respondent accepts to wait for the parcel:  |  |  |
|                              | 1. days  |  |  |
| 2. Delays (dummy)            | Uncertainty with respect to delivery time:   |  |  |
|                              | "No", "Yes, 1–2 days"  |  |  |
| 3. Information (dummy)       | Notifications by SMS or e-mail when (1) the good is approved for shipping and (2) the parcel is<br>shipped to the consumer:<br>"No", "Yes"   |  |  |
| 4. CO <sub>2</sub> -emission | CO <sub>2</sub> -emissions resulting from transport of the parcel. The emission levels differ with respect to transport mode, time, degree of consolidation etc.:<br>0, 0.28 kg, 1.40 kg |  |  |
| 5. Price (for the delivery)  | Price:<br>0 NOK <sup>a</sup> , 49 NOK, 99 NOK  |  |  |

<sup>a</sup>The average exchange rate between Euro (€) and Norwegian kroner (NOK) at the time of survey July 2020) was 1€=10.65Kr./1NOK = 0.094€ (Source: The Central Bank of Norway).

 $LL(\Omega) = \sum_{n=1}^{N} lnP_{n,t}$  that for the MMNL must be simulated. Following the specifications in the gmnl package (Sarrias and Daziano (2017), the Maximum Simulated Likelihood (MSLE) is used, although the Method of Simulated Moments (MSM) is an alternative (McFadden & Train, 2000). Hess and Rose (2009) suggest other model specifications where the taste coefficients vary between choice sets ( $\beta_t$ ) or between both choice sets and individuals ( $\beta_{n,t}$ ). The latter is an option also in this model but left for further analysis. Nested models are compared using the like-lihood ratio (LR) test.

A drawback with the MMNL is that the random distribution of the taste variation ( $\beta$ ) is unknown and must be specified (and thus restricted) by the researcher (Daziano & Achtnicht, 2013). Commonly used distribution in the literature are the normal, lognormal, triangular, uniform and Johnson SD distribution. The normal distribution allows the parameter values to shift sign and take on both negative and positive values, which might induce a problem (Daziano & Achtnicht, 2013), and result in the use of other distributions, like the log-normal, inducing the same coefficient sign for the whole population (Achtnicht, 2012).

### Willingness to pay

Willingness to pay (WTP) is the ratio of the marginal (dis)utility of a quality attribute to the marginal (dis)utility of the cost attribute and measures the amount of money that a consumer is willing to pay for an improvement of a good or service (Masiero & Hensher, 2010). It is commonly estimated as a point estimator, which for a linear specification of parameters is the parameter ratio:  $WTP = \frac{\beta_{quality}}{\beta_{cost}}$  (Daly et al., 2012; Masiero & Hensher, 2010). For interpretation of WTP to be meaningful, its distribution must have finite moments (probability, mean, variance), which implies that price (denominator) cannot be zero. When the parameter of price is allowed to be randomly distributed across individuals, as in the MMNL model, several distributions provide infinite moments of WTP (Daly et al., 2012), resulting in different correction approaches, each with their drawbacks (see for instance Sillano and Ortúzar (2005) and Carson and Czajkowski (2019)).

One of the suggested correction methods is estimating lognormal distributions keeping the price parameter strictly positive (Carson & Czajkowski, 2019; Daly et al., 2012), restricting variables to not cover zero. However, the wide tail of log-normal distributions tends to give extremely large WTP-values, and is thus not recommended for valuation purposes, including cases with variable restrictions to avoid zero (Sillano & Ortúzar, 2005). A normal distributed cost-parameter implies that the utility of price can be both positive and negative, which is often counterintuitive, and the ratio of two normal distributed parameters is not solvable analytically (Sillano & Ortúzar, 2005). Thus, to get WTP-estimates that are reliable within the scope of this research, the mixed logit model is estimated with the parameter for price kept constant across individual. Although a constant price parameter tends to overestimate the WTP-estimates as random distributed parameters tend to have higher mean than fixed parameters (see for instance Sillano and Ortúzar (2005)), it solves the issue of identification as pointed out above and is found acceptable in this research.

#### **Data collection**

Data was collected through a consumer survey composed of four parts: i) questions about habits and preferences for online shopping, ii) statements related to environmental attitudes, including some repeated questions to test if the response changes as respondents move through the questionnaire (as suggested by Mathews et al. (2007)), iii) stated choice scenarios including debriefing questions and rating of attributes to reveal whether the respondents consider all attributes (inspired by Hensher (2007)), and iv) socio-economic characteristics of the respondents including age, educational level, occupation, personal and household gross income.

#### Discrete choice experiment design

As the aim was to capture consumer preferences for different last mile delivery attributes, including  $CO_2$ -emissions, DCE was chosen above contingent valuation (CV), as suggested by Johnston et al. (2017). In order to design realistic experiments, attributes and attribute levels were inspired by consumer surveys conducted by Postnord (2020), Bring Research (2019), and World Economic Forum (2020), as well as existing knowledge **Did you know** that 35% of online shoppers are willing to pay for a climate compensated delivery, and that 25% prefer sustainable delivery over fast, precise, and flexible delivery? (Source: PostNord)

Imagine that you are to attend a birthday party, a wedding or a business meeting that is known to you in advance. You need an outfit, and decide to rent this online. After choosing the rental period, you are asked to choose how to get the outfit delivered.

Select your preferred option. You can take for granted that the outfit arrives at your preferred place of delivery and is tracked in the usual way.

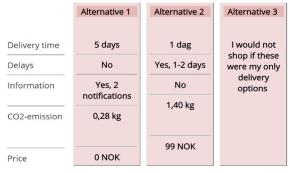


Figure 1. Example of choice question and choice card shown in the survey.

by the research team. The resulting experimental design included 5 attributes with 2–4 levels each, as presented in Table 1. The survey was designed using QuenchTec. A choice set example is given in Figure 1.

Delivery time of 20 days was included to investigate maximum delivery time for consumers. The levels of CO<sub>2</sub>-emission are calculated based on last mile delivery distance (from Statistics Norway) and emission levels (using the Handbook Emission Factors for Road Transport (HBEFA)) for light duty vehicles. The average distance per delivery (1.55 km) and average emission (0.18 kg/km) gave the middle value of 0.28 kg CO<sub>2</sub>-emission per delivery. This is comparable to the average emission of 0.181 kg CO<sub>2</sub> per delivery found by Edwards et al. (2010).<sup>1</sup> Delivery price was designed to take on values in the range of those found for online clothing retailers like Zalando, Boozt and H&M. Other commodity types and service levels might have different price levels.

