University Transportation Research Center - Region 2

Final Report

Crowdshipping: Evaluating its Impacts on Travel Behavior

Performing Organization: City University of New York (CUNY)

November 2019

Sponsor:
University Transportation Research Center - Region 2

University Transportation Research Center - Region 2

The Region 2 University Transportation Research Center (UTRC) is one of ten original University Transportation Centers established in 1987 by the U.S. Congress. These Centers were established with the recognition that transportation plays a key role in the nation's economy and the quality of life of its citizens. University faculty members provide a critical link in resolving our national and regional transportation problems while training the professionals who address our transportation systems and their customers on a daily basis.

The UTRC was established in order to support research, education and the transfer of technology in the field of transportation. The theme of the Center is "Planning and Managing Regional Transportation Systems in a Changing World." Presently, under the direction of Dr. Camille Kamga, the UTRC represents USDOT Region II, including New York, New Jersey, Puerto Rico and the U.S. Virgin Islands. Functioning as a consortium of twelve major Universities throughout the region, UTRC is located at the CUNY Institute for Transportation Systems at The City College of New York, the lead institution of the consortium. The Center, through its consortium, an Agency-Industry Council and its Director and Staff, supports research, education, and technology transfer under its theme. UTRC's three main goals are:

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The research program objectives are (1) to develop a theme based transportation research program that is responsive to the needs of regional transportation organizations and stakeholders, and (2) to conduct that program in cooperation with the partners. The program includes both studies that are identified with research partners of projects targeted to the theme, and targeted, short-term projects. The program develops competitive proposals, which are evaluated to insure the mostresponsive UTRC team conducts the work. The research program is responsive to the UTRC theme: "Planning and Managing Regional Transportation Systems in a Changing World." The complex transportation system of transit and infrastructure, and the rapidly changing environment impacts the nation's largest city and metropolitan area. The New York/New Jersey Metropolitan has over 19 million people, 600,000 businesses and 9 million workers. The Region's intermodal and multimodal systems must serve all customers and stakeholders within the region and globally.Under the current grant, the new research projects and the ongoing research projects concentrate the program efforts on the categories of Transportation Systems Performance and Information Infrastructure to provide needed services to the New Jersey Department of Transportation, New York City Department of Transportation, New York Metropolitan Transportation Council , New York State Department of Transportation, and the New York State Energy and Research Development Authorityand others, all while enhancing the center's theme.

Education and Workforce Development

The modern professional must combine the technical skills of engineering and planning with knowledge of economics, environmental science, management, finance, and law as well as negotiation skills, psychology and sociology. And, she/he must be computer literate, wired to the web, and knowledgeable about advances in information technology. UTRC's education and training efforts provide a multidisciplinary program of course work and experiential learning to train students and provide advanced training or retraining of practitioners to plan and manage regional transportation systems. UTRC must meet the need to educate the undergraduate and graduate student with a foundation of transportation fundamentals that allows for solving complex problems in a world much more dynamic than even a decade ago. Simultaneously, the demand for continuing education is growing – either because of professional license requirements or because the workplace demands it – and provides the opportunity to combine State of Practice education with tailored ways of delivering content.

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Principal Investigator(s):
Mahdieh Allahviranloo, Ph.D.
Assistant Professor
Department of Civil Engineering
The City College of New York
New York, NY 10031
Tel: (212) 650-8516
Email: mallahviranloo@ccny.cuny.edu

Co Author(s):
Shirin Najaf Abadi, Ph.D.
Department of Civil Engineering
The City College of New York
New York, NY 10031

Alison Conway, Ph.D.
Associate Professor
Department of Civil Engineering
The City College of New York
New York, NY 10031
Tel: (212) 650-5372
Email: aconway@ccny.cuny.edu

Quanquan Chen, Ph.D
Department of Civil Engineering
The City College of New York
New York, NY 10031

Performing Organization:
City University of New York (CUNY)

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Mailing Address:

University Transportation Reserch Center
The City College of New York
Marshak Hall, Suite 910
160 Convent Avenue
New York, NY 10031
Tel: 212-650-8051
Fax: 212-650-8374
Web: www.utrc2.org

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Ph.D. Student, Transportation Program

Sabiheh Fagigh*: Research Assistant;*
Ph.D. Student, Transportation Program

Patricio Vicuna*: Research Assistant*
Ph.D. Candidate, Transportation Program

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7. Author(s)
Mahdieh Allahviranloo, Ph.D.
Shirin Najaf Abadi, Ph.D.
Alison Conway, Ph.D
Quanquan Chen,Ph.D

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The City College of New York
West 137th Street and Convent Avenue
New York, NY 10031

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16. Abstract

The rapid emergence of direct-to-home delivery models has quickly changed the spatial and temporal distribution of both individual travelers' trips and of urban goods movements. A growing number of household and consumer products now being delivered directly to homes rather than being picked up in retail stores. For commercial carriers, this new last-mile is often expensive, as small shipments must be moved to geographically dispersed residences, often within increasingly constrained time windows. An emerging method of goods movement that may help to address this inefficiency is crowdshipping. Crowdshipping is a peer-to-peer delivery platform consisting of carriers and requesters.

As a result of these tradeoffs, neither the potential market for crowdshipping nor the possible impacts of crowdshipping on the upstream and downstream daily travel behavior of the requester or the carrier are well understood. Increased adoption of crowdshipping will have implications for both commercial freight demand and passenger travel demand; while understanding both will be critical to assessing the potential benefits of crowdshipping, this study aims primarily to provide insights specifically on the impacts of crowdshipping on personal travel behavior. While a number of travel behavior researchers have studied the general relationship between e-commerce and trips to the retail store, none have comprehensively assessed crowdshipping, the impacts of crowdshipping on trip chaining behavior of individual participants, or the potential replacement activities that may occur when additional time is made available for the requester through the elimination of store trips.

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Introduction

In recent years, communications technologies have quickly transformed the way that people shop. Whether goods are purchased from online retailers or in-store, shoppers now have many options for obtaining consumer products from global or local markets and for transporting these goods to their homes. The rapid emergence of direct-to-home delivery models has quickly changed the spatial and temporal distribution of both individual travelers' trips and of urban goods movements. A growing number of household and consumer products now being delivered directly to homes rather than being picked up in retail stores. For commercial carriers, this new last-mile is often expensive, as small shipments must be moved to geographically dispersed residences, often within increasingly constrained time windows.

An emerging method of goods movement that may help to address this inefficiency is crowdshipping. Crowdshipping is a peer-to-peer delivery platform consisting of carriers and requesters. A requester is a person who orders goods to be picked up from a specific location and to be delivered to another location at a specified time. A carrier performs the service on the way to his or her own daily activities. Globally, a number of companies such as RideShip, MeeMeep, Deliv, and Nimber have already implemented this framework for both local and long-distance shipping. As a freight mode, crowdshipping has the potential to reduce both the operating and social costs of last-mile goods movements by utilizing available passenger capacity, eliminating excess vehicle-miles traveled and related congestion, infrastructure, and emissions impacts from freight vehicles. However, crowdshipping also introduces some unique challenges, such as the risk of theft for the requester and risk of inadvertently carrying illicit products for the carrier (McKinnon, 2015).

As a result of these tradeoffs, neither the potential market for crowdshipping nor the possible impacts of crowdshipping on the upstream and downstream daily travel behavior of the requester or the carrier are well understood. Increased adoption of crowdshipping will have implications for both commercial freight demand and passenger travel demand; while understanding both will be critical to assessing the potential benefits of crowdshipping, this study aims primarily to provide insights specifically on the impacts of crowdshipping on personal travel behavior. While a number of travel behavior researchers have studied the general relationship between e-commerce and trips to the retail store, none have comprehensively assessed crowdshipping, the impacts of crowdshipping on trip chaining behavior of individual participants, or the potential replacement activities that may occur when additional time is made available for the requester through the elimination of store trips.

Here these gaps are addressed through (1) implementation of a survey to characterize crowdshipping requestors and carriers and (2) the development of an optimization modeling framework that can be employed to study the reciprocal effect of crowdshipping on individuals' travel behavior. The survey examines the following unknown variables: 1) individuals' willingness to perform crowdshipping; 2) individuals' willingness to use crowdshipping services; and 3) expected alternative uses for time saved by eliminating personal store trips. The modeling framework relies on existing regional activity data, as well as a field In order to provide some basic understanding of the potential impacts of crowdshipping on commercial vehicle activity, the survey will also address the same individuals' willingness to request traditional commercial services for direct to home delivery. In the second section of the study the modeling framework to assess the impacts of crowdshipping on mobility patterns is presented. We use geocoded household travel survey data to estimate potential impacts of crowdshipping on time-use behavior of carriers and requesters. The remainder of the report is organized in the following chapters:

- Chapter 2 provides a comprehensive review of relevant literature.
- Chapter 3 presents the structure of the survey that was developed through this project and summary of the results describing expected impacts of crowdshipping in the NYC context.
- Chapter 4 describes the mathematical formulation of the proposed model and discussed results from model implementation using the results of a California Household travel survey.

Relevant conclusions and key findings are detailed at the end of each chapter.

Literature Review

Transportation, like many other sectors, is being impacted by growth of the shared economy, wherein new forms of such systems as ride-matching (1–5), bike-sharing, crowdshipping, etc. are emerging (6–8). Crowdshipping, as one of the most recent modes of deliveries, is attracting growing attention in academia and industry. It is being tested and implemented by Amazon, Walmart (9), DHL(10), among others, to facilitate same day delivery service and resolve last mile delivery problems. Furthermore, the idea is being explored by such companies as Ebay, Google, Uber, Instacart, and Deliv (11). 'Friendshippr', and 'Roadie' are crowdshipping companies mainly active in carrying out long distance deliveries, whereas Instacart, Postmates, Deliv, Trunkrs, and Hitch are operating in short distance delivery activities (11).

As crowdshipping is a novel form of last-mile logistics, there is little published research specifically addressing the transportation impacts of its adoption; however, this project will draw knowledge from a number of related areas, including shopping-related travel behavior, city logistics, and pickup and delivery problems with time windows. This section provides a brief introduction to these three areas.

As noted in the preceding section, a growing body of empirical research has begun to explore the variables that impact shopping behavior and the relationship between online shopping and trip-making to a retail store. A few studies have employed household survey data to examine the variables that impact shopping trip generation (Cubukcu, 2001; Gonzalez-Feliu, Toilier, & Routhier, 2010). Travel behavior researchers have applied a variety of modeling approaches to explore the implications of technology-enabled online shopping for in-store trip-making. Cao (2009) provides a comprehensive summary and analysis of related studies conducted before 2009, classifying these into two primary categories: the effects of spatial attributes on online buying and the impacts of e-shopping on travel behavior. More recent studies by Calderwood and Freathy (2014), Zhou and Wang (2014), and Lee, Sener, & Handy (2016) have also examined these relationships. Overall, studies to date have produced very mixed results in both areas; this is unsurprising considering the broad range of products that can be purchased, the global market access provided by online retailers, and the emergence of omnichannel retail models that can result in a variety of trip-making combinations for the viewing, purchase, and return of products.

City logistics researchers have also developed a variety of modeling approaches to examine urban goods movement and have recently begun to study aspects of how e-commerce impacts transportation. Specific areas of study include changes in supply chain organization, unique characteristics of direct-to-home delivery trips, expected impacts of these trips on the surrounding network, and novel approaches to reduce these impacts. Browne & Goodchild (2013) provide a comprehensive summary of urban freight modeling approaches. Rodrigue (2016) summarizes the characteristics of direct-to-home retail movements compared to traditional commercial retail deliveries. Visser, Nemoto, and Browne (2014) discuss the impacts on urban goods movement from home delivery in the Netherlands, Japan, and the UK; Morganti et al. (2014) examine the same concept in France and Germany. Together, these publications reveal a number of unique aspects of direct-to-home deliveries; trips are frequently completed by parcel companies from local or regional distribution centers to disaggregate destinations, requiring more packaging and miles traveled than traditional commercial movements, and often resulting in failed delivery attempts. Visser, Nemoto, and Browne (2014) also note that tradeoffs between passenger shopping trips and freight distribution trips must be considered when estimating network impacts. Wygonik & Goodchild (2012) note that CO_2 emissions tradeoffs for home delivery of groceries compared to store shopping trips will vary depending on the density of the market served.

From a mathematical modeling perspective crowdshipping is a very complex, yet interesting, problem that introduces many challenging questions that need to be addressed. Research in this area can be divided into three main categories: (a) design of the elements of the crowdshipping platform, wherein questions regarding task submission procedure, matching, and underlying rules connecting carriers and requesters are explored. This area of research falls into the category of two-sided market matching (Roth, Sönmez, & Utku Ünver, 2005; Sotomayor, 2004), a very well-known problem in market studies; (b) delineating the operational aspects of the problem and developing mathematical formulations to optimize system performance under different binding constraints; and (c) assessing the impacts of crowdshipping on travel behavior and shift in travel demand for existing modes of transportation.

Carriers in the crowdshipping platform can be hired by companies as occasional drivers that deliver packages to the costumers if the pickup and drop off points are well-aligned with their original travel plans and the overall cost of such carrier is within a certain acceptable range for the company. In their work, Arcehtti et al. explain the formulation and associated constraints of such model, and using computational experiments they explore the benefits of the system (Archetti, Savelsbergh, & Speranza, 2015). According to Cohen and Munoz, optimal integration of shared urban systems helps with creation of more sustainable cities by efficiently utilizing shared resources (Cohen & Munoz, 2015). Following this idea some existing studies in literature propose integration of good delivery and passenger transportation systems instead of making capital investment in acquiring new vehicles or increasing fleet size to solve the last-mile delivery problem. Masson et al. propose a model which utilizes spare capacity of buses to distribute goods in the city center (Trentini, Masson, Lehuédé, & Malhéné, 2015). Li et al., present a methodology to combine parcel delivery with current scope of work of taxis. The analysis is based on taxi data from San Francisco under the assumption that taxi drivers can deliver parcels while maintaining a desirable level of service for the passengers. As expected, driving customers to their destination is given a higher priority than the parcel delivery (Li, Krushinsky, Reijers, & Van Woensel, 2014). This model has been later adapted to data from Tokyo city, which comprises of a transportation network with 130,000 crossing points and 20,000 requests, by Nguyen et al (Nguyen et al., 2015).

