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A public transport-based crowdshipping concept as a sustainable last-mile solution: Assessing user preferences with a stated choice experiment

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A R T I C L E I N F O

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A B S T R A C T

In this study, we analyse user preferences for a public transport based crowdshipping concept, where users carry parcels along on their ride. The concept offers potential economic, environmental and social benefits over other last-mile solutions. We set up a stated choice experiment in which respondents indicate whether they would be willing to bring a parcel along on their ride, while varying the number of parcels, their size, weight, the compensation and required extra time. Based on data from 524 public transport passengers in the Greater Copenhagen Area, we estimate a mixed logit model and find all main effects to be significant. Our results indicate that young(er) individuals, students and (to a lesser extent) employed and self-employed individuals are more likely to participate in the crowdshipping concept, while old(er) individuals (60 +) are less willing to participate. Our findings further show that the marginal disutility of time spent retrieving and dropping off parcels is higher for old(er) respondents and individuals with high(er) income, while it is lower for individuals with a short-term education. Finally, we find the value of time to be slightly higher than the official Danish value for waiting time but lower than the value of travel time delay. Findings can inform the design of a crowdshipping system as well as related engagement efforts.

1. Introduction

The growth of e-commerce gives rise to increasing environmental and social costs (Viu-Roig and Alvarez-Palau, 2020). In particular, last-mile delivery poses a challenge, as high customer expectations for delivery time, lacking possibilities of consolidation, and dispersed destinations make it the most inefficient and expensive part of the delivery process (Macioszek, 2018). Last-mile delivery leads to increasing environmental problems caused by emissions from stop-and-go traffic by diesel-powered delivery vans, while second-row parking and blocking of cycle and pedestrian paths challenge road safety (Groth et al., 2019).

Co-modal solutions have been applied and studied as part of the delivery chain, where parts of trams, trains or busses are used for freight transport (e.g. Arvidsson, Givoni and Woxenius, 2016), but final delivery to customer address or pick-up point is not addressed in such solutions.

In recent years, crowdshipping has received increasing attention in the search for solutions to mitigate challenges posed by these developments. Crowdshipping refers to the distribution of delivery tasks to “the crowd”, typically through an online platform.

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However, its application does not guarantee a solution balancing the environmental, economic and social challenges. Many crowdshipping concepts make use of private vehicles resulting in rebound effects from dedicated trips or detours, and thus increased fuel consumption (Paloheimo et al., 2016). At the same time, the sharing economy, under which crowdshipping could be labelled, has raised concerns for the rights of workers. The 'gig economy' is here seen by critics as a dystopic scenario where 'platform capitalists' profit and leave the on-demand workers fighting over the crumbs (Paus, 2018). Such applications of the crowdshipping term are accordingly not necessarily in line with the visions of the UN's sustainable development goals.

The use of non-dedicated public transport trips in combination with automated parcel lockers (APLs) represents an opportunity that at least in principle has the potential to mitigate the three-faceted challenge of last-mile delivery. APLs already serve as a delivery option to address pressure on the last mile, with a range of operational and service-related benefits in themselves compared to traditional last mile delivery (Zurel et al., 2018). By supplementing the vans delivering to these APLs, public transport trips could reduce the amount of van deliveries to city centres, instead allowing them to drop off at city outskirts. In the concept proposed and investigated in the present paper, public transport passengers are offered compensation for bringing along parcels from APL to APL on their trips in which matching itineraries allow it. When compensation for bringing a parcel along on the trip is provided in form of reduced travel expenses (as opposed to ready money), the service does not qualify as a precarious (side) job, and the potential to prevent negative social effects becomes evident. This concurrently ensures that only public transport trips that would be taken anyway are utilised.

However, both academically and practically, public transport based crowdshipping has received very little attention. A few papers (all connected to Roma Tre University's 'TRE Lab') have described and explored such a crowdshipping concept (Gatta et al., 2019; Marcucci et al., 2017; Serafini et al., 2018; Simoni et al., 2019). To our knowledge, no practical examples exist (the closest perhaps being the 'Ritzen Koeriers' operating in the 90′s, where students were employed to deliver parcels via public transport [University of Groningen, 2021]).

The efficiency and economic benefits for the freight provider will highly depend on user acceptance. The present paper therefore assesses contingencies related to the willingness to act as a crowdshipper on public transport trips. This is done through a Stated Choice (SC) experiment which was conducted as part of a survey distributed to a sample of citizens of the Capital Region of Denmark.

The main contribution of this paper is a greater level of detail on service and shipment characteristics, giving an improved starting point for work on realising a public transport based crowdshipping concept. More specifically, the included attributes will allow for a more precise estimate of appropriate compensation levels for various shipment characteristics and a comparison with average values of travel time as well as values of travel delays for Danish public transport commuters. In addition to shipment characteristics, also demographic characteristics of the potential crowdshippers are taken into account and will reveal which population segments are most likely to engage in the concept.

The remainder of the paper is structured as follows: Section 2 reviews the literature on last-mile crowdshipping solutions, service and shipment characteristics and sociodemographic characteristics of crowdshipping participants. Section 3 presents the design of the SC experiment, the data-collection procedure as well as sample characteristics and lastly the modelling methodology. In Section 4, the main results are presented and a policy analysis is performed. Section 5 concludes the paper with the main findings and implications for research and practice.

2. Literature review

Starting with an overview of previous work on last-mile crowdshipping solutions (Section 2.1), the scarce work on relevant attributes for the assessment of potential of a public transport based crowdshipping solution is highlighted in Section 2.2. Finally, Section 2.3 discusses sociodemographic characteristics of crowdshipping participants identified in previous work.

2.1. Last-mile crowdshipping solutions

As is the case for a major part of realised crowdshipping concepts, the main body of literature within transport research has dealt with concepts based on private vehicles. Le et al. (2019) review the literature on crowdshipping from the three-fold division of *supply* (crowdshippers), *demand* (customers), and *operations and management*. The focus of the present paper will be on the crowdshipper side. The results of previous research on the importance of customer side attributes are assumed to be more applicable to the case of public transport based crowdshipping than for the crowdshipper side. SC experiments have been deployed to identify influential service attributes on the acceptance of options faced by the customer side of private vehicle based crowdshipping platforms (Punel and Stathopoulos, 2017). As such, it is assumed that the most important attributes identified here, e.g. "Delivery Cost", "Package Received in its Integrity" and "Speed" (p. 27) are relevant for customers, independently of the crowdshippers' mode of transport.

As the private vehicle based crowdshipping delivery mode shares many features with more traditional last-mile solutions relying on road vehicles, a large part of research on crowdshipping has concerned itself with operations and management issues, such as formulating logistics optimisation problems (e.g. Wang et al., 2016; Devari, Nikolaev and He, 2017) or matching supply and demand side (e.g. Ermagun and Stathopoulos, 2018, Ermagun & Stathopoulos, 2020; Ermagun, Punel and Stathopoulos, 2020). Most trips undertaken as carrier in such crowdshipping platforms will not precisely match any originally planned trips. To accommodate the probabilistic nature of the uncertain user behaviour, dynamical models have been applied in the matching of demand and supply side in such optimisation efforts (Allahviranloo and Baghestani, 2019). The environmental sustainability of crowdshipping initiatives has been shown to be heavily influenced by the trip type – dedicated or existing – being utilised (Qi et al., 2018). Private vehicle based crowdshipping concepts that often result in additional trips or detours will therefore often result in higher emissions (Buldeo Rai et al., 2018). By contrast, Gatta et al. (2019) found substantial emission reduction potential of a public transport based crowdshipping service in Rome. Results were obtained from scenario analyses building upon results from a SC survey.

