



# Performance analysis of crowd-shipping in urban and suburban areas

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## Abstract

Crowd logistics is a novel shipping concept where delivery operations are carried out by using existing resources, namely vehicle capacity and drivers from the crowd, thereby offering potential for economic, social, and environmental benefits. Despite the promise of this new logistics model, little is known about its actual functioning, performance, and impact. This paper presents a pioneering study of the performance of a real crowd-shipping system in the U.S. using empirical data from 2 years of operations. We contribute to the literature by: (1) defining performance metrics and developing models that account for the specificity of crowd-shipping systems by distinguishing the essential stages from bidding to acceptance and delivery of shipments, (2) identifying the significant covariates, including shipment features, built environment, and socio-demographic factors giving rise to different delivery performance outcomes, and (3) deriving sensitivity analysis to study the performance and implications of crowd-shipping in urban and suburban areas. The analysis is formalized as two-level nested logit models with nests representing bidding and delivery outcomes. The results show that not only does the delivery outcome performance vary significantly between urban and suburban areas, but the explanatory factors also vary significantly for the two contexts. Additionally, several factors have ambiguous impacts depending on the stage. Larger shipment size (versus strict deadlines) leads to increasing (decreasing) the likelihood of bids being placed, while having the opposite effect when it comes to the delivery phase. The findings highlight the need for developing different strategies to foster and improve the performance of this novel system depending on both the urban–suburban shipping context and the stage of delivery.

**Keywords** Urban freight · Nested Logit · Crowd-logistics · Crowd-shipping · Shipping performance · Urban and suburban

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## Introduction

Many cities have begun to address mobility challenges by developing mobility visions and strategies for passenger transportation at the city and regional levels. However, comprehensive strategies for (last mile) urban delivery of goods are often lagging (Cui et al. 2015). The effective organization of urban logistics is essential to the vitality of modern urban economies and for maintaining livability for citizens and communities (Behrends et al. 2008; Taniguchi 2014; Taniguchi and Thompson 2018). Cities are places of intense consumption relying on frequent incoming deliveries of retail goods and groceries (Cui et al. 2015; Comi et al. 2018a, b). In addition, the growing role of e-commerce, coupled with increasing consumer expectations for express and home delivery performance, is further compounding the pressure on urban delivery systems (Morganti et al. 2014; Visser et al. 2014; Goodchild and Wygonik 2014; Barone et al. 2014; Comi and Nuzzolo 2016). At the same time, new opportunities for improving freight delivery performance are unlocked by unprecedented technological and service innovations (Savelsbergh and Van Woensel 2016; Macharis and Kin 2017). These innovations have fostered the creation of new enterprises and business models in the logistics sector. There is consensus in the field that strategies to optimize deliveries and reduce unwanted externalities, needs to rely on a mix of measures, e.g. off-hour delivery regulations (Verlinde and Macharis 2016), public–private partnerships (Lindholm and Browne 2013), company collaboration (Bram et al. 2018) telematics and loading bay reservation (McLeod and Cherrett 2011; Roca-Riu et al. 2017; Comi et al. 2018a, b) pricing (Holguin-Veras et al. 2006) and vehicle technology innovation (Gruber et al. 2014).

There is currently a growing interest in the role of freight delivery innovation related to the use of crowd-sourced vehicles and drivers, coordinated via connected online platforms (Rougès and Montreuil 2014; Mehmman et al. 2015; Carbone et al. 2015; Devari et al. 2017; Buldeo Rai et al. 2017, 2018). Crowd-shipping has the potential to offer several logistics alongside broader benefits, such as faster delivery time, lowered delivery prices and more shipping flexibility for customers, sustainability from using excess vehicle capacity for society, and new employment opportunities for carriers (Le et al. 2019). At the same time, important challenges have been identified related to critical network effects, trust and safety concerns, security and legal obstacles (see review by Le et al. 2019, and references within). The current paper is among the first to provide an empirical analysis of the emerging delivery concept of crowd-sourced logistics, or crowd-shipping. Crowd-shipping delivery is defined here as a shipping service coordinated via digital platforms that match demand for shipping with occasional carriers drawn from the crowd (Punel and Stathopoulos 2017). Crowd-shipping is becoming a serious contender in the shipping industry, often promoted by non-traditional stakeholders, such as technology firms and retailers (Dablanc et al. 2017). DHL experimented early on with MyWays (DHL 2013), a last-mile delivery scheme where e-purchased items could be picked up and delivered by neighbors. Currently many start-up companies, originating from outside the traditional logistics setting, are specializing in shipping via the crowd, such as RideShip, Nimber, Roadie, Deliv, and PiggyBee. In addition, major retail organizations are developing shipping by “regular people.” In the United States, Amazon and Walmart have piloted schemes where customers are paid or given discounts to pick up and make deliveries to other customers along their route (Walmart 2016; Amazon 2015).

The inclusion of transformative services such as crowd-shipping in urban mobility strategies, however, requires a comprehensive research plan. Specifically, the study of

crowd-shipping presents unique challenges. Crowd-shipping entails a departure from traditional logistics models, with non-traditional stakeholders, business models and the use of apps and communication technology, such as online platforms to organize and carry out deliveries (Macharis and Kin 2017; Frehe et al. 2017; Mladenow et al. 2016). There is an increasing interest in understanding how crowd-sourced deliveries can supplement existing goods delivery systems in a way that is collectively beneficial. At the same time, there is very little insight into how the emerging crowd-sourced systems function, how they are affected by the behavior of users, local economic and network effects, and ultimately how they impact society more broadly. An important reason for the dearth in understanding is the comprehensive lack of data on crowd-shipping operations, due to the emerging and competitive nature of the existing systems. The current analysis begins to address these gaps in understanding by analyzing platform performance using a unique 2-year data-base of U.S. crowd shipments obtained from one of the leading crowd-shipping companies from January 2015 through December 2016 period.

The goal of this paper is to study the performance determinants of crowd-shipping. In line with the critical importance of last-mile and urban deliveries in the shipping literature, our models will separately study the performance in *suburban* and *urban* settings. The specific objectives are to: *First*, define performance metrics and model structures that account for the specificity of crowd-shipping systems. Notably, crowd-shipping delivery performance relies on peer-to-peer exchanges mediated by online platforms. Therefore, the analysis highlights, the entire flow of transaction decisions, including the critical earlier stages where posted shipments compete for bids, to acceptance by a crowd-courier to final delivery. This perspective differs from the general focus in the field on performance measured from pick-up to delivery. *Second*, we develop separate bidding, acceptance, and delivery models that identify the main covariates, among shipping features, built environment, and socio-demographic factors, determining performance in each of the delivery progression stages. The *third* objective is to derive sensitivity parameters to study the performance and policy and practice implications of crowd-shipping in urban and suburban areas. The analysis is formalized as two-level nested logit models with separate nests representing the bidding process and delivery outcomes. An important contribution of this work is to provide an early investigation of crowd-shipping systems, with a focus on how the delivery performance can be viewed as integrated stages. As an emerging logistics concept, entailing both potential benefits and disadvantages in comparison to traditional delivery methods, this paper is among the first providing an analysis of actual crowd logistics performance and impact.

The rest of the paper is organized as follows. First, we summarize the growing literature on crowd-shipping in the “[Literature review](#)” section. In the section “[Crowdshipping delivery analysis: from data preparation to performance analysis](#)”, we describe the database used for the analysis, the model variables, and the descriptive performance of the urban and suburban crowd shipments. Section “[A 2-level nested logit model of crowdshipping delivery performance](#)” discusses the two-level nested logit models and the results to not only analyze the variables affecting the performance of the crowd-shipping system, but also to distinguish between the performance in urban and suburban areas. We conclude the paper with a summary of the main findings and implications for research, business analysis, and policy considerations.

## Literature review

The literature overview briefly summarizes the implications of increasing logistics pressure in both urban and suburban areas. Crowd-shipping has been identified as a possible solution to alleviate those pressures and we review, and evaluate, the main research findings. This sets the scene for the presentation of key studies and deeper analysis of the performance of crowd-shipping.

