**SELECTIVITY CORRECTION IN DISCRETE-CONTINUOUS MODELS FOR THE WILLINGNESS TO WORK AS CROWD-SHIPPERS AND TRAVEL TIME TOLERANCE**

**Tho V. Le**

Ph.D. Student

Lyles School of Civil Engineering

Purdue University

550 Stadium Mall Drive, West Lafayette, IN 47907, USA

Tel: +1 765 586 2836; Email: [le39@purdue.edu](mailto:le39@purdue.edu)

**Satish V. Ukkusuri, Corresponding Author**

Professor

Lyles School of Civil Engineering

Purdue University

550 Stadium Mall Drive, West Lafayette, IN 47907, USA

Tel: +1 765 494-2296; Fax: +1 765 494 0395; Email: [sukkusur@purdue.edu](mailto:sukkusur@purdue.edu)

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**Abstract**

The objective of this study is to understand the different behavioral considerations that govern the choice of people to engage in a crowd-shipping market. Using novel data collected by the researchers in the US, we develop discrete-continuous models. A binary logit model has been used to estimate crowd-shippers’ willingness to work, and an ordinary least-square regression model has been employed to calculate crowd-shippers’ maximum tolerance for shipping and delivery times. A selectivity-bias term has been included in the model to correct for the conditional relationships of the crowd-shipper’s willingness to work and their maximum travel time tolerance. The results show socio-demographic characteristics (e.g. age, gender, race, income, and education level), transporting freight experience, and number of social media usages significant influence the decision to participate in the crowd-shipping market. In addition, crowd-shippers pay expectations were found to be reasonable and concurrent with the literature on value-of-time. Findings from this research are helpful for crowd-shipping companies to identify and attract potential shippers. In addition, an understanding of crowd-shippers - their behaviors, perceptions, demographics, pay expectations, and in which contexts they are willing to divert from their route - are valuable to the development of business strategies such as matching criteria and compensation schemes for driver-partners.

*Keywords*: Crowd-shipping, Willingness to work, Last-mile delivery, On-demand delivery, Selectivity correction, Discrete-continuous model

**Introduction**

Urbanization is the rapidly increasing globally. In the past two hundred years prior to 1950 it is reported that around 400 million individuals moved to urban spaces. This number is expected to grow to more than 6 billion by the year 2030. Also urban areas will account for 70% of the world’s population in the next 10 years. (**Challenges and way forward in the urban sector**). This transition of population distribution to urban locations will result in many challenges including energy, safety, pollution and mobility.

As urbanization continues we will witness increased strain on our transportation infrastructure in manifold dimensions. Traffic congestion is one of the main challenges in urban set up which has been a pressing issue. The issue continues to grow as 88% of American own a car in order to save travel time. **(Why Traffic Congestion Is Here To Stay…And Will Get Worse)**. Another consequence of higher number of automobiles on the roads in the need for parking spaces. As the city area gets more and more expensive to live individuals start moving on the peripheries and hence that results in longer commuting time. Public transport in most places is inadequate or the network coverage is not good enough for individual to give up the comfort of a car. Increase in motorized traffic results mobility impacts on pedestrians and bicyclists for whom there is not enough consideration. One of the other main challenges on urban transportation is high maintenance cost of upgrading the infrastructure and also construction costs due to expansion. Higher number of automobiles on the roads also results in increasing levels of pollution which has adverse health impacts on the inhabitants. The area covered by roadways in urban areas can range from 30% to 60% which is really high. **(Urban Transport Challenges)**.

