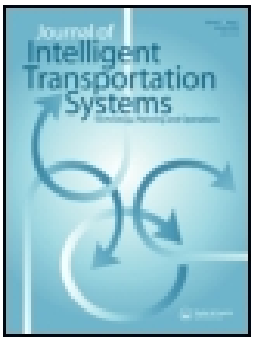

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Crowd logistics: Understanding auction-based pricing and couriers' strategies in crowdsourcing package delivery

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ABSTRACT
The growth of electronic commerce generates significant demand for the delivery of personal goods. Crowdsourcing applications have the potential to create more flexible alternatives to existing package-delivery services. However, the success of these applications is strongly related to the strategies of the crowd couriers, which are not well-understood in the current literature. In this paper, we analyzed data from a real-world crowdsourcing application that uses an auction-based mobile app to deliver small packages in urban, suburban, and intra-metropolitan areas. Our analysis reveals the spatial strategies of crowdsourced couriers, which are correlated with delivery pricing and the courier's experience. The couriers with strong relationships with specific customers create ongoing trust relations, which makes deliveries over medium distance routes financially reasonable for those couriers. We discuss how our findings can help to maximize package-delivery markets and crowdsourcing markets in general by supporting the couriers' strategies.

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Crowdsourcing; delivery; pricing; spatial strategies

1. Introduction

The tremendous growth of business-to-consumer electronic trading generates a high demand for package deliveries. Vehicles that carry freight move on city streets and substantially contribute to congestion, environmental pollution, and noise. Crowdsourcing package delivery is a growing phenomenon with the potential to provide cost-effective and environmentally friendly last-mile delivery solutions (Paloheimo et al., 2016). Multisided markets are efficient (Rochet & Tirole, 2004), and platforms such as Uber, Lyft, and TaskRabbit demonstrate this efficiency by enabling interactions between buyers and service providers and appropriately charging each side. These "crowdsourced logistics" (CSL) or "crowd logistics' are "initiatives that tap into the logistical resources of the crowd to perform logistics services" (Carbone et al., 2017). Carbone et al. (2017) list more than 50 crowd logistics services. Companies such as Deliveroo, Instacart, New Dada, Postmates, DoorDash, Fetchr, and Deliv have raised over \$2.5 billion in total funding since 2011 (Cunnane, 2018). Even DHL, one of the leaders in package logistics, was testing a mobile app that allows residents to deliver packages of ordered products (Slabinac, 2015).

The feasibility and success of a crowdsourcing network rely on the decisions of the agents involved in each transaction (Rai et al., 2017). In many crowdsourced courier services, couriers can have additional income sources and use deliveries to smooth the fluctuations in their income (Hall & Krueger, 2018). Couriers might have different preferences concerning pricing, distances, times, and proximities of deliveries. Each time couriers accept or reject a job to take a package from an origin point to a destination point, they decide according to some strategy. Understanding the factors that are connected to the couriers' policies significantly impacts the prices, availability, and overall success of the service. This understanding can help to design a user interface that will better serve the users' needs. Presenting the most relevant delivery requests to couriers can raise their acceptance rate. It can also increase their income, enhance shippers' and couriers' engagement, allow couriers to complete more delivery jobs, and optimize the usage of resources in the crowdsourcing platform.

Most of the research in courier and freight services investigated centralized fleet management (Amaral & Aghezzaf, 2015; Anand et al., 2012; Ballantyne et al., 2013; Crainic et al., 2004; Taniguchi et al., 2014;

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Vieira & Fransoo, 2015; Wisetjindawat & Sano, 2003). These works have examined shippers (companies that sell the goods), couriers (companies with fleets of vehicles that deliver the products to the desired destination), and clients (who get the goods at the desired target) and explored the design of freight systems for courier services that operate fleets with high freight volumes. However, analyzing the strategy of an individual courier in a crowdsourcing service can be very different. There are studies concerning the motivations and the decision making of a single player in auctions (Easley & Ghosh, 2015; Satzger et al., 2013; Slivkins & Vaughan, 2014), but none that explore this decision making in a transportation-oriented auction process.

In this work, we analyze an auction-based package-delivery system. The data include two years of logging of delivery offers and delivery jobs. It contains 115 couriers (licensed drivers), 294 shippers, and slightly more than 8000 calls. Based on shippers' requests and couriers' acceptance data, we establish the couriers' preferences concerning the delivery distance, delivery price, delivery time, and spatial delivery data such as the origin and target. We describe two clear strategies concerning the pricing and executing delivery jobs inside and outside urban areas. We categorize the couriers' strategic behavior by finding spatial characteristics and describing pricing patterns and suggest designing a user interface that will fit the needs of specific profiles of independent couriers.

2. Background

2.1. Crowdsourced delivery

The rapid growth in the popularity of business-to-consumer e-commerce significantly increased the demand for low-cost package shipping services. However, the courier service industry has negative environmental impacts through its vehicles' emissions (Hanson, 1989; Schindler & Caruso, 2014) and by increasing traffic congestion. Crowdsourced delivery or crowd logistics might be a potential alternative solution. Crowdsourced delivery enables new logistics services and improves existing logistical services (last-mile transport) in terms of costs, capacity, speed, and flexibility (Frehe et al., 2017). It is "the outsourcing of logistics services to a mass of actors, whereby the coordination is supported by a technical infrastructure" (Mehmann et al., 2015). In the process of crowd logistics, "a shipper procures transportation services via a mobile or computer application directly from members of the crowd who provide those services as an independent contractor using a personally owned vehicle asset" (Castillo et al., 2018). The technical infrastructure is a communication medium such as mobile phones with a GPS and the relevant applications with which the users can coordinate demand and supply for transport services.

Quality issues (Satzger et al., 2013), high stress, low payment (Graham et al., 2019), and specific associated risks related to the sharing economy (Tauscher & Kietzmann, 2017) are well-known problems of crowdsourcing in general. However, along with these potential difficulties, crowd logistics can result in improved services. Crowd logistics enables trends such as sharing and collaboration that redefine the process of delivery services, such as the usage of transfer points to change vehicles during the package's route (Masson et al., 2013). Additionally, in urban areas, where high densities of deliveries and potential couriers exist, crowd logistics can be a low-cost and efficient solution. Recent crowd-based delivery studies have explored cost reductions that increase efficiency (Erickson & Trauth, 2013; Schreieck et al., 2016); clients' expectations for cheaper, personalized, and faster services (Paloheimo et al., 2016; Rougès & Montreuil, 2014; Sadilek et al., 2013); matches between drivers' routes and transportation requests within a large dataset (Arslan et al., 2016; Schreieck et al., 2016; Setzke et al., 2017); the establishment of trust among platform users (Schreieck et al., 2016); and users' privacy issues (Schreieck et al., 2016). These studies indicate that employing individuals from a large pool of people instead of professional couriers to deliver items from senders to receivers can be successful. How to best match individuals in this market and how to assure that the mechanism will serve both sides have been attracting more interest over the last few years.