### Impact of freight distribution on urban and suburban areas

Freight transport is gaining increasing attention as a critical area to improve urban planning and the functioning and attractiveness of cities (Cui et al. 2015). Urban goods delivery analysis entails several challenges related to the coordination of multiple stakeholders (Taniguchi and Tamagawa 2005; Stathopoulos et al. 2012; Kiba-Janiak 2016), complex goods and mode selection strategies (Arencibia et al. 2015; Samimi et al. 2011), and diverse policy levers (Behrends et al. 2008; Russo and Comi 2011; Anderson et al. 2005). What is more, there are currently monumental changes occurring in distribution and logistics systems, affecting urban and suburban areas alike. Modern logistics is shaping urban development and urban land use. On the demand side there are fundamental changes, specifically in urban areas, towards e-commerce, smaller business and home-delivery aided by communication technology and mobile device diffusion (Morganti et al. 2014; Allen et al. 2018) leading to growing fragmentation of goods flows. On the supply chain side, a complex mix of concentration and decentralization is observed (Hesse and Rodrigue 2004; Cidell 2010). For example, suburban areas are attractive due to the availability of affordable land and transportation infrastructure connecting to a system of regional and national goods flows (Dablanc and Rakotonarivo 2010; Dablanc et al. 2014). In the United Kingdom and elsewhere in Europe there is evidence that warehousing is moving away from urban areas to suburban areas (Allen et al. 2012). The densification of urban land and growing challenges of urban logistics has led to increasing attention to transformative technology and management alternatives (Savelsbergh and Van Woensel 2016). In the following we review the operational, behavioral, and business analysis of the emerging concept of crowd-shipping.

### Overview of crowd-shipping research

Crowd-sourced shipping typically relies on online platforms to match demand and supply of logistics. The platforms engage the crowd to carry packages, whereby everyday commuters or travelers transport goods, ideally along commute itineraries or routes that are taken anyway (Van Cooten 2016; Mehmam et al. 2015; Carbone et al. 2015; Marcucci et al. 2017). This implies a novel model where businesses develop logistics models around existing travel flows of the crowd of citizens. Crowd-shipping operators frequently originate as startups from outside the traditional logistics industry and manage online platforms where senders and drivers from the crowd connect. The crowd-shipping firm is responsible for recruitment of users and drivers, and for developing pricing algorithms matching shipment supply and demand. Potential advantages from crowd-shipping are faster deliveries, access to new products, lower delivery costs, reduced operating costs, and minimizing environmental impact (Paloheimo et al. 2016; McKinnon et al. 2015; Mladenow et al. 2016). Important obstacles identified are trust and liability issues related to non-professional carriers, and the challenge of building a critical

mass of couriers and customers (Rougès and Montreuil 2014; Frehe et al. 2017). An outstanding research challenge is to gain fundamental understanding of the performance of crowd-shipping deliveries. To date, research has been limited on account of the novelty and limited publicly available data, leading to poor understanding on the side of both researchers and policymakers. The lion's share of investigations uses operational research frameworks, relying on auxiliary data, to study the fundamental properties of crowd-shipping. Other strands of literature have developed behavioral models and business model analysis relying mainly on using hypothetical data, expert interviews, and business case-studies.

## Analysis of crowd-shipping performance

A representative sample of studies from operational, behavioral and business analysis that study crowd-shipping performance are summarized in Table 1. For crowd-logistics, several operational frameworks have been proposed, typically using external (or synthesized) data from taxi-trajectories or public transit patterns to represent the potential demand by senders and/or the supply of drivers, seeking to underpin the analysis with realistic information (Archetti et al. 2016; Arslan et al. 2016; Wang et al. 2016; Kaffle et al. 2017). Importantly, most works assume that the new system will be applied for urban or last-mile deliveries, and study impacts only for specific applications. A general finding from this literature is that crowd-logistics could lead to several benefits including a reduction in costs, failed delivery risk, and overall delivery mileages. Yet, such results hinge critically on simplified assumptions about demand and acceptance factors. A small number of behavioral works have looked at the human decision aspects that determine acceptability, and thereby the performance, of crowd-shipping (Punel and Stathopoulos 2017; Miller et al. 2017; Le and Ukkusuri 2018a; Ta et al. 2018). This literature finds that senders are typically young, male or urban dwellers (Punel et al. 2018) and strongly impacted in their driver selection by the distance of the delivery and by driver ratings (Punel and Stathopoulos 2017). Partners are more likely to match when they are similar, especially for their ethnicity profile (Ta et al. 2018). On the side of carriers, there are significant variations in the willingness to pick up deliveries when it entails a detour from a planned commute (e.g. Marcucci et al. 2017; Miller et al. 2017; Le and Ukkusuri 2018b). In addition, several business model analyses for crowd-shipping have been proposed (Carbone et al. 2015). Rougès and Montreuil (2014) identify 5 ideal types of crowd-shipping services, based on examining real company business models. The main business model distinction is based on shipment distance classes, and the involved stakeholders. Crowd-shipping platforms generally tailor their service on either the shipment from businesses to individual households (B2C) or between peer consumers (C2C). There is similarly, often a clear distinction between long-distance and local delivery models. Relying on literature and interviews with logistics practitioners Buldeo Rai et al. (2017) identify 18 characteristics of crowd-logistics. The research shows that the evaluation criteria emphasize important implications for economic, social and environmental sustainability of crowd-logistics, with a potential for both positive and negative effects. Frehe et al. (2017) examine 12 dimensions of crowd-logistics and its environment using expert interviews, literature analysis and existing company profiles. The authors highlight that the reasons for using crowd-logistics, along with the overall macro effects, are mainly unknown.

**Table 1** Summary of literature from OR, behavior and business analysis on CS performance

Author	Research area	Study method	Application context	Distance focus	Crowd-shipping performance results	Results most sensitive to assumptions or effects
Archetti et al. (2016)	OR	Optimization of Vehicle Routing Problem with Occasional Drivers multi-start heuristic model	Theoretical computational study	Undefined	Study shows reduction of delivery costs for traditional logistics firms with occasional crowd drivers	Results depend on the number and flexibility of occasional drivers, in turn related to the compensation scheme
Arslan et al. (2016)	OR	Optimization of dynamic pickup and delivery problem. Vary both the departure time flexibility and the detour flexibility.	Simulation study based on features from city of Rotterdam, Belgium	Last mile (urban)	Study shows that total distance travelled is lower for the crowd-sourced system than for the traditional system (benchmark with dedicated drivers)	Results sensitive to arrival rates of requests and drivers, assumed static in modeling
Wang et al. (2016)	OR	Assignment optimization problem modelled as a network min-cost flow problem	Experiments were conducted with Singapore and Beijing datasets (bus taxi and commuting data)	Last mile (urban)	Crowd-delivery has advantage of using excess capacity, ensuring delivery tasks are independent from delivery sequence, and offers more tailored/participative solution	Results depend on size of worker pool, compensation and customer requirements
Kaffe et al. (2017)	OR	Last mile vehicle routing problems, the new formulation integrates crowdsourcing bids selection and relay points location with truck routes design	Theoretical computational studies	Last mile (urban)	Crowd-solution (cyclist / pedestrian) compared to truck only leads to total cost saving is around 9.25% and reduced VMT by 24%	Results depend on factors such as penalty for servicing outside customers' desired time windows, truck unit operating cost, time value of crowd-sources, and the crowdsourcing mode
Punel and Stathopoulos (2017)	Behavior analysis	Survey and stated choice experiment on sender's choice of driver; Discrete choice random parameter and error component model	Sample from USA, resp = 531	Local (urban) and long distance shipping	Sender decision on driver varies by distance; senders prioritize ranking of drivers on local deliveries and delivery conditions for long distance shipments	Results are most sensitive to the driver performance measured through ratings and past experience

**Table 1** (continued)

Author	Research area	Study method	Application context	Distance focus	Crowd-shipping performance results	Results most sensitive to assumptions or effects
Miller et al. (2017)	Behavior analysis	Survey and stated choice experiment on crowd-driver's acceptance of shipment; Discrete choice random parameter model	Sample from USA, resp = 152	Local shipping (increased trip travel time from base of 10 to 120 min)	Potential drivers prefer small trip detours from commute to deliver packages	Results for willingness to work are most sensitive to the pay compensation and detour levels of driver
Marcucci et al. (2017)	Behavior analysis	Survey with both potential senders and drivers	Sample from Italy, N = 190	Local shipping	87% and 93% of Italian students were willing to work as driver-partners and receive their packages via a CS system, respectively	Results are most sensitive to distance with respondents prepared to deviate for 2.4 km maximum, lowered to 1.5 km for non-motorized trips
Le and Ukkusuri (2018a)	Behavior analysis	Survey and stated choice experiment on crowd-driver's acceptance of shipment; Least-square regression model with selectivity bias correction	Sample from USA, resp = 430	Local shipping (anchored on 20 min trip)	Respondents who have experience transporting freight or goods are more willing to work as driver-partners	Results for willingness to work are most sensitive to age and experience of the driver
Le and Ukkusuri (2018b)	Behavior analysis	Survey and stated choice experiment in two countries	Sample from USA resp = 549 & Vietnam resp = 509	Local shipping (base 5 miles (US); base 8 km (VN))	Requesters favor CS carriers for specific goods categories (eg dry cleaning, groceries, food, with higher delivery fees and time urgency). Instead, traditional carriers are preferred for less urgent shipments	Results comparing the settings showed that time sensitivity was much higher in USA than Vietnam
Ta et al. (2018)	Behavior analysis	Survey and experiment with potential senders; Factor analysis and MANOVA	Sample from USA resp = 761	Local shipping	Senders prefer driver with profile disclosure but only when the drivers are similar to senders themselves	Results are most sensitive to disclosed ethnicity of driver

