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Market potential of bicycle crowdshipping: A two-sided acceptance analysis

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ABSTRACT

Crowdshipping has recently emerged as a sustainable option for urban parcel delivery, where transport tasks are carried out by regular citizens who are engaged in a passenger trip, instead of the usual professional carriers. A key challenge for such as service offering is to maintain a sustainable network of customers (demand) and couriers (supply). This paper quantitatively explores how demand and supply functions for bicycle crowdshipping meet in a parcel delivery market. Earlier literature has identified factors that determine the success of this business model. We build on this to estimate the potential of the new services, by means of a market equilibrium model. A case study is presented from the Netherlands which uses tailor-made surveys, bicycle trip data and online shopping statistics. The study quantifies the importance of influencing factors. The insights can be used to design a bike crowdshipping platform which brings together the demand and the supply sides effectively. Future research could go into platform design, more accurate behavioral models as well as into advanced pricing approaches.

1. Introduction

Academia and industry are continuously re-thinking the way logistics activities are managed and operated. The concept of crowdshipping has emerged as one of the solutions to overcome key city logistics sustainability challenges (Rougès & Montreuil, 2014). Crowdshipping can be defined as a sharing mobility service, which implies delivering goods using non-professionals, or the crowd (McKinnon, 2016). The concept entails the use of spare capacity of vehicles on journeys that already take place to facilitate delivery operations (Arslan, Agatz, & Klapp, 2019). In this way, deliveries are performed without having to deploy dedicated logistics services.

Crowdshipping studied by literature involves crowds with various transport modes: public transport (Gatta, Marcucci, Nigro, & Serafini, 2019), taxis (Chen, Pan, Wang, & Zhong, 2017) and private cars (Paloheimo, Lettenmeier, & Waris, 2016). This paper explores the possibility and practicality of involving cyclists to perform package delivery. Crowdshipping using bicycles has several advantages. First, it is an excellent, low-emission alternative for last mile deliveries, which is currently often carried out by a van. In addition to the reduction of carbon emissions, deliveries by bicycles bring considerable flexibility for the courier: bicycles are less affected by the congestion and traffic regulation of the city environment (Maes & Vanelslander, 2012). They can have lower travel times than cars, and can be parked on sidewalks (Rudolph & Gruber, 2017). Recent analysis suggests that half of the light cargos now delivered by vans can be delivered by cargo bikes (cyclelogistics.eu, 2019). The above implies that using bicycles for deliveries in city environments is a promising option. We can add that the testing ground of this paper, The Netherlands, sees an average of 2.8 million cycling trips made daily for passenger transport motives (Centraal Bureau voor de Statistiek, 2016), which seems fertile ground for offering crowdshipping services. Taken together, the advantages of the supply and demand sides could create a competitive business model for bicycle crowdshipping for last mile deliveries.

The objective of this paper is to investigate how factors from both the supply and the demand side influence the market potential of bicycle crowdshipping. The remainder of this paper is organized as follows. In Section 2 a literature review is carried out to summarize the current state-of-the-art and to define the research gap. Section 3 explains the method, the models used as well as the survey design. In Section 4, we conduct a case study by applying the methods to the city of Delft in The Netherlands. The results are presented in the same section. Section 5 concludes the article and points out future directions.

2. Literature review

Crowdshipping business models have widely been studied recently. Lozza (Lozza, 2016) points out that business-to-consumer (B2C)

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shipping in e-commerce is a large cluster, where large companies as well as startups have explored crowdshipping as the last mile delivery solution. The literature review by Le et al. (Le, Stathopoulos, van Woensel, & Ukkusuri, 2019) categorizes studies on crowdshipping business models according to the three pillars of crowdshipping markets: *supply*, *demand*, and *platform & operation*. Since business models bring together the supply and the demand aspects, and the platform & operation is from a management perspective, the literature review is then organized in the framework of these three aspects. A large portion of research focuses on one of the three aspects of crowdshipping. For the platform & operations aspect, literature mainly focuses on optimizing system-wise performance in task matching (Arslan, Agatz, & Klapp, 2019; Cen, Cheng, Lau, & Misra, 2015; Soto Setzke et al., 2017) or route assignments (Chen, Pan, Wang, & Zhong, 2017). On the supply side, literature largely focuses on the crowd's willingness to participate in deliveries (Chi et al., 2018; Ermagun & Stathopoulos, 2018; Le & Ukkusuri, 2019; Miller, Nie, & Stathopoulos, 2017); while on the demand side, literature looks into the factors contributing to customers' acceptance of crowdshipping services (Frehe, Mehmann, & Teuteberg, 2017; Punel, Ermagun, & Stathopoulos, 2018a; Punel & Stathopoulos, 2017). While these studies provide important partial insights it seems that, for implementation issues, the three aspects need to be considered together. Rougès and Montreuil (Rougès & Montreuil, 2014) point out that to start a crowdshipping business, a chicken-and-egg problem needs to be addressed. Unlike conventional business models (which can start by developing the supply side, internalizing resources, e.g. a team of couriers), the crowdshipping business models rely on a network effect, in other words, a simultaneous development of both the demand and the supply sides. This makes the problem less easily solvable (Rougès & Montreuil, 2014). Hence, compared with conventional business models, it is even more relevant to consider both the supply and the demand aspects in crowdshipping business models, as brought together by platform and operations.

A few studies address both the demand and the supply aspects at the same time. For instance, Marcucci et al. (Marcucci, Le Pira, Carrocci, Gatta, & Pieralice, 2017) develop surveys for both the demand and the supply side of crowdshipping, to investigate factors that may affect willingness to provide or buy crowdshipping services based on public transport. Gatta et al. (Gatta, Marcucci, Nigro, & Serafini, 2019) perform a joint investigation of the supply and the demand aspects of crowdshipping, estimating the potential amount of crowdshippers (supply) as well as the potential demand. They also observed that in their case study, the potential supply is higher than the potential demand. This observation could suggest that the services would be cheap and competitive, which however, is not further investigated and discussed.

In this paper we continue on this path by conducting a joint study on both the supply and the demand side of crowdshipping business with casual cyclists. Similar to Gatta et al. (Gatta, Marcucci, Nigro, & Serafini, 2019), we use discrete choice models to determine important factors that would influence preferences from both the demand and the supply side. In addition to that, however, we take a step further to investigate the potential market penetration of such business models, which gives quantitative insights on the competitiveness of crowdshipping services compared with the conventional delivery methods.

3. Methodology

The principal approach taken is one of choice experiments leading to demand and supply choice models. The demand side concerns the decision of a cyclist person who is not a professional courier to offer transport services to a sender of a parcel. The supply side concerns the decision of a customer, whether to employ the private cycle courier, or to resort to a regular service provider. Combining these decisions leads to a market equilibrium model, that allows to investigate the convergence between supply and demand. Below we explain the factors considered from the literature, the principles behind our survey design and the discrete choice experiment. Next, we present the models and their combined application to estimate market shares.

Table 1
Demand attributes summary.

Category	Attributes
Traditional Features	Cost
	Time
Delivery Options	Pickup Time Window
	Delivery Time Window
	Track and Trace Feature
Quality & Security	Performance Rating
	Courier Qualification
	Courier Experience
Environmental Impact	CO2 Emission Saving

Table 2
Supply attributes summary.

Category	Attributes
Rewarding Factors	Profit
	CO2 Emission Saving
	Calories burned record
Penalizing Factors	Additional Travel Time
	Package Size
	Package Weight
	Delivery Deadline
Travel Setting	Trip Direction
	Type of Weekday
	Time of Day
	Original Travel Time

3.1. Factors for demand and supply side

We firstly identify attributes from the literature that may affect the supply or demand aspects of bicycle crowdshipping. Then we select the most relevant ones to include in our model.

3.1.1. Demand attributes

We group service (demand) attributes in four categories: Traditional features, Delivery options, Quality & Security, and Environmental impact. These service attributes are summarized in Table 1.

Traditional features, namely delivery time and cost, are the two fundamental attributes that guarantee a successful service (Chen, Pan, Wang, & Zhong, 2017). In practice, most of the crowdshipping couriers perform same day delivery up to express delivery with 30 min delivery lead time. Delivery cost can take several forms such as negotiated price, hourly-based price, or parcel-based price (Lozza, 2016). In a local delivery context, customers show a high willingness-to-pay sensitivity for reductions in delivery lead time (Punel & Stathopoulos, 2017).

Delivery options are features that can be attractive to customers of delivery services (Punel & Stathopoulos, 2017), including online services such as tracking and tracing. Options also relate to the flexibility for customers to choose their preferred delivery time.

Quality & security relates to customers' concern about the proper care for parcels. Trust and reliability are essential to customers (Paloheimo et al., 2016). We use similar attributes as in Punel & Stathopoulos (Punel & Stathopoulos, 2017): courier's performance rating, courier qualification and courier experience.

Environmental impact is represented by providing the information of potential CO_2 emission savings when using the service (Punel, Ermagun, & Stathopoulos, 2018b).

3.1.2. Supply attributes

The success of attracting sufficient couriers to perform crowdsourced delivery depends on how the effort made by crowdshipping could be compensated by the rewards provided. In addition, contextual factors of

Table 3
Selected demand attributes.

