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Research paper

Feasibility of crowdshipping for outlier parcels in last-mile delivery

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ABSTRACT

As the rapid growth of urban e-commerce increases the volume of last-mile deliveries, logistics service providers have difficulty in meeting the demand of on-demand consumer requests. This increase in demand challenges traditional delivery, with some parcels becoming disproportionately costly to deliver to their destinations. To address this, we introduce a cost-based outlier parcel selection mechanism that identifies parcels with a high negative impact on the marginal delivery costs. These outlier parcels are then eliminated from their tours and outsourced to a crowdshipping market, where individuals combine the delivery task with their already planned trips. We use unique data on delivery tours of six service providers for the province of South Holland in the Netherlands. The cost-based decision rule for identifying outlier parcels results in a low proportion of outsourcing to the crowdshipping market compared to earlier literature. We identify only about 1 % of the total parcel demand as outliers across all carriers combined. Of these outlier parcels, the proportion selected for crowdshipping based on their cost efficiency ranges from 42.78 % to 3 %, depending on the scenario. While crowdshipping provides a viable solution for handling a small portion of last-mile deliveries, its environmental and economic sustainability is restricted by factors such as compensation rates and the delivery mode used. This study demonstrates that outsourcing high-cost outlier parcels to crowdshipping can be cost-efficient and reduce emissions of last-mile logistics companies; however, the proportion of these parcels is very small, limiting the overall impact on sustainability.

1. Introduction

Logistics service providers (LSPs) offering parcel delivery services have a wide variety of parcels to process and understanding which deliveries might cause monetary loss is important. Usually, these deliveries will require long driving distances, and the marginal costs will not weigh up against the revenues. Such outlier parcels will be considered for outsourcing to other service providers, to keep losses low (Qi et al., 2018). Unlike traditional delivery services which require dedicated routes and vehicles, crowdshipping (CS) relies on private individuals who are already making trips for personal reasons and are willing to deliver parcels in exchange for compensation (Buldeo Rai et al., 2017; Le & Ukkusuri, 2019). Hence, CS presents a potential flexible market that could partly absorb the volume of parcels that may be inefficient for professional couriers. CS platforms connect LSPs to private individuals which act as occasional carriers, offering the opportunity to sign up to deliver packages on a part-time or gig basis (Shen, 2022). We adopt a definition of CS, referring to the outsourcing of last-mile deliveries to non-professional couriers, i.e. occasional carriers who include parcel delivery in their existing or planned trips. These individuals act as occasional carriers, offering the opportunity to deliver packages on a part-time or gig basis.

The investigation of how CS fits into the broader landscape of urban logistics is necessary to understand its potential synergies or conflicts with other delivery modes, and eventually its system level impact on flows, costs and sustainability. Business models of CS are diverse, such as peer-to-peer model (Le et al., 2019; Stathopoulos et al., 2011), retailer-oriented (Ciobotaru & Chankov, 2021; Gatta et al., 2018; Ni et al., 2019), reverse logistics (Pan et al., 2015), and outsourcing (Archetti et al., 2016; Le et al., 2019). In this study, our focus centres on

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parcel delivery being outsourced by courier companies to the CS market.

While some studies explore the effects of CS from the standpoint of couriers, the primary emphasis in these studies lies in optimising routes for the individual firm (Archetti et al., 2016; Li et al., 2014). These optimisation studies provide a detailed analysis at the company level but lack a network level perspective, considering multiple clients, carriers, and service types. To understand the volumes of demand for the CS market, insight is needed in how all LSPs together determine their outlier parcels, in line with their logistics costs-based reasoning in the construction of delivery tours. To our knowledge such research has not yet been undertaken.

Various studies have explored the role of CS as a potentially disruptive force in the delivery service landscape. Our study is concerned with the capacity of CS to absorb parcels outsourced by regular service providers. We have identified only one study into the exploration of optimal strategies for an LSP to select portion of its parcels for fulfilment via a CS platform, Zhang and Cheah (Zhang & Cheah, 2024), based on a pragmatic approach using a proportion of total parcel volumes depending on the location of destination zones. Our study addresses a similar issue as Zhang and Cheah (Zhang & Cheah, 2024), concerning outlier parcels, but takes an entirely different approach. While they identify outliers based on spatial location, we define them based on marginal delivery costs, shifting the focus from geography to economic costs. This aligns more closely with the economic considerations of LSPs. We contribute to the literature by (1) connecting outlier parcel decisions with the CS market to arrive at a realistic estimate of CS demand; (2) operationalising outlier parcel decisions from the cost-based logic of a carrier and (3) using detailed data on tours, grounded in observations of parcel deliveries of individual firms, to provide an estimate of potential CS demand volumes. Besides being an addition to the literature, the above can also be of practical value for LSPs and CS platforms.

To date, no study has analysed the potential demand for CS services in which an LSP would be willing to engage from a profit, or cost perspective. In this paper, we focus on the delivery cost of parcels from the perspective of LSPs and define outlier parcels as those that generate disproportionately high delivery costs for LSPs, making them suitable candidates for outsourcing to occasional carriers via CS.

On one side, outsourcing CS services for spatially dispersed delivery destinations could be economically beneficial for a courier due to their higher delivery cost. On the other side, certain delivery trips might lead to higher costs for the courier due to lower truck loads on particular routes. Additionally, some tours in a courier's delivery plan could result in higher CO_2 emissions, a concern that might be mitigated by outsourcing specific delivery tasks to occasional carriers.

Hence, this study explores the influence of a cost-based decision rule on parcel segregation from the LSP's perspective, employing a simulation approach. We contribute to the literature by (1) connecting outlier parcel decisions with the CS market to arrive at a realistic estimate of CS demand; (2) operationalising outlier parcel decisions from the cost-based logic of a carrier and (3) using detailed data on tours, grounded in observations of parcel deliveries of individual firms, to provide an estimate of CS demand characteristics. Besides an addition to the literature, the above is of practical value for business development managers of parcel shipping platforms.

In the following sections, we provide a brief literature review on CS (Section 2) to position our work in the literature and state our contributions. This is followed by the modelling methodology (Section 3). Section 4 describes the study area and data used. Results are discussed in Section 5. Finally, we present our conclusions in Section 6.

2. Literature review

The literature on CS is large and addresses various questions, including business models, behavioural mechanisms, optimisation of services, and the evaluation of impacts on last-mile logistics. Many studies examine the feasibility of CS, focusing on how delivery tasks and available occasional carriers are matched; in other words, how CS demand is fulfilled by occasional carriers.

The literature indicates that the business model of a CS service and its mode of use are among the factors that influence the service's sustainability (Carbone et al., 2017; Tapia et al., 2023). Boysen, Emde and Schwerdfeger (Boysen et al., 2022) generate deterministic instances of number of parcels and number of occasional carriers. Similarly, Mousavi, Bodur, Cevik, amd Roorda (Mousavi et al., 2024) design a dynamic programming to assess the feasibility of CS by using predefined number of orders and crowdshippers. Le, Ukkusuri, Xue, and Van Woensel (Le et al., 2021) also apply an optimisation approach to match parcels with occasional couriers with hypothetical instances. These studies explore the influence of factors, such as detour distance, compensation, and service levels on CS. However, they lack decision-making processes of wilingness to send and bring a parcel and the challenges of synchronising deliveries with existing travel patterns. In this research, we build on these foundations by using an activity-based model to match demand and supply, leveraging synthetic trip diaries. The activity-based model has previously been used on a smaller scale in other study (Tapia et al., 2023) in the CS context. Our research extends this application by covering a larger geographical area and using the cost-logic of LSPs, providing a more accurate account of the potential for CS in diverse urban environments.

While behavioural elements, such as willingness to send or deliver, have gained increasing attention in the CS literature, they are rarely integrated into system-level allocation or outsourcing frameworks. Several studies have examined user preferences or perceptions, including Buldeo Rai et al. (Buldeo Rai et al., 2017), Punel and Stathopoulos (Punel & Stathopoulos, 2017), and Miller et al. (Miller et al., 2017), who focus on factors influencing participation intentions. Similarly, Le and Ukkusuri (Le & Ukkusuri, 2019) and Marcucci et al. (Marcucci et al., 2017) investigate behavioural intentions and preferences for crowd-based or alternative delivery methods. Wicaksono et al. (2022) develop a bi-level model that integrates bringer behaviour into cycle-based CS However, these studies often remain exploratory and do not link behavioural insights to parcel-level assignment or cost models. Other studies, such as Gatta et al. (Gatta et al., 2018) highlight attitudinal factors or mode selection, but do not operationalise these into decision-making processes for LSPs. These studies are reviewed in more detail in Cebeci et al., (Cebeci, de Bok, & Tavasszy, 2023), which has also inspired the conceptual model for the study.

