DEMAND AND SUPPLY MODELING OF CROWD-SHIPPING MARKETS

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For My Parents

Thank You for Your Love

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ABSTRACT

Le, Tho V. Ph.D., Purdue University, May 2019. **Demand and Supply Modeling of Crowd-shipping Markets**. Major Professor: Satish V. Ukkusuri.

The rise of technologies and the Internet have provided opportunities to connect logistics *demand* and *supply* using the crowd. In this system, named crowd-shipping (*CS*), a *requester* doing the shipping selects a *courier* via a platform. In reality, the idea of *CS* has been explored by many firms over the last several years. However, there is a lack of fundamental understanding of the issues related to: (1) the markets that are likely to be influenced by *CS*; (2) the considerations that govern the success of this system; and the (3) the impacts of *CS* and its design.

To address these issues, there is a need of understanding *CS* system's stakeholders, such as *requesters'* (i.e. *senders'*) and potential *couriers'* (i.e. *driver-partners'*) behaviors as well as *operations* and *management* of *CS* firms. This research will address these gaps by conducting a survey to understand *driver-partners'* behaviors and *requesters'* behaviors given the *CS* services availability in the logistics market. Then, pricing and compensation strategies are designed and modeled based on behavior rules of *supply* and *demand* generations as well as various *CS* market penetrations. As such, this research addresses the *CS* industry in a triad of *supply*, *demand*, and *operations and management.*

This research uses advanced econometrics, statistics analysis, mixed integer optimization, and data science techniques to analyze data and generate insights. The contributions of this research are to identify the contributing factors that impact the emerging logistics service. This research also reveals factors that influence the current and future shipping behaviors of *requesters*, as well as influencing factors of the individuals' willingness to work as *driver-partners.* The integrated matching and routing

models have been developed to examine different pricing and compensation strategies under several market penetration scenarios. 'Individual' price and compensation have found to provide the highest profit for *CS* platform providers.

This research provides meaningful knowledge for stakeholders, especially for the *CS* firms to develop business strategies. Several remarkable benefits that *CS* firms can obtain include: focusing on some specific population groups to recruit *driver-partners* (e.g. people with children, middle-aged people having lower incomes, or no car ownership); addressing certain market segments to promote *CS* services (e.g. tight-window delivery packages, peripheral products, or personal health and medicine items); implementing 'individual' or 'flatted' pricing and compensation strategies depending on the time of the day, the day of the week, or the market penetration; and improving platform features to incorporate *requesters'* and *driver-partners'* expectations.

1. INTRODUCTION

1.1 Background

Urban freight represents about 10-15% of vehicle-equivalent miles traveled in urban areas. Out of the total urban freight trips, about 25-40% of all truck kilometers is delivered within cities, 40-50% is incoming freight, and the rest is out-going freight [1]. The study on European urban freight transport shows that local convenient shops and independent stores account for 30-40% of all daily deliveries in city areas [2]. In fact, the last-mile delivery cost accounts for about 53% of the total transportation costs [3]. Moreover, the freight transport also significantly influences the on-line shopping business [4, 5].

E-commerce, which has been populating with a rocket trend all over the world, has already changed people's shopping habits, and brought new challenges to logistics service providers [6]. The top 10 growing e-commerce countries are China (35%), Germany (22.1%), Brazil (22%), Canada (17.4%), UK (16.5%), Russia (16%), USA (15.7%), Japan (14%), South Korea (13%), and France (12.1%). All the sales were in 2014, and the percentage increases were the changes from 2013 [7]. Moreover, it is forecasted that by 2020, world e-commerce sales will increase 85% compared to those of in 2015 [8]. The rise of e-commerce potentially pushes the urban logistics industry [9].

In a typical developed city, 1,000 people generate about 300-400 truck trips per year [10] that indeed, contribute to urban congestion, safety, pollution, and wear and tear of road infrastructures. A large fleet size challenges traditional logistics carriers' operations due to the lack of parking spaces and other issues, such as double parking tickets (a truck in Manhattan accumulates $750 weekly parking tickets [10]).

Furthermore, the demand for goods and services may remarkably rise in the future due to society's structure changes, such as the increasing of urban population and the growing of aging people. That demand, consequently, transfers into the upsurges of the delivery. The world population is growing, and people living in urban areas are also rising. By 2030, 6 out of 10 people will live in an urban area, while that of 2050 is 7 out of 10 people. In addition, the average age of the world population increases to 32 and 36.2 by 2025 and 2050, respectively. Aging society is forecasted as the percentages of people over 60 years old will be 15% in 2025 and 21.1% in 2050 [11]. The aging people may be less mobile or find it difficult to carry parts or all of their purchases, therefore, they may require various services, such as pharmaceuticals or grocery deliveries.

1.2 Motivations

Traditional Logistics Carriers ($TLCs$) are fueled by factors, but they are also facing some challenges. For instance, policies have been implemented in order to reduce the truck traffic in urban areas subjecting to create more livable communities. Policies include restrictions on truck delivery time, operated routes, or truck size and weight. One common implementation is the low-emission zone policy that requires trucks to be operated for a limited time or to not even be accessed to the zone. Therefore, the longer delivery/pick-up time can be expected. Moreover, as a countermeasure solution to the low-emission zone policy, urban centers have been built to consolidate freight. However, going to pick-up or send packages at/from consolidation centers may bring inconveniences to customers as they need to spend more time and travel extra distances.

High-tech has been explored as a solution to the last-mile delivery for decades. The ease of access the Internet and the increasing of smart-phone ownership may greatly accelerate on-demand logistics services from mobile devices. Real-time and direct communication, and potential of faster delivery time and lower delivery costs can facilitate app-based delivery services as appealing options. In fact, some companies, such as Roadie, Uber, Postmates, or Deliv have been exploring the freight logistics market, and they are currently providing services for food or package delivery. Those companies' business models are operated by partially employing crowds as *driver-partners*. The models are in a form of *CS* or, in other words, *crowdsourced* delivery.

In this study, *CS* is defined as an app-based platform that connects the individual or system wanting to ship a packet with an individual or system willing to carry the shipment in the first- or last-mile logistics in urban areas. A key distinction of the courier is that this is not necessarily an additional trip but a trip that leverages the travel patterns of the courier. The selected *driver-partner* can be the one who offers the cheapest delivery fee, is the closest to the delivery route, or has the highest reputation. A person can be a *requester* at one time, but be a *driver-partner* at another time.

CS attacks market segments where *TLCs* are hard to serve because of their current business models. In the traditional logistics system, dedicated vehicles are used to pick up packages which then are transferred to distribution centers. After being sorted, the packages are loaded on other dedicated vehicles for delivery. As a result, the traditional logistics operation model likely creates higher shipping cost and longer delivery time. *CS*, however, brings opportunities for lowering the shipping cost, optimizing the delivery time, generating income for travelers, reducing traffic congestion, improving environmental impacts, and creating social connections by utilizing vehicles' existing capacities and encouraging travel-anyway people to work as *driver-partners*. The visualization of the *TLCs* and *CS* systems is presented in Figure 1.1.

Challenges for *TLCs* are opportunities for *CS*. There are about 60% of parcels delivery in England urban areas are letter-sized, such as apparel, fashion, shoes, foods, beverages, and books [12]. Moreover, [13] have found orders arrive from time to time (i.e. vary by time of the day as well as by weekdays and weekend), and pick-up and drop-off locations are dispersed, after studying the New York UberRush

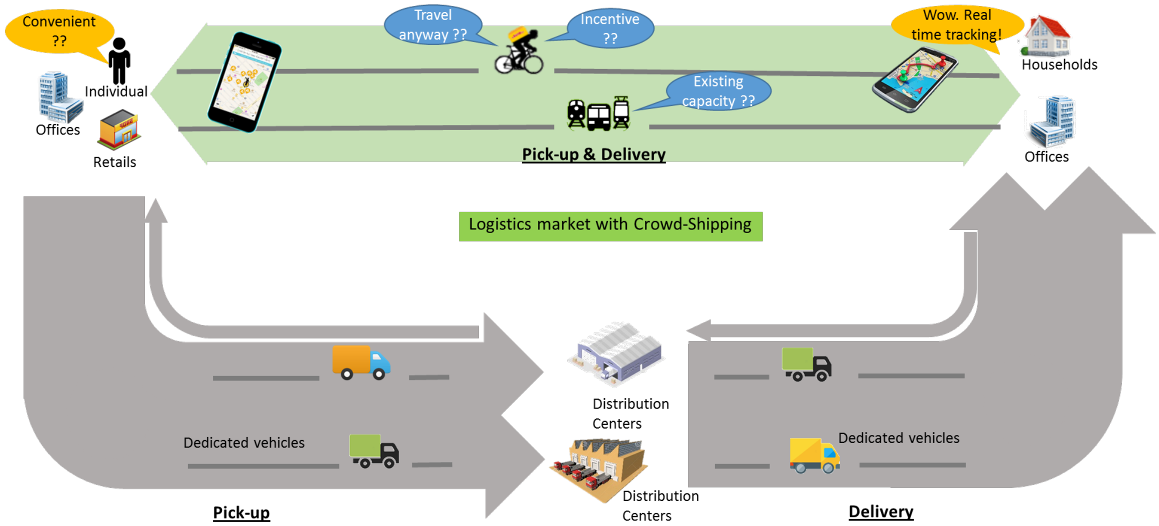


Figure 1.1.: Visualization of *TLCs* and *CS* systems

data. The *TLCs*, however, are facing trade-off between consolidating packages and missing orders which need a fast delivery. *CS* is then available to fill the gaps. *CS* is an alternative option which provides direct pick-up and drop-off services with a minimum diversion from the shortest delivery route. Moreover, [14] has revealed price, convenient, and speed of delivery are important features for on-line repeated purchases. The findings facilitate *CS* development as its potential of fast and low cost delivery, and personalized services.

Nevertheless, *CS* systems are facing challenges. *CS* companies need to address customers' concerns (e.g., trust, safety, and security) and governmental legals. Moreover, the companies also need to optimize their own operations by solving problems relating to uncertain number of people who are willingness to work (*WTW*) as *driver-partners*, uncertain number of *requesters* who are willing to use *CS* services, pricing and compensation strategies, and quality standards, etc., in order to compete with *TLCs*.

The challenges for *CS* are there; however, what makes *CS* possible? Firstly, smart-phone usages become immensely popular among ordinary people. Top countries having largest number of smart-phone ownership in 2014 are South Korea (88%), Australia (77%), Israel (74%), US (72%), Spain (71%), UK (68 %), and Canada (67%) [15]. Smart-phone users have ease to access various real-time information and apps which may facilitate *CS* apps' usages. In fact, about 75% of on-line food orders, as such, deliveries, are placed by smart-phones [16]. Secondly, the US average vehicle occupancy is about 1.67 (person miles per vehicle mile) as reported by [17]. It means there is available spaces for loading packages in the vehicle if the owners are willing to work as *driver-partners*. Thirdly, there is a potential market for *CS* services, such as the food delivery. UberEats, a delivery service which is available in more than 120 cities globally, is the only profitable service among all Uber services [18]. Moreover, Facebook has just newly started an order food service on Oct 13th, 2017. Fourthly, a real-time two-way communication between *requesters* and *driver-partners* may provide an excellent experience in the connected world. Lastly, other aspects, such as sharing-economy's popularity and increasing environmental awareness, also likely motivate people to use *crowdsourced* services which is expected to have less carbon footprints [19]. To sum up, all of those aforementioned factors, indeed, facilitate the business feasibility of the *CS* services.

1.3 Dissertation objectives

This dissertation offers innovative research ideas related to app-based urban freight delivery, in the context of transition from traditional logistics market to a market having both *TLCs* and *CS*. The dissertation's conceptual framework is illustrated in Figure 1.2. The goals of this framework are to envisage the future of a *CS* system that is synergistic, robust, and more sustainable. As such, the objectives of this research are defined as follows:

- To systematically reviews current practices, academic research, and empirical studies from the triads of *supply*, *demand*, and *operations and management*.

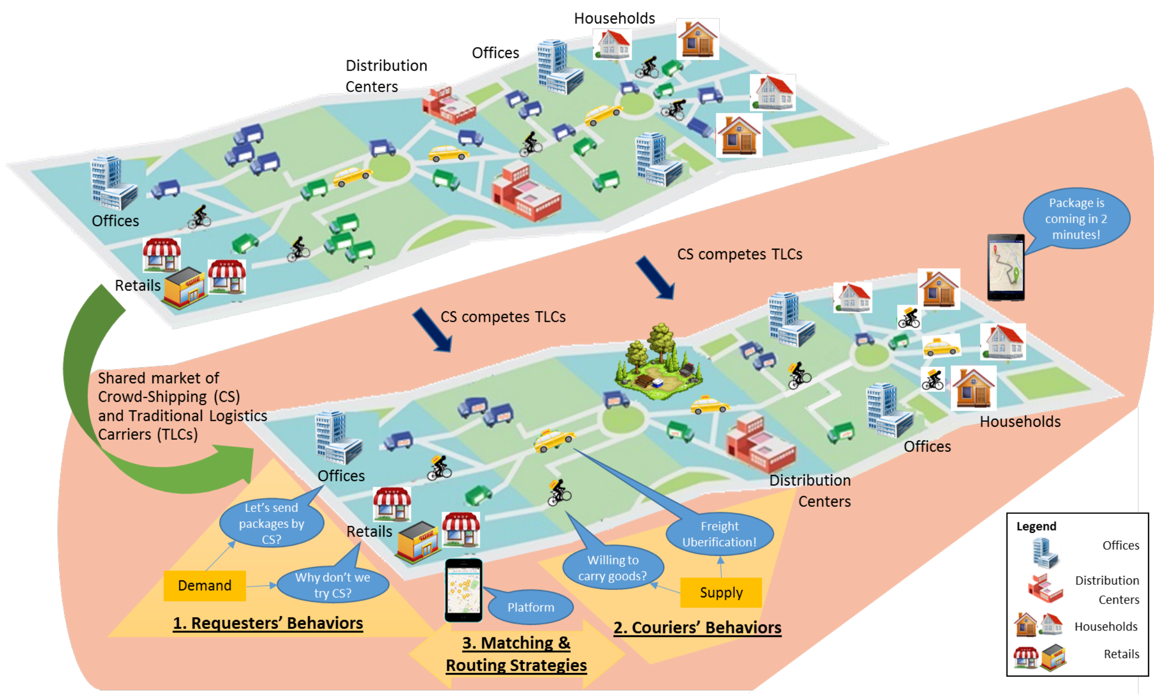


Figure 1.2.: Dissertation conceptual framework

- To provide a descriptive analysis and trends of the stakeholders in logistics market assuming *CS* availability. The stakeholders are *requesters*, people do not want to work as crowds-shippers, and potential *driver-partners*.
- To understand the *requesters'* (*senders'*) behaviors (i.e. *demand* side) for the willingness to use *CS* services and willingness to pay (*WTP*).
- To understand the potential *driver-partners'* behaviors (i.e. *supply* side) by developing models to capture the willingness to work as *driver-partners*, willingness to travel additional time/distance, and expected to be paid (*ETP*) behaviors.
- To develop pricing and compensation policies under several market penetrations, and matching and routing strategies with considerations of personalization services.

To achieve the goals, four datasets were collected or generated, including (1) demand data, (2) supply data, (3) ODs data of both packages and potential *driver-*

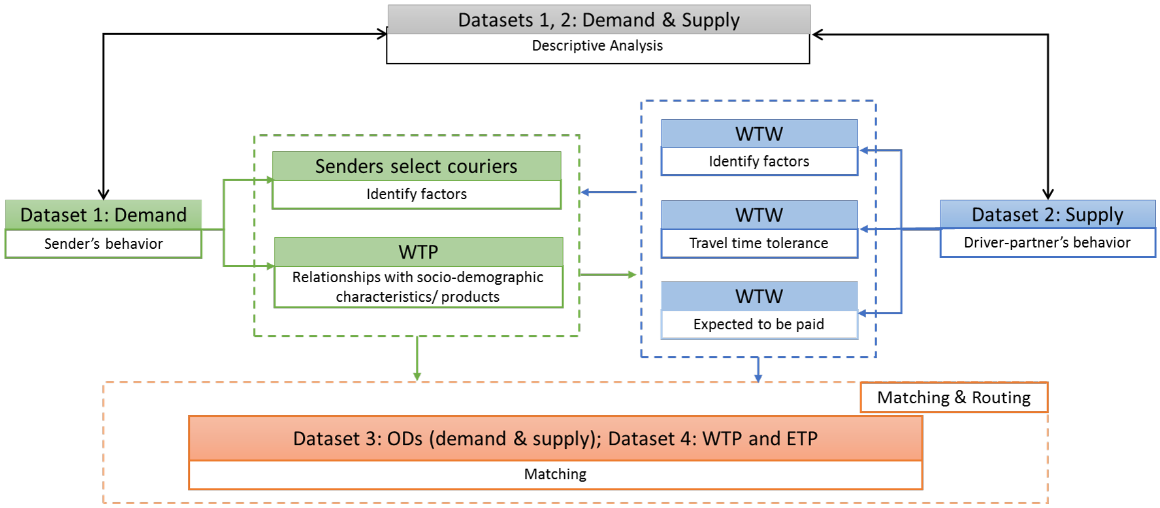


Figure 1.3.: Dissertation flowchart

partners, (4) *WTP* and *ETP*. The dissertation flowchart which displays dataset usages on different research objectives is presented in Figure 1.3.

1.4 Expected contributions

This dissertation provides various contributions in the following facets:

- This research extensively summarizes the up-to-date knowledge of the *CS* system in practice, research, and empirical studies from the triad of *supply*, *demand*, and *operations and management*.
- Drawing on the observed gaps in practice and scientific research, this paper provides several avenues for promising areas of applications, *operations and management*, as well as improving behavioral and societal impacts to create a *CS* system that is complex, integrated, dynamic, and sustainable.
- This study supplies initial knowledge on feasibility of doing a *CS* business with insights from triads of *supply*, *demand*, and *operations and management*.
- This research contributes to the literature a novel dataset on current and future shipping behaviors which was collected from a survey in the US.

- There is a lack of study on the changes of *senders'* behaviors in a context of having both *TLCs* and *CS* in the logistics market. This research examines factors which influence on *requesters'* behaviors in terms of selecting *driver-partners* and *WTP* for the shipping service.
- This study provides a better understanding on the different behavioral considerations that govern the choice of people to engage in a *CS* market in terms of *WTW*, maximum travel time tolerances, and pay expectations.
- Matching and routing algorithms are *CS* applications' core features. They play significant roles for gaining customers' higher satisfactions. By filling gaps in current *CS* applications and adding new features to a proposed *CS* system, this research will develop models for matching and routing problems which make a proposed *CS* application more sufficient and effective.
- Provide alternative solutions and strategies for *CS* companies to recruit potential *driver-partners* and develop business models (e.g., pricing and compensation strategies, and matching methods)
- Provide profound knowledge for policymakers or government officers to manage *CS* through legislations, regulations, and subsidies.

1.5 Dissertation organization

This report is organized into eight chapters. Chapter 1 introduces background, motivations, objectives, and contributions of this study. Chapter 2 presents a systematic and critical review of practices and academic studies in the triads of *demand*, *supply*, and *operations and management*. Chapter 2 also features the the potential benefits of the *CS* system. Chapter 3 provides descriptive analysis of stakeholders' behaviors by utilizing our survey data. Chapter 4 models and shows factors influencing on the usage of the *CS* service and the *WTP*. Chapter 5 models the willingness to work as *driver-partners*, decisions of maximize diversions from their main routes, and *ETP*. Chapter 6 presents optimal pricing and compensation strategies estimated from integrated matching and routing models. Chapter 7 summarizes the dissertation and presents directions for the future works.

2. LITERATURE REVIEW

2.1 Introduction

Crowd-shipping (*CS*) is an emerging trend in freight transportation, primarily accelerated by the rapid development of app-based platform technologies that facilitates the connection of *supply* with *demand*. *CS*, alongside other emerging sharing-economy phenomena, is still in transition, and researchers have defined the field in various ways. [20] states "*CS* can be conceived as an example of people using social networking to behave collaboratively and share services and assets for the greater good of the community as well as their own personal benefit." Moreover, [21] defines *CS* as "a web or mobile-based courier service which leverages large groups of geographically dispersed individuals to match *demand* with *supply* digitally" (Fung Business Intelligence Centre, 2015). [22], however, consider *CS* as "a goods delivery service that is outsourced to occasional carriers drawn from the public of private travelers and is coordinated by a technical platform to achieve benefits for the involved stakeholders".

In this paper, we follow the broader definition [23] who describe *CS* as "an information connectivity enabled marketplace concept that matches *supply* and *demand* for logistics services with an undefined and external crowd that has free capacity with regards to time and/or space, participates on a voluntary basis and is compensated accordingly".

The selected couriers may be closest to the delivery route [24], offer the cheapest delivery fee, or have the best reputation in the system platform. While minor differences in the definitions of *CS*, on-*demand* delivery, crowdsourced delivery and crowd-logistics are present in the literature, this study uses those terms interchangeably and defaults to the definition of [23]. Moreover, couriers, *driver-partners*, or *CS* drivers are all defined as the actors who transport freight. Senders are actors who request to send the shipment via *CS*. The *CS* system conceptualization is displayed in Figure 2.1.

Figure 2.1.: Conceptualization of a *CS* system

Building on the sharing economy popularity, technological developments, widespread wifi and smart phones, app-based *CS* start-ups are being launched worldwide. An app-based *CS* service provides a common platform where senders can announce their need for shipping freight and receive offers from system couriers. Furthermore, parties who are willing to carry packages, offer cost-effective logistics services for requests from the same platform [25]. In general, *CS* drivers can be categorized into three groups: (1) traditional logistics carriers (e.g., DHL or FedEx), (2) professional drivers, who engage in *CS* during their free time or utilize their unused vehicle capacity, and (3) the general public, who travel anyway (e.g. students, commuters, and retirees) [25]. *CS* operators either employ drivers directly, or solely provide a common platform to match senders and couriers; with couriers from the second and third categories mentioned above.

CS platforms include a common set of features, with the objective of ensuring user's satisfaction, and delivery safety, and security. A rating system allows senders and couriers to evaluate each other and provide testimonials for future users [22]. Real-time tracking and notification services *supply* both senders and couriers the exact freight location in real time [26]. *CS* platforms typically provide a personalized delivery-time window option to reduce the rate of missed deliveries [27].

In tandem with a rapidly growing and evolving market, the research community has investigated *CS* systems from a number of different angles in recent years. However, the bulk of these studies focus on specific research areas within a single system domain (e.g. operations with ad-hoc drivers). Furthermore, there are currently only few studies which provide a comprehensive synthesis of the existing body of literature and provide recommendations for future research in this area, including *CS* practice gaps. Additionally, existing studies do not base their recommendations on empirical data. Therefore, there is a need for a review of both the state-of-the-art literature and the current *CS* practice.

Accordingly, the objectives of this study are first to review previous *CS* research and practical projects under three pillars: (i) *supply*, (ii) *demand*, and (iii) *operations and management*. The literature analysis is augmented by presenting recently collected CS data in each section. Previously unpublished analysis and graphs are presented to emphasize and interpret several salient *supply* and *demand* features. Finally, we identify the gaps of *CS* systems' implementations, and provide suggestions to improve future design features of *CS* platforms.

This chapter is organized as follows. Section 2.2 presents the review methodology. Section 2.3 reviews current *CS* research and practice which are supplemented by the authors' data, in relation to the areas of *supply*, *demand*, *operations and management*. To provide ideas of potential benefits for stakeholders, section 2.4 presents a review on the topic. Section 2.5 summarizes the potential future topics of interest, gaps of implementing *CS* services, and several avenues for improving behavior and societal impacts. In Section 2.6, the study is concluded and possible directions for future research are suggested.

2.2 Methodology

CS is a topic of growing interest in the research community in the last five years. Using the keywords "*Crowd-shipping*," "Crowdsourced delivery," "Crowdsourced deliveries,"

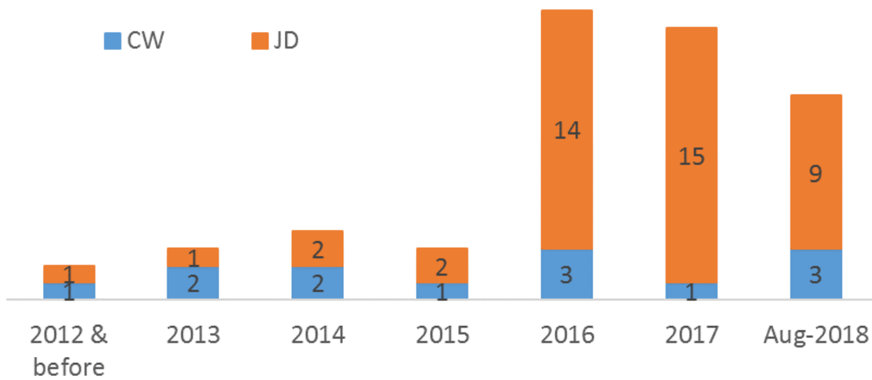


Figure 2.2.: Plot of numbers of published papers per year in *CS* (as of August 30th, 2018)

"Crowdsourcing delivery," "Crowdsourcing deliveries," "On-*demand* delivery," "On-*demand* deliveries," "Crowdsourced logistics," and "Crowd logistics", we performed our search on the principal online literature databases, including Google Scholar, ScienceDirect, Taylor & Francis, and ResearchGate. We found a total of 57 conference proceeding, white papers (CW) and journal papers, book chapters, and dissertations (JD) directly related to *CS* (as of August 30th, 2018). As can be seen in Figure 2.2 the number of *CS* publications emerged in 2012 and increased markedly in the last three years.

Following an examination of the literature and real market structure, this review is structured in three main themes, namely *supply*, *demand*, and *operations and management*. As a unique feature of this review, the authors incorporate unpublished empirical results from real operations and surveys. This adds important illustrations of unique realistic features and challenges of these platforms to strengthen the discussion and suggestions for practice.

- The first dataset (here after DATA1) is obtained from a survey, conducted from January to April 2017 in the United States (US). The dataset includes 549 respondents who answered questions about respondents' past shipping or ordering behaviors; courier-selection behaviors (stated preference); courier's history and

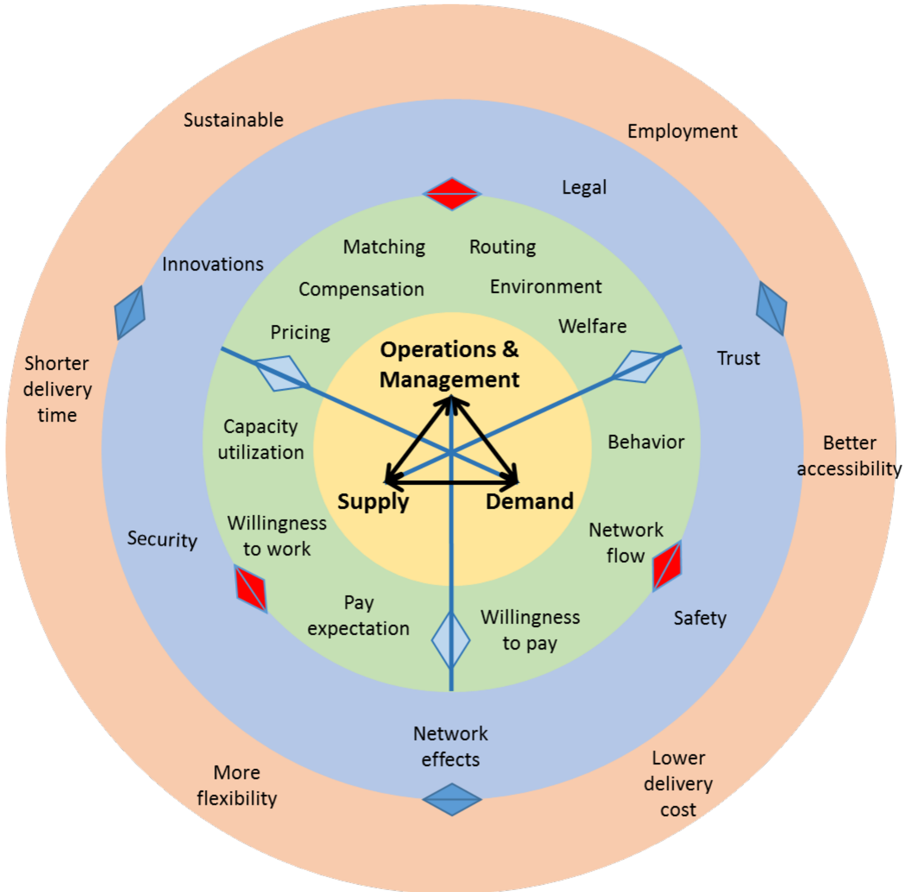


Figure 2.3.: *CS* components, relationships, challenges, and potential benefits (ordering from inner to outer circles)

preferences; willingness to join *CS* system behaviors (stated preference); and socio-demographic characteristics. For more detailed information on the survey design, implementations, and descriptive analysis, readers are referred to [26].

- The second dataset (here after DATA2) used in this study is a US survey including a choice experiment of sender's decision between *CS* and traditional options in different shipment contexts. The survey was designed to study barriers and motivations to CS usages, as well as sender orientation towards sharing services more broadly. Data was collected in June 2016 from 533 respondents. Detailed sample and experiment descriptions are given in [22].

- A third dataset (here after DATA3) represents real *CS* operations by US users of a leading *CS* platform. DATA3 covers two continuous years of operation from the start of 2015 to the end of 2016 with a total of 16,850 delivery requests, including timing, shipment attributes, and user characteristics. More details are available in [28].

While DATA1 and DATA2 are smaller data-sets with deep information about users and a detailed representation of the choice process derived from choice experiments, they suffer from a potential risk of hypothetical bias [29, 30]. However, these two datasets are complemented by DATA3 given more representative real-world *CS* decisions and outcomes.

CS components, relationships, challenges, and potential benefits are summarized from inner to outer circles, in Figure 2.3. The two inner circles display topics which are the focus of our review in section three, namely *supply*, *demand*, and *operations and management*. The second largest circle, however, shows challenges to the *CS* industry, for instance, network effects, trust, safety, security, legal [20, 31, 32, 33, 34, 35, 36, 37, 38], innovations, and platform design features which will be addressed for future improvements in Sections 2.5.1 and 2.5.2. The outermost circle presents the expected *CS* benefits, such as faster delivery time, lower delivery cost, more flexibility, improved accessibility, sustainability, and employment opportunities [20, 31]. To realize these benefits, several main channels are discussed in Section 2.5.3, for example, transportation system performance, industry competitiveness, consumers, labor market and regulation, and community and social connectivity.

2.3 Review, synthesis, and trends analysis

Given the emerging *CS* industry, most relevant studies are published within the last few years. Some researchers have reviewed *CS* operators and studies, such as [20, 23, 31, 39]. Our research, however, brings an additional perspective to the existing reviews. Specifically, we study the three fundamental pillars in a *CS* system, namely the '*supply* side', '*demand* side', and '*operations and management*'. This distinguishing angle of analysis allows us to explore in depth, using a range of literature sources, the functioning of *demand* versus *supply* and how they come together to define the performance of *CS*.

For each subsection, we review evidence from three sources 'Industry and business perspective', 'Operations and stakeholders', and 'Empirical results'. The 'Industry and business perspective' subsection illustrates and discusses various practice cases and pilots which were implemented or are ongoing. The 'Operations and stakeholders' subsection presents a number of current academic studies. 'Empirical results' includes unpublished findings and illustrations from our surveys or data from industry collaborations.

2.3.1 *Supply* side

It is clear that the *supply* of resources needed for *CS* is different than traditional delivery processes, where drivers are on the payroll of a logistics service provider. In the latter case, operations and drivers are centrally managed, and deliveries are planned by these companies. Accordingly, drivers are expected to be available whenever needed (assuming good planning processes). In a *CS* context where the drivers are participating in the market mostly on a voluntary basis, their availability and their willingness-to-work are important aspects that need to be considered.

On-demand services typically make use of independent providers (e.g., the crowd) to fulfill customer requests quickly and are paid accordingly. Work participation is highly dependent on the actual earnings. Hence, the compensation paid for drivers is a key driver for the *CS* success and their willingness-to-drive.

Industry and business perspective

Cargo hitching is a concept where the *integration of freight and passenger transport* plays an important role in efficient and reliable delivery services. Clearly, people and goods share the same infrastructure and might thus be combined into the same type of (people-based) transport resources, e.g. taxi, metro, bus, train, etc. [40, 41]. As such, this concept exploits the spare capacity available in public transportation networks.

In practice, cargo hitching applications already exist in long-haul transportation, i.e. airlines and rail, where both cargo and people are moved using the same resources. See, for example, applications like the DHL PostBus [42], where parcel transport and passenger service on long-distance intercity bus networks are managed. On the other hand, short-haul applications are limited. Effective and efficient coordination and synchronization is challenging. Moreover, so far only a limited number of research efforts are seen in the literature. Research which ranges from the use of scheduled transportation lines to the flexible use of taxis, is presented in the next section.

Traditional logistics carriers (e.g., DHL), tech-based firms (e.g., Instacart, Google (Express), Facebook (Order food), and Uber), and major retailers (e.g., Amazon and Walmart) directly or indirectly hire crowds for delivery. These crowdsourced shipping service platforms vary from international (e.g., Shipyzi, Entruster, and Piggybee), long haul (e.g., Roadie, Gogovan, and Trucker Path), short haul (e.g., Cargomatic, Convoy, and Shipster), to last-mile delivery (e.g., Amazon Flex, Instacart, and UberEats). Many crowdsourced delivery services have been implemented in urban areas where most of the world's population currently live [11]. For example, Amazon has its own delivery fleets and has long been considering crowdsourced delivery. In 2014, Amazon tested taxis for a speed delivery service in some California cities, but the experiment was not expanded [43]. In 2016, the company introduced Amazon Flex, a delivery service that hires ordinary people to deliver a range of packages, mostly food and other grocery products. This service is available in more than 30 US cities (https://flex.amazon.com/). Likewise, DHL has just started the "Parcel Metro" service in Chicago, Los Angeles, and New York City in March 2018 which use crowd-sourced and contract couriers. Uber, recently, has captured public attention by discussing the purchase of the food delivery company Deliveroo aiming to extend its market to Europe (https://www.bloomberg.com/news/articles/2018-09-20/uber-is-said-to-be-in-early-talks-to-buy-europe-s-deliveroo).

In addition to partnering with FedEx for package delivery, Walmart has its own Walmart Grocery Service (formerly Walmart To Go) delivery trucks. The Walmart Grocery program allows customers in some areas to order online and have packages delivered during a designated time window. Moreover, Walmart has also been testing *CS* for last-mile delivery. In 2013, Walmart introduced a program in which customers deliver packages to online buyers [44]. This program intended to shorten delivery times and cut transportation costs to compete with Amazon. In 2016, Walmart piloted delivery with Uber, Deliv, and Lyft [45]. Walmart also implemented a 2017 project in which employees voluntarily delivered packages on their way home from work [46].

[39] studied 36 *CS* platform providers (Table 2.1) which mainly provide services in urban areas. Those firms build on-line platforms to connect senders and driver-partners. In general, *CS* on-line platforms facilitate real-time communication, and tracking and tracing services which are more advanced than traditional logistics carriers. Additionally, *CS* potentially brings social, economic, and environmental benefits for stakeholders [31]. In fact, *CS* service users and driver-partners are the ones who are comfortable using digital platforms (e.g., via smart phones or computers). The digital platform, however, is a barrier for population segments that lack access to connected device technology or a transaction account. A significant part of *CS* activities are happening via digital platforms. Sub-section 2.3.3 discusses the main differences in firms' *pricing* operations and strategies.

Drawing on interviews with retailers, manufacturers, and logistics service providers, [47] found the top three factors that influenced the success of platform providers are "happy crowd" (38.24%), "good service" (27.36%), and "maximum profit" (18.32%). On the other hand, "compensation" (45.36%), "good working environment" (27.05%), and "good platform operation" (16.88%) were the most important factors influencing the willingness to work among potential crowd-drivers.

Table 2.1.: Crowd-shipping platform providers [39] (* means the platform provider offers more than one delivery service)

Range	**CS firms**	**Unit size**	**Market segmentation**	**Vehicle**
Urban	BigFoodie, Deliveroo, Delivery.com*, DiningIn/ Labite, Ele.me, FoodExpress, Foodora/ Hurrier/ Suppertime, Gousto, Jinn*, Just Eat Delivery, Marley Spoon, Mesh*, Postmates*, Uber Eats	Parcel	Prepared meals, Meal kits	Bikes, Scooters, Cars, Vans
Urban	Delivery.com*, Ebay Now*, Google Express*, Instacart*, Jinn*, PiggyBaggy, Postmates*, Yihaodian*	Parcel	Grocery	Bikes, Scooters, Cars, Vans
Urban	Delivery.com*, Minibar	Parcel	Beverage, Wine, Alcohol, Spirits	Bikes, Scooters, Cars, Vans
Urban	Delivery.com*, Laundrapp, Laundry Republic	Parcel	Laundy	Vans
Urban, Regional, Long distance	Amazon Prime, Ebay Now*, Google Express*, Instacart*, Jinn*, Mesh*, MyWays, Nimber, Postmates*, Roadie, Yihaodian*	Parcel	Retailing	Bikes, Scooters, Cars, Vans
Urban	Box2 Home, BuddyTruck, FleetZen, Ghosttruck	Parcel, Bulky goods, Oversize	Funiture, Moving, Others	Vans, Pickups
Urban, Regional, Long distance	Baghitch, UberVan, UberFreight			

Operations and stake-holders

- *Operational analysis*

  Scheduled transportation lines, like buses and trains, face a lot of under-utilization of their capacity for a significant amount of time. Clearly, based on contractual agreements, these resources need to be operated based on a given minimal fixed schedule, regardless of the actual passengers need. Due to those correlations, utilizing public transportation capacity is further discussed among the operations strategies which will be presented in sub-subsection 2.3.3.

Taxis are more flexible as passengers determine pickup and delivery locations as well as times. Within a narrow interpretation of crowd logistics, taxis can thus be used to move freight within the city. This business model will be jointly discussed with *operations and management* strategies shown in sub-subsection 2.3.3.

Alternatively, traditional logistics carriers may outsource packages to optimize their business (e.g., during peak-*demand* time). Given that some people are willing to make a single delivery for a small incentive, [48] developed a multi-start heuristic model that confirmed the reduction of delivery costs for traditional logistics firms depending on the number and flexibility of occasional drivers as well as the compensation scheme.

- *Behavioral analysis and surveys*

  Despite the fact that many studies proposed feasible *CS* system solutions, a few studies focused on the *behavior* of system stakeholders. A central question investigated is the *driver-partners* willingness to work as carriers. Findings vary significantly, whereas between 30% to 87% of respondents are willing to work for *CS* systems [49, 50, 51, 52, 53]. More broadly, the influencing factors on driver *behaviors* have been examined. [22] investigated potential senders' preferences for *CS* driver performance. Among the most notable findings, the driver reputation was in many settings even more influential than the delivery cost and speed. In a US study focusing on the crowd-courier decision to accept a delivery, commuters traveling for leisure or with more flexible schedules were most likely to be willing to work as occasional drivers, according to [51]. [26] presented a descriptive analysis of requesters and potential *driver-partners* using novel data collected from Vietnam and the US. In another study, respondents who had experience transporting freight or goods were more willing to work as *driver-partners* [53]. [50] found that 87% and 93% of Italian students were willing to work as *driver-partners* and receive their packages via a *CS* system, respectively. [49] conducted research on *CS* in Geneva. Their literature review and surveys concluded that stakeholder expectations varied, which created additional barriers and challenges in the implementation of *CS* systems.

Empirical results

Figure 2.4 displays distance tolerances of *driver-partners* from DATA1. Given the original trip distance of 5 miles, over 63% and 21% of respondents were willing to divert up to 10 miles or 20 miles to pick up and deliver packages, receptively. Figure 2.5 shows respondents' expected compensations. Interestingly, about 53% of respondents were willing to deliver packages at \$10 or less (i.e. equal to around 67% of the cost charged by the traditional logistics carrier which represented the base case of \$15). Important to realize, about 89% of potential *driver-partners*, in total, charged \$15 or less for their delivery trip. Moreover, respondents from the same survey also showed their interest in working as *driver-partners* at most times, except weekend evenings or after midnight, as can be seen from Figure 2.6. The time flexibility of potential *driver-partners* greatly facilitates *CS* companies ability to outsource packages once the *demand* exceeds their *supply*. If fact, there is a few studies on distance tolerances, respondents' expected compensations, and working time perceptions.