We approach this challenge and add a new perspective to crowd-based delivery services research by using the log activities of couriers and delivery calls to discover and formulate different courier strategies concerning price and space. These strategies concerning the willingness to deliver a specific package for a set price at a particular time and in a specific area have not yet been explored. Practically, recognizing, understanding, and differentiating these strategies can lead to a better and different presentation of the relevant delivery data in mobile applications. A typical courier must make quick decisions (in seconds) concerning the acceptance of delivery calls based on previous calls and even on potential future requests. Presenting only the relevant data can decrease the mental load of a courier and may improve his/her decision-making process.

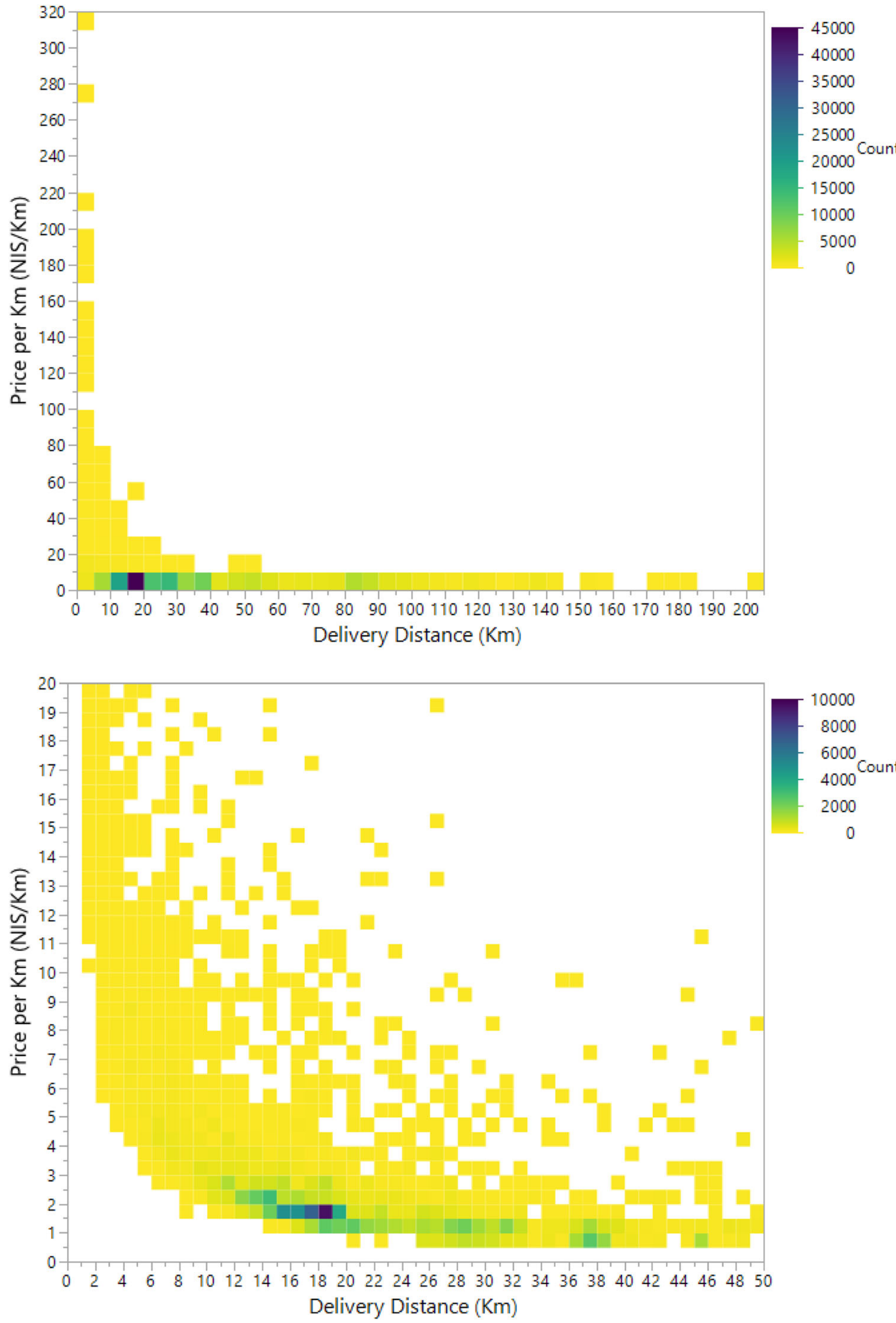

Figure 1. Distribution of deliveries – distance, price, and price per km.

Additionally, the presentation of highly relevant data that fits couriers' preferences can raise the acceptance rate of delivery calls, increase the overall crowd logistics activity, and improve global market utilization.

2.2. Sharing economy models

The economic benefits of crowdsourcing are based on the sharing economy. Sharing economy models are common to enterprises that disrupt traditional markets, leverage information technology to enable distribution, and share and reuse the excess capacity of goods and services (Act, 2011). Airbnb threatens the conventional hotel industry by allowing people to rent rooms or homes (Zervas et al., 2015). Uber enables people to serve as occasional drivers (Hall & Krueger, 2018) and raise their welfare (Cohen et al., 2016). These two sharing economy enterprises represent prominent models