To reduce the complexity of the survey, each choice set consisted of two unlabeled alternatives and an "opt-out" option; see Figure 1 The DCE consisted of 9 choice sets, drawn randomly from 16 blocks from a full factorial design being stripped for dominant alternatives and grouped and according to environment service criteria. Approximately half of the respondents were randomly assigned to get supplementary information about environmental aspects of last mile deliveries. In the DCE this included a sentence about online shopper preferences for climate compensated deliveries (see dotted box in Figure 1). The aim of this split-sample was to test if preferences could be altered, or nudged, by supplementary information; and was inspired by the work of Thaler and Sunstein (2009).

The survey was administered as a web-based survey in Norway using the  $NORSTAT^2$  internet panel. The panel

consists of 81 000 active panelists with 52% female and evenly distributed on age groups starting from 15 years. Respondents are rewarded a small incentive for their participation; they receive bonus points which can be exchanged for a gift card (1 minute of response time= 1 point = 1 NOK). When distributing the survey in question, only females between 18 and 70 years of age were targeted. The survey was conducted from June 29 until August 3, 2020; resulting in a sample of 605 respondents.<sup>3</sup> The frequency of the chosen DCE alternatives is presented in Appendix A.

Both qualitative pretesting (general feedback from testing the survey and one-on-one interviews with representatives from both experts and user group) and quantitative pretesting (using data from a pilot survey of the internet panel) were conducted as recommended by Mansfield and Pattanayak (2007), Champ and Welsh (2007), Krupnick and Adamowicz (2007), Harrison (2007), Mathews et al. (2007), and Johnston et al. (2017). Focus groups were not an option due to Covid-19 socializing restrictions; but the pretesting helped design attribute levels in the DCE as well as to fine tune questions and information text.

#### Results

In the following section all results, from data collection effort, estimation results, WTP calculations to a discussion of potential implications, are presented.

#### **Descriptive statistics**

Most respondents carefully consider their survey answers (Mansfield & Pattanayak, 2007). However, some of the

<sup>&</sup>lt;sup>1</sup>From Edwards et al. (2010): "A typical 50-mi delivery round by diesel van produces 21,665 g CO2 in total, and with an average delivery rate of 120 drops per trip, each successful first-time drop would be allocated 181 g CO2 or its share of the 21,665-g total (this calculation assumes that all drops are delivered successfully; i.e., there are no failed deliveries)." <sup>2</sup>https://norstat.no/

<sup>&</sup>lt;sup>3</sup>The sample was part of a survey collecting data from two DCEs. In total, 4602 persons from the internet panel were invited to take the survey. 1200 responded, yielding an overall response rate of 26%. Respondents were randomly allocated to one of the two DCEs, and of the 1200 respondents, 595 answered the other DCE, and is not included in this paper. The average time used to complete the survey for all 1200 respondents was 11.5 minutes.

#### Table 2. Descriptive statistics of respondents in the sample, and the Norwegian female population (from Statistics Norway).

|   | <b>Sample</b><br>(N = 460) | Female population    |
|---|----------------------------|----------------------|
| Average age and generation <sup>a</sup>   |                            |                      |
| Average age (18–70 years)   | 41.4 years                 | 43.7 years           |
| 1997–2001 (Generation Z)  | 10%                        | 9% <sup>b</sup>      |
| 1981–1996 (Millennials)   | 38%                        | 33%                  |
| 1965–1980 (Generation X)  | 33%                        | 32%                  |
| 1949–1964 (Boomers)   | 19%                        | 25%                  |
| Top25pop  |                            | 20,0                 |
| Lived in one of the 25 most populated Norwegian municipalities.   | 59%                        | 53% <sup>b</sup>     |
| Education   |                            |                      |
| Primary school  | 3%                         | 25% <sup>c</sup>     |
| High school   | 38%                        | 36%                  |
| College or university   | 59%                        | 39%                  |
| Employment status   |                            |                      |
| Employed  | 65%                        | 65% <sup>d</sup>     |
| Unemployed  | 3%                         | 3%                   |
| Not in work force (incl. students)  | 28%                        | 32%                  |
| Other   | 3%                         | 52/0                 |
| Annual gross personal income in NOK (2019)  |                            |                      |
| Average income (based on middle value of intervals)   | 479,000                    | 382,000 <sup>e</sup> |
| Less than or equal to 600,000 NOK   | 61%                        | ,                    |
| More than 600,000 NOK   | 18%                        |                      |
| NA  | 20%                        |                      |
| Frequent online shopper   | 20/0                       |                      |
| Shopped online at least once a month  | 47%                        |                      |
| Reduced consumption   | 17.70                      |                      |
| Agree that reduced consumption is our most important contribution to solving the environmental challenges                     | 83%                        |                      |
| Change habits   | 00,0                       |                      |
| Agree on being willing to change habits to solve the environmental challenges   | 79%                        |                      |
| Sustainable shopping  |                            |                      |
| One of the three most important attributes of online shopping are environmentally friendly shopping and delivery alternatives | 7%                         |                      |
| Time savings  | ,,,,                       |                      |
| One of the three most important attributes of online shopping is time savings   | 12%                        |                      |
| Lower price   | .2/0                       |                      |
| One of the three most important attributes of online shopping is that the price is lower than in stores                       | 47%                        |                      |
| Free delivery   |                            |                      |
| One of the three most important attributes of online shopping is free delivery  | 37%                        |                      |
| Supplementary information   |                            |                      |
| Received supplementary information of environmental aspects of home deliveries  | 43%                        |                      |
| N = number of observations. All variables are binary, taking on the values $1 = "Yes"$ or $0 = "No"$ .                        |                            |                      |

<sup>a</sup>As defined by Pew Research.

<sup>b</sup>Females 18–70 years.

<sup>c</sup>Females 16 years or older.