2.3.2 *Demand* side

This section summarizes the existing literature and points out the findings and gaps in understanding concerning the role and impact of *CS* from the *demand* perspective.

The main players that generate *demand* for *CS*, in the role of senders and receivers, are individual customers from the crowd, often in the form of e-tailers, retailers and logistics businesses, sending by themselves, or acting as brokers [23, 54]. Zooming in on the characteristics of the *demand* for *CS* is essential to understand the potential societal impacts of the shift of freight deliveries to the crowd. The network flow of *CS* packages is indeed determined by the spatial (as well as temporal) *matching* between sender's locations and courier's routes [20]. In other words, senders dictate the origin-

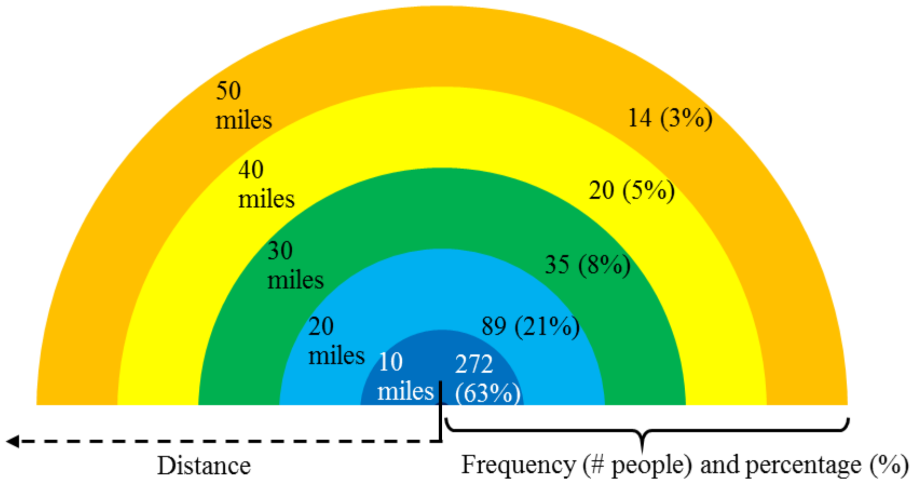


Figure 2.4.: Potential *driver-partners'* distance tolerances (based on original trip of 5 miles) and distributions

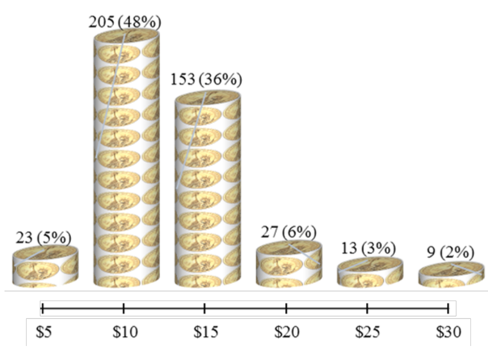


Figure 2.5.: Frequency (# people) and percentage (%) of potential *driver-partners'* expected compensation (base rate of $15)

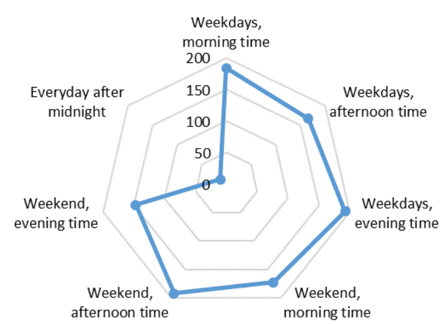


Figure 2.6.: WTW at different time of the day and day of the week (multiple-choice question) (numbers represent frequency (people))

destination dynamics of the shipments, and thereby how efficiently the *matching* can be done. This locational analysis is further complicated by e-tailing and customers propensity to accept delivery to lockers and other intermediary locations rather than home-delivery.

The following sub-sections will highlight the findings from different research areas, from case-studies to operational analysis and empirical works. Each subsection will discuss findings related to; a) the customer/receiver characteristics, b) spatio-temporal aspects, c) behavioral aspects.

Industry and business perspective

A number of researchers proposed business analyses based on literature and/or study of existing companies identify the factors that are most essential to understand the customer *demand* perspective. [55] study 57 crowd logistics initiatives and carry out content analysis on company web-site data. The authors find that, linked to *CS* system performance and impact, the focus of *CS* operations is predominantly at the local scale. The paper highlights that not just transportation, but also handling and storing are affected by crowd-sourcing. In each value chain, the common feature is the increasingly active role of the customer. [56] highlight the importance of service platform usability and customer trust in the crowd logistics company, along with the service itself, as the core features to augment *demand*. Furthermore, qualitative delivery (29.29%) and pickup (22.64%) (i.e. personalized time, undamaged), and *environmental* friendliness (20.76%) play the most significant role for customer *demand* [47].

Moreover, a few works have explored customer acceptance from revealed data. Among the limited empirical examples are [57] and [28] who model real *CS* operations from a 2-year data-base of US crowd shipments from 2015-2016. [28] show that couriers are less likely to bid on shipments from senders that ship long distances, across state boundaries or who request strict delivery deadlines. [57] compares *CS* performance in urban and suburban areas. Whether the sender is a business or an individual is among the most consequential for determining the delivery performance. The perceived reliability of a business sender appears to be the driving factor behind the improved performance.

Regarding potential market segments, [39] surveyed 36 *CS* firms and found prepared meals, groceries, retailing goods, and laundry are the most common delivery items. A few *CS* firms provide services for delivering books, wines, alcohols, beverage, furniture, or moving services. The market segmentations and associated *CS* service providers will be summarized together in sub-subsection 2.3.3.

Operations and stake-holders

- *Operational analysis*

  Promoting public acceptance of *CS* along with the growth of customers willing to use *CS* is essential for ‘the chicken and the egg problem’ related to the scalability of *CS* [31, 56, 58]. Indeed, the customer base needs to grow on par with the couriers managed by *CS* platforms for the new system to be viable.

  There is a growing body of work in the operation and optimization literature on crowd logistics. While these works typically do not explicitly study the behavior of senders, the assumptions about sender locations and motivations are valuable to gain theoretical insight about the important dimensions and their impact.

  The question about location of *demand*, and hence the feasibility of minimal detours by carriers, and creation of efficient logistics networks, are explored in several works. Specifically, existing studies have explored the spatial feasibility of crowdshipping by mining data from location-based social networks [59, 60] or inferring geolocations from mobile phone cell towers [61, 62] or mining GPS logs from taxi services to represent the potential for developing *CS* [63, 64].

These studies show how optimization analysis exploring *CS* frequently incorporates the customer perspective in the frameworks. However, this inclusion is not always based on actual behavioral findings.

- *Behavioral analysis and surveys*

  Meanwhile, behavioral research has been carried out using hypothetical choices of *CS* services. [52] bring to the fore customers concerns about reliability, privacy and accountability when contemplating the use of *CS* services. The authors employ a US survey (n=104) to show that a majority of respondents will however consider shipping via the crowd from an acquaintance, and that the proximity between the sender-driver dyad is crucial. Based on these insights, the authors define a realistic case-study for Alexandria, Virginia, relying on social networks to overcome customer reluctance and build a crowd-delivery system.

  [26] study the priorities of both requesters and carriers using on-line surveys from 2017 administered in USA (n=722) and Vietnam (n=617). Requesters were found to favor CS carriers for specific goods categories such as dry cleaning, groceries and home-delivered food, entailing higher delivery fees and requirements on delivery times. Instead, traditional carriers were preferred for less urgent goods, with an associated lover delivery cost. The main concern among US and Vietnamese respondents was the delivery condition "without damage" when carried by a crowd-carrier (around 85%). Concerning the timeliness of the delivery, US respondents were much more sensitive than the Vietnamese ones.

  Drawing on a stated preference experiment in the US, [22] explore the acceptance of deliveries fulfilled by non-professional shippers using random parameter and error component models. Most shipping attributes, from shipment duration to driver training had variable impacts corresponding to the shipment distance (i.e. different preference patterns in the urban, inter-city, and long distance markets). Overall, the attributes related to driver performance are the most influential in the decision process.

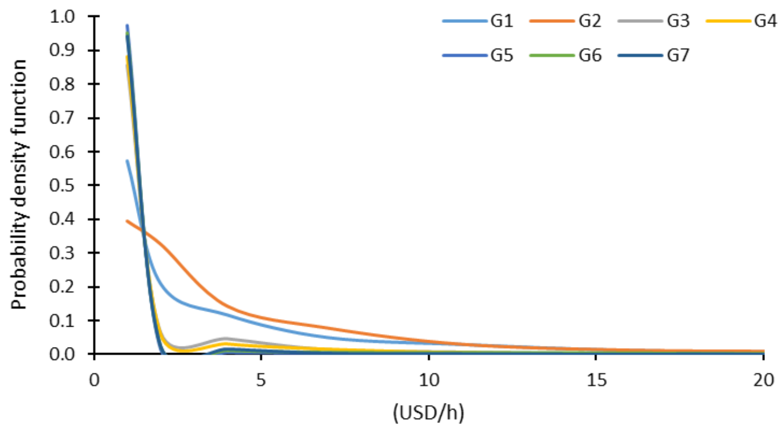


Figure 2.7.: WTP probability density functions for different product groups

In addition to this, [65] identify factors which have strong relations to the successful deliveries, such as package size, delivery distance, *demand* frequency and distribution, as well as requesters' age, and pricing strategy. Additionally, [66] study the factors separating users from non-users of *CS*, ranging from socio-demographics and attitudes of senders, to the broader built *environment*. *CS* is found to be more common among young people, men, and full-time employed individuals. Concerning the attitudinal motivations, individuals who have a strong sense of community and *environmental* concerns are more likely users.

Empirical results

Figure 2.7 presents willingness to pay (WTP) functions for seven product-groups which are coded from G1 to G7, using DATA1. G1 includes fast food, dry cleaning, etc products. G2 is coded for groceries products. G3 and G4 present beverage/dried foods and personal health/medicine products. G5 and G6 include apparel and consumer electronics products. G7 comprises the remaining products. As can be seen from the Figure 2.7, respondents were willing to pay the highest *price* for shipping groceries, fast food, dry cleaning, and similar products (i.e. G1 and G2). Meanwhile, apparel (i.e. G5) and consumer electronics (i.e. G6) had the lowest WTP for delivery.

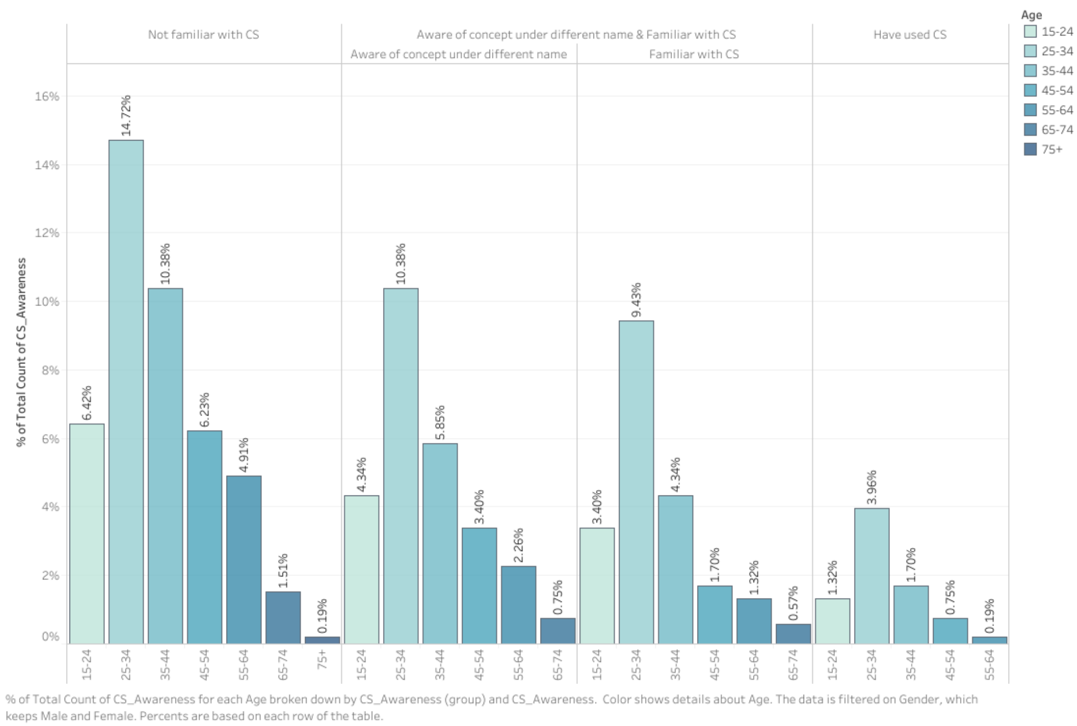


Figure 2.8.: Awareness and usage of *CS* by age groups

Figure 2.8, based on DATA2, reveals that the majority of prospective senders from the general public are unfamiliar with CS, with <8% having used this type of system [66]. In line with expectations, and similarly to passenger ride-hailing, the respondent age plays an important role [67]. The highest propensity for CS use and awareness occurs in the age class of 25-34. This suggests a promise of CS system acceptance to pick up in the future as this generation ages.

Figure 2.9 points to an intriguing aspect of the CS system use (DATA2). It shows that respondents with higher awareness of the service also consider it to be more complicated to use. This suggests that some of the practical challenges related to using CS are difficult to perceive for users that are not experienced with the service. Shipping via the crowd requires users to place a shipment request, secure bids and reaching an agreement with couriers, and these steps can present unforeseen challenges.

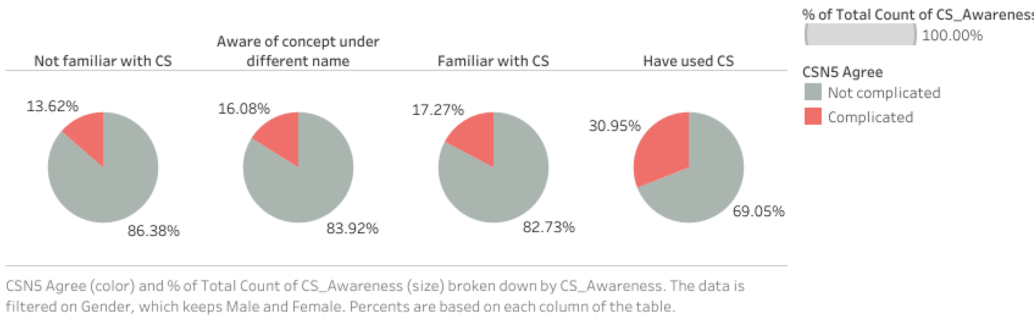


Figure 2.9.: Perceived difficulty to use service by awareness level

Understanding more about the behavior, motivations and goals of *CS* customers remains a challenging objective. Such insights would contribute to building and pacing critical mass, tailoring the service (especially *matching* parameters such as *price*), and fostering retention and repeat service among customers.

2.3.3 *Operations and management*

The previous sections discussed *CS* in terms of *supply* and *demand*, from practice to research and empirical findings. The successful expansion of this emerging industry, however, heavily depends on its operational and management strategies. In the following sub-sections, platform characteristics, *matching and routing*, *pricing* strategies, and *environmental* impacts are discussed.

Industry and business perspective

There are few real-world case studies. [68] developed planning and operation models that were tested in a San Francisco case study. Four scenarios of shared-mobility (passenger cars) and trucks were investigated. The study found potential economic benefits reducing the delivery truck size and suggested operational alternatives (e.g., avoid peak hours and low-*demand* areas). The authors also confirmed that dynamic

Table 2.2.: Crowd-shipping business models [31]

Name	**Clients**	**Offer**	**Area**	**Couriers**	**Revenue models**
Courier	B2C	Deliver from a shop, a restaurant, a pharmacy, etc.,	Intra-urban	Professional or non-professional dedicated couriers	Fixed prices
Intendant	B2C	An order is placed on the *CS*'s website. The courier purchases the product and delivers to the customer	Intra-urban	Professional or non-professional dedicated couriers	Fixed prices, resale margins, financial fees
Intra-urban	2P or B2B	Deliver a parcel	Intra-urban	Professional, non-professional dedicated couriers, or commuters	Fixed prices
National	P2P or B2B	Deliver a parcel	Inter-urban/ National	Travelers	Negotiated prices, financial fees
Social delivery	P2P or B2B or network	An order is placed on the business website. The courier proceeds to purchase, then to delivery	National/ International	Travelers	Reward barter, financial fees

wages and *CS* service *prices* impeded operational flexibility. Due to the induced trips, the expected *environmental* benefits are not yet achieved.

[31] investigated 18 *CS* companies categorized into five *business 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. As such, the market segmentation strategies and revenue models vary across these business models. The clients range from business-to-business (B2B), business-to-customer (B2C), and peer-to-peer (P2P). Details are presented in Table 2.2. In a similar way, [47] interviewed managers and higher position practitioners from 11 companies and defined five crowd logistics types which are “business marketplace,” “community marketplace,” “flex work platform,” “commissioner platform,” and “logistics marketplace”. Those five types also map to the above mentioned B2B, B2C, and P2P *business models*.

Pricing strategies are associated with the implemented *revenue models.* From their survey of 18 *CS* firms, [31] identified five revenue models, namely "fixed price," "negotiated prices,' "financial and matching fees," "resale margin," and "membership." Some *CS* firms use multiple *pricing* strategies applied for different services. Based on [31], we reviewed the pros and cons for each revenue model (Table 2.3). Alternatively, [39] found that a large part of 36 *CS* firms do not reveal their *pricing* strategies and algorithms. *CS* users are only informed of the surcharges, such as in peak time or late night, without knowing the exact *pricing* model. Some *CS* firms (e.g., Postmates) provide a *pricing* comparison to other logistics providers for any request. Collectively, the authors found a range of *CS* management strategies that can be characterized as two poles. In centralized (or top-down) strategies, the platform owner sets *pricing*, extracts candidates for courier selection and guides driver-partners on optimal dispatch strategy and delivery routes. In systems that tend towards peer-to-peer (bottom-up) strategies, non-professional peers freely set and negotiate prices, select among a set of non-curated (e.g. locally available) candidates, and driver-partners use their own judgment on dispatch and routing. Theoretically, implementing negotiated pricing/ bidding strategies will cost the *CS* operator more due to more complex algorithms and computation efforts. On the other hand, some empirical research has suggested that peer-to-peer negotiations lead to deteriorated performance of the platform, by causing less efficient bidding and delivery processes [28]. The tension between the need for simple pricing/selection scenarios suited to crowd resources, and the aspiration for optimal strategies based on sophisticated centralized procedures requires further understanding of the interaction of the non-professional crowd patterns of behavior and motivations and novel technical shipping platforms.

Environmental benefits are found from a pilot case study in Finland, where CS was used to deliver library books and media [69]. On average, the pilot study saved about 1.6 km per car delivery trip. The authors also estimated a potential 4% reduction of mobility related footprint if as many as half of the shopping and library trips were

Table 2.3.: Crowd-shipping pricing and revenue models (Based on [31]. Pros and cons are generated by authors)

Revenue model	Price determination party	Pros	Cons	Common implement-ation areas	Examples of platform providers
Fixed prices with incremental charges	Platform providers	Transparent price for customers. Easy to implement for CS firms.	Request for any individualized service will be charged additional costs.	Intra-urban	Postmates, UberEats
Negotiated prices/ bidding	Senders suggest a preferred price and driver-partners bid for the task. Final price is bargained.	Facilitates services customized to sender specific shipping needs and increases probability to reach sender-driver agreement for non-standard shipment. Final price reflects both parties' preferences.	Driver-partners may compete assertively to win the bid causing the final agreed price to fall below the minimum wage.	Inter-urban	Deliv, TaskRabbit
Financial and matching fees	Can be free shipping or different rewards. In case of charging for delivery, price is typically set by senders. Platform providers charge a certain percentage for matching fee.	System promotes social value by increasing probability of on-the-go delivery tied in with social networks.	This business model can limit ability to ensure a driver is enrolled thereby offering lower level of service. Can lead to legal issues (some products are regulated differently across countries).	International	Bernacle, Bistip, Kanga, Muber, Rideship, mm-Mule, PiggyBee, Easybring
Resale margin	Delivery can be free but CS firms have a cut from ordering commissions.	Promotes advantageous relationships between CS firms and retailers, possibly making the growing e-retail market more sustainable.	Limited coverage: CS platforms only offer shipment of customer products provided by retailers that are part of the CS firm have collaboration.	Intra-urban	Instacart
Membership	Platform providers set the membership fee and decide which services will be provided free and in which circumstances.	Assure a baseline *demand* from retailers who have frequent shipments.	Retailers have to pay a fixed cost, regardless of how many shipments they send.	Intra/inter-urban	Instacart

crowd-sourced. Future work should more systematically compute the environmental and energy impacts of the *CS* market using more comprehensive samples.

Research is currently limited by a lack of business operation and available information (typically of a proprietary nature). Under some abstracting conditions researchers still conduct studies in these areas, using a range of methods, to provide alternative insights. These are summarized as follows.

Operations and stake-holders

[70] developed a *CS* platform prototype for local retailers, identifying five main challenges: “smart matching algorithms”, “leverage network effect”, “platform governance”, “data privacy” and “trust”. Feasible countermeasures were then proposed to implement the platform.

Most research concentrated on some of these identified challenges of a *CS* platform. Specifically, the majority of available papers focus on *routing and matching* strategies. Clearly, *routing and matching* are intertwined decisions. The costs and feasibility of matches are depending upon the needed routes. Routes are relevant both for the supply (vehicle) to meet the demand (order), but also from the pickup to the delivery of the demand. Also note that the feasibility of matches also depends upon the available capacity and the actual demand requirements, e.g. time windows (both pickup and delivery). Moreover, these *routing and matching* decisions also cannot be observed independently from the *pricing* strategies. Overall, a comprehensive model, taking into account and integrating these decisions is not researched as far as we know. Specifically, it combines OR-based combinatorial optimization models, pricing/revenue management principles, consumer utility theory, and multi-stakeholders.

Matching approaches

[71] created an algorithm to match travelers and packages with origin-destination (OD) locations and time constraints for both stakeholders. This model is unable to

assign multiple requests to one courier, and cannot handle the transfer of a package between multiple couriers. [72] optimized travel routes under some business strategies of *CS* systems. The developed model provides the largest profit, smallest cost and risk compared to two other benchmark models.

Moreover, [10] designed and modeled a crowdsource-enabled system for the integration of truck carriers and *driver-partners* into urban relay and delivery. The designated system was developed to be sensitive to specific customer factors, e.g. the "penalty for servicing outside customers' desired time windows".

[73] reveal a trade-off between the benefits for taxi firms and the acceptance rate of parcels. Delivering more parcels will likely provide more benefits to taxi operators; however, once the number of parcels exceeds the maximum capacity of taxi firms, the acceptance rate will be low. Therefore, the taxi company may need to outsource the surplus parcels to traditional logistics carriers or *CS* firms.

[74] look into the ride-matching problem within the context of a peer-to-peer ridesharing system, i.e. drivers need to find riders. The authors developed an algorithm to optimally solve this ride-matching problem in real-time. Within a crowdsourcing context, [75] managed to find an efficient matching algorithm connecting around 10,000 pairs of ride offers and ride requests in real-time. [76] look into making real-time recommendations for matching workers to tasks, making the trade-off between skills and reliability. In their paper, [77] developed an algorithm leading to the assignment of drivers to transportation requests by matching them based on transportation routes and time constraints. They use a simulation based on mobility data from a German city, to test their algorithm.

Overall, the current literature has a number of matching algorithms available, mostly within a setting of offering empty seats to riders in real-time. More research on translating these "people transport" -based matching algorithms into a real-time crowdsourcing context (i.e. for freight delivery) is needed. Real-time matching in a real-time context considering the future effect of the current decisions is a hard combinatorial problem involving dynamic programming. Moreover, integrating these decisions with the pricing, willingness-to-pay and willingness-to-work decisions, is very worthwhile investigating. Note that in the latter case, there are three stakeholders (i.e. drivers, requesters and the platform provider) and their decisions involved, opening the door towards some interesting (non-)cooperative game theoretical aspects as well.

Pickup and delivery routing

[78] show that pickup and delivery is an important crowdsourced delivery problem. The study addressed the problem by optimizing the unused capacity of the available traffic flow. Results confirm the economic benefits of a *CS* service compared to a traditional delivery service. However, the authors assumed static arrival rates of requests and drivers, which is a less realistic setting in practice.

Along the same lines of utilizing unused capacity of existing flows, we mention the cargo hitching literature stream. The integration of passengers and freight transport is also explored in [79, 80]. [81] considered the feasibility and opportunity of incorporating scheduled public transportation in the distribution of goods. Pickup and Delivery (PD) vehicles are used to bring (collect) goods to (from) a bus station, and spare capacity on the scheduled bus services, especially in off-peak hours, is used to move goods for part of their journey to their end destination. [82] proposed a Mixed Urban Transportation Problem based on a two-tier network approach, using city buses for the first tier and regular service providers for the second tier. Other studies proposed time window solutions to pickup and delivery problems [83], schedule lines [81, 84, 85, 86], and stochastic *demand*s [87].

[73] introduce and explore the Share-a-Ride Problem, which is an extension of the Dial-a-Ride-Problem [88], but considering the different requirements to transport people and freight using a taxi network (e.g., maximum ride-time, detours, number of stops, etc.). Taxis are allowed to deliver parcels as long as the service level for the passenger does not deteriorate significantly. A Freight Insertion Problem (FIP)

is proposed to insert parcel collections in a given *routing* plan for passengers aimed at minimal passenger disruptions. Some other studies along these lines are [89, 90].

[59] used geotagged Twitter posts to approximate people's geolocations and estimated scenarios for a crowdsourced delivery service with different *routing* approaches. The study assumed that people are willing to carry packages during their daily travels. The tasks were formulated as graph-planning problems, and the results revealed significant speed and coverage: a slack of 800 meters and 90 minutes is sufficient to cover 83% and 100% of the source-origin location pairs in the Seattle and New York City Metropolitan areas, respectively.

More recently, [91] consider a crowdsourced system where drivers express their availability to perform delivery tasks for a given period of time and the platform communicates a schedule with requests to serve. The authors investigate the potential benefits of introducing transfers to support driver activities. At transfer locations, drivers can drop off packages for pick up by other drivers at a later time.

Routing strategies for *CS* systems need to be able to handle, match and route requests in real-time. [92] and [93] reviewed the literature on dynamic vehicle routing. Both reviews point to the need of more dynamic models, that are able to manage real-time requests. Following the taxonomy as presented by [93], the routing problems in *CS* context, would probably be labeled as part of the dynamic and stochastic class. In terms of solution methodology, it seems that dynamic programming algorithms which develop some policy, to determine which next request to handle by whom and its routes, are interesting to investigate deeper. A promising approach is to identify a well-performing strategy involving anticipation, leading to an anticipatory pickup and delivery routing problem (in a dynamic and stochastic context) [78, 94].

Pricing

Pricing is among the most important characteristics of crowdsourcing services. Existing studies proposed alternative methods to determine the most attractive *pric-*

ing strategies for both requesters and *driver-partners.* Bidding is a common suggestion [10, 22]. *CS* is usually more cost-effective than traditional shipping services [78, 95, 96]. For example, using *CS* services helps requesters save about 50% of costs on two-hour delivery services, while the cost saving on one-hour delivery services is 60% [95]. [96] developed three *pricing* schemes: "membership-based pricing," "transaction-based pricing," and "cross-subsidization". Interestingly, all three schemes derive the same equilibrium results. Moreover, using game-theory to study platforms as a revenue-maximization problem provides theoretical understanding of core parameters [97, 98]. The matching stability and revenue for the platform is a function of a number of market parameters (including the similarity of characteristics of actors and the relative sizes of the two sides of the matching market). This literature shows that the choice of optimal platform strategy needs to consider how large the demand and supply pools are and how well they match in terms of size, preferences and socio-demographics.

Environment and other aspects

New *CS* services are expected to be more *environmentally* sustainable than traditional freight-shipping services. Using social networks for delivery contributes to the reduction of greenhouse gases in both urban and suburban areas [99]. [100] found a 55% decrease in pollution in a case study on crowdsourced delivery using social networks. However, negative [68, 101] or contextually-dependent [99] *environmental* impacts are also identified. In line with this, [23] developed a set of criteria for evaluating the sustainability potential of *CS* services.

Researchers proposed various alternative countermeasures for a more *effective and efficient CS* systems, such as disclosing drivers' identity [102], but some areas still merit further investigation. For instance, how much time (how long a delay) should the platform allow driver partners to bid for shipping costs (i.e. their expected compensation). Some types of shipments need to be delivered immediately so any delay in the bidding procedure will influence delivery time, and thus, users' experience. Furthermore, we also need to discuss issues related to the trade-off between matching efficiency and empty trips, and the challenges related to environment and energy impacts.

Empirical results

The information of requesters' WTPs and driver-partners' pay expectations is vital for *CS* companies to create *pricing* models and compensation strategies. From comparing the Figures 2.5 and 2.7, it can be observed that the requesters' WTPs are much lower than the driver-partners' pay expectations. The *CS* providers should counterbalance this discrepancy to facilitate the popularity of *CS* services as well as to satisfy requesters' and driver-partners' aspirations. Moreover, Figure 2.9 suggests that *CS* providers should improve platform features to become more seamlessly, integrated, and collaborative.

Figure 2.10, using DATA3, illustrates ratios of drivers to senders for states in the US. Interestingly, the ratios of some states are quite high, such as Indiana (3.395), South Carolina (3.267), Kentucky (2.913), Arizona (2.882), Louisiana (2.365), Delaware (2.333), Rhode island (2.000), and Nebraska (2.000). Accordingly, the *supply* is much larger than the *demand* for sending packages in those states. On the contrary, some other states have relatively low ratios, such as Iowa (0.500), Maine (0.444), Idaho (0.429), Utah (0.428).As such, there are more senders than drivers in those states. In general, the ratios, which represent the mismatches between *demand* and *supply*, provide knowledge supporting logistics companies to develop appropriate business strategies (e.g., *pricing* and compensation strategies) for different markets.

2.4 Potential benefits of crowd-shipping for stakeholders

In this section, the potential benefits that *CS* services offer stakeholders will be studied. Each stakeholder uses the service for their own needs, and their corresponding

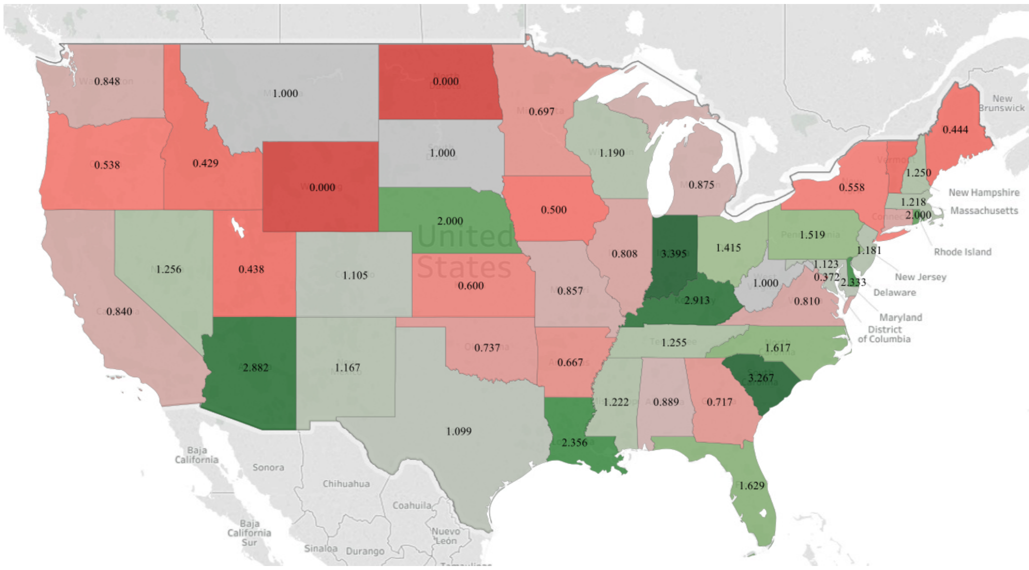


Figure 2.10.: Ratios of drivers to senders by the US states (green indicating an abundance of driver enrollment, red indicating a shortage of driver enrollment compared to requesters)

benefits vary. A review of the benefits for customers, merchants, and their communities is presented in the subsections that follows.

2.4.1 Customers

Shorter delivery time

Traditional logistics carriers optimize pickup and delivery trip turnaround. Such carriers have improved the pickup/delivery process, and same-day delivery is the most attractive delivery option (e.g., DHL, UPS, and FedEx). Some carriers have also opened local storefronts as an alternative parcel pickup option. However, this option requires customers' time and energy.

CS provides on-demand delivery service with minimal delays. Customers select a courier who travels on or is closest to the delivery route [103]. Therefore, the delivery requires a minimal diversion from travelers' typical routes. These couriers are familiar with the routes, so the delivery time will likely be faster. Many *CS* companies offer 24/7 on-demand delivery service, a feature that is stressed in their marketing. For example, Postmates' slogan is "The best of your city delivered in minutes" (https://postmates.com/) and UberRUSH claims "Deliver with UberRUSH faster than you can imagine..." (https://rush.uber.com). Honestbee, a *CS* company in Hong Kong, promises to deliver as soon as one hour after a grocery order is placed (https://honestbee.sg/en/groceries).

Some *CS* firms even hire individuals who do not own vehicles. Public transportation networks are generally designed to provide coverage and connectivity to airports, shopping malls, schools, and residential areas [104]. Therefore, it is possible for individuals who use public transportation to deliver freight and provides a reliable alternative to freight delivery.

Lower delivery costs

As mentioned earlier, delivery costs are a critical consideration for e-commerce customers. Traditional logistics carriers incur the following costs: transport, warehousing, inventory care, logistics administration, and packaging [105]. Logistics costs result in at least 10% of company turnover [105]. In some business, as much as 28% of shipping costs are related to last-mile delivery (Council of Supply Chain Management Professionals referred to in [106]). Large company and complicated organization structures make traditional logistics carriers less flexible to supply on-demand requests and optimize delivery costs. As a result, their delivery prices often cannot compete with *CS* suppliers.

The competitive pricing of *CS* services have been summarized in the previous chapter. Furthermore, a pricing comparison of *CS* and non-*CS* companies is presented in Figure 2.11

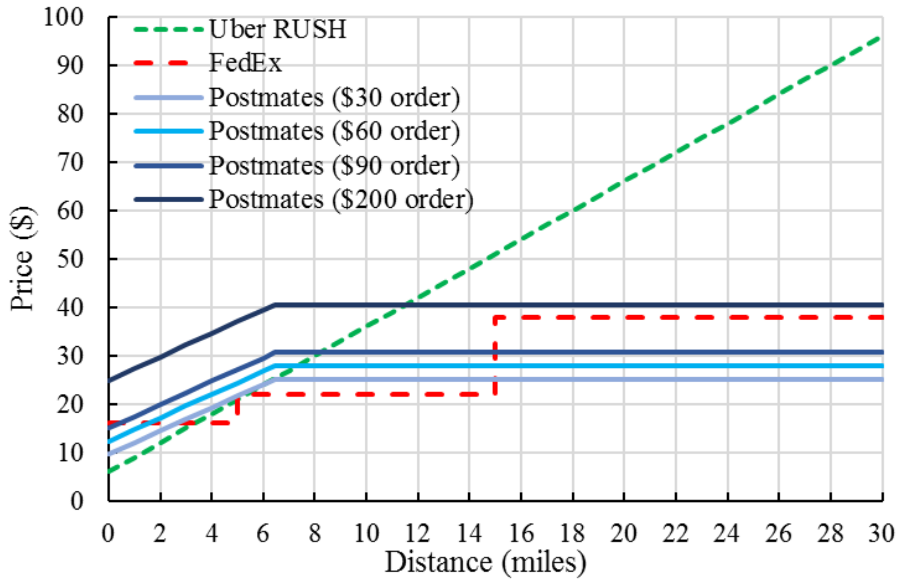


Figure 2.11.: The same-day delivery cost by distances for the San Francisco area offered by UberRush, Postmates, and FedEx (data in 2016) [107]

More flexibility

Traditional logistics has a repeated-delivery issue. 12% of deliveries in UK in 2010 must be delivered a second time, mainly due to customers not being present at home [108]. Failed delivery of on-line purchases in the UK cost about £771 million in 2014 [109]. Traditional logistics carriers have implemented countermeasures to solve the problem, including delivering to another address (e.g., office, next door, or car trunk) or pickup locations (convenient stores or carrier pickup locations). 50% of survey respondents reported they had stayed at home at an inconvenient time to receive their packages [108].

Most *CS* apps provide multiple options to make delivery faster and smoother. For example, in addition to real-time tracking services, the apps also provide individualized services for pickup and delivery time windows and locations. Customers can require their freight be transported to and from their preferred location, at their preferred time, or both [110]. Understanding convenience is crucial for last-mile logistics, and *CS* companies try their best to cater to customers' expectations. For example, Deliv offers "Delivery when you want it" (http://www.deliv.co/).

Better accessibility

Companies generally sell products in different markets on varied timetables, with gaps of up to months in length. For example, Apple first sold their newest iPhone model in the US. Customers in other markets, such as Asia and the EU, waited for months to purchase the phone or paid for international shipping services. Such a product could be delivered much faster and cheaper by a traveler. Some apps, such as Biggybee, Jetleap, Flytecourier, Airmule, and Packmule, provide platforms for *matching* requests with travelers' preexisting itineraries.

On the other hand, some businesses do not sell on-line or have delivery services. Therefore, asking family or friends is another approach. Friendshippr is a social application for friend-to-friend shipping exchanges.

2.4.2 Merchants

[4] noted that the price of merchandise and the delivery fee are important consumer considerations. According to [111], the price, convenience, and speed of delivery are important features for repeated on-line purchases. [14] reported that when it comes to delivery options, fast delivery was the priority of 86% of respondents, and approximately 50% of the US and UK consumers valued low-cost delivery. Moreover, about half of customers did not complete orders due to the following delivery concerns: too expensive (59%), too long (44%), unavailable (36%), or not guaranteed by a certain date (30%) [14]. Delivery options also influence consumer decisions [14]. Obviously, cost is one of the most important delivery service factors. Furthermore, consumers' previous delivery service experiences influence their long-term purchasing habits. Nearly 45% of on-line shoppers would place more orders if delivery services better suited their needs [112]. While most retailers consider on-line shopping and

delivery services to be lucrative [113, 114], another study offered conflicting evidence that over 30% believe delivery services have been detrimental to retailers' costs [112]. For retailers who process about 20 orders per day, running their own delivery platform may cost about $10,000 per month [115]. As a result, retailers may search for a tailored delivery service that meets retailers' and shoppers' expectations, and is cheaper, faster, and more convenient.

Limited delivery service capacities, longer delivery times, and higher delivery costs can be expected during Black Friday, Halloween, Christmas, or New Year shopping seasons. Despite these challenges, ordered goods still need to be delivered as soon as possible at reasonable costs. Additional delivery resources and decisions not only require time and money, but also distract retailers from their business operations.

CS companies provide platforms with multiples amenities and features. Several systems (e.g., Seamless, Postmates, Doordash, Yelp24, and Foodler) allow retailers to post their products on the platform, which customers can order directly. Then the software will match the ordered goods to crowd-shippers. Apps like Nimber even allow consumers to set preferred delivery fees. In these scenarios, retailers likely save delivery and/or operation costs, and also cheaply advertise their merchandise on the *CS* apps.

2.4.3 Community

Environmentally friendly

CS services may revolutionize the way people send and ship freight. Crowd-shippers may utilize unused capacity in their vehicles and deliver packages on their typical commute. In addition, freight is transported by people who register on the system and travel via private vehicles, bicycles, or public transportation. As a result, the app-based systems have improved mobility, safety, and environmental footprints [116].