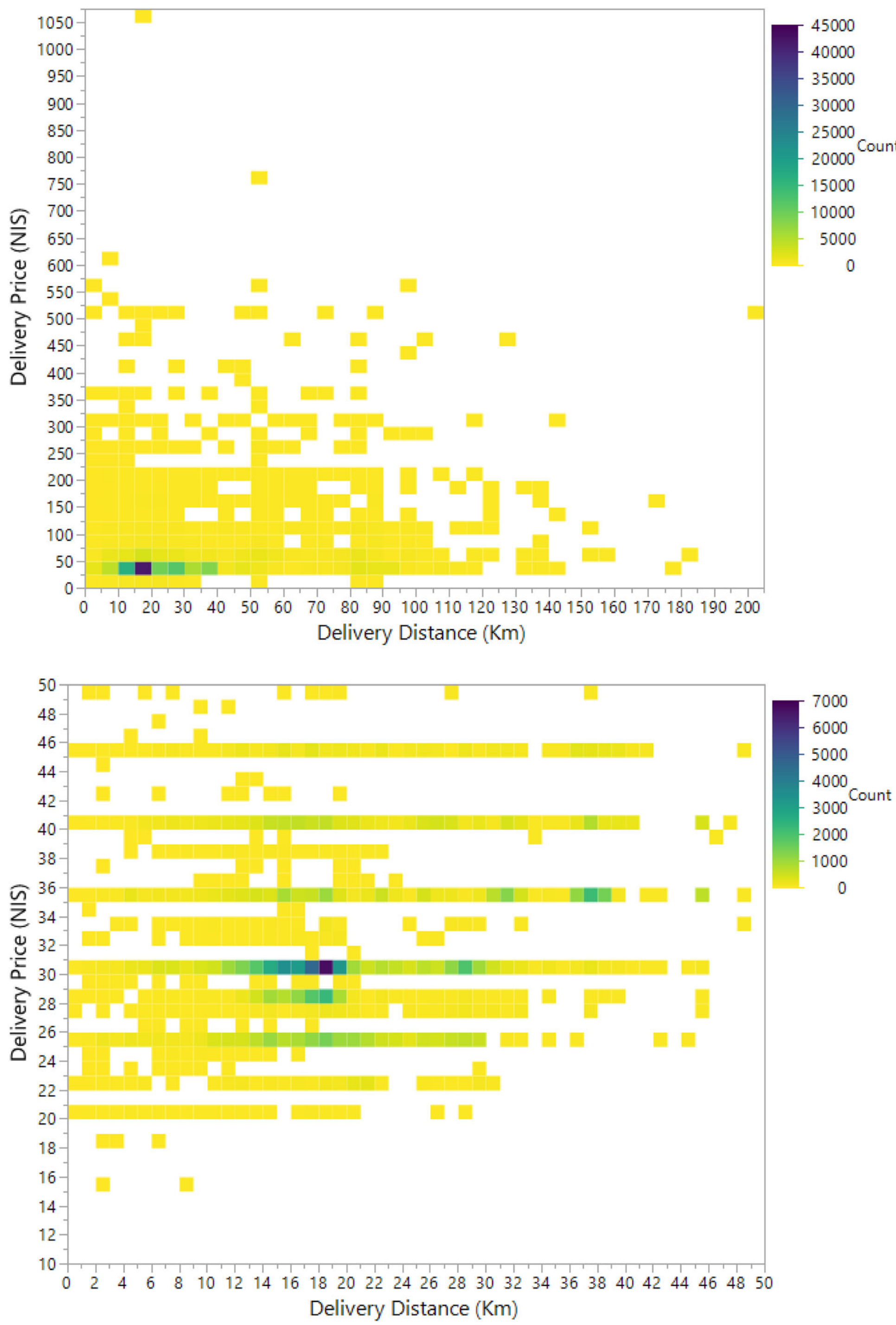

Figure 1. Continued

that disrupt entire industries. Platforms such as one-way vehicle-sharing or ride-sharing are dependent on the ability of their operators and users to obtain real-time data on the location and availability of the shared resources. The fact that market members look for a way to share services and goods opens the door for digital platforms that can enable interactions between end-users and appropriately charge each side while attempting to make money overall (Rochet & Tirole, 2004).

Sharing economy models are often based on auctions, which are market institutions with explicit sets of rules determining resource allocation and prices using bids from the many-to-many market participants where the knowledge of each bidder concerning

Table 1. Correlation between the delivery distance and the price per 1 km of delivery.

Type of offer		Average offer's delivery – distance
Accepted offers – average price of 1 km of delivery	Pearson correlation	−0.201**
	Sig. (2-tailed)	0.000
	N	8038
Rejected offers – average price of 1 km of delivery	Pearson Correlation	−0.157**
	Sig. (2-tailed)	0.000
	N	1667

**Correlation is significant at the .01 level (2-tailed).

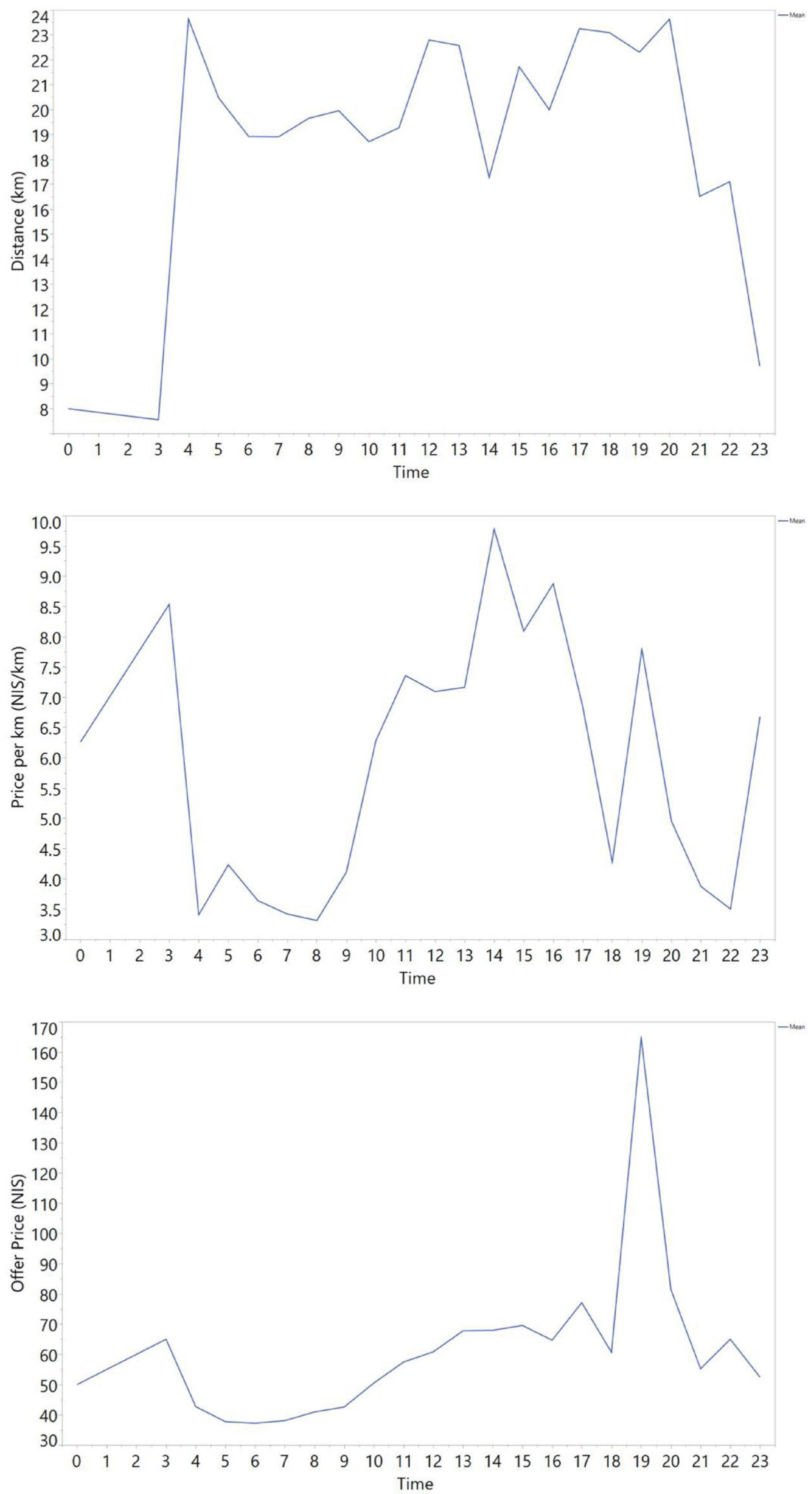

Figure 2. Distribution of the delivery pricing, the pricing of 1 km of delivery, and the delivery distance in 24 h.

the level of the current best bid is essential (McAfee & McMillan, 1987). The transportation market is an example of a market with a high level of variation in transaction volumes, and the prices reflect the status of demand and supply for given levels of service, reliability, and speed. Previous studies (Regan & Garrido, 2002; Song & Regan, 2003) explored online transportation auctions and models between shippers and couriers, and yet, our problem-definition is unique. In our study, we use some of the transportation market's features to better understand the strategy and decision making of each independent courier concerning accepting and pricing job delivery opportunities. Exploring the couriers' behavior in the auctions in which they participate can lead to new insights concerning the strategies of couriers in a one-time bidding process in peer-to-peer markets.