Additional constraints were added to the problem to reflect preferences of system users more realistically. Chen et al., propose the Multi-Driver Multi-Parcel Matching Problem (MDMPMP), where a parcel can be delivered by more than one driver. In this model each driver carries the parcel to an intermediate location where following driver picks it up and completes the delivery (Chen, Mes, & Schutten, 2016). The main objective in this model is to minimize the level of inconvenience and number of transfer points for the drivers. MDMPMP can be categorized as peer to peer delivery model (Arslan, Agatz, Kroon, & Zuidwijk, 2016). Similar to P2P ridesharing model, P2P delivery models match ad-hoc drivers with delivery operations.

The effects of crowdshipping can already be observed to disrupt the traditional mobility patterns of travelers. Therefore, it is safe to assume that it can, and will, have an impact on the space-time distribution of demand for transportation in urban areas. Despite the rising growth in utilization of shared logistic systems, transportation literature is mainly focused on the optimal design and operation of such systems without considering its correlation with behavior of travelers (Agatz, Erera, Savelsbergh, & Wang, 2010; Agatz et al., 2012; Herbawi & Weber, 2011; Nourinejad & Roorda, 2015). However, to gain extensive understanding on the issues pertaining to the discussed matter there is indeed a necessity to study the mutual relation among those systems and chain of activities that individuals chose to pursue throughout the day. This project fills the gap by assessing this reciprocal effect through a survey and proposing a methodology for combining activity based models with crowdshipping. The main contributions of this study are: (a) presenting formulations for integrating travel behavior models with crowdshipping by taking into account attributes of personal activity chains; (b) developing a methodology to assess the impacts of crowdshipping adaptation on time use behavior of travelers; and (c) to estimate the upper bound for the crowdshipping market based on the attributes of activity participation. To our knowledge, this is the first study which combines crowdshipping with travel behavior models. We believe that crowdshipping will change mobility patterns and travel-related choices of individuals in a way that the demand for conducting such integrated study is inevitable and timely.

Crowdshipping Survey

A survey was created to investigate the willingness of respondents to participate in crowdshipping as either a requestor, carrier, or both; to assess the existing shopping activities that could be replaced by crowdshipping; and to identify the expected changes is personal travel behavior that would result. The survey was distributed by email and through social media to a variety of social groups in the New York City region.

Survey Content

The survey consisted of 24 questions. These questions investigate respondent demographic and work characteristics, typical shopping behavior and time use, and willingness to participate in crowdshipping as either a carrier or a receiver. Specific shopping characteristics investigated include (1) time spent traveling or shopping, (2) the types of products purchases, (3) whether shopping was conducted in store or online, (4) the frequency with which these activities were carried out, and (5) the mode of transportation most frequently used by the survey respondents for in-store shopping trips. The full survey is provided in the Appendix.

Survey Results

Survey Respondent Demographics

In total, 115 individuals participated in this survey; Figure 3.1 shows the geographic distribution of these respondents. About 49 percent live within New York City's five boroughs, 22 percent elsewhere in the states of New York and NJ, 13 percent in another US state, and the remainder provided no location information. The city-based distribution is not representative of city residents, as Manhattan is heavily over-represented compared to other boroughs.

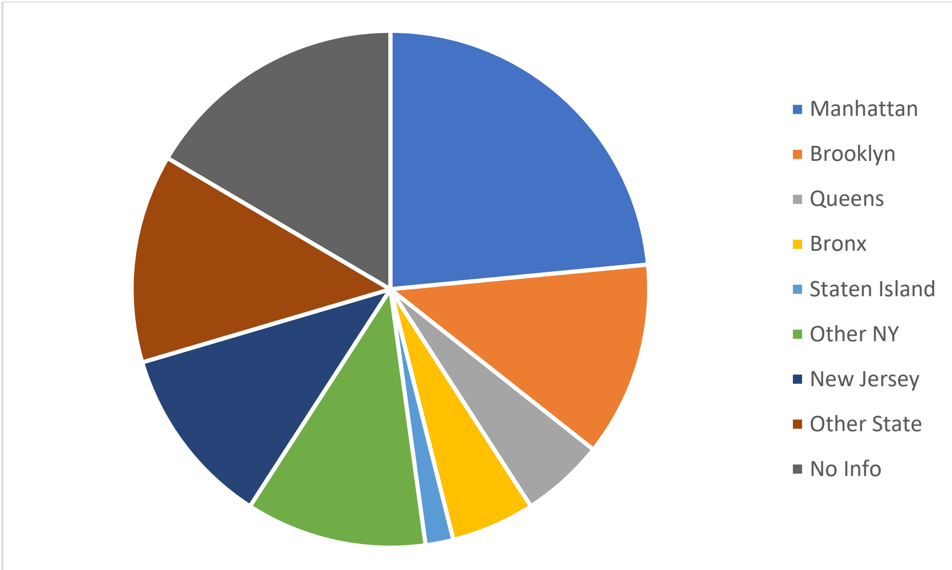

Figure 3.1. Home Location of Respondents

Responses were heavily biased towards younger age categories (Figure 2); 16 percent were between the age of 18 and 24, and 41 percent between the ages of 24 and 34.

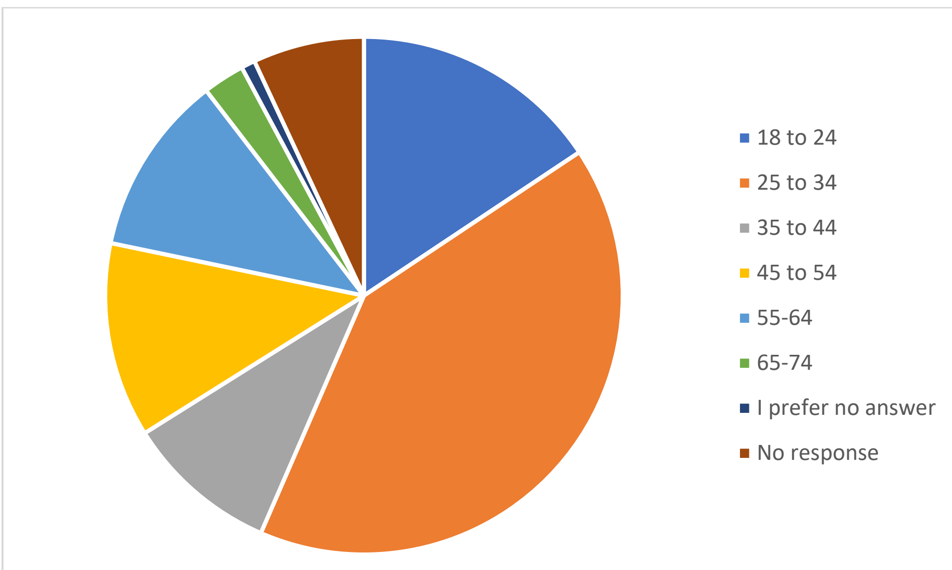

Figure 3.2. Age of Respondents

Respondents represent mixed income groups. Figure 3.3 illustrates the share of respondents belonging to each income group. The group with the largest stated share (27%) earned more than $100k annually. Twenty-six percent of respondents chose not to share their income. About 2/3 of respondents have full time employment, and 20 percent are full time students. Only two respondents were retired, and 4 unemployed. As can be seen in Figure 3.4, lower income responses represent a higher share of respondents in the youngest and oldest age categories.

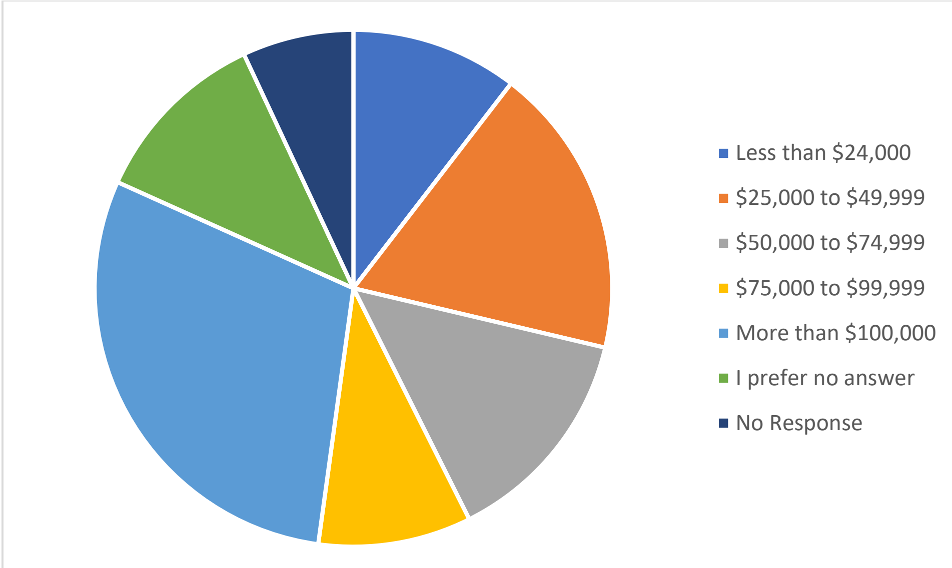

Figure 3.3. Income of Respondents

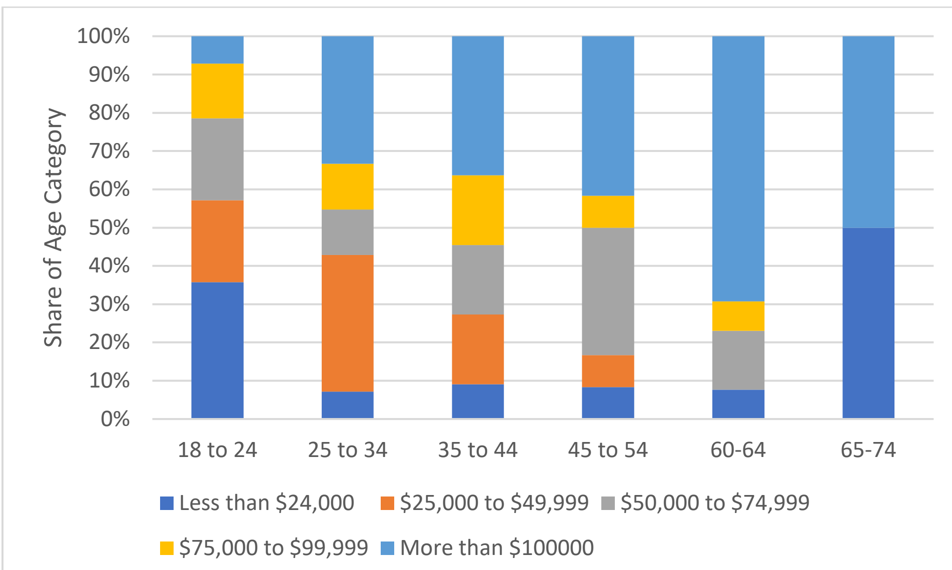

Figure 3.4. Respondent Age vs. Income (excludes missing and no response)

Typical Commuting Behavior

Figure 3.5 illustrates the typical time spent traveling by survey respondents on weekdays and weekend days. Most respondents spend longer durations traveling on weekdays compared to weekend days. On weekdays, about a third of travelers spend an hour or less traveling, compared to 55% on Saturdays and 70% on Sundays.

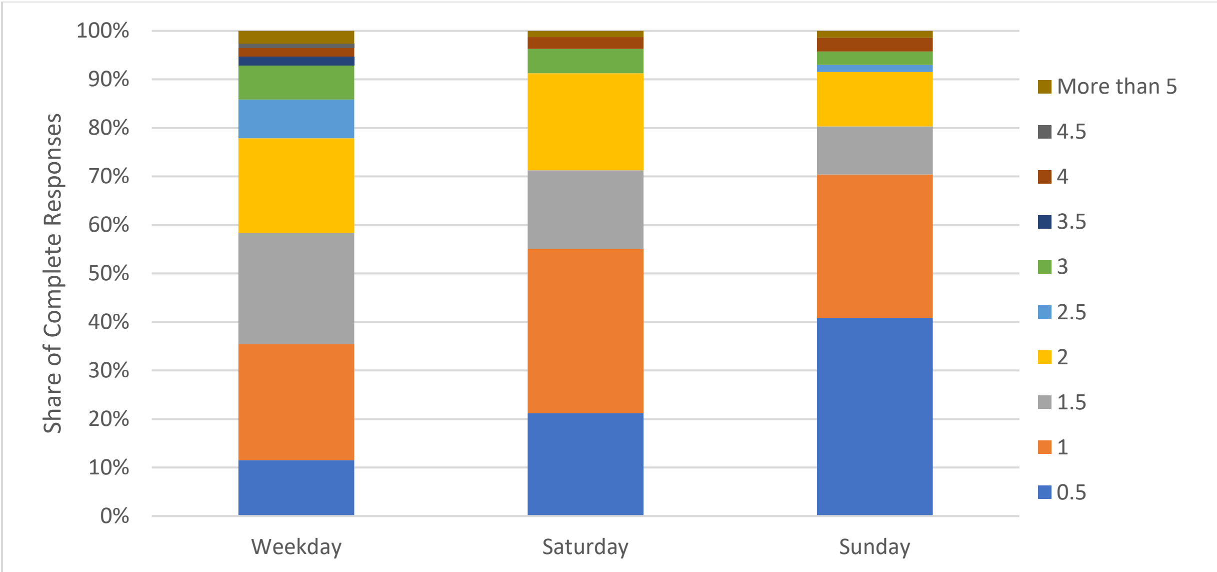

Figure 3.5. Daily Hours Spent Traveling

Figures 3.6 and 3.7 show the typical arrival times to and departure times from work on each type of day. A higher share of weekend workers arrive in the late morning and afternoon compared to weekday workers, whose arrival times are heavily concentrated between 7 and 10 AM. Departure times are generally more distributed than arrival times – occurring primarily from the late afternoon to the late evening on weekdays, and beginning earlier and ending later on weekend days.