Employment

App-based delivery services also provide flexible jobs and generate an additional source of income for crowd-shippers. Crowd-shippers can make their own schedules, earn money while traveling, and opt out of the system whenever they want. About 50% of Uber driver-partners work one full-time job, and 26% work one or more part-time jobs. Moreover, about 71% spend their Uber income on monthly bills [117].

Some notable trends are observed in our survey results [26]. The analyses show approximately 50% and 17% of people who are employed full-time or part-time, respectively, are willing to work as crowd-shippers.

In conclusion, potential benefits of *CS* systems vary from place to place. To maximize the benefits, stakeholders should take stronger actions. For instance, *CS* companies should actively lead the collaborations with governments. At the same time, policy makers should provide much complete legal guidances that facilitate the *CS* implementations.

2.5 Promising areas and gaps

CS is a promising alternative for city logistics [19], but it is still in its early stages, and service models and performance varies. While the participating companies have only a few challenges in terms of governmental regulations at this time, the industry faces various challenges in its implementation. The above review on *supply* side, *demand* side, and *operations and management* motivated us to look further for other promising areas and gaps to be considered to facilitate the implementation of *CS*. This section is organized into three sub-sections; *Promising application areas Operations and management*, *Behavioral* and societal impacts.

2.5.1 Promising application areas

This section presents gaps and challenges which stakeholders should address, individually or cooperating together, in order to facilitate *CS* implementations. Significant efforts should be invested to fill the gaps and address the issues, especially from *CS* firms and governments.

- *Market segments*

  demand forecasting is vital for *CS* firms to have sufficient *supply* resources for the expected *demand*. Many on-*demand* companies are starting up for food and grocery deliveries (e.g., UberEats, Seamless, Grubhub, Doordash, Instacart, Postmates, and Deliv). Those products are typically peripheral goods or other small-size shipments requiring a tight delivery time window or needing an urgent delivery. In fact, the study of [26] also reveals another potential market segment for *CS* that is personal health and medicine products. Nevertheless, more investigation is needed to understand which type of shipment categories have the highest potential to be delivered by *CS* services. Who are the most likely customers of *CS* systems? For instance, Roadie has identified a new tangible market of delivering lost luggage from delayed flights by partnering with airlines firms (i.e. Delta Air lines) (https://www.roadie.com/resources).

  CS platform providers can also use advanced techniques (e.g., data mining) to understand customers' tastes, behaviors, and preferences from analyzing various datasets, such as socio-demographic characteristics, searching and ordering history, and texts and images (from posts as some social media companies, such as Facebook, provide both ordering and delivery services). The insights are helpful to recommend products for customers and improve the likelihood of ordering the products. More creatively, a *CS* firm can even collaborate with retailers to provide niche products that are unique and only be ordered on its platform and be delivered by that *CS* firm.

- *Network issues (effects)*

  [118] pointed out that the two biggest risks of same-day shipping are the lack of market density and consumer *demand*. For instance, some startups, such as Kozmo.com and WebVan, proved to be unsuccessful due to a lack of critical volume. Similar, Myways is no longer an active service [20] and Metro Post (a service of USPS) was discontinued [31]. However, in the context of the sharing economy and technology boom, *CS* companies may overcome these limitations. For example, most app-based food delivery companies, including Deliveroo, Postmates, Seamless, and Doordash, are partnering with local restaurants. This strategy supplies companies with a frequent and stable *demand*. Meanwhile, several *CS* firms open their own kitchen ('virtual restaurant') as an alternative option to provide prepared meals. This business strategy enhances customers' experience and makes *CS* firms more independent in peak ordering times or after restaurants' working hours. In addition, these start-ups usually operate in urban areas or college towns with a large potential customer population. Last-mile delivery is complex in its operations, and it has been a critical part of the logistics industry. The last-mile delivery requires many resources to address faster and more affordable delivery expectations. Therefore, the *CS* service availability potentially lightens last-mile delivery issues as well as provide additional options for requesters.

- *Reverse logistics*

  Another issue in the last-mile delivery field is associated with reverse logistics. In the Chinese e-commerce market, the rate of returned goods can be as high as 40% for some products (http://www.sina.com/). Moreover, the cost of reverse logistics is around three to four times higher as for the forward flows [119]. Inspired by those issues, a few researchers discussed and proposed alternative counter-measure resolutions. For instance, [120] designed a collection network that is flexible, efficient, and feasible for taxi drivers. Furthermore, [121] proposed strategies using taxi data, package pickup points, and an urban transportation network to handle the e-commerce reverse flow issues. As such, studies of [120, 121] confirmed that using the crowd significantly reduces the reverse logistics costs by reducing the need to send a separate driver. The *environmental* and social benefits are also confirmed by those studies, based on real-world data. However, some areas in the reverse logistics field still warrant further investigation, such as efficient and effective logistics strategies for different types of reverse goods flows.

- *Future innovations*

  Innovative delivery vehicles may impact *CS* companies in the future. Advanced technology development may introduce unmanned aerial vehicles (UAVs) or drones [122, 123, 124, 125, 126], robots, and automated vehicles [127] to the logistics industry. These technological advancements are likely to reduce the need for delivery personnel [128]. However, it is too soon to tell if human crowd-drivers will become obsolete. The advances in autonomous technology is going to have a direct impact on the *CS* operations. In fact, [129] estimated that autonomous trucks will be feasible by 2040 at the earliest.

- *Insurance*

  One of customers' main concerns is *insurance*, especially for valuable shipments. Accounting for insurance costs in the delivery *pricing* to compensate for broken packages, theft, fraud, or lack of delivery on time may increase delivery cost for customers and make the shipping firm less competitive. Some *CS* companies only include a basic insurance package and let customers decide to pay for additional insurance.

- *Trust, safety and security*

  Trust is one of the key factors of *CS* service development. Concerns originate from both *demand* and *supply* sides. Senders may question whether the packages will be delivered on time and without damage, while *driver-partners* may worry about hazardous or illegal products. Therefore, *CS* companies have implemented processes to ensure that the services they offer gain customers' trust and protect their couriers.

Other *CS* challenges include privacy and *security* [10, 31]. Senders may be concerned about sharing their personal information, home address, and purchasing habits [41]. Most companies provide rating and comment systems to address these concerns. Other companies have an additional background check for driver-partners (e.g., UberRUSH and Deliv). Renren Kuaidi holds the packages' value on the *driver-partner's* credit card account after *matching* a request and prior to delivery. Furthermore, Renren Kuaidi deletes requester and receiver information as soon as the packages are confirmed "received" (mentioned in the study of [21]). Secure online payment systems have been widely used by *CS* companies as an additional safeguard. However, following the fast development of information, communications, and technology, *security* systems always need to be up-to-date.

Driver-partners also need to be protected from harmful or illegal freight [10, 31]. Therefore, requesters must agree to company terms and policies, including prohibited and restricted items. *Driver-partners* can rate and comment on requesters as well. However, *driver-partners* are not employees of a company, so they assume their own liability when delivering CS requests.

- *Legal*

  Legal issues are another obstacle for crowdsourced delivery implementation. One of the *legal* issues relates to *supply* side dynamics which either facilitates or hampers *CS* development. For instance, in some Chinese provinces, at least 30% of the driver partners in a delivery company are required to have delivery licenses [21]. One other *legal* issue relates to the intercity deliveries. A package can be requested to be transported across states' borders. However, the products inside the package may be *legal* in the state where the package is sent from, but illegal in the destination state. For example, some drugs are *legal* in Colorado state (in the USA), but illegal in many other US states. Moreover, *CS* services also face *legal* issues related to theft and fraud [130].

- *Other issues*

  Some *CS* companies have expanded their business in the last several years. However, those companies mainly have businesses within some metropolitan areas. A system may work for the last-mile delivery, but how will it perform for inter-city delivery? Will a given *CS* model perform beyond the last mile? For instance, can these systems work for medium distance travel (greater than 50 miles and less than 200 miles) and long distance travel?

  Another concern is that a business model may have differential performance in different contexts. For example, a system works in the US, but may not work in the EU or Asia and vice versa. A potential reason can be cultural differences, diversity in pay expectations, infrastructure networks that support CS markets, legal hurdles and the availability of good quality Internet and penetration of smart phones.

The promising application areas challenge stakeholders on both *supply* and *demand* sides (e.g., market segments, network issues), *operations and management* (e.g., revise logistics, future innovations, insurance, trust, safety, and security), and government (e.g., legal) to implement *CS* systems that function collaboratively, dynamically, and sustainably.

2.5.2 *Operations and management*: Platform designing features

This section discusses various issues related to current gaps in platform design features, and ideas to address them. How can we design a *CS* system that delivers benefits to both *driver-partners* and requesters that is more attractive and effective than the existing systems? How can we improve the current *CS* platforms? In order to answer these questions, we investigate the features of *CS* services and provide insights and alternative solutions. For each feature, we identify the gaps, and provide suggestions for *CS* services.

- *Pricing strategies*

  Requesters will typically be able to lower their shipment costs by using *CS*, but will also have to contend with being contacted by several *driver-partners*. If requesters have to evaluate and respond to multiple messages, they may become overwhelmed. To address this issue, *CS* providers may consider a platform that allows *driver-partners* to bid on a package within a designated time window which is set by the requester. Moreover, the *pricing* schemes can be designed based on the urgency of the delivery. Delivery time window options and the corresponding rates can be designed for requesters' selection based on the *driver-partners'* schedules (e.g., those who are registered in the system).

- *Matching Assignments*

  Rather than allowing open and unsupervised matching between requesters and couriers, based on accessing the entire pool of local couriers, some more tailored approaches are encouraged. *CS* providers could offer a selection of couriers the option to post their *prices* and other conditions. The requester would have the ultimate decision. This would enable the provider to model requests against couriers plans to travel in the same direction to make recommendations for consolidation. However, this approach complicates the *matching* process as a clear strategy of selection needs to be in place.

  The *matching* assignment is a core feature of a *CS* platform. *Matching* occurs in real time between a requester and a *driver-partner*. The *matching* strategies should balance business objectives (e.g. maximize benefit) and societal impacts (e.g. drivers' income security and *environmental* impact). This is a challenge since the *matching* strategies solely depends on the company' business model.

- *Quality controls*

  Survey respondents in DATA1 had two main concerns surrounding deliveries [26]. First, about 85% of the respondents were concerned about damage to their packages. Accordingly, mentoring and training (e.g., for loading, unloading, and carrying parcels) for newly-employed *driver-partners* is recommended. Second, 46% of respondents in Vietnam and 67% of respondents in the US were concerned about delivery timeliness. Thus, the CS platforms need to include estimated delivery time features to provide reliable information for requesters, especially during peak hours or in cities with considerable traffic.

- *Flexibility*

  CS aims to provide an adaptable service, especially for on-*demand* delivery. The service can be tailored to customers' delivery time and location preferences. However, there are still some challenges. The first challenge is that customers are often not present to receive their packages. This is problematic because couriers may have post-delivery constraints. The second challenge is redelivery. Couriers may have to re-attempt the delivery the next day, which can be costly and inconvenient.

  CS service providers are expected to foresee the problems that may occur during request and delivery. Providers should incorporate solutions into their platforms–via popup suggestions, for example–so that couriers, requesters, and recipients can solve the issues that may arise. One solution is to send an electronic notification of the courier's travel and estimated delivery time. Another solution is to ask receivers to provide a secondary location if they are unavailable at the initial delivery time, i.e. roaming delivery locations [131]. A network of electronic drop boxes is an alternative solution as well [132].

- *Crowd-shipping platforms and related features*

  There is a need to integrate *CS* systems with existing systems, especially third-party (requester) platforms, such that retailers can easily track inventory and manage shipments. A platform function should also allow customers to export their transaction history and financial report as well as customize these forms. Requesters should be able to send requests from their platform to a *CS* platform without significant effort. In addition, an auto-retrieval data feature for couriers' calendars is another worthwhile development [71]. Real-time assistance and voice-control features for hand-free capabilities are additional platform functions worth consideration. Separate modes allow users to seamlessly transition from requester mode to *driver-partner* mode or vice versa within the same account. Moreover, providing both ordering and delivery services help *CS* firms to obtain a richer dataset that enhances the understanding of customers' behaviors as well as facilitates their service customizations. Important to realize, coupons and incentives are traditional strategies, but that will also help *CS* companies to obtain customer data for forecasting and future service improvements.

The improvements of platform features mainly benefit platform providers by attracting senders and crowd-drivers to the *CS* systems. Nevertheless, efficient and effective *operations and management* also provide attractive platforms for senders (i.e. *demand* side) and crowd-drivers (i.e. *supply* side).

2.5.3 Behavioral and societal impacts

The increasing adoption of *CS* by companies and users poses important challenges for transportation researchers, policymakers, and planners, as there is limited information and data about how these services affect transportation systems and society more broadly. This sub-section discusses the main channels through which *CS* is most likely to make a societal impact.

- *Transportation system performance*

  The transportation system is affected by *CS* via the possible shifts in mode-shares, along with added mileage to existing travel. Crowdsourced deliveries have the potential to "harnesses the dormant logistics resources of individuals." [55]. This implies that not only can drivers make better use of their excess vehicle capacity, but public transit commuters and bikers can deliver goods to each other along their way or during their free time in exchange for additional income. Ideally, to ensure that the transportation system performance is not negatively affected, two aspects of the system warrant further study. First, more research is needed to understand whether the deliveries are effectively made with no to minimal detour, along the way of planned movement. A second factor to analyze in order to understand the potential social impact, such as health or environmental benefits, is related to the modal choices of potential crowd-couriers [69], such as biking and walking. There is need for further work to understand the comparative advantage in terms of mileage and mode split changes.

- *Industry competitiveness*

  The adoption of *CS* models by traditional logistics companies or tech entrepreneurs from outside the logistics industry, is likely to impact industrial competitiveness. Outsourcing to the crowd enables asset-light infrastructure and operational flexibility that leads to minimization of costs [25]. In terms of altering the competitive landscape, *CS* platforms specifically enable smaller retailers to expand their market reach and offer new services. This is due to more flexible working arrangements on the employment side, and more flexible logistics arrangements to get products to niche markets [133]. Thereby, the transition towards *CS* is likely to create new employment opportunities, increase market competition and provide better *matching* between *demand* and *supply*. From the early evidence, it appears that *CS* can level the playing-field for small and medium size businesses. Competing via *CS* platforms is likely to enable short-term delivery and personalized, traceable shipments that bring smaller companies closer to the service offerings by larger retailers.

- *Consumers*

  The impact on consumer satisfaction is mediated by both direct logistics-related experiences, and indirectly by expanding consumption opportunities. Early analysis by [31] suggested that *CS* has the potential to give consumers access to a more extensive range of products. Similarly, the experience with the shipment itself promises to be more flexible [22, 134], personalized [31] as well as faster and more affordable [78] than traditional delivery. The promise of *CS* needs to be weighted against the risks, such as lower reliability or challenges related to *matching demand* and *supply*. While broader examination of consumer experiences of *CS* are not available, stated preference data offers some insights. In studying declared advantages and disadvantages of *CS* among users and non-users, [66] found that users had a more negative opinion of some *CS* features.

- *Labor market and regulation*

  CS development is parallel to flexible labor arrangements. *CS* offers two main types of opportunities for employment for citizens. On the one hand, local commuters or long-distance travelers already on-the-go are given an opportunity to gain complementary revenues to help cover their travel costs [26, 51]. On the other hand, *CS* offers an opportunity for dedicated or part-time delivery-employment via a flexible job with a *CS* company. In line with the surge in regulatory action to curb ride-hailing, however, there is a need to examine the *CS* employment structures carefully. While a customized work schedule can be a job asset, the lack of employment security could be unfavorable for the flexible *CS* employee [23, 36].

- *Community and social connectivity*

  Finally, there is a promise that *CS* can promote broader community cohesion by fostering social connections. In the first instance, the emergence of *CS* technology platforms bring together unorganized individuals and provides a tool to match *demand* and *supply* of logistics services [23]. In the context of the companies that adopt *CS*, the platform inherently generates a more community-oriented relationship between the company and its customers [135]. Some research has suggested to develop *CS* around existing networks of acquaintances [100] thereby ensuring trust and accountability of shipments. However, the use of *CS* even with unfamiliar shippers from the crowd, has the potential to transform the way in which citizens deliver and receive packages. Ultimately, this can lead to a deeper entanglement between passengers and freight flows, and lead to developing new models for more efficient and socially sensible transportation and logistics services.

To summarize, there appears to be many connections between societal well-being and *CS* development, via companies, consumers, workers and the general public. In fact, there turns out to be many reciprocal connections between society's functioning and the development of *CS*. This is exemplified by the finding that urban population density plays a role in generating critical mass needed for *CS* platforms to function, matched by the reciprocal findings that *CS* development can improve firm competitiveness, consumer satisfaction and traffic performance.

2.6 Conclusions

CS is an emerging trend in freight transportation. Numerous startups are established worldwide to provide *CS* services. However, there are many challenges towards full-scale *CS* implementation. Accordingly, researchers invested a considerable amount of time and effort to examine these *CS* systems. This paper systematically reviewed contemporary *CS* business practice and studies in order to investigate the gaps for implementations. The review was conducted under three pillars including *supply*, *demand*, and *operations and management*. The findings are additionally supported by our recent surveys in the US and using real-world data.

CS supply, *demand*, and *operations and management* seem to vary by contexts. Nevertheless, we discovered gaps in the studies and current practice as well as potential areas for applications. Then, we proposed suggestions for a *CS* system that is complex, integrated, dynamic, and sustainable. Our findings led us to make suggestions regarding *pricing* strategies, *matching* assignments, quality control, flexibility, platforms related features, and to better understand behavioral and societal impacts.

In conclusion, more *CS* research is necessary and we hope our study shapes appropriate research directions and stimulates researchers to conduct research in this emerging field. The growth of the *CS* industry highly depends on governmental policies. In fact, policymakers are urged to: 1) create policy frameworks and legislations to regulate the *CS* industry and minimize *CS* operational uncertainty; 2) identify a clear border between peer-to-peer sharing and business activities so subsidies will be allocated to the appropriate parties; and 3) provide innovation subsidies to fuel the growth of the *CS* industry. In the same way, *CS* companies should take the initiative to communicate and collaborate with local governments to overcome their challenges.

3. DESCRIPTIVE ANALYSIS OF CROWD-SHIPPING STAKEHOLDERS' BEHAVIORS

3.1 Introduction

The *sharing economy* is a popular term, which has been widely used in recent years. "It includes the shared creation, production, distribution, trade and consumption of goods and services by different people and organizations" [136]. In transportation, there are two main forms of sharing, i.e. of passengers (real-time ridesharing and taxi share) and of freight (app-based services like crowd-shipping (*CS*)).

E-commerce has sharply increased all over the world, and it has already changed the shopping habits of people and created new challenges for logistics providers [6]. The top 10 national economies have seen double digit growth figures in the e-commerce market [7] . In addition, [4] pointed out that not only the price of merchandise but also delivery fees are important to consumers [4]. According to a survey presented in the European Commission, delivery, price, convenience, and speed of delivery are important features for repeated on-line purchases [111]. Accordingly, delivery services significantly influence the success of on-line shopping [4].

Numerous *CS* firms have been established worldwide. *CS*, or *crowdsourced* delivery, is "an app-based platform that connects an individual wanting to ship a packet with an individual willing to carry the shipment in the first or last mile logistics of urban areas. A key distinction of the courier (i.e. *driver-partner*, driver partner) as discussed in this research is that this is *not necessarily an additional trip but a trip that leverages the typical travel patterns of the courier*. The selected courier may be the closest to the delivery route, offer the cheapest delivery fee, or have the best reputation in the system" [137]. *CS* companies provide services for international, national, regional, and urban deliveries. In fact, the delivery and shipping companies founded between January 2015 and September 2016 have received the highest investment from entrepreneurs [138]. Consequently, there is a considerable need of understanding stakeholders in the mixed logistics market comprising of *CS* and traditional logistics players.

Therefore, the objective of this research is to understand the behaviors and characteristics of *requesters* and potential *driver-partners* in a logistics market with a given *CS* availability. As such, this study will first collect the current shipping behaviors to identify *requesters'* satisfactions for different delivery services. Then, carrier choice behaviors will be tested by providing multiple scenarios which comprise of both *CS* and traditional delivery options to requesters. Likewise, respondents will be asked if they are willing to work as *driver-partners* and their associated preferences. Items which need to be shipped under different delivery service scenarios will be presented for potential *driver-partners* to select. Accordingly, factors influence the willingness to work as *driver-partners* will be revealed.

The contributions of this study are service design, knowledge of *requesters'* experience and preferences, as well as prospective *driver-partners'* willingness to work and expectations. Clearly, knowledge of the demand (i.e. requesters) and supply (i.e. *driver-partners*) sides benefits *crowdsourced* delivery companies. Demand side details address the needs and expectations of customers (requesters). The up-to-date shipping behavior and *requesters* satisfactions are useful information for logistics companies to improve their services. Scenarios about the *CS* delivery options available with the traditional logistics services are helpful to examine *requesters'* behaviors. At the same time, this study also provides knowledge of respondents' willingness or unwillingness to work as *driver-partners*. Additionally, understanding the incentives of people to participate in a *CS* system is worthwhile for companies to establish their workforce. Without a doubt, expertise in the logistics market is critical for building sustainable business models. Pricing policies and incentives for drivers play a crucial role in these business models, in addition to an attractive and user-friendly platform.

This research is needed to understand the impacts of *CS* services not only for logistics companies but also for city agencies.

This study is organized as follows. Section one introduces the backgrounds and motivations for this study. In section two, we identify the gaps related to the research on *CS*. Section 3 discusses our questionnaire design, which includes the revealed preference (*RP*) and stated preference (*SP*) questions. The survey implementation is also included in section three. Section four illustrates the descriptive analysis and insights of our survey data. Further suggestions are offered in the discussions and recommendations section, which is followed by the conclusion.

3.2 Identifying the gaps

Various delivery services specialize in grocery, food delivery (e.g., Instacart, Postmates, and UberEats), book delivery (e.g., Piggybaggy), or all non-hazardous items (e.g., Doordash, OrderUp, and Roadie). These novelty services are expected to transform the way people ship and offer various advantages to consumers, retailers, and society at large [20, 21, 31, 137]. Given that *CS* is an emerging market, there are only a few behavioral studies on *CS* to date. A couple of publications examine the supply side of *CS* services. [51] developed models to better understand travelers willingness to work (WTW) as *driver-partners*. Interestingly, only 43 of 143 respondents (about 30%) were willing to work as *driver-partners*. The findings reveal that travelers have WTW values much higher than the conventional willingness to pay (WTP). Service attributes, socio-demographic characteristics, and attitudinal variables remarkably influenced respondents' WTW [51]. Furthermore, [53] developed discrete-continuous models to understand various insights related to WTW and travel time tolerance. Potential *driver-partners'* payment expectations were found to be reasonable and concurrent with the value of time in literature. Socio-demographic characteristics significantly affected respondents' WTW [53]. [69] studied a pilot *crowdsourced* delivery service for a library in Finland and identified various motivations for participation, including "try out something new," "make life easier for me," "support public services," and "support the environment." [139] display factors affecting friends crowdsourcing delivery for friends through social networks, such as ages, incomes, genders, and extra time demands. On the other hand, "compensation," "good working environment," and "good platform operation" were identified as the top three factors influencing potential *driver-partners'* participation [47]. Other papers presented results related to *CS* preferences, for instance, respondents who were willing to work as *driver-partners* were 64% [49] and 87% [140].

Several researchers have studied the demand side of *CS* services as well. [22] modeled the openness of consumers to *CS* services. Travelers' behaviors and preferences for *crowdsourced* deliveries were significant based on the travel distance as well as the following aspects: speed, real-time tracking (local delivery), service options, and driver experience (medium and long distance) [22]. Comparatively, 'package size,' 'delivery distance,' 'demand frequency and distribution,' middle age customers (i.e. 35-44 years old), and pricing strategies remarkably affected successful deliveries [65]. Whereas, 'care for environment,' 'care for society,' and 'price' were found significant influence on receivers behaviors [47]. [102] found disclosing drivers' identify brought trust and satisfaction to requesters, while *requesters'* loyalty had a close relationship to drivers' ethnicity. Interestingly, the percentage of respondents who had already used *CS* services was 7% [22] and 12% (as quoted in [141]). [49] reported that 74% of respondents (37 of 50) were willing to use *CS* services. Research by Acquity Group LLC found that 75% of respondents were willing to use delivery services from third parties (as mentioned in [141]), while that number in the research of [140] is 93%.

These preliminary studies have several limitations including survey's levels of details, sample sizes, and study areas. Therefore, more studies are necessary to further analyze the *CS* field. Accordingly, this study is designed as a preparation step to answer the following questions:

Factors related to *driver-partners*' behavior:

1. Question group (QG) 1: Who is willing to work as a *driver-partner*? Are there any specific socio-demographic characteristics associated with those people? What factors drive them? Do they have any preference for shipment types or requesters?
2. QG2: How much do *driver-partners* expect to be paid (ETP)? What is the sensitivity of *driver-partner* incentives and WTW?
3. QG3: What is the maximum distance or travel time a *driver-partner* would accept to divert their route to pick up and deliver packages? What factors influence these decisions?

Factors related to *requesters*' behavior:

1. QG4: What factors influence *requesters'* selection of couriers for different types of products?
2. QG5: How much are *senders* willing to pay for last-mile delivery? What is the nature of the relationships between socio-demographic characteristics, products, and WTP?

By answering those questions, a better understanding on the underlying behavior rules for the demand and supply generations will be achieved. The next section presents our questionnaire design, which addresses the aforementioned objectives.

3.3 Questionnaire design and survey implementation

CS is a modern concept for many people (about 43% have never heard about *CS* as of a survey in June 2016 [22]) so the questionnaire should be easy to understand and well-designed to capture the necessary information. This survey aims to investigate the behavior of stakeholders in the logistics market given the availability of *CS* services. The questionnaire consists of three main parts. Surveys were designed in Qualtrics, an on-line survey platform, and surveys links were distributed. The following sections discuss the *RP* sections of parts IA and IIA, and the *SP* sections of parts IB and IIB. The survey implementation methods are featured in the last section.

3.3.1 Revealed preference sections

In part IA, featuring the *sender's*/purchaser's behavior, questions were designed to ask respondents either: 1) their most recent shipping activity experience with carriers, or 2) their satisfaction with the delivery service from their most recent e-commerce purchase. Questions related to the commodity value, delivery carrier, shipping cost, delivery time, and delivery time satisfaction were included. In addition, questions related to the satisfaction with carriers' other services–tracking and tracing items on-line, electronic delivery notifications, and pickup/drop-off time windows and locations–were featured as well.

In the part IIA, regarding the courier's behavior, questions were designed to obtain the couriers' history and their perceptions. Respondents were asked: 1) whether they have transported freight for someone else, and 2) in the future, if they had a chance to transport freight for somebody else on their route or close to their route of travel, are they willing to work for some incentives? If so, they were asked in which situations they were willing to do the work. The maximum diversions (both for time and distance) the respondent would accept for picking up and dropping off a package were also included in the survey. Respondents were also asked their *ETP* once they began work as a *driver-partner*.

3.3.2 Stated preference sections: Attributes and levels of service

Regarding the *sender's* behavior, part IB is designed to understand the behavior of selecting couriers for each product shipping category (e.g., shipping beverages/dried foods, apparel, and personal health/medicine). The US grocery delivery market is expected to grow significantly to 20% of all grocery shippings by 2025 [142], therefore, we create the grocery category out of the “immediate delivery" category to examine the grocery shippings' behaviors. These *SP* questions were created with exactly the same attributes as the *RP* portion with the intent to use a combined model (*RP* and *SP*) for later data analysis. The choice set includes four alternatives (i.e. couriers

A-D). In addition to the two traditional attributes (i.e. shipping cost and delivery time) indicated as the main factors of delivery services [143, 144, 145], we introduce attributes based on the major differences between *CS* services and traditional logistics services.

The attributes to understand the requesters' behavior for selecting couriers and attributes' levels include:

1. Shipping cost:$14, $18, $22, $26 (4 levels)
2. Delivery time: 1.5h, 3h, 5h, Same day delivery, Delivery within 2-4 days (5 levels)
3. Reputation/ ranking: High, Medium, Low (3 levels)
4. Apps (sending, tracking and tracing): Yes, No (2 levels)
5. Apps (electronic delivery notification): Yes, No (2 levels)
6. Personalization for delivery time window: Yes, No (2 levels)
7. Personalization for location of delivery: Home, Other (i.e. your car's trunk), Pickup at a carrier's store (3 levels)
8. Payment method: On app/website (automatic), By cash (2 levels)
9. Willingness to tip: No tip, $1, $2, $3 (4 levels)

In addition to the *SP* questions, other questions related to the preference of delivery time windows, concerns about delivery by a *driver-partner*, and preferences on the delivery mode were also asked.

To capture the courier's behavior (part IIB), the *SP* was designed to identify prospective *driver-partners'* behaviors. Each alternative includes attributes which may influence their decision to deliver a package and their *ETP*. The choice set consists of four alternatives (i.e. items 1-4). The respondents were also asked for their perceptions of the product/ item category to be shipped, which packages or goods they would prefer to deliver, and their concerns regarding *driver-partner* employment. Only respondents who were *WTW* as *driver-partners* answered the part IIB.

The attributes and corresponding levels are:

1. Profit: $13, $11, $9, $7 (4 levels)

2. Trip time (addition to travel time of the original trip): +20 minutes, +40 minutes, +60 minutes (3 levels)
3. Compensation due to loss or damage: 80% price (20% less), 100% price (regular price), 120% price (20% more) (3 levels)
4. Weight - denoted as x. (pounds): x $\leq$0.5, 0.5 $<$x $<$1.5, x $\geq$1.5 (3 levels)

To generate an orthogonal design, we used IBM SPSS Statistics 22 [146]. Then, we eliminated options based on several rules, such as removing the dominant options, separated options into blocks, and selected representative options from each block. We followed previously established *SP* survey design techniques [147, 148, 149].

3.3.3 Survey implementation

A pilot survey was conducted to improve the quality of the questions and assess the time required for survey completion. A pilot survey was implemented on participants from various disciplines, ages, genders, and occupations. After conducting a pilot survey and the pre-test, the questionnaire was modified for the final survey.

The survey was conducted via multiple channels to access diverse population groups. Taking advantages of the Transportation Research Board 2017 conference and committee membership, the authors actively distributed fliers during these events. In addition, the surveys were emailed to students at various colleges, schools, universities, chapters, and organizations. The surveys were also advertised on social media (e.g., Facebook, LinkedIn, Reddit, and Craigslist). An additional source for the survey was Amazon Mechanical Turk where respondents got paid to answer the survey.

3.4 Descriptive analysis

This 2017 study intends to understand the behavior of stakeholders in the *CS* market and surveyed hundreds of people to gain insights into their preferences, concerns, and hesitations regarding *CS* services. Results were organized into different socio-demographic characteristics.

3.4.1 Summary of the data collection

The survey was implemented in the US between February and April 2017. Samples of 722 were collected. The data was then cleaned to remove incomplete and inconsistent samples. The final dataset included 549 samples.

3.4.2 A brief summary of socio-demographic characteristics of respondents

The age distributions of survey respondents are displayed in Figure 3.1. There were 46% male and 54% female respondents (Figure 3.2). The respondents' age and gender distributions are concurrent with the census data (https://www.census.gov/); hence, the dataset can be utilized to obtain insights for follow-up research. Other socio-demographic characteristics are presented in Table A.1. The potential *driver-partners'* characteristics in the "*WTW*" columns will be elaborated in section 3.4.4.

3.4.3 Requesters' experience and expectations

Regarding delivery carriers, USPS and UPS were the two main carriers for the respondents who sent packages (48%) and merchants (42%), respectively. Surprisingly, those carriers (i.e. USPS, and UPS) were also reported as the worst delivery service providers (i.e. late delivery, unable to track and trace the item on-line, and the service was not good or carriers did not provide services relating to electronic notification, pickup/drop-off time window). The *requesters'* experiences and expectations are summarized in Table B.1.

Requesters preferred to have "dry cleaning, fast foods, lunch, dinner, birthday cake, etc" and "groceries" delivered by *driver-partners*, which involves higher delivery fees and shorter delivery times. For other products, however, they were more likely

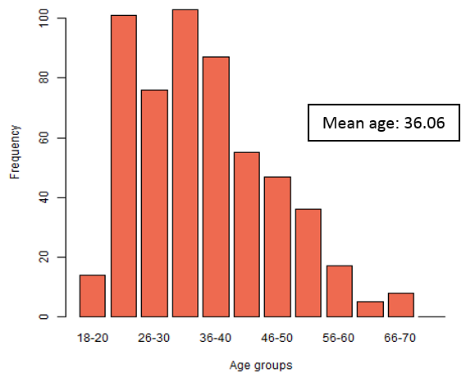


Figure 3.1.: Respondents' age distribution

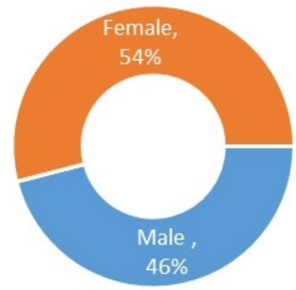


Figure 3.2.: Respondents' gender distribution

to use traditional carriers with lower delivery fees and longer delivery times (Table B.2). Respondents who were willing to receive goods being delivered by *CS* systems were at around 50.5% to 82.1%, depending on the shipment. Those values are a bit lower than the range of 74% to 93% from the literature [49, 140]. In theory, when respondents face a certain scenario of delivery services for sending a specific shipment, their behavior may change comparing to when they select a delivery service for shipping a general product. Nevertheless, various factors that *requesters* consider when selecting a courier are not yet clear, and require further research.

Respondents expected to have their packages delivered at different times on weekdays and weekends. Respondents preferred to receive their packages in the late afternoon or early evening (3 p.m.-8 p.m.) on weekdays, and from 9 a.m. to 6 p.m. during the weekend. This information is useful for *crowdsourced* delivery companies' operations (e.g., prepare *driver-partners* for high demand times, and prevent false delivery). In addition, we added drones as an option with other modes of transport to examine respondents' preference for courier modes. Interestingly, respondents did not have any preference ("it does not matter"), 65% and 37%, respectively. Additional information is included in Table B.2.

Respondents were then asked for a stated preference question regarding their concerns once their package is delivered by a *driver-partner*. The major concern (around 85%) related to the condition of the packages: “without damage or not." Moreover, “delivery on time or not" was another concern of 67% respondents.

To have a better understanding of different variables as well as their relationships, a clustering analysis was conducted. Out of data mining methods, mean shift is an appropriate method to be employed, since we do not know an optimal number of clusters of the dataset (http://scikit-learn.org/stable/modules/generated/sklearn.cluster.mean shift.html). The mean shift method works by first assigning a cluster mean to a random point, then keep searching points within an identified bandwidth, and updating a cluster mean. An optimal cluster number is then recognized. After the optimal cluster number, the variance hardly changes despite the number of clusters. In this analysis, six variables are included for investigation. The ‘concerns’ (to *CS* services) variable is represented as ‘C1’, ‘C2’, and ‘C3’ which are denoted for “delivery on time or not," “without damage or not," and other concerns, such as theft, respectively; The ‘age’ variable takes average values from 19, 23, 28 etc., to more than 68 (i.e. >68); The ‘gender’ is male (i.e. ‘M’) or female (i.e. ‘F’); The number of children (i.e. ‘No. Children’) is from 0 to more than 5 (i.e. >5); The ‘income’ variable takes values from <$16,000 to $220,000; ‘Car ownership’ selection is yes (i.e. ‘Y’) or no (i.e. ‘N’).

An optimal cluster number is identified as seven, at a bandwidth of 1.92, as presented in Figure 3.3. Cluster 1 is comprised of middle-aged males (i.e. 41-45 years old) who have four children, and an average annual income of $75,000. Cluster 2 contains males aged 56-60 who have three children, an average annual income of $40,000, and a concern about delivery time punctuality. Cluster 3 is composed of females who have five children, an average annual income of $175,000, and a concern about packaging fractures. Cluster 4 includes males aged 56-60 who have five children, an average income of $23,000, and a concern about delivery time punctuality. Cluster 5 is made up of middle-aged males (i.e. 36-40 years old) who have one child, an average annual income of $220,000, and some concerns about *CS* services. Cluster 6 includes middle-aged males (i.e. 41-45 years old) who have one child, an average annual income

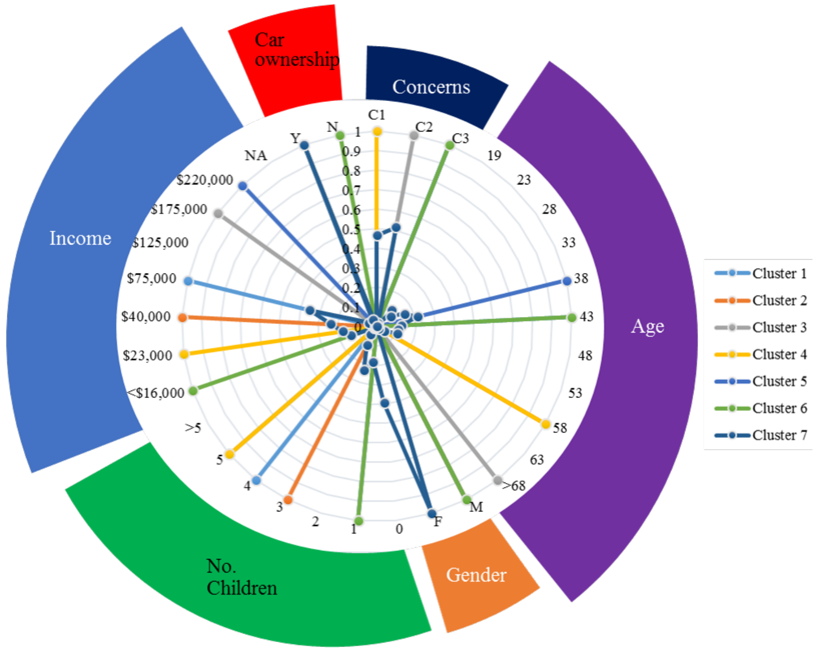


Figure 3.3.: Clusters of *requesters'* characteristics

of less than $16,000, and other concern about *CS* delivery services. Cluster 7 contains females who have a moderate concern about packaging fractures. All respondents own cars, except those in cluster 6. The findings help logistics companies to address different market segments as well as offer a tailored service to each customer group.

The *requesters'* other behaviors, such as which groups of people (or which type of commodities) are more sensitive to price, and which factors influence *requester* selection of couriers, will be extensively studied in another paper.

3.4.4 Prospective *driver-partners'* willingness to work and expectations

When asked about respondents' experiences delivering freights, the rate of respondents who had not delivered for someone else (not experienced) were about three times the rate of respondents who had (experienced) (Table B.1).

Respondents were asked whether they were willing to work as a *driver-partner*. About 78% of respondents were interested in *CS* employment. This value is within

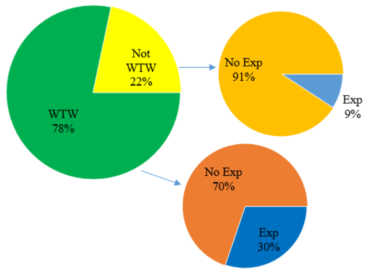


Figure 3.4.: Descriptive statistics of the *WTW* as *driver-partners*

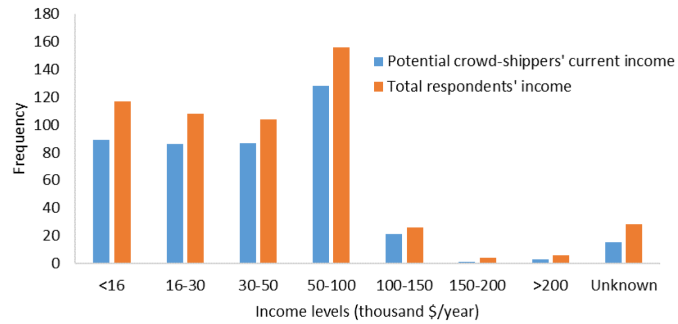


Figure 3.5.: Respondents' income distribution

the range of 30% to 87% from literature [49, 51, 140]. Of the respondents who were willing to work and not willing to work, 70% and 91%, respectively, did not have prior experience with carrying freight. The information is featured in Figure 3.4.