2.3. Research questions

Our research question concerns the decision making of independent couriers in the context of pricing delivery jobs.

All couriers share fundamental knowledge, based on their experience, concerning the minimum cost of 1 km of delivery. This collective knowledge of the market (McAfee & McMillan, 1987) should create a linkage between the distance and delivery cost per km, which diminishes as the distance grows. Each courier holds his or her personal preferences concerning working hours and shipment areas, causing some couriers to prefer short drives while others focus on wide spatial spaces. Based on these assumptions and the dataset of thousands of offers,

1. we expect different couriers to have distinct spatial strategies and pricing strategies.
   In addition, since shippers and couriers know each other over time, couriers use their experience and learning (Figliozzi et al., 2002), and
2. we expect the experience to correlate with the relevant pricing and spatial strategies.

3. Methodology

3.1. The platform and the bidding process

The crowdsourcing app is a free application that is based on a crowd logistics service operating in Israel. The application in the current research executes local deliveries and acts as a mediator that provides a mobile platform and coordinates and manages communication between customers (the shipper) and couriers. The application enables everyone to ask for proposals for the delivery of a package from its origin to its destination. Couriers should register in advance to gain permission to act as a courier. All couriers make their offers in real-time and without knowing their competitors' prices. The shippers' view all offers in real-time and choose the ones that best suit their needs. The application informs the winning courier. All financial transactions are done outside the boundaries of the application. The application's data-log includes accepted and non-accepted offers, delivery orders, delivery prices, delivery dates, shippers, couriers, and the addresses (as free text) of both the origins and destinations.

3.2. Data analysis

Figure 1 presents the distribution of the delivery distance (1.1), the delivery price (1.2), the delivery price per km (1.3), and the number of recurrent interactions between shippers and couriers (1.4). The presented results are discussed in Section 4.2.

Our dataset is based on the offers and orders and includes almost 10K records, including both accepted and rejected offers. Each record has the following attributes: the origin location, the destination location, the distance, the location variance of all delivery jobs that each courier executed, the number of offers each proposal received, and the number of offers and orders for each shipper and courier. Table 1 presents the correlation between the distance and the price per 1 km of delivery.

Our dataset contains all licensed drivers (115 couriers) who carry packages and downloaded the application. Figure 2 presents the distribution of the delivery pricing, the pricing of 1 km of delivery, and the total delivery distance in 24 h, respectively.

All parameters dramatically change during the activity hours. However, the price is the most interesting parameter, with a slow increase in the price of delivery jobs during the day and a sharp peak in the late evening (18:00–20:00). These hours are at the end of the working day, and the delivery distance is also at its peak during these hours.

Table 2. Differences between approved and rejected offers.

Offer status		Offer price	Price per km	Total distance
Rejected	Mean	95.37	7.018	21.886
	N	1667	1667	1667
	Std. deviation	117.168	13.561	22.119
Approved	Mean	45.35	4.720	19.5637
	N	8038	8038	8038
	Std. deviation	48.187	11.501	17.254
Total	Mean	53.94	5.115	19.962
	N	9705	9705	9705
	Std. deviation	68.088	11.911	18.201

Table 3. ANOVA analysis.

			Sum of squares	df	Mean square	F	Sig.
Offer price of approved/rejected	Between groups	(Combined)	3,454,210	1	3,454,210	806.97	.000
	Within groups		41,533,079	9703	4280		
	Total		44,987,290	9704			
Price per km of approved/rejected	Between groups	(Combined)	7291	1	7291	51.65	.000
	Within groups		1,369,573	9703	141		
	Total		1,376,865	9704			
Total distance of approved/rejected	Between groups	(Combined)	7444	1	7444	22.52	.000
	Within groups		3,207,400	9703	330		
	Total		3,214,845	9704			

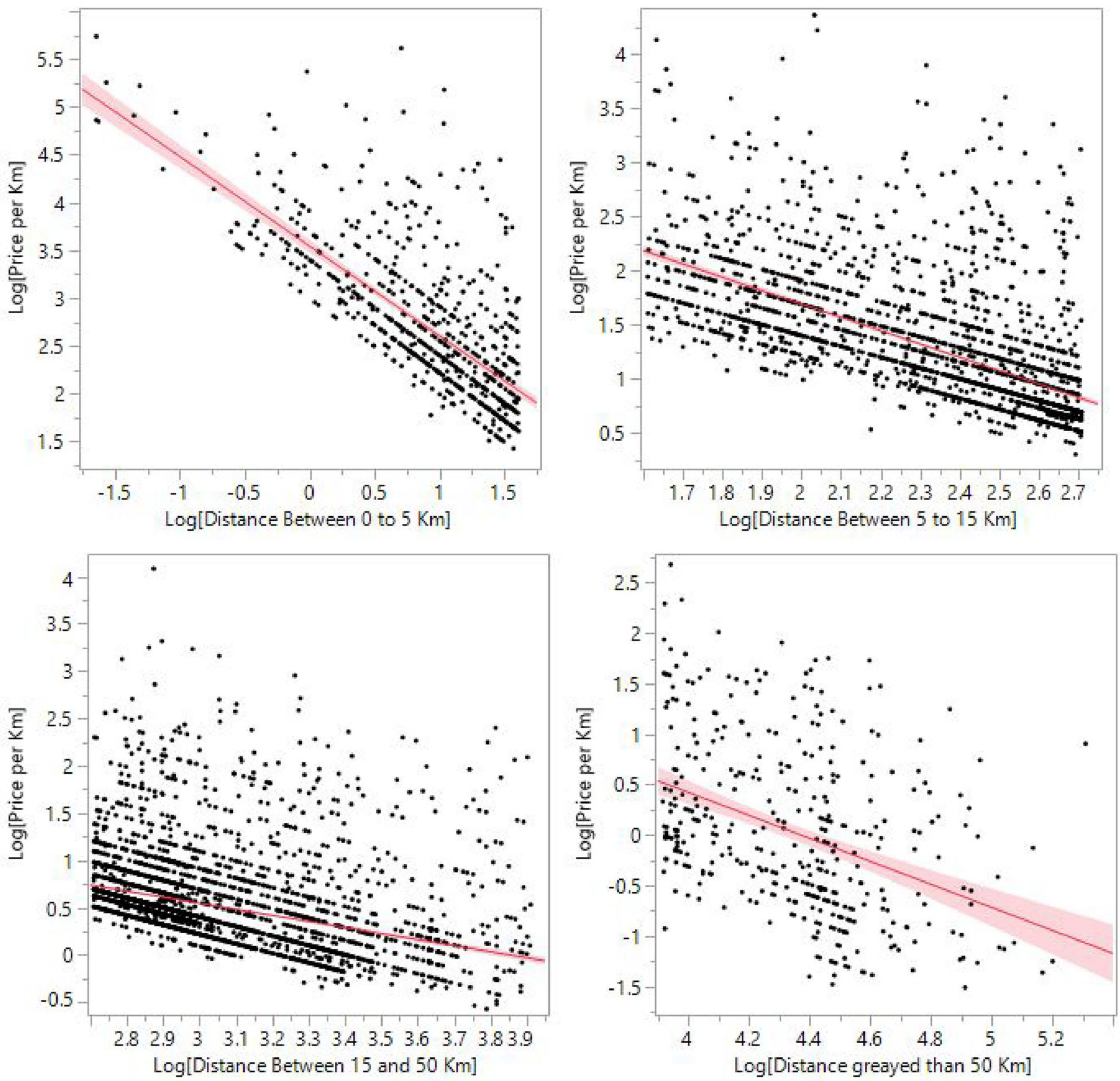

Figure 3. Different coefficients between the delivery distance and its price per 1 km of delivery.