<sup>e</sup>Average annual gross income for females 17 years and older in 2018 (2019 numbers are postponed until January 2021).

responses in the collected sample were flawed. After screening for respondents focusing on only one attribute in the DCE, inconsistencies in debriefing questions (i.e. answer honest and random at the same time), very quick or slow response,<sup>4</sup> 74 respondents were deleted. Additionally, as the interest in this paper is to extend consumer preferences to general online shopping, 52 respondents where the DCE could not extend to purchase of other commodities than clothes and 19 respondents who never shopped online were excluded, leaving 460 observations for analysis. Descriptive statistics for the remaining 460 observations are presented in Table 2 along with statistics for the Norwegian female population. The population is restricted to females aged 18 to 70 years where possible.

Table 2 shows that the sample is more educated than the overall Norwegian female population, which reflects the composition of the internet panel they are drawn from. High education is also reflected in the average annual wage,

which is almost 100,000 NOK higher in the sample than in the population. The sample is also somewhat more urban than the general population, which might explain the high average education and income levels. Personal gross income is coded as a binary variable (less than or equal to 600,000 NOK and more than 600,000 NOK) to capture potential income effects on the WTP.<sup>5</sup> Approximately half of the respondents (47%) are frequent online shoppers and buy online at least once a month, while the rest buys online less than once a month. This number seems to differ between studies of Norwegian online shopping behavior and framing of the question. Bjerkan et al. (2020) found that almost 12% (56 of 484 respondents) of male and female respondents aged 18 to 87 years living in the Oslo (capital) region are

<sup>&</sup>lt;sup>d</sup>Females 15 years or older.

 $<sup>^4</sup>$  Inspired by Hensher (2007), Mathews et al. (2007), and an example by Alberini et al. (2007).

<sup>&</sup>lt;sup>5</sup>In 2018, only 15% of Norwegian females had an average annual gross personal income of 600,000 NOK or more (Statistics Norway, Table 08411), indicating that 600,000 NOK is a relatively high wage. Lower numbers could have been used, but as the average annual personal gross income in the sample is high (600,000 NOK) and almost 1/5 of the sample had income above 600,000 NOK, this was found an appropriate level for defining the "high income" group.



On front door (signature)

Pickup point (postal office, supermarket etc.)

In mailbox, on doorstep etc. (no signature)

**Figure 2.** Preferred delivery location by frequency of online shopping. N = 460.

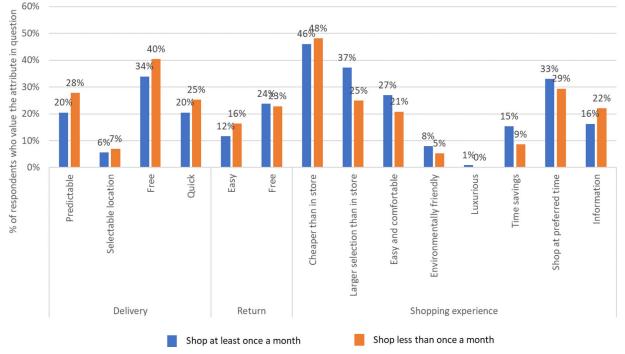


Figure 3. Respondents' votes on the most important aspects when shopping online. Each respondent was asked to vote for their three most important aspects. N = 460.

frequent online shoppers (shop at least once a month) based on data collected in the period November 2018 to January 2019 using a survey agency. Postnord (2020) found that approximately 67% of the male and female Norwegian population aged 18 to 79 years had shopped online last month (at the time of survey), based on data collected in the period January 2019 to December 2019 using a survey agency.

When asked about their preferred delivery location, a higher share of frequent online shoppers preferred their package to be delivered at home rather than at a pick-up point compared to infrequent online shoppers. This is presented in Figure 2 and represents general online purchases (not clothing rentals in particular).

Figure 3 presents respondents' ranking of the top three most important aspects of online shopping among a list of 14 alternatives relating to delivery, return and shopping experience. It is interesting to observe that infrequent online shoppers value delivery and return service, while frequent online shoppers value a convenient shopping experience. Cost seem to be an important aspect for both groups, with lower product price online than in the store and free

|   |                     | Model 2: MMNL        |                                 |                |  |
|---|---------------------|----------------------|---------------------------------|----------------|--|
|   | Model 1: MNL        | Mean                 | Median                          | Standard dev.  |  |
| α1  | 2.883***            | 4.812***             |                                 |                |  |
|   | (0.091)             | (0.151)              |                                 |                |  |
| X <sub>2</sub>                            | 2.794***            | 4.674***             |                                 |                |  |
| 2   | (0.088)             | (0.147)              |                                 |                |  |
| Price                                     | -0.020***           | -0.028***            |                                 |                |  |
|   | (0.002)             | (0.002)              |                                 |                |  |
| Price x Income $>$ 600,000 NOK            | 0.003**             | 0.003*               |                                 |                |  |
| ··· ··· · · · · · · · · · · · · · · ·     | (0.001)             | (0.002)              |                                 |                |  |
| Price x Free delivery                     | -0.006***           | -0.007***            |                                 |                |  |
|   | (0.001)             | (0.001)              |                                 |                |  |
| Price x Lower Price                       | -0.003**            | -0.004**             |                                 |                |  |
|   | (0.001)             | (0.001)              |                                 |                |  |
| Price x Time savings                      | 0.003*              | 0.004*               |                                 |                |  |
| nee x mile surings                        | (0.002)             | (0.002)              |                                 |                |  |
| Price x Reduced consumption               | 0.005***            | 0.006**              |                                 |                |  |
| nee x neudeed consumption                 | (0.001)             | (0.002)              |                                 |                |  |
| nformation services                       | 0.123**             | 0.165**              |                                 | 0.542***       |  |
|   | (0.042)             | (0.058)              |                                 | (0.096)        |  |
| Delivery time                             | -0.095***           | -0.251***            | -0.133***                       | 0.402***       |  |
|   | (0.004)             | (0.026)              | (0.01)                          | (0.093)        |  |
| Delays                                    | -0.140**            | -0.479***            | -0.095*                         | 2.369*         |  |
|   | (0.043)             | (0.079)              | (0.041)                         | (1.119)        |  |
| 20 <sub>2</sub>                           | -0.147              | -1.733***            | -0.542***                       | 5.267**        |  |
| 202                                       | (0.099)             | (0.291)              | (0.083)                         | (1.866)        |  |
|   | (0.099)             | Shift in $CO_2$ mean | Shift in CO <sub>2</sub> median | Model estimate |  |
| $CO_2 \times supplementary$               | -0.137              | 0.179                | 0.056                           | -0.109         |  |
| nformation                                | (0.076)             | 0.179                | 0.050                           | (0.328)        |  |
| $CO_2 \times Sustainable shopping$        | -0.734***           | -4.686               | -1.465                          | 1.309*         |  |
| co <sub>2</sub> x sustainable shopping    | (0.172)             | -4.080               | -1.405                          | (0.510)        |  |
| CO <sub>2</sub> x Frequent online shopper | 0.227**             | 0.684                | 0.214                           | -0.502         |  |
| 20 <sub>2</sub> x Frequent online shopper |                     | 0.084                | 0.214                           |                |  |
| CO. v. Changes habits                     | (0.072)<br>0.409*** | 0.070                | -0.275                          | (0.346)        |  |
| CO <sub>2</sub> x Change habits           |                     | -0.879               | -0.275                          | 0.410          |  |
| SO as Frankright                          | (0.085)             | 0.277                | 0.000                           | (0.299)        |  |
| CO <sub>2</sub> x Employed                | -0.301***           | -0.277               | -0.086                          | 0.148          |  |
|   | (0.074)             | 6000 404             |                                 | (0.320)        |  |
| AIC                                       | 7189.513            | 6089.101             |                                 |                |  |
| BIC                                       | 7297.096            | 6221.999             |                                 |                |  |
| Log-likelihood                            | -3577.756           | -3023.551            |                                 |                |  |
| N   | 4140                | 4140                 |                                 |                |  |