**Table 1** (continued)

Author	Research area	Study method	Application context	Distance focus	Crowd-shipping performance results	Results most sensitive to assumptions or effects
Rougès and Montreuil (2014)	Case study/business analysis	Extensive public document review of existing CS companies to categorize company types	Study of 18 worldwide companies	Local to national/international	Identifies 5 CS models: “Courier,” “intendant,” and “intra-urban” models target business efficiency control strategies, while “national” and “social delivery” models are based on business and trust, respectively	Performance most sensitive revenue models. Five main types namely “fixed price,” “negotiated prices,” “financial and matching fees,” “resale margin,” and “membership”
Carbone et al. (2015)	Case study/business analysis	Study of CS initiatives with content analysis on company website data	Study 57 international crowd logistics initiatives	Focus of CS operations is predominantly at the local scale	Identifies classification in four types of CS services	Performance of future CS is dependent on the complex nature of the system and integration in handling, storing, and transporting goods
Frehe et al. (2017)	Case study/business analysis	Document-based data analysis and expert interviews	Analysis of 13 German and international companies	Variable for analyzed firms, emphasis on local (food)	Identifies four relevant steps that companies should follow to implement sustainable crowd logistics	Performance most sensitive to the network (of both carriers and customers) which is suggested needs to be established before initiating the service
Buldeo Rai et al. (2017)	Case study/business analysis	Systematically analysed a set of 42 papers and interviewed with logistics practitioners	Interviews with 11 Belgian CS firms	Local delivery	Performance depends on 7 crucial factors: (1) Technological infrastructure; (2) Use of excess capacity; (3) Crowd network; (4) Unknown crowd identity; (5) External/flexible drivers provision; (6) Compensation design; (7) Voluntary drivers	Sustainability of performance impacted only by third party involvement, crowd motivation and modal choice



## Literature takeaways

To summarize, the literature analysis in Table 1 calls attention to several important issues. First, there is a lack of research on operations, behavior, or business performance of crowd-shipping using real or large-scale operational data. Second, there is limited understanding of the fundamental properties, motivations, and performance metrics for crowd-shipping. Third, the great majority of works only explore local delivery settings despite the observation by Buldeo Rai et al. (2017) regarding the interest among practitioners to go beyond the last mile focus. This paper aims to bridge the gap between the growing body of real-life operations and the lack of comprehensive investigation of the actual performance of crowd-shipping systems. The research employs a comprehensive US database of real operations to study the functioning and performance of crowd-shipping in urban settings, where goods deliveries face unique challenges, versus lower density suburban areas.

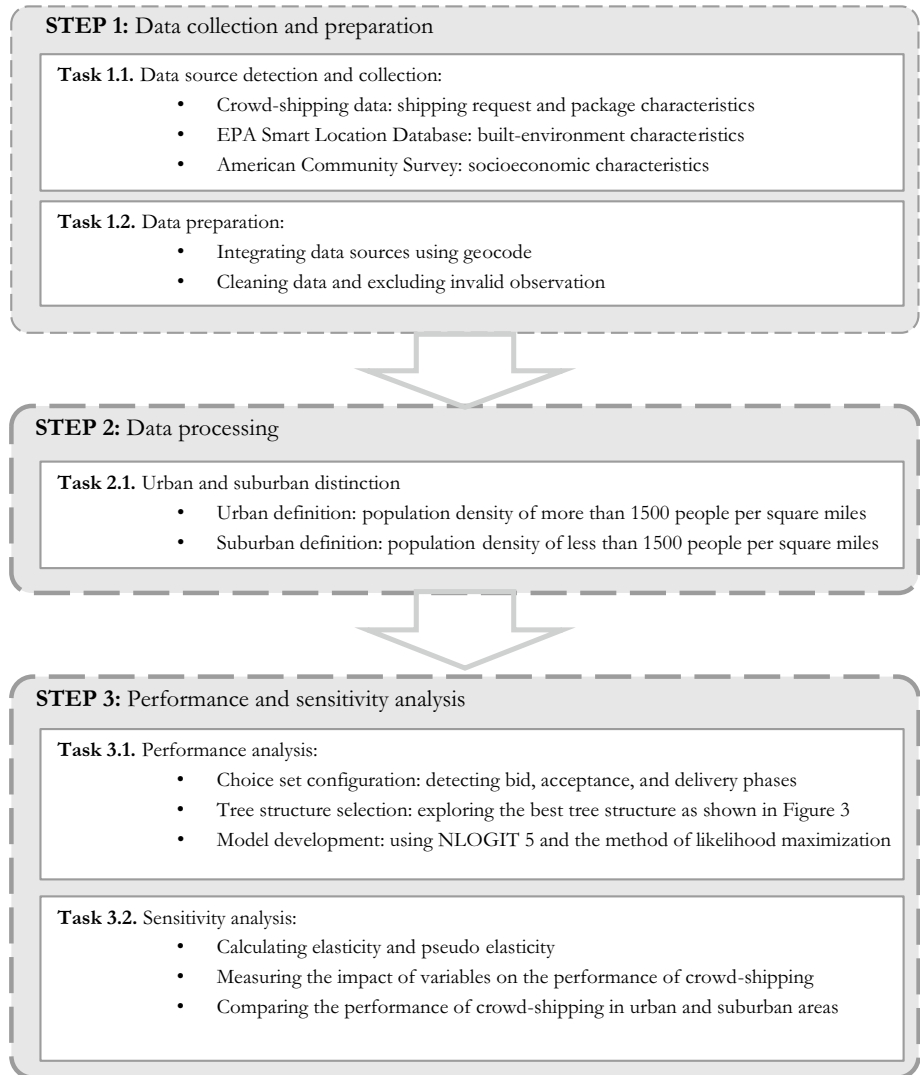
## Crowdshipping delivery analysis: from data preparation to performance analysis

Figure 1 outlines the main steps of the research. The data preparation and augmentation with block-group matched data, followed by the distinction between urban and suburban areas are covered in the “[Crowdshipping delivery analysis: from data preparation to performance analysis](#)” section. The definition and modelling of the performance, along with elasticity and practical implications are covered in the “[Analysis of results](#)” section.

## Crowd-shipping database

The core data used in this study were obtained from a leading US crowd-shipping firm. The company provides an app-based platform to connect shipping service requesters with occasional couriers in all 50 states and the District of Columbia. The company operational value proposition is to offer a broad range of shipping services, covering local to long-distance delivery for a range of package sizes. The company targets both private and business senders, and effectively covers all shipping distances, from local to inter-state. The database hence provides a unique opportunity to study the performance of a crowd-shipping firm for a range of package specifications and conditions owing to the broad operational repertoire of the firm. The database includes the shipping request and package characteristics of 16,850 transactions for a 2-year period of January 2015 through December 2016. The same data has been used to study supply generation by means of bidding and count models in Ermagun and Stathopoulos (2018). Each transaction data contains, but is not limited to, information on the package size, delivery deadline, timing of delivery events (publishing, bidding, and delivery), sender/carrier characteristics, and geographic coordinates of both the shipment origin and destination (Table 2 summarizes the variables).

The detailed nature of the data-base also allows us to model the entire delivery process, from inception of a posted request to final delivery. The crowd-shipping delivery process analyzed in the current research is comprised of five steps: (1) the sender **posts** a delivery request on the online platform specifying package size, distance and deadline, (2) registered couriers start **bidding** for the order, (3) if the request receives a bid,



**Fig. 1** Summary of research process

the sender might “**accept**” or “**decline**” the courier offers, (4) if the sender accepts one of the bids, they are connected to arrange the **pick-up** time, and (5) once the package is picked-up, the shipment enters the **delivery** step.