Attributes	Levels	Units
Costs	3/5/7/9	Euros
Time	1/3/5/7	Hours
Delivery Time Window	Adjustable/Non-adjustable	–
Performance Rating	5/4	Star
CO2 reduction	0.9/1.3/1.7/2.1	Kilograms

Table 4
Selected supply attributes.

Attributes	Levels	Units
Time of Day	Morning/Evening	–
Additional Travel Time	6/10/14/20	Minutes
Package Weight	1/3/5/7	Kilograms
Profit	2/4/6/8	Euro
CO2 reduction	0.9/1.3/1.7/2.1	Kilograms

travel during which the crowdshipping job is carried out can be important. These attributes are summarized in Table 2.

Rewarding factors are job attributes that improve the attractiveness of performing crowdshipping job. Profit is an important part of rewarding factor to encourage the participation of bicycle commuters to deliver packages (Le & Ukkusuri, 2018a; Miller et al., 2017; Paloheimo et al., 2016). In practice, the motivation behind the participation on crowdshipping platform is not merely related to monetary benefits. Frehe et al. (Frehe et al., 2017) has shown that considerable number of drivers acknowledged that they offered their service as courier to assist the neighborhood and to reduce CO_2 emission. In addition, some crowdshippers also consider physical exercise as another factor that also encouraged their participation (Paloheimo et al., 2016).

Penalizing factors can be defined as the effort each courier makes, which may discourage from performing the job. Miller et al. (Miller et al., 2017) observe that travel time negatively influences the utility of performing a delivery job. To maximize the job acceptance, crowdshipping services would usually limit the delivery range to an acceptable travel distance. Other penalizing factors are package size, weight and delivery deadline (Ermagun et al., 2019; Le & Ukkusuri, 2018a; Le & Ukkusuri, 2018b).

Travel setting relates to how crowdshippers perceive the delivery trip they make within different contexts. Paleti et al. (Paleti, Vovsha, Givon, & Birotker, 2015) point out that the value of time of commuters varies with trip pattern and schedule. As a result, different reward schemes might be needed to encourage couriers in diverse delivery settings. For instance, people performing trips in the evening might have a higher propensity to accept delivery job offers since they have a lower sensitivity to travel delays (Miller et al., 2017). In practice, ride-sharing platforms such as Uber apply this context-specific attribute by imposing surge-pricing to entice enough couriers to carry passengers during peak hours. Other attributes related to travel setting that can be considered are trip direction (to work or to home), type of weekday, and length of original travel time (Ermagun et al., 2019; Miller et al., 2017; Paleti, Vovsha, Givon, & Birotker, 2015).

3.2. Choice experiment design

Choice experiments on the demand and supply side were done to measure the importance of the different attributes. The above factors were considered as starting point. To avoid putting too much burden to respondents, five main attributes were included in each experiment. This number of attributes is seen as sufficient to prevent fatigue and facilitate the respondents' choice process, providing sufficient information to extract the attribute weights (Carson, 1994; Caussade, de Dios Ortuzar, Rizzi, & Hensher, 2005; Molin, 2016). The criteria for selecting the attributes are that the attributes need to be realistic, representing situations likely to be found in an actual market (Louviere, Hensher, & Swait, 2000); and that the attributes have to fall within the influence of crowdshipping platforms (Molin, 2016).

To strive for a balanced design, the number of levels for each attribute was based on the multiple of two (Louviere et al., 2000). For the CO_2 savings, the levels were obtained assuming an emission rate of 175 g CO_2 per km (European Environment Agency, 2015) and a two-way journey with an average distance of 4–12 km. Additional travel time was obtained with maximum travel distance of 7.5 km and an average cycling speed of 12.5 km per hour (KiM Netherlands Institute for Transport Policy Analysis, 2016). The remaining attribute levels were assigned based on literature. The selected attributes levels are depicted in Tables 3 and 4.

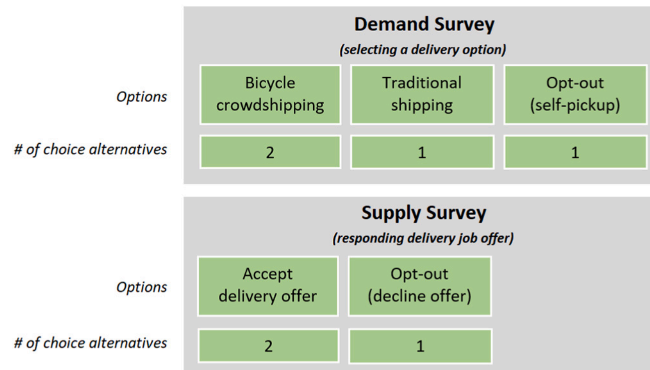


Fig. 1. Choice alternatives for demand and supply survey.

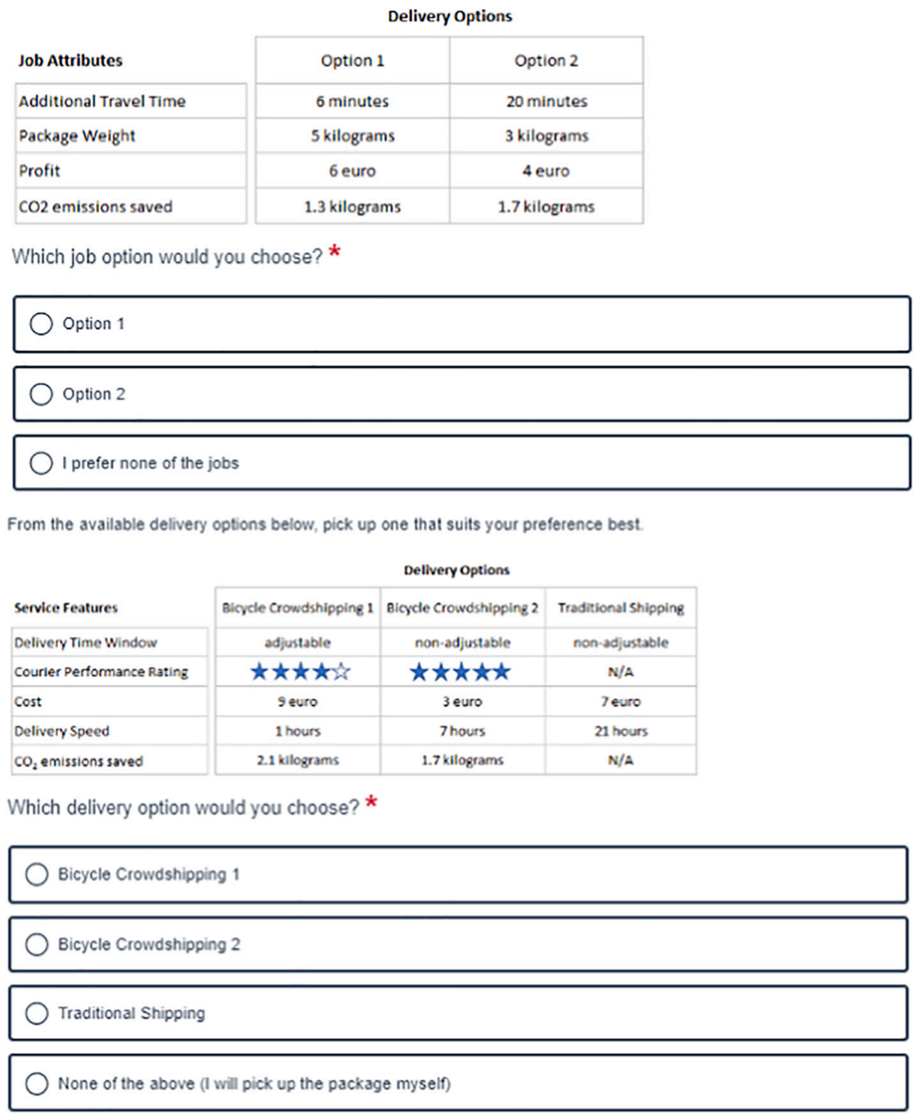
The choice experiment uses the results from the surveys to measure how customers and couriers perceive the attributes when using/participating in bicycle crowdshipping. The survey consists of three main parts:

- Preliminary questions to measure respondents' e-shopping experience and gauge their initial interest for the crowdshipping concept;
- Stated choice scenarios to measure the relative importance of the attributes;
- Personal characteristics questions to map the demographics of the sample.

In the demand survey, the experiment identifies customer choices between bicycle crowdshipping and other shipping options. The alternatives are confined to three types: 1) delivery via traditional couriers, 2) delivery via bicycle crowdshipping platform, and 3) delivery via a pickup/service point. The third option can also be interpreted as the opt-out option. Inclusion of opt-out alternative is needed to estimate a market penetration level that complies with demand theory (Carson, 1994; Kontoleon & Yabe, 2003).

In the supply survey, the aim is to identify choices between performing a delivery task or continuing a normal commute (opt-out). Hence, two types of labeled alternatives are used for this purpose. The structure of choice alternatives can be seen in Fig. 1. The number of alternatives for crowdshipping is higher (i.e. 2 alternatives each) to give respondents more exposure to the crowdshipping options.