Table 3. Parameter estimates and standard errors (in parenthesis) from estimation of Model 1 MNL- and Model 2 MMNL models.

Model 2 is presented with mean, median and standard deviation for random parameters. Significance: \*\*\*p < 0.001; \*\*p < 0.01; \*p < 0.05.

delivery being the overall top two aspects. This result coincides with other consumer studies. Postnord (2020) found that free delivery and return are important for the majority (three out of four) of consumers who shopped online the previous month, while Bring Research (2019) found that the price of delivery and return is the main reason for disrupted online purchases by both males and females. It is however interesting to notice that few respondents ranked being able to select the location of the delivery as one of their top three aspects, indicating that there might be room for adjusting the last mile delivery to reduce greenhouse gas emissions.

#### Parameter estimation and discussion

To identify consumer WTP for  $CO_2$ -mitigation in last mile deliveries from online shopping, and how this differs between consumers, the following model, inspired by the data and the literature review in section 1, is suggested:

$$U_{n,t,j} = \alpha_j + \beta_{1,n} \cdot Delivery \ Time_{n,t,j} + \beta_{2,n} \cdot Delays_{n,t,j} + \beta_{3,n} \cdot Information \ services \ _{n,t,j} + CO_{2n,t,j} \cdot (\beta_{4,n} + \delta_{1,n}Sustainable \ shopping$$

$$+\delta_{2,n}Frequent \text{ online shopper} + \delta_{3,n}Change \text{ habits} + \delta_{4,n}Employed + \delta_{5,n}Supplementary info) + Price_{n,t,j} \cdot (\beta_{5,n} + \delta_{6,n}High Income + \delta_{7,n}Free Delivery + \delta_{8,n}Lower Price + \delta_{9,n}Time Savings + \delta_{10,n}Reduced Consumption) (3)$$

where  $\beta$  denotes parameter estimates for attributes and  $\delta$  parameter estimates for interaction terms. The inclusion of alternative specific constants,  $\alpha$ , in the context of an unlabeled choice experiment is motivated to capture inertia (i.e. sticking to one alternative), as well as reading from left to right effects (Hess & Rose, 2009). Variables for urban residency, education and age were also tested but found insignificant in the introductory models and left out of further analysis. Correlations between variables are low (all are below 0.4) and greatly reduce the risk of multicollinearity between the variables included in the model.

The model is estimated using both multinomial logit model (MNL) and mixed logit model (MMNL). Although not suitable for discovering unobserved heterogeneity, the MNL provides a

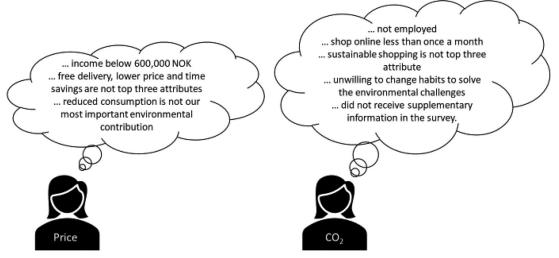


Figure 4. Base groups for price and CO<sub>2</sub>.

useful benchmark for comparison. The MMNL has been estimated using different distributions for price. Although the models with randomly distributed price parameter show a better fit to the data, the chosen model treats the parameter as fixed to secure defined WTP moments, as done by Achtnicht (2012) and Alberini et al. (2018) and explained above. Models with price following a normal and lognormal distribution are presented in Appendix B for comparison. The remaining four attributes (delivery time, delays, information service and CO<sub>2</sub>) follow either a log-normal or normal distribution. As in Achtnicht (2012), individuals are expected to be negative or indifferent toward CO<sub>2</sub>, not positive, which is estimated using a log-normal distribution. The same goes for the attributes of delivery time and delays. Although information is a service, some may think notifications from the retailer unnecessary or annoying, and the variable is kept normal. The MMNL model is simulated with Halton draws with 1000 replications for the maximum simulated likelihood estimation using the "gmnl-package" (Sarrias & Daziano, 2017) in R software (R Core Team, 2019).

The estimation results are presented in Table 3. The first column presents the variables to be estimated, the second presents parameter estimates for MNL, while the third to fifth columns present the results from the MMNL model with the parameter of price kept constant. For the attribute variables following a log-normal distribution (i.e. delivery time, delays and CO<sub>2</sub>,) mean, median and standard deviation are presented. Information service follows a normal distribution and its mean equals its median. The other parameters in the model are fixed. For the interaction terms between CO<sub>2</sub> and the chosen explanatory variables, the shift in CO<sub>2</sub> mean and median for the relevant groups are presented as well as the model estimates (last column).