Characteristics of respondents who were not willing to work as driver-partners

Surprisingly, incentive was not the major reason for respondents who were not willing to work as *driver-partners*. About 43% of the respondents reported that they did not have the time and refused *CS* work. The other 37% of respondents were simply not interested in *CS*.

The mean incomes of the respondents who were not willing to work were $51,700. This mean income is higher than that of all respondents in the dataset, which is approximately $48,700. These statistics are expected; those respondents with higher incomes are less likely to be interested in working as *driver-partners*.

For a better understanding of respondents' characteristics, we also use the mean shift clustering method. In this analysis, six variables are included. The "reasons" variable presents for a rationale of unwilling-to-work as *driver-partners*, namely "the incentive (money paid) is not high enough" (i.e. R1), "I do not have time" (i.e. R2), "I do not like to do it" (i.e. R3), and other reasons (i.e. R4). Other variables, such as age, gender, number of children, income, and car ownership have been explained

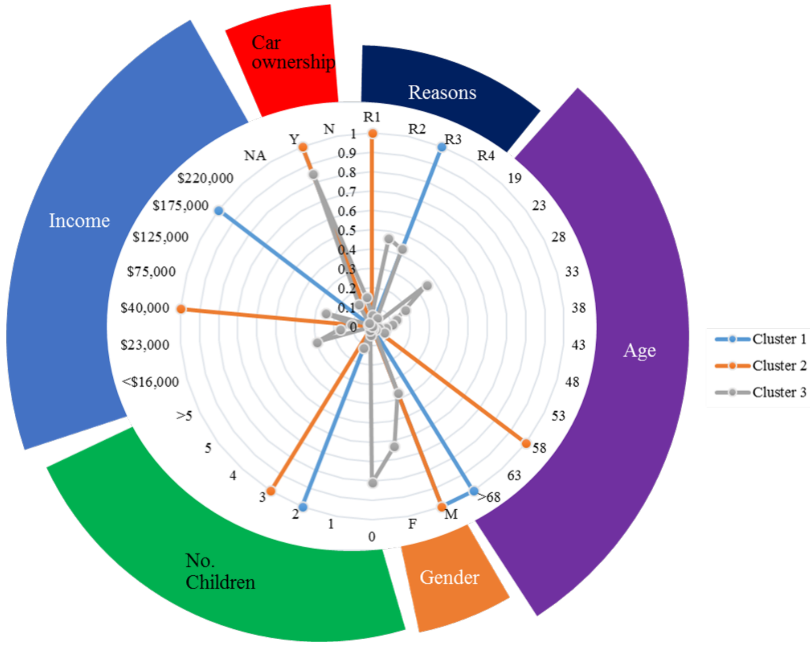


Figure 3.6.: Clusters of characteristics of respondents who were not willing to work as *driver-partners*

earlier. The clustering algorithm is converted at the bandwidth of 1.86 delivering three optimal clusters, as can be seen in Figure 3.6. Cluster 1 includes senior males (i.e. >68 years old) who have two children, an average annual income of $175,000, and simply do not like to work as *driver-partners*. Cluster 2 is made up of males aged from 56-60 years old who have three children, an average annual income of $220,000, and a concern about low incentives paid from *CS* system. Cluster 3 is comprised of respondents who majority have no child and a moderate concern of incentives being given from working as *driver-partners*. All respondents in clusters 1 and 2 also own cars, whereas that of cluster 3 is about 85%. The results reveal that high income seniors are less likely to participate in *CS* systems. These findings benefit *CS* companies to limit some groups when they recruit *driver-partners*. As such, the companies' resources will be used more effectively.

Who was willing to work as a driver-partner?

The average age of potential *driver-partners* was 36.42 years old, while the gender distribution was 47% and 53% male and female, respectively. The future *driver-partners* comprised of over 61% Caucasian and 17% Asian. Moreover, 43% potential *driver-partners* were single and 47% were married. Around 78% had obtained or expected to earn a college degree or higher, and slightly over 21% held high school degrees. Approximately 50% and 17% of potential *driver-partners* were employed full time or part-time, respectively. A car was the main mode of respondents' transportation (approximately 70%). Furthermore, potential driver partners earned $47,870 per year and had around one child on average. Potential *driver-partners'* income distribution in comparison to total respondents' income distribution is presented in Figure 3.5.

The main social media outlets used by respondents were Facebook (91%), YouTube (73%), Instagram (46%), and Twitter (46%). On average, respondents used social media with average of 4.07 outlets. In addition, about 95% of respondents used a smart-phone. Therefore, social media is a potential channel from *CS* promotion and driver partner recruitment. The socio-demographic characteristics of potential *driver-partners* are summarized in Table A.1.

Perceptions of respondents who were willing to work as driver-partners (Table C.1 and Table C.2)

Respondents were likely to work as *driver-partners* for different trip purposes. Respondents were willing to deliver packages during their commutes (70%), leisure trips (50%), and in their free time (70%). Potential *driver-partners* were likely to work during weekday evenings and weekend afternoons, times which highly matched with *requesters'* desired delivery times. This makes it much easier for *CS* companies to pair requests and *driver-partners*.

Potential *driver-partners'* average time and distance tolerances were 23.40 minutes and 12.16 miles, respectively, given a 5-mile travel distance or 20-minute travel

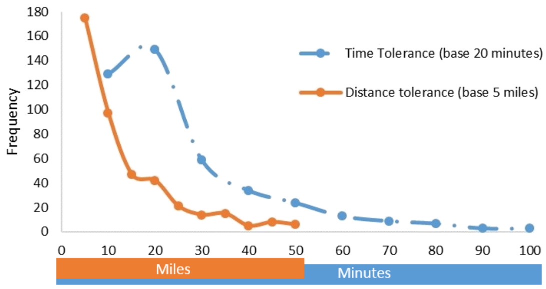


Figure 3.7.: Potential *driver-partners'* time and distance tolerances

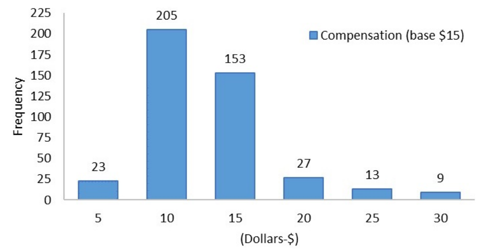


Figure 3.8.: Potential *driver-partners'* pay expectation

time on their main route. The tolerance distributions are displayed in Figure 3.7. Interestingly, the majority of respondents (87%) were willing to deliver any packages or goods, as long as they got paid. Given a traditional carrier charges $15 for delivering a package, potential *driver-partners'* pay expectation for delivering the same package in the same context was $11.70. Pay expectation distribution is shown in Figure 3.8. In addition, over 30% of respondents would also prefer to deliver to people they know (i.e. friends, colleagues, relatives, and neighbors). As such, *CS* can be linked to driver partners' social networks to increase system demand. Furthermore, about 60% of respondents did not have any preference for the type of item they deliver. Over 82% and 93% of potential *driver-partners* expressed concerns about transporting "Hazardous materials/dangerous items" and "Illegal substances/products," respectively.

Males and females had different preferences for the *CS* market. Figure 3.9 illustrates the desired working time of potential male and female *driver-partners*. Females were more likely to work during weekdays in daytimes, while male counterparts were more willing to work at evening times. Weekend evenings, however, were less attractive for all potential driver partners. As expected, only a few potential *driver-partners* were willing to work at other times (e.g., from midnight to the next day morning). In order to reveal insights of male and female behaviors, an ANOVA analysis has been conducted to explore the differences between means of variables of male and female groups. The ANOVA analysis is a common method which use to compare variances of variables' means. The list of hypotheses examined is presented as follows:

- H1: Male's *ETP* as a *driver-partner* is different with that of female counterpart.
- H2: Male *driver-partner* is in different age with that of female counterpart.
- H3: Male *driver-partner* has different number of children with that of female counterpart.
- H4: Male *driver-partner* has different car ownership status with that of female counterpart.
- H5: Male *driver-partner* earns different income with that of female counterpart.
- H6: Male *driver-partner* uses different number of social media outlets with that of female counterpart.
- H7: The maximum diversion distance of male *driver-partner* is different with that of female counterpart.
- H8: The maximum diversion time of male *driver-partner* is different with that of female counterpart.

The test results can be significant (i.e. 'Y') or insignificant (i.e. 'N'). If the test result is significant, male and female groups are remarkably different in terms of that variable. For instance, the 'car ownership' variable is significant which implies the car ownership of the male group is different to that of the female group. In addition, the *ETP* of the female group is statistically different than that of the male group, based on our samples. On the other hand, if the test result is insignificant, there is no difference between male and female groups in terms of that variable. For example, 'income' variable which is not significant indicates the potential male and female crowd-shippers are not remarkably different in their incomes. Furthermore, even the mean distance (or time) of the willingness to divert from original route of females is longer than that of males, the ANOVA test shows no remarkably difference between the two groups. The results are summarized in Table 3.1.

The ANOVA method, however, cannot provide detail levels of the tested variables (e.g., only the means) as well as relationships between variables. Therefore, a clus-

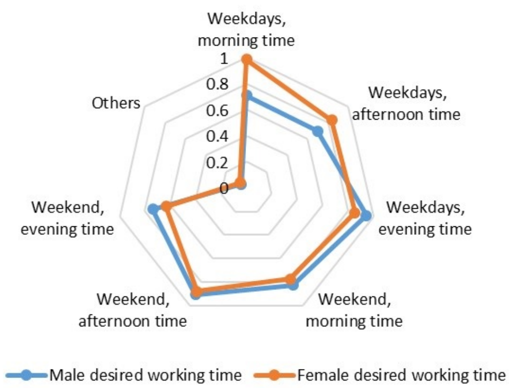


Figure 3.9.: Potential male and female *driver-partners*' desired working time

Table 3.1.: ANOVA test summary of potential *driver-partners'* behavior and socio-demographic characteristics by gender

Tested variables	**Male**	**Female**	**ANOVA test result**
Mean of *ETP* as a *driver-partner* ($)	11.42	11.95	Y
Mean of age (years old)	33.71	38.78	Y
Mean of number of children	0.69	1.27	Y
Mean of car ownership	0.79	0.84	Y
Mean of income ($)	46.82	48.82	N
Mean of number of social media usages	3.99	4.15	N
Mean of maximum diversion distance (miles)	11.69	12.57	N
Mean of maximum diversion time (mins)	22.55	24.16	N

ANOVA test: Y = significant, N = insignificant.

tering analysis is conducted for significant variables in Table 3.1. Again, mean shift is an appropriate method to be employed. Five variables are included in the analysis. The *ETP* variable which is represented by 31 values increments of \$1 starting from \$0 to \$30. Other variables, such as age, gender, number of children, and car ownership have been explained earlier. An optimal cluster number is identified as six, at the bandwidth of 1.82. The results are then visualized to observe magnitude levels of variables in each cluster, as can be seen from Figure 3.10. Cluster 1 is comprised of middle-aged males (i.e. 41-45 years old) who do not have child, and have an *ETP* of \$4. Cluster 2 is contained females aged 46-50 who also do not have child, but have an *ETP* of \$26. Cluster 3 is formed of middle-aged males (i.e. 36-40 years old) who have two children and *ETP* of \$15. Cluster 4 includes males aged 26-30 who have two children and an *ETP* of \$19. Cluster 5 is made up of females aged 51-55 years old who have one child and an *ETP* of \$6. Cluster 6 includes multiples variables at various levels. None of the respondents own cars, except the one in cluster 6. More discussion on clustered variables will be presented in the next section.

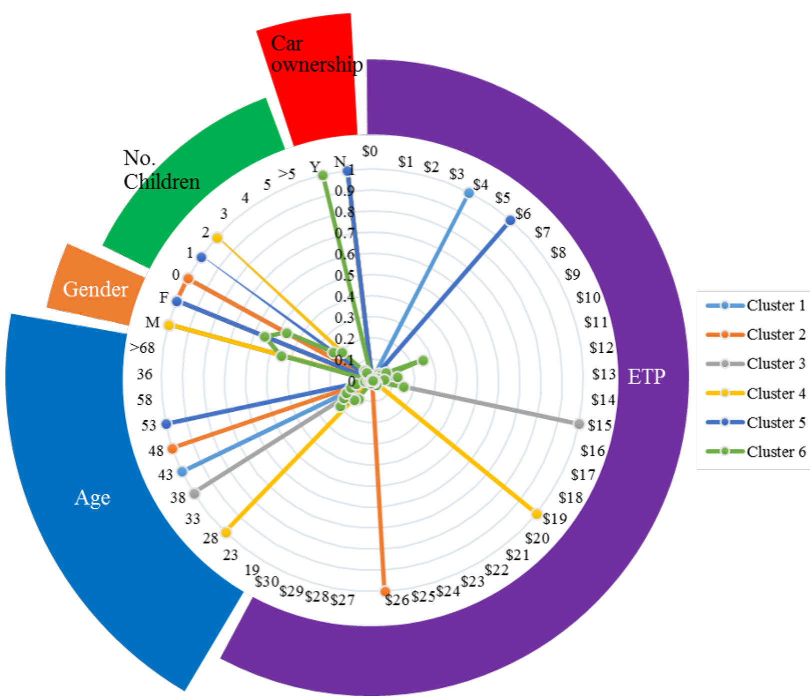


Figure 3.10.: Clusters of potential *driver-partners'* characteristics

3.5 Further discussions and recommendations

The available *CS* services in the logistics market provide additional options for customers. However, the following questions remain: what should *CS* firms address to develop sustainable and lucrative business models, satisfy customers, and retain driver-partners? What should policymakers and local government do to achieve improved mobility, safety, and environmental sustainability? This section will further discuss our survey data insights that address these important questions.

About 80% of respondents in our dataset were willing to work as *driver-partners*. This statistic could have a significant impact on logistics carriers and on society as a whole. Traditional logistics companies can reduce operation costs–for example, double-parking ticket costs–by outsourcing package delivery to *driver-partners*. Society can potentially benefit as well from the decreased environmental impact of fewer delivery vehicles. In order to attract people to work for the system, it is crucial to identify the motivations to work as *driver-partners*, as well as why people do not want to work for the system. Additional detailed analysis should be conducted to identify other factors related to these decisions.

It is important to consider that travelers are a heterogeneous group. Some may be willing to transport freight but do not know where to find it. Some may transport freight for a sufficient incentive. Others may only transport freight for people who they know. Some may never work in the system due to their personal preferences or constraints. As can be seen in Table 3.1, age, number of children, and car ownership are significant factors in the ANOVA analysis of potential male and female *driver-partners*. Additional analysis have been conducted using clustering analysis to better understand the characteristics of various potential *driver-partner* groups that are essential to *CS* business strategies (e.g., recruiting potential driver partners and developing compensation schemes). In particular, insights derived from the results may identify a target group of applicants; for example, people with children, middle-aged people having lower incomes, or no car ownership. Targeting a specific demographic will save time and costs for up-and-coming *CS* businesses.

Another key feature of this study is that the compensation scheme is a crucial factor to recruit and maintain occasional drivers in the *CS* system. The ANOVA test shows the payment expectations of potential male and female *driver-partners* is a significant factor (Table 3.1). Female *driver-partners' ETP* is higher than male driver partners' expectations. Further analysis is necessary to investigate the factors relating to how much *driver-partners ETP* for the time of the day and day of the week as well as the sensitivity of the incentive to the diversion in travel time or travel distance. These insights are valuable for business model development (e.g., to determine a delivery price that is attractive for *requesters* but also compensates driver partners to participate in the system).

Interestingly, some respondents who do not own a car (Figure 3.10) or smart-phone are willing to work as *driver-partners* (Table A.1). Therefore, providing a low-interest car loan or free smart-phone can be a potential solution to attract those respondents to become *driver-partners*. For those who use other modes of transport and are willing to work as *driver-partners*, matching the request to the public transportation schedule (e.g., metro or bus) on the same platform would facilitate increased participation.

Furthermore, individual marketing plays an important role in ridesharing service implementation [150]; accordingly, it may be a successful promotion strategy for *crowdsourced* delivery services. Our dataset illustrates that most respondents frequently use multiple social media platforms (Table A.1). As such, there is a high potential to attract participation and shippers via social media.

By all means, the *CS* system's performance needs to be examined. Since no operational data from *CS* companies exists at this time, using travel survey data to forecast the potential supply is essential to industry performance. Simulation scenarios could feature the acceptance rate of travelers who may be willing to work as *driver-partners*. The corresponding benefits to society, such as a reduction of congestion and pollution, and increased safety, should be estimated as well. Performance measurements of the *crowdsourced* delivery system, driver partners' incentive preferences, and long-term traveler behaviors are all important metrics that should be understood more clearly.

In fact, local governments can ensure the effective implementation of *CS* services by offering incentives to system stakeholders. Possible incentive examples include tax cuts on the income earned from *CS* services, free priority parking at designated locations, free congestion pricing fee, and driver partners use of high-occupancy vehicle lanes. Therefore, the effectiveness of the system can be measured by various incentives. Government then should identify which incentives or incentive packages are the most attractive to travelers and the most effective to modify travelers' behaviors. Moreover, the data (e.g., speed and travel time) collected from *CS* firms can be integrated into citywide management platforms to improve transportation operations.

3.6 Conclusions

CS is a relatively new research topic, and various aspects of the field are worthy of transportation experts' exploration. We have examined the current and future behaviors of *requesters* and potential *driver-partners* given the availability of *crowdsourced* delivery services in the logistics market. The contributions of this study are summarized in the following paragraphs.

Our work is focused on designing questionnaires and conducting a survey to investigate behavioral issues on both the demand and supply sides of *CS*. The questionnaires included *RP* and *SP* questions, which comprise new attributes, such as service's personalization, willingness to tip, compensation due to lost or damaged packages, and packages' weight consideration. The *SP* questions were carefully designed to maximize the reliability, validity, and generalizability of the data.

With those intentions, we have collected data on current shipping and purchasing delivery-related behaviors. The dataset is concurrent with the US census data. A brief description has been conducted to understand respondents' tastes and satisfaction levels regarding delivery time, track and trace, electronic delivery notification, pickup/drop-off time window, and pickup/drop-off location of the most recent shipping and delivery activities. Most respondents were satisfied with the services, but those services still require improvement for a seamless experience and maximized customer satisfaction.

In the same fashion, data on the awareness of *SP requesters* and potential *driver-partners* has also been collected. This study features descriptive, clustering, and ANOVA analyses, but further investigation is needed to reveal the behaviors of *requesters* and potential *driver-partners* under the assumption of *CS* service availability in the logistics market.

Several directions for further studies and analysis have been identified. First, target features of *CS* platforms related to cost effectiveness and convenience should be examined. The features include, but are not limited to, tracking and tracing the item on-line, electronic delivery notification and communications, and personalization of delivery time window and delivery location. These insights are crucial for *CS* business operations such as request-courier matching and dynamic routing.

Second, behavior differences by geographic location can be achieved for a bigger survey size or area. Then, we can build models with spatial explanatory variables like land-use, which includes the public transport density, living costs, intensity of commercial areas, developed areas, etc. Those independent variables may provide additional insights into the models as well as support for *CS* companies implementing the service and local governments assessing the *CS*'s potential benefits.

Third, questionnaires in this research were intentionally designed for first- and last-mile deliveries. However, this knowledge can be adapted to conduct studies for the middle- and long-haul delivery services.

Forth, conducting a survey with current driver partners who are working for *CS* companies would be beneficial. Insights derived from this dataset can be used to validate findings in the literature.

Lastly, the impact of *CS* is not yet clear, in particular its carbon footprint. Therefore, researchers should also investigate these issues. The successful implementation of *CS* service are likely fueled by positive environmental impacts worth measuring.

To sum up, this research is an important milestone in understanding the *CS* market and provides various useful insights based on the US data. Given this is only a descriptive analysis study, further research is necessary to get a fuller picture of various micro level details of the *CS* market.

4. INFLUENCING FACTORS THAT DETERMINE THE USAGE OF THE CROWD-SHIPPING SERVICES

4.1 Introduction

Across many industries, numerous sharing-economy companies have been established to provide common platforms for directly connecting *supply* and demand. However, only a fraction of the sharing-economy startups succeed at expanding their market share and maintaining customers [151]. One outstanding example of a sharing-economy startup is AirBnB [152, 153, 154]. AirBnB's value increased from $10 billion in 2014 to $31 billion in 2017 [155]. On the other hand, Uber, a popular car-sharing platform, offers various services supporting either passenger mobility (e.g., economy, premium, accessibility, and carpool), food delivery (e.g., Uber Eats), or freight transport (e.g., Uber Freight) (https://www.uber.com/). However, out of those services, only UberEats generates profits [18]. To recognize the supply-demand interactions, an important question is to understand the underlying factors that contribute to the growth of these services.

With the development of new Internet- and mobile-connected technologies, the last-mile delivery market has transformed into a shared market with both crowd-shipping (*CS*) and traditional logistics carriers (*TLCs*) competing with each other for shipments. *CS* is an example of the sharing economy in the logistics industry. The main idea of *CS* services is to encourage crowds to transport goods whenever they have flexibility or an opportunity. The "crowd" may be individuals or agencies. The goods can be transported by personal cars, bikes, buses, metros, taxis, or even pedestrians. Therefore, *CS* may differ from *TLCs* in operations and fare setting, bringing competition to the traditional logistics industry.

In a competitive market, *senders* have more delivery options. Therefore, they show varied behaviors in different shipping contexts. *senders*, who are not a homogeneous group, have various tastes for services. Some *senders* may be willing to pay more to get their packages to be delivered faster. Some *senders* may be willing to pay more for a certain shipment but not for others. Another subset of *senders* may never opt for personalized services, only wanting the lowest possible cost. As such, the following questions have been raised: What factors influence *senders'* choices of couriers for different types of shipments? How much are *senders* willing to pay for the last-mile delivery for different types of shipments? What are the relationships between an individual's socio-demographic characteristics, shipment types, and willingness to pay (*WTP*)? Which products are more likely to be sent via *CS* services?

The current situation suggests flexible and cost-effective delivery systems that utilize existing infrastructure and delivery services are needed, especially for the first- and last-mile delivery. Whenever a new service plans to be released or has just launched in the market, decision-making behaviors should be investigated to understand customers' expectations and satisfaction-levels in order to improve the service and make it more competitive in the marketplace. This research presents a set of factors influencing *senders'* choices of delivery couriers in the context of a shared market with the coexistence of *CS* and *TLCs*. In addition, the *senders' WTP* for certain shipping products and service features will also be studied. Insights from this study provide a better understanding of *demand* behaviors under various service levels which helps *CS* companies fine-tune their systems to satisfy *senders'* expectations.

This study is organized into eight sections. Section one introduces the context and motivations for the research. Section two reviews studies relating to the research topic. Section three explains our questionnaire designs, data collections, and data descriptions. Section four shows the modeling approaches including mixed logit and regret minimization models as well as our *WTP* computational method. Section five illustrates estimation results and insights. Section six discusses simulation results including *senders'* perceptions and sensitivity analysis. Section seven presents data-science testing techniques for evaluating our models' accuracy. The study is concluded in section eight.

4.2 Related studies

The sharing economy starts with the idea of renting out useful assets or services for a short period of time. Though it has become popular in recent years, the sharing economy's overall benefits are controversial and not yet clear [156, 157, 158]. Since there are limited studies of the *demand* side of a logistics market in which both *CS* and *TLCs* are available, in this section we will include in our review several studies that deal separately with the sharing economy and traditional logistics companies. This review does not aim to be exhaustive but rather to provide a big picture. With our review, we can still generate general ideas about factors influencing *demand* and shaping consumer behavior–ideas which will be valuable and applicable to *CS* firms.

4.2.1 Traditional logistics

Mode and service choices in traditional logistics have been well-studied. Factors commonly found to influence consumer behavior include price, delivery time, reliability [144, 159], flexibility, frequency [143, 160], carrier reputation, courier reputation, customer services, billing accuracy, facility/equipment availability, and intact packages [145].

With the emergence of e-commerce, however, traditional logistics companies have been challenged by decentralized orders and new requirements for flexibility and on-demand shipping. In the report of [161], the three product categories which saw the most e-shoppers declining their purchases due to long delivery time were "groceries" (27%), "medications" (26%), and "books, CDs, DVDs, and video games" (20%). It is apparent that delivery services can significantly affect e-shoppers' purchasing decisions.

4.2.2 Peer-to-peer accommodations and AirBnB

[162] collected data from approximately 650 users of peer-to-peer accommodations to investigate factors influencing users' satisfaction-levels. It turned out that the most salient factors were happiness, cost-savings, and household amenities. Furthermore, the "social benefits" factor was influential for private-room renters but not whole-home renters.

In recent years, AirBnB has sharply extended its market, recording 140 million guests using AirBnB services from 2008 to 2016, 120 million of those guests using the service in just 2015 and 2016 [163]. [164] found that a majority of travelers using AirBnB services were motivated by "interaction," "home benefits," "novelty," "sharing economy ethos," and "local authenticity."

4.2.3 Ride-sharing

For ride-sharing services, a few studies have outlined users' preferences compared to traditional taxi services and public transportation. [165] found that saving gasoline and time, environmental friendliness, and flexibility were the main motivations for the Washington, DC ride-share users. Moreover, ride-sharing users in San Francisco were motivated by payment convenience, shorter waiting times, and faster service as reported by [166]. Similarly, [167] found convenience (e.g., pickup point), cost and time saving as well as age and job situation drove casual carpooling or other mode-choice behaviors. Not to mention, [168] learned that users were more likely influenced to use or not to use car-sharing or ride-sourcing services by their age, education level, income, employment status, and residential density. In fact, [169] has found urban residents were major users of the US e-hailing services. Likewise, [170] revealed gender, convenience (e.g., personalization on pickup time and location), and comfort interacting with others significantly influenced ride-sharing system-users in the Lazio region of Italy.

In a study by [171], about two-thirds of Uber and Lyft users were in the age group of 25-55 years old. In that same study, women accounted for 52% and 58% of Uber and Lyft users, respectively. Users, across gender, liked that the services were convenient (e.g., can be e-hailed from a smart phone), had shorter waiting times, could be tracked in real-time, were cost-competitive, and could be advised in advance. Scraping data from Yahoo emails, [172] studied Uber users and found race, age, gender, income, ride-sharing service (e.g., UberX), matching strategy (e.g., to similar-aged driver), the time of the day (e.g., night time), the day of the week (e.g., weekend), and promotions remarkably affected riders' activities once using the services. In a nutshell, socio-demographic, service, and contextual factors all significantly influence ride- and car-sharing users. Service levels, nevertheless, have only been investigated in a couple of studies.

4.2.4 Crowd-shipping

CS systems provide potential benefits for a wide range of stakeholders. *CS* users can benefit from shorter delivery times, cheaper delivery costs, and increased flexibility and accessibility. Retailers, on the other hand, may have more delivery options, spend less for delivery, and attract more customers due to using better delivery services. When *CS* strategies are properly applied, societies can reduce traffic congestion, pollution, and accidents while increasing employment opportunities. Nonetheless, the young *CS* industry is also facing several challenges, such as the chicken-or-the-egg problem. The chicken is the *CS* services, while the egg is the *demand* for sending packages via the *CS* system. To overcome this challenge and achieve potential benefits, it is necessary to understand stakeholder preferences, particularly the *CS* users' behaviors.

While researchers have made significant efforts to collect data and evaluate *CS* systems, last-mile delivery research has been limited by data availability, especially that of behavioral data. One thing that data has revealed, however, is that a limited number of people currently know about or have already used *CS* services [22, 51]. Therefore, it is critical to figure out what needs to be done to attract more users to *CS* systems.

There are a few studies focusing on the topic *CS* supply. [49] found about three-fourths of respondents were potential *CS* service-users. Top factors which influenced respondents' choices were delivery cost (32%), flexibility (29%), and environmental benefits (22%). Additionally, [26] found potential *CS* users were concerned about damages and delivery-time punctuality. Users preferred to have packages delivered during late afternoon or early evening on weekdays, or from mid-morning to late afternoon on weekends. Elsewhere, [22] investigated the effects of contexts (i.e. distance) and experience on users' acceptance of *CS*. Public acceptance varied according to distance. For instance, short-distance users were more concerned about delivery speeds and couriers' reputations. Long-distance users, differently, preferred goods to be delivered by experienced couriers and via higher service levels. Not to mention, [22] also computed *WTP* and sensitivity for *CS* services' attributes. In sum, all available studies on the *CS demand* side only presented the results of descriptive analysis except for the study of [22].

In Table 4.1, factors influencing users of AirBnB, ride-sharing, traditional logistics, and *CS* are summarized. Those factors can be categorized into personal characteristics, service levels, post-purchase services, couriers' qualifications, contexts, social interactions, and social benefits.

To the best of these authors' knowledge, there is no available study about the influence of shipment classes on courier choices in a logistics market featuring both *CS* and *TLCs* that uses random-parameter modeling. Moreover, safety and security concerns are claimed as challenges to *CS* services. *senders* may consider to minimize regret once shipping some products but to maximize utility once sending another product. Notwithstanding, the *senders'* choices of couriers for different products are not clear in the literature. More studies in the area should be investigated.

Table 4.1.: Attributes for alternative choices from existing studies

Area	**Study**	**Variables**
Traditional logistics	[143, 144, 145, 159, 160]	Price, delivery time, reliability, flexibility, frequency, carrier reputation, courier reputation, customer services, billing accuracy, facility/equipment availability, and intact packages.
AirBnB	[162, 164]	Less expenses, venue advantageous, various amenities, enjoyment, local authenticity, social interaction, and supporting for sharing economy.
Ride- and car-sharing	[165, 166, 167, 168, 169, 170, 171, 172]	Race, age, gender, income, education level, employment status, residential density, time-of-day, day of week, cost saving and quoted in advance, travel time saving, waiting time saving, flexibility in pickup time and location, promotions, matching strategies, track live, payment convenience, interaction comfort, and environmental friendly.
Crowd-shipping	[22, 26, 49]	Age, gender, income, education, employment, distance, delivery cost, delivery time, flexibility, intact products, reliability, environment benefits, and couriers' experience and reputation.

4.3 Stated preference (*SP*) survey design and sample descriptions

4.3.1 Data source

This study will first design a set of questionnaires featuring *SP* questions to examine *senders'* preferences when shipping packages. The attributes are designed to understand the *senders'* behaviors for selecting couriers. In the *SP* part, attributes of services (e.g., fare, delivery time, and shipment characteristics) are designed with multiple levels of services. The alternatives' attributes and corresponding meanings are summarized in Table 4.2. Products commonly purchased from e-shopping, such as apparel, books, music, videos and consumer electronics, often require delivery from a courier service [173]. Those products, along with with fast foods, flowers, groceries, beverages, dried foods, personal health itema, and medicines, are grouped into 8 categories and included in the final questionnaire. Couriers 1-3 have been designed to have shorter delivery time but higher delivery cost than those of courier 4.

Imagine you are a person who needs to send something or you are an e-commerce customer/ retailer who **can select a courier to ship**. The package's size is equivalent to a backpack. Shipping distance is about 50 miles (about 80 kilometers). Among the four couriers who offer different delivery options, which one are you most likely to choose?

Traditional logistics carriers = TLC; crowd-shipper = CS

Attributes	Courier 1 (CS)	Courier 2 (CS)	Courier 3 (CS)	Courier 4 (TLC)
Shipping cost (USD or EUR)	18	18	26	14
Delivery time	1.5 hours	Once/day	3 hours	Once/day
Reputation/ ranking	Low	Low	Medium	High
Apps (tracking and tracing)	Yes	No	Yes	No
Apps (electronic delivery notification)	Yes	Yes	No	No
Personalization for delivery time window	No	Yes	No	No
Personalization for location of delivery	Carrier's location	Home	Other (i.e. your car's trunk)	Carrier's location
Payment method	On app/website	On app/website	On app/website	By cash

Note: Carrier's location = pickup point

	For each product on the left, select ONE courier, and select the option your willingness to tip the courier. Courier 1	Courier 2	Courier 3	Courier 4	Willingness to Tip
1. Dry cleaning, fast foods, lunches, dinners, birthday cakes, etc (multiple items)					
2. Groceries					

....

Figure 4.1.: Stated preference questions sample

Table 4.2.: Alternatives' attributes and corresponding meanings

Attributes	**Description**
Shipping cost	\$14, \$18, \$22, \$26 (4 levels)
Delivery time	1.5h, 3h, 5h, once/day, Delivery within 2-4 days (5 levels)
Courier's reputation/ ranking	High, Medium, Low (3 levels)
Apps (tracking and tracing features)	Yes, No (2 levels)
Apps (electronic delivery notification)	Yes, No (2 levels)
Personalization for delivery time window	Yes, No (2 levels)
Personalization for location of delivery	Home, Other (e.g., your car's trunk), Pickup at a carrier's location (3 levels)
Payment method	On app/website (automatic), By cash (2 levels)
Willingness to tip	No tip, \$1, \$2, \$3 (4 levels)

The survey was conducted in the US and distributed via multiple methods, such as at conferences and forums and through emails, newsletters, and social media. Each respondent was requested to answer two stated preference questions. The final dataset includes 549 respondents who responded in full. The survey details are presented in [26].

4.3.2 Data descriptions

The collected data was compared to the 2014 US census data (https://www.census.gov/data/tables/2014/demo/age-and-sex/2014-age-sex-composition .html). The share of male respondents was a bit lower than in the US data. Other statistics closely reflect the corresponding census data. The sample description is presented in Table 4.3.

Table 4.3.: Socio-demographic characteristics

Attributes	**Mean/ Standard Deviation or Distribution***
Survey time	Jan 2017 - Apr 2017
Survey location	US
Total respondents	549
Age	36.06/11.06
Gender: Male/ Female	45.50/ 54.50
Marital status: Single/ Married/ Others.	**45.00**/ **44.80**/ 10.20
Number of children.	0.94/ 1.25
Final academic degree: Some high school^1/ High school diploma^2/ Technical college degree^3/ College degree^4/ Post-graduate degree^5/ I prefer not to answer^6	0.40^1/ 12.90^2/ 8.60^3/ **48.50**^4/ 29.00^5/ 0.70^6
Annual income ($1,000)	48.71/ 36.00

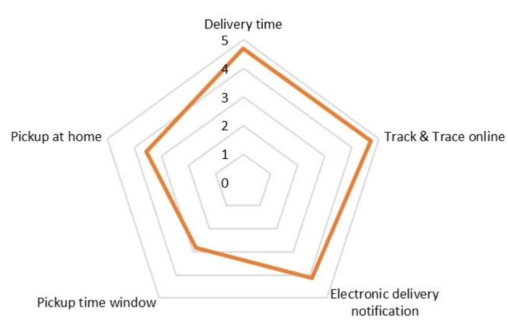


Figure 4.2.: Satisfaction levels to past delivery services (normalize into five levels)

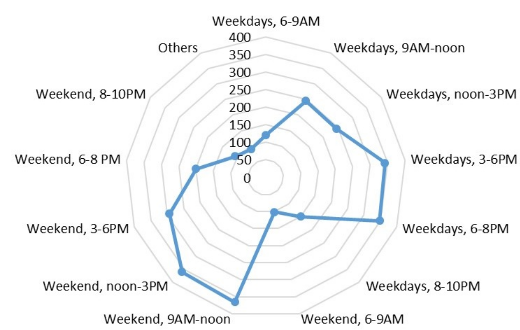


Figure 4.3.: Preference on delivery time (multiple choices) (unit: respondents)

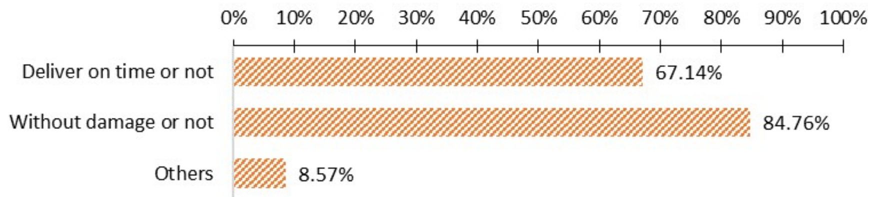


Figure 4.4.: *Senders'* concerns when their packages are delivered by *CS couriers* (multiple choices)

Figure 4.2 illustrates the satisfaction-levels of survey respondents who had previous experiences with shipping service providers. The majority of respondents were happy with the delivery time, online tracking info, and electronic delivery notification services. Nevertheless, some respondents expressed less satisfaction with the pickup at home or pickup time-window services.

Figure 4.3 shows delivery time preferences. A larger portion of respondents preferred goods being delivered from 3PM to 8PM during weekdays, or from 9AM to 6PM during weekends. Weekdays after 8PM, weekends after 6PM, or every day before 9AM were less preferred options. The information is valuable for *CS* companies setting up business operations strategies for the different time of the day or the day of the week.

The main concerns respondents have about their packages being delivered by *CS* couriers are exhibited in Figure 4.4. Predominantly, respondents worried about their packages being delivered in good condition and on time. The findings are consistent with the study of [145] in traditional logistics literature.

As can be seen in Figure 4.5, respondents were found more likely to select couriers 1-3 for sending dry cleaning, fast foods, groceries, beverages, and dried foods. Those products may need to be delivered in a short time, which is the advantage of couriers 1-3 even though the delivery costs are higher than that of courier 4. In contrast, apparel, books, music, videos, consumer electronics, or other goods were highly preferred to be delivered by courier 4., which offered the lowest cost.

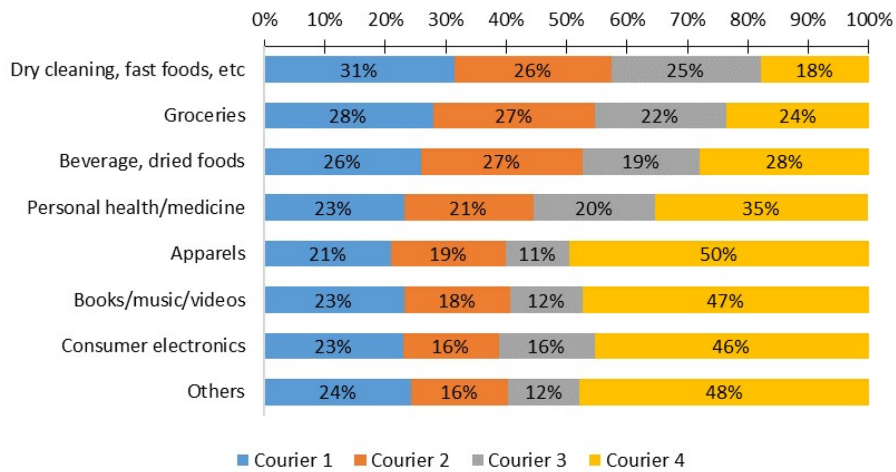


Figure 4.5.: *Senders* select *couriers* for sending different types of products (Stated Preference)

[26] have investigated how gender and age figure in to the respondents' willingness to work as *CS* couriers. In Figure 4.6, we extend the knowledge of *CS* stakeholders (i.e., *senders*) by displaying the most-chosen courier service for different product categories, classified by gender and age-range. As can be observed, dry cleaning, fast foods, groceries, beverages, and dried foods are more likely to be sent via couriers 1-3 by both men and women of any age. Meanwhile, apparel, books, music, videos, consumer electronics, and other products are more likely to be sent via courier 4, regardless of gender or age. Personal health and medicine shipments seem to be a potential market segment for both *CS* and *TLCs*.

The collected data was then analyzed to figure out the relative importance factors had on influencing the *senders'* choice of couriers and their *WTP* for the desired service. The models we used for analysis are presented in the next section.

4.4 Statistical Modeling Approaches

This section will present both the mixed logit and random regret formulations as modeling approaches for this research.