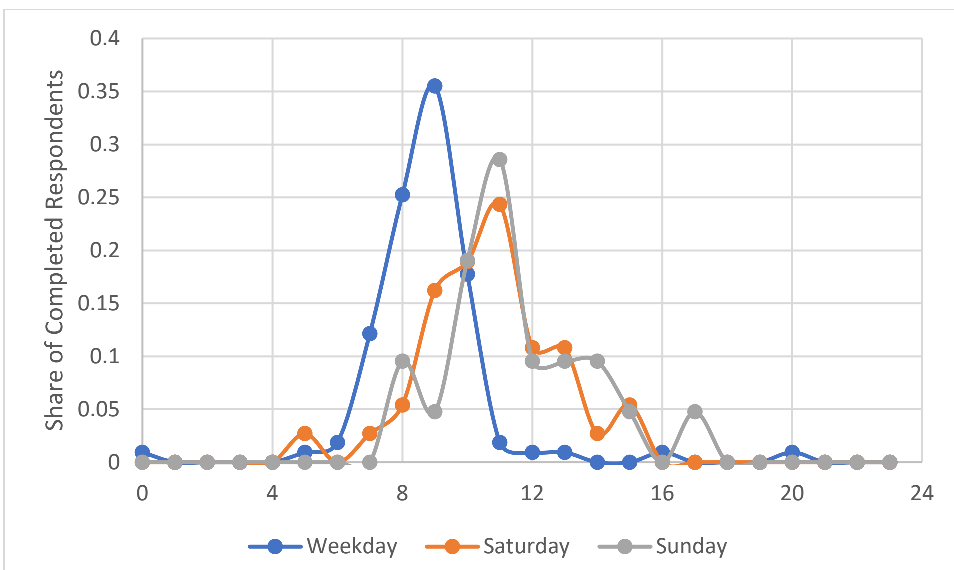

Figure 3.6. Time of Arrival to Work

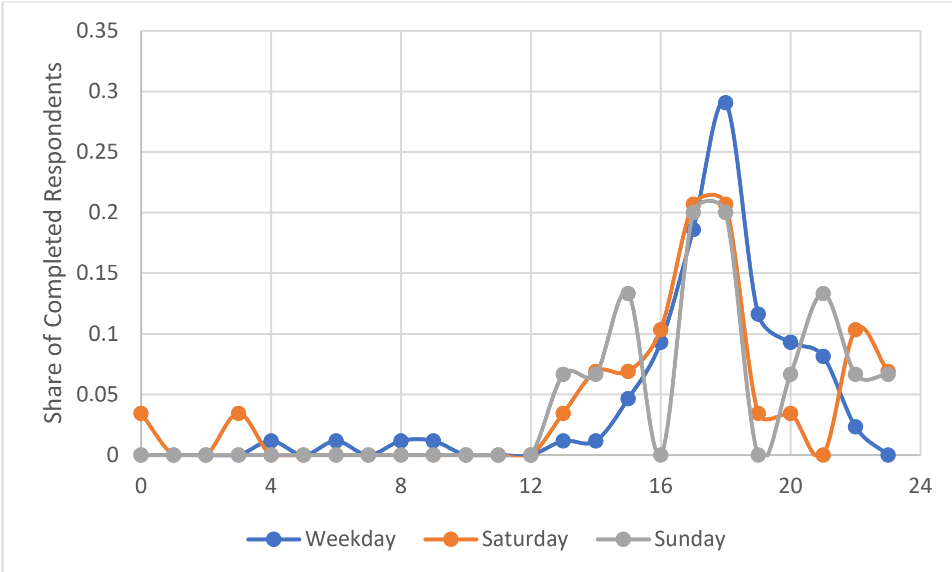

Figure 3.7. Time of Departure from Work

Typical Shopping Behavior

Figure 3.8 displays the estimated number of hours per week that respondents spend shopping in-store and online. The vast majority of respondents spend less than three hours shopping either in-store or online. Interestingly, a higher share spend a short amount of time (less than an hour) shopping online, but a small share also spend much longer shopping online. About 9 percent indicated that they do not typically shop in store; a slightly lower percentage do not shop online.

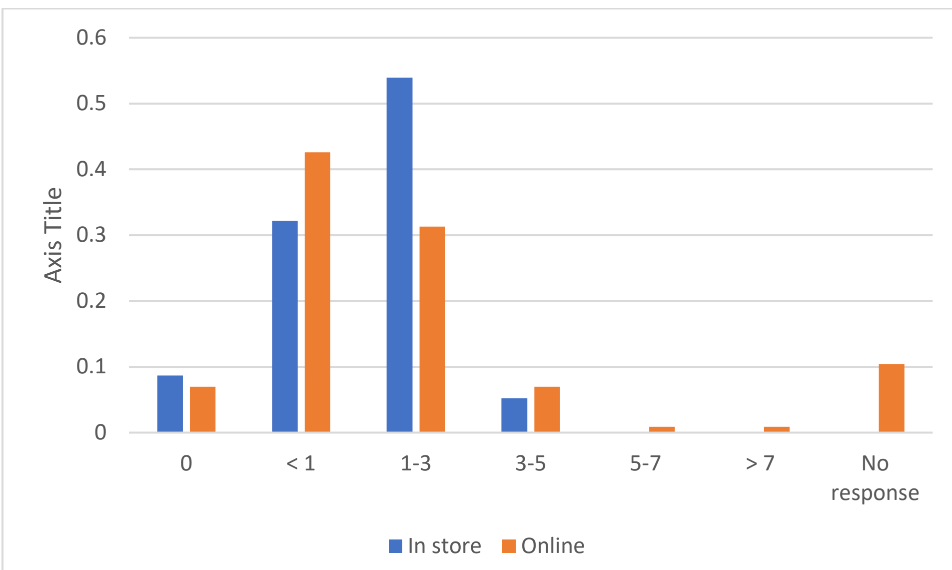

Figure 3.8. Hours per Week Spent Shopping

Figures 3.9 and 3.10 display the respondents' stated number of in-store and online shopping events monthly. Respondents were specifically asked about two delivery types – fresh food and household goods – which are typically delivered from local shops as well as through online-only ecommerce. More than 60 percent never shop for fresh food online, while nearly all make at least one store trip. Store trip frequencies vary considerably, with the highest share observed to make about one trip per week. Only about one-third of respondents never shop for household goods online. Online and in-store household product shopping events are distributed fairly similarly, with most respondents shopping for these products a few times a month.

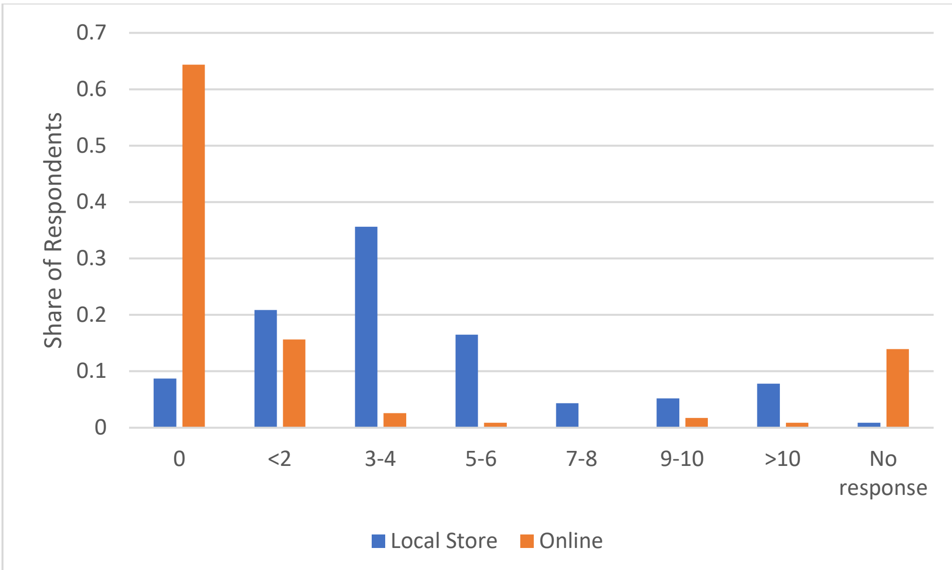

Figure 3.9. Number of Monthly Shopping Events for Fresh Food

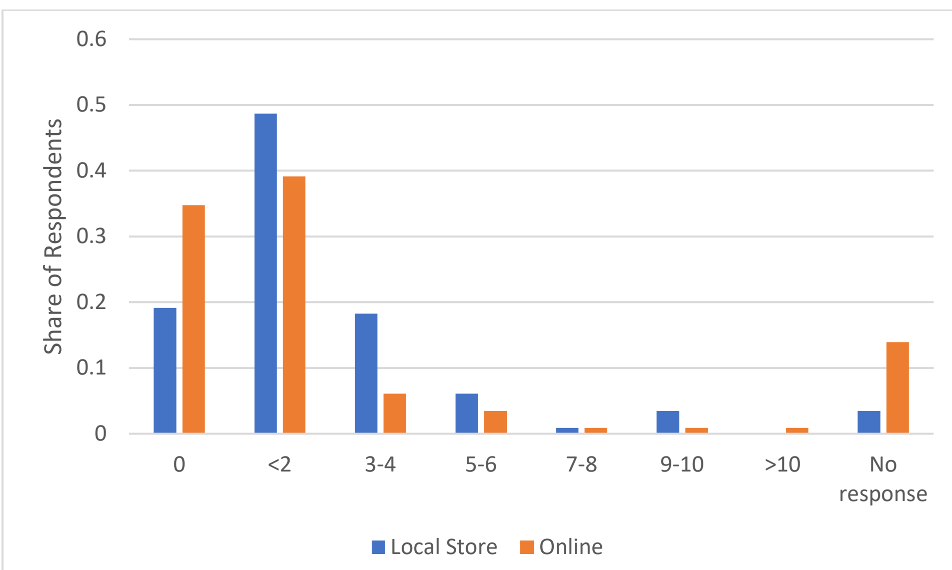

Figure 3.10. Number of Monthly Shopping Events for Household Products

Shopping Travel Mode

Respondents were also asked to identify by which modes of transportation they typically travel when conducting local shopping; results are detailed in Table 3.1. Overall, car is the most popular mode for shopping; however, major variation is observed based on the geographic location of the respondent. In New York City and New Jersey, walking, biking, and transit are used much more frequently than in other locations.

Table 3.1. Typical Mode of Travel for Local Shopping Trips

	Passenger Car	Uber/Lyft/Taxi	Transit	Bike	Walk	Ferry	Total Respondents
Bronx	16.7	0.0	33.3	16.7	66.7	0.0	6
Brooklyn	28.6	21.4	28.6	7.1	92.9	0.0	14
Manhattan	33.3	29.6	55.6	18.5	51.9	0.0	27
Queens	50.0	0.0	33.3	0.0	50.0	0.0	6
Staten Island	50.0	0.0	0.0	50.0	50.0	50.0	2
Other NY	84.6	7.7	7.7	7.7	23.1	0.0	13
NJ	61.5	30.8	46.2	15.4	30.8	0.0	13
Other State	100.0	0.0	0.0	0.0	6.7	0.0	15
No Info	94.7	0.0	15.8	0.0	26.3	0.0	19

Delivery Frequency

Shoppers may have goods delivered after shopping in store, or they may order goods online that originate either from a local store or from an ecommerce warehouse. Figure 3.11 shows the reported frequencies of delivery of each product type from both in-store and online shopping. Notably, only a small percentage of users receive delivery of fresh food from in-store shopping, with only a slightly higher share receiving delivery of fresh food purchased online. Only about a quarter receive delivery of household goods from a store. However, more than half receive deliveries of household products purchased online at least a few times per month.

Figure 3.11. Frequency of Shopping by Type

Willingness to Participate in Crowdshipping as a Requester

Participants were asked if they would be willing to use a secure app to request delivery. About one-third responded yes, 46% were willing to consider depending on cost, and 21% were not interested. Interestingly, willingness to use without cost information decreases with income (Figure 3.12). To investigate if this may be impacted by the relationship between age and income, Figure 3.13 shows the willingness to receive crowdshipping by age category. It appears there is no direct correlation, as high shares of millennials and seniors accept crowdshipping without cost information, while younger generations require cost information at a much higher rate.