4. Results

4.1. Auction-based pricing

By analyzing the differences between rejected and approved offers, we found that the offer price is significant (statistical $F = 806$) in explaining the acceptance or rejection of a delivery job. Shippers were found to be very sensitive to the offer price and the price per 1 km of delivery. Accepted offers have a lower price tag than rejected ones (see Table 2). The

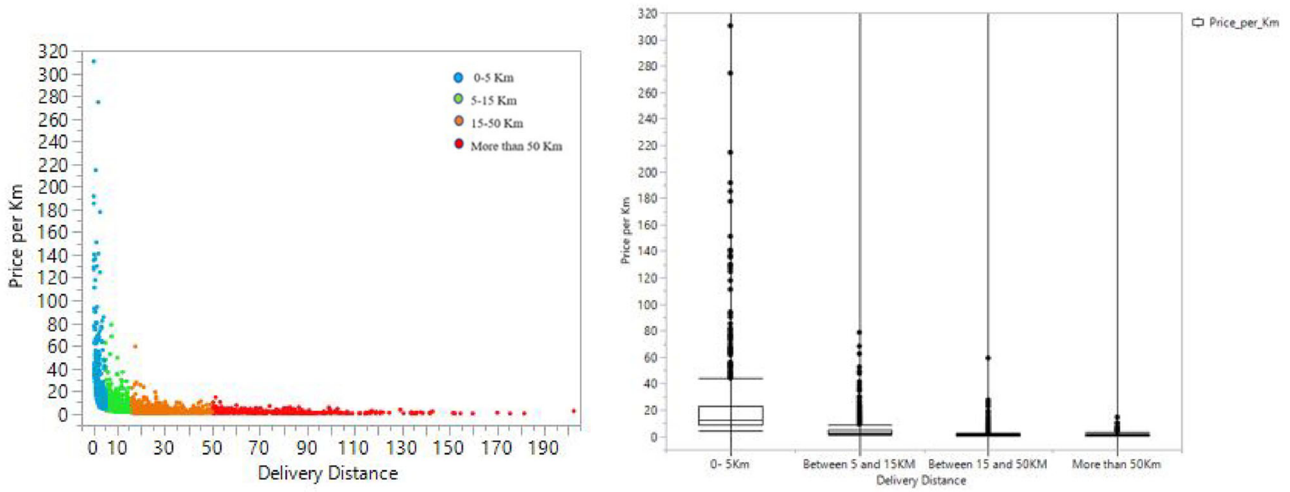

Figure 4. Distribution of delivery distance and price per 1 km of delivery.

differences in the average distance of delivery jobs between rejected and accepted offers are minimal (21.8 km versus 19.5 km, respectively). They cannot explain the acceptance or rejection of a delivery job (statistical $F = 22$) (see Table 3).

We created four distance categories:

Concise delivery (1) – an inner-city delivery from 0 to 5 km;

Short delivery (2) – either an inner-city or between neighboring cities delivery from 5 to 15 km;

Medium distance delivery (3) – a delivery between distant cities or areas from 15 to 50 km and

Long-distance delivery (4) – a delivery that occurs between remote regions of Israel at a distance of 50 km or more.

Figures 3 and 4 present the different coefficients of the delivery price of 1 km and the overall delivery distance. The average price of 1 km of delivery (we choose 1 km as the unit of delivery services) in long-distance deliveries will be cheaper than that in short-distance deliveries. The correlation between the distance and the price of 1 km of delivery is significant at the 0.01 level (2-tailed) and negative (-0.2). The price of one km of delivery is correlated with the overall delivery distance, and each delivery distance category (1, 2, 3, and 4) has a unique pricing function.

Figure 5 presents the standard deviations (SDs) of the sources and destinations of the delivery jobs of couriers with respect to the number of deliveries they execute. The shippers publish their delivery needs, and couriers can offer themselves to execute the delivery. The decision-makers in this situation are the couriers, and we analyze their behaviors and strategies. Correlating the number of rides with the variation of the sources of the delivery locations and the destinations of the delivery locations presents a clear pattern. Couriers executed more delivery jobs to specific areas. Figure 5 presents decreasing SDs for both the source and destination variation as the volume of activity in the application increased. Couriers, who delivered a few packages executed deliveries with a significantly high variation of sources and destinations. This negative and interesting correlation between the intensity of a courier on the application and the courier's spatial strategy is discussed below.

4.2. Couriers' strategies

Out of the 115 couriers, 86 used the application more than once. Table 4 presents the correlation between the standard deviations (SDs) of the origin and destination of all offered deliveries for each courier. A high SD of the origin means that the delivery calls are spread over a wide spatial area. A high SD of the destination means that the delivery calls are executed in destinations that are distant from each other. The standard deviation of the source and destination was calculated separately for the latitude and longitude for each courier's delivery jobs. Using both SD, we built a joint SD parameter for each courier ("working in small areas" or "working in spread areas"). We found that the origin's SD has a high positive correlation with the destination's SD. This correlation suggests that some couriers choose to work in a broad area, which includes distant origins and distant destinations. In contrast, others prefer to work in well-defined regions of origins and destinations.

To better understand this phenomenon, we applied clustering analysis to the couriers' accepted offers and found two groups of couriers. A majority of the

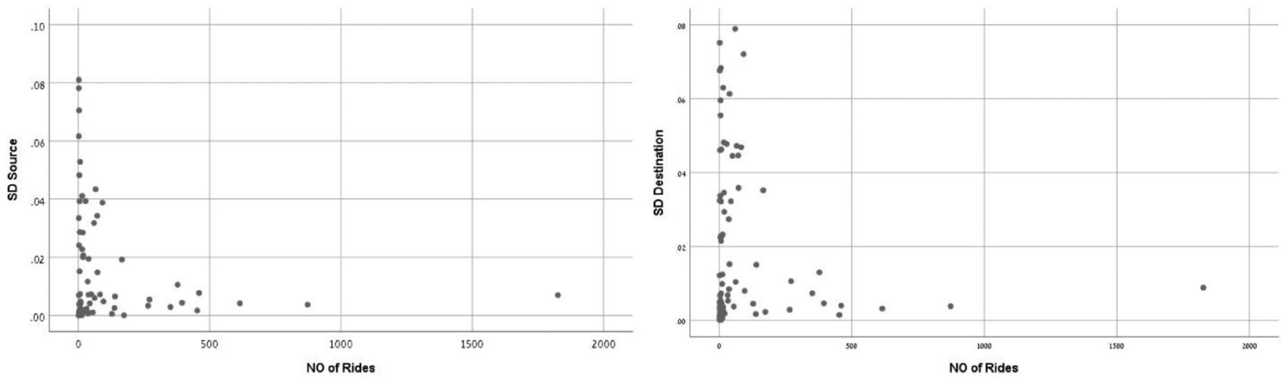

Figure 5. Spatial distribution of volume of delivery jobs.