Mousavi, Bodur, and Roorda (Mousavi et al., 2022) propose a stochastic routing model where the uncertainty in finding an occasional carrier for a specific task is considered. Arslan, Agatz, Kroon, and Zuidwijk (Arslan et al., 2019) propose a two-stage stochastic programming model to optimise the outsourcing decisions of LSPs under demand and supply uncertainties. Pricing models developed by Peng, Park, Eltoukhy, and Xu (Peng et al., 2024) develop a model to optimise pricing strategies between CS platform and LSPs to design a profitable outsourcing scheme. The authors assume that the LSP offers an outsourcing service price to the CS platform for all its parcels. Subsequently, the CS platform evaluates both parcel delivery and passenger ride requests to determine which ones to fulfil. Eventually, any unfulfilled parcel requests are handled by the LSP. The study draws a model for outsourcing delivery price, however, behavioural elements of the CS service such as willingness to send and receive a parcel are overlooked. In this study, we aimed to fill this gap.

Zhang and Cheah (Zhang & Cheah, 2024) is the only study that specifically addresses the outsourcing of outlier parcels to the CS market. In their work, outlier parcels are identified based on spatial location, with the assumption that parcels located far from other deliveries are likely to incur higher delivery costs. While spatial distance may indeed influence delivery costs, this approach might overlook parcels that are costly for other reasons, such as time-related constraints or routing inefficiencies. The current study addresses this specific point, filling a gap in the existing literature by identifying outlier parcels based directly on their marginal delivery cost. While spatial distance may indeed influence delivery costs, this approach might overlook parcels that are costly for other reasons, such as time-related constraints or routing inefficiencies. The current study addresses this specific point, filling a gap in the existing literature by identifying outlier parcels based directly on their marginal delivery cost.

3. Methodology

3.1. Conceptual framework

The conceptual framework presented in Fig. 1 illustrates the overall decision-making process, which involves two main stages: (1) selection of outlier parcels from the LSP's perspective (based on marginal costs), and (2) the fulfilment of these parcels via CS. First, outlier parcels are identified from simulated parcel delivery schedules generated by MASS-GT, an agent-based urban freight model, based on their marginal delivery cost, which reflects the additional cost of including a parcel in a delivery tour. An elbow-fitting method is used to select parcels with disproportionately high costs. Second, these outlier parcels are matched with existing trips of occasional carriers using an activity-based ALBATROSS model, which provides synthetic trip diaries representing daily travel patterns.

The first stage focuses on outlier selection by identifying parcels with disproportionately high marginal delivery costs and the second stage involves their allocation to CS services. In the first stage, carriers evaluate their planned delivery tours and costs, identifying outlier parcels based on a cutoff cost per parcel. Parcels with a marginal delivery cost above this threshold are deemed eligible for CS, as detailed in Section

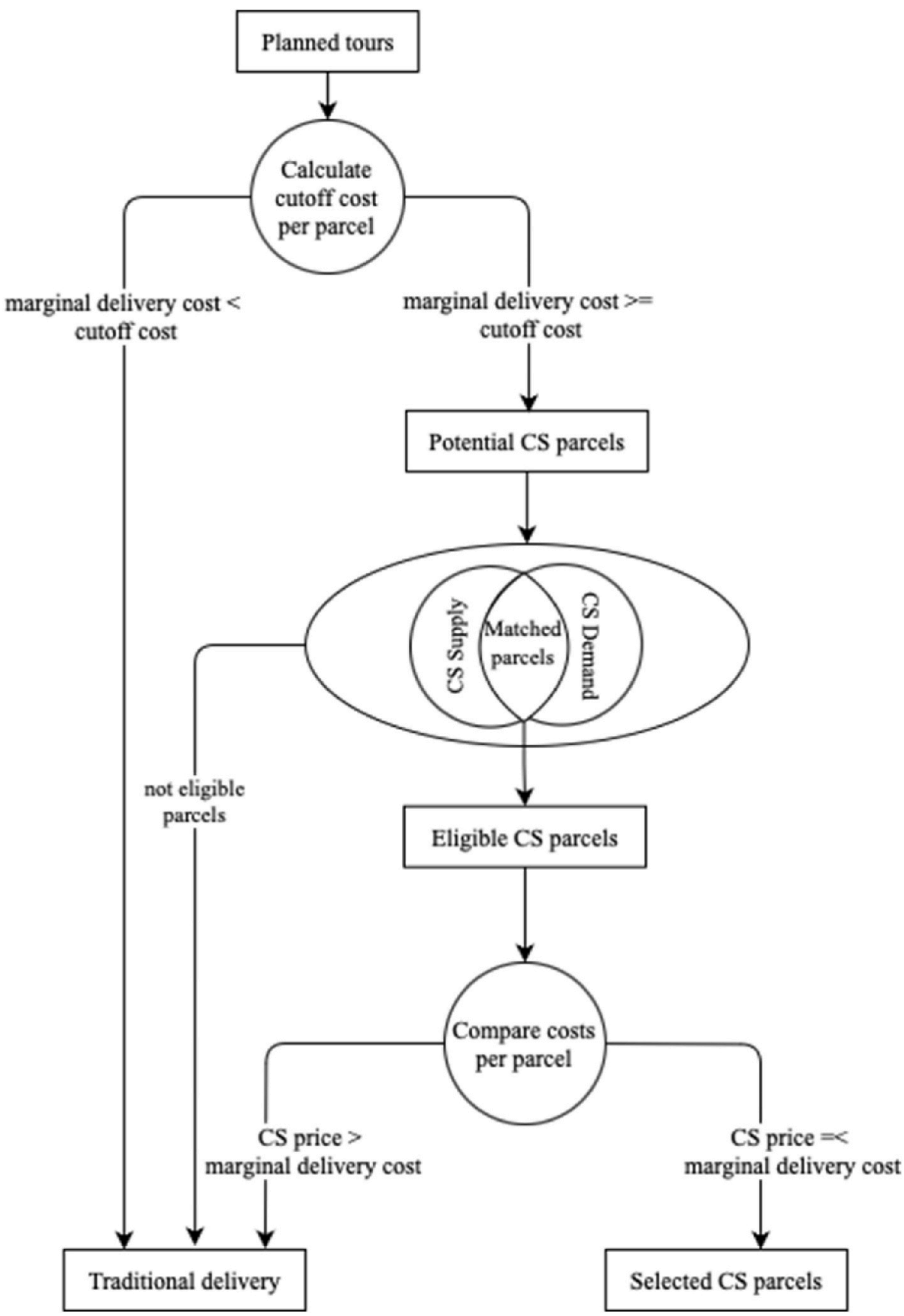


Fig. 1. Conceptual model.

3.2.

In the second stage, we use willingness-to-send and willingness-to-bring choice models to determine the share of outlier parcels that can be handled by occasional carriers. These parcels are then matched with existing trips of occasional carriers using the activity-based model described in Section 4. We use pre-generated synthetic trip diaries to realistically represent potential bringers and their travel patterns, focusing on trip characteristics relevant for parcel matching without re-simulating or adjusting activity schedules. After this stage, the CS cost per parcel can be obtained and compared with the traditional delivery cost for further economic and environmental analysis.

Outlier parcels identified for CS are matched with existing trips of occasional carriers using the activity-based model described in Section 4. We use pre-generated synthetic trip diaries to realistically represent potential bringers and their travel patterns, focusing on trip characteristics relevant for parcel matching without re-simulating or adjusting activity schedules. After this stage, the CS cost per parcel can be obtained and compared with the traditional delivery cost for further economic and environmental analysis.

3.2. Outlier selection model

Since the first objective of the paper is to define parcels that have high negative impacts (outliers) to LSPs, it is necessary to explore the marginal delivery costs produced by a parcel. A challenge in calculating the cost of service within the logistics sector is the distribution of transportation expenses across a specified route (Sun et al., 2015). To this end, cost allocation is mostly studied in collaborative networks to plan how to allocate the total cost and how to divide the savings (Dahlberg et al., 2018; Frisk et al., 2010; Guajardo & Rönnqvist, 2016; Sun et al., 2015).

By systematically assigning costs to activities, cost allocation allows for a detailed analysis of profitability and efficiency (Guajardo & Rönnqvist, 2016). The methodologies employed in cost allocation vary, each with distinct principles and implications for business strategy (Guajardo & Rönnqvist, 2016; Sun et al., 2015). For instance, the Nucleolus allocation method seeks the most stable costs or benefits, ensuring that no group of participants can deviate to achieve a more favourable outcome (Frisk et al., 2010). The Shapley value allocates costs (or profits) based on each participant's contribution to the collective outcome. Other cost allocation principles include allocation based on volumes or standalone cost, based on separable and non-separable costs, or the equal profit method. For more information, readers can refer to (Frisk et al., 2010; Guajardo & Rönnqvist, 2016; Sun et al., 2015). In this study, we opt to employ the marginal cost method which is used not only in transportation domain (Bickel et al., 2006; Dahl & Derigs, 2011) but also in other research areas (Massol & Tchung-Ming, 2010). This method reflects each service point's true economic footprint and effectively measures the additional expense incurred. Compared to complex techniques like the Nucleolus and the Shapley value (Frisk et al., 2010; Sun et al., 2015), marginal cost allocation is straightforward and easier to communicate, aligning costs directly with their causes and making it a practical choice for managerial decisions. In this paper, the marginal cost method is used to analyse the cost difference if a certain parcel is not delivered, shown in Fig. 2. In our model, customers are aggregated into zones based on the parcel generation process, meaning that each delivery zone may contain one or more customer deliveries. Thus, although the marginal delivery cost is calculated at the zone level, it reflects the cost of serving the customers (parcels) located within that zone. This approach enables a scalable analysis of delivery costs while accounting for the spatial distribution of parcel demand.