A likelihood ratio test rejects the MNL in favor of the MMNL ( $\lambda_{LR} = 1108.41$ ). Thus, considering the panel structure of the data and unobserved heterogeneity in the attributes significantly improves the model fit.<sup>6</sup>

As expected, increments in delivery time, delays, CO<sub>2</sub>-emissions and price all have a negative and significant effect on consumer utility of last mile delivery alternatives. The significant standard deviations of the random parameters indicate unobserved variation in parameter distribution and heterogenous consumer preference. Price and  $CO_2$  are estimated with interaction terms. The base group for price is shown to the left in Figure 4. The parameter of price is constant in both models and the interaction terms for price have the same size and magnitude: the sensitivity of price of last mile delivery decreases with income, impatience and environmental consciousness, and increases with the importance of getting a lower price online than in the store and with free delivery.

With regards to  $CO_2$ , the models differ as heterogeneity is introduced in the MMNL. The base group for CO2 is shown to the right in Figure 4. In the MNL model, the interaction terms explain most of the consumer preferences for CO<sub>2</sub>-emissions, as the effect on the base group is nonsignificant, indicating heterogeneity in consumer preferences for CO<sub>2</sub>-emission. By allowing for a randomly distributed parameter of CO<sub>2</sub>-emission, heterogeneity is accounted for in the MMNL model, where the CO<sub>2</sub>-emission parameter is negative and highly significant. A comparison with the models allowing the parameter of price to follow a normal and a log-normal distribution (Appendix B) shows that the price, CO<sub>2</sub> and delivery time variables are in the same range in the three MMNL-models, while the utility of information services is a bit lower in the model with a constant price parameter. The variable for delay is similar in the MMNLmodels with a constant price parameter and a price parameter following a normal distribution, but becomes insignificant when price follows a log-normal distribution. The explanatory power improves when the parameter of price is allowed to vary, indicating that keeping it fixed is a strict assumption.

#### Willingness to pay estimates

The MMNL mean of the fixed price (Table 3) is significant at a z-value of -14. This is sufficiently large to calculate willingness to pay (WTP) as suggested above, as well as using the delta method to estimate standard errors (Carson

<sup>&</sup>lt;sup>6</sup>A model with uncorrelated random parameters was also tested but could not produce covariance elements for some of the attributes and was rejected.

Table 4. Willingness to pay (WTP) in NOK for a change in the attribute level.

| Income at or below  | MNL  | MMNL   |   |  |
|---|--|--|---|--|
| 600,000 NOK/not reported  | WINL   | Median   | Mean  |  |
| Delivery time   | -4.9***  | -4.8***  | -9.1***   |  |
|   | (0.4)  | (0.5)  | (1.1)   |  |
| Delays  | -7.1**   | -3.4*  | -17.4***  |  |
|   | (2.3)  | (1.5)  | (3.1)   |  |
| Information service   | 6.3**  | 6.0**  | 6.0**   |  |
|   | (2.2)  | (2.2)  | (2.2)   |  |
| CO <sub>2</sub> (base group)  | -7.5   | -19.6***   | -62.8***  |  |
|   | (5.1)  | (3.3)  | (11.3)  |  |
| CO <sub>2</sub> (received supplementary information)  | -14.5*   | -17.6**  | -56.3**   |  |
|   | (5.7)  | (6.2)  | (19.8)  |  |
| CO <sub>2</sub> (favor sustainable shopping)  | -45***   | -72.7  | -232.6  |  |
|   | (10.7)   | (38.2)   | (130)   |  |
| CO <sub>2</sub> (frequent online shopper)   | 4.1  | -11.9**  | -38**   |  |
|   | (5.5)  | (4.6)  | (14.6)  |  |
| $CO_2$ (willing to change habits)   | -28.4***   |  | -94.7**   |  |
|   | (4.3)  | (9.4)  | (31)  |  |
| $CO_2$ (employed)   | -22.9***   | -22.8**  | -72.8**   |  |
| - · · · · ·   | (4.9)  | (8.0)  | (26.3)  |  |
| Income above 600,000 NOK  | MNL  | MMNL   |   |  |
|   |  | Median   | Mean  |  |
| Delivery time   | -5.9***  | -5.5***  | -10.4***  |  |
|   | (0.7)  | (0.5)  | (1.1)   |  |
| Delays  | -8.7**   | -3.9**   | -19.9***  |  |
|   | (2.9)  | (1.5)  | (3.1)   |  |
| Information service   | 7.7**  | 6.8**  | 6.8**   |  |
|   | (2, 2)   |  | (2.2)   |  |
|   | (2.8)  | (2.2)  | (2.2)   |  |
| CO <sub>2</sub> (base group)  | (2.8)<br>–9.1  | (2.2)<br>–22.5***  |   |  |
| CO <sub>2</sub> (base group)  | . ,  | -22.5***<br>(3.3)  |   |  |
| $CO_2$ (base group)<br>$CO_2$ (received supplementary information)  | -9.1   | -22.5***   | -71.9***  |  |
|   | -9.1<br>(6.2)<br>-17.6*<br>(7)   | -22.5***<br>(3.3)<br>-20.1**<br>(6.2)  | -71.9***<br>(11.3)<br>-64.4**<br>(19.8)   |  |
|   | -9.1<br>(6.2)<br>-17.6*  | -22.5***<br>(3.3)<br>-20.1**<br>(6.2)  | -71.9***<br>(11.3)<br>-64.4**   |  |
| CO <sub>2</sub> (received supplementary information)  | -9.1<br>(6.2)<br>-17.6*<br>(7)   | -22.5***<br>(3.3)<br>-20.1**<br>(6.2)<br>-83.2*<br>(38.2)  | -71.9***<br>(11.3)<br>-64.4**<br>(19.8)<br>-266.2*<br>(130)   |  |
| CO <sub>2</sub> (received supplementary information)  | -9.1<br>(6.2)<br>-17.6*<br>(7)<br>-54.7***<br>(13.8)<br>5                      | -22.5***<br>(3.3)<br>-20.1**<br>(6.2)<br>-83.2*<br>(38.2)<br>-13.6**                               | -71.9***<br>(11.3)<br>-64.4**<br>(19.8)<br>-266.2*<br>(130)<br>-43.5**                                |  |
| CO <sub>2</sub> (received supplementary information)<br>CO <sub>2</sub> (favor sustainable shopping)<br>CO <sub>2</sub> (frequent online shopper)   | -9.1<br>(6.2)<br>-17.6*<br>(7)<br>-54.7***<br>(13.8)<br>5<br>(6.7)             | -22.5***<br>(3.3)<br>-20.1**<br>(6.2)<br>-83.2*<br>(38.2)<br>-13.6**<br>(4.6)                      | -71.9***<br>(11.3)<br>-64.4**<br>(19.8)<br>-266.2*<br>(130)<br>-43.5**<br>(14.6)                      |  |
| CO <sub>2</sub> (received supplementary information)<br>CO <sub>2</sub> (favor sustainable shopping)  | -9.1<br>(6.2)<br>-17.6*<br>(7)<br>-54.7***<br>(13.8)<br>5                      | -22.5***<br>(3.3)<br>-20.1**<br>(6.2)<br>-83.2*<br>(38.2)<br>-13.6**<br>(4.6)                      | -71.9***<br>(11.3)<br>-64.4**<br>(19.8)<br>-266.2*<br>(130)<br>-43.5**<br>(14.6)<br>-108.3***         |  |
| CO <sub>2</sub> (received supplementary information)<br>CO <sub>2</sub> (favor sustainable shopping)<br>CO <sub>2</sub> (frequent online shopper)<br>CO <sub>2</sub> (willing to change habits) | -9.1<br>(6.2)<br>-17.6*<br>(7)<br>-54.7***<br>(13.8)<br>5<br>(6.7)<br>-34.5*** | -22.5***<br>(3.3)<br>-20.1**<br>(6.2)<br>-83.2*<br>(38.2)<br>-13.6**<br>(4.6)<br>-33.9***<br>(9.4) | -71.9***<br>(11.3)<br>-64.4**<br>(19.8)<br>-266.2*<br>(130)<br>-43.5**<br>(14.6)<br>-108.3***<br>(31) |  |
| CO <sub>2</sub> (received supplementary information)<br>CO <sub>2</sub> (favor sustainable shopping)<br>CO <sub>2</sub> (frequent online shopper)   | -9.1<br>(6.2)<br>-17.6*<br>(7)<br>-54.7***<br>(13.8)<br>5<br>(6.7)<br>-34.5*** | -22.5***<br>(3.3)<br>-20.1**<br>(6.2)<br>-83.2*<br>(38.2)<br>-13.6**<br>(4.6)<br>-33.9***<br>(9.4) | -71.9***<br>(11.3)<br>-64.4**<br>(19.8)<br>-266.2*<br>(130)<br>-43.5**<br>(14.6)<br>-108.3***<br>(31) |  |