In order to tackle the issue related to urban mobility is to provide Mobility on Demand systems which provides the individual with mobility but can also provide the mobility other individuals without increasing congestion. Currently, a car is parked 95% of the times. This not only results is high level of under utilization of the vehicle but also leads to vehicle wear vis corrosion, which takes place when the vehicle is standing still. **(Today’s Cars Are Parked 95% of the Time)**. These systems are a response to the ever evolving demand of the population for more efficient transportation systems. These systems can be defined as services which provide mobility to individuals as a service. The advantages of these services is that the individuals do not have to have ownership related issues/costs for example insurance, depreciation etc [1]. MODs are also a more sustainable solution to the ever increasing traffic and congestion problem. The mobility on demand services have grown in the past and continue to see a positive response from the users. In fact industry research says that the car sharing market will increase to USD 16.5 billion by 2024. **(Car sharing Industry)**

The initial business model started with the services which centered around round trip type of service. For example Zip Car provides rental cars at stations but they need to be returned to the point it was rented. As the rental industry evolved with the mobile technology there are many services which provide one way rental/transportation like Alamo, Enterprise and Budget. These systems provide the flexibility of using the vehicle and not having to replace them from the point of rental. However, one of the issues of this service is that certain destinations are more in demand as compared to other destination. Hence as they system evolves over time we see that vehicles distribution is imbalanced over the geography. Some of the solutions which are proposed to tackle this issue is to incentivize customers to share rides or by hiring individuals to rebalance the cars. Both these approaches result in higher cost for the customers.

With the advent of robotic/autonomous vehicles there soon will be emergence of autonomous MODs are robotic vehicles providing transportation services. The issue of rebalancing then would be solved more efficiently as in the case of autonomous vehicles there will the vehicles can rebalance itself after the trip is completed.

In this new area potential managers of these AMOD systems have some questions which need to be addressed. Which locations need to be rebalanced? How much will rebalancing improve the systems performance? What policies should be used to rebalance? What will be the impact of rebalancing in a stochastic network with uncertain travel times? This papers attempts to solve this problem using an optimization framework.

This paper includes six sections. The introduction presents the background and motivations of this study. The literature review section illustrates its state-of-the-art methodology. Section 3 features the methodology. The findings and insights are discussed in the estimation results section. Finally, the study is summarized in the conclusion section.

**literature review**

Even though the study of rebalancing of AMOD systems itself is a relatively new area of research, but it has some common themes with one-to-one pickup and delivery problems (PDPs), characterized by the absence of a central depot. PDPs can be dynamic or static. The DPDPs are further divided into dynamic stacker crane problem (Dynamic SCP), dynamic vehicle routing problem with pickup (Dynamic VRPPD) and deliveries and dynamic dial-a-ride problem. In dynamic SCP the vehicle transport only one unit from the pick site to the delivery location. This is mainly due to the capacity constraint of the vehicle. In dynamic VRPPD the number of items that can be carried is more than one but usually there are time windows for pickup and delivery. In dynamic dial-a-ride problem individuals can ask for a ride that need to be transported from one point to another. There are restrictions in this model on the time windows and the maximum length of the ride travel time. Rebalancing of AMOD systems differs from the DPDPs in having finite number of pickup and delivery locations, the destination of the customer is unknown and the optimization is done for the empty vehicles.

Rebalancing AMODs also have similarity to DTA wherein the time dependent flows are optimized over the network. The key point of deviation is the point where in rebalancing AMODs the empty trips are minimized instead of the passenger carrying trips.

Dimitris Papanikolaou, 2011 studied the problem of rebalancing using diffusion model. He modeled the rebalancing problem as diffusion of resource from areas of high concentration to areas of lower concentration. In this study though he did not account for the asymmetry in customer arrival. Similarly there have been other simulation based studies which looked at the rebalancing problem ( 11-14). The studies indicated that the car sharing systems are sensitive to the vehicle-to-trip ratio and the rebalancing scheme utilized. Also these simulation-based studies have significant number of parameters which need to be validated.

Later more studies [12-16] were done which had a more theoretical approach to solve the rebalancing problem. [12] analyzed the problem from fluidic approach where the customer, vehicles are assumed as a continuum. In [8] the MODs are studied assuming human rebalancers using a queuing network approach. They applied the approach to the lower Manhattan and showed that there is a need of 3-5 vehicle to driver ratio. These studies do provide added insights into the problem of rebalancing. There are a few gaps in these studies which we look to fill. The above works assumed that customers do not leave the system and the travel times are deterministic. In this paper we are going to adapt the fluidic approach to solve the rebalancing problem. This paper attempts to study the impact of stochastic travel time and customer leaving have on the rebalancing policy.