Fig. 2 illustrates the planned route as a closed loop, beginning and ending at the depot and covering zones identified as $Z = z_1, z_2 \ldots z_n$.

We define a graph structure where the depot d and the zones Z are the vertices of the graph. The edges represent the delivery trips between the vertices with associated costs. These costs are derived from the distance matrix D and time matrix T, that are elaborated in Section 3.3, coupled with the unit cost per kilometre u_d and cost per hour u_t. The generalised cost function for the path from i to j is expressed as:

$$c_i j = u_d \cdot d_i j + u_t \cdot t_i j \tag{1}$$

Under the marginal cost allocation mechanism, when removing a zone z_n from the delivery tour, the marginal cost is calculated by considering the costs of the incoming and outgoing legs associated with z_n and the cost of the new route that connects the nodes that were previously adjacent to z_n. Let c_{in} be the cost of the leg entering z_n, c_{out} be the cost of the leg exiting z_n, and $c_{by\ pass}$ be the cost of the new route z_n'. This represents the change in cost due to excluding zone z_n from the tour, considering the rerouting that takes place. The marginal cost ΔMC_{zn} of removing zone z_n is then given by:

$$\Delta \mathrm{MC}_{zn} = \left(\mathrm{c}_{i\ j\ (in)} + \mathrm{c}_{i\ j\ (out)}\right) - \mathrm{c}_{by\ pass} \tag{2}$$

The cutoff point for selecting the number of outlier parcels is calculated using the elbow-finding method. This method involves finding the point on the curve where the rate of increase in cumulative frequency with respect to cost changes most significantly, in other words, where the curve has the sharpest slope (Antunes et al., 2018). The gradient of the cumulative frequency curve is calculated by finding the difference between successive values of cumulative frequency and

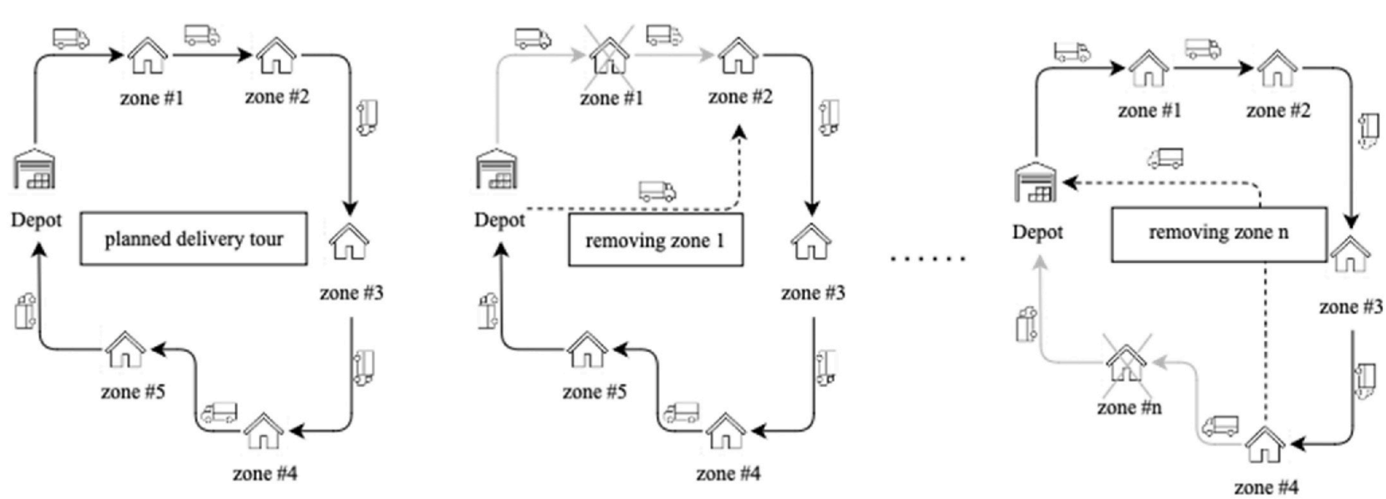


Fig. 2. Planned delivery tour.

dividing by the difference in cost. The index of the maximum gradient is considered the elbow point. Unlike z-score methods, elbow fitting does not assume a normal distribution of the data. As discussed in Section 5, our data is mostly skewed, which makes elbow fitting a better choice. Moreover, this method is commonly used in cluster analysis and outlier detection (Saraswat et al., 2023; Syakur et al., 2018). Additionally, the method is straightforward to implement in different areas (Syakur et al., 2018). In our context, the elbow point is leveraged for identifying parcels with a high negative impact—high delivery cost—compared to the rest of the parcels.

3.3. Shipping mode choice

After the selection of the outliers, the fulfilment of these parcels is simulated using the CS module of the MASS-GT model suite (De Bok et al., 2022; de Bok & Tavasszy, 2018; Thoen et al., 2020). Here, parcels are matched with travellers (i.e. potential bringers) based on their willingness to send and deliver parcels along their existing routes. The model evaluates potential trips using a utility-based approach by considering the behaviour of both senders and bringers (Tapia et al., 2023).

For the matching calculation, we have used a choice model for senders on the demand side (Cebeci, Tapia, et al., 2023) and a parcel delivery choice model for bringers on the supply side (Cebeci et al., 2024). On the demand-side we consider a hybrid choice model which includes the effect of trust on CS service choice. The demand function is the following:

$$U_{CS} = \beta_{Cost} * (Cost) + \beta_{Time} * (Time) + \beta_{\mathrm{Trust}} * (Trust) + \varepsilon_{CS} \tag{3}$$

$$U_{\mathrm{TR}} = ASC_{TR} \tag{4}$$

Considering the supply side of the system, we consider a multinomial logit model where delivery time and compensation are estimated as the following:

$$U_{pickup} = ASC_{pickup} + \beta_{Time} {}^{*}\left(Time_{pickup}\right) + \beta_{Compensation} {}^{*}\left(Compensation\right) + \varepsilon_{pickup} \tag{5}$$

$$U_{current} = \beta_{Time} {}^{*}\left(Time_{currenttrip}\right) + \varepsilon_{current} \tag{6}$$

The CS model considers three modes of transportation with specific adjustments for travel times, costs, and drop-off times associated with each mode: (1) cars, (2) public transport (PT) and (3) biking and walking. For the latter, we assume that the trips are mainly done by bikes due to the fact that the trips are relatively long between origin and destination pairs and the Netherlands has a large bike market share. For cars, travel time is calculated based on distance and average speed, with additional considerations for vehicle operating costs. For PT, a fixed time is used, and it is assumed that the origin and destination of the PT traveller and the parcel are the same resulting in no additional time and cost for PT travellers. For biking and walking, the time is calculated based on the distance and average speed for each mode. Compensation is determined by the parcel distance required to deliver the parcel. Each parcel is matched with the most suitable bringer who has the highest utility. Each traveller is coupled with a parcel providing a probability of picking up or not picking up the parcel. The traveller having the largest difference between picking up and not picking up is assigned to the parcel. This approach enables the efficient use of available trips for parcel delivery, optimising the CS process by maximising utility and minimising detours for the bringers across different modes of transport. Moreover, it allows to establish an individual matching between traveller and parcel, in the setting of an agent-based model. Although for the purposes of this study this individual match is not used further, it is the basis for a uniquely detailed crowd-shipping choice model.

4. Application: study area and data

This study focuses on the province of South-Holland, the most urbanised region in The Netherlands, with a population of 3.8 million (CBS, 2024). Due to this high population density, a significant proportion of parcel demand can be generated, making it an ideal area for testing and implementing last-mile delivery solutions. South Holland has a diverse urban landscape, including both large cities as well as major industrial regions like the Maasvlakte port landfill area.

Data on parcel demand is available for South Holland from the MASS-GT simulation model (De Bok et al., 2022; de Bok & Tavasszy, 2018; Thoen et al., 2020). This model divides the study area into 6668 zones and includes data from 29 depots operated by various parcel delivery companies in the Netherlands. The parcel demand module is developed using multiple datasets to realistically estimate Business-to-Consumer (B2C) and Business-to-Business (B2B) parcel demand in each zone. For B2B parcel demand, MASS-GT uses zonal employment, provided by the National Bureau of Statistics (CBS) (CBS), along with market monitor data from the Netherlands Authority for Consumers & Markets (ACM) (Autoriteit et al., 2024). This ensures that the model accurately reflects logistics demand. The B2C parcel demand is calculated using an ordered logistic regression model, incorporating individual and household characteristics from the Mobility Panel Netherlands (MPN) to predict the frequency of online shopping for each person, which in turn helps determine parcel demand across zones (Hoogendoorn-Lanser et al., 2015). The demand is calibrated against market monitor data from the base year to match actual market sizes, keeping differences in demand between zones and ensuring the overall demand volume is accurate. In the reference case, the total demand is estimated as 242,866 packages on a single day. ACM data also includes the market share of different courier, express, and parcel companies in the Netherlands. Once the parcel demand is established, it is allocated based on the market share of each courier. Parcels assigned to specific couriers are further distributed to their depots. Table 1 presents the market share statistics for each courier in the Netherlands, as used in the parcel demand module and Fig. 3 provides a spatial distribution of deliveries.