The choice sets are constructed according to the efficient design principle, to develop a utility-balanced experiment design without dominating alternatives (Huber & Zwerina, 1996). Two blocks are developed for each survey. Within each block, eight choice sets are provided. To assure that all respondents have the same perceptions in mind while making choices, the context they have to assume is defined. In the demand survey, the respondents are asked to imagine themselves shopping in an online shop and choosing one of delivery options during checkout process. In the supply survey, the respondents are asked to



Delivery Options

Job Attributes	Option 1	Option 2
Additional Travel Time	6 minutes	20 minutes
Package Weight	5 kilograms	3 kilograms
Profit	6 euro	4 euro
CO2 emissions saved	1.3 kilograms	1.7 kilograms

Which job option would you choose? *

- Option 1
- Option 2
- I prefer none of the jobs

From the available delivery options below, pick up one that suits your preference best.

Delivery Options

Service Features	Bicycle Crowdshipping 1	Bicycle Crowdshipping 2	Traditional Shipping
Delivery Time Window	adjustable	non-adjustable	non-adjustable
Courier Performance Rating	★★★★☆	★★★★★	N/A
Cost	9 euro	3 euro	7 euro
Delivery Speed	1 hours	7 hours	21 hours
CO_2 emissions saved	2.1 kilograms	1.7 kilograms	N/A

Which delivery option would you choose? *

- Bicycle Crowdshipping 1
- Bicycle Crowdshipping 2
- Traditional Shipping
- None of the above (I will pick up the package myself)

Fig. 2. Example of supply (Top) and demand (bottom) choice scenario.

imagine two trip contexts: home-bound and work-bound. Before the trip begins, they are given several optional delivery jobs and asked to decide whether to take any of the job offers. Examples of choice scenario for demand and supply survey in the experiment user interface are depicted in Fig. 2.

3.3. Discrete choice models

Multinomial logit models are used to estimate the probability of customers accepting crowdshipping options and of cyclists taking delivery jobs. The systematic part of the utility function in the demand survey is given by Eq. (1)-(4).

$$V_{\mathrm{CS1}} = \delta_1 + \beta_1 Cost_{\mathrm{CS1}} + \beta_2 Time_{\mathrm{CS1}} + \beta_3 DTW_{\mathrm{CS1}} + \beta_4 Rating_{\mathrm{CS1}} + \beta_5 \mathrm{CO2}_{\mathrm{CS1}} \quad (1)$$

$$V_{\mathrm{CS2}} = \delta_2 + \beta_1 Cost_{\mathrm{CS2}} + \beta_2 Time_{\mathrm{CS2}} + \beta_3 DTW_{\mathrm{CS2}} + \beta_4 Rating_{\mathrm{CS2}} + \beta_5 CO2_{\mathrm{CS2}} \quad (2)$$

$$V_{\mathrm{Trad}} = \delta_3 + \beta_1 Cost_{\mathrm{Trad}} + \beta_6 Time_{\mathrm{Trad}} + \beta_3 DTW_{\mathrm{Trad}} \quad (3)$$

$$V_{\mathrm{OptOut}} = \delta_4 \quad (4)$$

in which *Cost* represents delivery cost; *Time* represents delivery time; *DTW* denotes delivery time window; *Rating* represents courier performance rating; *CO2* denotes CO_2 emission savings. Parameters β and δ are to be determined in the later steps.

Given the demand utility function, one can then calculate the probability at which an individual customer would choose for bicycle crowdshipping to deliver a package. The probability is given by Eq. (5) below.

$$M_{S_n} = \frac{e^{V_{\mathrm{CS}}}}{e^{V_{\mathrm{CS}}} + e^{V_{\mathrm{Trad}}} + e^{V_{\mathrm{OptOut}}}} \times 100\% \quad (5)$$

Similarly, the utility functions for the supply survey are shown in Eq. (6)–(8).

$$V_{\mathrm{Deliv1}} = \delta_5 + \beta_7 TOD_{\mathrm{Deliv1}} TT_{\mathrm{Deliv1}} + \beta_8 TT_{\mathrm{Deliv1}} + \beta_9 Profit_{\mathrm{Deliv1}} + \beta_{10} Weight_{\mathrm{Deliv1}} + \beta_{11} \mathrm{CO2}_{\mathrm{Deliv1}} \quad (6)$$

$$V_{\mathrm{Deliv2}} = \delta_6 + \beta_7 TOD_{\mathrm{Deliv2}} TT_{\mathrm{Deliv2}} + \beta_8 TT_{\mathrm{Deliv2}} + \beta_9 Profit_{\mathrm{Deliv2}} + \beta_{10} Weight_{\mathrm{Deliv2}} + \beta_{11} \mathrm{CO2}_{\mathrm{Deliv2}} \quad (7)$$

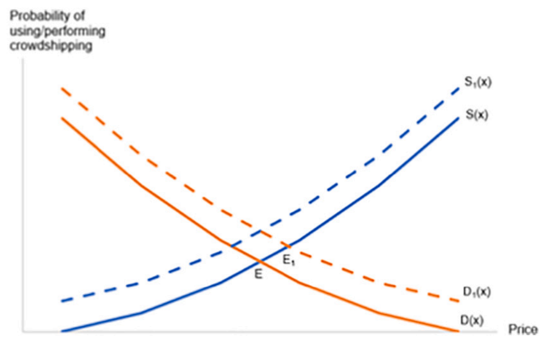


Fig. 3. An illustration of supply-demand relationship.

$$V_{\text{OptOut}} = \delta_7 \tag{8}$$

in which *TOD* represents time of day; *TT* represents additional travel time for performing delivery; *Profit* denotes courier's monetary compensation (in this study Profit is assumed to be a fixed fraction of the service cost); *Weight* represents package weight; *CO2* denotes CO_2 emission savings. Note that the additional travel time may be perceived differently by crowdshippers according to the time of day element. With this taken into consideration, we use *TOD* as one of the coefficients of *TT*.

Given the supply utility function, one can then calculate the probability at which an individual commuter would accept a delivery job. The probability function can be described in Eq. (9) below.

$$P_{S_n} = \frac{e^{V_{\text{Deliv}}}}{e^{V_{\text{Deliv}}} + e^{V_{\text{OptOut}}}} \times 100\% \tag{9}$$

3.4. Market share estimation

The derivation of the market penetration level of bicycle crowdshipping is grounded upon the assumption from economics that the parcel delivery market reaches equilibrium level at a certain price when demand of the service equals its supply (roughly illustrated in Fig. 3): the probability of a cyclist to act as a crowdshipper is defined as $S(x)$; the probability of a customer choosing crowdshipping service as the delivery option is $D(x)$. The two probabilities are related with the price. When the two sides reach an equilibrium (point E), the delivery commences. If a change of one of the attributes takes place (e.g., on the demand side), the probability is then changed to $D_1(x)$, resulting in a new equilibrium (point E_1).

We define the total amount of parcels to be shipped as the demand for bicycle crowdshipping, and the amount of bicycle commuting trips available to deliver the packages as the supply. When the supply and the demand reach an equilibrium state, we have Eq. (10). The left-hand-side represents the amount of parcels n to be delivered to the online shoppers multiplied by the market share $\widehat{M}_s$ of bicycle crowdshipping. The right-hand-side is the available service, consisting of a multiplication of the average probability that a cyclist would perform a delivery $\widehat{P}_s$, number of bicycle commuting trips c in the respective area, and productivity per courier μ which denotes the number of packages that can be dropped in one place. In this study we assume $\mu = 1$. Note that the parameters $\widehat{M}_s$ and $\widehat{P}_s$ are the aggregated form of individual probability to choose/perform crowdshipping (i.e. $\widehat{M}_{s_n}$ and $\widehat{P}_{s_n}$). By solving the equilibrium price level (in which Eq. (10) is fulfilled), one can obtain the market share of bicycle crowdshipping.