& Czajkowski, 2019). The delta method is found to be sensitive to any departures from normality in the data and small sample size, but appropriate for large datasets with low variation of the cost-parameter where it provides smaller standard errors than several of its counterparts (Gatta et al., 2015). Thus, the delta method is chosen to estimate standard errors for the WTP presented below.

The WTP calculations distinguish between different consumer groups and price sensitivity using parameter estimates in Table 3. The WTP calculations from the MNL and MMNL models with a constant price parameter are presented in Table 4. The top part presents calculations for respondents with income at or below 600,000 NOK, while the bottom part presents calculations for respondents with income above 600,000 NOK. The base group for CO<sub>2</sub> is as shown in Figure 4. As the mean of randomly distributed parameters tends to be higher than for fixed parameters (see for instance Sillano and Ortúzar (2005) and Achtnicht (2012)), WTP calculations based on both mean and median values from the MMNL model are presented. The median WTP is the center of the cumulative distribution function and thus a better proxy for the average person's WTP than the mean, which is influenced by outliers through the standard errors (Achtnicht, 2012). Hence, the median MMNL WTP is compared with the MNL WTP.<sup>7</sup>

Table 4 shows that the WTP from the MNL-model and the MMNL-model are quite similar for delivery time and information services, suggesting that people are willing to pay around 5 NOK/day in increased transportation cost for decreased delivery time, and around 6 NOK for information services. The WTP to avoid delay is more than twice as high in the MNL-model as (the median) in the MMNL-model. The WTP for reducing CO<sub>2</sub>-emissions for the base group differs between the models, being insignificant in the MNLmodel. In the MMNL-model, the average respondent in the base group is willing to pay around 20 NOK in increased transportation costs for reducing transport emissions of CO<sub>2</sub> by 1 kg. The WTP is higher for consumers who are employed or willing to change habits for the environment, and lower for frequent online shoppers or those who received supplementary information. It does not differ much with income above or below 600,000 NOK. The exception is for consumers favoring sustainable online shopping: when income increases to 600,000 NOK or more, the WTP becomes significant.

# Discussion of the results and implications for last mile transport

The results above reveal a positive WTP for CO<sub>2</sub>-mitigation among female consumers; this also being the attribute with the highest WTP (given the levels used in this survey). Preferences and WTP differ with both observed and unobserved heterogeneity. Among the observed heterogeneity increasing the WTP are pro-environmental attitudes (willingness to change habits for the environment and preferenfor sustainable online shopping and delivery ces alternatives), employment and income. This is as expected and reflects findings in the literature presented in the introduction. Urban or rural residency, education and age were insignificant in the model. The WTP for all attributes is within the range of the most common delivery prices for Norwegian last mile delivery service found for online clothing retailers (ranging from 0 to 99 NOK), but large compared to the WTP estimates in the literature. With a WTP of 20 NOK/kg  $CO_2$  (the base group), the WTP per t $CO_2$  is 20,000 NOK (approximately €1900), which greatly exceeds the estimates by Achtnicht (2012) (ranges from €90 to €257 per tCO<sub>2</sub>) and Alberini et al. (2018) (€133 per tCO<sub>2</sub> in Italy and €94 per tCO<sub>2</sub> in the Czech Republic). However, the levels under study are small (ranging from 0 - 1.40 kg) and preferences might not be constant for all levels of CO<sub>2</sub> or contexts. Although not included in the WTP-calculations in Table 4, the estimation results from Table 3 reveal that the WTP for last mile delivery is lower for consumers who have free delivery or lower price online than in store as one of their top three most important attributes of online shopping, and higher for consumers who value time savings and agree

<sup>&</sup>lt;sup>7</sup>WTP for the MMNL models with randomly distributed price (Appendix B) is not calculated as the distribution of the price variables covers zero.