To calculate the marginal delivery cost, we have used cost figures for freight transport in the Netherlands (The Netherlands Institute for Transport Policy Analysis (KiM and), 2023). The values for delivery time cost and vehicle kilometre cost are €32 per hour and €0.20 per kilometre, respectively, in line with the literature (Gevaers et al., 2014). The unit time cost includes fixed costs, personnel costs, and general operating costs, while the unit kilometre cost includes variable costs for fuel and depreciation. Besides transport time, drop-off times were included in the calculations. In line with (Allen et al., 2018; Ranjbari et al., 2023) a drop-off time of 3 min per parcel is used.

Data on passenger flows is obtained from ALBATROSS, a multi-agent, rule-based model designed to simulate and analyse personal activity pattern decisions (Arentze et al., 2000). The model generates synthetic trip diaries of individuals, considering their activities within specific household, institutional, and spatial-temporal constraints (Arentze et al., 2000). The data is used to match travellers with outlier

Table 1
Courier market shares.

Courier company	Market share (Netherlands, %)	Market share (Foreign, %)	Market share (Total, %)	Number of parcels
Company 1	0.62	0.24	0.51	123406
Company 2	0.28	0.13	0.23	56098
Company 3	0.025	0.28	0.10	24872
Company 4	0.025	0.08	0.04	10127
Company 5	0.025	0.24	0.09	21923
Company 6	0.025	0.03	0.03	6440
Total	1	1	1	242866

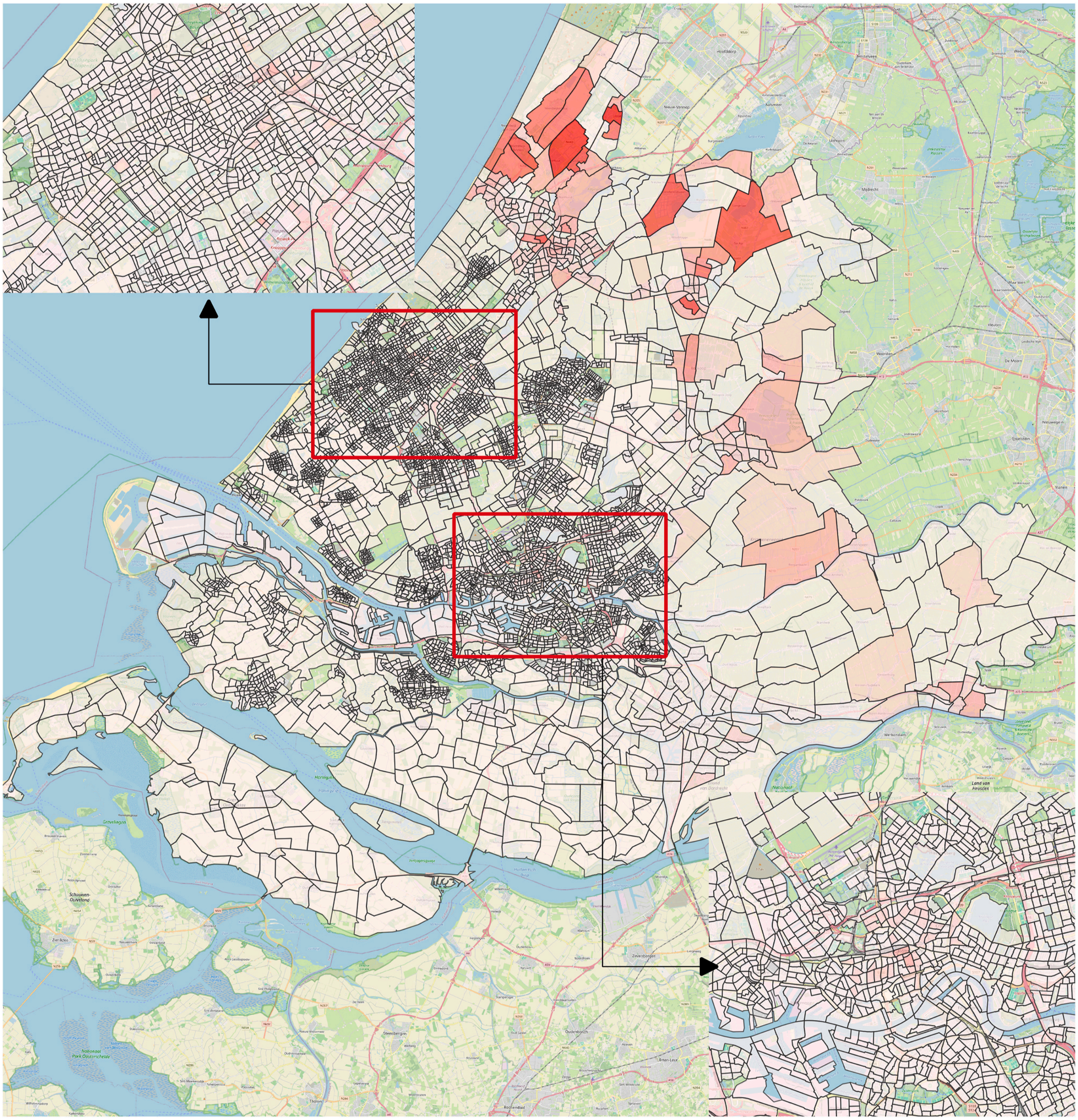


Fig. 3. Spatial distribution of deliveries.

parcels, allowing for realistic assignment of parcel delivery tasks.

Table 2 below provides an overview of the simulated trip diaries for the South Holland region, consisting of 3.5 million trips and 850 thousand travellers. which are 3.92 and 12.37 km per trip on an average day, respectively (Netherlands, 2024). For car trips as a driver and as a passenger, CBS reports average trip distances of 17.36 and 19.94 km (Netherlands, 2024), respectively, which are shorter in ALBATROSS trips. Cycling is particularly common for shorter trips, making up a significant portion of total trips across demographics. Car usage is also high, especially among higher-income and full-time workers, reflecting a demand for convenience and flexibility in commuting. PT, with the longest average trip distance, is commonly used for intercity or longer-distance travel, appealing especially to those under 35 or individuals with lower incomes.

Fig. 3 below provides an overview of the origin counts of the trip diaries (the spatial pattern is similar to the daily destination counts).

5. Results

5.1. Outlier selection

By using Equation (2), we calculate the marginal delivery cost of removing a zone from an existing simulated travel plan. As explained in Section 3.3, the delivery plan includes the six largest delivery companies in the last-mile delivery market in the Netherlands (Autoriteit et al., 2024). The proportion of parcel demand for each courier company is given in Fig. 4. As can be seen, more than half of the parcel demand is handled by Company 1, followed by Company 2.

Differences among the courier companies parcel demand structure is shown in Fig. 5. The violin plot displays the distribution of marginal

Table 2
Overview of ALBATROSS trip diaries.

		Bike	Car as driver	Car as passenger	PT
Gender	Female	1464815	1176042	323589	158431
	Male	220439	96840	41606	25082
Age	<35	928458	700972	197645	107757
	35=<55	340952	296487	69353	37478
	55=<65	143248	121244	30897	13410
	65=<75	137231	92373	32397	11747
	75+	135365	61806	34903	13121
Income	High	386529	437905	82642	39635
	Low	416779	169830	89983	53236
	Medium	365062	315321	76591	37021
	Minimum	516884	349826	115979	53621
Employment	<32hrweek	68943	52089	13756	7105
	≥32hrweek	901237	848155	177841	103888
	No work	715074	372638	173598	72520
Average distance per trip (km)		2.85	9.33	10.71	14.72
Number of travellers (total)		853993			
Number of trips (total)		3506844			

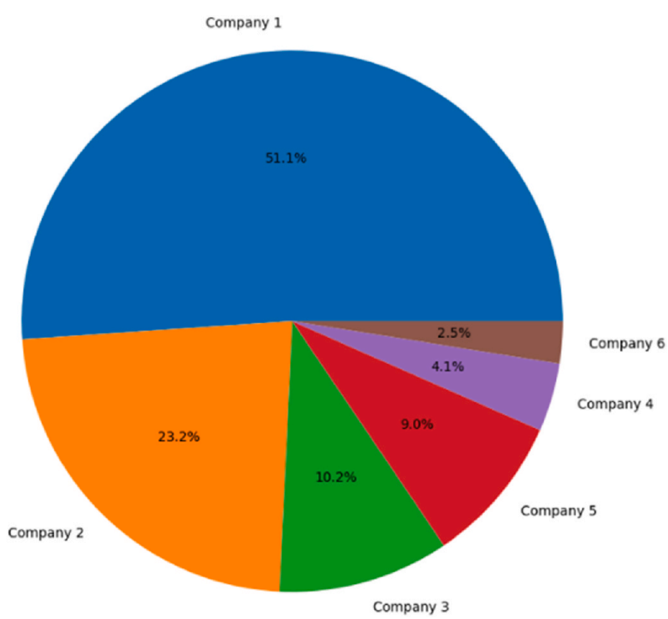


Fig. 4. Parcel distribution per courier.

costs per parcel for six courier companies, with varying widths indicating the frequency of different costs. For all companies, we see a similar range of costs, with some individual parcels exceeding the general cost range, as indicated by the points above the main body of the violins. Company 6 exhibits wide violins, suggesting a greater diversity in parcel costs, while Company 1, 2 and Company 5 have narrower shapes, implying more uniform costs. The figure shows a peak at the lower end of the cost scale as the main body of the violins are around €2. This indicates that the vast majority of parcels incur minimal marginal costs, suggesting a high level of operational efficiency across the companies. The overlapping nature of the distributions for companies suggests that their cost structures are similar, particularly in the most common cost range.