2.2. Service and shipment characteristics

Investigating a public transport based crowdshipping system, SC experiments have been used in several studies by the same research group to assess potential for user uptake on both crowdshipper and customer side (Serafini et al., 2018; Gatta et al., 2019). On the crowdshipper side, these studies identified APLs' location (inside metro station) as the most relevant feature, followed by bank credit mode (single delivery) and remuneration. Real-time booking was preferred over offline, but was found to be the least required feature. However, more evidence of the viability of a crowdshipping concept is still needed, as many aspects of a potential crowdshipping framework remain unclear. The usefulness of quantitatively treating the attributes such as remuneration, to calculate robust Willingness To Accept (WTA) measures, was highlighted for future work on public transport based crowdshipping (Gatta et al., 2019). As another example, parcel size has been shown to influence the willingness to act as a crowdshipper, but has not been included as an attribute in their SC experiments (Marcucci et al., 2017). In fact, no one has explored in detail how the characteristics of shipments impact the willingness to act as a crowdshipper and what tradeoffs are made with regard to the size, weight and number of parcels, which is essential information for potential crowdshipping providers.

2.3. Sociodemographic characteristics of crowdshipping participants

Punel et al. (2018, 2019) investigated the determinants of crowdshipping use. They found young people, men and full-time employed people to be more prone to partake in crowdshipping initiatives. Furthermore, they found higher willingness amongst individuals with a strong sense of community and environmental concern.

A comparison of demographic characteristics of drivers of the ride-sharing company Uber in the US with the general workforce and taxi drivers/chauffeurs based on two surveys and census data (Hall and Krueger, 2018) revealed that Uber drivers are overrepresented in the age group 30–39 and underrepresented among older age groups. Uber drivers more often have a college degree than the other two groups. The main motivation for their job was "to earn more income to better support myself or my family'' suggesting that people did not earn enough in their current job – one third of drivers worked for Uber in addition to a part-time, one third in addition to a full time job.

Serafini et al. (2018) also found older people to be less interested in acting as crowdshippers using public transport. Young people have previously been shown to be more open to try new services and are as digital natives more familiar with the digital tools needed for participation. In general they also show higher flexibility in terms of travel mode choice (Dias et al., 2017). In particular, millennials have shown higher attraction to sharing economy (Hwang and Griffiths, 2017). Males were also found to be more willing to participate in crowdshipping by Miller et al. (2017), while they found that both low-income and high-income earners as well as individuals with a graduate degree were less inclined to participate. The U-shaped income effect is suspected to be related to lacking schedule flexibility and work pressures in the extreme income classes, while demands and rewards of crowdshipping might be more aligned with the medium income classes.

3. Method

3.1. Design of the SC experiment

This section describes the process, considerations and decisions regarding the SC experiment. As mentioned in the introduction, very few studies have analysed the topic, so creating a suitable design is to some extent a pioneering task. To our knowledge, the only previous study that used a SC experiment for assessing public transport based crowdshipping effects is Gatta et al. (2019). They constructed an experiment, where four attributes were measured with two levels each. With an A, B and a 'No choice' option, using a Bayesian D-Optimality efficient design, four different questionnaire blocks were produced, each consisting of three SC questions, resulting in twelve different attribute level combinations. The four attributes were 'Location of APL' (Inside metro stations / Outside metro stations or by adjacent buildings), 'Remuneration' (1/3 € per delivery), 'Delivery booking' (Real-time booking / Offline booking) and 'Bank crediting modes' (Single delivery / Every 5 deliveries).

The motivation for this study is to move towards a more detailed concept description compared to Gatta et al. (2019), which can lead to more realistic scenarios. In the crowdshipping concept described to participants, APLs are placed directly at stations/stops (Danish stations are – in contrast to the metro stations of Rome – not closed off by ticketing facilities, and the inside/outside-distinction is thus more blurry). All interaction with the service – including the booking of parcels, the opening of APLs and immediate remuneration – is facilitated by an app. Having already defined these functionalities, we include characteristics of the shipment in the SC design. Thus, similar to Gatta et al. (2019) our SC design will include compensation to closely reflect the actual practical tasks that participants face. To improve the realism of the scenarios, we add four new attributes to the SC experiment. This gives a total of five attributes: compensation, extra time (in total), number of parcels, size (in total) and weight (in total). The addition of a specific time component allows for an assessment of the valuation of travel time in the sample.

The attribute levels were set based on several preliminary investigations. Firstly, 13 semi-structured interviews about the crowdshipping concept had been conducted prior to the SC design process (Fessler et al., 2021b). The interviews included men and women aged 19–55 living in outskirts and central districts of Copenhagen. The interview guide included a broad range of topics related

Table 1
Levels for the attributes in the SC experiment.

Attributes	Levels				
Compensation (DKK)*	5	10	20	30	50
Extra time (Minutes)	1	2	4	6	8
Number of parcels	1	2	3	4	5
Total size (Litre)	0.5	1	2	4	8
Total weight (kg)	0.5	1	2	3	5

* This corresponds to the compensation ranging between 0.67 and 6.72 EUR. Date of currency conversion: January 4th 2021.

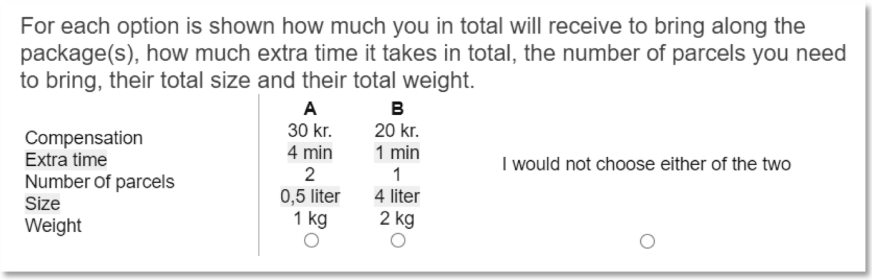

Fig. 1. Choice task example.

Table 2
Descriptive statistics of the sample.

Variables	n (sample)	% (sample)	% (TU)
Gender			
Female	261	49.8%	45.9%
Male	259	49.4%	54.0%
Other/Do not wish to answer	4	0.8%	
Age			
18–39 years	188	35.9%	56.9%
40–60 years	153	29.2%	20.8%
Above 60 years	183	34.9%	22.4%
Employment status			
Employed/Self-employed	266	51.0%	45.3%
Student	60	11.5%	28.9%
Not working	196	37.5%	25.8%
Education			
Higher education	257	49.0%	56.5%
Lower education	267	51.0%	43.5%
Income			
High: $\geq$ 50,000 DKK/month	86	16.4%	–
Medium	187	35.7%	–
Low $<$ 20,000 DKK/month	171	32.7%	–
Unknown	80	15.2%	–

Note: TU = Danish National Travel Survey (Transport DTU, 2020a).

to the service, including an imagined scenario with point of departure in their own use of public transport, which highlighted practical preferences and barriers for participation. Responses informed the selection of both relevant attributes and levels.