Table 4. Correlations of the SDs.

		Number of deliveries	Origin's SD	Destination SD	Offer price SD	Price per 1 km SD
Number of deliveries	Pearson correlation	1	−0.135	−0.163	−0.119	−0.082
	Sig. (2-tailed)		0.214	0.134	0.276	0.455
	N	112	86	86	86	86
Origin's SD	Pearson correlation	−0.135	1	0.462	0.287	0.063
	Sig. (2-tailed)	0.214		0.000	0.007	0.566
	N	86	86	86	86	86
Destination SD	Pearson correlation	−0.163	0.462	1	0.242	0.119
	Sig. (2-tailed)	0.134	0.000		0.025	0.274
	N	86	86	86	86	86
Offer price SD	Pearson correlation	−0.119	0.287	0.242	1	0.194
	Sig. (2-tailed)	0.276	0.007	0.025		0.073
	N	86	86	86	86	86
Price per 1 km SD	Pearson correlation	−0.082	0.063	0.119	0.194	1
	Sig. (2-tailed)	0.455	0.566	0.274	0.073	
	N	86	86	86	86	86

couriers, 65 total or 75% of the population, belong to Group A (local), which prefers to work in defined areas, and their origin and destination locations' SDs are less than 5%. Twenty couriers, or 25%, belong to Group B (long-distance). They prefer to work in broad areas (the SDs of the origin and destination locations are higher than 5%). The significances of the distributions of the two types of couriers are F stat $= 176$ for the SD of the origin's locations and F stat $= 58$ for the SD of the destination's locations. The explanatory power of the two types of couriers is 0.67 and 0.41 for the origin and destination, in accordance. In summary, Group A (75%) chooses to operate in small and close areas, gets to know its customers, drives to relatively nearby places, and charges a higher price for each km of delivery. Group B (25%) chooses to work in a wide area, does not know its customers, charges more for deliveries, and has a price for each km of delivery that is lower than that of Group A.

Next, we explored the relationship between the courier strategy (a wide area or small area) and (a) the courier's total delivery distance, (b) the monetary value of the deliveries, and (c) the total distance the couriers traveled. None of these three characteristics is correlated with the spatial strategy.

The only monetary value that was correlated with the spatial strategy was the mean price of the offer. In the strategy of delivering packages to and from source and destination locations with low SDs, the mean price of the offer is approximately 60 NIS. In the strategy of delivering packages to and from source and destination locations with high SDs, the mean price of the offer is around 104 NIS (see Table A1 in the Appendix for the detailed data).

4.3. Long-term relationships

The results suggest that the more the shipper and the courier interact with each other, the lower the following will be: (a) the average prices per 1 km of the delivery, (b) the overall prices of the delivery, (c) the variance of the prices of the offers and (d) the delivery

Table 5. Correlations between the number of interactions and the main offer parameters.

Offer Status			Interactions between customer and courier	Average offer price	The variance of the offer prices	The average price of 1 km of delivery	Average offer delivery – distance
Rejected	Interactions between customer and courier	Pearson correlation	1	−0.383	−0.309	−0.305	−0.178
		Sig. (2-tailed)		0.000	0.000	0.000	0.000
		N	1667	1667	1384	1667	1667
Approved	Interactions between customer and courier	Pearson correlation	1	−0.256	−0.147	−0.222	−0.124
		Sig. (2-tailed)		0.000	0.000	0.000	0.000
		N	8038	8038	7494	8038	8038

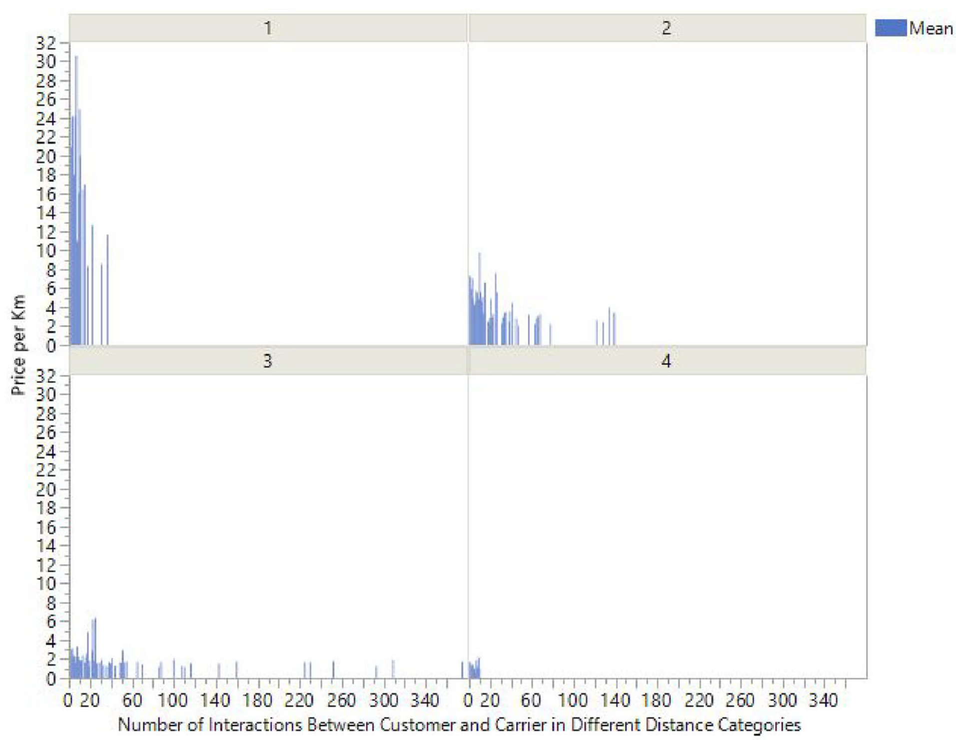

Figure 6. Correlation between price per km and number of interactions in four distance categories.

distances. These findings are valid for both accepted and rejected offers and presented in Table 5.

These numbers and Figure 6 present that over all distances (except the ones that are longer than 50 km), there is a clear negative correlation between the number of interactions between the shipper and courier and the average price of 1 km of delivery. Surprisingly, lowering the transaction's uncertainty did not increase the interaction's cost. In contrast, in the two years period, for a specific shipper, a known courier asked for a lower delivery price than does a random courier.

It seems that the shipper gains twice from interacting with a courier for a long time. First, since they know each other, trust is apparent in their relations, meaning that the shipper has a higher chance that a package will reach its destination; and second, the shipper benefits from a lower price. This phenomenon is unique, especially in the sharing economy, where interactions between customers and suppliers are based on occasional and nonrecurrent demands for services.