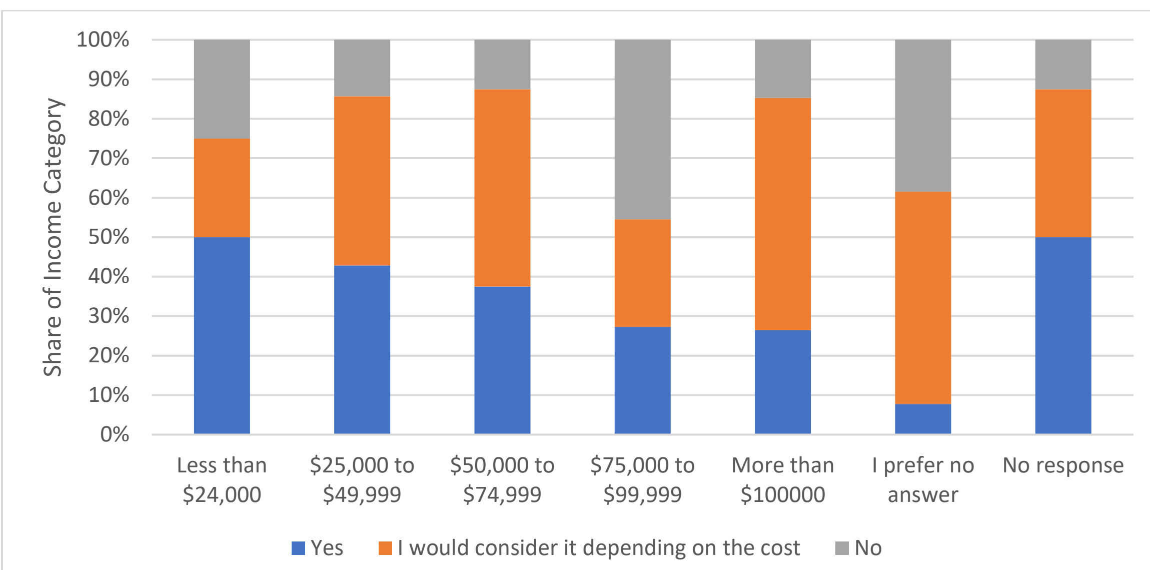

Figure 3.12. Willingness to Request Crowdshipping vs. Income Category

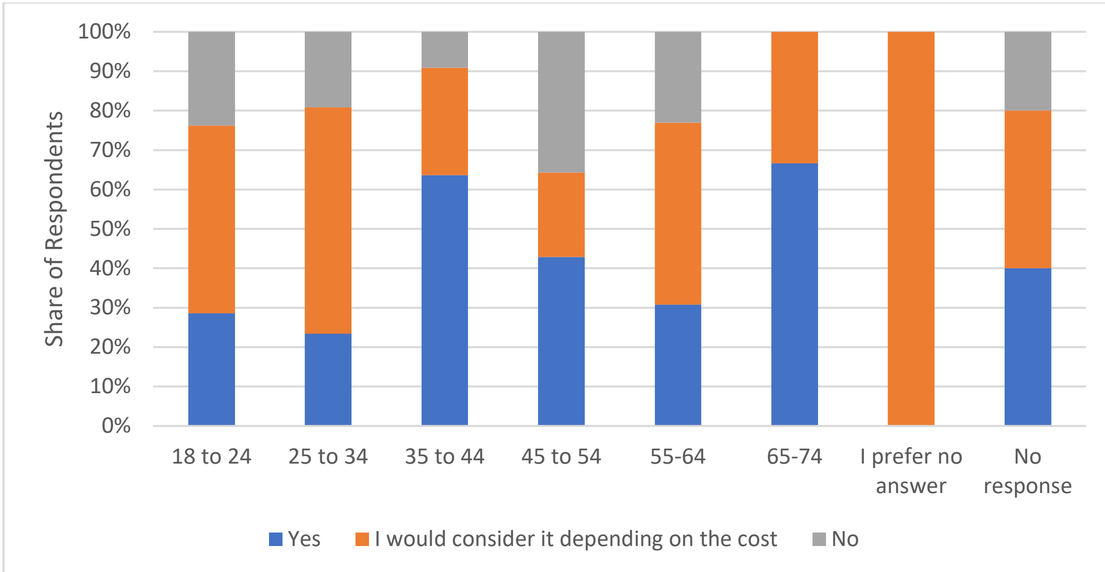

Figure 3.13. Willingness to Request Crowdshipping vs. Age Category

Willingness to Participate in Crowdshipping as a Carrier

Thirty seven respondents (32% of total) indicated willingness to consider serving as a carrier for a crowdshipping platform. The demographics of these carriers were investigated. Willingness to serve as carrier appears to decrease with increasing income (Table 13.2). Among the lowest income category, more than half of respondents are willing to serve as carriers; among the wealthiest group, this number falls to less than 15 percent. The least willing age group to serve as carriers was 25-34, and the most willing was 35-44; however, it should be noted that the sample size for the latter is only 11 observations (Table 13.3). Employment status of willing carriers was also examined. Unsurprisingly, 71% of those with full time employment were unwilling to participate in crowdshipping as a carrier. Slightly more full time students are willing; about 36 percent indicated interest in serving as a carrier. Sample sizes for part time employees/students, retired persons, and unemployed individuals were very small; however, three out of four with no employment were interested to serve as carriers.

Table 3.2. Willingess to Serve as Carrier by Income Category

Income Category	**% Willing to Carry**
Less than $24,000	58.3
$25,000 to $49,999	38.1
$50,000 to $74,999	37.5
$75,000 to $99,999	27.3
More than $100,000	14.7

Table 3.3. Willingness to Serve as a Carrier by Age Category

Age Category	**% Willing to Carry**
18 to 24	38.1
25 to 34	25.5
35 to 44	54.5
45 to 54	28.6
55-64	30.8
65-74	33.3

Willing carriers identified the expected modes by which they would provide service (Table 3.4). Seventy three percent of carriers expect to use a car; of these about half expect to use car alone and about half to use car as well as other modes. About 27 percent of respondents expect to use public transit – alone or in combination with other modes, and 11 percent expect only to use human powered modes of biking and walking.

Table 3.4. Expected Modes Used by Willing Carriers

Mode	**% Willing Carriers**
Car Only	37.8
Transit Only	2.7
Bike Only	2.7
Walk Only	2.7
Car and Transit	8.1
Car and Bike	10.8
Car and Walk	5.4
Public Transit and Bike	2.7
Public Transit and Walk	5.4
Bike and Walk	5.4
Public Transit, Bike, and Walk	8.1
All Four Modes	10.8

Time of Crowdshipping

The survey also investigated the time availability of respondents to participate in crowdshipping. Among those who identified as willing carriers, the average number of available hours per day was higher on the weekend compared to the weekday (Table 3.5). However, the share of carriers willing to conduct deliveries on the weekend is slightly lower than on a weekday.

Table 3.5. Time Availability for Crowdshipping

	Weekday	**Weekend**
Average # Hours Available	4.7	6.2
% Willing to Deliver	91.9	86.5

Figures 3.14 and 3.15 compare the preferred delivery times stated by willing crowdshipping receiviers – including those who must be home to accept delivery and those who can receive deliveries unattended – with the available times stated by willing carriers to offer service. On weekdays, these time distributions are relatively well aligned, with requestors preferring evening delivery and carriers willing to

provide it. A slightly higher share of carriers are willing to operate during the day than requestors willing to accept them. On the weekends, carriers are willing to provide delivery throughout the day, with a peak during daytime hours. While unattended deliveries can also be received throughout the day, those who need to be home prefer morning deliveries.

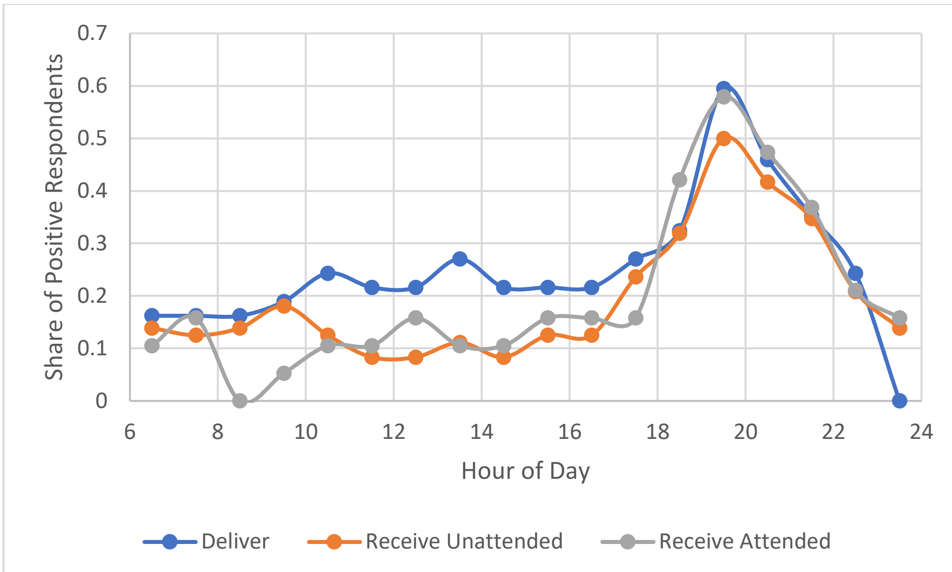

Figure 3.14. Preferred Times for Crowdshipping Activities on Weekdays

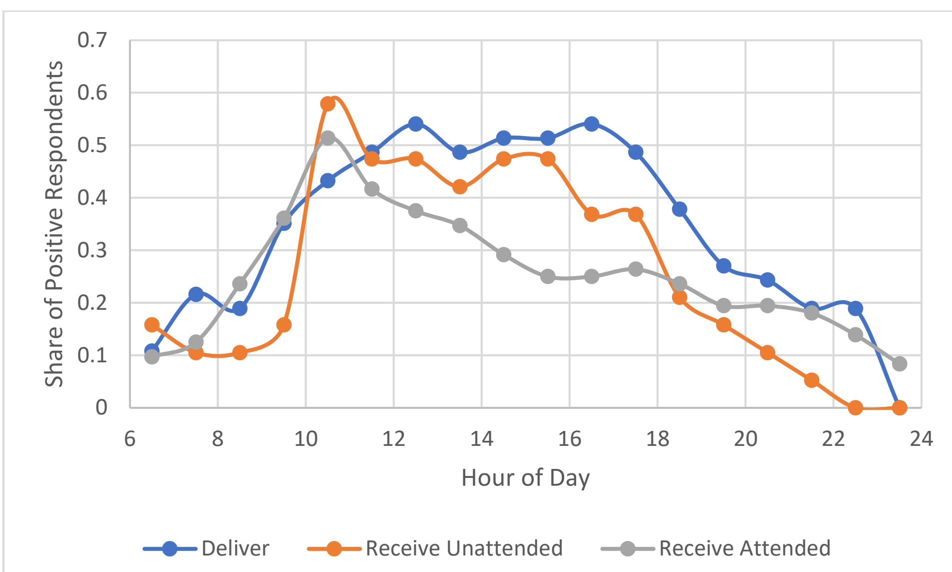

Figure 3.15. Preferred Times for Crowdshipping Activities on the Weekend

Cost of Crowdshipping

Table 3.6 provides the average stated willingness to pay for small and large deliveries for those willing to serve as requesters and those who would consider it depending on price. Unsurprisingly, the latter group is willing to pay less per delivery. The willingness to pay more by the first group may be due to a higher perceived time savings; the former group estimates an expected time savings of 2.7 hours/week compared to 2.3 hours for the latter group. However, no direct relationship between these factors could be observed.

Table 3.6. Requester Willingness to Pay

	Small Delivery	Large Delivery
Yes	$5.39	$10.17
I would consider it depending on the cost	$3.64	$6.84

Table 3.7 summarizes the average expected payment stated by willing carriers when making deliveries by each mode. For large deliveries, higher wages are expected for human-powered modes; for small deliveries, the higher wages are expected for car operators. Comparing with the rates of willing requestors, the rates seem reasonable; to earn the expected hourly wages stated, carriers would need to make 2.2 – 3.4 small deliveries per hour or 1.7 – 2.2 large deliveries per hour.

Table 3.7. Expected Hourly Wage by Mode

Mode	Small Delivery	Large Delivery
Car/Truck	$18.20	$17.48
Public Transit	$11.90	$18.33
Bicycle	$13.65	$21.67
Walking	$15.31	$22.71

Expected Activity Impacts

Finally, the survey investigated how crowdshipping requestors would use time savings from reduced shopping activity; results are summarized in Table 3.8. Requestors expect to use time saved for a wide variety of activities. Almost two third indicated that they would increase time spent on family activities, and around 40 percent would spend more time on social or work activities. "Other" uses identified included recreational and athletic activities as well as pursuit of new educational/professional opportunities.

Table 8. Use of Time Saved

Replacement Activities	Share of Users
Family Activities	62.6
Social Activities	39.6
Work	42.9
Other	14.3

Summary of Key Findings

The key findings from this survey are:

Willingess to Participate in Crowdshipping

- Close to 80 percent of survey respondents were willing to request crowdshipping services.
    - More than half of those indicted that their willingness depends on the price.
    - Willingness to request crowdshipping without knowing cost information decreases with income.
    - Members of the youngest age categories (34 and under) are less willing to request crowdshipping without knowing cost information.
- About a third of survey respondents are willing to consider providing crowdshipping services as a carrier.
    - Willingness to serve as carrier decreases with increasing income.
    - Individuals with full-time employment are least willing to serve as carriers.
    - Willing carriers have more time availability to conduct deliveries on weekends, but a slightly smaller carriers are willing to provide weekend deliveries vs. weekday.

Feasibility of Crowdshipping

- There appears to be temporal alignment between demand for crowdshipping deliveries and availability of crowdshipping services; willing carriers are generally able to provide services at times when requesters can accept deliveries.
- There appears to be cost alignment between expected cost for crowdshipping deliveries and expected wages for crowdshipping services; the number of deliveries per hour required to earn the expected wage from expected costs are reasonable.

Activity Impacts of Crowdshipping

- Replaced shopping trips are expected to belong to a variety of modes based on geographic location and built environment of the shopper.

- New crowdshipping activities are also expected to belong to a variety of modes based on geographic location and built environment of the service provider.
- A broad variety of activities are expected to be conducted instead of in-store shopping; more than half of respondents indicated an increase in family activities, and 40 percent both work and social activities.