$$\widehat{M}_s n = \widehat{P}_s c\mu \tag{10}$$

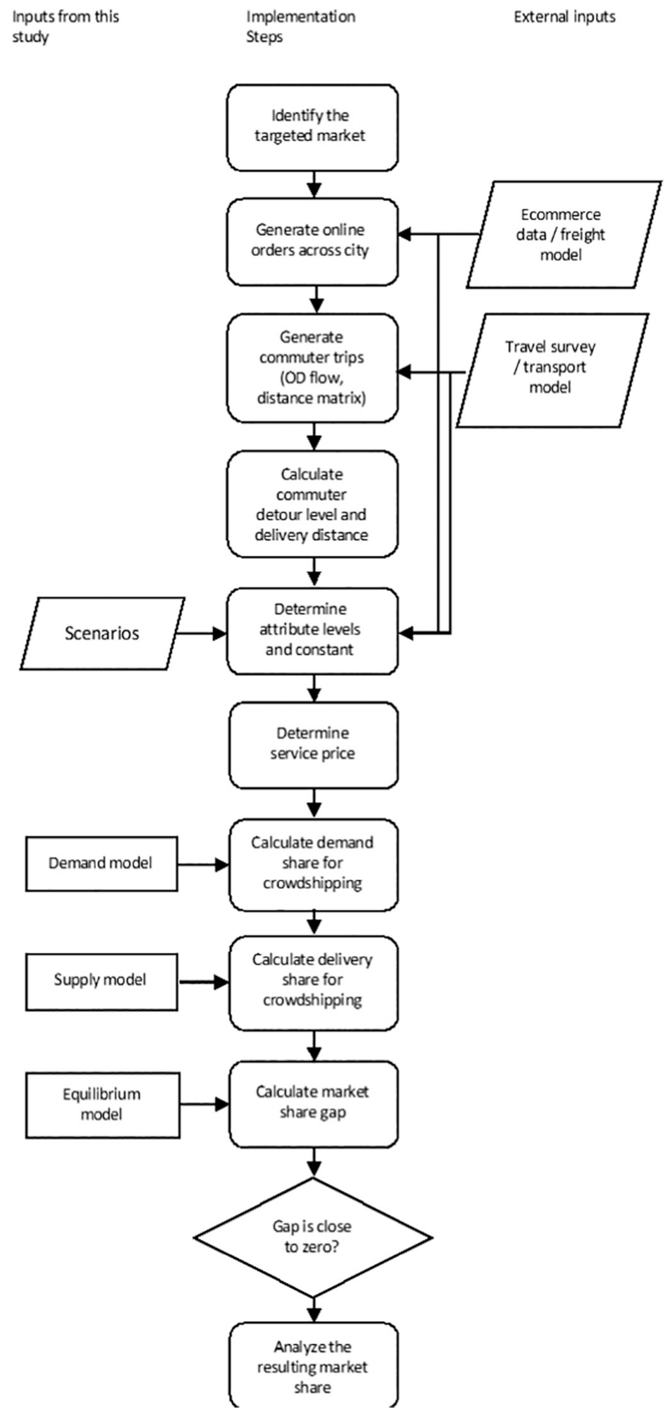


Fig. 4. Steps to implement the market share estimation model.

3.4.1. Model implementation

Fig. 4 shows the process flow to implement the market share estimation. The first step is to identify the market segment to be served by the crowdshipping service. This selection determines the number of orders to be delivered (n). Next, the orders are distributed among the city population. The distribution can be proportional to household numbers or inhabitants for each neighborhood. Subsequently, the commuting trip dataset needs to be obtained. This includes number of trips per OD and the corresponding distance matrix. Possible data sources are travel surveys. In this step, the number of bike trips c is obtained. The following stages are to calculate the extent of detours per OD and delivery distance between pickup points and delivery

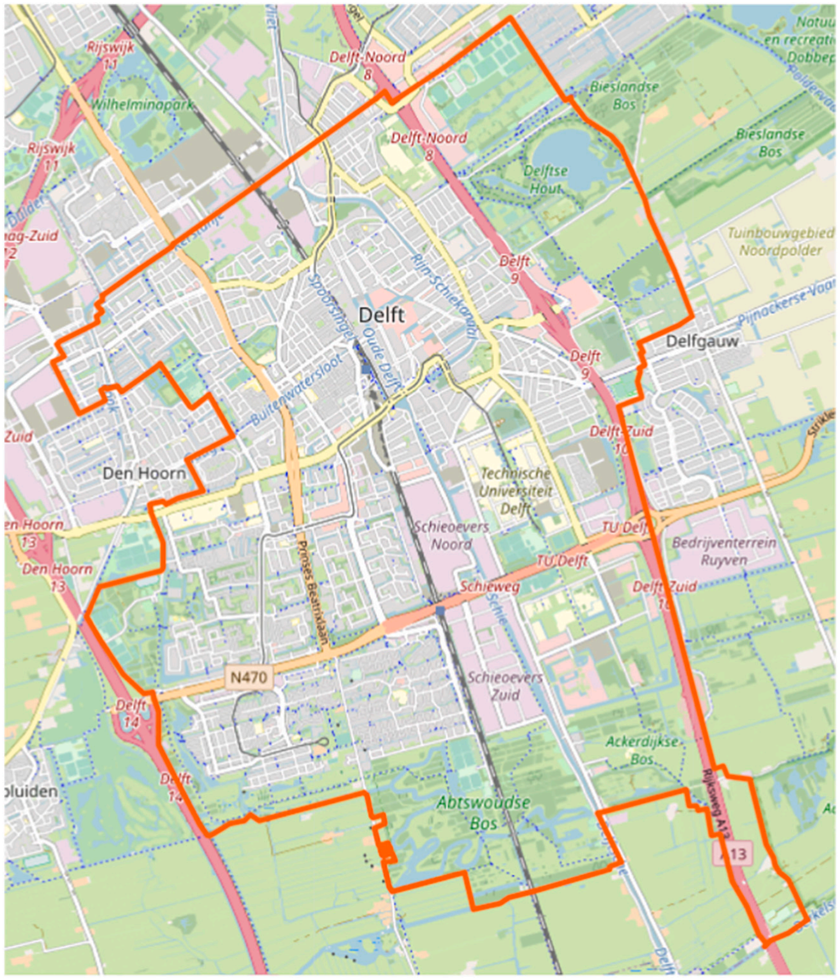


Fig. 5. City of Delft (city boundaries highlighted in red, source: OpenStreetMap). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

destination. The latter is used to calculate the CO_2 emission saved per customer. After attribute levels and constants are determined, scenarios can be developed by varying the input parameters. For instance, the model can be used to identify the impact of price change in competing options (i.e., traditional shipping) on bicycle crowdshipping market share, or the effect of increasing number of cyclist commuters on the market share. Once the service price is determined, demand and supply share of crowdshipping can be calculated. The market is in equilibrium state when the demand and the supply converge.

4. Case study: Delft

We applied the model for the city of Delft, The Netherlands (see Fig. 5 for a map). With an area of about 24 km^2 and a population of 100,000, Delft is a city where people commute internally mostly by bicycle. The experiment design software Ngene was used to generate a suitable design for the experiment. The BIOGEME software was utilized (Bierlaire, 2003) to estimate the models. Subsequently, bike trip data from the city was used to evaluate the potential market share of this form of crowdshipping.

4.1. Sample description

The stated choice survey was launched through online media. We sourced responses for demand and supply survey from different pools of respondents in order to reduce the chances of the same person answering two surveys. For the demand survey, the targeted survey distribution channels included Facebook pages of the TU Delft student community and email addresses of TU Delft employees and students. The supply survey was distributed to the members of the Dutch Cycling Embassy LinkedIn group.

In total 330 responses were gathered for the demand survey while for the supply survey 141 responses were collected. Surveys with unusually short completion time, incomplete and duplicated responses were removed from the datasets. Checks resulted in 319 usable responses for the demand survey and 136 usable responses for the supply survey.

Table 5 displays the sociodemographic properties of the respondents from both surveys. The higher percentage of university students on the sample explains the over-representation of single-household type, young-aged persons, and highly educated persons. In the demand survey, bicycles account for 85% of the transport modes for commuting (either as main or access/egress mode), which is higher by 25% than the estimation of the Statistics Netherlands (Centraal Bureau voor de Statistiek, 2016). Noticeable differences with Dutch statistics imply that the result of the study should be used with caution if one would like to transfer the model to a different geographic area. Respondents of the survey were avid online shoppers, around 70% of them shop online more than once a month. It is also noticeable that home delivery remained the most favored delivery destination, which is aligned with the data from previous surveys in which 74% of the consumers preferred home delivery (Statista, 2015).

Table 5
Statistics of surveyed samples.

Gender	Demand	Supply	CBS
Female	41.4%	37.4%	49.6%
Male	58.6%	62.6%	50.4%
Household type			
Family with children	20.0%	18.3%	29.4%
Two-person	15.4%	29.0%	32.6%
Living alone	65.2%	53.0%	38.0%
Age			
>64	0.3%	1.5%	18.5%
55–64	0.6%	3.8%	13.2%
45–54	1.3%	11.5%	15.0%
35–44	3.8%	14.5%	12.2%
25–34	31.3%	42.7%	12.4%
18–24	62.7%	25.2%	12.3%
Education			
Bachelor	46%	40%	18.20%
Master	18%	44%	10.50%
PhD	4%	8%	0%
Secondary	32%	8%	38.50%
Commuting mode			
Bike	48.0%	–	–
Bike + Public Transport	37.0%	–	–
Car	4.1%	–	–
Car + Public Transport	2.2%	–	–
Public Transport	5.3%	–	–
Walking	3.4%	–	–
E-shopping frequency			
Less than once a month	30.1%	–	–
Once a month	43.3%	–	–
2–4 times a month	21.0%	–	–
> 4 times a month	5.6%	–	–
Delivery location preference			
Home	75.2%	–	–
Office/School	1.9%	–	–
Pickup point	22.9%	–	–

Table 6
Parameters estimation output for demand model[a]

Attribute	Coefficient	Value	Robust *p*-value	Relative importance score
Constant CS Choice 1	δ_1	0	–	–
Constant CS Choice 2	δ_2	0	–	–
Constant TS	δ_3	−0.888	0.01	–
Optout	δ_4	−2.56	0	–
Cost	β_1	−0.506	0	3.036
CS Time	β_2	−0.124	0	0.744
Delivery Time Window	β_3	1.16	0	1.160
Rating	β_4	0.137	0.04	0.137
CO_2 Emission	β_5	0.507	0	0.608
TS Time	β_6	−0.0352	0.02	0.315

[a] Relative importance score = value range × coefficient value, CS = Crowdshipping, TS = Traditional Shipping.