Figure 6 presents the average price per 1 km of delivery for different volumes of interactions between shippers and couriers in four categorical distances (less than 5 km, from 5 to 15 km, from 15 to 50 km, and over 50 km).

In addition, an interesting U-shaped pattern describes the relationship between the distance and the number of interactions between shippers and couriers. The number of interactions between shippers and couriers gradually increases with the delivery distance until reaching 50 km. From that tipping point, the number of interactions declines as the distance

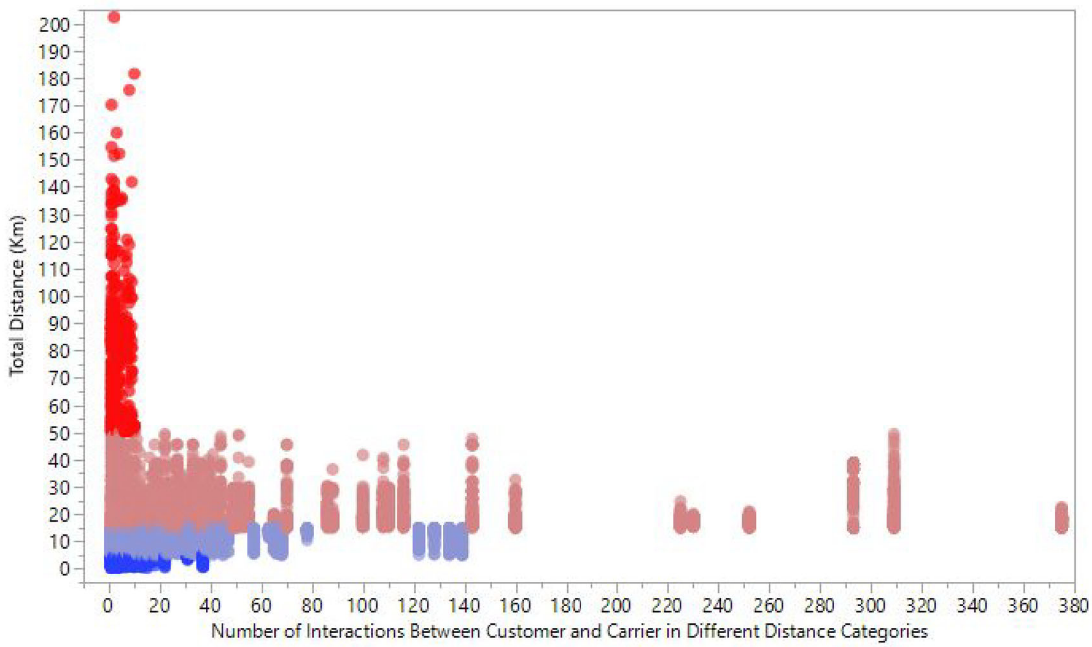

Figure 7. Distribution of the number of interactions in four distance categories (different distance categories are with different colors).

increases. This phenomenon yields another interesting question concerning the loyalty between shippers and couriers and distance. Figure 7 presents the distance categories and the different numbers of interactions between shippers and couriers.

Most of the recurrent interaction is for the middle range (from 15 to 50 km), which in Israel is the distance between cities, meaning that most of the delivery jobs where shippers and couriers preferred to work with someone they knew previously are delivery jobs between cities and not within urban environments.

5. Discussion

In this study, we show that couriers are strategic players and offer their services in a specific context using a spatial strategy. Our study joins previous ones that have identified and proved the strategic behavior of taxi drivers (Cheng & Nguyen, 2011; Tang et al., 2019). Our study finds this kind of strategic decision making in courier crowdsourcing markets. Our findings point to two basic profiles (local and long-distance) of delivery strategies and specific delivery jobs that are appropriate for certain types of couriers.

Most couriers (75%) choose to operate in small and close areas. They know their customers and drive to relatively nearby places. In contrast to the negative correlations between customer density and delivery costs (Boyer et al., 2009), we found that short-distance couriers in dense urban spaces charge higher prices for each km of delivery. A potential explanation for this phenomenon might be that the couriers on the application did not aggregate several deliveries and treated each delivery as a separate job. A minority of couriers (25%) chose to work in a wide area, did not know their customers, charged more for deliveries, and had lower prices for each km of delivery than the short-distance couriers did.

While shippers think they face a single market with a defined supply side, the market is composed of two different supply curves, and each type of courier has different preferences concerning delivery distances and prices. This finding should be known to the shippers since remembering the preferences of suppliers can help consumers to optimize their delivery job execution. Additionally, we broaden Camerer et al. (1997) findings concerning the loose daily income target that taxi drivers set. We claim that since the supply side is composed of two separate profiles (local couriers and long-distance couriers), under certain circumstances, couriers might move between the supply curves to reach their daily income. This move should bring new couriers to each area (local and long-distance) and might change the rules of the game in the late hours of each working day on the application.

5.1. Auctions and spatial strategies

Our dataset includes customers (shippers) who had all the relevant data from the bidding offers. The potential couriers could send only a single offer without any negotiating process or data concerning their opponents' offers. Once the shipper decided on a courier, the application sent an acceptance (rejection) message to the winning (losing) bidders. This process creates a unique kind of auction in which the bidders supposedly give their lowest prices in each bid. Nevertheless, analyzing the data reveals that occasional couriers offer and get higher rates for deliveries than known and frequent couriers. Our analysis of the mechanism and the conclusion that we drew from it can serve many other small-scale players in one-time bidding processes in various peer-to-peer markets.

5.2. Trust, loyalty, and spatial strategies

Trust is a prerequisite of social behavior, especially in the e-commerce arena (Gefen, 2000). Trust is an essential element in helping potential customers to overcome perceptions of risk and allows parties to act in commercial-based activities (McKnight et al., 2002). Based on our analysis, we did not find a temporal trend between the number of interactions between the shipper and courier and the average price of 1 km of delivery. We found that the frequent delivery jobs between a courier and a shipper are correlated with low delivery rates. We do not know how and how much shippers paid couriers and cannot give a sufficient answer to the phenomenon. Nevertheless, we found that a trusted courier charges less than an unknown courier.

We can suggest three possible explanations: (a) an early acquaintance between the parties caused the prices to be lower, (b) the low price caused the shippers to keep choosing the specific courier, and (c) a known and agreed upon high-volume of future deliveries decreased the prices of all future interactions. The meaning of trust in users' connectivity in logistics and supply chain management can have many forms (see, in detail, Whipple et al., 2013). We consider two forms (Lee & Choi, 2011): (a) initial trust-based connectivity and (b) ongoing trust-based connectivity (i.e., whether shipper x and courier y want to keep doing business over time). The experience that shipper x and courier y has can affect the ongoing trust-based connectivity. We assume that the service quality (with or without respect to the delivery price) can explain the continuous ties between shippers and couriers over the medium distances (from 5 to 15 km and 15 to 50 km). The diversity in the quality of between-cities service (in terms of time and reliability) is higher than that inside the city (short-distance deliveries), and the loyalty of customers to couriers is apparent over these distances.