We conducted a validation process for each transaction and excluded test transactions published by the company along with incomplete records. This resulted in 14,858 valid shipment observations. In the following, the classification procedure for urban–suburban shipments is described, followed by summary statistics and exploratory analysis of crowd-shipping performance for the urban and suburban origin contexts.

**Table 2** Definition and basic statistics of variables used in this study

Variables	Description	Average	SD
<i>Shipping request and package characteristics</i>			
OVERSIZED	1: If the package size is oversized/0: Otherwise	0.265*	0.441
LARGE	1: If the package size is large/0: Otherwise	0.098*	0.298
LONG	1: If the package size is long/0: Otherwise	0.100*	0.300
HOLIDAY	1: If demand request is posted on federal holiday/0: Otherwise	0.022*	0.147
WEEKEND	1: If demand request is posted on weekend/0: Otherwise	0.182*	0.386
MORNING	1: If demand request is posted between 6:00 A.M. and 3:00 P.M./0: Otherwise	0.643*	0.479
MIDNIGHT	1: If demand request is posted between midnight and 4:00 A.M./0: Otherwise	0.027*	0.163
DEADLINE	1: If the delivery has a deadline/ 0: Otherwise	0.735*	0.441
DEADLINE < 1H	1: If the deadline of the delivery is less than an hour/0: Otherwise	0.063*	0.244
DEADLINE > 2D	1: If the deadline of the delivery is more than two days/0: Otherwise	0.002*	0.050
DEADLWKND	1: If the deadline of the delivery is on a weekend/0: Otherwise	0.166*	0.372
SAGE < 24	1: If sender is younger than 24 years/0: Otherwise	0.019*	0.139
SAGE 25–34	1: If the age of sender is between 25 and 34 years/0: Otherwise	0.099*	0.299
SAGE 45–54	1: If the age of sender is between 45 and 54 years/0: Otherwise	0.040*	0.197
SAGE 55–65	1: If the age of sender is between 55 and 65 years/0: Otherwise	0.075*	0.263
OUTSTATE	1: If the delivery request is for out-of-state/0: Otherwise	0.293*	0.455
DISTANCE	Distance between pick-up and drop-off points (Mile)	268.65	514.53
B2C	1: Business-to-customer market/0: Otherwise	0.248*	0.432
EXPERIENCE	Number of times that service requester used the system since enrolment	37.243	124.52
<i>Built environment characteristics</i>			
O_POPDENS	Residential density of the trip origin (Household unit per Acre)	5.674	16.065
D_POPDENS	Residential density of the trip destination (Household unit per Acre)	5.809	18.253
O_NDENS	Total road network density of the trip origin	16.044	9.024
O_ACCESS	Number of jobs within 45 min auto travel time at the trip origin	214,775.6	186,491.0
<i>Socioeconomic characteristics</i>			
O_BLACK	Percentage of African-Americans at the block group level of the origin	0.173	0.198

**Table 2** (continued)

Variables	Description	Average	SD
D_BLACK	Percentage of African-Americans at the block group level of the destination	0.198	0.241
O_HAWAIIAN	Percentage of Hawaiian at the block group level of the origin	0.001	0.002
O_LOWWAGE	Percentage of low wage workers at the block group level of the origin	0.219	0.065
D_LOWWAGE	Percentage of low wage workers at the block group level of the destination	0.225	0.069
O_VEHICLE > 2	Percentage of families with two or more vehicles	0.495	0.233
O_NOVEHICLE	Percentage of families without any vehicles in the trip origin	0.108	0.151
D_NOVEHICLE	Percentage of families without any vehicles in the trip destination	0.108	0.158
O_USERS	Number of crowd-couriers in the origin of the trip	11.472	15.533
D_USERS	Number of crowd-couriers in the destination of the trip	9.601	14.228

\* %Share for dummy variables

## Data augmentation with built environment and socioeconomic factors

The modeling studies the performance of the crowd-shipping system not only as a function of the shipping request and package characteristics, but also in relation to the built-environment and socioeconomic characteristics of local residents, at both the trip origin and destination. In particular, we hypothesize that the performance of the crowd-shipping system including bidding, acceptance, and delivery outcomes may be explained in part by socioeconomic and built environment variables. As a result, we study the association between the performance of the crowd-shipping system and:

- Ethnicity of local residents in line with findings by Ta et al. (2018) on the role of ethnic similarity.
- Car availability due to its likely role in facilitating shipments among carriers.
- Level of income as it is a likely determinant of interest in making extra money for carriers (Miller et al. 2017).
- Residential density as a metric of compactness is found important in nearly all crowd-shipping analysis. The compactness concentrates origins and destination and is likely to facilitate the development of crowd-shipping rather than traditional delivery solutions. Density could also discourage crowd-shipping if many competing options are available.
- Road network density as it impacts the transport system efficiency and consequently affects the delivery performance and the willingness of carriers to accept shipments.
- Accessibility to jobs (reachable with 45 min of car travel). This measure might discourage use of crowd-shipping due to competing labor market options.

To capture the impact of these socioeconomic and spatial characteristics, we augmented the data using two additional data sources: (1) 2014 EPA Smart Location Database and (2) 2015 American Community Survey. The former measures built-environment characteristics, including employment density, residential density, road network density, and accessibility to jobs. The latter collects socioeconomic characteristics such as population density, ethnicity, education, age, and gender. Both datasets are provided at the census block group level of geography. Table 2 summarizes the description and basic statistics of variables used in the analysis. As shown in Table 2, we classified variables into three distinct categories:

- (1) Shipping request and package characteristics: This category includes variables extracted from the core data used in this study such as the size of packages, the time-of-day and day-of-week of posting the shipping request, the delivery deadline, the age of sender, distance of delivery, and the type and experience of the sender. Looking at Table 2, it is found that most of the packages are smaller in size, are posted between 6:00 A.M. and 3:00 P.M. (64%), have a deadline (74%), fall in the customer-to-customer market (75%), and are requested to be shipped in-state (71%).
- (2) Built environment characteristics: The variables that fall in this category were extracted from 2014 EPA Smart Location Database and include residential density, road network density, and cumulative accessibility to jobs by automobile in a 45-minute threshold.
- (3) Socioeconomic characteristics: This category encompasses ethnicity, level of income, and vehicle ownership variable, which were extracted from 2015 American Community Survey. Looking at Table 2, it is inferred that in the block group of the trip origin, on

average, 17% of families are African-American, about a half of them own two or more vehicles, 10% of them have zero vehicles, and 21% of them are low wage workers.

### Definition of urban–suburban shipments

To distinguish the performance of crowd-shipping in urban areas from suburban areas, we separate shipping requests using the geographical coordinates of the trip origin. The literature suggests different definitions for urban and suburban areas. For example, the Census Bureau defines urban areas as a densely settled core created from census tracts that have a minimum population of 50,000 people. We, however, adopted the more comprehensive definition from Ewing et al. (2014) and define urban and suburban areas as follows:

- Urban areas: Census tracts with population density of more than 1500 people per square mile.
- Suburban areas: Census tracts with population density of less than 1500 people per square mile.

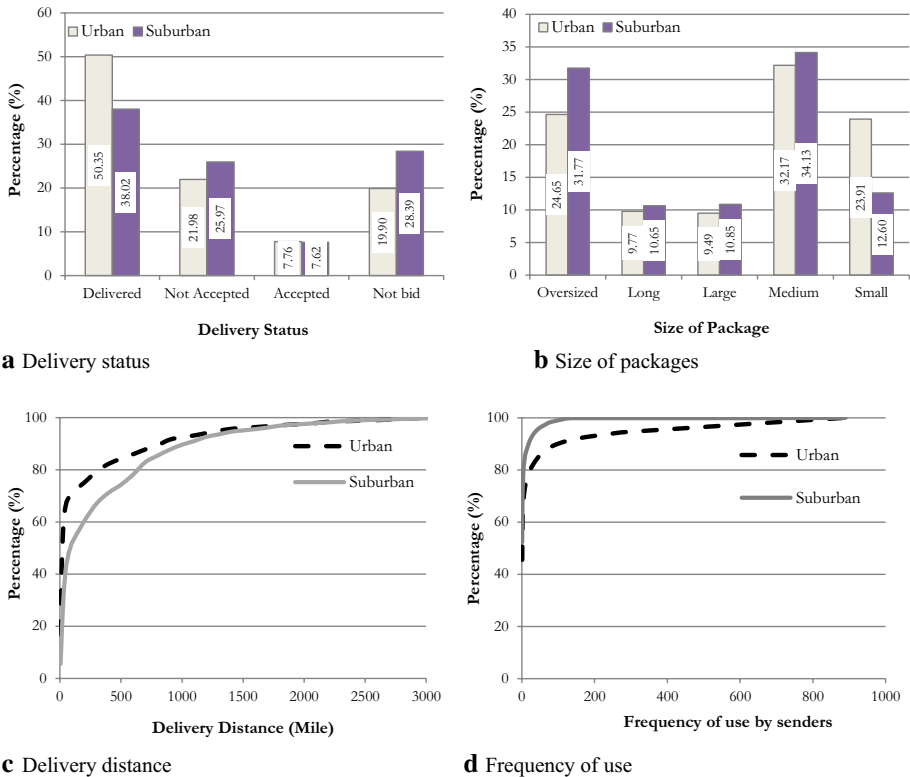
For the purpose of this analysis, we distinguish urban shipping requests from suburban shipping requests considering the origin of the request as the characteristics of the origin is more dominant than the destination. That is, a shipment requested from an urban area to a suburban area, is classified in the urban area category. Consequently, the results show that 3935 out of 14,858 (26%) shipping requests originate in suburban areas.