Secondly, upper boundaries for compensation levels were informed by existing data on last-mile costs, which have been shown to constitute from 13% up to 75% of supply chain costs (Gevaers et al., 2009). In order to increase the span available for interpretation, the time attribute was set relatively high, considering that the APL interaction itself can be handled in less than 30 s with an app developed for a subsequent real-life experiment (Fessler et al., 2021a). The time attribute was iterated from an earlier pilot-tested design (N = 77), where an interpretable range of time of 1–5 min was shown to be too narrow. The final design was based on the attribute levels shown in Table 1 (tested in pilot with N = 59).

The design was constructed using the software package Ngene (ChoiceMetrics, 2012). An efficient design was chosen in the construction of the SC experiment, where participants were asked to choose between two shipment options, ‘A’/’B’, and a ‘No Choice’ option: ‘I would not choose either of the two’. While efficient designs were originally motivated by their higher efficiency in maximising effects in smaller sample sizes in comparison with orthogonal designs (Rose and Bliemer, 2009), we use them to allow for the insertion of ’conditions’, in order to avoid dominated alternatives. The design rejected choice tasks where 1) one of the alternatives had

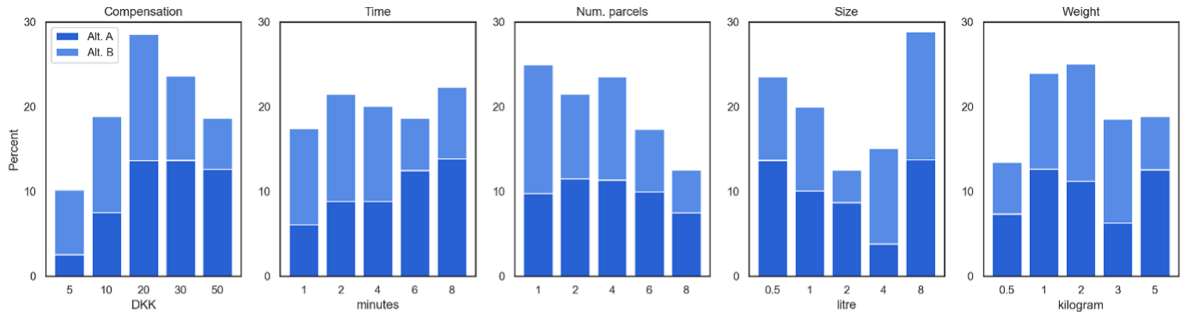

Fig. 2. Distribution of level values across alternative A and B for all five attributes.

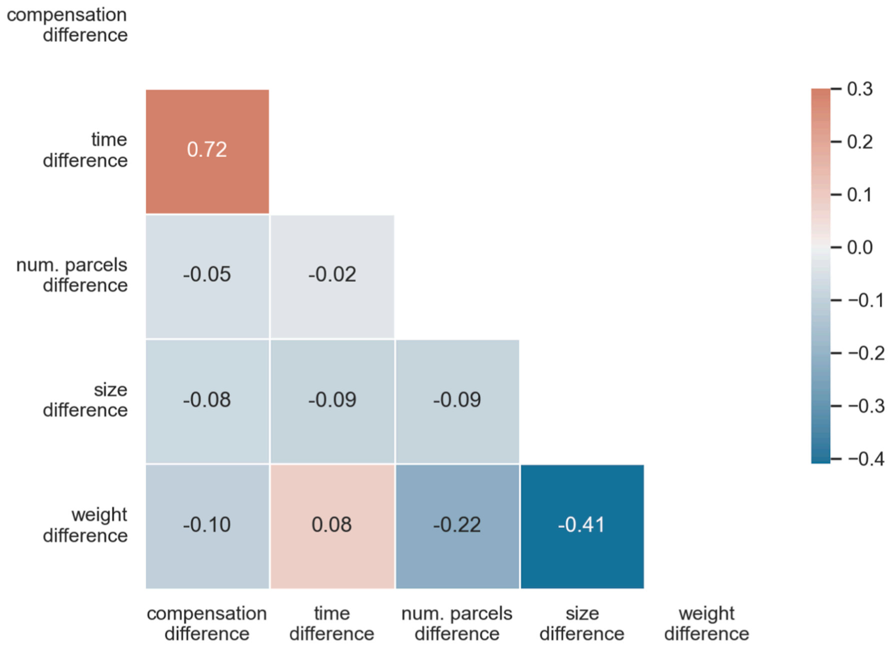

Fig. 3. Correlogram of attributes differences between alternative A and B.

4 advantageous attributes or 2) both Compensation and Time was advantageous for the same alternative and 3) an attribute had the same level in both alternatives. No constraints were imposed on combinations of number of parcels, size, and weight within each alternative. In total 40 choice tasks were constructed and divided into 10 blocks, resulting in 4 choice tasks presented to each respondent. The scenarios appeared as shown in Fig. 1:

3.2. Procedure and participants

The data was collected in May and June 2020 through an online survey. The survey was distributed by Epinion, a private data analytics enterprise. We aimed for a representative sample for the Capital Region population in terms of age, gender and level of education. Criteria for inclusion in the survey were residence in the Capital Region of Denmark and using public transport at least monthly. The respondents were explicitly instructed to answer from the context of their own lives and transport habits prior to the COVID-19 outbreak, that had brought the country to a lockdown at the time of data collection.

In Table 2, the sample characteristics are compared with weighted values from the Danish National Travel Survey (Transportvaneundersøgelsen, TU) (Transport DTU, 2020a). The TU sample includes respondents from the same region with public transport use on the sample day and/or with an active public transport season ticket. As this extraction favours more regular public transport users compared to our sample, this may explain the higher proportion of young people, students and employed people in the TU sample[1].

[1] Due to differences in income-registration (after vs before taxes), this variable is not included from TU.

Table 3
Model summary and comparison.

	ML1 (Linear specification)	ML2 (Log specification)	ML3 (BoxCox specification)	ML4 (Linear specification, unobserved preference heterogeneity)
Model Summary				
Number of parameters:	17	17	18	21
Sample size:	524	524	524	524
Observations:	2,096	2,096	2,096	2,096
Number of draws:	10,000	10,000	10,000	10,000
Algorithm:	CFSQP	CFSQP	CFSQP	CFSQP
AIC:	2972.2	2957.4	2958.1	2877.7
BIC:	3044.6	3029.9	3034.8	2967.2
Final log likelihood:	−1469.1	−1461.7	−1461.1	−1417.9
Model Summary				
LR-test against BoxCox-model:	ChiSq = 16.05 > 3.84 => BoxCox-model significantly better	ChiSq = 1.31 < 3.84 => BoxCox-model not significantly better		
T-test of λ against 1:			−5.033	
T-test of λ against 0:			1.222	
MU of Compensation:	$\beta_{Compensation}$	$\frac{\beta_{Compensation}}{Compensation}$	$\frac{\beta_{Compensation}}{Compensation^{(1-\lambda)}}$	$\beta_{Compensation}$
MU of Compensation = 10:	0.045	0.110	0.172	0.067
MU of Compensation = 20:	0.045	0.055	0.098	0.067

In the crowdshipping concept presented to survey participants, APLs were placed at public transport stations and stops. Through a smartphone app, registered users[2] were offered the possibility to bring one or several parcels along on their public transport trip from departure point to the matching end- (or transit-) point. Crowdshippers were compensated with public transport fare credits.