Figure 4.6.: *Courier* choice's classification by genders, ages, and products

4.4.1 Random utility maximization (RUM) model

The mixed logit model, which is sometimes called a random-parameter multinomial logit model, is a popular approach used to capture variables' heterogeneities across observations. The utility function for an alternative i of observation n is defined in Equation 4.1.

$$U_{in} = V_{in} + \xi_{in} \tag{4.1}$$

where the observable utility is denoted as V_{in}; the disturbance term that is represented as ξ follows the IID *Gumbel* distribution. The probability that an observation n selecting an alternative i from a given choice set of J alternatives is then computed by Equation 4.2.

$$P_n(i) = \int_X \frac{exp\big(\beta_i X_{in}\big)}{\sum_{j=1}^{J} exp\big(\beta_j X_{jn}\big)} f(\beta|\varphi) d\beta \tag{4.2}$$

where β_i is a vector of estimable parameters for the alternative i; X_{in} is a vector of variables for the alternative i of the observation n; $f(\beta|\varphi)$ is a density function. The mixed logit model is usually estimated by using utility maximization methods. Therefore, it is also known as the random utility maximization (RUM) model.

4.4.2 Random regret minimization (RRM) model

The regret model, however, is based on choice theory, which holds that a decision-maker will try to select the best option from the choice set in order to avoid a regret experience. Otherwise, the decision-maker will be in regret as the non-selected option is outweighed by the selected one [174]. Assume any alternative in the choice set of J alternatives has K attributes ($k = 1..K$). The regret of choosing an alternative i instead of an alternative j in terms of attribute k is defined in Equation 4.3.

$$R_{i\leftrightarrow j}(k) = ln\big[1 + exp\big(\beta_k(x_{jk} - x_{ik})\big)\big] \tag{4.3}$$

where β_k is an estimable parameter for the attribute k; x_{jk} and x_{ik} are the attributes k of the j and i alternatives.

The regret function for an alternative i with K attributes is displayed in Equation 4.4.

$$R_i = \sum_{i\neq j} \sum_{k=1..K} ln\big[1 + exp\big(\beta_k(x_{jk} - x_{ik})\big)\big] \tag{4.4}$$

Since the computation for minimizing a function is equal to maximizing the negative of that function, the probability of choosing an i alternative is then computed by Equation 4.5.

$$P_i = \frac{exp\big(-R_i\big)}{\sum_{j=1}^{J} exp\big(-R_j\big)} \tag{4.5}$$

4.4.3 Willingness-to-pay estimation method

In this study, WTP will be computed by traditional methods [175]. All variables relating to CS services, such as shipping cost, courier's reputation, tracking and tracing ability, electronic delivery notification, personalization for delivery time window/location, and tipping, will be estimated for WTP by Equation 4.6.

$$WTP = \left|\frac{\beta_{time}}{\beta_i}\right| (\$/h) \tag{4.6}$$

where β_{time} is an estimable parameter of the delivery time. β_i is an estimable parameter of the i variable (i.e. the attribute i of the CS service).

4.5 Estimation results

For model estimation, we use stated preference data which includes eight product (PD) categories. PD1 includes dry cleaning, fast food, and similar products which typically require quick delivery. PD2 includes groceries. PD3 contains beverages and dried foods. PD4 contains personal health and medicine products. PD5 contains apparel products. PD6 contains books, music, and videos products. PD7 contains consumer electronics products. PD8 contains other products. In addition, the choice-set has four alternatives (i.e. couriers 1-4). The variables of models include alternatives' attributes and respondents' socio-demographic characteristics.

Using the aforementioned data, two models, namely RUM and RRM, are used to estimate factors which are influence courier choices for sending each PD category. Overall, the two models' goodness-of-fit values are found comparable, even though those of RUM models are a bit larger than those of the corresponding RRM models. In those RUM and RRM models, the shipping costs were estimated as a random parameter while other shipping attributes were computed as non-random parameters. The socio-demographic variables were also examined in the models. All variables were found to be significant at 90% level or more, except some constant terms. The estimation results are summarized in Table 4.4. The following subsections will discuss insights from the estimated parameters.

Table 4.4.: Estimation results

Variables	PD1		PD2		PD3		PD4		PD5		PD6		PD7		PD8	
	RUM	RRM	RUM	RRM	RUM	RRM	RUM	RRM	RUM	RRM	RUM	RRM	RUM	RRM	RUM	RRM
Random parameters																
Shipping cost - mean	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**
Shipping cost - std	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)*	(+)**	(+)*	(+)*	(+)**	(+)**	(+)**	(+)**
Non-random parameters																
Shipping attributes																
Delivery time	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)*	(−)*	-	-	(−)**	(−)**	(−)*	(−)**
Courier's reputation/ ranking	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**
Tracking and tracing ability	(+)**	(+)**	(+)**	(+)*	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**
Electronic delivery notification	(+)**	(+)**	(+)**	(+)*	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**
Personalization for delivery time window	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	-	-	-	-	-	(+)**	-	(+)**
Personalization for location of delivery (not home or pickup point)	(+)**	-	-	-	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	-
Willingness to tip (for couriers 1, 2, and 3)	-	-	-	-	-	-	-	-	(+)*	-	(+)**	-	(+)**	-	-	-
Willingness to tip (for courier 1)	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	-	-	-	-	-	-	-	-
Willingness to tip (for courier 2)	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	-	-	-	-	-	-	-	-
Willingness to tip (for courier 3)	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	(+)**	-	-	-	-	-	-	-	-
Willingness to tip (for courier 4)	0	0	0	0	0	0	0	0	0	-	0	-	0	-	-	-
Concerns on packages of being damaged	-	-	-	-	-	-	-	-	-	-	(+)*	-	-	-	-	-

continuation on the next page

Table 4.4.: Estimation results (cont.)

	Variables	PD1		PD2		PD3		PD4		PD5		PD6		PD7		PD8	
		RUM	RRM	RUM	RRM	RUM	RRM	RUM	RRM	RUM	RRM	RUM	RRM	RUM	RRM	RUM	RRM
Social demographic	21-25 years old	-	-	(−)*	-	(+)**	-	-	-	-	-	-	-	-	-	-	-
	26-30 years old male	(+)**	-	(+)**	-	(+)**	-	-	-	-	-	-	-	-	-	-	-
	36-40 years old	-	-	(+)**	-	(+)**	-	-	-	-	-	-	-	-	-	-	-
	Personal annual income of $100 -$150 million	(+)*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Married	(+)*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Married and living with people (more than 64 years old)	-	-		-	-	-	(+)**	-	(+)*	-	-	-	-	-	-	-
	Living with people (less than 18 years old)	-	-	-	-	-	-	(+)*	-	-	-	(+)**	-	(+)**	-	(+)**	-
	Living with people (from 18 to 64 years old)	-	-	-	-	(+)**	-	-	-	(+)**	-	-	-	-	-	-	-
	Full-time employees	(−)*	-	-	-		-	-	-	-	-	-	-	-	-	-	-
	Full- and part-time employees	-	-	(+)**	-	(+)**	-	-	-	-	-	-	-	-	-	-	-
	Full-time male employees	-	-	-	-	-	-	(+)*	-	(+)**	-	-	-	(+)**	-	(+)**	-
Constants	Constant - courier 1	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)*	(−)**	(−)	(−)**	(−)**	(−)**	(−)**
	Constant - courier 2	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)	(−)**	(−)	(−)**	(−)**	(−)**	(−)**
	Constant - courier 3	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)**	(−)	(−)	(−)	(−)*	(−)	(+)	(−)	(−)
	Constant - courier 4 (base)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Model fits																	
Observation numbers		1098	1098	1098	1098	1098	1098	1098	1098	1098	1098	1098	1098	1098	1098	1098	1098
Null log likelihood		-1522	-1522	1522	-1522	-1522	-1522	-1522	-1522	-1522	-1522	-1522	-1522	-1522	-1522	-1522	-1522
Final log likelihood		-1303	-1313	-1337	-1347	-1364	-1379	-1321	-1329	-1137	-1148	-1149	-1158	-1175	-1188	-1159	-1177
Rho square		0.144	0.137	0.122	0.115	0.104	0.094	0.132	0.127	0.253	0.246	0.245	0.239	0.228	0.220	0.239	0.227
Adj Rho square		0.139	0.134	0.117	0.112	0.098	0.090	0.127	0.123	0.250	0.244	0.243	0.237	0.225	0.217	0.236	0.224

1. 'PD1': Dry cleaning, fast foods, lunches, dinners, birthday cakes, etc (immediate delivery); 'PD2': Groceries; PD3: Beverage/ dried foods; 'PD4': Personal health/ medicine; 'PD5': Apparels; PD6: Books/ Music/ Videos; 'PD7': Consumer electronics; 'PD8': Others.
2. ** and *: Significance at 5% and 10% levels, respectively.
3. (+) and (−): Positive and negative parameters.
4. -: Variable is not included in the model.

4.5.1 Attributes related to shipping services

The significant parameters of various *CS* service variables indicate the remarkable roles that service characteristics plays in the *senders'* choices of couriers. Together with the shipping cost and delivery time, other shipping attributes related to personalized services and services' quality are also noteworthy because they had a significant impact on *senders'* choices.

Shipping costs were found to be statistically significant and randomly distributed. The negatively estimated parameters suggest that *senders* prefer to send packages by a courier who offers a lower cost. This finding is consistent with the common knowledge on consumers' behaviors. While *senders'* behaviors are remarkably influenced by shipping cost, they also vary from *sender* to *sender*. As such, the shipping costs' parameters are heterogeneous across *senders* following a normal distribution. Meanwhile, delivery time parameters are also negative and significant for all PDs, from PD1 to PD8 (except PD6). *senders* prefer to have shipments delivered in a shorter time. These findings are expected.

"Courier's reputation (ranking)," "Tracking and tracing ability," and "Electronic delivery notification" parameters were found to be positively significant. Those are three notable variables which *senders* tend to take into account when sending packages. Reputation reflects a courier's performance and delivery quality, while tracking and tracing provides a package's location in real-time. The electronic delivery notification service informs *senders* of changes in activity associated to their shipments. As expected, those three service features profoundly influence the *senders'* choice of couriers. Consequently, *CS* companies should provide such services and maintain those in a high level to attract more *senders*.

Furthermore, personalized services, such as setting the delivery time window and the preferred location of delivery, were found to be significant. Allowing for a customizable time-window positively influences the choice to ship packages with a certain courier. As a side note, the personalized time window does not necessarily mean immediate delivery. Interestingly, the personalized location of delivery parameters are found to be positive in situations where *senders* request *CS* services to deliver PD1 items (dry cleaning, fast food, etc.), but negative for other product categories. *senders* shipping PD1 products prefer them to be delivered in a short time to places other than home or pickup points, such as offices for example. In contrast, on-line buyers typically expect other products to be delivered to home or be picked up at one of the carriers' pickup points. These findings on personalized services are supported by revealed preference (*RP*) data from a study of [26]. In that study, many respondents were not happy with personalized time windows and delivery location options. About 44% of respondents said "the carrier did not offer a pickup time window", while approximately 30% of respondents said either the pickup at home service was bad or that they did not know about the service. Moreover, about 34% of respondents reported that "carriers offer pickup at home," but for some reason they "have never used the service". For those reasons, our findings and the supported *RP* data are helpful for logistics firms identifying services which could be improved.

Tipping, an appreciation given to couriers from customers in the form of additionally payment, have been found to have positive significance on the choice of some *CS* couriers over some traditional logistics carriers. Respondents are willing to tip to maximize their utility for all products (except "Other" products–PD8). Interestingly, the willingness to tip in the RRM models reveals respondents are more likely to tip for some *CS* couriers to get dry cleaning, fast food, beverages, dried foods, groceries, personal health, and medicine products delivered.

On the other hand, safety has been identified as one of the challenges for implementing *CS* services [31, 176]. Concerns about shipped items being damaged have been found to be significant for books, music, and videos products (PD6) in our study. *CS* companies should consider different forms of insurance or product guarantee for customers in case of damaged products.

The findings are valuable for *CS* companies to address and improve service components which can attract more customers and influence *senders'* choices. More discussion on the parameter sensitivity and *WTP* for each service component will follow in the next sections.

4.5.2 Socio-demographic characteristics

senders may have diverse considerations that govern their choice of courier for sending different types of packages. The choices also vary across population groups. An individual's socio-demographic characteristics significantly influence their behavior in attempt to maximize utility. The estimated results reveal PD1, PD2, and PD3 are more likely being sent by married, 21-40 years old, and middle income people. Likewise, living with young people, adults, or elderly people have certain influences on behaviors of the *senders* of PD3 to PD8. Full- and part-time employees are found remarkably for sending all kind of shipment categories. The findings of some particular socio-demographic characteristics of *CS* users are valuable for *CS* companies in addressing potential market segments and developing revenue models (i.e. pricing strategies).

4.6 *Senders'* perceptions and sensitivity analysis

This section aims to provide additional insights for *CS* companies to improve their business strategies and services by understanding *senders'* perceptions of their services along with their competitors' services. With that intention, results were computed for all products (i.e. PD1 to PD8) to reveal *senders'* behaviors. Accordingly, we decided to conduct analysis on both RUM and RRM models and compared absolute dissimilarities as well as percent differences. The results, insights, and discussions are presented in the following sub-sections.

4.6.1 Willingness to pay

It is essential to know how much *senders* are willing to pay for a better service, especially in the logistics market in which new *CS* firms compete against *TLCs*s. For each product category, even the RUM and RRM models' performances are similar but the parameters' sizes vary. Parameters' sizes are important since the implementation are generally based on these parameters' magnitudes. In terms of WTPs, for each PD, results from the RRM model are remarkably different from those of the RUM model because of its attribute- and alternative-defined estimations, naturally by the RRM function's formulation. The values which are computed from the RUM and RRM models can be considered as lower and upper bounds for each corresponding WTP. As such, *CS* firms have *WTP* ranges for references. The result details are presented in Table 4.5.

Among seven PDs, respondents were willing to pay higher rates for PD1 and PD2 and lower rates for PD5, PD7, and PD8, for any service. The findings are consistent with common knowledge. People are typically willing to pay more to receive personalized or better services. The *WTP* value of RUM model for PD1 is similar to the finding in the study of [22]. In addition, the probability distribution functions of the *senders'* WTPs for a delivery service for the seven PDs are displayed in Figure 4.7.

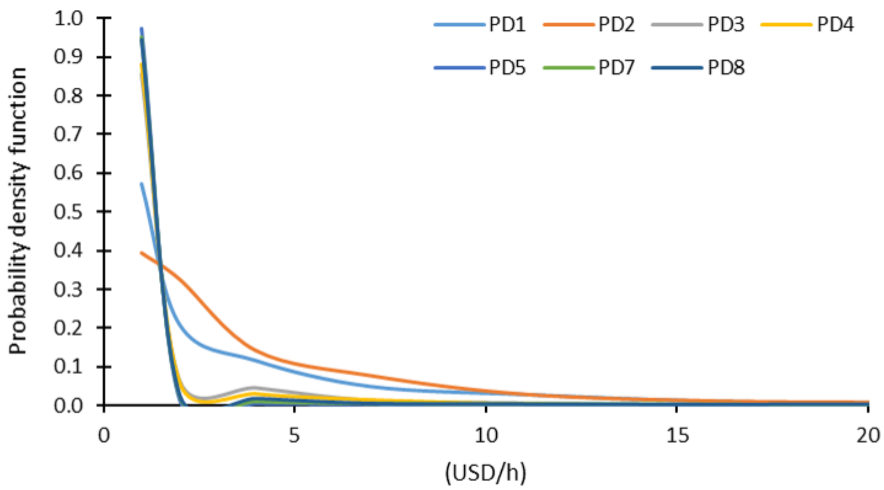


Figure 4.7.: Probability density functions of the *WTP* for a delivery service for different products

Table 4.5.: WTP estimation results

WTP for	**PD1**			**PD2**			**PD3**			**PD4**			**PD5**			**PD7**			**PD8**		
	RUM	RRM	Ratio	RUM	RRM	Ratio	RUM	RRM	Ratio	RUM	RRM	Ratio	RUM	RRM	Ratio	RUM	RRM	Ratio	RUM	RRM	Ratio
Delivery service	2.097	3.065	1.462	1.848	4.741	2.566	0.586	3.738	6.380	0.528	1.020	1.931	0.130	0.286	2.212	0.101	0.363	3.599	0.097	0.594	6.129
Reputation	0.094	0.203	2.154	0.102	0.240	2.338	0.054	0.130	2.406	0.028	0.071	2.535	0.009	0.030	3.134	0.009	0.037	4.096	0.009	0.039	4.170
Tracking	0.090	0.272	3.035	0.106	0.276	2.605	0.056	0.144	2.582	0.039	0.110	2.845	0.009	0.030	3.320	0.008	0.038	4.718	0.007	0.037	4.971
E-notification	0.129	0.213	1.653	0.123	0.293	2.385	0.044	0.102	2.310	0.026	0.068	2.662	0.006	0.018	3.204	0.006	0.027	4.528	0.006	0.043	7.751
P-Time	0.063	0.128	2.029	0.058	0.129	2.201	0.052	0.122	2.329	0.056	0.120	2.125	-	-	-	-	0.119	-	-	0.070	-
P-Location	0.135	-	-	-	-	-	0.063	0.141	2.244	0.033	0.090	2.773	0.008	0.025	3.253	0.009	0.044	4.857	0.007	-	-
Tip	-	-	-	-	-	-	-	-	-	-	-	-	0.028	-	-	0.025	-	-	-	-	-
Tip1	0.097	0.210	2.173	0.127	0.259	2.044	0.051	0.122	2.400	0.076	0.171	2.239	-	-	-	-	-	-	-	-	-
Tip2	0.081	0.191	2.346	0.071	0.138	1.935	0.043	0.107	2.488	0.043	0.095	2.240	-	-	-	-	-	-	-	-	-
Tip3	0.065	0.130	1.992	0.062	0.112	1.800	0.030	0.060	2.010	0.029	0.057	1.966	-	-	-	-	-	-	-	-	-

1. 'PD1': Dry cleaning, fast foods, lunches, dinners, birthday cakes, etc (immediate delivery); 'PD2': Groceries; PD3: Beverage/ dried foods; 'PD4': Personal health/ medicine; 'PD5': Apparels; 'PD7': Consumer electronics; 'PD8': Others.
2. 'Reputation': Courier's reputation/ranking; 'Tracking': Tracking and tracing ability; 'E-notification': Electronic delivery notification; 'P-Time': Personalization for delivery time window; 'P-Location': Personalization for location of delivery (not home or pickup point); 'Tip': Average tip for the first three couriers (couriers1-3); 'Tip1', 'Tip2', 'Tip3': Tip for couriers 1, 2, and 3, respectively.
3. 'Ratio': RRM/RUM.

4.6.2 Elasticity analysis

Elasticity analysis is commonly conducted to capture the changes in probability of selecting an alternative once changing in a certain variable while fixing other variables. In this research, direct elasticities were computed. Details of products' elasticities are presented in Table 4.6a to Table 4.6h. Moreover, the differences in percentages of attributes in RRM and RUM models for each product are illustrated in Figure D.1 (Appendix D). The differences were computed by Equation 4.7.

$$\Delta A_i(\%) = \frac{A_i(RRM) - A_i(RUM)}{A_i(RRM)} * 100 \tag{4.7}$$

where A_i is an attribute i in the RRM or RUM models.

Overall, the shipping costs have the largest absolute elasticity magnitudes. The elasticities of personalized delivery time-window or tipping behaviors are remarkably large for PD1 to PD4, but not for others. Meanwhile, personalized delivery location elasticities are not significantly different for PD1 and PD2, but are significantly different for PD3 to PD7. As such, delivery times and delivery locations play important roles in selecting couriers for sending PD1 to PD4 and PD3 to PD7, respectively. Consequently, *CS* companies should provide various services to address different shipment categories.

The following notes are for Table 4.6a to Table 4.6h.

1. All "%" columns were computed by Equation 4.7.
2. 'C1', 'C2', 'C3', and 'C4' represent for four alternatives, namely Courier 1, Courier 2, Courier 3, and Courier 4.
3. 'SCost': Shipping cost; 'DTime': Delivery time; 'Reputation': Courier's reputation/ranking; 'Tracking': Tracking and tracing ability; 'E-notification': Electronic delivery notification; 'P-Time': Personalization for delivery time window; 'P-Location': Personalization for location of delivery (not home or pickup point); 'Tip': Willingness to tip.

Table 4.6.: PD's elasticity summary

(a) PD1's elasticity summary

Variable	C1			C2			C3			C4		
	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%
SCost	-0.632	0.362	274.703	-0.625	0.380	264.412	-0.050	0.538	109.268	-1.003	0.326	407.666
DTime	-0.506	-1.713	70.494	-0.232	-0.236	1.653	-0.067	-0.091	26.484	-1.600	-0.911	-75.628
Reputation	0.472	1.161	59.309	0.447	0.850	47.435	0.439	0.588	25.332	0.885	1.265	30.080
Tracking	0.236	0.412	42.746	0.152	0.217	29.949	0.110	0.130	15.355	0.178	0.168	-6.444
E-notification	0.151	0.494	69.528	0.121	0.323	62.697	0.095	0.248	61.724	0.046	0.281	83.476
P-Time	0.089	0.171	48.219	0.350	0.807	56.633	0.094	0.154	38.827	0.255	2.378	89.279
P-Location	0.156	-	-	0.062	-	-	0.141	-	-	0.113	-	-
Tip	0.503	1.176	57.211	0.622	1.170	46.862	0.714	1.822	60.799	-	-	-

(b) PD2's elasticity summary

Variable	C1			C2			C3			C4		
	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%
SCost	-0.764	-1.423	46.311	-0.791	-1.429	44.672	-0.387	-1.529	74.697	-0.996	-1.435	30.596
DTime	-0.482	-1.636	70.546	-0.210	-0.198	-6.212	-0.063	-0.076	16.909	-1.431	-0.821	-74.272
Reputation	0.427	0.936	54.412	0.394	0.591	33.299	0.385	0.429	10.266	0.721	0.834	13.606
Tracking	0.198	0.390	49.179	0.119	0.164	27.306	0.093	0.118	20.681	0.132	0.131	-0.992
E-notification	0.156	0.350	55.317	0.117	0.189	37.916	0.093	0.158	41.098	0.043	0.141	69.307
P-Time	0.106	0.178	40.641	0.357	0.626	42.990	0.102	0.138	25.654	0.241	0.999	75.906
Tip	0.387	0.977	60.444	0.662	1.229	46.148	0.705	1.711	58.830	-	-	-

(c) PD3's elasticity summary

Variable	C1			C2			C3			C4		
	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%
SCost	-1.366	-0.656	-108.216	-1.458	-0.661	-120.645	-0.369	-0.840	56.054	-1.886	-0.555	-239.564
DTime	-0.275	-0.560	50.964	-0.126	-0.141	10.100	-0.039	-0.058	33.505	-0.789	-0.624	-26.342
Reputation	0.495	1.045	52.674	0.459	0.808	43.188	0.445	0.631	29.472	0.750	1.024	26.789
Tracking	0.231	0.445	48.146	0.135	0.222	39.225	0.107	0.237	54.588	0.139	0.164	15.633
E-notification	0.275	0.633	56.624	0.200	0.325	38.478	0.165	0.396	58.264	0.065	0.118	45.478
P-Time	0.071	0.198	64.026	0.241	0.464	48.050	0.072	0.168	57.126	0.154	0.589	73.824
P-Location	-0.206	-0.483	57.279	-0.077	-0.128	39.860	-0.184	-0.472	60.991	-0.132	-0.540	75.607
Tip	0.514	1.072	52.070	0.583	0.986	40.884	0.785	2.375	66.954	-	-	-

(d) PD4's elasticity summary

Variable	C1			C2			C3			C4		
	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%
SCost	-1.507	-0.881	-71.133	-1.639	-0.904	-81.352	-0.330	-1.090	69.761	-1.705	-0.668	-155.256
DTime	-0.223	-0.469	52.508	-0.106	-0.123	13.599	-0.030	-0.049	37.832	-0.556	-0.502	-10.793
Reputation	0.773	1.722	55.121	0.739	1.450	49.024	0.670	0.952	29.650	0.995	1.452	31.499
Tracking	0.285	0.640	55.408	0.165	0.303	45.631	0.122	0.276	55.806	0.145	0.164	11.470
E-notification	0.392	0.919	57.388	0.288	0.462	37.616	0.231	0.577	59.903	0.069	0.091	24.642
P-Time	0.056	0.246	77.289	0.191	0.487	60.730	0.054	0.161	66.168	0.101	0.387	73.999
P-Location	-0.327	-0.727	55.021	-0.134	-0.212	36.882	-0.286	-0.703	59.266	-0.189	-0.564	66.489
Tip	0.280	0.779	64.022	0.478	1.056	54.730	0.621	2.154	71.158	-	-	-

Table 4.6.: PD's elasticity summary (continued)

(e) PD5's elasticity summary

Variable	C1			C2			C3			C4		
	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%
SCost	-2.501	-3.059	18.234	-2.634	-3.176	17.071	-0.941	-2.896	67.508	-1.914	-2.074	7.730
DTime	-0.070	-0.174	60.023	-0.034	-0.052	34.043	-0.011	-0.021	49.275	-0.135	-0.186	27.805
Reputation	0.755	2.581	70.764	0.768	2.471	68.924	0.696	1.035	32.737	0.697	1.037	32.771
Tracking	0.408	1.656	75.377	0.235	0.601	60.872	0.197	1.068	81.599	0.158	0.195	19.231
E-notification	0.590	2.499	76.378	0.431	0.772	44.178	0.361	1.421	74.632	0.061	0.082	26.309
P-Location	-0.457	-1.842	75.195	-0.191	-0.322	40.807	-0.434	-2.137	79.696	-0.213	-0.388	45.063
Tip	0.210	-	-	0.211	-	-	0.194	-	-	-	-	-

(f) PD6's elasticity summary

Variable	C1			C2			C3			C4		
	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%
SCost	-2.514	-3.020	16.753	-2.632	-3.231	18.550	-1.091	-2.882	62.134	-1.967	-2.095	6.100
Reputation	0.648	2.293	71.757	0.686	0.946	27.516	0.587	0.933	37.056	0.612	0.941	35.002
Tracking	0.430	1.646	73.869	0.257	0.727	64.598	0.204	0.371	45.008	0.170	0.210	19.163
E-notification	0.480	1.923	75.029	0.368	0.676	45.598	0.297	1.233	75.937	0.051	0.067	24.739
P-Location	-0.405	-1.639	75.284	-0.169	-0.295	42.804	-0.381	-1.810	78.931	-0.192	-0.311	38.360
Tip	0.219	-	-	0.229	-	-	0.202	-	-	-	-	-

(g) PD7's elasticity summary

Variable	C1			C2			C3			C4		
	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%
SCost	-2.138	-2.186	2.195	-2.300	-2.342	1.793	-0.143	-2.333	93.867	-1.844	-1.476	-24.975
DTime	-0.080	-0.265	69.785	-0.041	-0.081	49.444	-0.011	-0.031	65.176	-0.159	-0.280	43.082
Reputation	0.884	2.596	65.949	0.884	2.565	65.554	0.729	1.179	38.155	0.842	1.346	37.467
Tracking	0.510	1.526	66.575	0.299	0.737	59.449	0.203	0.730	72.247	0.204	0.243	16.097
E-notification	0.617	1.776	65.240	0.478	0.923	48.163	0.360	1.387	74.008	0.068	0.086	20.468
P-Time	-	0.219	-	-	0.437	-	-	0.160	-	-	0.133	-
P-Location	-0.431	-1.135	62.035	-0.191	-0.325	41.316	-0.371	-1.388	73.258	-0.212	-0.409	48.103
Tip	0.299	-	-	0.305	-	-	0.254	-	-	-	-	-

(h) PD8's elasticity summary

Variable	C1			C2			C3			C4		
	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%	RUM	RRM	%
SCost	-2.146	-1.638	-30.989	-2.368	-1.818	-30.254	-0.194	-2.019	90.384	-1.785	-1.014	-75.927
DTime	-0.062	-0.173	64.067	-0.032	-0.066	51.205	-0.009	-0.025	62.992	-0.123	-0.224	45.094
Reputation	0.677	1.705	60.285	0.711	2.266	68.618	0.625	0.953	34.393	0.640	0.963	33.551
Tracking	0.432	1.055	59.064	0.265	0.680	61.091	0.200	0.652	69.387	0.171	0.191	10.658
E-notification	0.515	0.800	35.629	0.415	0.527	21.317	0.331	0.946	65.015	0.059	0.045	-31.180
P-Time	-	0.270	-	-	0.686	-	-	0.209	-	-	0.119	-
P-Location	-0.421	-	-	-0.193	-	-	-0.402	-	-	-0.203	-	-

4.7 Prediction results

The objective of this section is to validate the RUM and RRM models. As such, we collected the choice prediction values to evaluate the models' accuracies.

To begin, we randomly divided the dataset into five folds. For each fold, 80% of the dataset (i.e. training set) are first used to estimate for the model parameters which are then fixed to estimate the model's performance for the second time with the remaining 20% of the dataset (i.e. testing set). We ran each model five times. The choice prediction values of the five runs for each model are collected and compared to the actual choices in the corresponding 20% of the dataset. In this study, the choices are scalable. Therefore, the Mean Absolute Percentage Error (MAPE) is an appropriate method to evaluate for the accuracies of the prediction models. The MAPE value is computed by Equation 4.8.

$$MAPE = \frac{100\%}{N} \sum_{i=1}^{N} \left| \frac{Y - \widehat{Y}}{Y} \right| \tag{4.8}$$

in which Y and $\widehat{Y}$ are the actual value (i.e. actual choice) and the predicted value (i.e. prediction choice). N is the number of fitted points (e.g., N=5 in our estimation).

Summarized results are illustrated in Figure 4.8. The RRM models have better predictions (i.e. less errors) for PD1, PD3, PD4, PD5, and PD8, while RUM models fit better for PD2, PD6, and PD7. Nonetheless, as can be seen, the average MAPEs of the RUM and RRM models are very close for all PDs (fluctuated lines). In fact, taking the averages of RUM's and RRM's average MAPEs (straight lines), values are about 13% and 14%. In other words, the RUM and RRM models' average accuracies are approximate 87% and 86%, respectively. As such, there is not much difference in the models' accuracies.

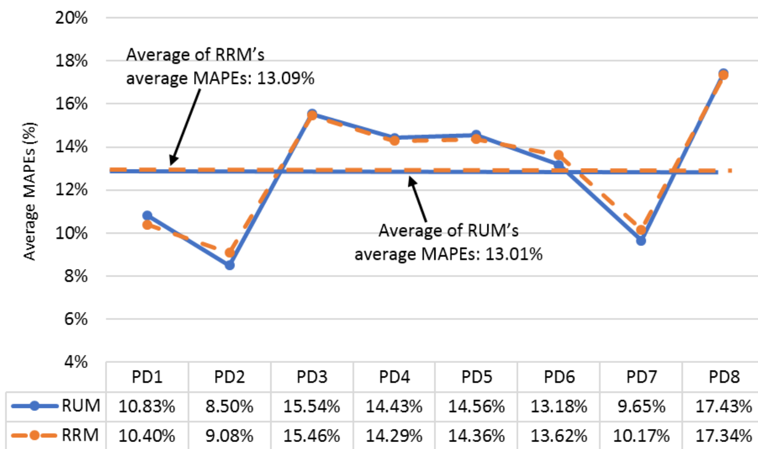


Figure 4.8.: Average MAPEs of RUM and RRM models over PDs' testing samples

4.8 Conclusions

This study is the first investigation on *senders'* choice of couriers for the different PD types under the availability of both *CS* and traditional carriers in a logistics market. Using RUM and RRM models to estimate the US survey data, we have revealed factors influencing *senders'* choice of courier service and the *senders'* *WTP* for different PDs. The shipping cost, delivery time, courier's reputation, tracking and tracing services, electronic delivery notification, and personalized delivery location and time window all may have a remarkable influence on a *senders'* choices. Similarly, age, marital status, income, occupation, and number of family members may also significantly contribute to the *senders'* decisions. PDs which are found more likely to be sent via *CS* systems include foods, beverages, and groceries. Apparel, books, music, videos, consumer electronics, and some other products are more likely to be sent via *TLCs*, regardless of gender and age. Personal health and medicine deliveries are shared by both *CS* and *TLCs*. Interestingly, the *WTP* for shipping food, groceries, beverages, and medicine are found to be higher than those for other PDs. Moreover, a big adjustment in the shipping cost, which has the largest elasticity, needs to be made to change a *sender*'s> mind regarding couriers. Finally, to evaluate accuracies of the

RUM and RRM models, we used data-science testing techniques. Those models found comparable performances even though the RUM models are better for predicting courier choice for sending groceries, books, music, videos, and consumer electronics.

In conclusion, insights from this study can *supply* new matrices to help both *CS* and traditional logistics firms improve their services as well as to know which retailers to approach for marketing their services. The future research should investigate markets in which there is fierce competition between *CS* and *TLCs*, particularly where personal health and medicine PDs are more likely to be sent by *CS* or *TLCs*, and under what circumstances.

5. MODELING THE WILLINGNESS TO WORK AS DRIVER-PARTNERS AND TRAVEL TIME TOLERANCE IN EMERGING LOGISTICS SERVICES

5.1 Introduction

The sharing economy has been an emerging phenomenon that challenges traditional enterprises and motivates new businesses worldwide. The sharing economy is trendy in industries, such as real estate (e.g., AirBnB, Couchsufing), finance (e.g., crowdfunding, peer-to-peer banking), and technology (e.g., cloud computing, open-sourced software). In transportation, passenger and freight sharing services are available in the market. Regarding systems which serve passenger mobility, there are some popular services, such as bike sharing, carpool, carsharing, cycling, real-time ridesharing, shared taxis, and shared parking spaces. Several common companies are Citi Bike, Uber, Zipcar, and Lyft. On the other hand, there also is an increase of freight delivery app-based services. Companies provide various delivery services for packages, groceries, foods, or anything legal (e.g., Roadie, Uber, Deliveroo, Postmates, Nimber, and Renren Kuaidi).

As a matter of fact, e-commerce has increased remarkably in the last decade, and is projected to grow significantly in the future [177]. While the worldwide's e-commerce sales (in billion US dollars) in 2016 and 2017 were 1,845 and 2,304, respectively, it is forecast to increase to 4,878 in 2021 [178]. Among on-line product categories, electronics, fashion, apparel, and books are reported as the most popular items [173]. Various retailers—supermarkets, foods, beverages, apparel stores, bookstores, stationery stores, drug stores, electrical supply stores, florist shops, and souvenir shops—deliver small packages via regular transporters, carriers, or by retailers' staff. As a result, logistics carriers have delivered a considerable number of small packages. Remarkably, the express delivery service of e-commerce purchases in China had a massive rise of 820% within 5 years, from 2009 to 2014 [179]. Furthermore, [12] revealed that letterbox-sized packages and small parcels accounted for nearly 60% of all UK on-line purchase deliveries in 2013. Letterbox-sized packages can fit through a standard UK letterbox, while small parcels are no larger than a standard UK shoebox. Moreover, [180] estimated the US parcel volume was approximately 12 billion in 2015, while [181] stated there were over 2 billion local deliveries per year in the US alone. Both studies of [12] and [181] acknowledged a significant demand for the delivery of small packages in urban areas.

In response to the demand for delivery services, the rise in e-commerce, and the improved Internet and smart-phone technologies, a substantial number of *crowd-shipping* (*CS*) firms have been established worldwide. Researchers have defined *CS* in several ways, but there is still no consensus on a single definition for *CS*. In this study, we have defined *CS* as a system which connects couriers and *requesters* through an app-based platform for a first or last mile intra-urban delivery. Couriers are the ones who are willing to carry packages, while *requesters* are the ones who send packages. Couriers and *requesters* can be an individual or a company. Even though many *CS* firms are using dedicated couriers for deliveries, in our study, we consider that couriers deliver during their travel anyway. The commuters who are already traveling can offer a lower price for delivery packages close to their routes than people solely making a delivery trip. The commuters who travel anyway may also be better navigators due to familiarity with their daily travel routes, so they can shorten the delivery time.

One challenge for *CS* companies is to provide sufficient workforce to accommodate this demand. Therefore, identifying potential third-party suppliers is crucial for *CS* companies. One possible solution is to attract people who already travel to utilize the unused capacity in their vehicles to transport freight. The 2009 US National Household Travel Survey revealed the national average vehicle occupancy of all trip purposes was 1.67 (person miles per vehicle mile); in which the "commute" and "social

Table 5.1.: The American's average vehicle occupancy in 2009 (person miles per vehicle mile) [17]

Trip purpose	**Average vehicle occupancy**
Commute to or from work	1.13
Shopping	1.78
Other family/personal errands	1.84
Social and recreational	2.20
All purposes	**1.67**

and recreational" trips had the lowest and highest occupancy, respectively [17]. The data summary can be seen in Table 5.1.

Similarly, delivery distance information is helpful for *CS* companies' operational strategies (e.g., to alert potential crowd-sourced drivers of jobs within their distance preferences). The minimum and maximum distances computed from a one-day dataset of requests for freight delivery in Shanghai, China were 0.18 km (i.e. 0.11 mile) and 87.50 km (i.e. 54.37 miles), respectively [182]. The delivery requests were collected from traditional logistics carriers and local shops. The traditional logistics carriers outsourced e-commerce packages, while the local shops requested on-line-to-off-line package deliveries. The average distance of all delivery trips was 6.5 km (i.e. 4 miles). The average delivery distance of packages ordered from local shops was about 3 km (i.e. 1.86 miles).

The potential *CS* supply, however, is not yet clear. The following research questions are the focus of this study: Who are the prospective *driver-partners*, and which population segments are they from? What motivates people to work or not to work as *driver-partners*? What is the maximum time tolerance a *driver-partner* is willing to devote, and in which circumstances? The *driver-partners'* behaviors and their participating levels are driven by which factors? What are appropriate compensation rates for *driver-partners*?

Answers to these questions are imperative to the success of any *CS* service. Nevertheless, clear research-based answers have not yet been available. Accordingly, this research will investigate these questions via discrete-continuous approach models for two interrelated behaviors. These models examined prospective *driver-partners'* willingness to work (WTW) as well as the maximum travel time tolerance (TTT) of respondents who are willing to work as *driver-partners*. This study provides *CS* companies a better understanding of potential effective and efficient system operations. The insights will also help *CS* firms to recruit part-time drivers, understand which circumstances affect prospective *driver-partners'* WTW, and decide upon operational strategies (e.g., matching and routing strategies and compensation rates for *driver-partners*).

This study includes six sections. Section one introduces the background and motivations of this study. Section two reviews studies in this field. Section three presents methodology. Section four shows survey design and descriptive statistics. The findings and insights are discussed in section five. Finally, the conclusion summarizes findings and suggests ideas for implementations.

5.2 Literature review

As the sharing economy emerges, behavioral studies on its supply side have got significant interest from researchers. [183] conducted a stated preference (SP) survey to evaluate the suppliers' motivations in car, ride, accommodation, tool, and meal sharings. The findings reveal that accommodation providers were mainly motivated by economic reasons while people who were willing to share their meals were primarily motivated by social values. The car, ride, and tool sharings were predominantly environmentally motivated. In particular, people less than 40 years old were more likely motivated for economic reasons, whereas those who were more than 65 years old or with lower education levels may be motivated by both social and environmental senses.

Since its founding in 2008, AirBnB has attracted over 35 million guests who have stayed at about 1.2 million listing properties [152]. Those AirBnB supplies include accommodations from both professional and non-professional hosts. AirBnB providers were more likely to be people having lower income or holding bachelor's and higher degrees [153].

With regard to Uber, drivers were mainly motivated by "able to choose their own schedule", "being their own boss", and "earning more income". About 40% of Uber drivers were white or Caucasian. The numbers of people who were married and having aged from 30-49 years old were nearly 50% and 56%, respectively. Approximately 50% of Uber drivers had college or advanced degrees. The study interviewed drivers who were working for passenger mobility services (e.g., UberX and UberBLACK), and freight and food related delivery services (e.g., Uber Freight, UberRUSH, and UberEATS). More detailed results can be found in a report of [184].

CS is a new-born industry and its service's performance has not yet been revealed clearly. In general, *CS* firms conduct business under various models which are summarized in Table 5.2. Numerous *CS* companies provide freight, grocery, food, medical, etc. delivery services which mainly are for small-sized packages (parcels). Examples include: GoPeople, PostRope (Australia); Renren Kuaidi, JD (China); mShipper (India); Honestbee (Singapore); PiggyBaggy (Finland); Trunkrs (Netherland); Roadie, UberRUSH, Deliv, Instacart, Postmates, Seamless, Grubhub, Eat24, Doordash, and UberEATs (US); Deliveroo, Foodora (Europe); giaohangnhanh, Proship (Vietnam). Moreover, some pilot programs relying on crowd resources have been tested. For instance, Walmart introduced a pilot program in which in-store customers can deliver groceries for on-line shoppers on their ways back home. DHL also implemented a program called Myways which aimed to facilitate the last-mile deliveries by involving local residents.