### Preliminary data analysis

Figure 2a–d summarizes the delivery outcome statistics in both urban and suburban areas. The plots show the share of total counts for key variables over the study period.

Looking at Fig. 2a, it is inferred that the delivery and bidding performance is significantly different between urban and suburban areas. In urban areas, 50.4% of shipping requests are delivered and only 19.9% of shipping requests did not receive a bid. In suburban areas, however, the delivery percentage diminishes to 38.0% and the no bid percentage increases to 28.4%. Figure 2b displays the share of shipping requests in terms of the size of packages in urban vs. suburban areas. There are significant differences between urban areas (24.6% of packages are oversized and 23.9% of packages are small) and suburban areas (31.7% of packages are oversized and 12.6% are small) suggesting different demand structures.

The average delivery distances are relatively elevated, far higher than the last-mile focused works reviewed in Table 1. This is reflective of the undisclosed company data that focuses on both short and long distance shipments. Figure 2c, d graphs the cumulative distribution function according to the delivery distance of the shipping request and the distribution of use, respectively. In urban areas, the shipment distance ranges from 0.03 to 4264.4 miles, with an average of 239.4 miles. As shown in Fig. 2c, 80% of shipping requests from urban areas have a distance of less than 300 miles. In suburban areas, the shipment distance ranges from 0.07 to 4007.7 miles, with an average of 349.8 miles. As shown in Fig. 2c, 80% of suburban shipping requests have a delivery distance of less than 700 miles. This reveals that the delivery distance in suburban areas is significantly higher than for urban shipments. The disparity is likely explained by the fact that the demand and supply network is denser in urban areas, leading to a higher chance to find a well aligned



**Fig. 2** Descriptive plots of shipping request and package characteristics in urban and suburban areas. (Percentage of total occurrence over 2-year study period.) Notes: \* Package sizes are defined as: Small (size of a book); Medium (fits in a car front seat); Large (fits in the back seat of a car); Long (requires a hatchback or SUV); Oversized (requires a pickup truck)

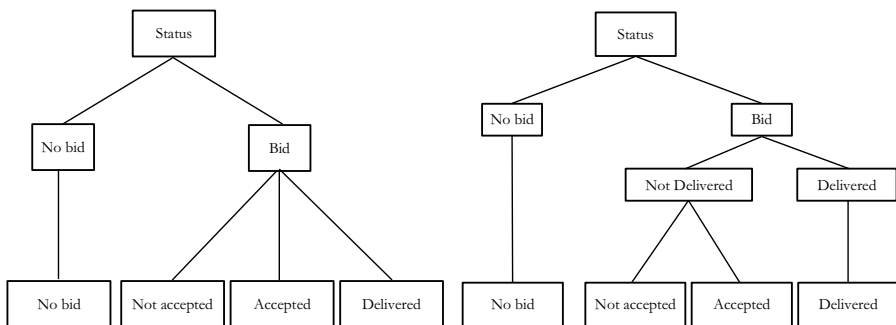
sender request and driver availability that minimizes vehicle mileages. More details of the performance differences are discussed in Sect. 5. Looking at Fig. 2d, we find that 80% of urban area users published less than 30 shipping requests, while this number equals 5 for suburban users. More specifically, per capita shipping requests in urban and suburban areas equal 47.7 and 8.1, respectively. This means that urban residents are more frequent users of crowd-shipping as senders, albeit with a large concentration among a subset of platform participants.

## A 2-level nested logit model of crowdshipping delivery performance

The delivery process on the crowd-shipping platform occurs in several stages that are critical for the delivery performance definition. Unlike traditional shipping analysis, the detailed records for the online platform allows analysis of the bidding, matching and process of pickup that has not been studied empirically in the past. For the proposed discrete choice model, we categorize the intermediate delivery steps as model alternatives. The process starts when a sender posts a shipment on the platform. Then the possible outcomes

are: (1) shipment receives no bids, (2) receives at least a bid from a courier, but is not accepted by the service requester, (3) receives bids and is accepted by the requester. From stage (3) the possible outcomes is that the package is not picked up or delivered (due to a failure in the peer-to-peer negotiation or lack of appropriate courier vehicle) or that pick-up is followed by a successful delivery. To model the delivery status of crowd-shipping, we develop a nested logit (NL) model (Ben-Akiva and Lerman 1985; Koppelman and Wen 1998). The NL model has the potential to partially relax the independence of irrelevant alternatives property of the commonly used multinomial logit model by nesting alternatives. This property is empirically violated in our case according to the choice set partitioning test. The nesting structure allows the exploration of common characteristics for multiple alternatives in the same nest. For crowd-shipping this is consistent with the idea that shipments receiving more bids have a latent attractiveness (such as more manageable shipment features or more complete descriptions) that makes a successful delivery more likely. Earlier applications of NL models in the freight literature include Rich et al. (2009), using a 2-level NL model to understand the choice of long-distance freight mode and crossing. The proposed tree structure consisted of five travel modes, namely, truck, combination rail, combination ship, conventional rail, and conventional shipping at the upper level, and 40 crossing combinations as the choice of nesting. Wang and Hu (2012) addressed the decision of vehicle mode choice by businesses and commercial sectors in urban areas testing a 2-level NL model. Their tree structure placed small vehicles (i.e. auto, pickup, and SUV) in one nest and large vehicles (i.e. single-unit and multi-unit trucks) in another. A 3-level NL model was also tested by Nuzzolo and Comi (2014) in an agent-based freight simulation framework. The model distinguished between decisions of retailers and wholesalers in the uppermost level. The second level split showed the choice of outsourcing to third party sectors versus relying on own account shipping, while the third-party sectors are decomposed into two separate categories of transport companies and couriers at the lowest level. However, there is no research targeting the delivery status of shipments, and this paper is the first to test a 2-level NL model to explore crowd-shipping delivery performance.

To select the best tree structure, a number of specifications were tested and compared. Figure 3 represents the two best specifications based on examining overall model fit and the inclusive value criteria. However, the structure shown in 3a was superior in reproducing the behavioral process consistent with the empirical data. Both formulations show evidence of higher substitution in the subset of requests that were attractive enough to receive bids. The structure



**a** Two-level nested logit

**b** Three-level nested logit

**Fig. 3** Tree structures of nested logit models



in Fig. 3a forms the basis for our modeling and contains two main alternative branches: (1) No bid and (2) Bid. The former includes only one alternative (no bid), while the latter embeds three alternatives in its nest, representing all other possible outcomes for a shipment once it has received at least one bid from a courier.