**Methodology**

In this study, respondents were first asked whether they were willing to work as crowd-shippers (discrete variable). If so, they were asked what is the maximum TTT (continuous variable) that they would accept to pick up and deliver packages. Those decisions are interrelated; therefore, the discrete-continuous models are the best fit to analyze the data (*29*). In addition, the interconnected discrete-continuous data is generally considered as a problem of selectivity. The observed data (i.e. TTT) was the outcome of a selection process related to the non-random sample of data from observed discrete decisions (i.e. WTW as crowd-shippers). The relationships of the decisions are illustrated in **Figure 1**.

|  |
| --- |
| **Figure 1.** Relationships of the two decisions |

The goal of this study is to identify which factors relate to the maximum TTT of respondents willing to work as crowd-shippers. The continuous TTT is defined as:

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| --- | --- |
|  |  |

Where ** is the tolerance for travel time of crowd-shipper *i*; ** are estimable parameters; ** is a vector of respondent *i*’s social demographic variables; **is an unobserved term assumed to be normally-distributed. However, since this model is applied to the subset of respondents who are willing to work as crowd-shippers, ** 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 crowd-shippers. Several approaches have been developed to correct for such selectivity bias (*30*, *31*). Denote **is a conditional mean of ** given that respondent *i* chooses to be a crowd-shipper (*31*).

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| --- | --- |
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Where **is the standard deviation of the normally-distributed unobserved term **; **is the standard deviation of the logistic unobserved term **in the discrete choice model (Equation 6);** is the correlation between ** and **; and **is defined as:

|  |  |
| --- | --- |
|  |  |

Where **is the probability of the decision of WTW as a crowd-shipper of a respondent *i*.

Then

|  |  |
| --- | --- |
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Substituting (4) in in (*1*), the equation becomes:

|  |  |
| --- | --- |
|  |  |

where** is an estimated parameter which equals **;**has a conditional zero mean by construction.

In Equation (5), the parameter** of theselectivity-bias term is estimated as a random parameter. As such, a parameter is estimated for each observation. The hypothesis under this assumption of a random parameter is the variety of behavioral observations. In other words, all observations used in this model are willing to work as crowd-shippers, and their TTT varies. This Equation (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. Using a discrete-choice model to estimate a probability for each discrete decision (i.e. willingness to work as crowd-shippers). The data set from all respondents is employed in this step.
2. Using the outcomes from step one to estimate values of selectivity.
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. Only a subset of data, from respondents who are willing to work as crowd-shippers, 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 IIA, which is suitable for independent choices. Therefore, a multinomial logit model is commonly employed to infer the self-determined behavior of respondents. The utility of decision *k* of a respondent is expressed as *Uk*.

|  |  |
| --- | --- |
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Where ** is the observed utility, and . The choice model is then written as:

|  |  |
| --- | --- |
|  |  |

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 crowd-shippers or not) in the choice set.