Apart from the four choices related to the SC experiment (see Section 3.1), socio-demographic information was requested including age, gender, household type, income, level of education, employment and working hour flexibility. The terms ‘Lower education’ and ‘Higher education’ used in the paper refer to respectively ‘Short-term further education or below’ (below 2 years education after high school) and ‘Medium-term further education or above’ (2 + years education after high school). On average, it took 10–15 min to complete the survey (the survey collected other information not relevant for this paper).

The data – consisting of 567 respondents - was cleaned by removing responses from participants who completed the survey in less than 4 min (=less than 40% of the median duration) as well as participants with suspicious answer patterns. After data cleaning, the final sample consisted of 2096 observations collected from 524 respondents. In approximately half of the choice tasks (46%), the “no-package” option was chosen. Table 2 presents descriptive statistics of the final sample, while Fig. 2 presents the attribute level distribution in the data, and Fig. 3 shows the correlation among attribute differences between alternative A and B.

3.3. Modelling methodology

In order to estimate user preferences, we rely on discrete choice models based on random utility maximisation (RUM), see e.g. Train (2009). We define a Mixed Logit (ML) model, in which the utility U_{nti} for individual n, alternative i, and choice task t takes the form:

$$U_{nti} = V_{nti}(\beta_n, x_{nti}) + \varepsilon_{nti} \tag{1}$$

where V_{nti} is the systematic part of the utility, β_n is a vector of taste parameters that follow a density $f(\beta)$ in the population, and ε_{nti} is the standard i.i.d. extreme value type 1 error term. The inclusion of random taste parameters that only vary across individuals allows the model to account for potential panel effects across observations from the same respondents. The probability P that individual n chooses a series of alternatives $i = \{i_1, \cdots, i_T\}$ over T choice tasks is then given as:

$$P_{ni} = \int \prod_{t=1}^{T} \frac{\exp(V_{nti}(\beta_n, x_{nti_t}))}{\sum_j \exp(V_{ntj}(\beta_n, x_{ntj}))} f(\beta) d\beta \tag{2}$$

In this notation, we use j to sum over the alternatives in choice task t for individual n. We suppress this to keep the notation simpler. Since the integral does not have a closed form, we rely on simulation in order to estimate the parameters that maximise the loglikelihood function:

$$LL = \sum_{n=1}^{N} \sum_i \ln(P_{ni}^{y_{ni}}) \tag{3}$$

[2] This paper does not involve the demand (customer) side, and references to *users* therefore relate to crowdshippers.

Table 4

Parameter estimation. * T-test and p-value against 1. ** Main effects included in the crowdshipping alternatives using the “No choice” as the reference alternative. For ML4, the column indicating the percentage with the right sign is computed for the relevant group in the sample.

	ML1 (Linear specification)			**ML2 (Log specification)**			**ML3 (BoxCox specification)**			**ML4 (Linear specification, unobserved preference heterogeneity)**			
Estimated parameters	**Value**	**Rob. *t*-test**	**Rob. p-value**	**Value**	**Rob. *t*-test**	**Rob. p-value**	**Value**	**Rob. *t*-test**	**Rob. p-value**	**Value**	**Rob. *t*-test**	**Rob. p-value**	**% right sign**
ASC, NoChoice	0.739	1.007	0.314	2.635	3.390	0.001	1.974	2.222	0.026	0.191	0.196	0.845	
ASC, NoChoice, S	−5.841	−11.220	0.000	−5.875	−11.221	0.000	−5.885	−11.217	0.000	−6.647	−9.601	0.000	
Age: 18–39 years**	2.483	3.081	0.002	2.519	3.104	0.002	2.517	3.099	0.002	2.813	2.700	0.007	
Age: Above 60 years**	−1.945	−2.343	0.019	−1.920	−2.295	0.022	−1.932	−2.306	0.021	−2.022	−1.944	0.052	
Employment: Employed/Self-employed**	1.474	2.049	0.040	1.462	2.026	0.043	1.469	2.031	0.042	1.658	1.751	0.080	
Employment: Student**	2.923	2.359	0.018	2.943	2.366	0.018	2.943	2.362	0.018	3.814	2.132	0.033	
Compensation	0.045	10.121	0.000							0.067	9.046	0.000	
Log(Compensation)				1.097	9.845	0.000							
BoxCox(Compensation)							0.622	2.012	0.044				
BoxCox(Compensation, λ*							0.195	−5.033	0.000				
Number of parcels	−0.120	−3.448	0.001	−0.170	−4.845	0.000	−0.158	−4.421	0.000	−0.275	−4.220	0.000	73.6%
Number of parcels, S										0.435	3.746	0.000	
Total size	−0.127	−7.641	0.000	−0.128	−7.649	0.000	−0.127	−7.581	0.000	−0.216	−6.818	0.000	90.6%
Total size, S										−0.164	−3.314	0.001	
Extra time	−0.088	−2.390	0.017	−0.112	−2.880	0.004	−0.114	−2.953	0.003	−0.148	−2.408	0.016	62.9%
Extra time, Age: Above 60 years	−0.137	−2.677	0.007	−0.143	−2.736	0.006	−0.143	−2.726	0.006	−0.303	−3.727	0.000	84.3%
Extra time, Income: High	−0.160	−2.753	0.006	−0.169	−2.805	0.005	−0.168	−2.807	0.005	−0.277	−2.940	0.003	82.9%
Extra time, Income: Unknown	−0.107	−1.564	0.118	−0.110	−1.617	0.106	−0.110	−1.607	0.108	−0.202	−1.913	0.056	78.3%
Extra time, Education: Higher education	0.062	1.559	0.119	0.059	1.479	0.139	0.060	1.501	0.133	0.082	1.221	0.222	55.9%
Extra time, S										0.447	7.573	0.000	
Total weight	−0.330	−6.360	0.000	−0.350	−6.635	0.000	−0.346	−6.537	0.000	−0.602	−6.412	0.000	94.2%
Total weight, Income: Low	0.224	3.280	0.028	0.215	3.188	0.001	0.220	3.222	0.001	0.310	2.830	0.005	77.7%
Total weight, Income: High	0.183	2.202	0.001	0.198	2.314	0.021	0.196	2.311	0.021	0.289	2.314	0.021	79.3%
Total weight, S										0.383	3.861	0.000	

where y_{ni} is 1 if the series of alternatives i is chosen by individual n, 0 otherwise.