The selected tree structure allows for: (1) capturing some degrees of correlation among different alternatives of each nest, and (2) estimating different scales for the alternatives included in different nests. The nesting structure, however, requires normalization of the scale, due to a theoretical identification problem. Equation 1 formulates the utility function of the model. In this equation,  $V_{ni}$  is the observed utility associated with the occurrence of alternative  $i$  for decision-maker  $n$ , where  $Z_k$  is a vector of variables related to the nesting structure, and  $X_{ik}$  is a vector of variables specific to the alternative in the nest. Outcome probabilities are formulated in Eq. 2 where  $B_k$  denotes nest  $k$  ( $k = 1, 2$ ), and  $\gamma_k$  is its associated nest parameter, which is known as the Inclusive Value (IV) parameter. The IV parameter is determined in the estimation process and is used for model specification analyses. In a 2-level nested logit model, the  $\gamma_k$  corresponding to each nest should fall between 0 and 1, and be significantly different from these boundary values. Statistical significance of the parameter’s distance from 0 and 1 are usually tested using t-test and Wald test.

$$V_{ni} = Z_k a + X_{ik} \beta + \varepsilon_{ni} \quad i = 1, \dots, J_k \tag{1}$$

$$P_{ni} = \frac{e^{V_{ni}/\gamma_k} \left( \sum_{j \in B_k} e^{V_{nj}/\gamma_k} \right)^{\gamma_k - 1}}{\sum_{l=1}^K \left( \sum_{j \in B_l} e^{V_{nj}/\gamma_l} \right)^{\gamma_l}} \tag{2}$$

We estimated the models using NLOGIT version 5. Table 3 outlines the results of estimation for both urban and suburban areas. We use Student’s t-test to evaluate significance levels and include only variables that are significant at the 90% confidence level. We also calculated the elasticity of variables. For continuous variables, we used Eqs. 3 and 4 to calculate the direct and cross elasticities, respectively. For dummy variables, we calculated the pseudo-elasticity, which is the magnitude of change in the probability of the decision variable when the dummy variable is changed from 0 to 1. Tables 4 and 5 depict the elasticity of continuous and dummy variables, respectively.

$$E_d = \frac{\sum_k P_k P_{ik} \left[ (1 - P_i) + \left( \frac{1}{\gamma_k} - 1 \right) (1 - P_{ik}) \right]}{P_i} \beta x_i \tag{3}$$

$$E_c = - \left[ P_i + \frac{\sum_n \left( \frac{1}{\gamma_k} - 1 \right) P_k P_{ik} P_{i'k}}{P_{i'}} \right] \beta x_i \tag{4}$$

**Table 3** Results of the 2-level NL model for both urban and suburban areas

Variables	Model 1: Urban areas			Model 2: Suburban areas				
	No bid	Bid; Not accepted	Accepted	Delivered	No bid	Bid; Not accepted	Accepted	Delivered
<i>Constant</i>	–	2.38 (1.64)	1.35 (0.94)	3.62 (2.52)	–	0.65 (0.22)	–1.30 (–4.45)	0.50 (1.49)
OVERSIZED	–0.49 (–5.05)	–	–	–0.78 (–13.04)	–0.63 (–6.77)	–	–	–
LARGE	–	1.60 (2.98)	1.58 (2.90)	1.34 (2.51)	–	0.54 (2.96)	–	0.54 (3.06)
LONG	–	1.79 (3.00)	1.95 (3.24)	1.50 (2.51)	–	1.50 (3.73)	1.50 (3.56)	1.50 (3.75)
HOLIDAY	0.45 (2.89)	–	–	–	–	–	–	–
WEEKEND	0.34 (5.24)	–	–	–	–	–	–	–
MORNING	–	–0.32 (–6.02)	–	–	–	–0.37 (–4.69)	–	–
MIDNIGHT	0.43 (2.89)	0.47 (3.05)	–	–	–	–	–	–
DEADLINE	0.79 (11.52)	–	–	–	0.77 (8.98)	–	–	–
DEADLINE < 1H	–	–2.14 (–2.66)	–1.94 (–2.40)	–2.35 (–2.94)	–	–0.82 (–2.46)	–	–0.88 (–2.84)
DEADLINE > 2D	–	–	1.01 (1.92)	–	–	–	–	–
DEADLWKND	–	–	–	–0.18 (–2.73)	–	–	–	–
SAGE < 24	0.67 (3.93)	–	–	–	1.61 (7.71)	–	–	–
SAGE 25–34	0.47 (5.78)	–	–	–	–	–	–	–
SAGE 45–54	–	–0.62 (–4.47)	–	–	–	–	–	–
SAGE 55–65	–	1.02 (9.60)	0.70 (4.56)	–	–	0.73 (6.31)	0.44 (2.51)	–
OUTSTATE	0.41 (5.40)	–	–	–	–	–	–	–
DISTANCE	0.0001(2.70)	–	–	–	0.0003 (4.73)	–	–	–
B2C	–1.25 (–12.04)	–	–	–	–1.42 (–8.04)	–	–	–
EXPERIENCE	–	–	–	0.001 (4.05)	–	–	–	0.02 (8.34)
O_POPDENS	0.003 (3.12)	–	–0.002(–1.87)	–0.007 (–6.09)	–	–	–	–
D_POPDENS	–	–	–	–0.002 (–2.37)	–	–	–	–
O_NDENS	–	–	–	0.02 (4.80)	–	–	–	–
O_ACCESS	–1.12 × 10 <sup>–6</sup> (–6.36)	–	–	–	–2.77 × 10 <sup>–6</sup> (–4.80)	–	–	–
O_BLACK	–0.75 (–4.88)	–	–	–	–	–	–	–

**Table 3** (continued)

Variables	Model 1: Urban areas			Model 2: Suburban areas				
	No bid	Bid; Not accepted	Accepted	Delivered	No bid	Bid; Not accepted	Accepted	Delivered
D_BLACK	-0.30 (-2.36)	-	-	-	-0.76 (-4.31)	-	-	-
O_HAWAIIAN	17.09 (2.37)	-	-	-	31.82 (2.34)	-	-	-
O_LOWWAGE	1.08 (2.23)	-	-	-2.57 (-6.61)	-	-	-	-2.08 (-3.07)
D_LOWWAGE	0.78 (1.94)	-	-	-	-	-	-	-
O_VEHICLE > 2	-	0.41 (3.34)	-	-	-	-	-	-
O_NOVEHICLE	0.66 (3.22)	-	-	-	1.01 (1.91)	-	-	-
D_NOVEHICLE	0.50 (3.29)	-	-	-	-	-	-	-
O_USERS	-0.02 (-7.12)	-	-	0.02 (11.01)	-0.02 (-3.27)	-	-	0.01 (2.49)
D_USERS	-0.01 (-5.83)	-	-	0.01 (7.60)	-0.03 (-6.35)	-	-	0.009 (3.06)
<i>Inclusive value parameters</i>								
Bid	0.46 (2.87)				0.67 (4.11)			
No bid	1.0 (Fixed parameter)				1.0 (Fixed parameter)			
<i>Summary statistics</i>								
McFadden	0.33				0.21			
Pseudo-R-squared:								
Sample size:	10,923				3935			

**Table 4** Elasticity of continuous variables

Variables	Utility	Model 1: Urban areas			Model 2: Suburban areas				
		No bid	Bid; Not accepted	Accepted	Delivered	No bid	Bid; Not accepted	Accepted	Delivered
		O_USERS	Delivered	-0.094	-0.213	-0.213	0.075	-0.014	-0.023
	No bid	-0.330	0.028	0.028	0.028	-0.066	0.010	0.010	0.010
D_USERS	Delivered	-0.046	-0.105	-0.105	0.042	-0.023	-0.036	-0.036	0.027
	No bid	-0.177	0.017	0.017	0.017	-0.190	0.026	0.026	0.026
O_LOWWAGE	Delivered	0.121	0.291	0.291	-0.255	0.121	0.203	0.203	-0.290
	No bid	0.181	-0.049	-0.049	-0.049	-	-	-	-
O_POPDENS	Delivered	0.016	0.041	0.041	-0.060	-	-	-	-
	Accepted	0.001	0.003	-0.029	0.003	-	-	-	-
	No bid	0.032	-0.015	-0.015	-0.015	-	-	-	-
D_POPDENS	Delivered	0.004	0.012	0.012	-0.015	-	-	-	-
O_NDENS	Delivered	-0.022	-0.053	-0.053	0.028	-	-	-	-
EXPERIENCE	Delivered	-0.019	-0.042	-0.042	0.007	-0.103	-0.161	-0.161	0.064
O_VEHICLE > 2	Not accepted	-0.019	0.134	-0.049	-0.049	-	-	-	-
DISTANCE	No bid	0.026	-0.012	-0.012	-0.012	0.076	-0.044	-0.044	-0.044
O_BLACK	No bid	-0.121	0.022	0.022	0.022	-	-	-	-
O_HAWAIIAN	No bid	0.012	-0.005	-0.005	-0.005	0.015	-0.009	-0.009	-0.009
O_NOVEHICLE	No bid	0.066	-0.021	-0.021	-0.021	0.030	-0.014	-0.014	-0.014
D_BLACK	No bid	-0.051	0.01	0.01	0.01	-0.114	0.033	0.033	0.033
D_NOVEHICLE	No bid	0.043	-0.014	-0.014	-0.014	-	-	-	-
D_LOWWAGE	No bid	0.137	-0.036	-0.036	-0.036	-	-	-	-
O_ACCESS	No bid	-0.236	0.060	0.060	0.060	-0.169	0.052	0.052	0.052