The *CS* service is expected to change the way of shipping and the traveling pattern of some population segments. The nature of these changes and their resulting long-term impacts are unclear, but they will most likely vary from market to market.

Table 5.2.: Crowd-shipping business models [31]

Business model	**Clients**	**Offer**	**Area**	**Couriers**
Courier	B2C	Deliver an order from a shop, a restaurant, a pharmacy, etc.,	Intra-urban	Professional or non-professional dedicated couriers
Intendant	B2C	An order is placed on the *CS*'s website. It is the courier who purchases the article from a shop and delivers the article to the customer	Intra-urban	Professional or non-professional dedicated couriers
Intra-urban	P2P or B2B	Deliver a parcel	Intra-urban	Professional, non-professional dedicated couriers, or commuters
National	P2P or B2B	Deliver a parcel	Inter-urban /National	Travelers
Social delivery	P2P or B2B or network	An order is placed on the business website. The courier proceeds to purchase, then to delivery	National/ International	Travelers

Since operational data is hardly obtained from the *CS* industry, comprehensive questionnaire sets were designed to address the research gaps presented in the previous section. The survey design and descriptive statistics are presented in section four.

This research was motivated by gaps in literature and questions related to survey responses (i.e. WTW and TTT choices). A logit model was employed to estimate the discrete choices of WTW as *driver-partners* or not. An ordinary least-square regression model was used to estimate *driver-partners'* maximum tolerance for shipping and delivery times. The selectivity-bias term was added to the regression model to correct for the correlations of discrete and continuous variables.

Various studies in the field of transportation have used discrete-continuous approaches. Bhat and his colleagues published a series of works using this technique [185, 186, 187]. For example, [185] developed a multiple discrete-continuous extreme value model to test time-use allocation decisions. The results showed the significant influence of demographic and employment patterns on time-use patterns.

Relationships between variables (e.g., discrete and continuous) have been found in various transportation datasets. [188] developed a new method to correct these correlations. As such, the choice to go home from work was modeled as discrete, and the travel time to home from work was modeled as continuous. Those models were linked by a selectivity correction term. Selectivity bias was presented in the model given that the travel time data was only available from the subset of respondents who decided to go directly home from work. The authors employed a binary logit model to analyze the activity/home choice and an ordinary least-square regression model for the travel time from work to home. The results showed that the selectivity correction term was statistically significant; in other words, correlations are present in the dataset [188]. Numerous works related to the discrete-continuous choice analysis have addressed selectivity correction issues [189, 190, 191, 192, 193, 194, 195, 196, 197]. Our goal in this study is to apply this methodology to an innovative CS dataset and obtain various insights related to WTW and TTT choices.

Behavioral research on CS's supply side is limited. [69] studied a crowd-sourcing pilot program for delivering library materials (i.e. books and library media) in Finland, and found an average detour of 2.2 km (i.e. 1.37 miles) per delivery. Of all the reasons that respondents reported for participating in the trial, the most common motivations were "try something new," "make life easier for me," "support public service," and "support the environment". In another study, 64% of respondents were willing to transport parcels, and 44% were motivated by ecological interest [49]. [50] found 87% of university students willing to work as *driver-partners* were mainly motivated by economic reasons. Those respondents were concerned about additional time that should be diverted from their original trips, and they showed their limited time dedication engaging in CS activities. The average travel distance tolerance was 2.4 km (i.e. 1.49 miles), and about 80% of respondents accepted to deliver for one or two stops. Moreover, [139] revealed 72% of respondents accepting to deliver packages for their friends.

Few publications on the value of potential *driver-partners'* WTW have been found. In a recent study, [51] estimated the value of WTW, which is defined as giving up one's time to make a profit. In fact, the estimated WTW value was higher than the typical willingness to pay values presented in the literature. The socio-demographic and attitudinal variables were also reported to have a significant influence on the WTW decision in the same study. Altogether, the behavioral studies on CS's supply side are summarized in Table 5.3.

[51] is one of the earliest studies on the topic; however, the authors only modeled a single discrete behavior. Explicitly, none of the available studies examines integrated behaviors and selectivity bias in their modeling approaches. Failure to correct for the selectivity bias leads to significant limitations of the insights and conclusions drawn from the estimated results [198]. Therefore, the goals of this study are to provide objectives and consistent results as well as contribute to the emerging field of the CS research.

5.3 Methodology

In this study, respondents were first asked whether they were willing to work as *driver-partners* (discrete variable). If so, they were asked the maximum TTT (continuous variable) they would accept to pick up and deliver packages. These decisions are interrelated; therefore, the discrete-continuous models are the best fit to analyze the data [198]. In addition, the interconnected discrete-continuous data is generally considered as a problem of selectivity. The observed data subset (i.e. WTW as *driver-partners*, therefore, TTT) was the outcome of a non-random selection process from samples of a larger dataset of discrete decisions (i.e. willing to work as *driver-partners* or not). The relationships of the decisions are illustrated in Figure 5.1.

Table 5.3.: Summary of behavioral studies on the *CS's* supply side

Study	**Data collection method**	**Sample's size**	***WTW* as *driver-partners* (%)**	**Average derivation distance/time**	**Factors influence *WTW***	**Modeling approaches**
[69]	Experiment	123	-	2.2 km	Incentives, health benefits, support the environment and public services.	Descriptive analysis
[49]	Survey	50	64	-	Incentives, reduced traffic, and ecological interest.	Descriptive analysis
[50]	Survey	190	87	2.4 km (i.e. 21% trip distance)	Incentives, packages' size, gender, frequent e-shoppers, pickup/delivery location, maximum derivation time (distance), safety, and security.	Descriptive analysis
[139]	Survey	104	72	8 minutes*	Age, gender, income, and maximum derivation time.	Logistic regression
[51]	*SP* survey	143	30	46 minutes*	Maximum derivation time, profit earned, original trip time, income, trip purpose, education level, gender, delivery time (of day), time availability, time-used efficiency in the car, and teamwork skills.	Mixed logit models

*: Approximate values were computed from available data in the corresponding papers.

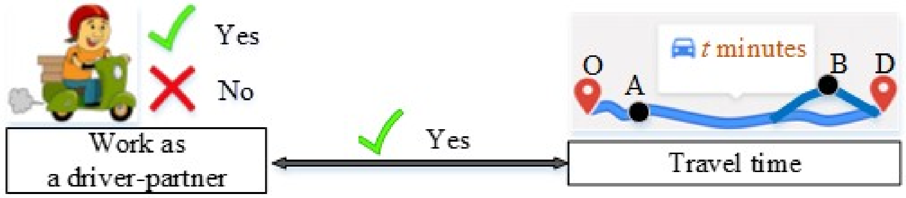


Figure 5.1.: Relationships of the WTW as *driver-partners* and TTT

The goal of this study is to identify which factors relate to the maximum TTT of respondents who are willing to work as *driver-partners*. Continuous TTT is defined as:

$$TTT_i = \alpha_0 + \alpha_1 X_i + \epsilon_i \tag{5.1}$$

where TTT_i is the tolerance for travel time of *driver-partner* i; α's are estimable parameters; X_i is a vector of respondent i's preferences and social demographic variables; ϵ_i is an unobserved term assumed to be normally-distributed.
However, since this model is only applied to the subset of respondents who are willing to work as *driver-partners*, ϵ_i does not have a zero mean as assumed. Therefore, we need to use the selectivity bias to correct for the discrete-continuous models. The selectivity bias indicates a conditional TTT value given that respondents are willing to work as *driver-partners*. Several approaches have been developed to correct for such selectivity bias [199, 200]. Denote $E(\epsilon_i|k)$ is a conditional mean of ϵ_i given that respondent i chooses to be a *driver-partner* [199].

$$E(\epsilon_i|k) = \rho\left(\frac{\sigma_\epsilon}{\sigma_\xi}\right)\prod_{ik} \tag{5.2}$$

where σ_ϵ is the standard deviation of the normally-distributed unobserved term ϵ ; σ_ξ is the standard deviation of the logistic unobserved term ξ in the discrete choice model (Equation 5.6); ρ is the correlation between ϵ and ξ ; and $\prod_{ik}$ is defined as:

$$\prod_{ik} = \left(\frac{(1-p_{ik})log(1-p_{ik})}{p_{ik}} + log\Big(p_{ik}\Big)\right) \tag{5.3}$$

where p_{ik} is the probability that a respondent i decides of WTW as a *driver-partner*. Then

$$\epsilon_i = E(\epsilon_i|k) + \tilde{\epsilon_i} \tag{5.4}$$

Substituting ϵ_i in Equation 5.4 into Equation 5.1, the Equation 5.1 becomes:

$$E\Bigg(TTT_i|k\Bigg) = \alpha_0 + \alpha_1 X_i + E(\epsilon_i|k) + \tilde{\epsilon_i} = \alpha_0 + \alpha_1 X_i + \beta \prod_{ik} + \tilde{\epsilon_i} \tag{5.5}$$

where β is an estimated parameter which equals to $\rho\Bigg(\frac{\sigma_\epsilon}{\sigma_\xi}\Bigg)$; and $\tilde{\epsilon_i}$ has a conditional zero mean by construction.

In Equation 5.5, the parameter β of the selectivity-bias term is estimated as a random parameter. As such, a parameter is estimated for each observation. The hypothesis of a random parameter under this assumption is the variety of behavioral observations. The treated parameter is not continual across observations. In other words, all observations used in this model are willing to work as *driver-partners*, and their TTTs vary. Equation 5.5 is then computed using the ordinary least-squares method.

The discrete-continuous model with the selectivity correction term is consequently solved in the following three steps:

1. A discrete-choice model is used to estimate the probability of each discrete decision (i.e. willing to work as *driver-partners* or not). The data from all respondents is employed in this step.

2. The outcomes from step one are used to estimate selectivity values (only estimate for respondents who are willing to work as *driver-partners*).

3. The regression model is employed to evaluate the continuous data. This model includes the computed selectivity variable from step 2 that corrects for the selectivity bias of the discrete-continuous decision process. A data subset, from respondents who are willing to work as *driver-partners*, is used in this model.

The multinomial logit model is widely used in studies of choice modeling. One property of this model is an assumption of independence of irrelevant alternatives, which is suitable for independent choices. Therefore, a multinomial logit model is commonly employed to infer the self-selective behavior of respondents. The utility of decision k of a respondent is expressed as U_k.

$$U_k = V_k + \xi_k \tag{5.6}$$

where V_k is an observed utility, and ξ is an error term which follows the IID $Gumbel(0,1)$ distribution. The choice model is then written as:

$$P_k\left(V_k^* > V_k\right) = \frac{exp\left(V_k\right)}{\sum_{k=1}^{K} exp\left(V_k\right)} \tag{5.7}$$

In this study, the multinomial logit model is collapsed to a binary logit model since there are only two alternatives (i.e. willing to work as *driver-partners* or not) in the choice set.

Expectation to be paid (ETP) is a potential *driver-partners'* expected compensation for their additional time spending on diversion from their route to pickup and deliver packages. ETP, nonetheless, has not yet been clearly defined. The closest concept to ETP is the value of time (VOT) which is the amount that travelers are willing to pay for saving their travel time [175]. VOT is computed as a ratio of time parameter divided by cost parameter [201]. In this study, the ETP is computed following the VOT's computational approach as presented in Equation 5.8.

$$ETP = \frac{\beta_{delivery-time} * 60}{\beta_{driver\text{-}partner\text{'}s-pay-expectation}} (\$/h) \tag{5.8}$$

where $\beta_{delivery-time}$ and $\beta_{driver\text{-}partner\text{'}s-pay-expectation}$ are estimated parameters of the delivery time and "*driver-partner's* pay expectation" variables, respectively.

Nonetheless, values of the "*driver-partner's* pay expectation" variable have been normalized to amounts per one hour, therefore, the $\beta_{delivery-time}$ in Equation 5.8 was collapsed into one in our final model.

5.4 Survey design and data statistics

5.4.1 Survey design

The dataset used in this study was collected from a survey spanning from February to April 2017 in the US. The survey was designed to understand the behavior of stakeholders (e.g., *requesters* and prospective *driver-partners*) and assumed the availability of *CS* services in the logistics market. The questionnaire was then double-checked for its validity, reliability, and generalizability by a pilot survey before implementing the main survey. At the beginning of the questionnaire, we presented definitions for terms that we think are unfamiliar to ordinary people (e.g., crowd-shipping, *driver-partner*, courier, carrier, *sender*, and consumer electronics products). We also restated terms' definitions in a couple of appropriate places in the questionnaire to make sure respondents are aware of those terminologies. Furthermore, we have used various ways to obtain survey respondents, such as distribution at conferences, on social media and forums, sending emails, and using Amazon Mechanical Turk. The surveys were distributed to reach as many people as we can and also to obtain representativeness within the sample. In addition, we have carefully reviewed the data from Amazon Turk and only data which has all of the information was used for our purpose. The data from Amazon Mechanical Turk was confirmed as valid and reliable data as shown in many previous studies, such as [202, 203, 204, 205, 206].

In the survey, shipping experience as well as *SP* questions regarding crowd-sourced delivery were asked. Respondents reported their experience with transporting freight, and then were asked whether they were willing to work as *driver-partners* in the future. Logic conditions were applied to direct respondents to the follow-up questions depending on their response of "Yes" or "No." For example, the respondents who were willing to work as *driver-partners* were asked for the maximum TTT that they are willing to divert, and how much do they expect to be paid for picking up and delivering a package. Furthermore, answers for questions about transporting freight under various purposes and at different weekday and weekend time-frames were instructed as "select all that apply" from several options. Similarly, multiple answers were designed to realize potential *driver-partners'* concerns about shipments which contain hazardous materials, dangerous items, or illegal substances. Those concerns possibly influence on the *CS* participation behavior. Therefore, a question on "whose packages or goods you prefer to deliver" has been included in the questionnaire. Aside from responses to the hypothetical questions, the dataset also includes socio-demographic characteristics, such as age, gender, race, and education level. Personal socio-economic data—income, number of children, number of adults in his/her household, and accommodation ownership—is also provided in the dataset. An example of revealed preference and hypothetical questions is shown in Figure 5.2.

Q44. Have you ever transported goods for somebody else at least once?
○ Yes ○ No

Q45. In the future, if you have a chance to transport goods for somebody else on your route or close to your route of travel, will you do that for some incentive?
○ Yes ○ No

....

Q50. Suppose you are a driver-partner, and the travel time of your main route is 20 minutes, what is the maximum diversion (in time) you would accept to pick up and deliver a package?

	0	10	20	30	40	50	60	70	80	90	100
minutes											

Figure 5.2.: An example of revealed preference and hypothetical questions

5.4.2 Descriptive statistics

There were total 722 responses, but the final dataset only includes 549 respondents, as some responses were incomplete or inconsistent. Respondents' age and gender distributions are presented in Figure 5.3 and Figure 5.4, respectively. Those distributions are convergent to the 2014 US census statistics (https://www.census.gov/data/tables/2014/demo/age-and-sex/2014-age-sex-composition.html). Regarding to the *WTW* as *driver-partners*, the result shows 78% of respondents were interested. This result is among the statistics' range which has been presented in Table 5.3. In addition, the average TTT and its standard deviation are 23 and 18 minutes, respectively. As such, prospective *driver-partners* were willing to divert–on average–approximately as much as their original route's travel time which was assumed to be 20 minutes. The respondents' TTT distribution is illustrated in Figure 5.5. Additionally, characteristics of the variables used in this study are summarized in Table 5.4.

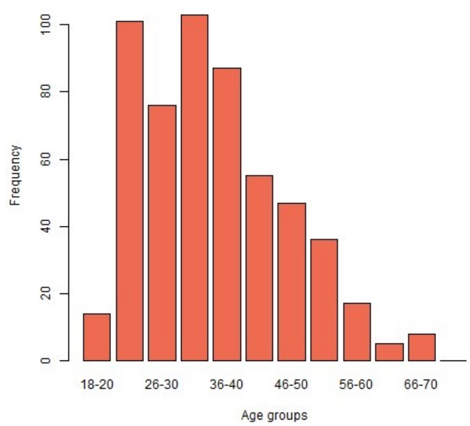


Figure 5.3.: Respondents' age distribution

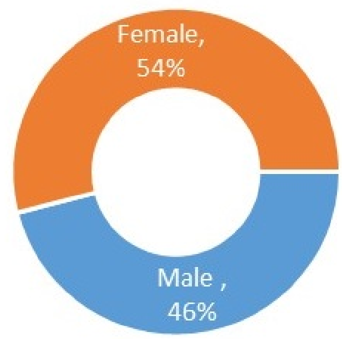


Figure 5.4.: Respondents' gender distribution

The authors utilized NLOGIT 6 for all modeling works, including the preliminary statistical analysis (as presented) and model building [200]. The model development procedures and insights from the achieved results are provided in the following section.

5.5 Estimation results

The potential explanatory variables for the models were selected from theoretical and empirical studies on the sharing economy, ride-sharing, carpooling [207, 208], and other CS studies [49, 50, 51, 69, 139]. In addition, hypothetical variables (e.g., transporting freight during a commute, transporting freight for people whom potential *driver-partners* know, and *driver-partner's* pay expectation) were also tested during

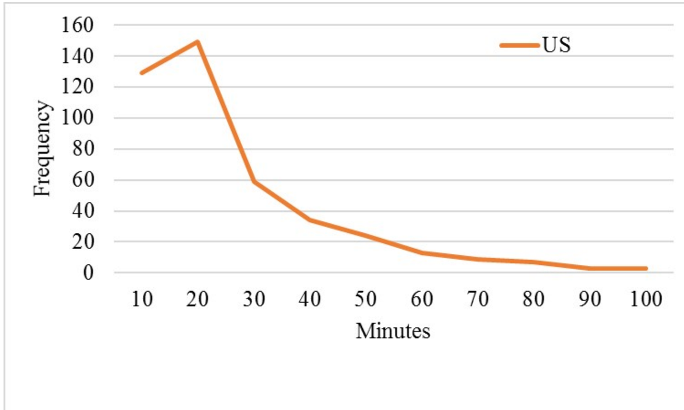


Figure 5.5.: Distribution of tolerance for travel time (minutes)

Table 5.4.: Descriptive statistics of explanatory variables

*percentages for dummy variables; (DV): Dummy variable: 0- No; 1- Yes

Variable Description	**Min/ max or values**	**Mean (*Standard deviation*)***
Numbers of respondents (dataset used for discrete choice model): 549		
Experience of transport freight for someone else. (DV)	0/1	74.30/25.70
Will you work as a *driver-partner*? (DV)	0/1	21.68/78.32
Age >30 years old. (DV)	0/1	34.74/65.26
Male and number of children	0/5	0.29 (*0.75*)
African American/American Indian/Alaska native and income is <$50,000/year. (DV)	0/1	93.58/6.42
Numbers of people in your household are ≥65 years old	0/6	0.18 (*0.63*)
Having college degree or higher and income is <$50,000/year. (DV)	0/1	55.60/44.40
Income ($1,000/year)	15/220	48.71 (*36.00*)
Living in a house with mortgage. (DV)	0/1	80.00/20.00
Total numbers of social media usages	0/10	4.00(*2.10*)
Numbers of respondents (dataset used for continuous model): 430		
Maximum tolerance for travel time would you accept to pickup and delivery a package (Minutes)	1/100	23.40 (*17.50*)
I can be a *driver-partner* during my commute. (DV)	0/1	30.00/70.00
driver-partner's pay expectation (USD)	0/30	11.70 (*4.59*)
I can deliver whosoever packages or goods if I get paid. (DV)	0/1	27.73/72.27
Age <31 years old. (DV)	0/1	68.55/31.45
Female. (DV)	0/1	47.27/52.73
African American/American Indian/Alaska native male. (DV)	0/1	96.00/4.00
Income is less than $30,000/year and deliver at weekday nights. (DV)	0/1	73.20/26.80

the model building process. It is worth noting that the correlations between variables were calculated to identify highly-correlated variables and prevent multicollinearity issues before building the models. Pair-wise variables, including newly-created variables and survey variables, were not highly correlated; therefore, there is no issue of multicollinearity with the developed models. The estimated model results are presented in the following sub-sections.

5.5.1 Willingness to work as *driver-partners* model

As discussed, respondents selected whether or not they were willing to work as *driver-partners* (i.e. "Yes" or "No") from the choice set. Therefore, the binary-logit model was developed, and *driver-partners' WTW* was selected as a dependent variable. Various explanatory variables were tested for statistical significance. There was no instrumental variable (i.e. endogenous variable associated with the corresponding alternative) that varied across alternatives. Explanatory variables included respondents' transporting freight experience and their socio-demographic characteristics. The results are presented in Table 5.5. All parameters (except the constant parameter) have plausible signs and a significance of more than 90%.

Respondents who transported freight or goods for someone else in the past are willing to work for the *CS* system. This may be a result of the respondents' familiarity with the field and confidence to participate in a similar system. Moreover, the positive and statistically-significant parameter of "age" suggests that people who are more than 30 years old are more likely to be *CS* driver partners. Perhaps these respondents have daily routines; therefore, they can more easily accommodate this additional task.

The parameter of males with children is positive which indicates that men with children are more likely than women with children to work as *driver-partners*. Males may consider themselves the bread winners of their families, and therefore allocate more time for work than their female counterparts. People who earn less than \$50,000/year (e.g., African American, American Indian, Alaskan native, and respon-

Table 5.5.: Binary logit model estimation results of *WTW* as *driver-partners* and average marginal effects

Variable Description	**Coefficient *(t-stats)***	**Average marginal effect**
Constant	0.021 *(0.11)*	-
Experience of transport freight for someone else. (DV)	1.486 *(8.47)*	0.182
Age >30 years old. (DV)	0.909 *(7.24)*	0.149
Male and number of children. (DV)	0.320 *(3.12)*	0.049
African American/American Indian/Alaska native and income is <\$50,000/year. (DV)	0.530 *(1.84)*	0.073
Numbers of people in your household are ≥65 years old	-0.207 *(-2.48)*	-0.032
Having college degree or higher and income is <\$50,000/year. (DV)	0.583 *(4.10)*	0.088
Income	-0.004 *(-2.27)*	-0.001
Living in a house with mortgage. (DV)	0.432 *(2.80)*	0.063
Total numbers of social media usages	0.067 *(2.46)*	0.01
Model fit statistics		
Number of respondents	549	
Restricted Log Likelihood	-1148.01	
Log Likelihood at convergence	-1041.10	
Pseudo-R square	0.09	

Note: all variables are defined for the *WTW* as *driver-partners.*

dents with a college degree or higher education) are more likely to work for the *CS* system. Earning about an average or less than average national income may motivate them to work as *driver-partners* (the average US income in 2015 was $48,100 per capita [209]). Low-income people consider *CS* as an opportunity to earn additional income. This is potentially an extra job with flexibility. Our findings also show that respondents who are living with elderly people are less likely to work as *driver-partners*. This is probably due to the constraints that they may need to be available for their elderly family members. Therefore, it reduces their flexibility to participate in a *CS* system.

The expected, negatively-significant income coefficient suggests that respondents who earn higher incomes are less likely to work as *driver-partners*. Conversely, respondents who are living in mortgaged houses are more motivated to work as driver partners for crowd-sourced delivery companies. This suggests their desire to earn additional income to pay loans and other debts. The respondents who use multiple social media outlets are more likely to work as *driver-partners*. These people may be more technologically savvy, familiar with using apps, and open to sharing economy gigs.

Model outputs reveal congruent findings to the literature as well as interesting results. Influenced factors, such as incentive, age, gender, and income influence on WTW as *driver-partners* were found concurrent with *CS* literature [49, 50, 51, 69, 139]. Our findings reveal lower income people were more likely to participate on *CS*, but [51] found people who earned less than \$35k were less interested to be *driver-partners*. Also, [51] found people who held a graduate degree were less likely to participate in *CS*, whereas, we have found graduate degree holders who earned less than \$50k/year were more likely to work as *driver-partners*. The findings on income and education levels, however, are concurrent with results of a study on Uber drivers [184]. Some new factors, for instance, race, transport freight experience, and social medial usages, have been found remarkable influences on potential *driver-partners'* decision. Therefore, to promote *CS* and address prospective driver partners, crowd-sourced delivery companies could filter crowds by multiple criteria for their promotion and recruitment programs. Certainly, insights from this study provide initial ideas for better understanding these factors.

The marginal effects were calculated to assess the effect of explanatory variables on the WTW as *driver-partners*. Given that elasticity is generally used for measuring continuous explanatory variables, and the majority of the estimated variables in this research are dummy variables, all marginal effects other than elasticity were selected. In this study, the marginal effects measure the variation of the decision to work as a *driver-partner* as a function of a change in a certain variable, while maintaining the other variables. Of the total variables, freight transportation experience and age greatly influence the WTW for crowd-sourced delivery companies. For example, experience with delivery freight increases WTW 18.2%, while all other variables remain the same. Uniquely, the 30 years and older age group's WTW is 15% higher. The income variable has the least marginal influence on WTW. An increase of $1,000 in annual individual income will lower the possibility of working as a *driver-partner* by 0.1%. All other variables have marginal effects in the range of 1-9%. All marginal effect coefficients are statistically significant, and have the same signs as the corresponding coefficients from the logit model.

5.5.2 Tolerance of travel time model

This section presents results from the corrected and non-corrected TTT regression models. The selectivity-bias approach was employed to correct for the TTT of respondents who were willing to work as *driver-partners*. Discrete logit model outputs presented in Table 3 and data from 430 respondents were employed to evaluate the regression model. Moreover, the differences between the two models are noteworthy; therefore, the results of the model without the selectivity correction term are also presented in Table 5.6.

Regarding the model estimated the selectivity correction term, the commuting trip parameter is negative and significant influences TTT. Respondents are willing to carry freight on their commuting trips, but less likely to divert for longer times compared to other trip purposes. This finding is consistent with the fact that respondents may have more flexibility in their schedules during leisure trips or their free time; therefore, they can make a longer diversion to transport packages. On the other hand, the parameter of "*driver-partner's* pay expectation" is positive and significant. Thus, the more respondents think they might get paid, the longer distances they are willing to travel. Accordingly, the compensation schemes should be carefully designed to attract occasional drivers, but not to increase the vehicle miles traveled. Extended driving by driver partners may counteract the savings (e.g., fuel consumption per package delivery); therefore, it violates the objectives of implementing CS systems with improved mobility, safety, and environmental sustainability. A possible solution

Table 5.6.: Corrected and un-corrected regression models of tolerance for travel time

Variable Description	**Parameter estimates with selectivity correction *(t-stats)***	**Un-corrected parameter estimates *(t-stats)***	**Changes in parameters (Corrected/Un-corrected) (%)**
Non-random parameters			
Constant	11.099 *(6.60)*	8.245 *(3.69)*	135
I can be a *driver-partner* during my commute	-5.076 *(-6.63)*	-4.902 *(-8.90)*	104
driver-partner's pay expectation	4.988 *(23.22)*	5.043 *(25.37)*	99
I can deliver whosoever packages or goods if I get paid	-3.976 *(-4.84)*	-4.374 *(-4.48)*	91
Age. Dummy variable: 1- if <31 years old; 0- otherwise	2.322 *(2.37)*	<u>0.340 *(0.37)*</u>	683
Female	2.418 *(2.88)*	1.780 *(10.30)*	136
African American/American or Indian/Alaska native males	8.564 *(4.64)*	10.216 *(4.06)*	84
Having income is <$30,000/year and willing to deliver at weekday nights	1.991 *(2.23)*	2.370 *(2.66)*	84
Random parameters			
Mean of selectivity correction term	5.936 *(4.39)*	-	-
Standard derivation of selectivity correction term	14.954 *(63.04)*	-	-
Model fit statistics			
Number of respondents	430	430	-
R-square	0.270	0.261	-
Corrected R-square	0.266	0.258	-
Number of Draws	1,000	1,000	-
Computed values			
Expectation to be paid (*ETP*)	$12.029/h	$11.898/h	101

Note: Insignificant parameters are underlined.

is to divide long delivery trips into multiple legs so *driver-partners* can cooperate to deliver one request. As such, *driver-partners'* route deviation is minimized.

We were interested to identify potential *driver-partners'* package ownership preference during our model design process. Interestingly, the coefficient of the variable for "I can deliver whosoever packages if I get paid" negatively influences delivery TTT. As such, respondents are more likely to travel longer when they transport freight or goods for friends, colleagues, relatives, or neighbors. This suggests that *driver-partners* are more willing to divert from their routes to transport packages for people who are closely linked to them. One way to potentially improve the *CS* market would be to link *CS* with individuals' social networks. Similarly, young people (i.e. less than 31 years old) and females are willing to travel longer to deliver packages.

The results also clearly show that the African American, American Indian, and Alaska native males parameter is positive and statistically significant. Therefore, this population segment is more likely to travel longer to deliver for *CS* companies. Likewise, respondents with low incomes (i.e. less than $30,001/year) are likely to travel longer to deliver freight at night. This result indicates that low-income respondents are more likely to accept work at times that are unattractive to other people.

Furthermore, the selectivity-bias parameters are statistically different from zero in the random parameter model that is estimated with the selectivity correction term. As such, the selectivity correction parameter varies significantly across observations. Therefore, the null hypothesis of the selectivity-bias parameter equals to zero can be rejected at the confidence level of more than 99%. These results also concur with our sample selectivity hypothesis; therefore, omitting the selectivity correction term leads to serious model misrepresentation. For instance, when comparing the two models estimated with and without the selectivity correction term, the parameters are remarkably different, especially the constant and "age" parameters. As such, when the selectivity bias terms are ignored, erroneous interpretation and conclusions are produced from the estimated results.

Above all, the parameters identified by both models are worth noting. Ratios of parameters estimated from the corrected model divided by the same variables' parameters computed from the un-corrected model have been recognized in various magnitudes (Table 5.6). Of all those ratios, the "*driver-partner's* pay expectation" and "age" ratios were the smallest and biggest (absolute) amounts, respectively. With regard to model estimations, all common parameters are found significant, except for the "age" parameter. The "age" parameter is not significant in the model estimated without the selectivity correction term.

In sum, it is crucial to realize the constructive role of having a selectivity correction term in a model. As presented above, the differences between the two models' goodness-of-fit values are small indeed. Nevertheless, the analogous importance of attributes, which practical implications are procured from, can vary considerably between the two models.

Expect-to-be-paid values

In this research, *ETP* is the amount *driver-partners* expect to be paid for their delivery driving time and other expenses (e.g., gasoline and vehicle maintenance costs). This amount is similar to the *WTW* value in [51]. The *ETP* value of the model with selectivity correction is approximately $12/hour, lower than the average *WTW* value reported by Miller et al. (2017) ($19/hour). Notwithstanding, this *ETP* value is within the $9.2 to $15.6 hourly value range of travel time saving published by the [210].

These *ETP* findings recommend that *CS* companies set compensation schemes that align with drivers' expectations. Consequently, applicants for working as *driver-partners* will potentially increase, and *driver-partners* are more likely to retain in the system afterwards. Likewise, knowing this average *ETP* value will help potential *driver-partners* to have a strategic compensation bidding for a shipment in a certain context.

5.6 Conclusions

Crowd-shipping and crowd-sourced delivery companies provide platforms that connect package *senders* to couriers who already travel. The system offers potential benefits to society, including mobility improvement, congestion reduction, and vehicular greenhouse gases emissions' deduction. In order to implement an effective and efficient system, a better understanding of the stakeholders, especially the *driver-partners* themselves, is needed. There was a lack of research on this topic; therefore, this study addressed the central questions regarding the factors that influence the behaviors (i.e. WTW and TTT) of those interested in joining the CS system. A survey was conducted to collect data for the discrete-continuous model estimations. A binary logit model was used to examine the factors that influence the WTW as *driver-partners*. An ordinary least-square regression model was employed to better understand the factors that affect the travel time decisions of potential *driver-partners*. The correlations of the discrete and continuous variables were corrected by a selectivity-bias term in the regression model. This correction is to prevent erroneous insights and conclusions derived from the results. Overall, the results show that the parameters have plausible signs and are statistically significant.

The contributions and suggested implementations of this research are of value to researchers, policymakers, CS companies, and couriers. First, the use of discrete-continuous approaches captures the maximum and random-utility behaviors derived from heterogeneous samples. A selectivity-bias term included in the regression model corrects for the conditional selection behavior of potential driver partners' maximum TTT. Additionally, the statistical significance of the random-selectivity bias parameter confirms the variation in respondents' behaviors. Second, the findings for the main socio-demographic characteristics that influence prospective *driver-partners'* WTW may potentially help CS companies to more successfully recruit employees. Future works should consider additional factors, such as package characteristics (e.g., weight and size), incentives, and scenario contextualization. As such, insights from the estimated results are helpful to assess the importance of the variables and circumstances in which individuals are willing to be driver partners. Those insights are also valuable to *CS* companies' operational strategies (e.g., matching criteria). Third, the use of incentives has a significant influence on the willingness of *driver-partners* to travel additional time for package pickup and delivery. *ETP* information is also helpful for *CS* companies' operational strategies. For example, driver partner compensations can be designed based on the time of the day and the day of the week. Similarly, couriers also have this *ETP* value for reference when bidding in the system for delivering packages. Fourth, there is a potential to share the data (e.g., trips' ODs, speed, and travel time) collected by *CS* firms, and integrate the data with daily transportation operation/management centers to improve the urban mobility, safety, and environment by optimizing traffic planning and management (e.g., traffic flow and public transport). By providing the data, *CS* companies also build trust with their regulators. Lastly, government agencies play a crucial role in growing the *CS* industry via legislations, regulations, and subsidies. For example, providing appropriate incentives, such as tax subsidies, to local industries to attract ordinary drivers to become *CS* driver partners is a recommended strategy.

In conclusion, this research has provided important insights into the behaviors regarding the supply generation of the *CS* system. Nonetheless, future research is still needed to validate those findings in different contexts and extend the knowledge within this field.

6. PRICING AND COMPENSATION SCHEMES FOR CROWD-SHIPPING SYSTEMS

6.1 Introduction

Delivery and shipping startups received considerable venture capital in the past several years [138]. A number of crowd-shipping (*CS*) and delivery firms received a substantial investment in the first quarter of 2018, for instance DoorDash–$535 million, BigBasket–$300 million, Instacart and Zomato–$200 million each, and Swiggy–$100 million [211]. *CS* companies offer services for different distances, such as for international, national, inter-city, and urban areas.

App-based services have become popular in logistics. A platform can bridge two agents: (1) '*couriers*' who are regular people or people who travel anyway by either public transport (i.e. metro or bus), taxi couriers, motorbike taxi couriers, people traveling by their private vehicles (e.g., car or bicycle), and (2) *'senders'* who are looking to send packages with saving cost and deliver as fast as possible. On the other hand, some people are willing to handle goods to work as *couriers*, but they do not know *demand* of goods and their origin or destination. A platform possibly provides additional incomes for *couriers* who do not even have vehicles, such as passengers of metro, tram and bus systems, but are willing to deliver parcels. The platform provides solutions for both *senders* and *couriers*, which represents the *demand* and *supply* sides, respectively.

Any *CS* platform should be able to match *senders* and *couriers* under their time constraints. In addition, the *senders* and *couriers* should be matched in order to maximize platform providers' revenues, hence, the matching algorithms should incorporate behavior rules of *demand* generation (i.e. willingness to pay–*WTP*) and *supply* generation (i.e. expected to-be-paid–*ETP*) as well as the *CS* firm's revenue model. These behavioral considerations in the model will improve the rule generation and their applicability to the real-world setting.

The goals of this paper are to design several pricing and compensation schemes under different scenarios and objectives, and to integrate matching and routing procedures. The contributions of this paper are threefold:

- We provide a comprehensive framework that integrates matching and routing strategies, together with pricing and compensation schemes. This integration is closer to the real-world business models, and it presents a better decision making process of *CS* firms.
- We develop and evaluate various pricing and compensation schemes under different *demand* and *supply* levels as well as consider the platform provider's profit, the sender's surplus, and the courier's surplus.
- We utilize real-world survey data of *WTP* and *ETP* to improve the reliability of our study. Moreover, our research is one of pioneer studies that use *WTP* and *ETP* values to examine the sensitivity of *CS* platform provider's profits. The findings help *CS* firm to improve operational models and better control external impacts.

Literature on *CS* systems generally integrates matching, routing, pricing, and compensation as four main important components in operations and management. However, there is no study that integrates three or four of those components together. Many studies focus on developing solutions to handle matching and routing issues [212, 213, 214]. Whereas, some other researchers investigate the relationship of matching and pricing decisions [215, 216, 217, 218]. A few studies explore the interactions of other two components, such as pricing and routing [219] or revenue and compensation [220]. There is no available study that considers pricing and compensation, routing and compensation, or matching and compensation. Study on the combination of more than two components potentially brings benefits for stakeholders. Consequently, there is a need for a solution approach that integrates pricing, compensation, matching, and routing [221].

This paper is organized as follows. Section 1 introduces background, motivations, literature gaps, and contributions of the paper. Section 2 describes the research's conceptual environment. Section 3 presents mathematical model formulation. Section 4 elaborates on our solution approach. Section 5 explains experimental design. Section 6 provides numerical results and gives a sensitivity analysis. Finally, Section 7 concludes the research and provides some suggestions for future studies.

6.2 Crowd-shipping environment description

If *couriers* are willing to carry packages, (s)he will turn the app on and be notified for any matching. The courier agrees to carry the package, then (s)he needs to accept the request. In addition, *couriers* can agree to collect or deliver goods within a distance from their preferences. All packages that need to be picked up and delivered are considered for trip sharing with *couriers*. In the following sections, the real world settings are reviewed to provide a conceptual foundation for our study.

Pricing strategies

There are several pricing strategies that *CS* companies apply. [31] studied 26 *CS* firms and realized that their pricing services are starting from $3.99 with an additional cost of $10 depending on requesting an express service or the package characteristics. Looking into several *CS* companies' websites, competitive services have been found. For example, Roadie offers a flat rate of $12 for a 10 lbs. box sized 20"*18"*12" delivered within 2 hours to an 11-mile radius in downtown Chicago. USPS, FedEx Express, and UPS delivery costs for the same package are $24, $31, and $32, respectively, for overnight or same-day delivery (computed from Roadie's website [222]). Deliv will ship the package same-day for $20.25, within 3 hours for $22.50, and within 2 hours for $32.50 (computed from Deliv's website [223]).

Instacart uses different *pricing* strategies for delivering groceries. Groceries are delivered free of charge if the bill exceeds $35. Otherwise, the delivery fee depends on the order size and selected delivery time [224]. Moreover, UberRUSH, available in New York City, San Francisco, and Chicago, has a fixed price for the first mile (\$5-6) and an additional fee for each subsequent mile (\$2.50- \$3) [225]. Postmates offers prices based on both delivery distance and shipment value. For all Chicago deliveries exceeding 15 miles, Postmates is reported as the cheapest courier compared to UberRUSH and FedEx [107].

Compensation strategies

The compensation probably is one of significant influential factors on occasional *couriers'* loyalty. In app-based taxi services, firms generally deduct about 10%-25% as the commission fee from what they charge *senders* [226]. In the *CS* market, *CS* firms often charge commission fees of 10% to 30%, such as RideShip–10%, Easybring–15%, TaskRabbit–20% [31], and UberEats, Grubhub, and Postmates–30% [227]. However, a *CS* company may apply a different commission fee strategy for a similar service offered in another city.

Furthermore, based on our survey results [26], the US respondents who are willing to work as *couriers* expect to be paid as high as 78% of the traditional carriers' charges. These statistics are an additional evidence for the potential competitiveness of the *CS* system.