**Data source**

The data set used in this study was collected from a US survey spanning from February to April 2017. The survey was designed to understand the behavior of stakeholders (e.g. requesters and prospective crowd-shippers) and assumed the availability of crowd-shipping services in the logistics market. There were 1,176 responses, but the final data set only includes 549 respondents, as some responses were incomplete or inconsistent. In the survey, shipping experience, as well as preferences and stated preference questions on crowdsourced delivery were asked. Respondents reported their experience of transporting freight for someone else in the past, and then were asked whether they were willing to work as crowd-shippers in the future given a number of contexts. The logic conditions were applied to direct respondents to the follow-up questions depending on their responses of “yes” or “no”. For example, the respondents who were willing to work as crowd-shippers were asked for the maximum TTT they were willing to divert for picking up and delivering a package. Aside from responses to the hypothetical questions, the data set also includes socio-demographic characteristics, such as age, gender, race, education level, etc. Personal socio-economic data - income, number of children, number of adults in his/her household, and accommodation ownership - are also provided in the data set. The results show 78% of respondents are willing to work as crowd-shippers. The TTT average and standard deviation are 23 and 18 minutes, respectively, for 20-minutes of travel on the original route. TTT distribution is displayed in Figure 2. Readers can refer to the details of the questionnaire design, survey implementation, and descriptive variables in Le and Ukkusuri (2018) (*12*). In Table 2, only the characteristics of variables used in this study are summarized.

Figure 2. Distribution of tolerance for travel time (minutes)

Table 2. Descriptive statistics of explanatory variables

\*percentages for indicator variables

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable Description** | **Unit** | **Min/ max or values** | **Mean (*Standard deviation*)\*** |
| **Numbers of observation (respondents): 2,196 (549)** | | | |
| Experience of transport freight for someone else. Dummy variable: 1- Yes; 0- No | NA | 0/1 | 25.70/74.30 |
| Will you work as a crowd-shipper? Dummy variable: 1- Yes; 0- No | NA | 0/1 | 78.32/21.68 |
| Age. Dummy variable: 1- If >30 years old; 0- Otherwise | NA | 0/1 | 65.26/34.74 |
| Male and number of children | NA | 0/5 | 0.29 (*0.75*) |
| African American/American Indian/Alaska native and income is less than $50,000/year | NA | 0/1 | 6.42/93.58 |
| Numbers of people in your household are >=65 years old | Number | 0/6 | 0.18 (*0.63*) |
| Having college degree or higher and income is less than $50,000/year | NA | 0/1 | 44.40/55.60 |
| Income | $1,000/year | 15/220 | 48.71 (*36.00*) |
| Household ownership. 1- Living in a house with mortgage; 0- Otherwise | NA | 0/1 | 20.00/80.00 |
| Total numbers of social media usages | Number | 0/10 | 4.00(*2.10*) |
| **Numbers of observations (respondents): 1,720 (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 crowd-shipper during my commute | NA | 0/1 | 70.00/30.00 |
| ETP as a crowd-shipper | USD | 0/30 | 11.70 (*4.59*) |
| I can deliver whosoever packages or goods if I get paid | NA | 0/1 | 72.27/27.73 |
| Age. Dummy variable: 1- If <31 years old; 0- Otherwise | NA | 0/1 | 31.45/68.55 |
| Gender. Dummy variable: 1- Female; 0- Male | NA | 0/1 | 52.73/47.27 |
| African American/American Indian/Alaska native male | NA | 0/1 | 4.00/96.00 |
| Income is less than $30,000/year and deliver at weekday nights | NA | 0/1 | 26.80/73.20 |

The authors utilized NLOGIT 6 for all modeling work, including preliminary statistical analysis (as presented) and model building (*32*). The model development procedure and insights from the achieved results are provided in the following section.

**Estimation results**

The potential explanatory variables for the models were selected from theoretical and empirical studies on the sharing economy, ride-sharing and carpooling studies (*33*-*34*), and other crowd-shipping studies (*28*). In addition, hypothetical variables (e.g. transport freight during commute, transport freight for people who potential crowd-shippers know, ETP, and packages ownership) were also tested in the models during the model building process. It is noted 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 variables from the survey, were found to have no highly correlated; therefore, there is no issue of multicollinearity with the developed models. The results of the estimated models are presented in the sections that follow.

**Willingness to work as crowd-shippers model**

As discussed, respondents selected whether or not they were willing to work as crowd-shippers (i.e. “Yes” and “No”) from the choice set. Therefore, the binary-logit model was developed, and the WTW as crowd-shippers was selected as a dependent variable. Various explanatory variables were tested for statistical significance. There is no instrumental variable (i.e. endogenous variables associated with the corresponding alternative) that varies across alternatives. Explanatory variables only include respondents’ socio-demographic characteristics. The results are presented in Table 3. All parameters (except the constant parameter) have plausible signs and a significance of more than 95%.