**Table 5** Pseudo-elasticity of dummy variables

Variables	Model 1: Urban areas				Model 2: Suburban areas			
	No bid	Bid; Not accepted	Accepted	Delivered	No bid	Bid; Not accepted	Accepted	Delivered
	OVERSIZED	-21.06	73.66	73.66	-21.04	-34.06	28.13	28.13
LARGE	-43.51	33.54	30.57	3.38	-18.86	22.33	-30.11	21.73
LONG	-47.50	35.20	59.37	1.19	-49.75	41.08	40.58	41.21
DEADLWKND	4.67	11.72	11.72	-6.34	-	-	-	-
DEADLINE < 1H	102.11	-17.82	-0.05	-33.03	26.68	-30.24	55.48	-34.45
DEADLINE > 2D	-4.69	-10.93	141.35	-10.93	-	-	-	-
DEADLINE	98.81	-11.74	-11.74	-11.74	65.78	-24.68	-24.68	-24.68
AGE 44-54	3.72	-41.55	9.25	9.25	-	-	-	-
AGE 55-65	-13.01	100.05	45.86	-28.35	16.69	21.45	-13.59	62.95
AGE 25-34	41.10	-11.00	-11.00	-11.00	-	-	-	-
AGE < 24	62.65	-16.76	-16.76	-16.76	78.46	-64.80	-64.80	-64.80
WEEKEND	28.45	-7.61	-7.61	-7.61	-	-	-	-
OUTSTATE	34.00	-9.10	-9.10	-9.10	-	-	-	-
B2C	-67.71	18.12	18.12	18.12	-63.58	52.50	52.50	52.50
HOLIDAY	40.44	-10.82	-10.82	-10.82	-	-	-	-

## Analysis of results

The utility functions for the delivery outcomes in urban and suburban areas consist of alternative specific parameters illustrated in Table 3. The coefficients, barring the constants, are all significant at the 90% level of confidence. The model fit of the urban model is significantly higher than for the suburban model, with a larger number of significant explanatory parameters. Several factors are shown to significantly impact the probability of a successful bidding or delivery outcome. The discussion will focus on comparing the variability in impact across different delivery performance phases, and between urban and suburban settings. In tandem, the elasticity estimates shown in Tables 4 and 5 will be discussed. The elasticity computations are valuable to compare all variables on a similar plane, removing the effect of difference in measurement units. Finally, the elasticity values also provide an intuitive and practical illustration of the effective impact of variables. The bid nesting parameter is highly significant in both the urban and suburban setting. This supports the idea that substitution is higher among the alternatives that received at least one courier bid, in comparison to the requested shipments that failed to receive any bids.

### Analysis of model results for shipping features

For the shipping request features, the dummy-coding of all variables except “Experience” allows a straightforward comparison of coefficient importance across alternatives and variables. The negative and zero coefficients for the larger shipments (as compared to small and medium sizes) in the *no-bid-nest* indicates that overall, larger shipments (namely large, long, and oversized) are more likely to get bids, likely due to the higher associated delivery prices, hence driver revenues. However, comparing the different delivery outcomes in the *bid-nest* reveals more insights. Observing the pseudo-elasticities in Table 5, we note that in urban areas an oversized package is indeed more likely to get at least a bid, but even as it does, it is less likely to be delivered than any other package size. This highlights the importance of studying the various phases of the delivery process, from bidding to final delivery. In particular, for the case of a larger shipment size, its higher earning potential might lead to higher bidding potential, but, due to practical challenges, is less successful when the actual delivery is negotiated. Concerning the shipments where requesters set deadlines, findings regarding the bidding process are reversed. Imposing any deadline leads to a highly significant decrease in the ability to attract any initial bids on a shipment. Moreover, the significantly negative parameters in the *bid-nest* also suggest that when deadlines are imposed, in particular strict 1-h deadlines, the probability of successfully moving to the next shipping stage decreases. Indeed, the pseudo elasticity computation (Table 5) for the 1-h deadline suggests that among cases that receive at least one bid, there is an 18% lower chance of not reaching a final acceptance, and a 33% lower chance of delivery in urban areas. In suburban areas, similar broad trends are seen, with consequences of strict (1-h) deadlines being even more pronounced.

Interesting differences between urban and suburban shipments emerge when studying the type of sender and comparing elasticities. When the sender is a business (B2C), the chance of getting a bid goes up by 18% in the urban areas, while the probability goes up by 52% in suburban settings. This indicates that the sender status is more consequential in suburban areas where crowd-shipping services are less developed. Another important urban/suburban distinction pertains to the impact of long-distance and out-of-state

shipments. The shipment distance has a similar impact on either setting, by making bids less likely overall. For suburban shipments, each additional delivery mile has a more pronounced negative effect. For an out-of-state shipment, a similar trend is observed for the urban setting with a 9% lower probability of achieving any outcome in the *bid-nest*, while this factor does not influence outcomes in the suburban case. Lastly, the experience of the sender has a unique role in the crowd-shipping analysis.

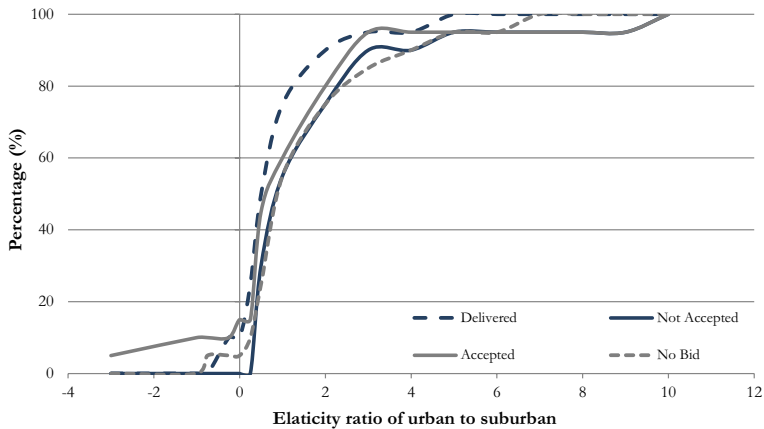
As shown in Table 4, the number of past shipments that a sender has requested makes the likelihood of all outcomes less likely, except for a successful delivery. In the urban setting, each previous delivery experience raises the probability by 0.7% while the effect is even stronger in the suburban setting where it increases by 6.4%.

### **Analysis of built-environment factors**

Moving on to consider the built-environment factors we note that suburban areas are less impacted overall, with only the accessibility to jobs in the origin playing a significant role. It is likely that the critical densities for residents, roads, and access to jobs are not encountered in the suburban areas. In the urban areas, these factors play a larger role, with the strongest effects due to employment density and population density in the shipment origin. Notably, a higher job access density leads to a higher probability of outcomes in the bid-nest, namely 6% higher for every percentage improvement in job accessibility. The critical role of population density (assumed to translate into more requests and available carriers) for collaborative consumption systems is demonstrated using optimization models and heuristics in Behrend and Meisel (2018). The broader concept of critical mass of users is also discussed in Frehe et al. (2017).

### **Analysis of local socioeconomic factors**

Concerning the socioeconomic characteristics, while coefficient signs are comparable across urban/suburban areas, there are important observations to make regarding the magnitude of the effects. On the whole, the features measured at the origin of the shipment have a stronger impact on outcomes than those measured at the destination. The share of low-income workers has a similar effect in urban and suburban areas, namely, it stimulates bids from the crowd, but ultimately does not contribute to higher probability of delivery. Instead, the number of household vehicles has a variable impact. A higher share of zero-vehicle households leads to a higher risk of a shipment getting no bids, and a lower chance of any of the bidding outcomes, with significantly stronger effects in urban areas. In areas with a higher share of households with more than 2 vehicles, the risk of not getting any bid goes down as expected, but there is more variation in the outcomes following a bid. Surprisingly, the bids do not lead to acceptance and delivery for car-rich households, possibly reflecting a more complex negotiation between sender and carriers. This effect is only observed in the urban setting. Finally, we draw attention to the effect of courier supply in the areas around the shipment origin and destination. The “O\_USERS” is a proxy for courier supply and reveals that the number of registered crowd-couriers can have a strong impact on the performance of crowd-shipping systems. For every percentage increase in registered potential drivers, the probability of being without any bids goes down by 33%. For cases where at least one bid is secured, there is a 7.5% higher probability of delivery, and a significantly lower chance that the bid is merely accepted but not delivered. Results for the suburban areas go in the same directions, while the effects are attenuated. This



**Fig. 4** Cumulative density function for the elasticity ratio of urban to suburban areas

finding points to the critical role of driver recruitment in vicinity to the areas where shipments originate to increase the odds of building a high performing system. In connection to this, there is a need to further understand driver’s existing travel and willingness to detour (Miller et al. 2017; Stiglic et al. 2016) and to explore complementary strategies of hiring dedicated drivers (Lee and Savelsbergh 2015) for more challenging deliveries.