Data Limitations

While results from the survey provide interesting insights, the sample size for this survey was very small, skewed toward younger age groups, and included a disproportionate number of observations in Manhattan. A more robust sample is needed to better understand impacts at a regional scale and to conduct a more detailed investigation of activity tradeoffs from crowdshipping.

Predicting the Impacts of Crowdshipping on Traveler Time-Use Behavior

In this section, a methodology is proposed to assess the impacts of crowdshipping on travel behavior and also to find an upper bound for crowdshipping platform considering activity patterns of individuals in such market. A mixed integer optimization model is proposed to formulate optimal task transaction behavior among requesters and carriers. Since the size of population in our survey was not large enough to draw solid regional conclusions about the active participation of New Yorkers in a crowdshipping platform, we used Household Travel Survey data to make predictions on the impacts of this emerging concept on activity patterns. In addition, instead of using NYC household data, California 2001 survey was used because it contained geocoded locations of activities.

Terminologies

- **Requesters** submit their eligible tasks to the platform to be conducted by 'carriers'. More than one task can be submitted by each requester, R represents the set of requesters and index r refers to each requester, $(r \in R)$.
- **Carriers** are individuals that would agree to complete the list of tasks submitted by the requesters if the reward compensates the generated inconvenience. More than one task can be performed by each carrier, C represents the set of carriers, and c refers to each carrier, $(c \in C)$.

Protocol

In the context of this study, tasks are submitted to the platform sequentially and are evaluated by all carriers in FIFO order. Figure 19, illustrates task transaction flowchart. In this chart K represents set of tasks, and each task is denoted by k_r, r refers to the requester submitting the task. We drop the index r from k_r and each task is represented by k. Each carrier c proposes a price Z_k^c for the completion of the task k. Z_k^c is evaluated based on carrier's value of time (VOT_c) and required adjustments in the daily activity routine of the carrier to accommodate the task. If Z_k^c is less than the amount that the requester is willing to pay, V_k, the transaction will occur between the requester and the carrier with the minimum proposed price.

$$\begin{cases} V_k \le Z_k = \min\left\{Z_k^1,\ldots,Z_k^c\right\}, \; \textit{task 'k' will be assigned to the carrier with the least proposed price} \\ V_k > Z_k = \min\left\{Z_k^1,\ldots,Z_k^c\right\}, \; \textit{task 'k' will not be assigned to any carrier.} \end{cases}$$

Different task submission strategies, sequential versus simultaneous, will result in different allocation.

Types of Adjustments

Carriers need to make some adjustments to their original activity routine to be able to accomplish requested service. The types of adjustments considered in this model are (i) changing the duration of existing activities; (ii) rescheduling the existing activities; and, (iii) re-routing. Ideally, the level of flexibility in the activity agenda should be measured based on the stated or revealed preferences of the carriers, which is not currently available. We use travel survey data to cluster activity patterns to homogenous groups of trips chains and use the statistical parameters of activity duration and arrival time to different activity locations in homogenous activity patterns as a surrogate to the degree of flexibility in activity duration and scheduling.

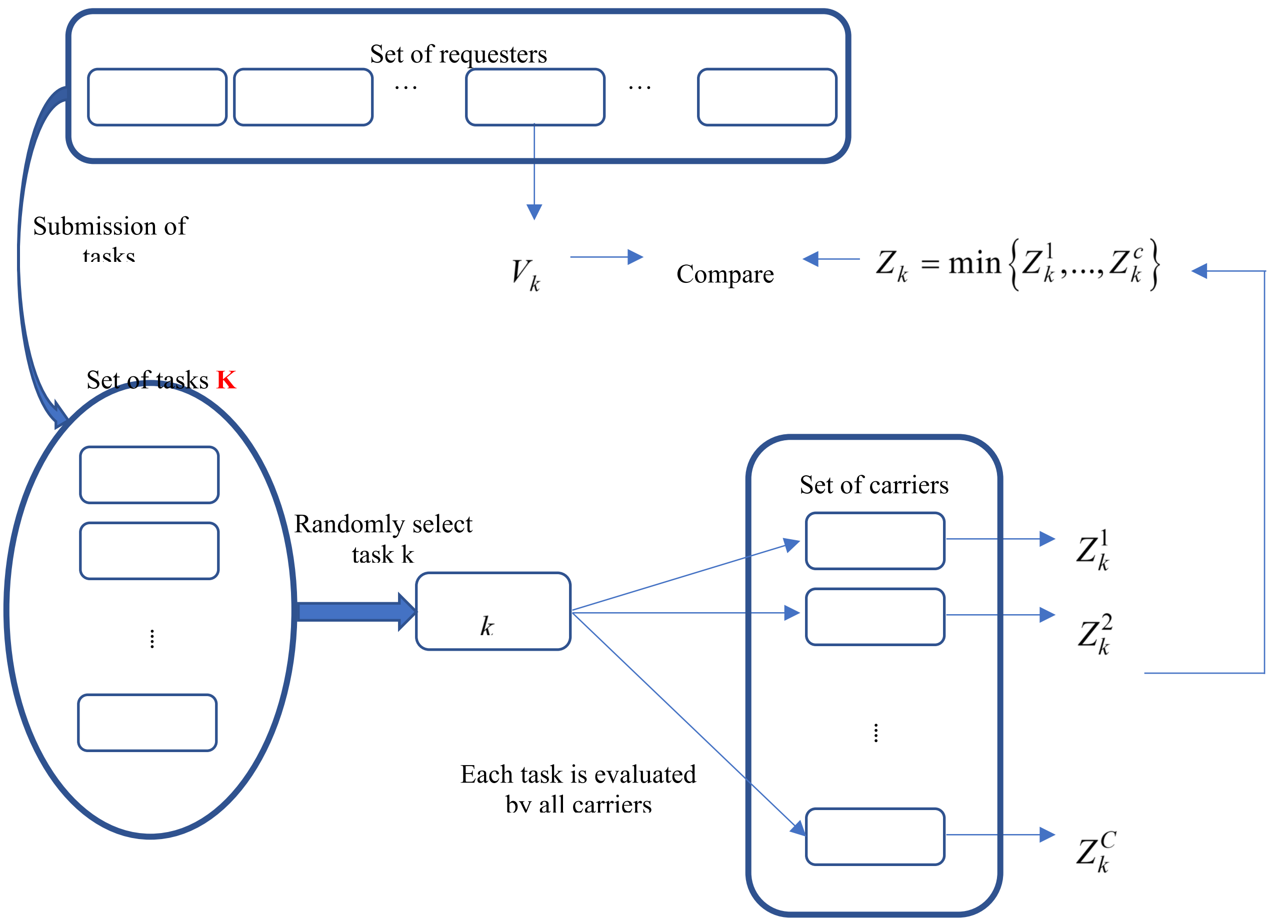

Figure 4.1 Task transaction flowchart

Pricing Strategy

In crowdshipping system, it is, in fact, the 'value of time savings' that carriers and requesters are trading. The concept of time allocation among household members and its relation to wage was initially introduced by Becker, *(23)*. Under this theory, the time spent at work generates income, which can be spent on leisure activities. Later DeSerpa extended the concept and defined the utility to be a function of goods, time spent at work and at other activities subject to budget, time, and activity duration constraints *(24)*. Here we briefly explain the basics of the value of time savings. Lets' define U to be the utility based on consumption of goods, G , time spent at work, $Time_w$, and time spent on other activities, $Time_l$. Y is the value of unearned income, $wage$ is the hourly wage rate, $\overline{T}_l$ is the minimum duration of activity l , and TB is time budget. The model of value of time-saving *(24)* is structured as follows:

$$Y + (wage)(Time_w) = G, \qquad (1)$$
$$Time_w + Time_l = TB \ \ \forall l \in L$$

Solution to this problem is the derivation of the first order condition for its corresponding lagrangian, as shown in equation (2).

$$\begin{aligned} L = \ & U\{G, Time_w, Time_l\} + \lambda\left(Y + (wage)(Time_w) - G\right) + \mu\left(TB - Time_l - Time_w\right) \\ & + \sum_l \varphi_l \left(Time_l - \overline{T}_l\right). \end{aligned} \qquad (2)$$

If $U_{Time_w} = \dfrac{dU\{G, Time_w, Time_l\}}{dTime_w}$ and $U_{Time_l} = \dfrac{dU\{G, Time_w, Time_l\}}{dTime_l}$, using first order conditions the value of time savings for non-leisure activities equals to[1]:

$$VOT_l = wage + Time_w . \frac{dwage}{dTime_w} + \frac{U_{Time_w}}{\lambda} - \frac{U_{Time_k}}{\lambda} \qquad (3)$$

λ represents the increase in the value of utility function with respect to unearned income. Transferable tasks are undesirable activities to the requesters and to the carriers since they create inconvenience. Equation (3) can be used to compute the value of time savings for carriers and requesters.

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[1] For leisure activities the last term $Time_l > \overline{T}_l$ meaning $\varphi_l = 0$; however for non-leisure activities, $\varphi_l \neq 0$, since the activity has negative utility and individuals want to keep it short.

If we assume $\frac{dwage}{dTime_w} = 0$ equation (3) is reduced to:

$$VOT_l = wage + \frac{U_{Time_w}}{\lambda} - \frac{U_{Time_k}}{\lambda} \tag{4}$$

Also, it is assumed that utility U is a linear function of time spent on work $Time_w$ and other activities $Time_l$, then the value of the time-saving function can be simplified to $VOT_l = wage + \frac{wage}{\lambda} - \frac{\beta}{\lambda}$ *(25)*. In this formulation β represents the hourly value of time spent on any non-work activity. Calibration of β, λ is subject to the availability of supporting data. Due to the lack of such data for crowdshipping platform, we will generate random numbers to assess changes in the time-use behavior. Noteworthy that authors are aware of the existence of a rich literature on the subject of value of time analysis and its wide spectrum application in transportation problems; However, this paper is mainly focused on the evaluation of interplay between carriers and requesters and we tailor the review on the value of time to a limited number of main references.

Model Formulation

Requesters' Model

Suppose task 'k' is submitted by requester 'r'to the platform. If the task is successfully transferred to any carrier, the requester will have a value of time savings of V_k^r from transferring the task. The task will be evaluated by all carriers and each carrier will propose a price of Z_k^c to accomplish the task, Z_k^c is estimated in constraint (6.20) of the equation set 6. The objective function from the requester's point of view, Obj_r, is represented by (5.1). It minimizes the value paid by the requester by selecting the carrier with the minimum requested price.

$$Obj_r = Min \sum_c \alpha_c Z_k^c \tag{5.1}$$

s.t.:

$$\sum_c \alpha_c = 1, \forall c \in C \tag{5.2}$$

$$\sum_c \alpha_c Z_k^c \le V_k^r, \forall c \in C \tag{5.3}$$

$$\alpha_c \in \{0,1\}, Z_k^c \ge 0, \ \forall c \in C. \tag{5.4}$$

α_c : is a binary variable. Takes the value of 1 if the task is allocated to carrier 'c' and 0 otherwise. By using binary variables, the assignment of only one carrier to each task is guaranteed through (5.2). Constraint (5.3) sets the upper bound for the cost that the requester r is willing to pay for the task k, denoted by V_k^r. Infeasible solution to problem set 5, means that task 'k' cannot be matched with the activity pattern of any carrier 'c'.

Carriers' Model

Carriers will set the price for their service based on their own activity schedule and new constraints imposed by the addition of the new task to their agenda. Equations (6.1) to (6.27) present the scheduling model for each carrier 'c'. Equation set 6 is in the form of pickup and delivery problem, wherein each activity is specified by 3 attributes: location, duration, and time-windows, additional information regarding flexibility in duration and time-windows to perform these activities are the inputs to this model. Similarly, any task submitted by the requester is defined by these three attributes.

<u>Sets:</u>

Each carrier has $n_{1,c}$ set of activities on the original agenda to carry out, and by adding the attributes of the submitted task the total number of activities for carrier 'c' is $n_c = n_{1,c} + n_{2,c}$; $n_{2,c}$ represents the number of additional nodes corresponding to the task. If the submitted task is in the form of pickup/delivery activity, which requires picking up from one location and delivering at another location, we define two sets of Q_1 and Q_2, where Q_1 is a set consisted of pickup locations, and Q_2 refers to the set of corresponding delivery locations. For every 'i' in the set of pickup location, there is a corresponding delivery location j such that $\{j = Q_2(i), \forall i \in Q_1\}$.

$P_c^+ = \{1,\ldots,n_c\}$ is the set of all out of home activity locations, and $P_c^- = \{n_c+1,\ldots,2n_c\}$ indicates the corresponding return home locations from activities. Lets' define P_c as $P_c = \{P_c^+, P_c^-\} = \{1,...,2n_c\}$ and N_c as $N_c = \{0, P_c, 2n_c+1\}$, the set of all locations, including an initial and final return home.

<u>Input parameters:</u>

T_i^d : desired arrival time to activity i,
S_i^d : desired duration of activity i,
TT^d : desired total time spent on travel,
OHT^d : desired values for 'total out of home time spent',
$u\_\varepsilon_T^i$: upper bound for the deviation from the desired arrival time to activity location i,
$u\_\varepsilon_S^i$: upper bound for the deviation from the desired activity duration,
u_ε_{OHT} : upper bound for the deviation from the desired total out of home time spent,
t_{ij} : travel time between every pair of nodes (i,j) in the network,
VOT_c : the rate of the value of time-saving.