Table 3. Binary logit model estimation results of WTW as crowd-shippers and average marginal effects

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable Description** | **Coefficient** | **t-stat** | **Average marginal effect** |
| Constant | 0.021 | 0.11 | - |
| Experience of transport freight for someone else. Dummy variable: 1- Yes; 0- No | 1.486 | 8.47 | 0.182 |
| Age. Dummy variable: 1- if >30 years old; 0- otherwise | 0.909 | 7.24 | 0.149 |
| Male and number of children | 0.320 | 3.12 | 0.049 |
| African American/American Indian/Alaska native and income is less than $50,000/year | 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 less than $50,000/year | 0.583 | 4.10 | 0.088 |
| Income ($1,000/year) | -0.004 | -2.27 | -0.001 |
| Living in a house with mortgage | 0.432 | 2.80 | 0.063 |
| Total numbers of social media usages | 0.067 | 2.46 | 0.010 |
| Number of observation (respondents) | 2,196 (549) | | |
| Restricted Log Likelihood |  |  | -1148.010 |
| Log Likelihood at convergence |  |  | -1041.100 |
| Pseudo-R square |  |  | 0.093 |

*Note:* all variables are defined for the WTW as crowd-shippers.

Respondents who transported freight or goods for someone else in the past were willing to work in the crowd-shipping system. This may be due to 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 tend to be crowd-shipping driver partners. Perhaps these respondents are more likely to have routine daily activities, therefore, they can more easily accommodate an additional task. The parameter of males who have multiple children is positive. This indicates that they are more likely to work as crowd-shippers, while females who have multiple children are less likely to do so. Males possibly consider themselves bread winners of the family and potentially have more flexible time schedules as compared to their female counterparts.

African American, American Indian, and Alaskan native respondents with a college degree or higher who earn less than $50,000/year are more likely to work for the crowd-shipping system. Earning about average or less than average income may motivate them to work as a crowd-shipper (e.g. the average income of the US in 2015 was $48,100 (*35*)). Low income people consider crowd-shipping as an additional opportunity to earn income. This is potentially an extra job with flexibility. In addition, the negatively significant income coefficient suggests that respondents who earn higher incomes are less likely to work as crowd-shippers, as expected.

Our findings also show that respondents who are living with elderly people are less likely to work as crowd-shippers. This is probably because of the constraints imposed by living with elderly family members. They may need to spend more time with and be available to the elderly citizens; therefore, it reduces the flexibility to participate in crowd-shipping. However, respondents who are living in mortgaged houses are more motivated to work as driver partners for crowdsourced delivery companies. This indicates the desire to potentially earn additional income to pay loans and other debts. Moreover, individuals who use more social media outlets are more likely to work as crowd-shippers. These people may be more technology savvy, familiar with using apps, and open to gigs in the sharing economy.

Different population group may be engaged in crowd-shipping by different reasons. Some may want “to earn money while looking for a full-time job”. Some may be motivated to “maintaining steady income” or “earning more income” at a certain stage in their life. Others may work “to have more flexibility” or “to be your own boss” (*12*). Therefore, to promote crowd-shipping and address prospective driver partners, crowdsourced delivery companies could filter crowds by multiple criteria for their promotion and recruitment program. Certainly, insights from this study provide initial ideas for understanding these issues.