The base utility specifications are presented below where the two unlabelled options (i.e. options A and B) are defined based on five attributes. Since the SC design also include a “no choice” option, which has no characteristics, we model this on the basis of an alternative-specific constant (ASC). More specifically, we define the systematic part of the utility V_{int} as shown below. Note that for the final model specification we also test non-linear effects as well as systematic and random preference heterogeneity, which are omitted here for simplicity.

$$V_{nti}^{A} = \beta_{Compensation}*Compensation_{nti}^{A} + \beta_{Time}*Time_{nti}^{A} + \beta_{Detour}*Detour_{nti}^{A} + \beta_{Size}*Size_{nti}^{A} + \beta_{Weigth}*Weigth_{nti}^{A} \tag{4a}$$

$$V_{nti}^{B} = \beta_{Compensation}*Compensation_{nti}^{B} + \beta_{Time}*Time_{nti}^{B} + \beta_{Detour}*Detour_{nti}^{B} + \beta_{Size}*Size_{nti}^{B} + \beta_{Weigth}*Weigth_{nti}^{B} \tag{4b}$$

$$V_{nti}^{NoChoice} = ASC^{NoChoice} + \eta_{ni} \tag{4c}$$

4. Results

4.1. Model estimation

Models are estimated in PandasBiogeme (Bierlaire, 2020) using 10,000 MLHS-draws (Hess et al., 2006) and the CFSQP-algorithm (Lawrence et al., 1997). A model summary and comparisons among various models are presented in Table 3, while the final parameter estimates are presented in Table 4. Table 4 shows that all parameters have the expected signs, thus an increase in monetary compensation increases the utility – and thus the probability – for bringing a parcel. Contrary, an increase in time, size, weight, or number of parcels decreases the utility – and thus the probability – for bringing parcels.

We tested for socio-demographic differences and heterogeneity in preferences, and in the final model kept the effects found to be significant. Note that all main effects are included in alternatives A and B (‘No choice’ is used as reference). More specifically, younger respondents (below 40 years of age) have a higher base utility for bringing parcels, while older respondents (above 60 years of age) have a lower base utility for bringing parcels. These findings are similar to the results of Gatta et al. (2019) who also found interest in participating in public transport based crowdshipping to decline with age. With respect to primary occupation, we see that both students and (to a lesser extent) individuals in jobs are more likely to pick up a parcel compared to individuals not studying or working. This seems plausible as both students and workers would usually/frequently commute to the location of their main occupation. Furthermore, older respondents and respondents in the highest income groups (50,000 or more DKK/year) have a higher marginal disutility for time, which is in line with existing literature (Börjesson et al., 2012; Mackie et al., 2001), while individuals with a higher education are more willing to accept extra time used for picking up parcels. We also tested for income effects in compensation in various ways [beta*compensation*(income/mean income)^gamma], but did not find any significant effects in our data.

The ML models include a normally distributed error component which accounts for correlation among observations from the same respondents (panel effect). The error component is seen to be significant across all four specifications, and while the mean ASC coefficient is highly dependent on specification, the variation (ASC_NoChoice_S) is rather stable.

We tested for non-linear effects in all attributes, and found compensation to possess non-linear effects, while the remaining attributes were not significantly different from a linear specification. In Table 3, we have compared the linear specification with models with a log and BoxCox transformation of compensation. We find that lambda in the BoxCox transformation is significantly different from 1 (i.e. a linear specification) and that the BoxCox model overall has a significant improvement in fit compared to the model with a linear specification for compensation. However, we find that lambda in the BoxCox model is not significantly different from 0 (i.e. a log-transformation) and that the BoxCox model overall does not have a significant improvement in fit compared to the model with log specification. For completeness, we also tested a model that included compensation with both a linear and log-transformed component, and find that only the parameter for Log(compensation) is significantly different from 0 (rob T-test = 3.82), while the parameter for compensation is not (rob. T-test = 1.01). The final loglikelihood is −1461.0, which yields that the model is not significantly better than the Log-model at 1 degree of freedom. Hence we disregard this model for further investigation.

We cannot directly compare the linear and log specifications using a Likelihood Ratio (LR) test, but we can compare their behavioural effects. More specifically, in the non-linear specification the marginal utility is a function of the attribute. In the linear specification, the marginal utility remains unchanged for the full range of compensation, however, for the log-specification the marginal utility halves when the attribute doubles, which in turn means that the WTA doubles when compensation doubles. We believe this could lead to some unrealistic effects and an undesirable interpretation of the behaviour, and therefore we prefer the linear specification as the differences in model fit to data are relatively small. For comparison, we present the linear, log, and BoxCox specification below, and it can be seen that results remain fairly stable across the three models.

We also tested for unobserved preference heterogeneity. More specifically, we specified normally distributed preferences in the sample. We found that all attributes had unobserved preference heterogeneity. However, the assumption of normal distributed preferences is not without issues. Firstly, a portion of the sample will due to the tails of the distribution end up with a counterintuitive sign. Secondly, simulation of WTA measures and marginal rates of substitution becomes highly unstable when draws are included in the denominator both due to draws with a “wrong” sign and – in particular – draws close to 0, which will make the WTA measures explode. To alleviate these issues, we tested both lognormal and triangular distributions, which both solved the first issue, however, the lognormal distribution also provided highly unstable WTA measures during simulation, while the triangular distribution provided stable WTAs, but this came at the cost of forcing the spread of the distribution to be equal to the midpoint of the distribution to avoid

Table 5
WTA measures and marginal rates of substitution. Numbers in brackets represent a 95% confidence interval.