4.2. Estimated attribute coefficient

4.2.1. Demand attribute coefficients

As indicated in Table 6, the estimation results revealed that all the selected demand parameters exert a significant effect on crowdshipping choices at a 95% confidence level. The signs of the parameters are aligned with our expectations. CO_2 reduction positively influences the attractiveness of the crowdshipping option. This result reinforces the arguments that consumers are getting more environmentally conscious. The same pattern applies for the delivery time window. People respond positively when there is an option to adjust the delivery time. Coefficients associated with the cost and the delivery time have negative signs, which is intuitive: an increased value in cost or time would reduce delivery satisfaction.

Table 7
Willingness to pay marginal value per demand attribute.

Willingness to pay for	Value	Unit
Increased delivery time in crowdshipping	0.25	Euro/h
	6	Euro/day
Adjustable delivery time window	2.29	Euro
CO2 emission reduction	1	Euro/kg
Performance rating improvement	0.27	Euro/star rating
Increased delivery time in traditional shipping	0.07	Euro/h
	1.68	Euro/day

Table 8
Parameters estimation output for supply model[a]

Attribute	Coefficient	Value	Robust p-value	Relative importance score
Constant D1	δ_5	0	–	–
Constant D2	δ_6	0	–	–
Optout	δ_7	−0.888	0.01	–
Travel Time	β_8	−0.506	0	1.15
Profit	β_9	−0.124	0	1.01
Weight	β_{10}	1.16	0	1.08

[a] Relative importance score = value range × coefficient value, D1 = Delivery Option 1, D2 = Delivery Option 2.

Another interesting finding is that the performance rating turns out to have only a slight influence on the propensity to use crowdshipping. Concerns about trust apparently are not strongly evident among the respondents. This would make sense given the communicated choice context: it was stipulated that all couriers had undergone a background check and the package is covered by insurance in case of any misconducts. Moreover, the lowest rating of courier was 4 stars out of 5, implying that from this point upwards customer's sensitivity towards performance rating improvement could be minimal.

Multiplying the resulted parameter coefficient by attribute value ranges (the difference between highest and lowest value in attribute level) would give us the relative importance of the attributes. Delivery cost appears as the most important demand attribute (score: 3.036), followed by adjustable delivery time window (score: 1.160), delivery time (score: 0.744), CO_2 emission savings (score: 0.608), and performance rating (score: 0.137).

Table 7 indicates that a day of delivery time saved is worth to be paid as much as 6 euros. This number is lower than the finding of previous research in (Punel & Stathopoulos, 2017) that obtained USD 41 (33 euros) worth for a day of delivery time saved, yet 6 euros seems to be more reasonable from a practical sense. However, one should notice that baseline parcel shipment price in US market could be different with that of The Netherlands.

4.2.2. Supply attribute coefficients

Initial parameter estimation resulted in 4 (out of 7) attributes being significant at 95% confidence level. The three non-significant parameters (p-value >0.05) include CO_2 emission reduction, time of day, and the alternative specific constant for bicycle crowdshipping. The final model excluded these insignificant parameters and the likelihood ratio test concluded that the model after the parameter reduction is not statistically worse that the initial model. The resulting parameters are displayed in Table 8. The sign of all the final parameters seems intuitively correct. The coefficient linked to the profit is found to have

Table 9
Willingness to work marginal values per supply attribute.

Willingness to work for:	Value	Unit
Additional travel time	0.39	Euro/min
Package weight	1.00	Euro/kg

positive influence on the willingness to work as crowdshippers. As expected, an increased additional travel time or package weight can reduce crowdshippers' motivation to work in crowdshipping.

When it comes to the relative attribute importance, the additional travel time has the highest importance score (score: 1.15), followed by the package weight (score: 1.08) and the profit (score: 1.01). Only slight differences are observed in importance scores between the three attributes, suggesting that cyclist commuters hold relatively comparable utility valuations with respect to those parameters.

Willingness to work (WTW) represents the profit or compensation level under which commuters would be willing to have higher travel time to perform delivery jobs. Unlike the conventional value of time (VoT) measurement, in which the trade-off between time and cost is analyzed, WTW examines the trading of time for profit (Miller et al., 2017). Table 9 shows WTW based on the job attribute values. For every minute increased in travel time, a bicycle crowdshipper would need a compensation of 39 cents, mounting up to 24 euros per hour increase in travel time. The value is higher than the Dutch commuting VoT of 10.12 euros/h. (KiM Netherlands Institute for Transport Policy Analysis, 2016) and the WTW obtained from a previous study (19.6 euros/h.) (Miller et al., 2017). The relative difference between VoT and WTW supports prior findings that people would generally like to gain more than they spend (Miller et al., 2017). The noticeable gap between WTW of this study and WTW from a car-based survey (Miller et al., 2017) indicates that cyclist commuters have more aversion towards travel detours than car commuters.

4.3. Application of the market share model

Market shares were estimated applying the flow chart in Fig. 6. The majority of the respondents being residents of Delft, data consistency relating to the survey could be obtained and bias could be minimized. The city area was divided into several zones according to four-digit postal codes. In this way, all the commuting trips as well as the delivery demand was defined based on the same postcodes.

Following the sketched approach, firstly the market scope of parcel delivery was determined. In our case this implied that all types of products purchased via online shops and delivered either via stores or pickup points could be served by bicycle crowdshipping. It was assumed that 85% of the packages fit the carrying capacity (volume and size) of a normal bicycle (Guglielmo, 2013). Next, online order data was gathered. For this study, data from various sources was combined to calculate the number of parcels to be delivered in each zone. The average number of parcels per online population at the country level was used to give delivery demand per zone. The step is indicated in Fig. 6.

Following the order generation step, commuting trips of cyclists were estimated. GPS trips data from the Fietstelweek survey (http://fietstelweek.nl/data/resultaten/) was translated into an OD matrix of cyclists, based on the Delft postcodes (Fig. 7). Trips originating from or

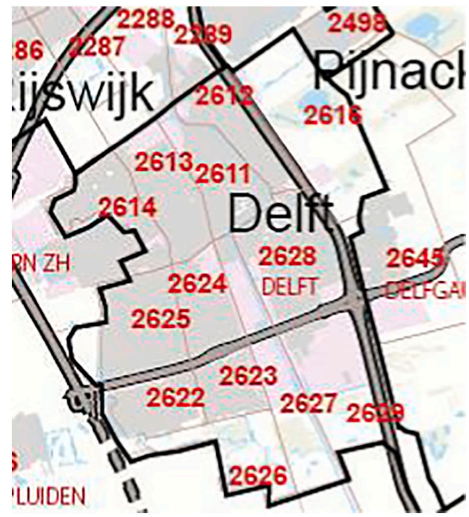


Fig. 7. Postcode map of Delft (www.reclamedienstverspreidingen.nl).

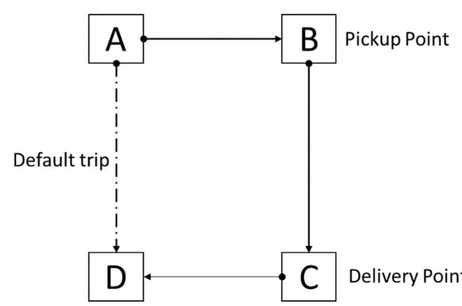


Fig. 8. Detour illustration.

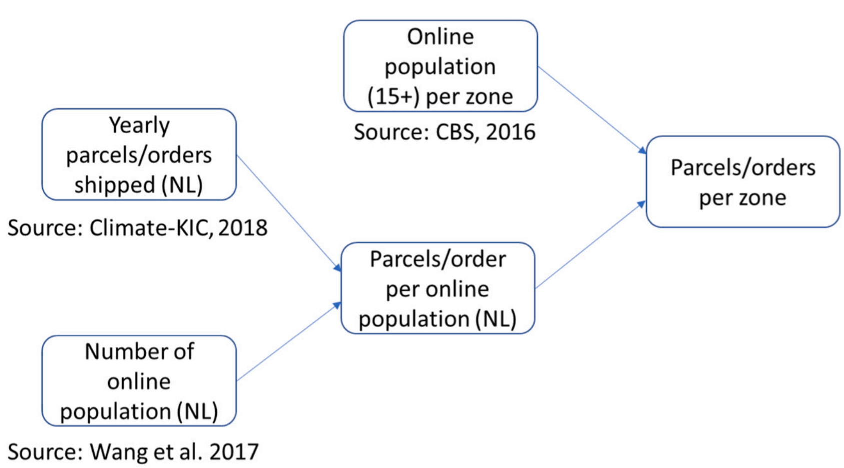


Fig. 6. Steps to generate deliveries demand per zone.