Decision variables:

x_{ij} : a binary variable. It takes the value of 1 if activity at location i is followed immediately by an activity at location j ,

T_i : arrival time to activity i ,

T_0 : the earliest departure time from home,

T_{2n_c+1} : the latest return time to home,

S_i : duration of activity i ,

ε_T^i : deviation from the desired arrival time to activity location i ,

ε_S^i : deviation from the desired activity duration,

ε_{OHT} : deviation from the desired total out of home time spent,

Z^c : the minimum value that the carrier would ask for the completion of the task.

Model:

The formulated model to optimize the utility for carrier is provided by equation set 6 as follows:

$$Min\ Obj_c = \alpha_1 \times \sum_{i \in N_c} \sum_{j \in N_c} t_{ij} x_{ij} + \alpha_2 \times \sum_{i \in P_c, i \neq n_{2,c}} \left(\varepsilon_T^i + \varepsilon_S^i + \varepsilon_{OHT} \right) \tag{6.1}$$

Subject to:

$$\sum_{j\in N_c} x_{ij} = 1, \forall i \in P_c^+, \tag{6.2}$$

$$\sum_{i\in N_c} x_{ij} = \sum_{i\in N_c} x_{ji}, \forall i \in P_c, \tag{6.3}$$

$$\sum_{j\in N_c} x_{ij} = \sum_{j\in N_c} x_{i+n,j}, \forall i \in P_c^+, \tag{6.4}$$

$$T_i + S_i + t_{ij} - T_j \le \left(1 - x_{ij}\right) M, \quad \forall i, j \in P_c, \tag{6.5}$$

$$T_i + S_i + t_{i,i+n_c} - T_{i+n_c} \le \left(1 - x_{i,i+n_c}\right) M, \quad \forall i \in P_c^+ \tag{6.6}$$

$$T_0 + t_{0,j} - T_j \le \left(1 - x_{0,j}\right) M, \quad \forall j \in P_c, \tag{6.7}$$

$$T_i + S_i + t_{i,2n_c+1} - T_{2n_c+1} \le \left(1 - x_{i,2n_c+1}\right) M, \quad \forall i \in P_c^-, \tag{6.8}$$

$$a_i \le T_i \le b_i, \quad \forall i \in P_c, \tag{6.9}$$

$$a_0 \le T_0 \le b_0, \tag{6.10}$$

$$a_{2n_c+1} \le T_{2n_c+1} \le b_{2n_c+1}, \tag{6.11}$$

$$T_i + S_i + t_{ij} \le T_j, \quad \forall i \in \{Q_1\}, j = Q_2\{i\}, \tag{6.12}$$

$$\sum_{i\in N_c} x_{ij} = \sum_{i\in N_c} x_{rj}, \qquad \forall i \in \{Q_1\}, r = Q_2\{i\}, \tag{6.13}$$

$$-\varepsilon_T^i \le T_i - T_i^d \le \varepsilon_T^i, \quad \forall i \in P_c^+, i \ne n_{2,c}, \tag{6.14}$$

$$-\varepsilon_s^i \le S_i - S_i^d \le \varepsilon_s^i, \quad \forall i \in P_c^+, i \ne n_{2,c}, \tag{6.15}$$

$$-\varepsilon_{OHT} \le \left(T_{2n_c+1} - T_0\right) - OHT^d \le \varepsilon_{OHT}, \tag{6.16}$$

$$\varepsilon_T^i \le u\_\varepsilon_T^i, \quad \forall i \in P_c^+, i \ne n_{2,c}, \tag{6.17}$$

$$\varepsilon_s^i \le u\_\varepsilon_s^i, \quad \forall i \in P_c^+, i \ne n_{2,c}, \tag{6.18}$$

$$\varepsilon_{OHT} \le u\_\varepsilon_{OHT}, \quad \forall i \in P_c^+, i \ne n_{2,c}, \tag{6.19}$$

$$\frac{VOT_c}{2} \times \left(\left(\sum_{i\in N_c} \sum_{j\in N_c} t_{ij} x_{ij} - TT^d \right) + \left(\sum_{i\in P_c} S_i - \sum_{i\in P_c, i\ne n_{c,2}} S_i^d \right) \right) = Z^c, \tag{6.20}$$

$$\sum_{\substack{i\in D, j\in D \\ i\ne i}} x_{ij} \le |D| - 1, \; D \subset N_c, 2 \le |D| < N_c/2, \tag{6.21}$$

$$\sum_i x_{0,j} = 1,\ \forall j \in P_c^+, \tag{6.22}$$

$$\sum_i x_{j,2n_c+1} = 1,\ \forall j \in P_c^-, \tag{6.23}$$

$$\sum_i x_{0,j} = 0,\ \forall j \in P_c^-, \tag{6.24}$$

$$\sum_i x_{2n_c+1,i} = 0,\ \forall i \in N_c, \tag{6.25}$$

$$\sum_i x_{ii} = 0,\ \forall i \in P_c, \tag{6.26}$$

$$x_{ji} \in \{0,1\}; T_0, T_{2n_c+1}, S_i, T_i, Z^c, \varepsilon_T^i, \varepsilon_s^i, \varepsilon_{OHT} \geq 0, \forall i \in N_c\ . \tag{6.27}$$

The objective function (6.1) is composed of two terms: (i) the total travel time spent by the carrier, (ii) the total deviation from the desired activity attributes (ε_T^i , ε_S^i , ε_{OHT}). Ideally, the values of the deviations along with the coefficients of each term in the objective function should be measured through the survey conducted on the population, a new research direction requiring further explorations and is beyond the scope of the current paper. Here we use attributes of homogenous activity patterns in the population as surrogate measures. The details will be provided in the numerical results. (6.2) makes sure that every activity location in the set of P_c^+, which also includes the location of the new tasks, should be visited by the carrier. (6.3) to (6.11) are common sets of constraints used in PDPTW, they model network connectivity and time windows constraints. (6.12) is added to guarantees that a delivery activity (e.g. delivering the parcel submitted by the requester) cannot start prior to pickup and (6.13) denotes if a parcel was picked up by a carrier it should be delivered by the same carrier. (6.14) to (6.19) limit the value of deviation from the desired arrival time to activity location, activity duration, and total out of home time spent within a specified range, respectively. (6.20) computes the total value of time savings for the carrier caused by the addition of the new task to the agenda. It takes into account the excess time caused by the travel and time spent on the activities compared to the original activity agenda of the carrier. Equality constraint is used to find the upper bound for the crowdshipping matches in the market. (6.21) eliminates the cycles in the tours, $|D|$ refers to the length of the cycle. According to (6.22), only one node can be visited after the initial departure from home and correspondingly (6.23) limits the number of final return home trips to 1. (6.24) prohibits the trip from home to dummy return home locations and (6.25) prohibits trip from the last return home to any other location in the network. Finally, (6.26) eliminates trip from a node to itself.

If the constraint space created by equation set 6 is infeasible it means that the task cannot be inserted to the carrier's agenda and the price requested by the carrier to deliver the task will be set to infinity, $Z^c = \inf$.

Numerical Results

Two numerical examples of the model application are presented. First, for a small problem, we explain different components of the model along with the expected results. Second, we apply the model to large-scale data and assess the impacts of the crowdshipping on a larger scale.

Case I

Suppose a case where a total of 10 pickup/delivery tasks are requested by 8 requesters, Table 4.1(a). Each task is defined by five attributes: pickup location, pickup time windows, delivery location, delivery time windows, and the maximum price that the requester is willing to pay for this service. The duration of each task for the carrier is assumed to be 10 minutes (per each pickup and drop off).

Total of 5 carriers are enrolled to operate in this system. The chains of activities for carriers along with their value of time savings ($/hour) are provided in Table 4.1(b). Every carrier has a list of activities and the location of activities along with their attributes and flexibility in activity start time, duration, and flexibility in total time spent out of home is provided. For instance, the first carrier resides in node 32 and is planning to perform two out of home activities at node 39 and 7 (Figure 4.1). The first activity in the agenda is scheduled for 9 am with 1-hour duration; however, the activity is flexible and it can be rescheduled to another time between 7:00 to 11:00, also it can be shortened or extended for 10 minutes.

Table 4.1 Information on the carriers and tasks in the platform

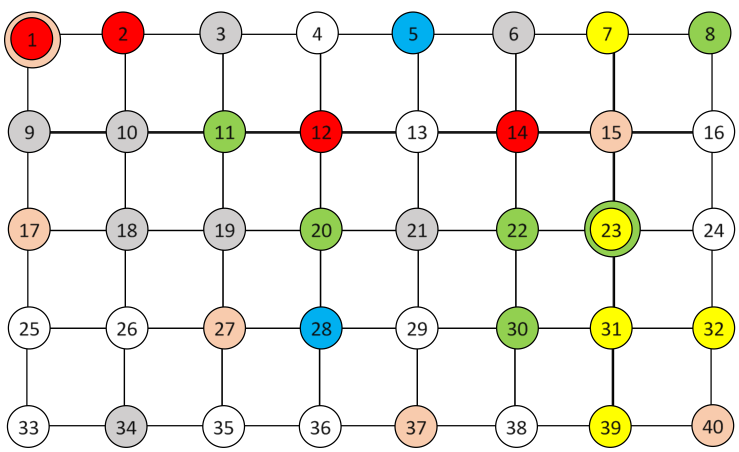
(a) Properties of tasks submitted to the platform

Task	Requester #	Pickup Node	Pickup time windows	Delivery Node	Delivery time windows	Maximum price ($)
1	1	11	[06:00, 24:00]	22	[17:00, 20:00]	15
2	2	8	[06:00, 24:00]	23	[08:00, 09:00]	15
3	1	2	[06:00, 24:00]	14	[16:00, 20:00]	12
4	3	40	[06:00, 24:00]	27	[13:00, 15:00]	15
5	4	19	[06:00, 24:00]	34	[14:00, 18:00]	9
6	4	31	[06:00, 24:00]	23	[18:00, 20:00]	8
7	5	21	[06:00, 24:00]	9	[21:00, 24:00]	12
8	6	10	[06:00, 24:00]	6	[16:00, 24:00]	18
9	7	15	[06:00, 24:00]	37	[12:00, 14:00]	16
10	8	28	[06:00, 24:00]	3	[11:00, 13:00]	12

(b) Carriers' original itinerary and preferences

Carriers	Home node	Activity node	Desired activity start time	Flexibility of activity start time	Desired activity duration	Flexibility activity duration	VOT ($/hour)	Desired OHT	Flexibility of OHT	Total travel time
1	32	39	09:00	02:00	01:00	00:10	8	05:00	03:00	00:30
		7	16:00	01:00	03:00	01:00				
2	5	28	14:00	02:00	1:00	00:10	7	02:00	03:00	00:30
3	12	14	08:00	-	01:00	-	6	03:00	03:00	01:40
		2	16:00	01:00	00:30	00:05				
		1	18:00	01:00	01:00	00:20				
4	30	20	07:00	00:30	01:00	00:20	5	03:00	03:00	01:00
		23	13:00	00:30	01:00	00:10				
5	1	17	16:00	02:00	02:00	00:20	6	03:00	03:00	00:30

The second activity is scheduled for 16:00, but it can start anytime between 15:00 to 17:00. The duration of the activity varies in the range of 2 to 4 hours (preferably 3 hours). Total time that this carrier is willing to spend out of home is 5 hours however it can be extended up to 8 hours. Finally, according to the original activity itinerary the total time spent on travel was 30 minutes and if providing parcel delivery requires more time, this will be taken into account to measure the degree of inconvenience caused by the carrier. Figure 4.2 demonstrates the optimal task allocations to each carrier. Only 5 tasks (1, 2, 4, 6, and 9) are assigned to carriers. Carrier 1 is matched with task 6, carrier 4 is matched with task 1 and 2, and carrier 5 is matched with task 4 and 9. Figure 4.2 also illustrates the detailed itinerary of each carrier in the system. In this figure the new tasks are highlighted in orange color, the requested price for service completion is stated. Carrier 1 is paid $4.64, carrier 4 gets a total of $7.80, finally, and carrier 5 is paid $29.85. The locations visited by each carrier are highlighted in 5 different colors (carrier1: yellow, carrier2: blue, carrier3: red, carrier4: green, and carrier5: pink).



Carrier 1		
Node	*Arrival time*	*Price($)*
39	09:00	
7	16:00	
31	18:35	4.64
23	19:00	
Carrier 2		
Node	*Arrival time*	*Price($)*
28	14:00	28
Carrier 3		
Node	*Arrival time*	*Price($)*
14	08:00	
2	16:00	
1	18:00	
Carrier 4		
Node	*Arrival time*	*Price($)*
20	7:00	
8	08:35	3.00
23	09:00	
23	13:00	
11	16:35	4.80
22	17:00	
Carrier 5		
Node	*Arrival time*	*Price($)*
15	13:30	15.42
37	14:00	
40	14:15	14.43
27	15:00	
17	16:00	
Unassigned tasks		

Figure 4.2. Network topology and detailed itinerary of carriers after task allocation (travel time generated from a uniform random distribution in the range of [1-30] minutes

Case II

With the goal of assessing the impacts of crowdshipping on time use behavior of population and defining parameters to set the upper bound for the crowdshipping based on the activity patterns, we construct of a second case study using the household travel survey data, California 2001 *(29)*. Household travel surveys contain detailed information on the activity participation (activity type, duration, location, and etc.) and demographics of the participating individuals (age, gender, household size, income, etc.) The case study presented here demonstrates the potential application of the model in integrating crowdshipping into activity-based models. We focus on the travel behavior of the residents of 'Los Angeles County' and 'Orange County', comprised of activity patterns for 1650 individuals. Using time use behavior of participants in the survey and the list of activities in their agenda, we divide surveyed people into 2 groups of potential requesters and carriers.