	Unit	ML1 (Linear specification)	ML2 (Log specification)	ML3 (BoxCox specification)	ML4 (Linear specification, unobserved preference heterogeneity)
Willingness To Accept (WTA)					
Time/Compensation	DKK/min	3.26 (1.14, 5.34)	3.88 (1.75, 6.05)	3.60 (0.30, 15.52)	4.24 (1.97, 6.65)
Lower Edu. & Age ≤ 60 & Low-Medium Inc.	*DKK/min*	*0.61 (-0.88, 1.97)*	*1.18 (-0.30, 2.66)*	*1.12 (-0.58, 4.54)*	*0.98 (-0.72, 2.49)*
Lower Edu. & Age ≤ 60 & High inc.	*DKK/min*	*4.18 (1.46, 6.76)*	*4.90 (2.18, 7.46)*	*4.52 (0.37, 19.11)*	*5.15 (2.29, 8.28)*
Lower Edu. & Age ≤ 60 & Unknown inc.	*DKK/min*	*2.98 (0.14, 5.90)*	*3.63 (0.94, 6.79)*	*3.35 (-0.62, 15.02)*	*4.03 (0.99, 7.21)*
Lower Edu. & Age > 60 & Low-Medium Inc.	*DKK/min*	*3.69 (1.51, 5.88)*	*4.31 (2.16, 6.60)*	*3.99 (0.48, 17.46)*	*5.52 (3.42, 8.15)*
Lower Edu. & Age > 60 & High inc.	*DKK/min*	*7.25 (4.00, 10.58)*	*8.85 (5.42, 12.40)*	*8.07 (1.62, 36.12)*	*9.69 (6.46, 13.78)*
Lower Edu. & Age > 60 & Unknown inc.	*DKK/min*	*6.06 (2.36, 9.63)*	*6.25 (3.05, 9.83)*	*5.84 (0.71, 27.93)*	*8.55 (4.92, 12.70)*
Higher Edu. & Age ≤ 60 & Low-Medium Inc.	*DKK/min*	*1.97 (0.39, 3.45)*	*2.55 (0.90, 4.06)*	*2.39 (0.21, 9.48)*	*2.20 (0.46, 3.87)*
Higher Edu. & Age ≤ 60 & High inc.	*DKK/min*	*5.56 (3.10, 8.19)*	*6.30 (3.82, 8.94)*	*5.80 (1.11, 23.00)*	*6.33 (3.47, 9.22)*
Higher Edu. & Age ≤ 60 & Unknown inc.	*DKK/min*	*4.36 (1.50, 7.11)*	*5.10 (2.22, 8.13)*	*4.71 (0.33, 20.08)*	*5.23 (2.16, 8.54)*
Higher Edu. & Age > 60 & Low-Medium Inc.	*DKK/min*	*5.05 (2.84, 7.27)*	*5.74 (3.36, 7.97)*	*5.30 (1.10, 24.64)*	*6.74 (4.48, 9.43)*
Higher Edu. & Age > 60 & High inc.	*DKK/min*	*8.63 (5.74, 11.62)*	*9.07 (6.15, 12.30)*	*8.40 (2.17, 37.22)*	*10.89 (7.67, 14.89)*
Higher Edu. & Age > 60 & Unknown inc.	*DKK/min*	*7.43 (3.71, 11.08)*	*7.87 (4.46, 11.73)*	*7.29 (1.22, 35.01)*	*9.75 (6.10, 14.00)*
Num. Parcels/Compensation	DKK/#	2.67 (1.02, 4.34)	3.80 (2.31, 5.55)	3.23 (0.64, 13.79)	4.10 (2.39, 6.14)
Size/Compensation	DKK/L	2.83 (2.04, 3.71)	2.86 (2.06, 3.77)	2.61 (0.74, 11.99)	3.23 (2.35, 4.19)
Weight/Compensation	DKK/kg	5.07 (2.53, 7.88)	5.55 (3.03, 8.43)	4.96 (0.45, 22.12)	6.78 (4.02, 9.90)
Marginal rates of substitution (MRS)					
Num. Parcels /Time	min/#	1.64 (-9.82, 14.52)	1.47 (-3.65, 7.74)	1.33 (-3.41, 7.43)	
Size/Time	min/L	1.74 (-10.34, 14.26)	1.10 (-2.96, 5.80)	1.07 (-2.23, 5.87)	
Weight/Time	min/kg	2.95 (-18.56, 27.20)	2.11 (-4.67, 10.75)	2.00 (-4.65, 10.77)	
Num. Parcels/Size	L/#	0.94 (0.40, 1.55)	1.33 (0.80, 1.99)	1.24 (0.69, 1.88)	
Num. Parcels/Weight	kg/#	0.69 (-0.77, 3.23)	0.84 (0.42, 3.03)	0.82 (0.38, 3.01)	
Size/Weight	Kg/L	0.73 (-0.73, 3.17)	0.63 (0.39, 2.13)	0.66 (0.38, 2.34)	

draws with a wrong sign. In the end, we decided to stick with the model including normally distributed preferences on all attributes except for compensation. This allowed us to compute stable WTAs because we did not have draws in the denominator (a similar approach is found in Basu and Hunt, 2012), however, the marginal rates of substitution still remained unstable, and thus are not presented here. The model with unobserved preference heterogeneity is presented alongside the other models in Tables 3, 4, and 5 (for completeness, base models are included in appendix, see Tables 6 and 7). As mentioned, due to the assumption of normally distributed preference heterogeneity, some respondents will inherently have a counterintuitive sign. In Table 4, we computed the percentage with the expected sign within each segment. Finally, to circumvent unstable WTPs when mixing compensation we also attempted to estimate the model in WTP space, where we specified a lognormal distribution on the scale parameter to ensure positive values. We found the final loglikelihood to be −1416.19 with one additional parameter compared to M4. As the WTP-space model cannot reject M4 in a LR test, we keep M4 as our final model for further analysis.

4.2. *Willingness to Accept and marginal rates of substitution*

Table 5 presents the WTA measures and marginal rates of substitution among attributes. Table 5 presents average values of WTA and marginal rate of substitution in the sample, which takes into account the socio-demographic distribution in the sample. For all non-linear effects (i.e. compensation in ML2 and ML3) the WTA measures are functions of the attribute values, hence for these we simulate the WTA for both alternative 1 and 2, and present the average value to circumvent outliers. Furthermore, for completeness, Fig. 4 plots the raw WTA measures as a function of compensation.

In the following, we focus on the linear specification, but the other models show similar values, and are all well within the confidence interval. The WTA related to time is found to be slightly below 200 DKK/h (∼26 Euro/h). For comparison, the official Danish values of time (Transport DTU, 2020b) for commuters are 91 DKK/h (∼12 Euro/h) for (in-vehicle) travel time, 183 DKK/h (∼25 Euro/h) for waiting time, and 274 DKK/h (∼37 Euro/h) for travel delays. Our WTA for time is fairly close to the value of waiting time, albeit slightly higher. We believe this value is indeed realistic as the time for retrieving the parcel would (in many cases) otherwise be spent waiting for the next departure. One possible explanation for our WTA to be higher than the waiting time value could be that it also introduces an element of uncertainty, which could lead to missing the next departure while picking up a parcel, and thus ultimately facing a delay.

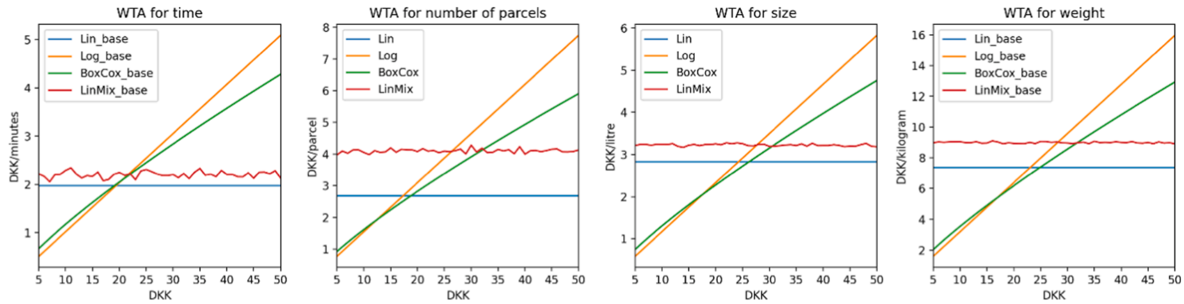

Fig. 4. WTA as a function of compensation. Note for the attributes time and weight (for which we found systematic preference heterogeneity) we present only the base WTA for simplicity.