	2611	2612	2613	2614	2616	2622	2623	2624	2625	2626	2627	2628	2629
2611	1.45	0.00	1.42	1.38	0.07	1.37	1.25	1.32	1.42	1.22	1.14	0.88	0.96
2612	1.45	1.45	1.45	1.45	1.45	1.45	1.45	1.45	1.45	1.45	1.45	1.45	1.45
2613	1.45	0.03	3.10	3.05	0.08	2.65	2.25	2.38	2.83	2.22	1.95	1.27	1.56
2614	1.45	0.07	3.09	4.59	0.09	3.46	2.77	2.83	3.73	2.79	2.32	1.34	1.82
2616	1.45	1.38	1.42	1.40	3.15	1.76	1.94	1.78	1.63	2.01	2.08	2.24	2.34
2622	1.45	0.08	2.70	3.47	0.46	8.79	6.95	5.34	6.82	7.67	6.01	3.16	5.43
2623	1.45	0.20	2.42	2.90	0.77	7.07	7.68	5.36	5.81	7.65	6.74	3.66	6.13
2624	1.45	0.13	2.47	2.89	0.54	5.39	5.29	5.42	5.07	5.26	4.90	3.10	4.32
2625	1.45	0.03	2.82	3.69	0.28	6.77	5.63	4.97	7.04	5.87	4.85	2.66	4.18
2626	1.45	0.23	2.42	2.95	0.86	7.81	7.67	5.36	6.07	9.69	7.11	3.81	7.03
2627	1.45	0.31	2.23	2.57	1.02	6.24	6.85	5.08	5.14	7.20	7.29	3.98	6.61
2628	1.45	0.57	1.80	1.84	1.43	3.65	4.02	3.54	3.20	4.15	4.24	4.40	4.40
2629	1.45	0.50	2.03	2.24	1.46	5.85	6.42	4.69	4.65	7.30	6.80	4.33	8.45

Fig. 9. Additional distance matrix (km) to perform a delivery in Zone 2612.

Table 10
Scenarios for demand elasticity test.

Scenario	Parameter values			
	$Time_{CS}$	DTW_{CS}	$Rating_{CS}$	$CO2_{CS}$
Default	8	0	0	1
Adjustable DTW	8	1	0	1
5-star rating	8	0	1	1

heading to areas outside Delft were excluded. We assumed one parcel pickup location in zone 2611, the city center area, where most of the stores, supermarkets, restaurants, and residents are concentrated.

The next step was to estimate the potential detour if a commuter delivers a package. Some simplifications were introduced. Firstly, the delivery trip was divided into three legs as indicated in Fig. 8. From the original trip (A to D), the cyclist would take a detour through point B (pickup point) and C (delivery point) before ending the commuting trip in the destination D. Secondly, the distance between OD-pair was calculated based on great-circle distance between zone centroids. Centroids are defined by selecting arbitrary points around the centers of the postcode areas.

For every OD-pair, the total detour distance was calculated for all possible delivery zones, as shown in an example in Fig. 9. Finally, the market equilibrium model could be solved for every OD-pair.

4.4. Elasticity analysis

In order to obtain system-level insights into behavior, an elasticity analysis was performed for each demand and supply market share model. Elasticities were calculated by changing the value of a variable while holding the other variables constant. For each model, the assumption of the baseline situation (the variables held constant) was defined beforehand, aiming to resemble the "average" situation in a real case. Since service price (profit) links the supply and the demand sides, we measure price elasticity.

4.4.1. Demand elasticity with respect to price

Before conducting the elasticity analysis, parameter values were defined. As to the traditional delivery, all its attributes were set to constant. The shipping price was set as 4 euros for a next day delivery service, with an assumed lead time of 30 h. Delivery time windows were set as non-adjustable. For bicycle crowdshipping, the input variable is shipment cost, hence any attributes besides cost were fixed as well. The delivery time was assumed to be 8 h, while the CO_2 emission savings were set at 1 kg, assuming that the distance between the store/pickup point and customer is 3 km (Weltevreden, 2008). The detailed scenarios for the elasticity test are depicted in Table 10.

Fig. 10 shows the crowdshipping choice probability as a function of price. It can be seen that overall, the demand is quite sensitive to the price change. The difference between the default and 5-star rating scenario is subtle: the latter add merely around 3.5% probability gain at the

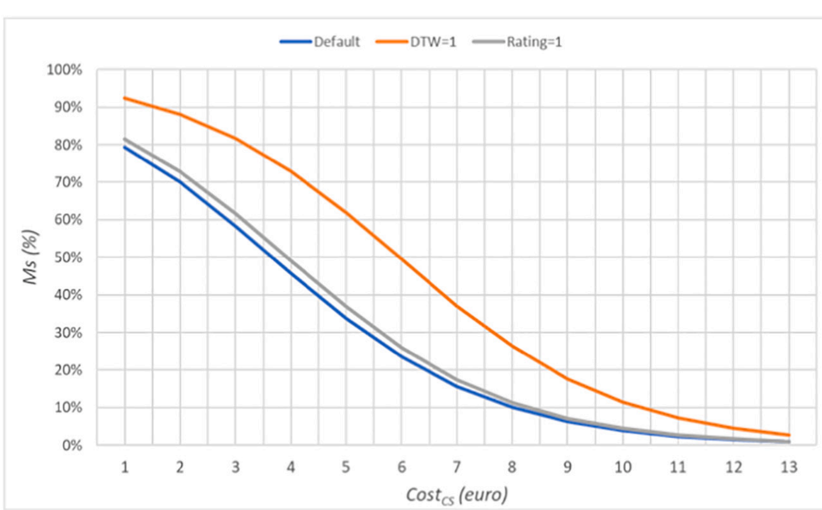


Fig. 10. Cost of crowdshipping affecting probability of service chosen by customers.

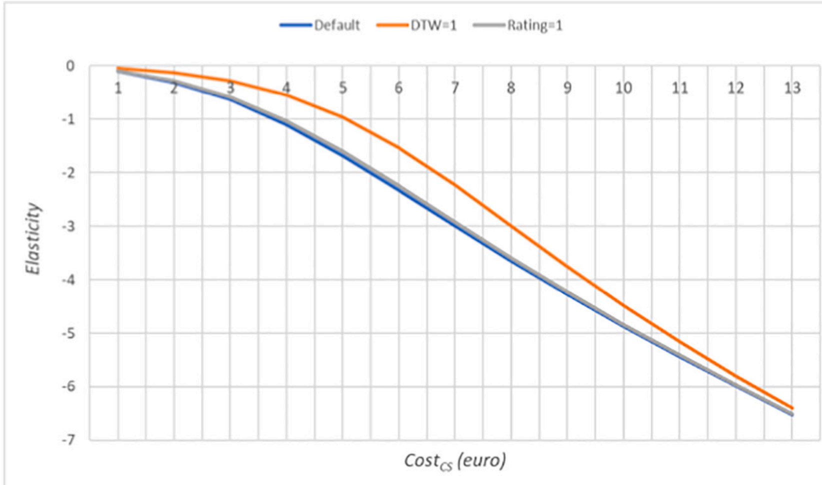


Fig. 11. Price vs elasticity.

Table 11
. Scenarios for supply elasticity test.

Scenario	Parameter values		
	Profit$_{Deliv}$	*TT*$_{Deliv}$	*Weight*$_{Deliv}$
Default	8	0	0
Adjustable DTW	8	1	0
5-star rating	8	0	1

greatest extent. It implies that imposing all 5-star couriers would not bring any considerable market gain. In contrast, the provision of adjustable delivery time windows leads to a substantial improvement in choice probability, with a maximum probability increase of roughly 28% compared to the default case. This indicates that the adjustable delivery time window is a strong feature that can attract customers to opt for crowdshipping.

In Fig. 11 we can recognize that crowdshipping choice probability is elastic to price from the demand side, as the elasticity always takes a value above 1. Scenarios with lower service levels (default scenario) are more elastic to price change. This means when the service level is higher, customers would be more indifferent towards price increases. Unit elasticity occurs at a price level of around 4 euros for the default and 5-star scenario and at a price level of 5 euros for the adjustable DTW scenario. Customers would show less concern for any price decrease below this point.

4.4.2. *Supply elasticity with respect to profit*

For the supply elasticity analysis, three scenarios were made, with additional travel time as the parameter varied between scenarios. The package weight is assumed to be 3 kg, which characterizes the majority of e-commerce parcel, following the information from (Guglielmo, 2013). The scenario setup can be seen in Table 11.

Unlike the demand function, the supply probability is less sensitive to profit, which is characterized by a flatter curve as shown in Fig. 12. This fact might be associated with less emphasis on profit from the supply survey (as can be referred to its relative importance score). Nonetheless, there is a pattern that sensitivity towards profit (steeper line) is more evident for a lower price range. Additional travel time has indeed a noticeable effect towards the market gain. For every additional 5 min in travel time, there is a maximum decrease of around 10% in choice probability. This choice probability gap narrows down as the profit increases.