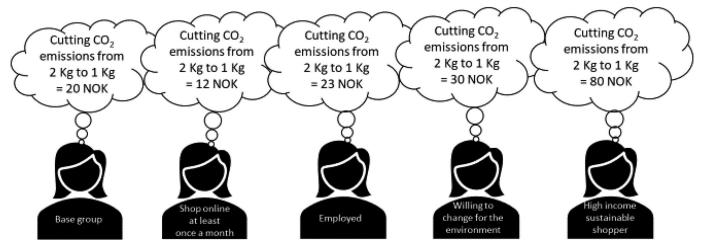


Figure 5. Willingness to pay for CO<sub>2</sub>-mitigation for different consumer types.

that reduced consumption is the most important contribution to solving the environmental challenges. These results correspond well with the findings by Vakulenko et al. (2019).

Reduction measures for  $CO_2$ -emissions were not specified in the choice experiments in order to avoid influencing respondents' choices and avoid creating potential protest or strategic behavior. Thus, the WTP estimates are generic and allow transport operators and policy makers to design their own solutions for  $CO_2$ -mitigation using the findings in this paper. Additionally, policy makers can back up their claims toward freight operators reducing their  $CO_2$ -emissions who (along with the online retailers) should be able to transfer (some of) the cost to the consumers. However, when designing measures to support the transformation to environmentally sustainable last mile deliveries, some key points might be considered, as illustrated in Figure 5 and described below.

Firstly, frequent online shoppers have a lower WTP than infrequent shoppers. Frequent shoppers might reflect consumers with a high consumption who are less concerned about their environmental footprint and are thus less willing to pay to reduce it. It might also be explained by frequent online shoppers being accustomed to getting free delivery (50% of shoppers were offered free delivery on their last online purchases (Bring Research, 2019)) and would incur higher total transport costs for all their purchases; thus having a lower WTP per transaction (in the DCE) than infrequent online shoppers. Figures 2 and 3 showed that frequent online shoppers have their homes as the preferred delivery location and value convenient deliveries. Thus, inexpensive measures altering as little as possible, like memberbenefits, subscriptions coupons ship or favoring environmental behavior, might motivate frequent online shoppers to choose more climate-friendly transport. Less frequent online shoppers do to a larger extent prefer delivery in a location outside of their homes. Thus crowd-shipping using public transport (or other CO<sub>2</sub>-mitigating solutions) might be an alternative for this group, which they might even be willing to pay for. However, few respondents (among both frequent and infrequent online shoppers) ranked delivery location as one of their top three important attributes (Figure 3). This suggests that there might be even more room for adjusting the delivery location than argued above. Females who are employed or have income above 600,000 NOK are willing to pay more than others, but the difference seems to be small. However, data on income and education may be easily collectable from consumers and can be used for price differentiation. A larger difference is found for respondents with environmental concerns, but these aspects are harder to measure and collect from the consumer. A solution is to target the goods: if sustainable products like organic food or clothing rentals are sold, consumers should be offered last mile delivery solutions with low or no  $CO_2$ -emissions at a cost.

A caveat with implementing the results from this paper is that the willingness to pay in a survey context might differ from the actual willingness to pay. Thus, transport operators and policy makers might benefit from a careful implementation of costs. In fact, independent of consumer type, identifying CO<sub>2</sub>-measures adapted to customer attitudes and communicating the effects of the measures is important. Esper et al. (2003) find that transparency and being able to select the carrier increase consumers' willingness to purchase in an e-retail setting, which can be assumed to extend to delivery service preferences (Punel & Stathopoulos, 2017). Further, trust in effective implementation of CO<sub>2</sub>-reducing measures makes people more willing to pay and contributes to its success (Yang et al., 2014). Past experience, however, may discourage future participation intention; as found for crowdshipping (Punel & Stathopoulos, 2017), self-collection services (Wang et al., 2019) and parcel lockers (Vakulenko et al., 2019). Hence, when enforcing new solutions for the consumers, professionality is important and defines the future of the solution (Vakulenko et al., 2019). Municipalities and urban planners should facilitate and contribute to reliable and smooth implementations of CO<sub>2</sub>-mitigating last mile delivery solutions.

## Conclusion

This paper documents an analysis of female consumers' willingness to pay (WTP) for climate friendly home deliveries of online shopping. Their WTP for a reduction in  $CO_2$ emissions compared to other last mile delivery attributes is analyzed, along with how consumer characteristics influence the WTP for  $CO_2$ . The findings are seen in relation to the environmental transformation of last mile deliveries from online shopping.

The results show that the WTP for last mile delivery attributes differs with observed and unobserved heterogeneity, where the latter is measured using the mixed logit model. The attributes delivery time, delays and information service are found to have an average WTP ranging from 3 to 8 NOK per level of service. CO2-emission reduction is the most valued attribute (at the given levels), although there are great variations between consumer types. The average WTP ranges from 12 to 30 NOK per 1 kg of CO<sub>2</sub>-mitigation and is significantly higher for respondents with an annual income above 600,000 NOK than below, although the overall difference is small. The results suggest that public policy makers can back up their claims for CO<sub>2</sub>-mitigation from last mile deliveries as freight operators and online retailers can transfer (some of) the costs to their female customers.

As females might exhibit more sustainable behavior (White et al., 2019) and a slightly higher WTP for green transportation than males (Achtnicht, 2012; Schniederjans & Starkey, 2014) and the commodity type might influence the (environmental) preferences for last mile deliveries (Collins, 2015; Janjevic et al., 2019; Nguyen et al., 2019), similar studies should be performed on samples including males and for other commodity types to determine the generalizability of the results. A follow up survey after the COVID-19 pandemic could also be useful to evaluate and strengthen the findings. Although the data collection was performed at a time with low infection rates and few mobility restrictions in Norway (summer 2020), the willingness to pay for last mile delivery services might have still been influenced by the ongoing pandemic.

In any case, the study provides evidence that female online shoppers accept paying for last mile delivery services, and that they are willing to pay extra to reduce greenhouse gas emissions of last mile deliveries. The results are in line with the observed consumer consciousness with respect to environmentally friendly consumption (Fjeld & Krekling, 2020), and could be used by policy makers to support new carbon pricing policies for freight transportation as online shopping has surged during the COVID-19 pandemic (Prisjakt.no, 2020). This would provide incentives for consumers to choose climate-friendly deliveries and curb greenhouse gas emissions in the age of e-commerce.