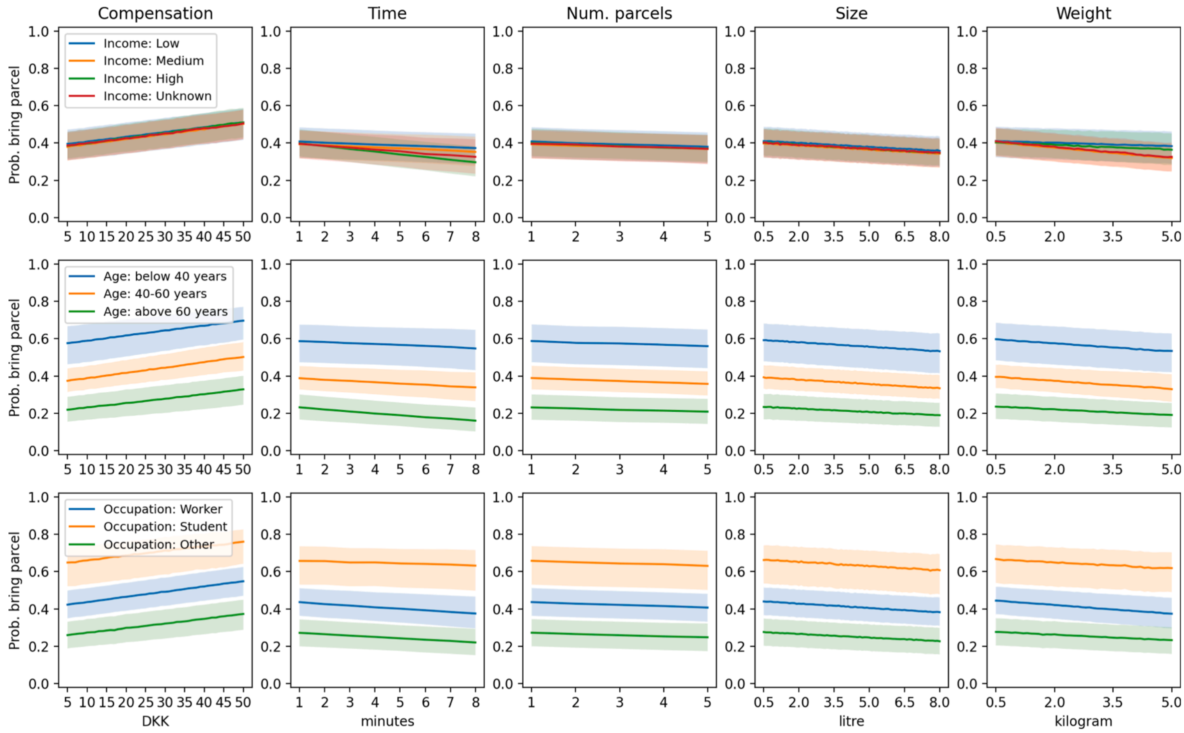

Fig. 5. Segment probability of bringing parcel as function of attribute.

We also segmented the value of time based on various socio-demographic characteristics found to be significant in the model. We note that the WTA increases for the segment above 60 years and with high income. The value of an additional parcel, litre, and kg is found to be 2.67, 2.83 and 5.07 DKK respectively. The marginal rates of substitution indicate how individuals (on average) value certain characteristics against each other. For example, Table 5 shows that respondents are willing to bring one additional parcel if they can reduce the total weight by 0.69 kg (or vice versa), or increase the total parcel size a litre if they can reduce the pickup time with 1.74 min (or vice versa).

4.3. Policy analysis

In order to evaluate the sensitivity of various groups in the sample towards the measured attributes we perform a policy analysis. However, since the data is based on a SC experiment it does not make sense to assess policy measures directly using the model and data from the previous section. In order to approach a somewhat realistic policy analysis we:

1) Define a binary outcome: bring parcel vs. do not bring parcel.
2) Update all attribute values in the sample for the "bring parcel" alternative to values from a full scale field experiment testing the concept (Fessler et al., 2021a)[3]. Those values were: compensation = 10 DKK, time for retrieving/dropping off parcels = 1 min, number of parcels shipped = 1, size of parcel = 1 L, and weight of parcel = 1 kg.
3) Calibrated the ASC so that the model reproduced "actual" market shares[4]. The best real life information we had available to calibrate the model was a full scale field experiment undertaken shortly after the current data was collected (Fessler et al., 2021a). This field test showed that parcels were taken on ~ 40% of the trips. Note that in the field test participants (who can be characterised as 'first-movers') did not receive reminders about bringing parcels, which would likely be the case in an actual realised crowdshipping concept.

Please note that the abovementioned adjustments were done with the same sample as used in the model estimation, thus the socio-demographic distribution in the policy analysis is the same as in the model estimation, see Table 2. Fig. 5 presents the probability that various segments would bring a parcel as a function of the five attributes (compensation, time, number of parcels, size, and weight) in the SC design using the level range as bounds. For the income groups, we see that the probabilities to crowdship are similar across income groups, however for time and weight it is visible that the low and high income groups have respectively the highest and lowest probability to bring a parcel. This tendency is more visible as the compensation levels increase. For segmentation based on age and occupation, we see an even clearer distinction in the probability to bring a parcel. More specifically, younger individuals have the highest probability to be a crowdshipper, while older individuals have the lowest. And in line with our expectations, we see that students have the highest probability to bring a parcel. The fact that individuals with a job have a higher probability to be a crowdshipper seems intuitive as they would have a natural commute to and from work (unlike retired/non-employed individuals).

We also computed the probability for bringing a parcel as a function of compensation for various levels of time, number of parcels, size, and weight (graphs not presented). In line with our expectations, lower levels of time, number of parcels, size, and weight have higher probabilities to crowdship that increase as compensation increases.

Despite entailing many characteristics of the most positively rated service-level combinations of Gatta et al. (2019), our resulting probabilities are generally lower than the highest rated crowdshipping concepts of this previous work. However, with the greater level of detail on service and shipment characteristics and calibration based on a full scale field experiment, the results may be less prone to hypothetical bias issues, which often leads to optimistic evaluations of future behaviour (Ajzen et al., 2004). Further, Gatta et al. (2019) measured the probability of adopting the crowdshipping concept in a broader sense, whereas our results are based on the acceptance of more specific trips, which could be assumed to yield lower acceptance probabilities.

5. Conclusion

Due to growing e-commerce, last-mile delivery brings increasing environmental and social challenges. On this background, this paper investigated the acceptance of a public transport based crowdshipping concept that is suggested as a sustainable alternative to existing last-mile solutions. In the suggested concept, public transport passengers can bring parcels along their trip and get automatically compensated by reduced travel expenses. This ensures that the system solely makes use of non-dedicated trips and does not become a catalyst for unregulated precariat jobs lacking workers' rights.

We explored user preferences by developing a five-attribute SC experiment in which respondents were presented with four choice tasks containing two crowdshipping alternatives as well as an 'opt-out'-alternative. The survey was distributed through an online panel to a sample of regular public transport users in the Greater Copenhagen Area. We estimated mixed logit models in order to assess user preferences while accounting for panel effects across observations from the same respondent. In line with our expectations, we found that utility of bringing a parcel is positively associated with the (monetary) compensation provided to individuals, while utility is negatively associated with the (additional) time usage as well as the weight, size, and number of parcels. We tested all attributes for non-linear effects, but found it to be relevant only for the compensation attribute. For comparison, we presented the results with linear, logarithmic and BoxCox transformations of compensation, and despite differences in the assumption of the marginal utility of compensation the overall results remained reasonably stable. Although the model with a linear compensation specification is not statistically superior, we argue that it is more sensible from a behavioural point of view as the marginal utility is constant for all values of compensation within the range covered in our data.