Fig. 6 below shows a comparative analysis of marginal delivery cost (€) distributions for six different companies. Each subplot combines a Kernel Density Estimation (KDE) plot and a cumulative frequency curve. The KDE, indicated by a light blue area, shows the density of marginal delivery costs, with the vertical axis representing the frequency of costs and the horizontal axis representing cost values. The cumulative frequency, shown with blue dots, indicates the proportion of shipments with their marginal cost, summing the frequency as costs increase. A red vertical line, shows in a red dashed line, highlights a specific cost cutoff point of interest across all companies. Fig. 6 shows that the majority of marginal delivery costs are clustered at the lower end, with an increase in cumulative frequency at this lower cost range, meaning that most shipments fall below the cutoff point.

With the cutoff point determined through the elbow curve, we find 2700 parcels as outliers which together for all carriers represent about 1 % of the total parcel demand in the study area. The cutoff cost per courier company and the percentage of parcels considered as outliers is shown in Table 3. Typically, these costs lie around 2 Euro/parcel for all carriers. The consequences for the outlier volumes vary strongly, however, with an order of magnitude (between 0.23 % and 8.1 %).

The validity of Table 3 can be discussed in more detail, to determine if our approach to the elbow point cutoff mechanism is economically reasonable in the urban freight market. It is important to note that the delivery cost for last-mile deliveries includes several components. The main cost factors are variable and fixed costs. In the context of this research, we consider only variable costs based on delivery time and distance and the fixed costs are not considered as there is no information available. In our calculations, using the elbow point outlier selection, we find that the average delivery cost at which a courier company would be willing to deliver a parcel is around €2 per parcel, meaning that above this rate an LSP might be willing to outsource CS service. In the literature, Gevaers et al. (Gevaers et al., 2014) model the parcel delivery cost using various sources, such as expert interviews and literature on a variety of cost items. In their study, the base cost is calculated based on a 200 km distance with a delivery person working 7.5 h and delivering 175 parcels. The delivery cost is estimated as €1.3 per parcel for dense urban areas. Although our selection mechanism does not specifically target urban areas and does not include all the cost components considered in Gevaers et al. (Gevaers et al., 2014), with a unit cost of €32.21 per hour and €0.20 per kilometre for the Netherlands (The Netherlands Institute for Transport Policy Analysis (KiM and), 2023) and using the average tour distance of all couriers (103 km), the delivery cost per parcel becomes €1.7. Additionally, another study found that the total cost of a parcel ranges between €1.36 and €1.41 (InnoEnergy, 2024). These findings further validate our cost estimates.

Besides the delivery cost calculation on average terms, the position at which the cutoff is found per courier company is critical for measuring the network structure of the courier as well as determining the number of inefficient parcels. In their recent study, Zhang and Cheah (Zhang & Cheah, 2024) use spatial density and neighbourhood distance as indicators of outliers in parcel delivery patterns. By using local outlier

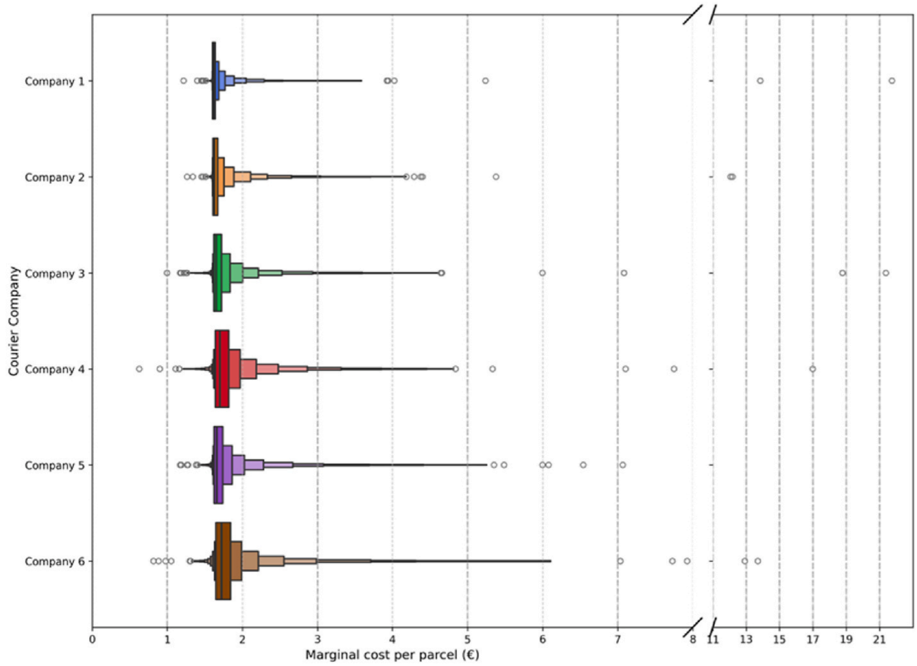


Fig. 5. Violin plot of marginal costs per parcel for each courier.

factor (LOF), the authors identify local density deviations of parcels relative to their neighbours. The LOF approach assumes that isolated parcels, defined by their low density relative to nearby parcels, have higher delivery inefficiencies. The LOF approach resulted in 11 % of the parcels being classified as outliers (Zhang & Cheah, 2024). The share found here, based on cost logic, is considerably lower. By only considering spatial density and neighbourhood distance, the LOF algorithm may misclassify the inefficient parcels, even if these parcels do not add significant costs. Not all isolated parcels are necessarily inefficient to deliver; for instance, a parcel in a low-density area might still be cost-effective if it aligns well with existing delivery routes. In contrast, our cost-based method directly evaluates the economic impact of each parcel on delivery routes, ensuring that outsourcing decisions are based on actual cost inefficiencies rather than spatial dispersion alone. This is particularly relevant for CS, as a cost-based approach better aligns with the operational logic of LSPs by ensuring that only parcels with disproportionately high delivery costs are outsourced.

Fig. 7 shows that the outlier parcel distribution in the network is dispersed around the network. As expected, a greater number of parcels are located in areas remote from urban areas. Considering the concentration of courier companies in the densely populated central and northern areas, the southern part of the network appears to have a higher number of high-cost parcels, due to the longer detours required for deliveries.

When analysing the cost dynamics of parcel delivery for individual couriers, it may seem counter-intuitive that some zones near the depot location have outlier parcels to be served compared to those further away. However, this can be attributed to how the delivery plan is simulated. Firstly, zones with fewer parcels often have a higher per-parcel delivery cost. This is because the fixed costs associated with starting a delivery trip (e.g., vehicle kilometres, driving time and drop-off time) are spread over a smaller number of deliveries. Thus, even if a zone is geographically close to the depot, if it only requires a few parcels to be delivered, the per-parcel cost can be disproportionately high. Secondly, direct routes to more distant locations can be more cost-effective if a high number of parcels is delivered in those areas. For instance, a large number of parcels helps to spread the costs, reducing the per-parcel cost compared to closer zones with fewer deliveries. Hence, choosing an optimal route that balances distance and parcel quantity can optimise cost.

Fig. 8(a–f) provides a detailed representation of the outlier parcels per courier. As shown, Company 1 and Company 2 have 9 and 8 depots in the region, respectively. The main reason for comparing these two couriers is their dense distribution centre structure. A common feature of the outlier parcels is that they typically appear away from the depot locations, particularly in the southern part of the network. However, the distribution of outliers is dispersed across the network. Potential reasons for this include market coverage, delivery density at destination locations, and operational strategy differences between the two couriers. Fig. 8d and f shows the distribution of outlier parcels for Companies 4 and 6. Although the distribution of outlier parcels varies for each courier, some regions are highlighted across both couriers, possibly indicating areas with an overall high marginal cost per parcel. For instance, the southern parts of the network show a high number of outlier parcels for all the couriers. Fig. 8c and e illustrate the outlier parcel structure for Companies 3 and 5. These couriers exhibit a similar distribution pattern, particularly in the northern and southern parts of the network. There are also similarities in their depot locations, with one main depot in the centre and the rest positioned outside the network. As shown in Fig. 8, the distribution of outlier parcels varies depending on several factors. Consequently, some outliers appear in the urban areas like in Companies 4–5 and 6, in other cases, they appear far away zones. This highlights that solely focusing on spatial concentration of parcels within specific geographic areas might lead to under- or overestimation of inefficient parcels and overlook company-specific attributes. Interestingly, the company-based outlier parcel distribution shows differences when analysed at the zonal level in terms of outlier parcel volume, which could encourage collaboration among couriers to handle outlier parcels.