The spatial strategies of the couriers, such as urban deliveries versus between-city deliveries, are correlated with long-term relations. The couriers involved in stable relationships with specific shippers create ongoing trust relations, which makes it financially reasonable to focus on these medium distance routes. Their spatial strategy based on long-term trust relations makes sense, and the costs of moving to the short-distance/occasional deliveries are too high. The fact that fewer couriers are willing to conduct these medium distance deliveries and the lack of choice is an additional explanation for the long-term relations between shippers and couriers.

The spatial strategies of the short-distance couriers can be explained in the same way. In an urban area, many couriers are working and executing short-distance deliveries. Hence, the competition in this market is high, and short-distance couriers do not form long-term relations with shippers. The strategy of short-distance couriers is based on quick deliveries for many sporadic shippers. In these deliveries, there are many alternatives (couriers) for short distances, and the diversity of the service is limited. There is no reason for shippers and couriers to be loyal to each other in such a competitive and dense market of short-distance deliveries in an urban space.

All of the explanations mentioned above are based on the study dataset. Other factors, such as the values of the delivery job (expensive goods, for example) and the relations and business between shippers and couriers, were not considered.

5.3. Implications for design

Our findings include several implications for the design of open crowdsourcing delivery systems. First, these systems should include different scales (local and long-distance) to optimize the potential of the market.

We argue that the application's user interface must depict the different data needs of each courier. A proper user interface can help to optimize the fulfillment of orders on the app. Local-based delivery jobs are carried out by couriers who frequently work in a well-defined spatial radius. The couriers' relations with shippers are frequent, and the delivery prices are considerably low. Their decision-making process (to accept or reject an offer) is frequent and quick. Hence their user interface must reflect the immediate data needs where no negotiation process occurs, such as: what are the alternative offers, and is there a simple way to combine delivery offers within a small radius. The long-distance couriers occasionally work with fewer shippers. The low volume of deliveries and the high price of each ride dictate different data needs. These needs include relevant data of similar deliveries, estimated delivery time, and potential traffic jams (which can be supplied with a third-party application such as Waze or Google maps).

Second, to help all carriers, the application must include real-time data concerning roads and traffic jams. Providing real-time traffic data for trucks that deliver freight to destinations was explored before (Flamini et al., 2018; Wang et al., 2019; Swee Tuan et al., 2006). The potential value of combing future delivery jobs with real-time traffic data is vast in a real-time decision making of the courier. Third, following Zheng et al. (2019), we suggest collecting and use the routine data within the couriers' application, to improve service performance. Due to the nature of their profession, couriers are knowledgeable about alternative routes and time-dependent traffic conditions, same as taxi drivers (Zheng et al., 2019). The user interface of the suggested application should enable sharing and incorporating online data with others in a convenient and rewarding manner.

5.4. Limitations

When considering the implications of our work, the reader should take into account several limitations. The dataset included less than 10K interactions over two years in a particular location and context. Our cleansing and cleaning of the data were mainly manual, and it is possible that test interactions were not fully cleaned. The fact that we could not talk with the users (shippers and couriers) damages our ability to develop a better way to assess the shipper-courier action process. Therefore, some factors that may be important were not part of our analysis, such as the values of the delivery job (expensive goods, for example) and the relations and business between shippers and couriers. Also, we were not able to analyze user interactions on the app.

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Appendix

Table A1. Correlations of the interactions' characteristics.

		Offer price SD	Offer price mean	Price per km SD	Price per km mean	Categorical Distance mean	Source lat SD	Source long SD	Destination lat SD	Destination long SD	Price per km mean 1 mean	Number of mutual Interactions
Offer price SD	Pearson correlation	1	0.675**	0.247**	0.235**	0.204**	0.203**	0.169**	0.294**	0.265**	0.235**	−0.063
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.120
	N	607	607	607	607	607	607	607	607	607	607	607
Offer price mean	Pearson correlation	0.675**	1	0.172**	0.232**	0.389**	0.163**	0.168**	0.288**	0.285**	0.232**	−0.088**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
	N	607	1434	607	1434	1434	607	607	607	607	1434	1434
Price per km SD	Pearson correlation	0.247**	0.172**	1	0.801**	−0.258**	0.109**	0.061	0.034	0.011	0.801**	−0.030
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.007	0.133	0.405	0.784	0.000	0.467
	N	607	607	607	607	607	607	607	607	607	607	607
Price per km mean	Pearson correlation	0.235**	0.232**	0.801**	1	−0.453**	−0.058	−0.073	−0.098*	−0.100*	1.000**	−0.071**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.152	0.071	0.015	0.014	0.000	0.007
	N	607	1434	607	1434	1434	607	607	607	607	1434	1434
Categorical distance mean	Pearson correlation	0.204**	0.389**	−0.258**	−0.453**	1	0.379**	0.353**	0.440**	0.436**	−0.453**	0.038
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.154
	N	607	1434	607	1434	1434	607	607	607	607	1434	1434
Source lat SD	Pearson correlation	0.203**	0.163**	0.109**	−0.058	0.379**	1	0.770**	0.409**	0.364**	−0.058	−0.012
	Sig. (2-tailed)	0.000	0.000	0.007	0.152	0.000		0.000	0.000	0.000	0.152	0.777
	N	607	607	607	607	607	607	607	607	607	607	607
Source long SD	Pearson correlation	0.169**	0.168**	0.061	−0.073	0.353**	0.770**	1	0.410**	0.449**	−0.073	−0.022
	Sig. (2-tailed)	0.000	0.000	0.133	0.071	0.000	0.000		0.000	0.000	0.071	0.592
	N	607	607	607	607	607	607	607	607	607	607	607
Destination lat SD	Pearson correlation	0.294**	0.288**	0.034	−0.098*	0.440**	0.409**	0.410**	1	0.642**	−0.098*	−0.061
	Sig. (2-tailed)	0.000	0.000	0.405	0.015	0.000	0.000	0.000		0.000	0.015	0.136
	N	607	607	607	607	607	607	607	607	607	607	607
Destination long SD	Pearson correlation	0.265**	0.285**	0.011	−0.100*	0.436**	0.364**	0.449**	0.642**	1	−0.100*	−0.056
	Sig. (2-tailed)	0.000	0.000	0.784	0.014	0.000	0.000	0.000	0.000		0.014	0.172
	N	607	607	607	607	607	607	607	607	607	607	607
Price per km mean 1 mean	Pearson correlation	0.235**	0.232**	0.801**	1.000**	−0.453**	−0.058	−0.073	−0.098*	−0.100*	1	−0.071**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.152	0.071	0.015	0.014		0.007
	N	607	1434	607	1434	1434	607	607	607	607	1434	1434
Number of mutual interactions	Pearson correlation	−0.063	−0.08**	−0.03	−0.07**	0.038	−0.01	−0.02	−0.06	−0.05	−0.071**	1
	Sig. (2-tailed)	0.120	0.001	0.467	0.007	0.154	0.777	0.592	0.136	0.172	0.007	
	N	607	1434	607	1434	1434	607	607	607	607	1434	1434

*Correlation is significant at the .05 level (2-tailed).
**Correlation is significant at the .01 level (2-tailed).