To assess of the effect of explanatory variables on the decision of willing to work as crowd-shippers or not, the marginal effects were calculated. Marginal effects other than elasticity were selected since the elasticity is generally used for measuring continuous explanatory variables and the majority of estimated variables in this research are indicator variables. In this study, the marginal effects measure the variation in the decision of working as a crowd-shipper as a function of a change in a certain variable, while keeping other variables constant. Of the total variables, the experience of transporting freight in the past and age greatly influence the WTW for crowdsource delivery companies. For example, experience with delivery freight increases WTW 18.2%, while all other variables remained the same. Moreover, the 30 years and older age group’s WTW was 15% higher. The income variable has the least marginal influence on the WTW decision. An increase of $1,000 in annual individual income will lower the possibility of working as a crowd-shipper 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 with the corresponding coefficients in the logit model.

**Tolerance of travel time model**

This section presents results from the corrected TTT regression model. The selectivity-bias approach is employed to correct for the TTT of respondents who were willing to work as crowd-shippers. Data from 1,720 observations (430 respondents) and discrete logit model outputs presented in Table 3 were employed to evaluate the regression model. Moreover, it is noteworthy to see the differences between the two models; therefore, results of the model estimated without the selectivity correction term are also presented in Table 4.

Regarding the model estimated with the selectivity correction term, the commuting trip parameter is negative and significant influence on the TTT. Respondents were 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 in other contexts, e.g. during leisure trips or free time. Therefore, they can make a longer diversion to transport packages during these latter scenarios. On the other hand, the parameter of “expected to be paid as a crowd-shipper” is positive and significant. Thus, the more respondents are paid, the longer distances they are willing to travel. Considering this, the compensation schemes should be carefully designed to attract occasional drivers, but not to induce considerable vehicle miles traveled. Long extra driving by driver partners may overcompensate the resource savings (e.g. fuel consumption per package delivery); therefore, violate the objectives of implementing crowd-shipping systems that are improved mobility, safety, and environmental sustainability. One possible solution is to break-down long delivery trips so multiple crowd-shippers can cooperate to deliver the same request on their travel anyway. As such, crowd-shippers’ route deviation is minimized.

During the design of the model, we were interested to identify potential crowd-shippers’ package ownership preference. Interestingly, the coefficient of the variable for “I can deliver whoever’s packages if I get paid” negatively influenced delivery TTT. As such, respondents are more likely to travel longer once they transport freight or goods for friends, colleagues, relatives, or neighbors. This suggests that crowd-shippers 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 crowd-shipping market would be to link the crowd-shipping with individuals’ social network. 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, Alaska native males parameter is positive and statistically significant. Therefore, this segment of the population are more likely to travel longer to deliver once they work as driver partners for crowd-shipping companies. Moreover, respondents with low incomes (i.e. less than $30,001/year) are likely to travel longer to deliver freight at night. This result suggests that low-income respondents are more likely to accept work at times that are unattractive to other people.

The parameters identified in both the models are worth noting. In the two models, all common parameters are found significant, except the “age” parameter. The “age” parameter is not significant in the model estimated without the selectivity correction term. Furthermore, in the random parameter model that is estimated with the selectivity correction term, the selectivity-bias parameters are statistically different from zero. As such, the selectivity correction parameter varies significantly across observations. Therefore, the null hypothesis of the selectivity-bias parameter equal to zero can be rejected at the confidence level of more than 99.99%. These results also concur with our sample selectivity hypothesis. Thus 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

Table 4. Corrected and un-corrected regression models of tolerance for travel time