Revenue models

[31] presented five revenue models which are "fixed prices," "negotiated prices," "financial and matching fees," "resale margins," "and memberships," applied by 26 *CS* companies. The "fixed prices" are often offered for standard packages which are sent within an urban area. The "negotiated prices" which is generally in a form of bidding among *couriers* for delivering an inter-city request. In the "financial and matching fees" model, *CS* companies play as a middle man to match *senders* and *couriers* and charges a matching fee. *senders* are negotiated prices with *couriers*. This model is

generally applied for international deliveries. Whereas, in the "resale margins" model, *CS* companies will be awarded commission from retailers based on the number of items ordered from the *CS* platform. In the "membership" model, customers will pay a fixed fee (e.g., per year) and have their items be delivered by *CS* companies. Each model has several advantages, and it can only be applied strategically to some market segments. As such, some companies only employ one revenue model, whereas some other companies use a combination of more than one model.

Deliveroo and UberEats estimate the total delivery fee by summing up the fixed pick-up fee, the fixed drop-off fee, and the distance fee [228, 229]. The distance is measured from the selected courier's location to the delivery location (Deliveroo), or from the pick-up location to the drop-off location (UberEats). A minimum delivery cost is applied and varies from the service location (e.g., city) or a mode of delivery (e.g., bicycle, scooter, or car). Tips are optional, and *couriers* typically receive all the tips. In addition, Uber has also applied 'busy fee' (i.e. surge price) when the *demand* for delivery is higher than the supplied *couriers*.

6.3 Mathematical model formulation

Table 6.1 presents an overview of all variables and parameters used in this paper. In the model building, the following assumptions are made:

- Requests for sending packages are known, including location and time for pick-up and drop-off.
- *Couriers'* schedules (i.e. the pick-up and drop-off time windows) are pre-defined.
- The ODs of *couriers* are pre-defined, and accordingly all parcels' ODs are matched.
- Packages are portable (i.e. appropriate weight and volume) and do not need any special preservation.

- Once being accepted as a transporter, the *courier* is responsible for picking up and dropping off the package. *Couriers* cannot return the packages to the *senders*, and every matched package assumes to be successfully delivered.

Table 6.1.: Overview of variables and parameters used

Sets	
A	Set of all package pickup nodes, $A = \{1, 2, .., n\}$
A'	Set of all package delivery nodes, $A' = \{n+1, n+2, .., 2n\}$
K	Set of all package sizes, $K = \{1, 2, 3\}$
H	Set of all couriers able to deliver packages, $\|H\| = m$
Indices	
i, j	Link of a request. $i \in A, j \in A'$
k	Index of the package size, $k \in K$
h, h'	Index of the courier willing to deliver a package, $h \in H, h' \in (H - h)$
Parameters	
n, m	Number of packages and couriers, respectively.
τ_h, τ'_h	Origin and destination of courier h, $\tau_h = 2n + h, h \in H$ and $\tau'_h = 2n + m + h, h \in H$.
$G(V, E)$	Graph with a set of nodes $V = A \cup A' \cup \{\tau_1, ..., \tau_m\} \cup \{\tau'_1, ..., \tau'_m\}$ and a set of links $E = V * V$ when $x^h_{ij} = 1$, $(i, j) \in E, \forall h \in H$.
WTP_i	Maximum price that a *sender* is willing to pay (WTP) for sending a package i, $\forall i \in A$.
ETP_h	Minimum compensation that courier h expects to be paid (ETP) per km, $\forall h \in H$.
$R^{h,k}$	Capacity of courier h for package size k, $\forall h \in H, \forall k \in K$.
d_{ij}, t_{ij}	Travel distance and travel time in link ij.
z_i	Binary variable, $z_i = 1$ if the request i is placed in the request bank, $z_i = 0$ otherwise.
Decision variables	
$c/C/C^h_{ij}$	Compensation rate per km (platform operator pays for *couriers*).
$p/P/P^h_{ij}$	Shipping price per km.
$x^{h,k}_{ij}$	Binary variable represents a matching status. $x^{h,k}_{ij} = 1$ if package i is matched with courier h. $x^{h,k}_{ij} = 0$ otherwise. $(i, j) \in E$, $\forall h \in H, \forall k \in K$.
S^h_i	Non-negative integer variable representing the time that courier h starts at location i.
$L^{h,k}_i$	Non-negative integer variable representing the upper bound the number of packages k that courier h carrying after serving node i.
z_i	Binary variable presenting if package i is placed in the request bank.

Objective function:

$$\underset{p,c,x_{ij}^{h,k},S_i^h,L_i^{h,k},z_i}{\text{Max}} \left[\sum_{i,j\in E} \sum_{h\in H} \sum_{k\in K} (p-c) * x_{ij}^{h,k} * d_{ij} \right] \tag{6.1}$$

Subject to:

$$p * d_{ij} \leq WTP_i, \forall (i,j) \in E, \forall h \in H \tag{6.2}$$

$$c \geq ETP_h * x_{ij}^{h,k}, \forall (i,j) \in E, \forall h \in H, \forall k \in K \tag{6.3}$$

$$p \geq c \tag{6.4}$$

$$\sum_{h\in H_i} \sum_{k\in K} \sum_{j\in E} x_{ij}^{h,k} + z_i = 1, \forall i \in E, \forall k \in K \tag{6.5}$$

$$\sum_{j\in V_h} \sum_{k\in K} x_{ij}^{h,k} - \sum_{j\in V_h} \sum_{k\in K} x_{j,i+n}^{h,k} = 0, \forall i \in A_h, \forall h \in H, \forall k \in K \tag{6.6}$$

$$\sum_{j\in A_h \cup \{\tau_h'\}} \sum_{k\in K} x_{\tau_h,j}^{h,k} = 1, \forall h \in H, \forall k \in K \tag{6.7}$$

$$\sum_{i\in A_h' \cup \{\tau_h\}} \sum_{k\in K} x_{i,\tau_h'}^{h,k} = 1, \forall h \in H, \forall k \in K \tag{6.8}$$

$$\sum_{i\in V_h} \sum_{k\in K} x_{ij}^{h,k} - \sum_{i\in V_h} \sum_{k\in K} x_{ji}^{h,k} = 0, \forall j \in A_h', \forall h \in H, \forall k \in K \tag{6.9}$$

$$x_{ij}^{h,k} = 1 \rightarrow S_i^h + s_i + t_{ij} \leq S_j^h, \forall (i,j) \in E_h, \forall h \in H \tag{6.10}$$

$$a_i \leq S_i^h \leq b_j, \forall i \in V_h, \forall h \in H \tag{6.11}$$

$$S_i^h \leq S_{n+i}^h, \forall i \in A_h, \forall h \in H \tag{6.12}$$

$$x_{ij}^{h,k} = 1 \rightarrow L_i^{h,k} + l_j \leq L_j^{h,k}, \forall (i,j) \in E_h, \forall h \in H, \forall k \in K \tag{6.13}$$

$$L_i^{h,k} \leq R^{h,k}, \forall i \in V_h, \forall h \in H, \forall k \in K \tag{6.14}$$

$$L_{\tau_h}^{h,k} = L_{\tau_h'}^{h,k} = 0, \forall h \in H, \forall k \in K \tag{6.15}$$

$$x_{ij}^{h,k} \in \{0,1\}, \forall (i,j) \in E_h, \forall h \in H, \forall k \in K \tag{6.16}$$

$$z_i \in \{0,1\}, \forall i \in A \tag{6.17}$$

$$S_i^h, L_i^{h,k} \geq 0, \forall i \in V_h, \forall h \in H, \forall k \in K \tag{6.18}$$

$$R^{h,k} \geq 0, \forall h \in H, \forall k \in K \tag{6.19}$$

$$P_{ij}^h, C_{ij}^h \geq 0, \forall (i,j) \in E, \forall h \in H \tag{6.20}$$

Table 6.2.: Description of the model constraints

Equation	Description
(6.1)	Maximize platform provider's profits.
(6.2)	Price should not be greater than WTP for sending a package i.
(6.3)	Courier's compensation should not be less than expected to be paid.
(6.4)	Price should not be less than compensation per km.
(6.5)	Package i either picked up or in the request bank.
(6.6)	The package is delivered if it is matched, and that package is picked up and delivered by the same courier.
(6.7)	Assures that a courier starts at its origin.
(6.8)	Assures that a courier arrives at its destination.
(6.9)	Eliminate sub-tour.
(6.10)	Courier follows the matched paths.
(6.11)	Courier follows the pickup and deliver time window of package i.
(6.12)	Pickup is happened before delivery.
(6.13)	Courier has a capacity that is enough for the next loading of package size k.
(6.14)	Courier cannot carry over its capacity.
(6.15)	Courier leaves its origin and arrives its destination empty.
(6.16-6.20)	Variables definitions.

6.4 Solution approach

Our optimization problem can be solved by either exact or heuristic approaches. An exact approach provides optimal solutions, but is time consuming and useful for small problem sizes only. On the other hand, heuristic approaches aim to produce good solutions in a reasonable time for any size instances. Therefore, in this paper, a specifically designed heuristic is employed to solve our problem on-hand.

In this study, the original problem is a mixed-integer non-linear problem (in both objective and constraints) which is NP-hard and difficult to solve in a reasonable time for larger instances. Therefore, we simplify the problem in two steps. First, in the routing part, rather than simultaneously computing route (i.e. distance), we separately compute the distances that are taken as inputs to the matching part. Secondly, we linearize the remaining problem into a mixed-integer linear problem.

A solution framework for routing and matching packages and *couriers* is illustrated in Figure 6.1. In the routing model, distances need to be computed using the inputs of packages' and couriers' characteristics. A distance from the current courier's location to the pickup point is calculated to assign a courier to a package(s). The output of the routing part is a matrix of distances. In the matching model, constraints of *senders* and *couriers* will take inputs from the routing model (i.e. distance matrix) as well as the pick-up and drop-off time, WTP and ETP values, etc., and be evaluated for the valid matches. The matched *couriers* and packages are picked up at origins and delivered to the final destinations.

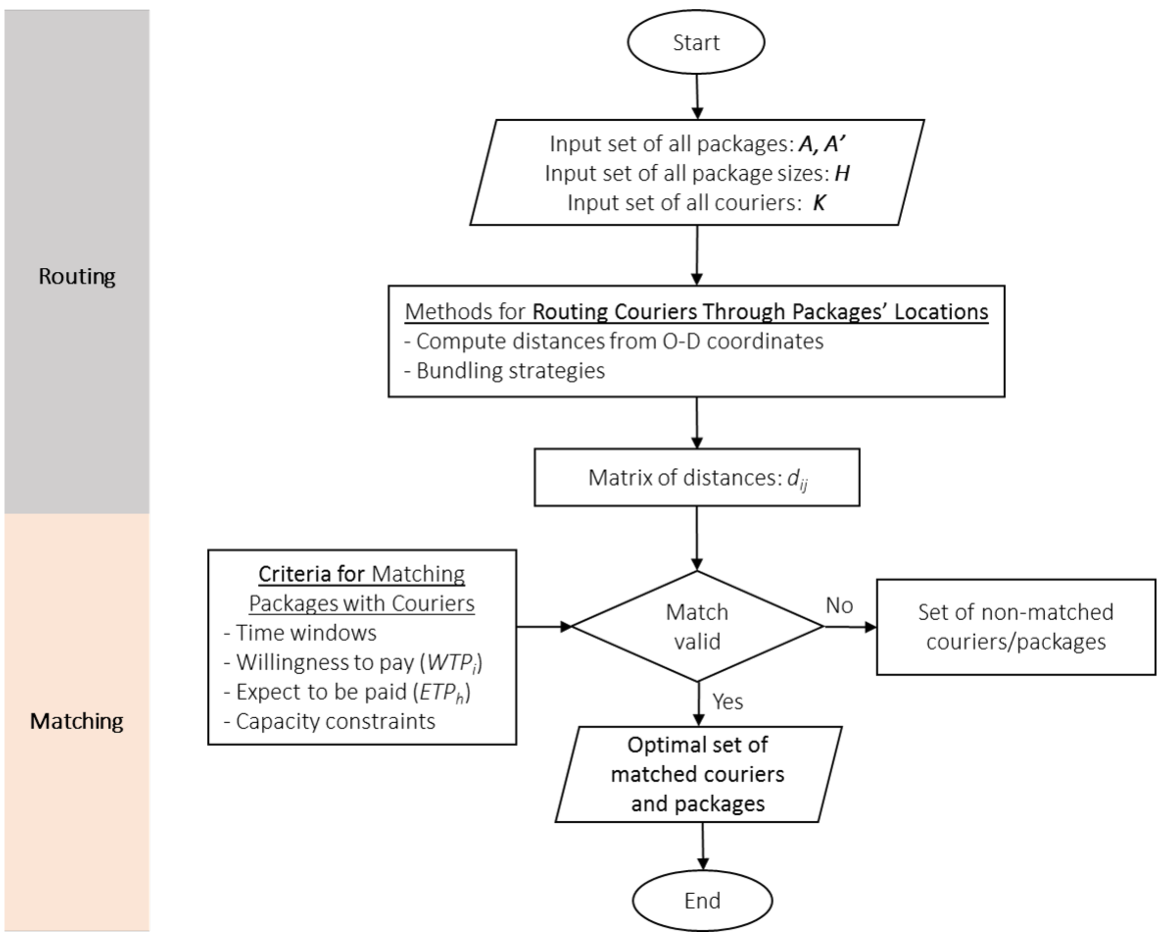


Figure 6.1.: An integrated framework of matching and routing

The next two sections introduce the distance calculations and the problem linearization employed.

Distance calculations

We distinguish between two ways to compute travel distance, namely the pure route distance versus the detour distance. In the former way, it is based on d_2 that is the distance from O_i to D_i (i.e. from package's pickup to drop-off points). In the latter way, it is $(d_1 + d_2)$ where d_1 is the distance from O^h to O_i (i.e. from courier's origin to package's pickup point). In this paper, the latter way is used (as we can always assign $d_1 = 0$, then the formulation is collapsed into the former way). A visualization of travel and delivery distances are presented in Figure 6.2.

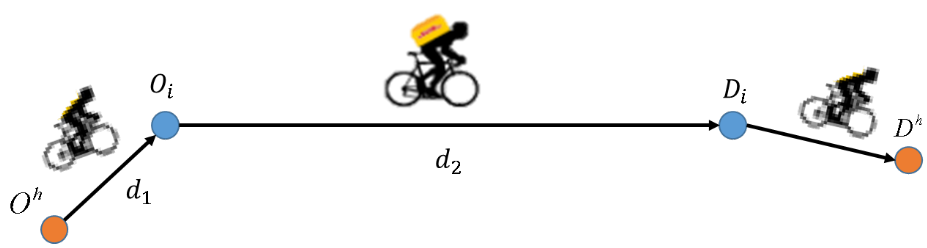


Figure 6.2.: A visualization of travel (d_1) and delivery (d_2) distances

Linearization

The optimization problem (6.1-6.20) is linearized utilizing the big M method:

$$p \geq P_{ij}^h, \forall (i,j) \in E, \forall h \in H \tag{6.21}$$

$$\sum_{k \in K} x_{ij}^{h,k} * M \geq P_{ij}^h, \forall (i,j) \in E, \forall h \in H, \forall k \in K \tag{6.22}$$

$$C_{ij}^h + (1 - \sum_{k \in K} x_{ij}^{h,k}) * M \geq c, \forall (i,j) \in E, \forall h \in H, \forall k \in K \tag{6.23}$$

Table 6.3.: Pricing and compensation schemes

Scheme	**Meaning**
FPFC	Flat Price, Flat Compensation
FPIC	Flat Price, Individual Compensation
IPFC	Individual Price, Flat Compensation
IPIC	Individual Price, Individual Compensation

6.5 Experimental design

This section presents the experiment design of the pricing and compensation schemes as well as the computational methods to estimate the surplus (SP) value for the different stakeholders.

Pricing and compensation schemes

We examine different pricing and compensation schemes, based on 'flat' versus 'individual' scheme settings. The 'flat' setting means that the price and compensation are the same for all requests and delivery trips. The 'individual' setting means that the price and compensation are applied to each request and delivery trip, respectively. Consequently, four different schemes are generated from combinations of these settings (Table 6.3).

The FPFC scheme can be applied when there is little difference in *demand* and *supply* levels. On the other hand, the other three remaining schemes can be used when *demand* and *supply* levels are significantly imbalanced.

Define P and C as flat price and flat compensation, respectively. Then, the objective functions under the four different schemes become as follows:

$$FPFC: \underset{P,C,x_{ij}^{h,k},S_i^h,L_i^{h,k},z_i}{\text{Max}} \left[\sum_{(i,j)\in E} \sum_{h\in H} (P-C) * d_{ij} \right] \tag{6.24}$$

$$IPFC: \max_{P_{ij}^h, C, x_{ij}^{h,k}, S_i^h, L_i^{h,k}, z_i} \left[\sum_{(i,j)\in E} \sum_{h\in H} (P_{ij}^h - C) * d_{ij} \right] \tag{6.25}$$

$$FPIC: \max_{P, C_{ij}^h, x_{ij}^{h,k}, S_i^h, L_i^{h,k}, z_i} \left[\sum_{(i,j)\in E} \sum_{h\in H} (P - C_{ij}^h) * d_{ij} \right] \tag{6.26}$$

$$IPIC: \max_{P_{ij}^h, C_{ij}^h, x_{ij}^{h,k}, S_i^h, L_i^{h,k}, z_i} \left[\sum_{(i,j)\in E} \sum_{h\in H} (P_{ij}^h - C_{ij}^h) * d_{ij} \right] \tag{6.27}$$

The value for the different stakeholders

Within the proposed setting, we have three stakeholders: (1) the platform provider, (2) the senders, and (3) the *couriers*. The described methodology can also be used to evaluate and optimize the value for each of these stakeholders.

We always aim to maximize the total profit, as given by 6.1, denoted here as OF_P. In addition to this objective (i.e. maximize profit–OF_P), we also examine the realized SP for the senders (i.e. SP_S) and the *couriers* (i.e. SP_C). The two SPes are realized given the difference between their WTP and the actual price paid (for the senders), and the actual compensation versus the ETP (for the couriers). As such, the value obtained for the three stakeholders is defined as follows:

- The platform providers (maximize profits, denoted as OF_P):

$$\sum_{(i,j)\in E} \sum_{h\in H} (P_{ij}^{h*} - C_{ij}^{h*}) * d_{ij} \tag{6.28}$$

- Senders (denoted as SP_S):

$$\sum_{(i,j)\in E} \sum_{h\in H} (WTP_i - P_{ij}^{h*} * d_{ij}) \tag{6.29}$$

- Couriers (denoted as SP_C).

$$\sum_{(i,j)\in E} \sum_{h\in H} (C_{ij}^{h*} * d_{ij} - ETP_h) \tag{6.30}$$

Equations (6.28), (6.29), and (6.30) are examples with denotations under the IPIC scheme.

6.6 Numerical results

The numerical results are summarized in the following sections. We first discuss the instance design. Then, we present the results on the number of matches for all pricing and compensation schemes. We also illustrate the analysis for the value of the different stakeholders.

All "% change" values are obtained from comparing the value of a scheme to that of the corresponding Flat Price, Flat Compensation (FPFC) scheme. The methodology is coded in Matlab and linked to CPLEX for solving the linear program. The computer used is an Intel(R) Core(TM) i7-6700, CPU 3.40GHz, and 16GB of RAM.

6.6.1 Instance design

First, different scenarios presenting several *demand* and *supply* levels are created. Secondly, the instance's characteristics are generated. Finally, relevant *CS* data obtained from previous research is used to illustrate the key insights of some instances' generated characteristics.

Supply versus Demand

We examine two scenarios of fewer *couriers* than *senders* (i.e. 50% and 80%), a scenario of equaling *couriers* and *senders*, and two scenarios of more *couriers* than *senders* (i.e. 120% and 140%). The five scenarios, its corresponding meaning, and tested instances are given in Table 6.4.

Graph information

We generated two datasets. Each dataset includes information on longitude, latitude, early pick-up time, late pick-up time, early drop-off time, and late drop-off time. Couriers' capacities are also created. In this study, package sizes k are simplified to have the same size. Furthermore, the values of WTP (of *senders*) and ETP

Table 6.4.: List of scenarios, meanings, and tested instances

Scenario	**Meaning**	**Tested instance**
SPL0.5DMD	*Supply* is 50% of *demand*	10 *couriers*, 20 Packages
SPL0.8DMD	*Supply* is 80% of *demand*	16 *couriers*, 20 Packages
SPL1.0DMD	*Supply* equals *demand*	20 *couriers*, 20 Packages
SPL1.2DMD	*Supply* is 120% of *demand*	24 *couriers*, 20 Packages
SPL1.5DMD	*Supply* is 150% of *demand*	30 *couriers*, 20 Packages

(of *couriers*) are also generated in the datasets based on the corresponding trends revealed from our previous studies.

All variables are randomly generated using a normal distribution. The range of longitude and latitude variables are from 10^{-3} to $2 * 10^{-1}$, while the pick-up time and drop-off time are in-between 9 AM and 21 PM. The late pick-up or drop-off times are always after the early pick-up or drop-off times. In this study, the distance between any two locations is computed by Haversine formula [230].

Crowd-shipping data

Regarding to the *WTP* and *ETP* data, we obtained corresponding values from our previous studies. The *WTP* values are from about $0.6 to $5 per delivery [27]. The *ETP* values are about $12 per hour [231]. However, some studies pointed out that respondents tend to lower their *WTP* and higher their expected utility. Therefore, in this study, the values of *WTP* for sending a package are defined between $5 and $10 per delivery, whereas the *ETP* per km for delivering a package takes any value between $0.5 and $1.

6.6.2 Number of matches

When applying the flat pricing and flat compensation scheme (i.e. FPFC), the number of matches is less than those of the 'individual' settings (FPIC, IPFC and IPIC). The results are summarized in Table 6.5. These findings are reasonable as *senders* and *couriers* are harder to be matched in the 'flat' settings compared to the 'individual' schemes. Moreover, all 'individual' settings appear to generate the same total number of matches, *couriers* in the matched situation are actually paired with different packages under distinct schemes.

The FPIC and IPIC schemes under the SPL1.2DMD scenario have the same 16 total number of matches. In which, 4 matches are the same. Table 6.6 shows 12 different matches of the two schemes. For example, in the match number 10, courier 18 in the FPIC scheme is matched with package 1, while courier 18 is matched with package 7 (i.e. new matched package) in the IPIC scheme. Meanwhile, package 1 is matched with courier 17 (i.e. new matched courier) in the IPIC scheme.

Table 6.5.: Number of matches under five scenarios across four schemes

	MPM	**FPFC**	**FPIC**	**% change**	**IPFC**	**% change**	**IPIC**	**% change**
SPL0.5DMD	10	8	8	0%	8	0%	8	0%
SPL0.8DMD	16	10	13	30%	13	30%	13	30%
SPL1.0DMD	20	6	14	133%	14	133%	14	133%
SPL1.2DMD	20	10	16	60%	16	60%	16	60%
SPL1.5DMD	20	11	15	36%	15	36%	15	36%

MPM: Maximum possible matches

(for each scenario, MPM = minimum {number of *couriers*, number of packages}).

6.6.3 Profit of the platform provider

The platform provider's profit increases from FPFC, FPIC, IPFC, to IPIC schemes under all scenarios (Table 6.7). Higher profits are obtained when the *supply* is close

Match ↓	**FPIC**		**IPIC**	
	Courier	Matched package	New matched courier	New matched package
1	2	17	x	10
2	4	8	13	4
3	6	11	23	5
4	8	5	x	15
5	12	4	4	x
6	14	9	x	20
7	15	10	x	17
8	16	15	8	x
9	17	7	x	1
10	18	1	17	7
11	20	12	21	3
12	21	3	20	12

Table 6.6.: An example of 12 different matches for FPIC and IPIC schemes under SPL1.2DMD scenario. The two schemes have the same total of 16 matches, but the table does not show 4 same matches. ('x' means not applicable)

Table 6.7.: Profits ($) of the platform provider under 4 schemes and 5 scenarios

	FPFC	**FPIC**	**% change**	**IPFC**	**% change**	**IPIC**	**% change**
SPL0.5DMD	14.14	16.32	15%	55.06	289%	56.66	301%
SPL0.8DMD	18.25	25.39	39%	70.63	287%	79.67	336%
SPL1.0DMD	7.18	12.56	75%	81.81	1039%	92.95	1194%
SPL1.2DMD	11.63	18.11	56%	95.23	719%	102.07	778%
SPL1.5DMD	9.55	18.23	91%	91.98	863%	96.92	915%

to or over the *demand*. Interestingly, for each scenario, all the 'individual' settings create the same number of matches (Table 6.5), but the benefits under the FPIC scheme are always about 3.5 to 7.5 times lower than those of IPFC or IPIC schemes.

The benefits of the IPFC and IPIC schemes significantly increase when the *supply* increases over the *demand*. However, the growth slightly decrease when the *supply* is about 1.5 times of the *demand*. On the other hand, the benefits of the FPFC and FPIC schemes hit maximum at the *supply* equals to 0.8 times of the *demand*. As such, different pricing and compensation strategies should be considered to apply for different time of the day or day of the week where the *demand* and *supply* are imbalanced.

The profit changes mainly come from three sources. The first source is from the FP to IP changes. In the FP scheme, packages can be sent at a price as low as $5 (i.e. minimum of senders' *WTP*), whereas, in the IP scheme, most of the packages need to be shipped at the prices of the senders' *WTP*, which can be as high as $10 in our settings. The second source is from the FC to IC changes. In the FC scheme, couriers can receive compensations as high as $1 per km (i.e. maximum of couriers' *ETP*), while, in the IC scheme, most of couriers can be paid at the compensations of the couriers' *ETP*, which can be as low as $0.5 per km in our settings. The third source is from the increasing number of matches. The number of matches under the FP scheme is much lower than under the IP scheme. The difference can be as high as 133%, as can be seen in Table 6.5.

Figure 6.3 presents an example of three sources of profits for FPFC and IPIC schems, under SPL1.2DMD scenario. As can be observed, benefits of the IPIC scheme which are generated from 3 same matches, 7 different matches, and 6 new matches are substantially larger than profits of the FPFC scheme. Indeed, profits of the IPIC scheme boost from the changes of FP to IP, FC to IC, and the new matches. The difference in profits of the two schemes is 778%.

6.6.4 Value analysis for the different stakeholders

Different stakeholders search for their own needs from *CS* systems. For example, the platform provider wants to increase new users and sustain the old users in its

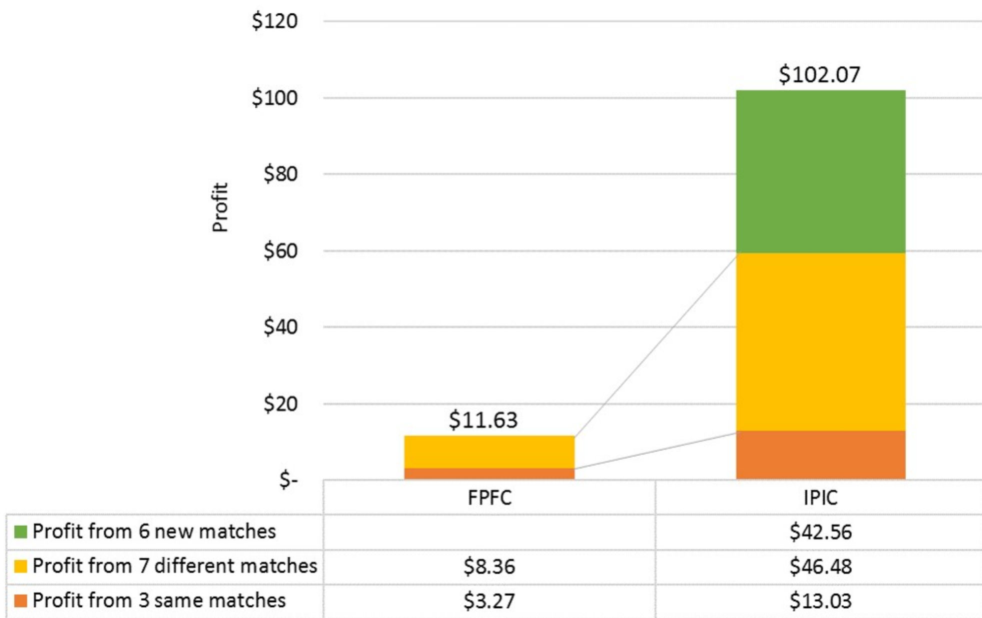


Figure 6.3.: An example of profits under SPL1.2DMD scenario for FPFC scheme vs IPIC scheme

system, but it also expects to have as much profit as possible. Senders, on the other hand, expect to ship at a low cost. Meanwhile, couriers may want to be paid high when they work as a *CS* driver-partner. Therefore, it is helpful to compare the benefits of platform providers, *couriers*, and senders under different schemes, and *demand* and *supply* scenarios. This subsection will discuss and provide insights about the comparisons. Benefits are summarized in Table 6.8. Note that the OF_P stands for the objective function of the platform provider, SP_S is the one for the sender and SP_C is related to the courier.

In general, under the FPFC scheme, when supply is about 80% of demand, the total benefits of stakeholders are maximize, while under the other schemes, the maximum benefits happen when supply is about 120% of demand. Moreover, total benefits of schemes that individualized price or compensation or both are always at least 1.5 times higher than those benefits under the FPFC scheme (except the SPL0.5DMD scenario in the FPIC scheme).

It is confirmed from the results that charging higher price to senders and paying higher compensation to couriers bring much higher total profits and surpluses to all stakeholders. The integrated models represent business model of some *CS* firms who potentially implement models developed from this study.

Table 6.8.: Value comparisons of the platform provider's profit, couriers' surplus, and senders' surplus under 3 objectives, 4 schemes, and 5 scenarios.

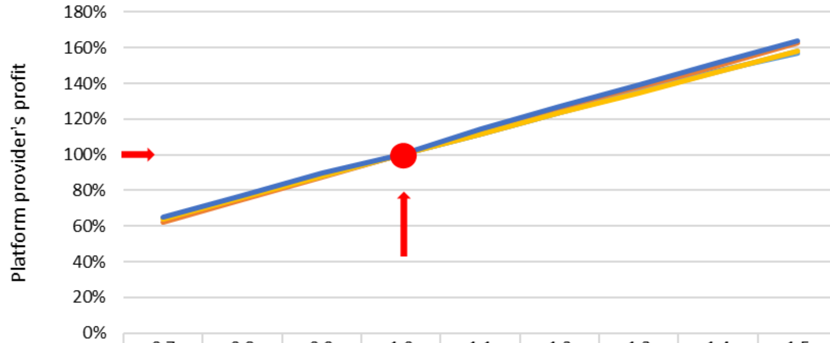
Scheme↓	**Scenario →**	**SPL0.5DMD**			**SPL0.8DMD**			**SPL1.0DMD**			**SPL1.2DMD**			**SPL1.5DMD**		
	Objective →	OF_P	SP_S	SP_C	OF_P	SP_S	SP_C	OF_P	SP_S	SP_C	OF_P	SP_S	SP_C	OF_P	SP_S	SP_C
FPFC	Platform provider' profit	14.14	3.75	6.58	18.25	4.92	8.57	7.18	1.86	3.29	11.63	3.94	6.27	9.55	4.34	6.25
	Senders' surplus	2.13	2.13	9.70	5.19	5.19	14.87	1.06	1.06	4.95	2.02	2.02	7.38	3.07	3.07	6.37
	Couriers' surplus	27.12	37.52	27.12	36.15	49.48	36.15	27.53	32.86	27.53	40.67	48.36	40.67	31.77	36.99	31.77
FPIC	Platform provider's profit	16.32	3.31	6.57	25.39	4.73	9.80	12.56	4.75	7.26	18.11	5.77	9.39	18.23	5.97	9.61
	Senders' surplus	27.13	40.15	27.13	49.98	70.65	49.98	67.71	75.52	67.71	72.05	84.39	72.05	64.93	77.19	64.93
	Couriers' surplus	0.00	0.00	9.75	0.00	0.00	15.59	0.00	0.00	5.30	0.00	0.00	8.72	0.00	0.00	8.61
IPFC	Platform provider's profit	55.06	2.39	13.40	70.63	5.72	19.85	81.81	4.24	20.60	95.23	5.55	24.60	91.98	5.77	24.17
	Senders' surplus	0.00	52.67	0.00	0.76	65.67	0.76	0.00	77.57	0.00	0.00	89.68	0.00	0.17	86.38	0.17
	Couriers' surplus	1.61	1.61	43.26	8.17	8.17	58.95	4.03	4.03	65.23	4.45	4.45	75.08	6.21	6.21	74.02
IPIC	Platform provider's profit	56.66	2.07	13.40	79.67	4.07	20.00	92.95	3.41	22.00	102.07	4.19	24.60	98.92	4.42	24.20
	Senders' surplus	0.00	54.60	0.00	0.00	75.60	0.00	0.00	89.54	0.00	0.00	97.88	0.00	0.00	94.50	0.00
	Couriers' surplus	0.00	0.00	43.26	0.00	0.00	59.67	0.00	0.00	70.95	0.00	0.00	77.47	0.00	0.00	74.72

6.6.5 Sensitivity analysis

Sensitivity analysis is generally conducted to investigate the robust of an outcome given the changes of an input. In this section, we evaluate the sensitivity of platform provider's profits by changing either senders' *WTPs* or couriers' *ETPs*. The senders' *WTPs* and the couriers' *ETPs* are key references for platform providers to determine price and compensation of a *CS* service. We set the platform provider's profits as well as *WTP* and *ETP* values under the IPIC scheme as base cases. Each input (either *WTP* or *ETP*) is varied from 0.7 to 1.5 times, compared to the corresponding base, with the interval of 0.1. In each evaluation, we only change one input and collect the changes of platform provider's profits under different *demand* and *supply* scenarios.

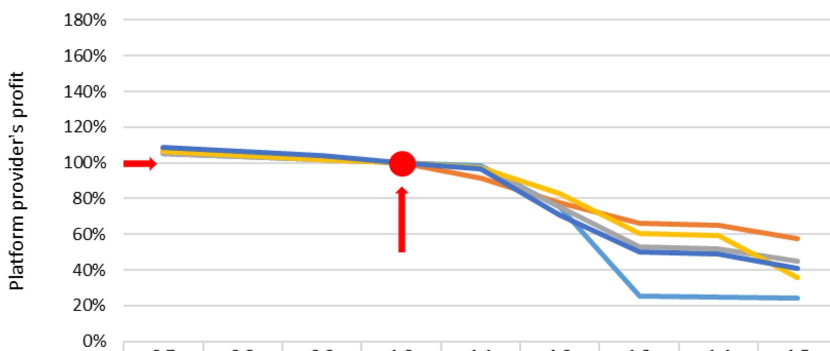
The sensitivity results are illustrated in Figures 6.4 and 6.5. As can be observed from Figure 6.4, the *WTPs* and the platform provider's benefits are strongly and positively correlated and only has proportional relationship when the changes of *WTPs* are small. When the changes are big (e.g., more than 1.4 times of the *WTP* bases), profits are more sensitive. In contrast to the *WTPs*, the *ETPs* and the platform provider's benefits are negatively correlated, as can be observed from Figure 6.5. When *ETPs* are low or just a bit higher than the bases, profits are a bit sensitive. Whereas, *ETPs* equal to 1.2 times or more of the base values, profits are highly sensitive in a negative way and significantly vary to the *demand* and *supply* levels. This is reasonable because the higher the *ETPs* are, the more difficult to match couriers with senders. As a result, the platform provider can only earn a limited amount.

Senders and couriers are both *CS* platform users. The users' behaviors, especially the *WTP* and *ETP*, significantly influence on *CS* firms' business model. Therefore, findings on the sensitivity of the platform provider's profit to the changes of senders' *WTP* and couriers' *ETP* provide helpful knowledge for *CS* firms to control external impacts and manage their operational strategies.



	0.7	0.8	0.9	1.0	1.1	1.2	1.3	1.4	1.5
SPL0.5DMD	64.5%	76.4%	88.2%	100.0%	111.8%	123.6%	135.5%	147.3%	157.0%
SPL0.8DMD	62.3%	74.9%	87.4%	100.0%	112.6%	125.1%	137.6%	150.2%	162.7%
SPL1.0DMD	64.5%	76.3%	88.2%	100.0%	111.6%	123.4%	135.3%	146.6%	158.0%
SPL1.2DMD	63.8%	75.9%	87.9%	100.0%	111.4%	123.4%	134.7%	146.3%	158.2%
SPL1.5DMD	64.8%	77.3%	89.7%	100.0%	114.5%	127.0%	139.0%	151.5%	163.9%

Figure 6.4.: Sensitivity of platform provider's profits due to *WTP* changes to its base (horizontal axis), under different *demand* and *supply* levels.



	0.7	0.8	0.9	1.0	1.1	1.2	1.3	1.4	1.5
SPL0.5DMD	105.5%	103.6%	101.8%	100.0%	98.2%	75.1%	25.1%	24.6%	24.1%
SPL0.8DMD	107.7%	105.1%	102.6%	100.0%	91.7%	77.4%	66.4%	65.1%	57.3%
SPL1.0DMD	105.5%	103.7%	101.8%	100.0%	97.1%	75.5%	52.8%	52.0%	45.2%
SPL1.2DMD	106.2%	104.1%	102.1%	100.0%	97.1%	82.6%	60.6%	59.3%	36.0%
SPL1.5DMD	108.9%	106.6%	104.3%	100.0%	96.8%	70.7%	50.3%	49.2%	41.0%

Figure 6.5.: Sensitivity of platform provider's profits due to *ETP* changes to its base (horizontal axis), under different *demand* and *supply* levels.

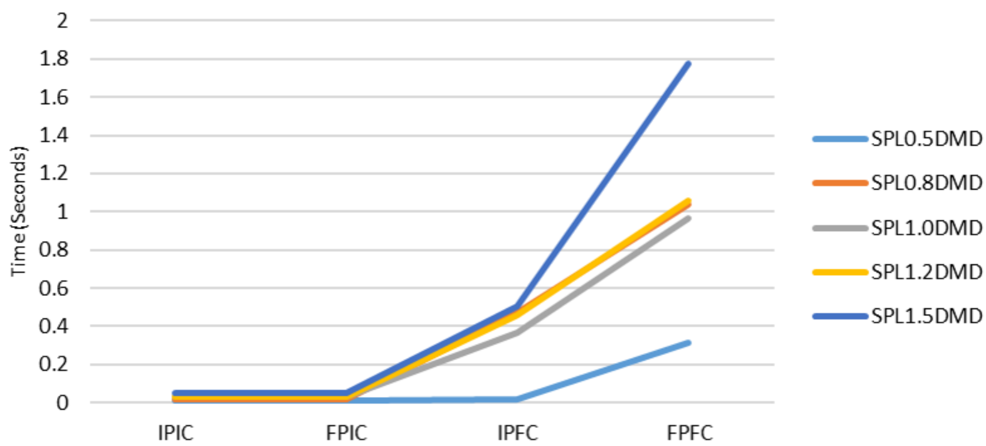


Figure 6.6.: Trends of computation time

6.6.6 Computation time

The computation time exponentially increases when the size of the instances becomes larger. The computation time trend for all scenarios of *supply* and *demand* are illustrated in Figure 6.6. As expected, scenarios under the FPFC scheme take the highest time to compute. Likewise, scenarios having bigger instances (i.e. number of couriers and packages) consume more time for estimation. In future work, more effective methods will be developed to evaluate larger instances sizes in an acceptable computation time.

6.7 Conclusions

The research is the first study in the *CS* field to combine matching and routing decisions incorporation with the *WTW* values of *couriers* and *WTP* values of *senders*. Instances have been generated and tested for the modeling approach under four pricing and compensation schemes and five *demand* and *supply* scenarios. Approximate distances have been computed and exact matching optimization problems have been estimated for the OF_P, SP_S, and SP_C objectives. The results show that under the IPIC scheme, the SP_S objective minimizes the *senders'* costs, whereas the

OF_P and SP_C objectives maximize platform providers' profits and *couriers*' compensations, respectively. The 'individual' settings are found to create more matches. Moreover, platform provider's profits are found more sensitive with the increases of *WTP* than the rises of *ETP*. The findings will help *CS* companies to further advance their business operations, policies, and strategies

Collectively, this study has provided alternative suggestions for *CS* companies to develop pricing and compensation strategies under some *demand* and *supply* scenarios and different objectives. However, this research has only solved a static problem and same size packages. The future research should develop a dynamic model, a penalty charge for cancellation *senders*, and new estimation methods (e.g., distributed algorithm) to sufficiently handle a big dataset (i.e. large *demand* and *supply*) in a timely manner. Additionally, to prevent *senders'* or *couriers*' regret of offering high *WTP* values or low *ETP* rates, the platform should be able to provide a suggested price for *senders* and a suggested compensation for *couriers*, depending on the contexts, for example of *demand* and *supply* levels.