5.2. *Crowdshipping*

By integrating willingness-to-deliver and willingness-to-send through CS choice models, as described in Section 3.3, we assess the potential for delivering the 2700 identified outlier parcels via a CS service. Using synthetic trip diaries from the ALBATROSS activity-based model, we match outlier parcels with existing trips of occasional carriers to evaluate the feasibility, costs, and environmental impacts under

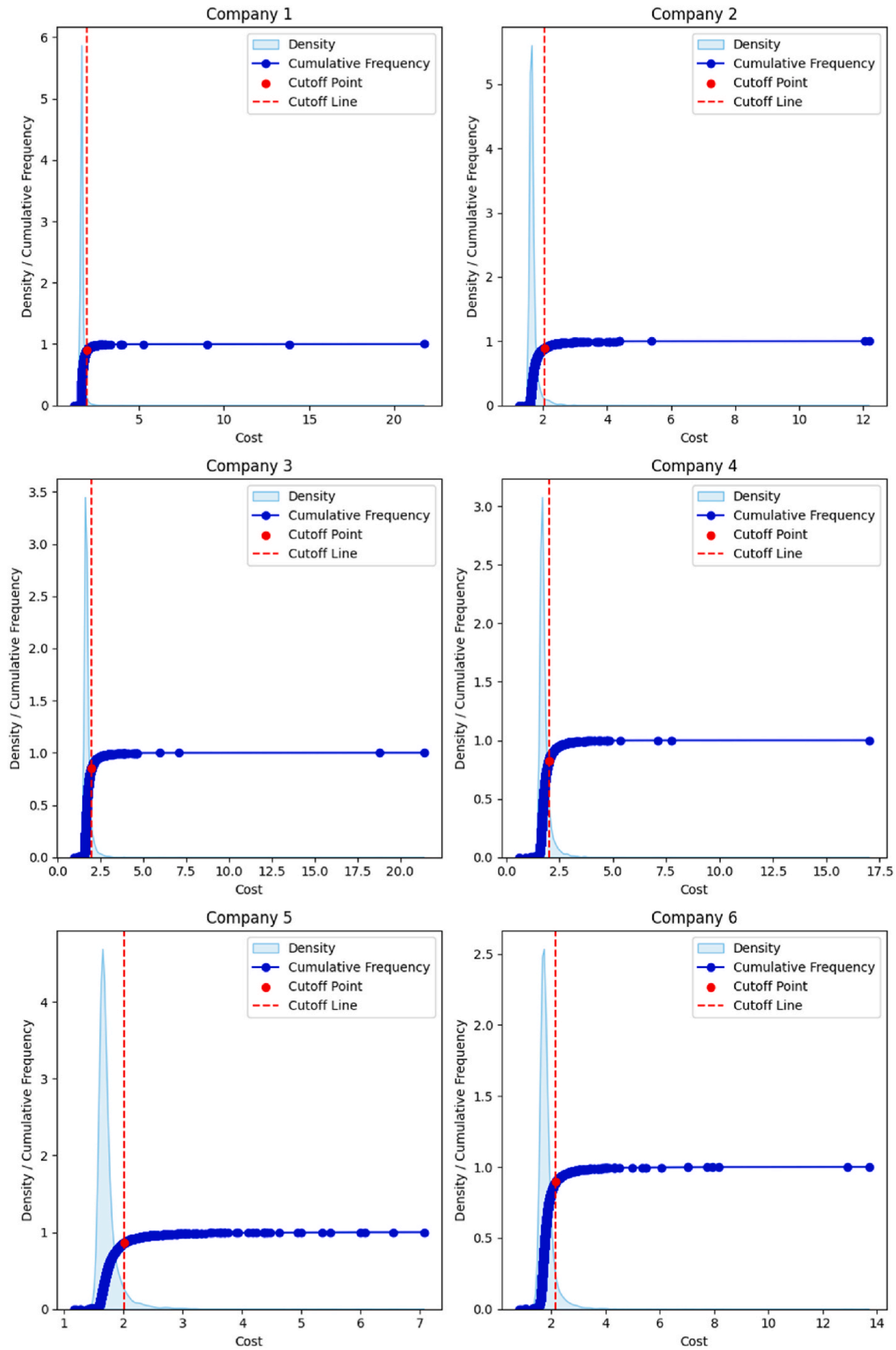


Fig. 6. Combined cumulative frequency and density plot with outliers for each CEP company.

Table 3
Overview of the outlier parcels per courier company.

Courier company	Cutoff cost (€)	Number of outlier parcels (%)
Company 1	1.94	0.23
Company 2	2.04	0.61
Company 3	2.00	1.99
Company 4	2.01	6.27
Company 5	2.01	2.21
Company 6	2.01	8.1

different compensation scenarios. To do this, the scenarios are run for different compensation levels per kilometre, ranging from €0.1 to €1 per kilometre. As described in Section 4, the ALBATROSS synthetic trip diaries are used which result in a pool of 16878 travellers with 19410 trips. Table 4 presents the results of the CS model for the total number of outlier parcels. As shown, because of the increase of the compensation the prices for CS increase from €2.37 to €23.66 per trip.

Considering all potential outlier parcels being crowdshipped, regardless of their costs, and allowing CS only when the CS price does not exceed the marginal delivery cost per parcel, referred to as selected parcels, lead to two distinct outcomes. Firstly, the number of matched parcels decreases marginally when CS is limited to only selected parcels. The ratio of matched parcels for CS ranges between approximately 72 %

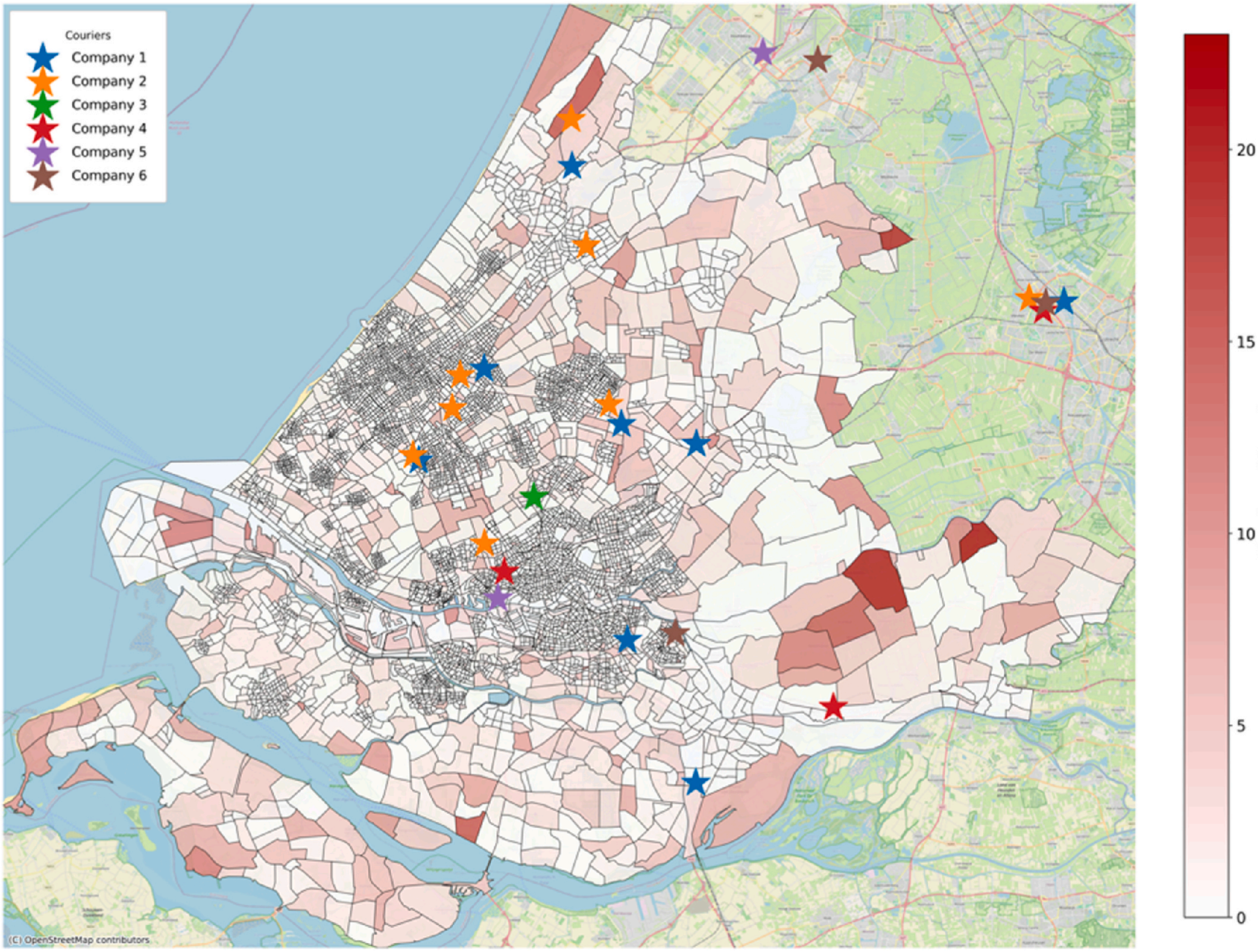


Fig. 7. Outlier parcel distribution in the network, for all LSPs.