The acceptance from the supply side is somewhat less elastic to profit (price) change compared to the demand side. Fig. 13 indicates that the elasticity value is never higher than 1 throughout the curves. As a result,

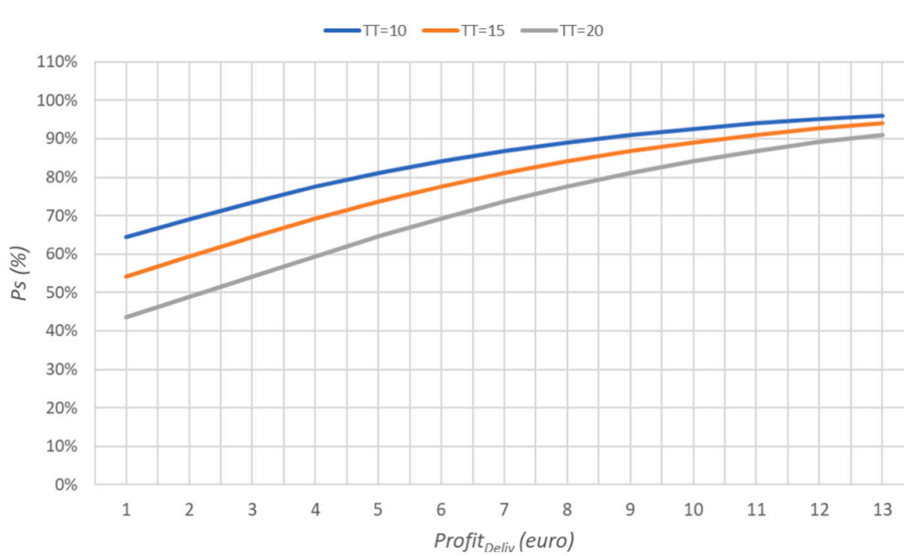


Fig. 12. Profit of crowdshipping affecting probability of working as crowdshipper.

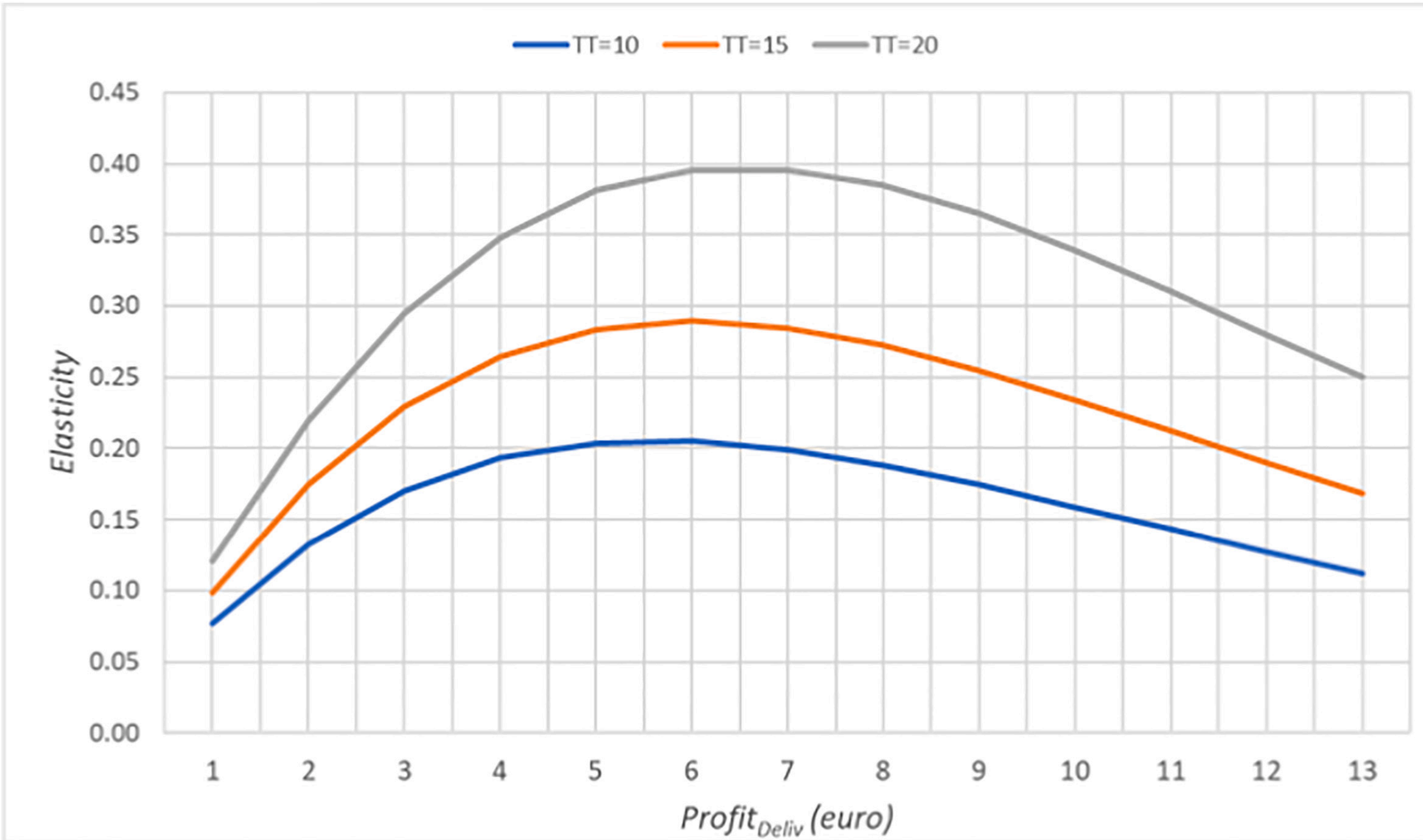


Fig. 13. Profit vs elasticity.

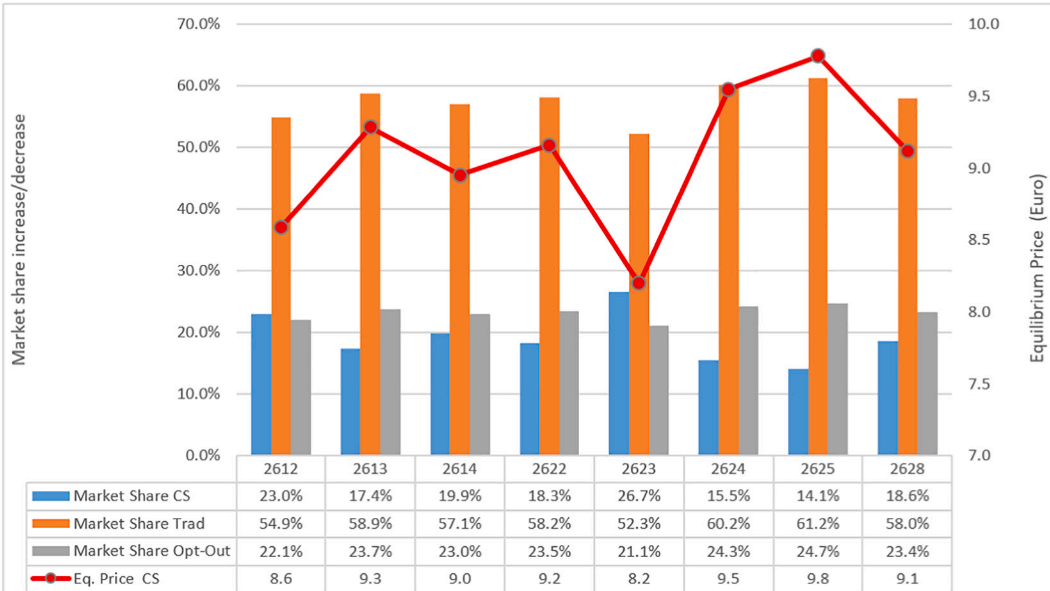


Fig. 14. Market share when α = 0.5%.