### Comprehensive analysis of urban–suburban differences

Finally, it is valuable to have a comprehensive summary of the differences between bidding and delivery outcomes in the suburban and urban settings. Figure 4 plots the cumulative density of the elasticity ratios for urban compared to suburban settings, over all studied variables. About 40% of the ratios are in the positive domain with a ratio above one, showing that urban areas have higher elasticity measures driving each of the delivery outcomes.

We observe that for the no-bid outcome, constituting the main hurdle to overcome when fostering new crowd-shipping systems, the relatively flat curve reveals the larger difference in ratios between urban and suburban areas. This implies that the less favorable delivery performances in lower density areas, not only tends to be limited already at the early stage of bidding, but is also driven by more pronouncedly different factors and magnitudes. In particular, for “Accepted; Not Delivered” and “Received bid; Not Accepted” cases where a bid was received, there are a number of covariates that have a starkly different effect on the probability of these outcomes. For the successful delivery outcomes, the two shipping contexts differ less, with a larger share of the outcomes displaying smaller urban/suburban elasticity ratios.

### Practical implications

The emergence of numerous crowd-shipping initiatives in the delivery industry calls for critical analysis of the performance and societal impacts of these platforms. The growing research has established that the operations of crowd-sourced logistics depend on local network effects, as well as human factors on the platform (see recent papers e.g. Punel et al. 2019; Yildiz and



Savelsbergh 2019). The current paper adds to the literature by providing a foundation for performance analysis that takes into account the specificity of building logistics capacity by means of existing non-logistics resources.

From a research perspective, the findings complement existing literature by providing analytical results enabled by a one-of-a-kind empirical database and thereby provides realistic operational and performance insights. This adds nuance to some of the current assumptions underpinning operational and behavioral perspectives in the literature (Table 1). We note that the availability of the crowd is not uniform and that the interaction between senders and drivers does not progress linearly from posting to bidding and actual deliveries. The modeling in this paper begins to pinpoint where the opportunities and hurdles exist considering an actual shipping platform.

There are a number of platform managerial implications. Firstly, relative to crowd-shipping business development, crowd-shipping companies can draw insights on the critical elements that allow them to scale up their business models. This paper reveals that there is notable and systematic variation in performance for the different stages of shipments depending on built environment and demographic factors. This insight can guide the selection of recruitment efforts and promotional strategies to develop successful benchmarking in a competitive industry. Urban areas appear to have the critical densities of population, courier enrollment and dynamic labor markets to support the promotion and scaling of crowd-shipping. More specifically, by studying population density, vehicle ownership, wage rates and ethnic composition within urban areas, crowd-shipping entrepreneur efforts can identify local communities or areas in cities where the critical early stages of bidding will be favored.

From the perspective of designing the platform to maximize successful bidding and matching, the results offer several further practical considerations for platform managers. In terms of driver-sender matching, we note the crucial role of the delivery experience for determining successful interactions, and leading to successful delivery outcomes. This mirrors the finding in Punel and Stathopoulos (2017) that senders are highly sensitive to carrier ratings and past delivery experiences. The finding on experience impacts should be taken with caution, however, due to the relatively short data-panel and the non-normal distribution of shipping experience, dominated by a few heavy service users. Managers are also offered guidance on the development of recommender systems that have been shown to be key to improving crowdsourced system performance (Safran and Che 2017). Notably, platform providers can use the model insights to target delivery requests to couriers that are not just geographically proximal but to maximize chances of bidding and delivery success by knowledge of past performance. Specifically, given the concentration of shipment requests in a small subset of senders, offering better service to first time users will lead to higher repeat use of the platform.

Additionally, the broader logistics industry is provided with analytical insights as to how crowd-shipping systems function and how they might be complementary or a competitor for certain shipment categories. Importantly, across these domains, findings from this research suggests that different strategies need to be implemented to curb or foster crowd-shipping depending on the context of operation.

## Summary and conclusion

Crowd-inspired logistics with delivery by occasional drivers has received growing attention in industry, among policy-makers and in the research community. The research on crowd-shipping has been limited due to the lack of consolidated real-world systems that

disseminate operational data. This paper is among the first to provide an empirical performance analysis of this emerging delivery concept. The models draw on data from a unique 2-year database of crowd-shipments between January 2015 and December 2016 coupled with variables drawn from external data-sources matched with the crowd-shipment origin and destination at the block level. The research objectives are to: (1) define performance metrics and develop models that account for the specificity of crowd-shipping systems, namely the need to successfully move shipments guided by an online platform from the bidding stage to acceptance and delivery, (2) identify the most influential explanatory factors in this process, including shipping features, built environment, and socio-demographic factors giving rise to different delivery outcomes, and (3) derive sensitivity parameters to study the performance and implications of crowd-shipping in urban and suburban areas. This distinction is important in a phase of growth of this innovative business model, coupled with the critical pressure that traditional goods delivery systems are faced with, particularly related to last-mile deliveries. The analysis is formalized as two-level Nested Logit models, representing both bidding and delivery outcomes.

Findings reveal that the crowd-shipping delivery processes has unequal performance in urban and suburban areas, and is driven by different explanatory factors. Important differences are found for socioeconomic factors around the shipment origins. In particular, the area population density, income distribution and household vehicle ownership concentration has much more pronounced impact on urban area shipping performance. An important observation needs to be made for the effects of supply of occasional drivers surrounding the delivery request areas. When the supply of potential drivers is higher, the probability of securing shipment bids, and of successful deliveries, increases. The effect is again more pronounced for the urban context, confirming the importance of the critical mass concept discussed in the literature (Rougès and Montreuil 2014). Several factors related to the shipment and senders are also studied. A notable distinction is found when the sender status is B2C, namely, the chance of getting a courier to bid goes up by 18% in the urban areas, and by 52% in suburban settings. This suggests that the perceived credibility of a business is more consequential in suburban areas where crowd-shipping services are less developed.

Our analysis also reveals that some explanatory variables have a critical impact for the process of securing a bid at the start of the shipment process, compared to later stages of acceptance and delivery. Specifically, the presence of (strict) deadlines by the sender has a detrimental effect that persists throughout the bidding and delivery process. Instead, large and bulky shipments are more likely to attract bids, but less likely to achieve a successful final delivery. An overall observation can be made with regard to the different structures of the urban and suburban markets and the explanatory variables. Notably, the success-factors, e.g. the covariates that contribute to a successful delivery outcome, are overall quite similar between the two study settings. Instead, for the limiting factors of these systems, namely the risk of getting no bids for a shipment or of not completing the delivery due to peer-to-peer negotiation challenges, urban and suburban areas are driven by different causal factors. Specifically, the density effects related to couriers, potential demand and vehicle ownership appear to be more consequential for urban areas, whereas the concentration is too low to have a discernable impact in suburban areas. From the policy perspective, the research brings evidence of the main drivers of performance, with detailed information, including elasticities for a range of factors, that can guide the fundamental understanding, as well as regulation and policy stimulation of crowd-shipping operations. These results pave the way for looking at the potential impacts in terms of shipping externalities and benefits for local communities, such as connection to local labor markets.

An important caveat to note is that the current data is based on analyzing one of the major crowd-shipping companies. While this research makes a contribution to understanding the real operational contours of crowd-shipping operations, our findings are likely to be impacted by studying a specific firm and reflecting specific operational strategies along with the limitation in data-base size. We have sought to minimize the selectivity effect by controlling for a large number of explanatory variables and carefully testing our model structure. The opportunity to learn from 2 years of operational data from a company with a broad spatial coverage and in the absence of any comparable public data-source reinforces the value of the current findings. Ongoing and future work is focusing on studying the peer-negotiation process in more detail and exploring the opportunity to design dynamic shipping systems around the revealed movements of passengers, to optimize the use of crowd-sourced shipping moving forward.

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## Compliance with ethical standards

**Conflict of interest** On behalf of all authors, the corresponding author confirms that there is no conflict of interest.

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