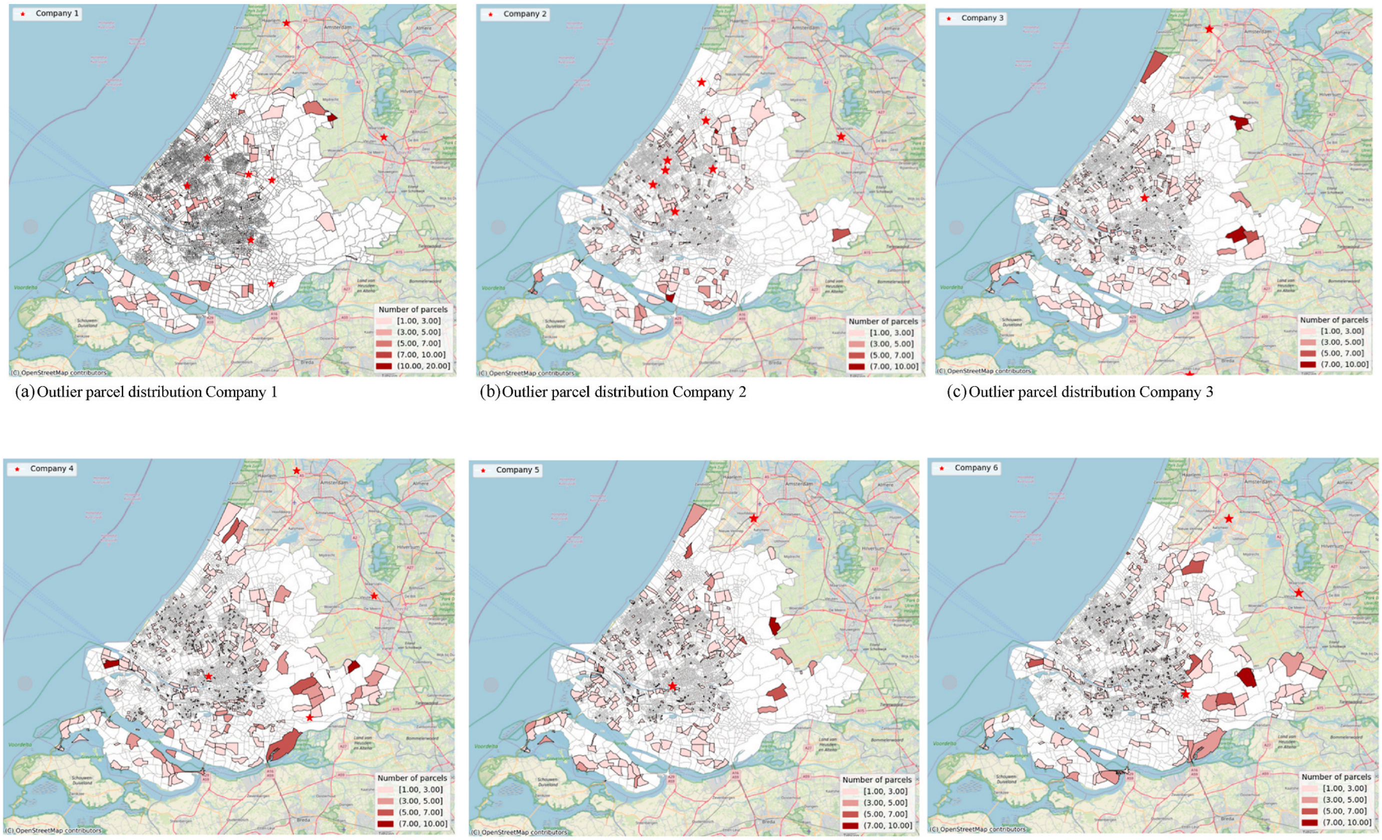
and 100 % across all CS simulations. This ratio drops to between 43 % and 9 % when only selected parcels are allowed to be crowdshipped. Secondly, the average compensation is higher in the case of all parcels being CS due to the lack of a cost constraint on the service. Interestingly, increasing the compensation rate per kilometre, and consequently the average compensation, does not positively affect the matching rate of parcels in the selected parcels. This is because the compensation is capped by the parcel delivery cost, thus limiting the effect of a larger compensation per km.

Fig. 9 illustrates the effects of increasing compensation rates on both mode shares and CS demand. As compensation increases, CS demand declines, and traditional delivery becomes dominant. In both cases, car-based and PT-based CS take the largest shares, while bike-based CS remains limited. Although PT emissions are considered negligible, its small share means the environmental benefits are minor. These results differ from earlier studies, such as Zhang et al. (Zhang & Cheah, 2024; Zhang et al., 2023), who reported significant reductions in emissions and costs. The difference highlights the importance of the choice of method for the identification of outlier parcels, in our case recognizing marginal delivery costs, as well as behavioural constraints like willingness to deliver. Additionally, the concept of matched parcels refers to the parcels that are successfully assigned to occasional carriers for delivery through CS. The matching rate is the proportion of outlier parcels for which a suitable occasional carrier is found. Because higher compensation rates reduce the number of parcels selected for CS (as fewer parcels remain cost-efficient), there are enough carriers to deliver all selected parcels in the all-parcels scenario, resulting in high matching rates. In contrast, in the cost-efficient scenario, the number of parcels that can be matched declines gradually as compensation increases, due to the cap imposed by parcel marginal delivery costs.

As can be seen from Fig. 9, as expected, the number of parcels delivered with CS decreases quickly when the compensation increases. Both cases provides the highest CS platform revenue when the compensation per kilometre is €0.5 (see Fig. 10).

When compensation is low, more parcels are crowdshipped, resulting in higher CO_2 emissions due to the large proportion of car-based CS trips similar to the results found in Tapia et al. (Tapia et al., 2023). This indicates that car-based CS is being used more frequently, which increases its environmental negative impact, similar to the findings of Simoni et al. (Simoni et al., 2020). Specifically, detours are longer compared to those in dense urban areas, leading to lower usage of bikes for CS. When compensation increases, CS flow decreases, leading to fewer trips and lower CO2 emissions. The potential of using CS as a sustainable alternative exists only when it is economically viable, meaning that the service offers a cost-competitive price for both senders and bringers. This can positively impact emissions reduction. However, the overall impact remains limited due to the small volume of parcels that can be shared through CS.

Exploring the geographical distribution of crowdshipped parcels in the network can specify potential delivery patterns. We focus on Scenario 5, as the other scenarios show similar patterns, and Scenario 5 yields the highest CS platform revenue. However, no distinct spatial



(a) Outlier parcel distribution Company 1
(b) Outlier parcel distribution Company 2
(c) Outlier parcel distribution Company 3
(d) Outlier parcel distribution Company 4
(e) Outlier parcel distribution Company 5
(f) Outlier parcel distribution Company 6

Fig. 8. Outlier parcel distribution per courier.

Table 4
CS model results for outlier parcels.

Scenarios (1–10)	1	2	3	4	5	6	7	8	9	10
Compensation €/per km	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Potential CS parcels (2700)										
CS demand	2681	2633	2479	2169	1854	1563	1307	1093	902	752
Matched parcels	1938	1959	1927	1881	1756	1537	1303	1091	902	752
Matched parcels (%)	72.3	74.4	77.7	86.7	94.7	98.3	99.7	99.8	100	100
Traditional parcels	762	741	773	819	944	1163	1397	1609	1798	1948
Average compensation (€)	2.37	4.73	7.1	9.46	11.83	14.19	16.56	18.92	21.29	23.66
CS platform revenue (€)	598.1	1223.3	1778.4	2280.6	2539.3	2444.4	2204.6	1915.6	1603.7	1359.6
Traditional delivery (%)	28	27	29	30	35	43	52	60	67	72
CS (%)	72	73	71	70	65	57	48	40	33	28
Selected CS parcels (CS price < marginal delivery cost)										
Selected CS parcels	1155	527	360	297	264	207	160	129	96	71
Total traditional parcels	1545	2173	2340	2403	2436	2493	2540	2571	2604	2629
Matched parcels (%)	43	20	14.5	13.7	14.2	13.2	12.2	11.8	10.6	9.4
Average compensation	1.38	1.35	1.41	1.30	1.29	1.88	1.41	1.41	1.53	1.69
CS platform revenue (€)	270.8	258.3	287.5	346.8	393.3	333.6	279.5	243.9	178.3	126.2
Traditional delivery (%)	57	80	87	89	90	92	94	95	96	97
CS (%)	43	20	13	11	10	8	6	5	4	3
CS CO_2 (tonne)	3.38	1.50	1.23	1.02	0.86	0.75	0.54	0.46	0.25	0.23
Traditional delivery CO_2 (tonne)	2.87	3.76	3.93	3.98	3.95	4.04	4.11	4.18	4.21	4.17

pattern emerges, suggesting that CS activity is dispersed variably across regions without clear areas of concentration.