Identifying potential requesters

Requesters were selected based on the following criteria:

- There exist transferable activities in their agenda (e.g. grocery shopping)
- The duration of the transferable activities cannot exceed 90 minutes, assuming longer activities have higher utilities to the requesters and they are not willing to transfer them. Noteworthy, here, we only consider pickup and delivery tasks and the duration of these tasks for the carriers is set to 10 minutes/pickup and 10 minutes/delivery.

The total number of requesters meeting these criteria is 371 individuals in the dataset and the total tasks submitted to the system is 625.

Identifying potential carriers

The main criterion to select carriers is based on the scheduling flexibility in the agenda. In the context of this paper, individuals who spend less than 5 hours for out of home activities are selected as potential carriers, resulting in the total of 312 individuals.

Value of time savings

The value of time-saving for carriers and requesters is computed using equation (4), which later can be simplified as $VOT_l = wage + \frac{wage}{\lambda} - \frac{\beta}{\lambda}$. Hourly wages are computed based on the annual income of the surveyed population. Values of λ and β are generated from normal distributions. We set $\lambda > 0$ and $\beta < 0$ (a common practice in the literature *(30)*). Clearly, different values of these parameters will impact the tradeoff behavior among requesters and carriers and it would be interesting to evaluate the impacts of these parameters on the behavior of travelers, due to the size of paper, we only present the results of one test case.

Flexibility of carriers' agenda

As mentioned in equation set 6, inserting service activity to carriers' agenda, requires making some adjustments to their original activity pattern (e.g. some activities might be rescheduled or shortened). Possible adjustments depend on the degree of flexibility in the agenda ($u\_\varepsilon_T, u\_\varepsilon_S, u\_\varepsilon_{OHT}$), and due to the lack of stated/revealed preferences data on the crowdshipping concept, we cluster chains of activity patterns to homogenous groups of patterns and use the statistics of the clusters to infer the degree of flexibility.

Using the same dataset, Allahviranloo et al., presented a clustering methodology to segment chains of activities and derive a set of representative patterns, *(31)*. In their analysis, they classify 8684 patterns of Southern California to 8 clusters. Using clustered patterns, differences in the distribution of arrival time and activity duration for different groups of patterns can be narrowed down. Table 4.2 illustrates the statistical parameters for activity duration and arrival time for each cluster per activity category, respectively *(32)*. The degree of flexibility in the agenda of every carrier is inferred based on the standard deviation of the cluster that the activity pattern of carrier belongs to. Suppose activity pattern of carrier 'j' belongs to cluster 2, and if this carrier has a 'personal' activity in the agenda, then the value of standard deviation for the duration of personal activity is 204 minutes and the value of standard deviation for arrival time to this activity is 192 minutes. We measure the degree of flexibility of each activity proportional to the standard deviation of the activity to the corresponding cluster, $u\_\varepsilon_T = \gamma\sigma_T, u\_\varepsilon_S = \gamma\sigma_S, u\_\varepsilon_{OHT} = \gamma\sigma_{OHT}$. For the numerical experiment presented here, we set γ to be 0.2. Clearly, the results of the task allocation are sensitive to the value of γ, here we demonstrate the potential application of the concept and we could have presented the results of a complete sensitivity analysis if the paper length limit would have allowed.

Table 2.2. Statistical parameters of activity duration and start time in 8 Clusters (minutes)

Statistical Parameters of Activity Duration in 8 Clusters (minutes)

Cluster	work		maintenance		Recreational		Personal		School		Pickup		Other	
	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
1	397	228	38	66	94	129	71	47	194	98	23	79	24	79
2	134	166	64	102	189	209	158	204	257	251	31	71	70	162
3	96	109	72	118	104	115	113	137	283	104	27	80	160	278
4	160	142	43	65	92	97	68	40	191	100	21	48	52	60
5	371	193	29	48	103	140	58	33	161	69	22	80	45	130
6	331	197	36	56	95	127	68	42	172	86	20	62	63	164
7	197	106	99	142	183	204	121	120	418	101	113	183	52	103
8	174	186	40	60	96	112	79	76	252	156	37	103	43	114

Statistical Parameters of Activity Start Time in 8 Clusters (minutes)

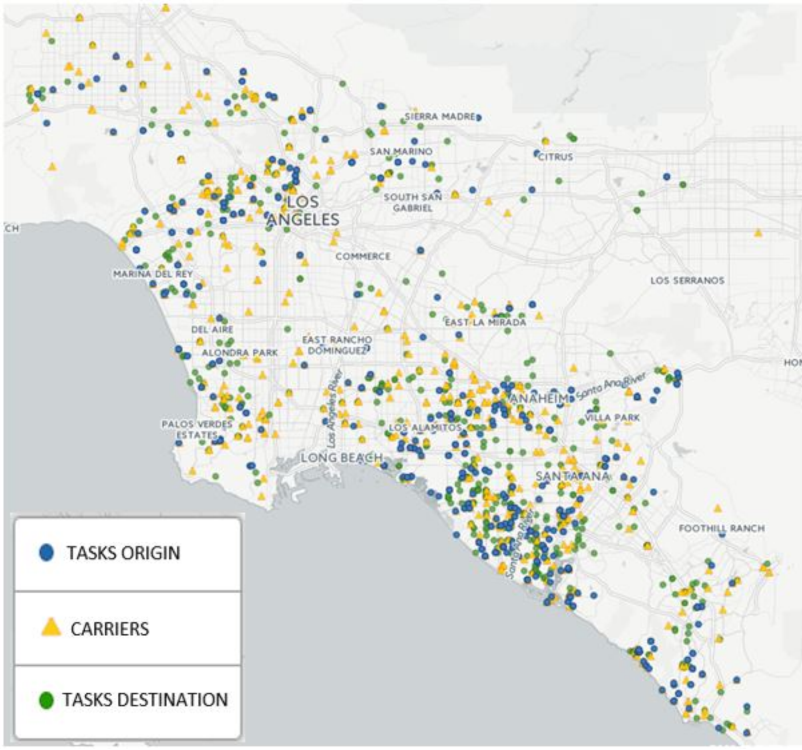
Cluster	work		maintenance		Recreational		Personal		School		Pickup		Other	
	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
1	583	167	917	263	933	240	874	280	763	312	764	313	770	330
2	735	268	822	186	806	211	714	192	611	177	782	228	781	289
3	644	181	711	182	765	254	645	193	525	120	736	242	708	249
4	720	156	846	200	925	237	836	277	708	188	797	256	745	278
5	483	171	890	246	883	266	910	189	886	250	786	268	632	294
6	590	164	888	247	924	233	879	264	901	275	780	282	745	306
7	892	265	930	242	960	248	913	189	494	116	736	296	707	302
8	806	368	829	201	932	239	777	210	633	227	734	239	775	242

Results

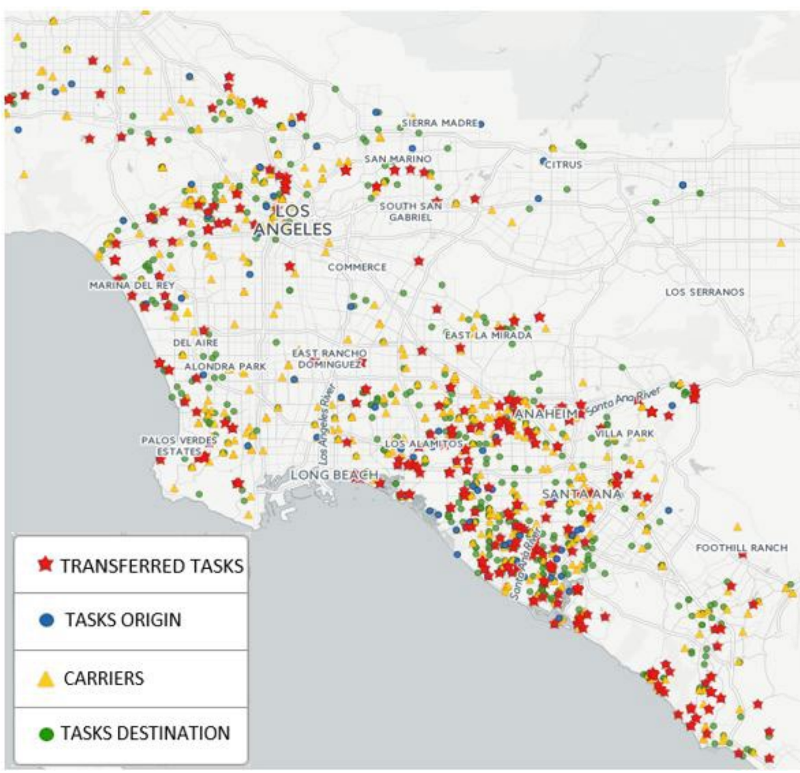
Figure 4.3(a) illustrates spatial distribution of carriers and tasks in the study region. In this figure the location of carriers are marked by an orange triangle and the origin and destination of tasks are marked by blue and green circles, respectively. Figure 4.3(b) shows the distribution of transferred tasks in the crowdshipping system.

Based on the assumptions made on the value of time estimation, and the flexibility of the agenda, out of 625 tasks submitted to the system, 404 of them were successfully transferred to carriers. In other words, the upper bound for crowdshipping platform subject to the assumptions made by the authors is %64. Participation in crowdshipping has resulted in total 13,074 hours of time savings for the requesters, and also reduction of 1,468.53 miles traveled by the requesters. The total value of time savings for the carriers is $1,122 and the added miles traveled for the carriers is 1201 miles.

Figure 4.4 demonstrates the impacts of crowdshipping on time use behavior of carriers and requesters. In these graphs, the horizontal axis indicates the time of day and vertical axis refers to the share of each type of activity along the day. Each color represents the type of activities and as shown in the legend we use letter 'H' as the indicator to 'in-home', 'W' for 'work', 'P' for 'personal', 'R' for 'recreational', 'S' for 'school', 'M' for 'maintenance', 'K' for 'pickup/drop off', 'O' for 'other', 'N' represents 'new delivery activities' added to the agenda of carriers, and 'F' indicates the 'free' time created in the agenda of requesters by transferring their eligible tasks to carriers. Figure 4.4(a) and Figure 4.4(b) represents the time use behavior of requesters and carriers prior to enrollment in the crowdshipping system. Figure 4.4(c) and Figure 4.4(d) show their pattern after participation in the system. As it is illustrated in these figures the introduction of crowdshipping system will impact activity participation behavior of travelers and consequently will change the demand for travel for different modes of transportation. A proportion of maintenance activities of requesters has been eliminated from their agenda and freed up some vacant time-windows, and on other hand, carriers are spending more time out of their home and some shifts in the share of other activities along the day are observed. Clearly, variations in the time-use behavior depend on the demographics of the participants and their willingness to pay and value of time savings, which is an interesting research topic demanding further explorations and it is beyond the scope of the current analysis.



(a) spatial distribution of tasks and carriers in Los Angeles and Orange County



(b) spatial distribution of tasks and carriers in the region with allocated tasks

Figure 4.3. Spatial distribution of tasks and carriers

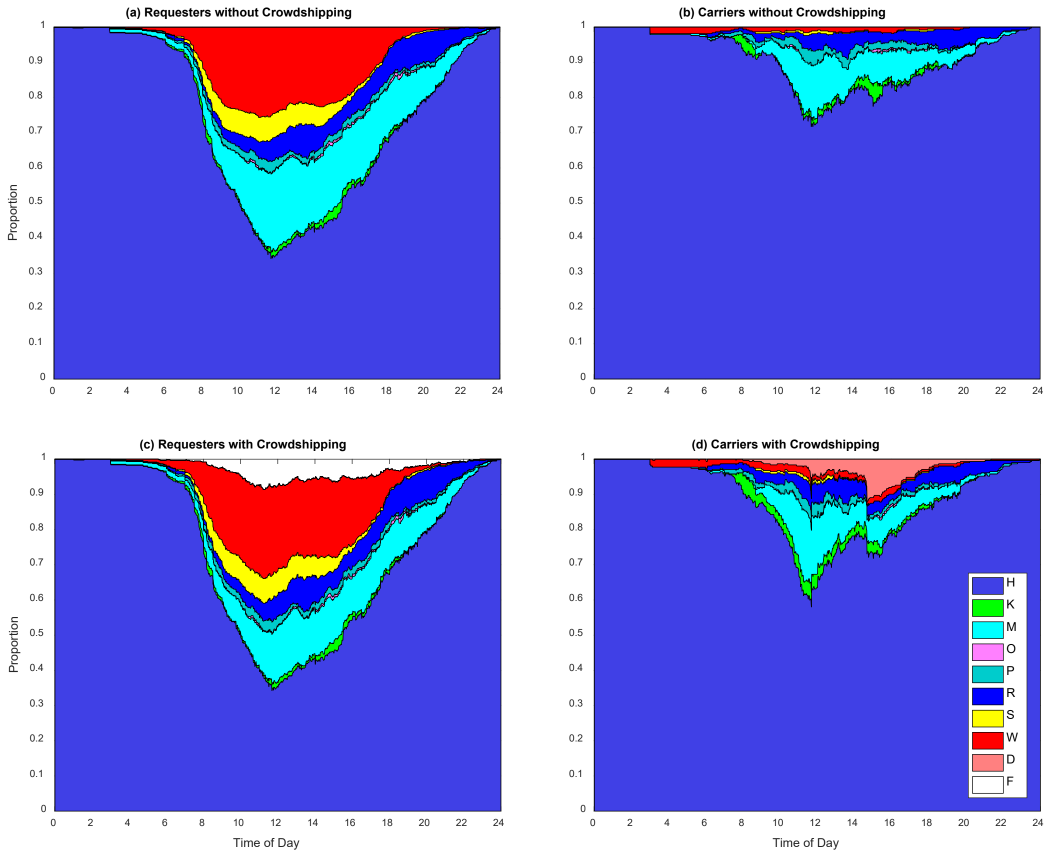


Figure 4.4. Time use behavior of requesters and carriers before and after the participation in crowdshipping

Conclusions

In recent years we have witnessed dramatic changes in the social behavior of population mainly due to the technological advancements. Social media and the internet are creating a virtual world wherein new friendships are made, new norms and social values are formed, and new activities are born. Not only internet and technology have broadened the range of accessibility for every individual but also it have created a new domain of trust such that within less than a second someone books a room in another part of the globe from a total stranger, based on the reviews made by strangers. Virtual networks have created a tremendous opportunity for the growth of P2P trading markets. In these markets, individuals trade their goods, homes, personal space, personal car, and even their time with others in an exchange of service or money. In P2P crowdshipping market, carriers trade their time to carry out pickup/delivery request of others, we postulate that such market will influence the travel and time use behavior of the population, it will eliminate some activities in a section of the network and add new activities in other parts of the network. The work presented here proposes a methodology to assess the impacts of crowdshipping on travel behavior and also to find an upper bound for the crowdshipping platform considering activity patterns in P2P market.