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variable Description** | **Estimate with selectivity correction** | | **Estimate without selectivity correction** | |
| **Parameter** | **t-stat** | **Parameter** | **t-stat** |
| **Non-random parameters** |  |  |  |  |
| Constant | 11.099 | 6.60 | 8.245 | 3.69 |
| I can be a crowd-shipper during my commute | -5.076 | -6.63 | -4.902 | -8.90 |
| ETP as a crowd-shipper | 4.988 | 23.22 | 5.043 | 25.37 |
| I can deliver whosoever packages or goods if I get paid | -3.976 | -4.84 | -4.374 | -4.48 |
| Age. Dummy variable: 1- if <31 years old; 0- otherwise | 2.322 | 2.37 | 0.340 | 0.37 |
| Female | 2.418 | 2.88 | 1.780 | 10.30 |
| African American/American Indian/Alaska native males | 8.564 | 4.64 | 10.216 | 4.06 |
| Having income is less than $30,000/year and willing to deliver at weekday nights | 1.991 | 2.23 | 2.370 | 2.66 |
| **Random parameters** |  |  |  |  |
| Mean of selectivity correction term | 5.936 | 4.39 | - | - |
| Standard derivation of selectivity correction term | 14.954 | 63.04 | - | - |
| Number of observation (respondents) | 1,720 (430) | | 1,720 (430) | |
| R square |  | 0.270 |  | 0.261 |
| Corrected R square |  | 0.266 |  | 0.258 |
| Number of Draws |  | 1000 |  | 1000 |
| **Computed values** |  |  |  |  |
| Expect to be paid (ETP) ($/h) |  | 12.029 |  | 11.898 |

*Note:* Insignificant parameters are underlined.

constant and “age” parameters. As such, when the selectivity bias terms are ignored, erroneous interpretation and conclusions are produced from the estimated results.

In this research, ETP is the amount crowd-shippers expect to be paid for their delivery driving time. This value is similar to the WTW value in Miller et al. (2017) (*15*). The ETP value of the model with selectivity correction is $12/hour, lower than the average WTW value reported by Miller et al. (2017) ($19/hour). However, this ETP value is within the $9.2 to $15.6 hourly value range of travel time saving published by the US Department of Transportation (*36*). The finding of an ETP value might suggest crowd-shipping companies to set compensation schemes that align with driver expectations. This will potentially increase the recruitment and retaining crowd-shippers in the system.

**Conclusions**

Crowd-shipping or crowdsourced delivery companies provide platforms to connect senders who need to send packages to couriers who travel anyway. The system brings potential benefits to society, including improved mobility and reduced congestion and greenhouse gases. However, to implement an effective and efficient system, more understanding of the stakeholders, especially the crowd-shippers themselves, is needed. There is a lack of research on this topic; therefore, this paper addressed the central questions of identifying the factors that influence the behavior (WTW and TTT) of those interested in joining the crowd-shipping system. A survey has been conducted to collect data for the discrete-continuous model estimations. A binary logit model has been used to examine factors’ influence on the WTW as crowd-shippers. An ordinary least-square regression model has been employed to understand the factors that affect the travel time decisions of potential crowd-shippers. 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 of this research are of value to researchers, policy makers, and crowd-shipping companies. In summary, the contributions and suggested implementations are as follows:

* The use of discrete-continuous approaches that capture 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. Moreover, the statistical significance of the random selectivity-bias parameter confirmed the variation in respondent behavior.
* The findings for the main socio-demographic characteristics that influence prospective crowd-shippers’ WTW may potentially help crowd-shipping 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 variables and the circumstances in which individuals are willing to be driver partners. Those insights are also valuable for crowd-shipping companies’ operational strategies (e.g. matching criteria). For example, the information help to match requests and couriers and potentially allow couriers to deliver goods around the clock and thereby avoid peak travel period.
* The use of incentives is a significant influence on the willingness of crowd-shippers to travel additional time for package pickup and delivery. ETP information is also helpful for crowd-shipping companies’ operational strategies. For example, driver partner compensations can be designed based on the time of the day and the day of the week.
* It has potential of sharing the data (speed and travel time) collected by crowd-shipping firms, and integrating the data with daily transportation operation/management centers to improve the urban mobility, safety, and environment. By providing the data, crowd-shipping companies also build trust with regulators.
* Certainly, government bodies play a crucial role to grow a crowd-shipping industry through legislations, regulations, and subsidies. For example, provide appropriate incentive packages to attract ordinary drivers to switch to crowd-shipping driver partners are a feasible initiative.

In conclusion, this research has provided for the first time important insights into the behaviors regarding the supply generation for crowd-shipping system. Future research is still needed to validate the findings in different contexts and extend the knowledge in this field.

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