The next study also is envisioned by promoting tradable credits generated from employing *couriers* who travel anyway. For instance, *CS* firms can compute carbon footprint savings from hiring travel anyway people, and then earn credits or subsidies from governments. This can be a fair way for government to promote for this kind of business towards sustainable delivery. Likewise, *couriers* can trade their credits for using some infrastructure in a certain time, such as a parking spot.

7. CONCLUSIONS

7.1 Summary

This dissertation has introduced contexts that illustrate the needs of effective and efficient services to fulfill the increasing demand for delivery as well as to create a sustainable society. Some contexts are the booming of e-commerce, changing in population structures and shopping tastes, increasing urban population, and raising congestion and double parking in urban areas. The dissertation has also presented contexts which leverage the *CS* implementations, such as the ease to access the Internet, high percentage of smart-phone usages, potential market for *CS* delivery, popularity of sharing-economy, and increasing concerns about environment.

In chapter 2, the potential benefits that *CS* services offer stakeholders are surveyed. Each stakeholder uses a *CS* service for their own needs, and their corresponding benefits vary. A review of the benefits for customers, merchants, and their communities is presented. This summary features theoretical and empirical inputs as practices and academic studies are reviewed. Meanwhile, our survey data is also used to strengthen statements and highlight the insights where appropriate. Customers can benefit from delivery time and cost saving, convenience of delivery time window and location personalization, and better accessibility to new or limited products. Retailers can reduce delivery costs, potentially generate more business, and have more delivery options. Society can achieve potential benefits from social equity, less traffic congestion, reduced pollution, and improved safety.

The main objective of chapter 2 is to review current practices, academic research, and empirical studies from the triad of *supply*, *demand*, and *operations and management*. After a systematic review, no single obstacle is surmounted that will raise the willingness to use *CS* services and the willingness to work as *CS driver-partners*.

Rather, the *CS* challenges are a series of behavioral, innovated and integrated technological, and law and regulation barriers to be considered. Drawing on the observed gaps and challenges in practice and scientific research, this chapter provides several avenues for promising areas of applications, *operations and management*, as well as improving behavioral and societal impacts to create a *CS* system that is complex, integrated, dynamic, and sustainable.

Chapter 3 analyzes current and future shipping behaviors, potential employees' *WTW* as *driver-partners*, as well as stakeholders' characteristics. *RP* and *SP* survey questionnaires were designed and implemented in the US. This descriptive study makes use of the survey dataset to understand the behavior of *requesters* and potential *driver-partners* in the logistics market and assumes that *crowdsourced* delivery is available. We studied sentiment of *requesters* and potential *driver-partners* as well as people who are not willing to work as a *driver-partner* in today's stage of *CS* availability in the logistics market, and seek to better understand their perceptions, thinking, and preferences on tomorrow's future logistics market. The results show various behaviors, expectations, and characteristics of *requesters*, as well as of prospective *driver-partners*.

The objective of chapter 4 is to understand how *senders* choose shipping services for different products, given the availability of both emerging *CS* and traditional carriers in a logistics market. Using data collected from a US survey, Random Utility Maximization (RUM) and Random Regret Minimization (RRM) models have been employed to reveal factors that influence the diversity of decisions made by *senders*. Shipping costs, along with additional real-time services such as courier reputations, tracking info, e-notifications, and customized delivery time and location, have been found to have remarkable impact on *senders'* choices. Interestingly, potential *senders* were willing to pay more to ship grocery items such as food, beverages and medicines by *CS* services. Moreover, the real-time services have low elasticities, meaning that only a slight change in those services will lead to a change in *sender*'s> behavior.

Finally, data-science techniques were used to assess the performance of the RUM and RRM models and found to have similar accuracies.

Chapter 5 investigates the different behavioral considerations that govern the choice of people to engage in a *CS* market. A binary logit model and an ordinary least-square regression model have been developed. Those models are integrated by a selectivity-bias term. The results suggest that socio-demographic characteristics, freight transportation experience, and social media usage significantly influence respondents' decisions to participate in the *CS* market. The selectivity is found available in the dataset and has strong heterogeneity. Moreover, the *driver-partners'* expect to-be-paid rate is found concurrent with value-of-time literature.

Chapter 6 is designed to identify optimal price and compensation strategies under five market penetration scenarios to achieve three objectives, namely the *CS* platform providers' benefit maximization, couriers' compensation maximization, and senders' cost minimization. As such, integrated matching and routing models have been developed. A routing strategy is established to estimate for distances that driver-partners need to travel for picking up and delivering packages. A matching model is developed to assign *CS* customers to driver-partners and to achieve objectives. Four different policies of pricing and compensation are developed and evaluated under five market penetration scenarios. *CS* firms are found to have the highest profits once applied the 'individual' pricing and compensation strategies. The insights are helpful for *CS* firms to retain customers and driver-partners in the system by setting up optimal prices and optimal compensations based on their expected profits.

7.2 Contributions

This dissertation contributes to literature, *CS* firms, traditional logistics industry, policymakers and government officers, and general public in manifolds.

7.2.1 Contributions to literature

The review provides up-to-date practices and research in the *CS* field. Researchers can find a systematic knowledge classified into a triad of *supply*, *demand*, *operations and management*. Researchers can also get some ideas for future studies which are suggested in our review.

Moreover, this dissertation contributes to the literature of designing *RP* and *SP* questionnaires assuming the *CS* service availability in the logistics market. The survey was designed using rigorous techniques to capture various aspects related to *requesters'* and prospective *driver-partners'* behaviors.

Other chapters developed models using statistics analysis, advanced econometrics, mixed integer optimization, and data science techniques. The processes of building and estimating the models benefit researchers and contribute to the literature in this field.

7.2.2 Contributions to *CS* firms

We review and look at startups' business models and assist *CS* firms a better understanding of challenges as well as areas to improve, what are potential market segments for *CS* systems, who are potential *driver-partners*, and suggest a clear go forward strategic directions.

Understanding both *demand* and *supply* sides is a key to promote for widespread *CS* services. The insights from this study allow *CS* firms to manage, understand, and utilize crosscutting data to identify potential market and develop business strategies. There are some remarkable benefits that *CS* firms can obtain. This study supplies several classifications of people who are *WTW* as *driver-partners* which help *CS* firms to focus on some specific population groups to recruit *driver-partners*. Meanwhile, knowing which classes of population are willing to receive packages from *CS* deliveries, *CS* firms can address the certain market segments to promote *CS* services. In addition, findings from this research provide knowledge for *CS* firms to make informed decisions of price and compensation strategies depending on the time of the day, or the day of the week as well as at different market penetration (rationales of *supply* and *demand*). *CS* firms also learn from insights to improve platform features to incorporate *requesters'* and *driver-partners'* expectations.

7.2.3 Contributions to *TLCs*

Even though research first appears to have strong focus on *CS* industry, it supplies valuable insights for *TLCs* as well. The questionnaires were designed with an assumption of the availability of *CS* services together with *TLCs* in a logistics market. As competitors, *TLCs* can also extract insights to clearly know which market segments have more or less competitive from *CS* firms as well as the ways *CS* firms operate and manage. Meanwhile, *TLCs* can also understand more about *requesters'* behaviors so they can tailor their services to address the *demand*. As such, *TLCs* can build effective and efficient business strategies.

7.2.4 Contributions to consulting companies

This study supplies consulting companies knowledge of *CS supply*, *demand*, *operations, and management*. The insights assist companies better understand the coming changes in logistics industry and the transportation and mobility future as a whole.

7.2.5 Contributions to government officers and policy makers

Maximizing public welfare is the alternate goals of government officers and policy makers. This study provides a systematic knowledge which will be helpful for enhancing policies and management qualities subjecting toward a better urban logistics industry. This research has offered some suggestions for: 1). facilitating the cooperation of *CS* firms and governments; 2). regulating the *CS* systems; and 3). maximizing public welfare.

7.2.6 Contributions to general public

This study also furnishes general public a better understanding of the *CS* system and its impacts. Other than providing information, this research also guides and facilitates the decision process of general public toward a sustainable society.

7.3 Future research directions

We have explored and solved several challenges in *CS* systems, but there are some more areas that future studies should address. First, after drop-off packages, the platform should suggest a location where *driver-partners* who continue to work in the system can wait so they will be highly matched to the next requests. This post-delivery suggestion will reduce the searching-travel of *driver-partners*, therefore, improve efficiency of the *CS operations and management* as well as reduce non necessary travels of *driver-partners*. The suggestions can be generated based on historical data of *driver-partners* and *demand* in that area, and real-time *driver-partners* locations using some machine learning and data mining techniques. Those advanced approaches will provide a better prediction of *demand* and *supply*, therefore, more helpful suggestions of waiting locations can be made.

Dynamic matching and routing models are worth to be examined for a better reflection of the real world operations. Also, bundling multiple packages for delivering by one *driver-partner* or multiple *driver-partners* delivering one package are also an interesting ideas to be considered. Moreover, *CS* platform should also integrate with ride-share cars and public transit schedules that facilitate people to deliver packages when they have a chance.

In this study, we are more of addressing on-the-way delivery and less emphases on the on-demand delivery since we think it is more affordable and efficient. Nevertheless, impacts of *CS* systems has not yet cleared in terms of environment, societal, and travel behaviors and need to be investigated in the future studies. Multiple questions still need to be answered, such as how much *CS* companies can really do to balance their benefits and control emissions; how much *requesters* are *WTP* to support sustainability? The preferred way to validate our findings and also examine the potential impacts is to utilize data from real operations which future researchers need to obtain, even thought it is a huge challenge.

Furthermore, this study has not investigated problems associated with *CS* in middle and long distance deliveries. Also, at different market penetrations of the *CS* and *TLCs*, many more business strategies should be investigated. Future studies should examine *CS* firms' business strategies in responses to the levels of *demand* of each product category as well as the levels of *supply* from *driver-partners* for the middle and long distance deliveries.

Likewise, this study has not yet investigated potential services for aging society (i.e. the changing in the societal structure, in general). The potential *demand* for delivering pharmaceuticals, health-care products, groceries, etc. for general public and particularity for the aging population segment needs to be examined.

In another aspect, the significant changes of technology as well as consumers tastes and behaviors also require fast adaptations of business strategies. Those interactions and relationships are envisioned. In addition, many cities are developing road maps for implementing connected and autonomous vehicles in the future. Those plans should not forget to include automated freight delivery. As such, future studies should also research on on this area where *CS* firms can employ robots, drones, and other machines for deliveries.

7.4 Conclusions

Collectively, we have correlated our findings and insights horizontally and vertically with contemporary literature to support, extend, or compliment the *CS* knowledge. The dissertation has revealed unobserved behaviors, preferences, and characteristics of stakeholders involving in *CS* systems. We have developed models by using statistics analysis, advanced econometrics, mixed integer optimization, and data science techniques that allow for examining stakeholders' characteristics and preferences. This dissertation provides informative knowledge for stakeholders to support for their decision makings.

Understanding how stakeholders in *CS* systems perform under a booming technology and other changes requires comprehensive and timely examinations of data from real operations. The *CS* industry is in its early stages and successes are necessary to be proven. However, it could bring potential values by ensuring better trust and transparency among *requesters* and *driver-partners* as well as being provided legal supports to facilitate services. This study has laid a foundation and provided several avenues for connecting to the future of technologies and urban mobility in up-coming studies.

APPENDICES

A. APPENDIX A: RESPONDENTS' SOCIO-DEMOGRAPHIC CHARACTERISTICS

For all tables at Appendixes A, B, and C, following notations and meanings have been applied:

- * values and distribution by percentage are statistics for indicator and other variables;
- - (sign): the variable/option is not available in the questionnaire;
- Bold font: the largest portion(s);
- ˆnumber: corresponding answer's option.

Table A.1.: Socio-demographic characteristics

Variables	**Min/ Max or Values***	**Mean/ Standard Deviation or Distribution***	
		Total samples (549 individuals)	***WTW* (430 individuals)**
Age (Years old)	19/ 68	36.06/11.06	36.42/ 10.79
Gender: Male/ Female.	1/ 2	45.50/ 54.50	47.20/ 52.80
Race/ ethnicity: African American^1/ American Indian, Alaska Native^2/ Asian^3/ Caucasian^4/ Hispanic, non-white^5/ Hispanic, white^6/ Others^7/ I prefer not to answer^8.	1/8	4.60^1/ 3.60^2/ 17.70^3/ **60.80**^4/ 3.30^5/ 5.30^6/ 3.30^7/ 1.50^8	4.90^1/ 4.20^2/ 16.50^3/ **61.40**^4/ 3.00^5/ 5.80^6/ 2.80^7/ 1.40^8
Marital status: Single/ Married/ Others.	1/3	**45.00**/ **44.80**/ 10.20	**43.30**/ **47.20**/ 9.50
Number of children.	0/ 6	0.94/ 1.25	1.00/ 1.27
Number of people living in your household are less than 18 years old.	0/ 6	0.84/ 1.23	0.90/ 1.23
Number of people living in your household are from 18 to 64 years old.	0/ 6	1.59/ 1.23	1.62/ 1.23
Number of people living in your household are 65 years old or older.	0/ 6	0.17/ 0.60	0.17/ 0.56
Final academic degree: Some high school^1/ High school diploma^2/ Technical college degree^3/ College degree^4/ Post-graduate degree^5/ I prefer not to answer^6.	1/6	0.40^1/ 12.90^2/ 8.60^3/ **48.50**^4/ 29.00^5/ 0.70^6	0.50^1/ 13.00^2/ 8.10^3/ **49.80**^4/ 28.40^5/ 0.20^6

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Table A.1.: Socio-demographic characteristics (cont.)

Variables	**Min/ Max or Values***	**Mean/ Standard Deviation or Distribution***	
		Total samples (549 individuals)	***WTW* (430 individuals)**
Employment status: Employed full time^1/ Employed part-time^2/ Student (RA/ TA) ^3/ Student (having scholarship/ fellowship)^4/ Student (self-funded)^5/ Retired and looking for job^6/ Retired and not looking for job^7/ Unemployed^8/ Unemployed^9/ Others^10/ I prefer not to answer^11.	1/11	**48.10**^1/ 16.00^2/ 9.50^3/ 5.50^4/ 6.20^5/ 0.40^6/ 2.20^7/ 4.60^8/ 4.40^9/ 2.90^10/ 0.40^11	**49.80**^1/ 16.50^2/ 8.60^3/ 4.90^4/ 5.60^5/ 0.50^6/ 1.90^7/ 4.90^8/ 3.50^9/ 3.50^10/ 0.50^11
Annual income ($1,000)	15/ 220	48.71/ 36.00	47.87/ 33.38
Type of accommodation: Owned/ Mortgage/ Rented/ Others.	1/4	29.50/ 20.00/ **49.00**/ 1.50	31.20/ 21.40/ **46.30**/ 1.20
Have car or motorbike operator license: No/ Yes.	0/ 1	12.60/ 87.40	11.40/ 88.60
Ownership (car): No/ Yes.	0/ 1	19.30/ 80.70	18.10/ 81.90
Mode usually used for commute to work/ school: Walking^1/ Bike^2/ Motor^3/ Car^4/ Bus^5/ Others transit mode (e.g., subway)^6/ Others^7.	1/ 7	14.60^1/ 5.10^2/ 2.70^3/ **65.90**^4/ 8.60^5/ 2.20^6/ 0.90^7	13.70^1/ 4.90^2/ 3.30^3/ **66.50**^4/ 8.40^5/ 2.30^6/ 0.90^7
Mode do you usually use for other purpose: Walking^1/ Bike^2/ Motor^3/ Car^4/ Bus^5/ Others transit mode (e.g., subway)^6/ Others^7.	1/ 7	13.70^1/ 6.60^2/ 2.20^3/ **69.20**^4/ 6.40^5/ 1.30^6/ 0.70^7	13.00^1/ 7.90^2/ 2.80^3/ **68.80**^4/ 5.60^5/ 1.20^6/ 0.70^7
Total access time to the closest transit station/ bus stop (Minutes)	0/ 32	23.68/ 11.18	23.43/ 11.30
Using smart phone: No/ Yes.	0/ 1	4.70/ 95.30	5.10/ 94.90

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Table A.1.: Socio-demographic characteristics (cont.)

Variables	Min/ Max or Values*	Mean/ Standard Deviation or Distribution*	
		Total samples (549 individuals)	***WTW*** (430 individuals)
Social media usages: Yes, frequently^1/ Yes, sometimes^2/ Yes, occasionally^3/ Yes, rarely^4/ No, not at all^5.	1/5	**77.60**^1/ 10.40^2/ 5.30^3/ 4.00^4/ 2.70^5	**77.90**^1/ 10.20^2/ 5.10^3/ 4.00^4/ 2.80^5
What social media do you use: Facebook^1/ Twitter^2/ YouTube^3/ Reddit^4/ Tumblr^5/ Instagram^6/ Pinterest^7/ Vine^8/ Ask.fm^9/ Flickr^10/ Google+^11/ LinkedIn^12/ VK^13/ Meetup^14/ Others^15.	1/15	**90.89**^1/ 43.89^2/ **70.86**^3/ 22.95^4/ 8.20^5/ 45.90^6/ 36.43^7/ 1.82^8/ 0.54^9/ 4.00^10/ 28.42^11/ 37.52^12/ 0.36^13/ 4.00^14/ 2.19^15	**90.93**^1/ 45.58^2/ **73.25**^3/ 24.19^4/ 8.84^5/ 46.05^6/ 36.51^7/ 1.86^8/ 0.70^9/ 3.72^10/ 30.00^11/ 37.67^12/ 0.46^13/ 3.72^14/ 1.86^15
Total number of social media uses	0/ 10	4.00/ 2.05	4.07/ 2.08

B. APPENDIX B: COURIER SELECTION BEHAVIOR

Table B.1.: Courier selection behavior (RP)

Variables	**Min/ Max or Values***	**Mean/ Standard Deviation or Distribution*** $\mathbf{n1 = n11 + n12 = 549}$	
Experience: Sending package/purchase online.	1/2	38.25/ 61.75	
I: Sending package; II: Purchase online		**I.** (n11 = 210)	**II.** (n12 = 339)
What have you sent to someone else/ you bought (multiple choices): Dry cleaning, fast foods, lunch, dinner, birthday cake, etc (immediate delivery)^1/ Groceries^2/ Beverage, dry foods^3/ Personal health, medicine^4/ Apparel^5/ Books, Music, Videos^6/ Consumer electronics^7/ Others^8.	1/8	6.48^1/ 6.78^2/ 5.30^3/ 12.97^4/ **38.93**^5/ **34.51**^6/ 25.68^7/ 22.41^8	10.95^1/ 14.28^2/ 10.95^3/ 23.80^4/ **34.76**^5/ 25.71^6/ **30.95**^7/ 17.61^8
(I) From where did you ship the item: Home/ Office/ Others; (II) Which website/shop did you buy the item from: Ebay^1/ Amazon^2/ ModCloth^3/ CololBlue^4/ Others^5.	(I) 1/3; (II) 1/5	**74.90**/ 13.30/ 11.80	6.20^1/ **71.00**^2/ 1.00^3/ 0.50^4/ 21.40^5
(I) Approximate value of the item you requested to deliver; (II) How much did you pay for the item which you have bought it online ($).	(I) 5/6,000; (II) 4/3,000	176.2/ 492.72	115.02/ 336.53
Delivery carrier: (I, II) DHL^1/ UPS^2/ FedEx^3/ USPS^4/ By retail's personnel^5/ Others^6.	(I, II) 1/6	6.20^1/ 28.60^2/ 15.30^3/ **47.50**^4/ 1.20^5/ 1.20^6	4.30^1/ **42.40**^2/ 20.50^3/ 26.20^4/ 5.20^5/ 1.40^6

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Table B.1.: Courier selection behavior (RP) (cont.)

Variables	**Min/ Max or Values***	**Mean/ Standard Deviation or Distribution*** **n1 = n11+ n12 = 549**	
Experience: Sending package/purchase online.	1/2	38.25/ 61.75	
I: Sending package; II: Purchase online		**I.** (n11 = 210)	**II.** (n12 = 339)
Payment method: (I) Paid for the courier by payment card (credit/ master/ etc) ^1/ Paid at store by payment card^2/ Paid for the courier by cash^3/ Paid at store by cash^4/ Paid online^5/ Others^6; (II) Paid for the courier once the package was delivered at home (or office/ shop/ etc) by cash^1/ Paid at store by cash^2/ Paid for the courier once the package was delivered at home (or office/ shop/ etc) by payment card^3/ Paid at store by payment card^4/ Paid online^5/ Free shipping (annual/prime member) ^6/ Free shipping (since one have paid over a certain amount for my purchase) ^7/ Others^8.	(I) 1/5; (II) 1/4	20.90^1/ 28.90^2/ -^3/ 13.60^4/ **33.60**^5/ 2.90^6	-^1/ 3.30^2/ -^3/ -^4/ 21.00^5/ **44.80**^6/ 31.00^7/ -^8
Time for deliver (Hours)	(I) 0.75/23; (II) 0.5/ 19	7.65/ 1.27	4.25/ 2.01
Time for deliver (Days)	(I) 1/28; (II) 1/18	3.22/ 0.09	3.46/ 0.13
Satisfaction with the delivery time: No/ Yes.	0/1	5.90/**94.10**	9.00/ **91.00**

continuation on the next page

Table B.1.: Courier selection behavior (*RP*) (cont.)

Variables	**Min/ Max or Values***	**Mean/ Standard Deviation or Distribution*** **n1 = n11+ n12 = 549**	
Experience: Sending package/purchase online.	1/2	38.25/ 61.75	
I: Sending package; II: Purchase online		**I.** (n11 = 210)	**II.** (n12 = 339)
Able to track and trace the item online: Yes, I could track via carrier's website (and/or app)/ No, I could not track it.	1/2	**94.40**/ 5.60	**91.90**/ 8.10
Satisfaction with electronic delivery notification: Yes, I was satisfied with the service/ No, the service was not good/ No, they did not provide the service.	1/3	**82.60**/ 3.80/ 13.60	**84.30**/ 4.80/ 11.00
Choose the pickup (I)/delivery (II) time window: Yes, I could, and I used that service/ Yes, I could, but I did not use that service/ No, I could not. The carrier did not offer that service.	1/3	19.50/ 36.60/ **44.00**	30.00/ 20.50/ **49.50**
Carriers offer pickup at home (I)/ provide convenient drop-off location (II): Yes, but I have never used the service^1/ Yes, the service is excellent^2/ Yes, the service is good^3/ No, the service is bad^4/ I have no idea about the service^5.	1/5	**33.90**^1/ 19.80^2/ 17.40^3/ 5.00^4/ 23.90^5	20.00^1/ **36.20**^2/ 24.80^3/ 1.90^4/ 17.10^5
Did you tip the delivery person: No/ Yes.	0/1	92.90/ 7.10	97.60/ 2.40
Number of times did: you use the service of the carrier per year.	(I, II) 1/300.	18.41/ 35.92	19.23/ 27.98

Table B.2.: Courier selection behavior - Sending a package (*SP*)

Variables	**Min/ Max or Values***	**Percentages or Mean/ Standard Deviation (1098 observations (549 individuals))**
Courier selection (Dry cleaning, fast foods, lunch, dinner, birthday cake, etc (immediate delivery)): couriers 1 - 4	1/4	**31.40/ 26.00/ 24.80**/ 17.90
Courier selection (Groceries): couriers 1 - 4	1/4	**27.90/ 26.70**/ 21.90/ 23.60
Courier selection (Beverage, dried foods): couriers 1 - 4	1/4	**26.00/ 26.70**/ 19.30/ **28.10**
Courier selection (Personal health, medicine): couriers 1 - 4	1/4	23.10/ 21.40/ 20.20/ **35.20**
Courier selection (Apparels): couriers 1 - 4	1/4	21.00/ 19.00/ 10.50/ **49.50**
Courier selection (Books, Music, Videos): couriers 1 - 4	1/4	23.10/ 17.60/ 11.90/ **47.40**
Courier selection (Consumer electronics): couriers 1 - 4	1/4	22.90/ 16.00/ 15.70/ **45.50**
Courier selection (Others): couriers 1 - 4	1/4	24.30/ 16.00/ 11.90/ **47.90**
When do you prefer to get your packages to be delivered to your house (multiple choices): Weekdays, 6-9AM^1/ Weekdays, 9AM-noon^2/ Weekdays, noon-3PM^3/ Weekdays, 3-6PM^4/ Weekdays, 6-8PM^5/ Weekdays, 8-10PM^6/Weekdays, 10PM-6AM next day^7/ Weekend, 6-9AM^8/ Weekend, 9AM-noon^9/ Weekend, noon-3PM^10/ Weekend, 3-6PM^11/ Weekend, 6-8 PM^12/ Weekend, 8-10PM^13/ Weekend, 10PM-6AM next day^14/ I do not have any preference. Any time is ok^15	1/15	10.00^1/ 16.67^2/ 19.52^3/ 30.47^4/ **35.23**^5/ 19.04^6/ 7.61^7/ 10.95^8/ **33.80**^9/ **38.09**^10/ **34.76**^11/ 20.95^12/ 12.85^13/ 5.71^14/ 24.76^15
Your concerns once your package is delivered by a *driver-partner* (multiple choices): Deliver on time or not/ Without damage or not/ Others	1/3	67.14/ 84.76/ 8.57
Preference on the mode that the courier chooses (multiple choices): Drone^1/ Walking^2/ Bike^3/ Motor^4/ Car^5/ Bus^6/ Others transit mode (i.e. subway) ^7/ I do not have any preference; it does not matter^8/ Others^9	1/9	7.14^1/ 10.00^2/ 12.38^3/ 14.76^4/ 29.52^5/ 8.09^6/ 5.23^7/ **64.76**^8/ 2.38^9

C. APPENDIX C: WILLINGNESS TO JOIN A *CS* SYSTEM

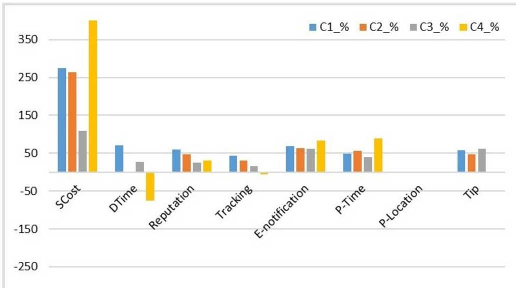
Table C.1.: Willingness to join a *CS* system (*RP* and perceptions)

Variables	**Min/ Max or Values***	**Percentages or Mean/ Standard Deviation (430 individuals)**
Experience with transporting packages for somebody: No/Yes.	0/ 1	**74.32**/ 25.68 (n=549)
WTW as a *driver-partner*: No/ Yes.	0/ 1	21.68/ **78.32** (n=549)
Situations would you like to be a *driver-partner* (multiple choices): During my commute/ During my leisure trips/ In my free time/Others.	1/ 4	**70.00**/ 50.00/ **70.23**/ 1.62
Total numbers of situations where you would be a *driver-partner*.	1/ 4	1.50/ 1.05
When would you like to ship the freight (multiple choices): Weekdays, morning time^1/ Weekdays, afternoon time^2/ Weekdays, evening time^3/ Weekend, morning time^4/ Weekend, afternoon time^5/ Weekend, evening time^6/ Others^7.	1/ 7	**42.79**^1/ 38.60^2/ **44.88**^3/ 40.00^4/ **44.65**^5/ 34.18^6/ 2.79^7
Total time slots you like to ship the freight	1/ 7	1.94/ 1.61
Maximum diversion (as a percent of distance) (%)	3/ 100	31.24/ 19.22
Maximum distance (base 5 miles) (Miles)	0/ 50	12.16/ 10.66
Maximum diversion (in time) (base 20 minutes) (Minutes)	0/ 100	23.40/ 117.51
ETP as a *driver-partner* (base $15) ($)	0/ 30	11.70/ 4.59
Why you may NOT deliver freight for somebody else: The incentive (money paid) is not high enough/ I do not have time/ I do not like to do it/ Others.	1/4	9.20/ **42.90**/ 37.00/ 10.90. (n = 119)

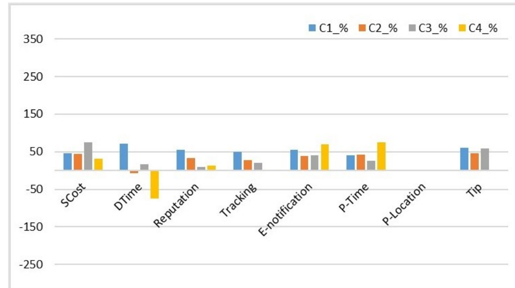
Table C.2.: Willingness to join a *CS* system (*SP* and preference)

Variables	**Min/ Max or Values***	**Percentages or Mean/ Standard Deviation (430 individuals)**
Selecting packages: items 1 - 4.	1/ 4	21.60/ 37.30/ 24.90/ 16.20
Preference for the item to be shipped: Dry cleaning, fast foods, lunch, dinner, birthday cake, etc (immediate delivery)^1/ Groceries^2/ Beverage, dry foods^3/ Personal health, medicine^4/ Apparel^5/ Books, Music, Videos^6/ Consumer electronics^7/ No preference-do not care^8.	1/ 8	23.72^1/ 25.58^2/ 26.04^3/ 36.51^4/ 48.13^5/ 46.74^6/ 33.72^7/ **60.00**^8
Whose packages or goods would you prefer to deliver: Your close friends, close colleagues^1/ Your friends, colleagues^2/ Your relatives^3/ Your neighbors^4/ Whosoever, I do not care once I get paid^5/ Others^6.	1/ 6	42.32^1/ 36.74^2/ 39.76^3/ 32.55^4/ **87.44**^5/ 1.16^6
What would be your concerns if you choose to work as a *driver-partner*: Hazardous materials, dangerous items^1/ Illegal substances, products^2/ Insurance if something bad happens^3/ Person is not at home^4/ Others^5.	1/5	**82.09**^1/ **93.02**^2/ 2.79^3/ -^4/ 11.62^5

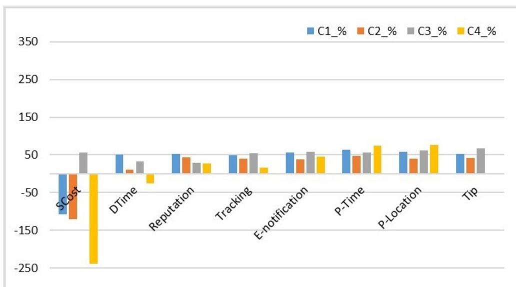
D. APPENDIX D: PD'S ELASTICITY DIFFERENCES



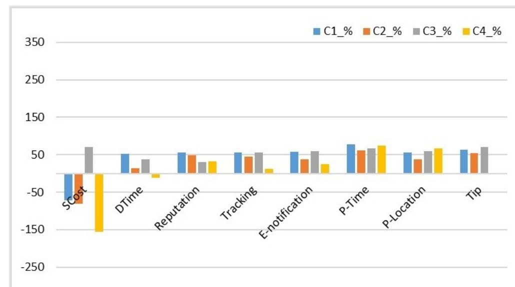
(a) PD1's elasticity differences (%)



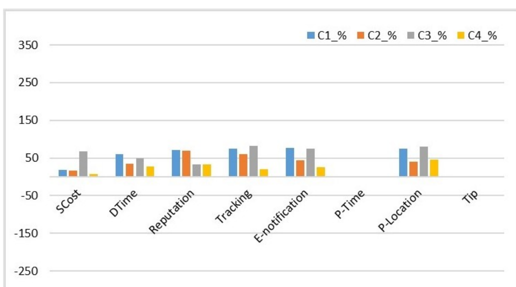
(b) PD2's elasticity differences (%)



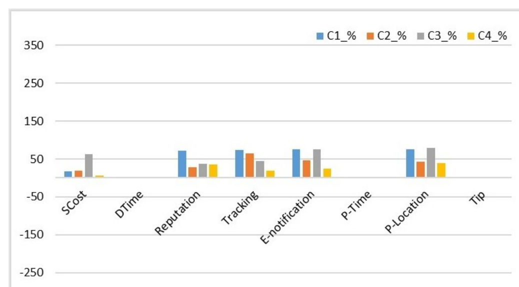
(c) PD3's elasticity differences (%)



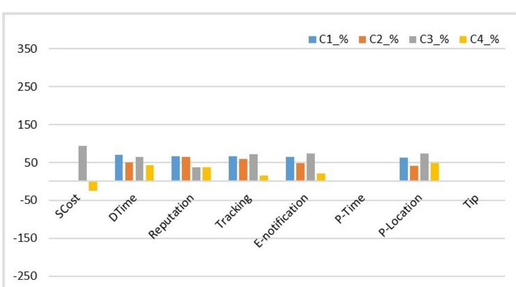
(d) PD4's elasticity differences (%)



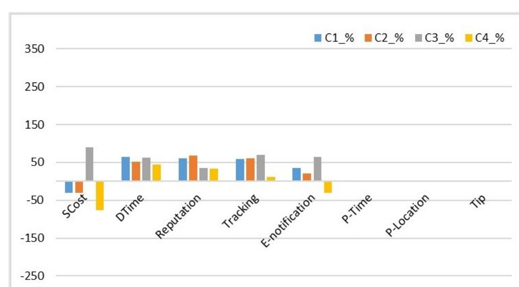
(e) PD5's elasticity differences (%)



(f) PD6's elasticity differences (%)



(g) PD7's elasticity differences (%)



(h) PD8's elasticity differences (%)

Figure D.1.: Differences of RUM and RRM models' elasticities on alternatives' attributes

E. APPENDIX E: IRB APPROVALS

CoeusLite

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List of All Protocols

Protocol Number	Title	Status	Approval Date	Expiration Date
1701018620	SURVEY TO UNDERSTAND THE BEHAVIOR OF STAKEHOLDERS IN CR ...	Active - Open to Enrollment	01/30/2017	01/29/2018

coeus-system@lists.purdue.edu
Mon 1/30, 12:58 PM
Tho Van Le; UKKUSURI, SATISH V <SUKKUSUR@PURDUE.EDU>

Reply all

SYSTEM GENERATED EMAIL - PLEASE DO NOT REPLY

Your IRB Protocol has been APPROVED by the IRB.

HRPP-IRB –

FINDING CONSENT FORMS

For all protocols requiring Consent Forms, the most recent approved consent forms, with watermark, can be found as pdfs in the Attachments Tab. Alternatively, you can

- go to Protocol History on the left hand side of the screen,
- then to the "Amendments/Renewals History" tab.
- Click on the submission of interest. You will then see all the documents you submitted under "Attachments".
- Select the pdf versions of the consent forms to retrieve the approved documents with the IRB watermark (aka approval stamp).
- For any questions regarding these approved forms, please contact IRB-Questions@purdue.edu.

FINDING IRB CORRESPONDENCE
o The IRB correspondence for your protocol can be found in the protocol under Protocol History from the left hand side of the screen, at the View History tab.
o Expand on the Action you want to review (Approval, Revision, etc.) near the top/center of the view field, by clicking the "plus" sign.
o Below will appear a section containing "Correspondences". This is in WHITE font, so may be hard to see.
o Under Correspondences, select "View" to see the Letter that you want to see. "View" is in small font, toward the middle of the screen.

Extension Educators - To view the Requested Revisions Letter, see attached memo, or click on the first link below, log into CoeusLite with your Career Account, and select IRB Admin Attachments from the left navigation. The document explaining the necessary revisions and how to complete them may be reviewed by clicking "View" next to the most recent Revisions Requested letter.

Protocol #: 1701018620
Sequence #: 2
Investigator: UKKUSURI, SATISH V
Title: SURVEY TO UNDERSTAND THE BEHAVIOR OF STAKEHOLDERS IN CROWD-SHIPPING MARKET

Please use the link given below for the project details.

You can view this protocol through CoeusLite at the following address: https://coeus.itap.purdue.edu/coeus/getProtocolData.do?SEARCH_ACTION=SEARCH_WINDOW&protocolNumber=1701018620&PAGE=G&sequenceNumber=2

For Assistance with CoeusLite, please contact coeushelp@purdue.edu

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HUMAN RESEARCH PROTECTION PROGRAM
INSTITUTIONAL REVIEW BOARDS

To:	SATISH UKKUSURI HAMP
From:	JEANNIE DICLEMENTI, Chair Social Science IRB
Date:	11/08/2017
Committee Action:	Expedited Approval for Renewal - Category(7)
IRB Approval Date	11/08/2017
IRB Protocol #	1701018620
Renewal Version	Renewal-001: Renewal-001:
Study Title	SURVEY TO UNDERSTAND THE BEHAVIOR OF STAKEHOLDERS IN CROWD-SHIPPING MARKET
Expiration Date	11/07/2018
Subjects Approved:	10000

The above-referenced protocol has been approved by the Purdue IRB. This approval permits the recruitment of subjects up to the number indicated on the application and the conduct of the research as it is approved.

The IRB approved and dated consent, assent, and information form(s) for this protocol are in the Attachments section of this protocol in CoeusLite. Subjects who sign a consent form must be given a signed copy to take home with them. Information forms should not be signed.

Record Keeping: The PI is responsible for keeping all regulated documents, including IRB correspondence such as this letter, approved study documents, and signed consent forms for at least three (3) years following protocol closure for audit purposes. Documents regulated by HIPAA, such as Authorizations, must be maintained for six (6) years. If the PI leaves Purdue during this time, a copy of the regulatory file must be left with a designated records custodian, and the identity of this custodian must be communicated to the IRB.

Change of Institutions: If the PI leaves Purdue, the study must be closed or the PI must be replaced on the study through the Amendment process. If the PI wants to transfer the study to another institution, please contact the IRB to make arrangements for the transfer.

Changes to the approved protocol: A change to any aspect of this protocol must be approved by the IRB before it is implemented, except when necessary to eliminate apparent immediate hazards to the subject. In such situations, the IRB should be notified immediately. To request a change, submit an Amendment to the IRB through CoeusLite.

Continuing Review/Study Closure: No human subject research may be conducted without IRB approval. IRB approval for this study expires on the expiration date set out above. The study must be close or re-reviewed (aka continuing review) and approved by the IRB before the expiration date passes. Both Continuing Review and Closure may be requested through CoeusLite.

Unanticipated Problems/Adverse Events: Unanticipated problems involving risks to subjects or others, serious adverse events, and serious noncompliance with the approved protocol must be reported to the IRB immediately through CoeusLite. All other adverse events and minor protocol deviations should be reported at the time of Continuing Review.

Ernest C. Young Hall, 10th Floor - 155 S. Grant St. - West Lafayette, IN 47907-2114 - (765) 494-5942 - Fax: (765) 494-9911

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HUMAN RESEARCH PROTECTION PROGRAM
INSTITUTIONAL REVIEW BOARDS

To:	SATISH UKKUSURI HAMP
From:	JEANNIE DICLEMENTI, Chair Social Science IRB
Date:	10/30/2018
Committee Action:	Expedited Approval for Renewal - Category(7)
IRB Approval Date	10/30/2018
IRB Protocol #	1701018620
Renewal Version	Renewal-002: Renewal-002:
Study Title	SURVEY TO UNDERSTAND THE BEHAVIOR OF STAKEHOLDERS IN CROWD-SHIPPING MARKET
Expiration Date	10/29/2021
Subjects Approved:	10000

The above-referenced protocol has been approved by the Purdue IRB. This approval permits the recruitment of subjects up to the number indicated on the application and the conduct of the research as it is approved.

The IRB approved and dated consent, assent, and information form(s) for this protocol are in the Attachments section of this protocol in CoeusLite. Subjects who sign a consent form must be given a signed copy to take home with them. Information forms should not be signed.

Record Keeping: The PI is responsible for keeping all regulated documents, including IRB correspondence such as this letter, approved study documents, and signed consent forms for at least three (3) years following protocol closure for audit purposes. Documents regulated by HIPAA, such as Authorizations, must be maintained for six (6) years. If the PI leaves Purdue during this time, a copy of the regulatory file must be left with a designated records custodian, and the identity of this custodian must be communicated to the IRB.

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