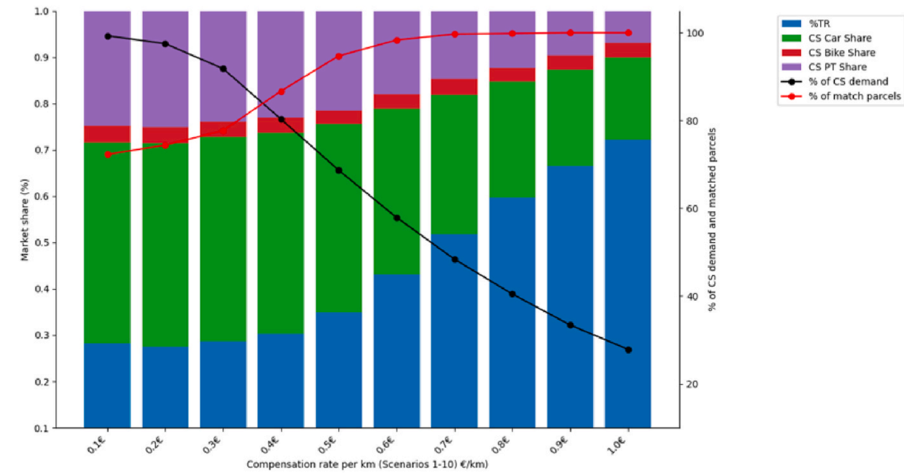
Another analysis of compensation rates and CS demand is presented through a sensitivity analysis, as shown below (Fig. 11).

The elasticity curve shows that CS is sensitive to price and strongly elastic above a price of €0.7/km. This highlights the limited scalability of CS under high compensation scenarios and suggests that careful pricing strategies are essential to maintain operational and environmental sustainability.

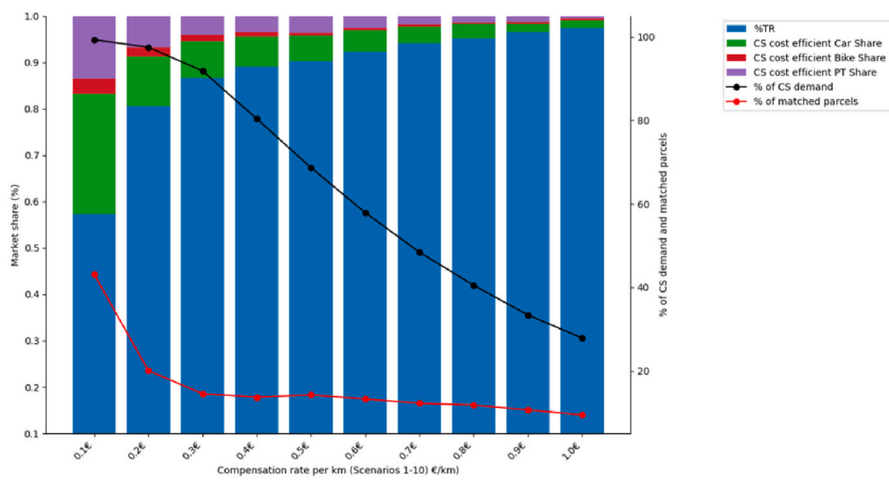
6. Conclusions

In this study, we introduce a cost-based outlier parcel detection mechanism using the marginal delivery cost method, applied to a simulated delivery plan from the MASS-GT simulation model. Next, we evaluate the use of CS for delivering outlier parcels—those with a high negative impact on last-mile delivery.

The outlier parcels identified with a logistics-costs driven approach constitute only of 1 % of the total parcel demand. Most parcels have low



(a) Potential CS parcels



(b) Selected CS parcels

Fig. 9. Market shares, CS demand and matched parcels.

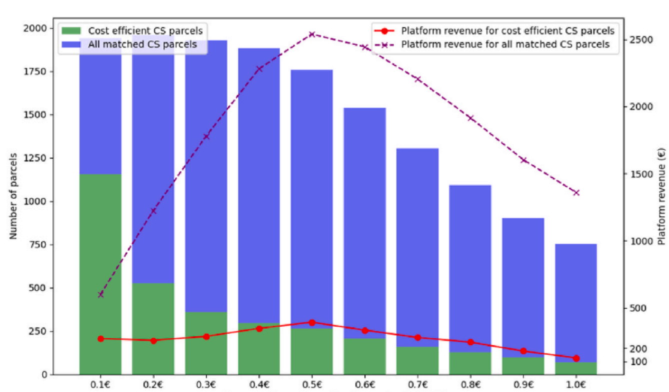


Fig. 10. CS platform revenue and the number of parcels delivered by CS for all and cost-efficient scenarios.

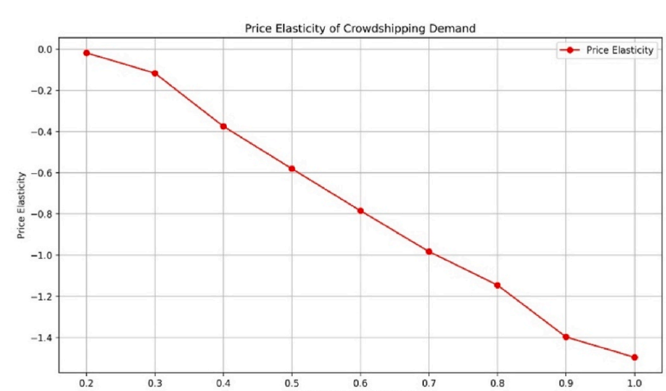


Fig. 11. Compensation rate elasticity of CS demand.

marginal costs, while a small fraction of outliers drives up overall delivery expenses, underlining the efficiency of last-mile delivery planning. We show in our case that while cut-off costs are similar across companies, the consequences for volumes vary widely, from less than 1 % to more than 8 % of all shipments in the region. While the proportion of parcels selected for CS is low within the overall network, this study provides insights into the significance of couriers' delivery networks and emphasizes that CS remains a niche market.

Our findings show that while CS can help address last-mile delivery inefficiencies for only a small proportion of parcels, its economic and environmental impacts are sensitive to several factors, such as compensation rates, delivery distance, and demand availability. Given the existing low delivery costs in the last-mile market, CS might better serve customer-to-customer deliveries or more time-sensitive parcels rather than courier services.

The results are relevant for policy and logistics managers in several ways. Firstly, we find that the potential market for outsourced deliveries is significantly lower than identified earlier with a crude, distance-based approach; CS volumes will even be smaller due to the acceptance gap, and strongly price dependent. This should dampen the expectations of the impact of CS on delivery movements. Secondly, the model helps to identify areas that are underserved and where deliveries are relatively expensive, even when different LSPs are considered together, which implies a lower overall accessibility for goods. These insights could help service providing platforms as well as local governments to focus their attention on the areas where the need for affordable shipping is relatively high. Thirdly, the approach allows to assess policy scenarios that influence behavioural preferences or cost drivers for carriers. Financial or regulatory incentives could be considered to help reduce delivery movements, either to support LSPs with efficiency and consolidation, or to support occasional carriers, to leverage existing trips. Which of these incentives would be most effective could be the subject of new research, using the presented approach.

A limitation of this study is that we only include the transport related variable costs in our analysis, as data about other costs are not available. Other costs, such as vehicle insurance, and infrastructure, could influence the overall profitability of traditional last-mile delivery and, consequently, the impacts on CS. Additionally, this study evaluates CS as an alternative delivery option for LSPs, without considering any related services such as parcel lockers or micro hubs. Future research could explore the integration of CS with these last-mile solutions. Moreover, it could investigate diverse sources of parcel delivery demand, including C2C and B2C, as well as the potential of CS for handling delivery returns. Although the sustainability effects of CS alone are limited, the potential of hyperconnecting services as a chain is more promising than relying on individual services alone, which requires further investigation. Future research could compare cost-based outlier selection with alternative methods, such as density-based clustering approaches to better understand the implications of different selection mechanisms on outsourcing outcomes and system-wide sustainability. While our study reports CO_2 emissions from both traditional and CS deliveries, it does not quantify the full environmental impact, including factors such as particulate matter, energy consumption, or urban congestion. Moreover, the model assumes that all CS deliveries are combined with existing trips, based on pre-scheduled synthetic diaries. This assumption ignores the generation of new trips. Future work could incorporate these effects along the lines of (Tapia et al., 2023). While this study systematically tested fixed compensation levels per kilometre, future research could explore dynamic and surge pricing strategies. Investigating such pricing mechanisms could help align incentives more effectively and enhance the flexibility and scalability of CS services.

CRediT authorship contribution statement

Merve Seher Cebeci: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Michiel de Bok:** Writing – review & editing, Supervision, Investigation. **Rodrigo Tapia:** Writing – review & editing, Supervision, Software, Methodology, Investigation. **Ali Nadi:** Writing – review & editing, Visualization, Supervision, Methodology. **Lóránt Tavasszy:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Merve Seher Cebeci reports financial support was provided by the EU Horizon Europe Programme in the framework of the "Upscaling Innovative Green Urban Logistics Solutions Through Multi-Actor Collaboration and PI-Inspired Last Mile Deliveries" project (URBANE), under GA Number 101069782. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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