#### **Disclosure statement**

No potential conflict of interest was reported by the authors.

#### Funding

This work was supported by the Research Council of Norway and the Norwegian Public Roads Administration under grant number 250432 NORSULP (Sustainable Urban Logistics Plans in Norway); and the Research Council of Norway under the grant number 309977 "Fjong 2025 – an endless, sustainable wardrobe. Powered by research in behavioral economy, environmental impact and artificial intelligence".

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# **Appendix A**

Frequency of choices from the discrete choice experiment. The 460 respondents received 9 choice sets each, resulting in a total of 4140 choices (observations). Table A1 reveals that nearly equal fractions of respondents' chose alternatives 1 or 2, while less than 18% of the choices were optouts in terms of choosing alternative 3 (i.e. the alternative stating: "I would not shop if these were the only delivery options").

Table A1. Alternatives chosen in the choice tasks, frequency distribution and percentage (N = 4140).

| Alternative | 1    | 2    | 3 (Opt-Out) |
|-------------|------|------|-------------|
| Frequency   | 1717 | 1689 | 734         |

# **Appendix B**

Table B1. Mixed logit model with price following a normal and a log-normal distribution.

|                                     | MMNL – price is normal |                               | MMNL – price is log-normal      |                |                               |                          |
|-------------------------------------|------------------------|-------------------------------|---------------------------------|----------------|-------------------------------|--------------------------|
|                                     | Mean                   | Median                        | Standard deviation              | Mean           | Median                        | Standard deviation       |
| α1                                  | 5.660***               |                               |                                 | 5.581***       |                               |                          |
|                                     | (0.192)                |                               |                                 | (0.186)        |                               |                          |
| α2                                  | 5.519***               |                               |                                 | 5.460***       |                               |                          |
|                                     | (0.187)                |                               |                                 | (0.183)        |                               |                          |
| Price                               | -0.034***              |                               | 0.025***                        | -0.037***      | -0.027***                     | 0.033***                 |
|                                     | (0.002)                |                               | (0.002)                         | (0.003)        | (0.002)                       | (0.004)                  |
| Information services                | 0.219***               |                               | 0.564***                        | 0.227***       |                               | 0.482***                 |
|                                     | (0.066)                |                               | (0.105)                         | (0.062)        |                               | (0.112)                  |
| Delivery time                       | -0.295***              | -0.156***                     | 0.471***                        | -0.275***      | -0.145***                     | 0.444***                 |
|                                     | (0.024)                | (0.012)                       | (0.077)                         | (0.02)         | (0.011)                       | (0.062)                  |
| Delays                              | -0.45***               | -0.099*                       | 1.997*                          | -0.991         | -0.039                        | 25.272                   |
|                                     | (0.072)                | (0.045)                       | (0.8)                           | (2.216)        | (0.035)                       | (90.281)                 |
| CO <sub>2</sub>                     | -1.856***              | -0.587***                     | 5.57***                         | -1.773***      | -0.563***                     | 5.294***                 |
|                                     | (0.251)                | (0.091)                       | (1.582)                         | (0.234)        | (0.089)                       | (1.433)                  |
|                                     | Model estimate         | Shift in CO <sub>2</sub> mean | Shift in CO <sub>2</sub> median | Model estimate | Shift in CO <sub>2</sub> mean | Shift in CO <sub>2</sub> |
|                                     |                        | -                             | _                               |                | -                             | median                   |
| CO <sub>2</sub> x Supplementary     | -0.091                 | 0.161                         | 0.051                           | 0.029          | -0.052                        | -0.017                   |
| information                         | (0.491)                |                               |                                 | (0.413)        |                               |                          |
| $CO_2$ x Sustainable shopping       | 1.284*                 | -4.849                        | -1.533                          | 1.427*         | -5.611                        | -1.782                   |
|                                     | (0.539)                |                               |                                 | (0.710)        |                               |                          |
| $CO_2 \times E$ -commerce frequency | -0.712                 | 0.945                         | 0.299                           | -0.619         | 0.818                         | 0.260                    |
|                                     | (0.428)                |                               |                                 | (0.587)        |                               |                          |
| $CO_2$ x Change habits              | 0.660                  | -1.734                        | -0.548                          | 0.399          | -0.870                        | -0.276                   |
|                                     | (0.566)                |                               |                                 | (0.504)        |                               |                          |
| CO <sub>2</sub> x Employed          | -0.075                 | 0.134                         | 0.042                           | 0.149          | -0.284                        | -0.090                   |
| 2 . ,                               | (0.420)                |                               |                                 | (0.573)        |                               |                          |
| Price x Income $> 600,000$ NOK      | 1.58E-04*              |                               |                                 | -0.005         | 0.00018                       | 0.00013                  |
|                                     | 8.72E-05               |                               |                                 | (0.003)        |                               |                          |
| Price x Free delivery               | -1.45E-04*             |                               |                                 | 0.004          | -0.00014                      | -0.00010                 |
|                                     | 6.92E-05               |                               |                                 | (0.002)        |                               |                          |
| Price x Lower price                 | -1.35E-04*             |                               |                                 | 0.004*         | -0.00015                      | -0.00011                 |
| ·                                   | 6.20E-05               |                               |                                 | (0.002)        |                               |                          |
| Price x Time savings                | 1.21E-04               |                               |                                 | -0.005         | 0.00018                       | 0.00013                  |
| 5                                   | 1.00E-04               |                               |                                 | (0.003)        |                               |                          |
| Price x Reduced consumption         | 8.99E-05               |                               |                                 | -0.003         | 0.00012                       | 0.00009                  |
| ····                                | 5.55E-05               |                               |                                 | (0.002)        |                               |                          |
| AIC                                 |                        | 5722.504                      |                                 | ()             | 5731.338                      |                          |
| BIC                                 |                        | 5861.729                      |                                 |                | 5870.564                      |                          |
| Log-likelihood                      |                        | -2839.252                     |                                 |                | -2843.669                     |                          |
| N                                   |                        | 4140                          |                                 |                | 4140                          |                          |

Significance: \*\*\* = p < 0.001; \*\* = p < 0.01; \* = p < 0.05.