We also tested for socio-demographic differences and heterogeneity in user preferences and found:

- Students, the working population and young(er) individuals (below 40 years of age) are more likely to participate in public transport based crowdshipping.
- Old(er) individuals (above 60 years of age) are less likely to participate in public transport based crowdshipping.

[3] In a full scale field experiment conducted after data of the current paper was collected, the concept was tested by public transport passengers in Denmark. APLs were placed at selected stations and a smartphone app was developed, allowing participants to collect/hand in small (19 x 12 x 4 cm) empty test parcels in less than 30 seconds per interaction. They were rewarded with 10 kr. per transported parcel.

[4] Note that it is also possible to calibrate the scale rather than the ASC. We tried both, but since the uncalibrated market shares for crowdshipping from the SP model is>50%, and the observed market share for crowdshipping is below 50% this means that calibrating the scale yields a negative scale. Having multiple data points for calibration would allow us to calibrate both the constants and the scale.

- Old(er) individuals and individuals in the high-income group have a higher marginal disutility of time spent retrieving the parcels, while individuals with a lower education show a lower marginal disutility.

Individuals in the low- and high-income groups have a lower marginal utility of the total weight of the parcels. From the demographic profiles, people interested in the service do not belong to the typical profile of early adopters of new transport technologies, who are mostly found to be male, young/middle aged, with high education and income (Haustein and Jensen, 2018; Nielsen and Haustein, 2018). Their characteristics differ from sharing economy service providers like Uber drivers (Hall & Krueger, 2018) but to a large extent match the profiles for sharing economy users and seem to be typical public transport commuters. This is not surprising as it makes most sense for people with regular public transport trips to participate in the service, as the mental effort will be comparably low when they get into a habit of taking a parcel along compared with irregular users, where the initial effort is less likely to pay off. We found the WTA (for the linear model) to be slightly below 200 DKK/h (~26 Euro/h), which is between the value for waiting time of approx. 183 DKK/h (16 Euro/h) and the value for travel time delays of approx. 274 DKK/h (37 Euro/h). This seems reasonable, as the time spent retrieving a parcel can be considered as waiting time while also introducing some travel time uncertainty, i.e. there is a risk of missing the train while retrieving the parcel. The model also provides information about how individuals rank attributes (such as non-monetary) against each other. On average respondents are willing to:

- Carry an additional parcel in order to 1) reduce time usage by 1.64 min, total parcel weight by 0.69 kg or total parcel size by 0.94 L (or vice versa) or 2) increase the compensation by 2.67 DKK (or vice versa).
- Increase the total parcel size by 1 L in order to 1) reduce time usage by 1.74 min or total parcel weight by 0.73 kg (or vice versa) or 2) increase the compensation by 2.83 DKK (or vice versa).
- Increase the total parcel weight by 1 kg in order to 1) reduce time usage by 2.95 min (or vice versa) or 2) increase the compensation by 5.07 DKK (or vice versa).

While a payment through reduced transport costs is in the first instance expected to prohibit unnecessary trips, rebound effects cannot be totally ruled out, as it is possible that saved travel expenses are reinvested in additional trips or in other areas of consumption. More importantly, travellers may feel that they – by bringing parcels along their way – have “done their bit” and feel licensed to consume more in other areas of consumption. Likewise to these negative spillover effects, also positive spillover effects are possible; that people feel more motivated to also act more environmentally-friendly in other areas of consumption (see, e.g. Sorrell et al., 2020). Generally, more knowledge about the potential users that goes beyond demographic variables is highly relevant, as well as a segmentation that also includes psychological factors and could be used for tailored measures (e.g. dos Reis et al., 2020), both to motivate potential crowdshippers as well as to optimise the achievable environmental effects. More knowledge on the transferability to other contextual, geographic and cultural settings would also be relevant scopes for future work on the subject.

The findings of the present study could help inform the design of a public transport based crowdshipping system in several ways, and add plausibility to the economic feasibility of the service; that sufficient financial incentive for crowdshippers is possible within the current economic margins of goods delivery. Engagement efforts could benefit from the results on differences between various demographic profiles, while the identified marginal rates of substitution might further the setup of the most optimal and attractive delivery “bundles”, in order to design the most efficient delivery system.

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7. Author contributions

The stated choice experiment was designed by Andreas Fessler, Mikkel Thorhauge, and Stefan Mabit. Survey development and data collection was undertaken by Andreas Fessler and Sonja Haustein. The model design and estimation was performed by Mikkel Thorhauge in close collaboration with Stefan Mabit. All authors contributed to the writing of the manuscript, and approved the final version.

Declaration of Competing Interest

This study was conducted as part of an industrial doctoral dissertation on “Crowdsourcing Logistics in Cities”. As industrial PhD Fellow for this dissertation, Andreas Fessler is employed by Atkins Denmark.

Appendix A

Table 6
Parameter estimates and model summary for base models.

	Base model (MNL)			Base model (ML)		
	Value	Robust *t*-test	Robust p-value	Value	Robust *t*-test	Robust p-value
Estimated parameters						
ASC_NoChoice	0.027	0.194	0.847	−0.384	−1.059	0.290
ASC_NoChoice_S				−6.357	−11.342	0.000
B_Compensation	0.027	9.784	0.000	0.042	9.669	0.000
B_NoPack	−0.083	−3.243	0.001	−0.113	−3.229	0.001
B_Size	−0.105	−8.692	0.000	−0.125	−7.791	0.000
B_Time	−0.053	−3.211	0.001	−0.111	−4.339	0.000
B_Weight	−0.181	−7.323	0.000	−0.214	−5.905	0.000
Model Summary						
Number of parameters:	6			7		
Sample size:	2,096			524		
Observations:	2,096			2,096		
Number of draws:				10,000		
Algorithm:	CFSQP			CFSQP		
AIC:	4,261.0			3,075.4		
BIC:	4,294.9			3,105.2		
Final log likelihood:	−2,124.5			−1,530.7		

Table 7
Simulated probabilities, WTA and marginal rate of substitution for the two base models.

	Unit	Base model (MNL)	Base model (ML)
Willingness To Accept (WTA)			
Time/Compensation	DKK/min	1.95 (0.81, 2.89)	2.66 (1.67, 3.56)
Num. Parcels/Compensation	DKK/#	3.04 (1.16, 5.05)	2.71 (1.07, 4.57)
Size/Compensation	DKK/L	3.87 (2.84, 5.17)	3.00 (2.16, 4.02)
Weight/Compensation	DKK/kg	6.63 (4.41, 9.19)	5.15 (3.14, 7.59)
Marginal rates of substitution (MRS)			
Num. Parcels/Time	min /#/	1.56 (0.54, 4.40)	1.02 (0.38, 2.04)
Size/Time	min/L	1.98 (1.14, 5.00)	1.13 (0.73, 2.03)
Weight/Time	min/kg	3.39 (1.79, 9.56)	1.94 (1.08, 3.70)
Num. Parcels/Size	L/#	0.79 (0.31, 1.32)	0.90 (0.36, 1.54)
Num. Parcels/Weight	kg/#	0.46 (0.18, 0.77)	0.53 (0.22, 0.92)
Size/Weight	L/kg	0.58 (0.44, 0.79)	0.58 (0.44, 0.82)

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