Here we developed a mathematical model to solve crowdshipping model using household travel survey data for California. In this model, based on the premise that each individual in crowdshipping platform – regardless of being carrier or requester – maximizes his/her utility, optimal task transaction between requesters and carriers are identified. Requesters minimize the price they are willing to pay for task accomplishment and carriers minimize the inconvenience caused by accommodating the new task. We measure carrier's inconvenience based on the adjustments made into their original itineraries. Both carriers and requesters set their price based on the value of time savings, which is a function of their income. Using California Household Travel Survey data, 2001, we identified sets of potential requesters, potential carriers, and eligible transferable tasks. Out of 1650 individuals, 371 individuals were identified as requesters and 312 individuals met the criteria to be carriers, whereas the total number of tasks submitted to the platform was 625. We used the statistical distribution of activity duration and arrival time in clustered activity patterns to infer the degree of flexibility in the itinerary of carriers. The final results indicate allocation of 404 tasks in the platform and significant changes in time use behavior and spatial distribution of the population in the region. Midday activities of the requesters were transferred to carriers, creating a large proportion of free time in the schedule of requesters and shifting some activities in the agenda of carriers.

It should be taken into account that the number of allocated tasks, value of time savings, changes in space-time distribution of activities and etc. depend on the set of input parameters - (a) utility of time spent on different activities in order to quantify value of time savings; and (b) degree of flexibility in the agenda of carriers - that can be further explored by conducting a more robust survey of the population. However, this research effort is purely devoted to developing and testing a new methodology to merge crowdshipping and travel behavior models, and also to find an upper limit for such a market considering demographics and activity patterns of carriers and requesters.

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Appendix

Crowdshipping Survey

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This survey is being conducted as part of on-going academic research project at the City College of New York. The purpose of this project is to examine the market for the emerging type of shopping/home delivery called crowdshipping.
In crowdshipping, ordinary people, rather than professional service providers, deliver goods. Using an internet-based platform, individual shoppers can request delivery services from individual participating providers, who, for a negotiated cost, deliver goods from local stores, warehouses, or other origins.

This survey should take about 10 minutes to complete. Thanks for your participation!

1. What is your typical daily work schedule? Please state the typical times that you arrive at work and depart from work.

	Start time	End time
Weekday		
Saturday		
Sunday		

2. What is your occupational status?

- Full time employee
- Part time employee
- Full time student
- Par time student
- Retired
- Unemployee

3. How many hours per day do you estimate you spend traveling on a typical day?

	In hour(s)
Weekdays	
Saturday	
Sunday	

Other (please specify)

4. In a typical week, how much time do you spend shopping? (Do not include transportation time)

	Hours
In-store shopping	
Online shopping	

Other (please specify)

5. In the past month, how many times have you shopped for the following goods?

	In-store Shopping	Online order from local store
fresh food		
Household products		

6. During the last month, how many time(s) you have received the following types of deliveries?

	Delivery of goods that you shopped for in person at a local store	Delivery of goods that you shopped for online
Fresh food		
Household products		

7. What mode(s) of transportation do you frequently use to travel to your local grocery store ?

☐ Passenger car

☐ Uber/ Lyft/ Taxi

☐ Transit

☐ Bike

☐ Walking

☐ Other (please specify)

____

8. Can you receive deliveries when you are not home (e.g. they can be left with a doorman, in a secure room, or on a porch)?

○ Yes

○ No

9. For deliveries that cannot be accepted unattended, during which hours would you typically schedule deliveries on a weekday (Please select all that apply)?

- ☐ 6 AM - 7 AM
- ☐ 7 AM - 8 AM
- ☐ 8 AM - 9 AM
- ☐ 9 AM - 10 AM
- ☐ 10 AM - 11 AM
- ☐ 11 AM - 12 PM
- ☐ 12 PM - 1 PM
- ☐ 1 PM - 2 PM
- ☐ 2 PM - 3 PM
- ☐ 3 PM - 4 PM
- ☐ 4 PM - 5 PM
- ☐ 5 PM - 6 PM
- ☐ 6 PM - 7 PM
- ☐ 7 PM - 8 PM
- ☐ 8 PM - 9 PM
- ☐ 9 PM - 10 PM
- ☐ 10 PM - 11 PM
- ☐ 11 PM - 12 AM

10. For deliveries that cannot be accepted unattended, during which hours would you typically schedule deliveries on a weekend day (Please select all that apply)?

- [ ] 6 AM - 7 AM
- [ ] 7 AM - 8 AM
- [ ] 8 AM - 9 AM
- [ ] 9 AM - 10 AM
- [ ] 10 AM - 11 AM
- [ ] 11 AM - 12 PM
- [ ] 12 PM - 1 PM
- [ ] 1 PM - 2 PM
- [ ] 2 PM - 3 PM
- [ ] 3 PM - 4 PM
- [ ] 4 PM - 5 PM
- [ ] 5 PM - 6 PM
- [ ] 6 PM - 7 PM
- [ ] 7 PM - 8 PM
- [ ] 8 PM - 9 PM
- [ ] 9 PM - 10 PM
- [ ] 10 PM - 11 PM
- [ ] 11 PM - 12 AM

11. Would you be willing to use a secured app to request services from a third-party to deliver goods to you from your local store?

- ○ Yes
- ○ I would consider it depending on the cost
- ○ No

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12. How much would you be willing to pay as a delivery fee (in $) for the following types of deliveries?

A small delivery
(e.g. 1-3 grocery bags)

A large delivery
(e.g. 4+ grocery bags)

13. How much shopping time (in hours) do you expect you would save per week by using a delivery service?

14. How would you use the time saved by using this delivery service?

☐ Spend time with family

☐ Social activities

☐ Work

☐ Other (please specify)

15. Would you consider working as a delivery person, completing delivery of goods from local stores to customers requesting services through a secured app?

◯ Yes

◯ No

Crowdshipping Survey

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16. During what time frame would you be willing to complete these deliveries on a weekday? (Please check all that apply)

- ☐ 6 AM - 7 AM
- ☐ 7 AM - 8 AM
- ☐ 8 AM - 9 AM
- ☐ 9 AM - 10 AM
- ☐ 10 AM - 11 AM
- ☐ 11 AM - 12 PM
- ☐ 12 PM - 1 PM
- ☐ 1 PM - 2 PM
- ☐ 2 PM - 3 PM
- ☐ 3 PM - 4 PM
- ☐ 4 PM - 5 PM
- ☐ 5 PM - 6 PM
- ☐ 6 PM - 7 PM
- ☐ 7 PM - 8 PM
- ☐ 8 PM - 9 PM
- ☐ 9 PM - 10 PM
- ☐ 10 PM - 11 PM
- ☐ 11 PM - 12 AM

17. During what time frame would you be willing to complete these deliveries on a weekend? (Please check all that apply)

- ☐ 6 AM - 7 AM
- ☐ 7 AM - 8 AM
- ☐ 8 AM - 9 AM
- ☐ 9 AM - 10 AM
- ☐ 10 AM - 11 AM
- ☐ 11 AM - 12 PM
- ☐ 12 PM - 1 PM
- ☐ 1 PM - 2 PM
- ☐ 2 PM - 3 PM
- ☐ 3 PM - 4 PM
- ☐ 4 PM - 5 PM
- ☐ 5 PM - 6 PM
- ☐ 6 PM - 7 PM
- ☐ 7 PM - 8 PM
- ☐ 8 PM - 9 PM
- ☐ 9 PM - 10 PM
- ☐ 10 PM - 11 PM
- ☐ 11 PM - 12 AM

18. By which mode(s) would you likely travel to conduct these deliveries?

- ☐ Car/Truck
- ☐ Public Transit
- ☐ Bicycle
- ☐ Walking

19. What rate would you expect to paid (in $/hour) to conduct small deliveries by each mode? (Please enter rates only for the modes by which you would consider making a delivery)

Small Package (less than 3 grocery bags)

Car/truck

Public Transit

Bicycle

Walking

20. What rate would you expect to paid (in $/hour) to conduct large deliveries by each mode? (Please enter rates only for the modes by which you would consider making a delivery)

Large Package (more than 3 grocery bags)

Car/truck

Public Transit

Bicycle

Walking

21. What is your age range?

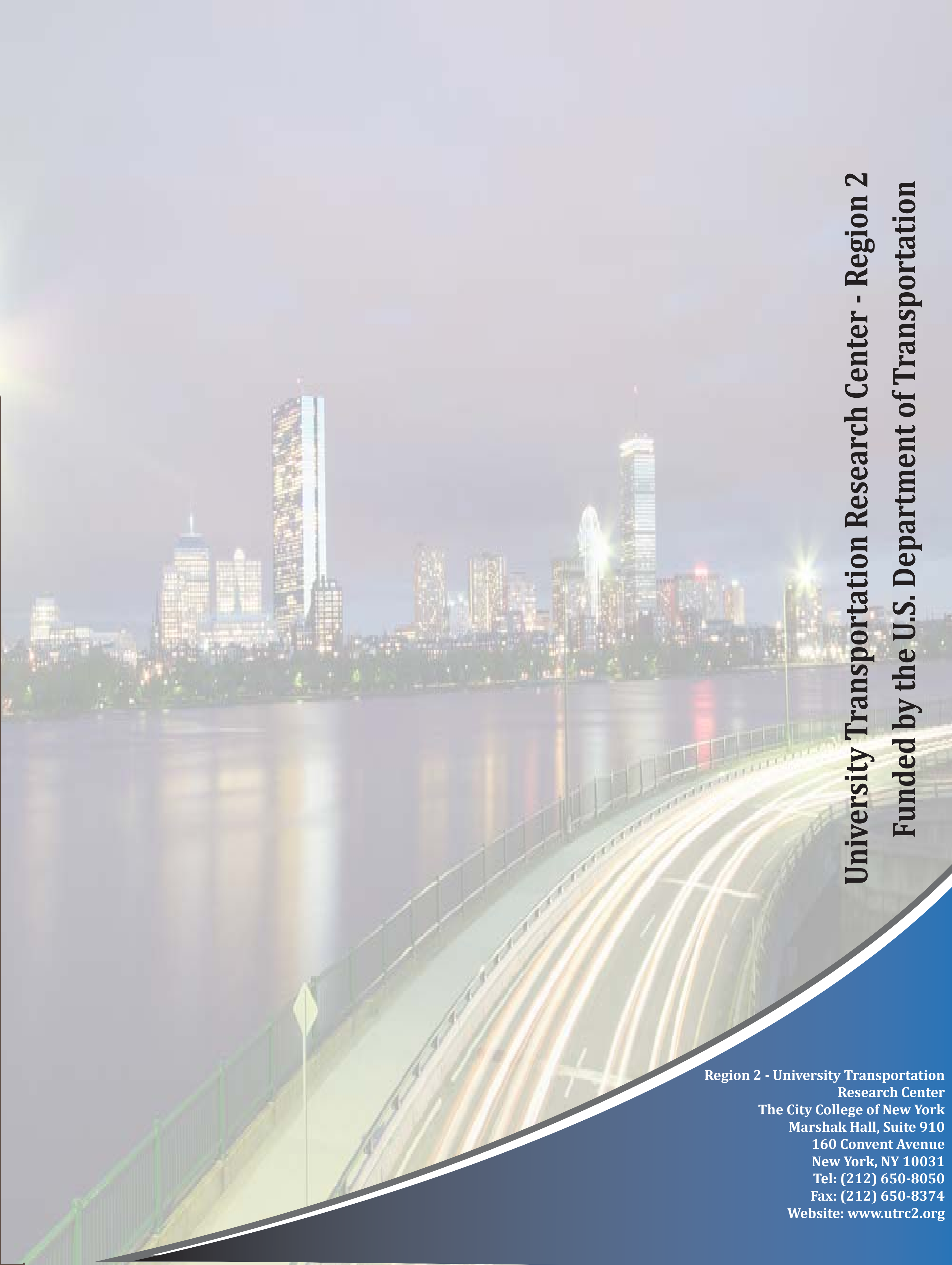
- 12 to 17
- 18 to 24
- 25 to 34
- 35 to 44
- 45 to 54
- 55 to 59
- 60-64
- 65-74
- 75 and over
- I prefer no answer

22. What is your annual household income category? (optional)

- ○ Less than $24,000
- ○ $25,000 to $49,999
- ○ $50,000 to $74,999
- ○ $75,000 to $99,999
- ○ More than $100000
- ○ I prefer no answer

23. What is your home zip code?

24. Feedback



University Transportation Research Center - Region 2
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Region 2 - University Transportation Research Center
The City College of New York
Marshak Hall, Suite 910
160 Convent Avenue
New York, NY 10031
Tel: (212) 650-8050
Fax: (212) 650-8374
Website: www.utrc2.org