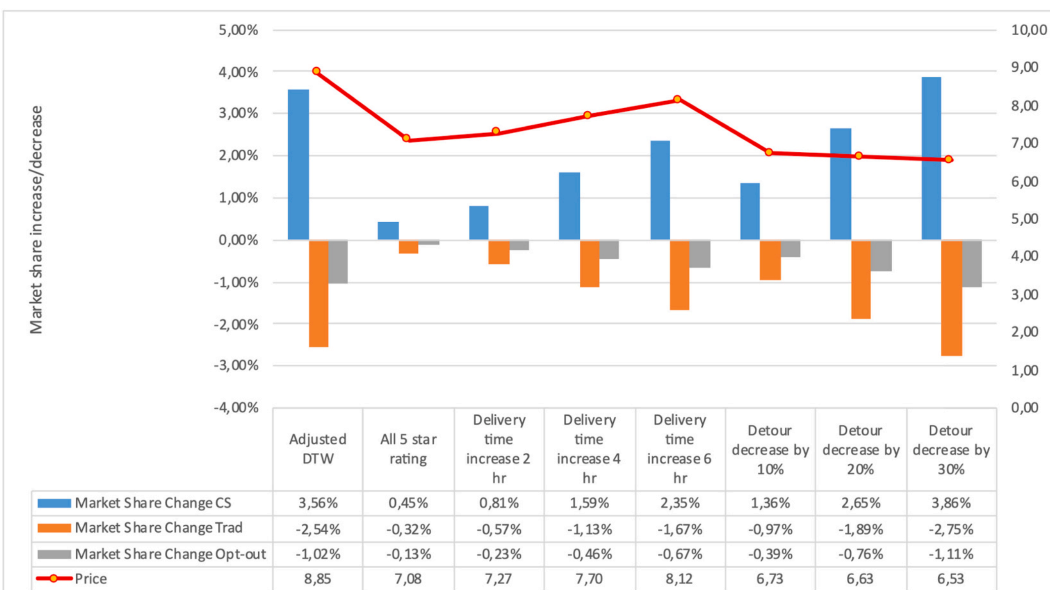


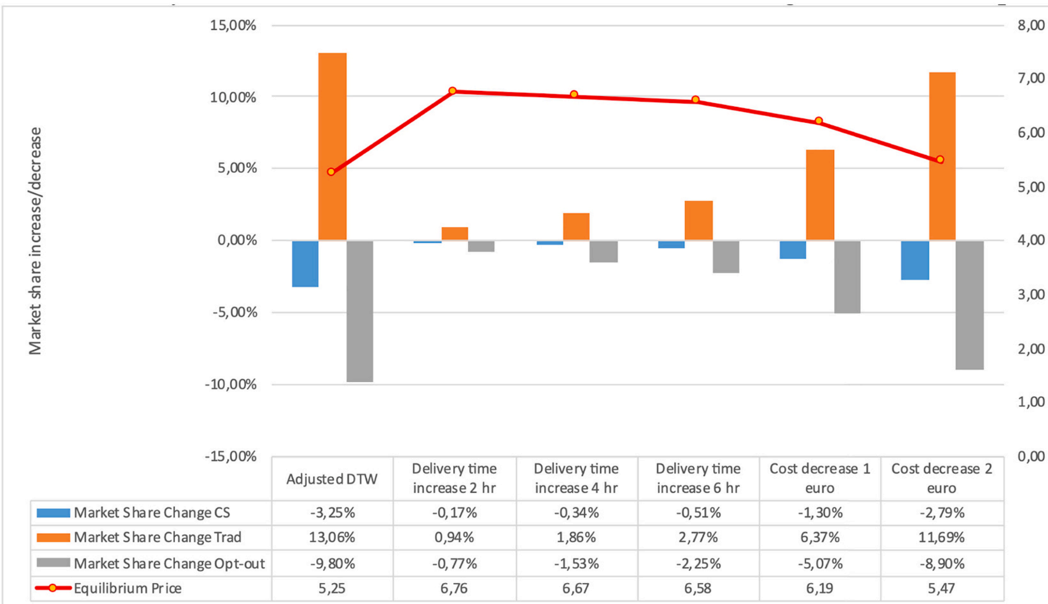
Fig. 15. Market share sensitivity against change in bicycle crowdshipping service level.

one should not expect a massive gain in delivery probability share by adjusting the profit level. Such condition is acceptable given that cyclists perceive delivery jobs to be performed as a voluntary decision (i.e. when there is no interesting offer, they could easily discard the jobs). Interestingly, the acceptance would be higher than 30% even if the profit approaches zero. This might be attributed to altruistic motivations of cyclists that have not been explicitly discussed in this study. The overall elasticity towards profit tends to increase when the travel time is longer. A practical implication is that when the additional travel time could be lowered, reducing the profit would not cause as much effect as if it is imposed when the additional travel time is higher.

4.5. Market share evaluation

Solving the market share for each individual delivery zone results in imbalance between the supply and the demand across zones. Therefore, we incorporate a membership rate α to represent the percentage of cyclist registered as a crowdshipping member. It serves as a multiplier to the number of trips made. The value of membership rate is assumed to be comparable with ridesharing industry, which is less than 2% (PYMNTS, 2018; Statista, 2020). As such, three arbitrary values of membership rate are chosen for the analysis: 0.5%, 1%, and 1.5%.

From the result, a general pattern appears: the extent of market share is higher when more commuters are registered as member in the crowdshipping platform. Moreover, the equilibrium price level tends to decrease along with the increased membership rate, because of a higher availability of crowdshippers. For 0.5% membership rate (see Fig. 14), equilibrium prices range between 7.2 and 9 euros. For the remaining scenarios (1% and 1.5%) the equilibrium price varies respectively from 5.1 to 7.3 euros and 2.9 to 6.1 euros. It is also noticeable that zones with a closer distance to the pickup point have a higher market share. Within 0.5% membership rate, bicycle crowdshipping market share ranges from



	Adjusted DTW	Delivery time increase 2 hr	Delivery time increase 4 hr	Delivery time increase 6 hr	Cost decrease 1 euro	Cost decrease 2 euro
Market Share Change CS	-3,25%	-0,17%	-0,34%	-0,51%	-1,30%	-2,79%
Market Share Change Trad	13,06%	0,94%	1,86%	2,77%	6,37%	11,69%
Market Share Change Opt-out	-9,80%	-0,77%	-1,53%	-2,25%	-5,07%	-8,90%
Equilibrium Price	5,25	6,76	6,67	6,58	6,19	5,47

Fig. 16. Market share sensitivity against change in traditional shipping service level.

14.1% to 26.7% in various zones. As for 1% and 1.5% membership rates, the market share ranges between 26% to 47.1% and 36.7% to 63.6%, respectively. Nevertheless, the resulting figures are quite dependent on the study case. Therefore, it is wiser to focus on the pattern that represents the market properties resulting from the experiments, instead of on single zones.

Fig. 15 suggests that altering the service attributes of bicycle crowdshipping would generate a modest impact on its market share. The most impacting service attribute change is an adjustable delivery time window, which gives a 3.6% raise of market share. Similarly, changing job attributes by reducing the detour travel time (30% reduction) would increase the market share by 3.9%. It is also apparent that bicycle crowdshipping mainly competes with traditional shipping. From the scale of changes in share, we can conclude that the bicycle crowdshipping market share is not that sensitive towards improvements of the service and of job attributes. This brings an interesting insight. On the demand side, one would expect a leap of around 10% in demand share when offering an adjustable delivery time window. However, in practice, the crowdshipping market is also reliant on the supply side. As shown earlier, the supply side of crowdshipping is less elastic than the demand side. This indicates that crowdshipping platforms may find it more challenging to attract crowdshippers than attracting customers.

Fig. 16 suggests that changing the service attributes of traditional shipping brings a significant impact to its market share: the positive change ranges from 1% up to 13%. Adjustable delivery time windows and cost reductions turn out to give the most impact.

The opt-out alternative could be the most impacted option, which is apparent from its huge reduction in share. On the other hand, the market share of bicycle crowdshipping is also moderately impacted. Stronger improvements in traditional shipping market share could be linked to the fact that traditional shipping is not as strictly limited by its supply of couriers as bicycle crowdshipping. More flexibility in the supply side implies higher market sensitivity towards changes in service attributes. Another finding is that bicycle crowdshipping can adjust its price level as a response of the attribute change of traditional shipping. It indicates that to be competitive, bicycle crowdshipping should be responsive to the market dynamics.

5. Conclusions

Crowdshipping has been gaining ground as innovation in the field of urban logistics due to its potential with regards to sustainability, flexibility and affordability. This paper quantifies the interactions between the supply and the demand factors in crowdshipping markets, comparing it to traditional delivery options. Ultimately, we investigate the market potential of bicycle crowdshipping by conducting a simultaneous examination of crowdshipping supply and demand acceptance. A case study was carried out for a city in the Netherlands. Crowdshipping platforms can use this insight to develop their business models and adjust their management strategies with the consideration of both the demand and the supply side.

Two stated choice surveys were conducted to investigate (1) the acceptance of customers to use crowdshipping services and (2) the willingness of commuters to work as potential couriers. Analysis shows that delivery cost, adjustable delivery time windows and CO_2 emission reduction are influencing customer preferences towards bicycle crowdshipping. With regards to the supply side, the study finds that additional travel time, profit, and package weight can significantly influence the propensity to perform crowdshipping jobs. Cyclists weigh these three job attributes similarly. Analysis also shows that the demand side of crowdshipping is highly sensitive to price changes. In contrast, the supply side is rather less sensitive and less elastic towards change in profit. Such a finding implies that crowdshipping platforms should find it more challenging to attract a supply of couriers than to attract potential customers using monetary gains as the sole stimulator. Therefore, to stimulate and build up the supply side community separately would be essential for a platform. An example to increase the attractiveness from the supply side could be improving task assignment, routing efficiency and courier productivity.

The study presents a market equilibrium model that combines the supply and the demand aspects in crowdshipping to identify its market share and equilibrium price. Implementation steps are formulated to aid crowdshipping platforms in using the market share model. A case study carried out in city of Delft concludes that with 0.5% of membership rate, bicycle crowdshipping could attain as much as 14–26% in market share. Improvement in the membership rate would lead to increased market share and reduced delivery price. The provision of adjustable delivery time window is found to be the most impacting service attributes, by contributing around 3.5% increase in the crowdshipping market share. Service level improvements in traditional shipping would moderately affect the market share of crowdshipping.

One limitation of the study is that the survey samples are specific for the case study, characterizing the university city of Delft, however still deviating from the country level average population. As a result, our sample over-represents the young-aged in the lower-income group. When applying this method to other regions, differences in socio-demographic properties should be considered. As an additional point, the research did not consider delivery scheduling and routing. The detour for delivering a package was modelled in a simplified way using distances in an OD chart; including a transport network with more details at the operational level may provide more practicable results. Incorporating the model into an agent-based simulation could be an interesting option for future research. Another direction of research is to study advanced pricing concepts in the market share model from an economical perspective.

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