Determinants of Using Ride-Hailing Service: Evidence from Malaysia

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Abstract: With the entrance of Uber into the land transportation industry, ride-hailing service has gained popularity and changed the way people travel in urban areas in Malaysia. Despite the growing popularity of this new mode of cab service, studies about factors that influence consumers' choice to use ride-hailing service are limited in developing countries. This study used primary data that was collected via a survey in Penang, Malaysia. This study aims to examine the factors that affect consumers' decision to utilise ride-hailing service. The novelty of this study is the adoption of a Heckman probit selection model to account for the possibility of sample selection bias and the introduction of an important explanatory variable, i.e., consumers' comparative satisfaction with the attributes of ride-hailing and traditional taxi service that affect consumers' choice of cab service. The results show that age, gender, education, marital status, income, cost considerations and vehicle ownership significantly determine the probability of using cab service. Consumers' choice between ride-hailing and traditional taxi service is affected by gender and their comparative rating of both services in terms of waiting time and the disposition of drivers. This suggests that it is necessary for cab service providers to improve their service in order to remain competitive in the industry.

Keywords: Heckman probit selection model, transportation industry, ride-hailing, sharing economy, taxi
JEL classification: C13, D12

1. Introduction

Traditionally, sharing can be seen as an action or a process of distributing something (in terms of goods or services) between two or more parties. Most traditional sharing activities are non-reciprocal in nature. The presence of digital platforms has changed this fundamental idea of sharing. The evolution of digital platforms has turned traditionally under-utilised assets (including services) into profitable sharing-

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based business models. This is often referred to as the sharing economy, and this sharing paradigm has begun to gain popularity in the business world today. Other synonyms used for the sharing economy include platform economy, access economy and collaborative consumption (Yaraghi & Ravi, 2017). The sharing economy platform matches individuals who wish to share their under-utilised goods and services with those who wish to use these goods and services. One may share their physical assets such as accommodation, office space, transportation, or services ranging from basic skills such as housecleaning activity to even more complex services such as consumer credit (Dillahunt & Malone, 2015).

According to PricewaterhouseCoopers (PwC), the estimated global revenue of sharing economic activities in 2013 was approximately US$15 billion, which accounts for 0.019% of global GDP (US$77,960.6 billion) (Lee, 2016). According to Lee (2016), this figure underestimated the actual value of sharing economic activities. Based on the forecast of PwC, the value of the sharing economy is projected to increase to approximately US$335 billion by 2025, which is more than 20 times its size (US$15 billion) in 2014 (Statistic Research Department, 2010). The boom in the sharing economy has dramatically affected various industries worldwide. In the transportation industry, digital platform companies and ride-hailing service providers are competing with and creating new challenges for traditional taxi service providers. Other terminologies frequently used to describe ride-hailing service include ride-sourcing (Dias et al., 2016), ride-sharing (Gargiulo et al., 2015), on-demand ride (Flores & Rayle, 2017), e-hailing service (Ubaidillah et al., 2019) and ride-hailing (Mitra et al., 2019; Sadowsky & Delson, 2017). The entry of ride-hailing service provided by transportation network service providers (for instance, Grab, MULA, MyCar and EzCab) has provided cab users with an alternative transport option, and hence has intrensified competition in the point-to-point transport market in Malaysia. To date, there is a total of 42 ride-hailing firms operating in Malaysia (Choong & Lai, 2019). In Southeast Asia, the sharing economy concept is still relatively new but its impact is already discernible in a few major cities. Among the Southeast Asian countries, Singapore is ahead of the rest in this respect and is followed by Malaysia (Lee, 2016). In the Southeast Asian region, Malaysia has the highest car ownership (82% of households have a car) (Lee, 2016). Nonetheless, in general, these private vehicles go unutilised for 95% of their lifespan (Yaraghi & Ravi, 2017). Hence, there is a viable option for car owners to provide ride-hailing service by sharing their underutilised vehicles to earn an income. The number of ride-hailing and taxi users in Malaysia is estimated to increase to 7.7 million in 2026, and approximately 29% of the total revenue from the ride-hailing and taxi segment is generated via online platforms (Statista, 2021). Empirical studies observed that the usage of ride-hailing service is higher among individuals residing in metropolitan areas (Conway et al., 2018). There have been only a few studies on the actual uptake of ride-hailing service in developing countries (Giang et al., 2017; Nistal & Regidor, 2016), and studies on the determinants of ride-hailing service are lacking, particularly in a multivariate setting. Hence, little is known concerning factors that affect consumers' decisions on the usage of ride-hailing service. Given the rapid growth of ride-hailing service in recent years, it is pertinent for policymakers to have a better understanding of the determinants of the actual uptake of ride-hailing service.

In view of the aforementioned, this study sought to fill the existing gap to identify the factors that affect the actual uptake of ride-hailing service. The study contributes to the existing empirical literature in the following three ways. First, this study adopted a two-stage modelling approach, i.e., the Heckman probit selection model (Heckman, 1976, 1979), by layering a consumer's decision choice of utilising ride-hailing service into a two-stage decision process whereby consumers are faced with two separate and related decisions: (1) the decision whether to use cab service or not, and (2) the decision whether to choose ride-hailing or traditional taxi service. Second, the study uses a novel perspective to examine the impact of consumers' satisfaction towards the attributes of cab service. A set of novel explanatory variables is introduced to explore how consumers' comparative satisfaction rating towards various attributes of ride-hailing and taxi service affects their choice between the two types of cab service. This differentiates the current study from scant empirical studies that examined the role of consumers' perception towards ride-hailing service attributes on the actual uptake of ride-hailing services (Alemi et al., 2018). Last, this study also includes a discussion on the theoretical basis underpinning consumers' choice of cab service, which is scarcely discussed in the existing empirical literature.

2. Theoretical Framework

Consumers make choices every day. The underlying theoretical framework is the theory of the consumer choice model, which is based on the random utility model. A utility function measures the level of satisfaction that a consumer receives from any combination of goods (including services). Consumers choose various goods and services and are assumed to make their choices rationally. A rational consumer will choose to buy a combination of goods that maximises his net utilities subject to his budget constraint. To describe the problem of optimal consumer choice, let U(x, y) represent the consumer's utility from purchasing a bundle of goods, x and y. The consumer chooses the combination of goods x and y that maximises his utility, but subject to the budget constraint $P_x x + P_y y \leq M$. A consumer's optimal choice problem can be expressed as follows:

$$\text{Max}_{x,y}\ U(x, y) \text{ subject to } P_x x + P_y y \leq M$$

The underlying consumer's discrete choice model is a theory of consumer behaviour. A utility function may express a consumer's preferences for various bundles of goods. By modifying the discrete choice model for substitute goods introduced by Hanemann (1984), the utility function for different brands or types of goods with differing prices and attributes (which may be regarded as substitutes for one another) can be specified as follows:

$$U = u\ (x, b, w, t, z) \tag{1}$$

where

x_j = the consumption of brand *j* (j = 1, ……, N)

$b_j = (b_{j1}, \ldots b_{jk})$, where b_{jk} is the set of *k*th attributes associated with the consumption of brand *j*

w = the consumption of all other goods
t = consumers' taste and preference
z = other factors

The underlying utility function for a consumer's decision to use a particular type of good or service is given by equation (1). According to the random utility model, which was formalised by Manski (1977), the choice made by consumers can be explained in two steps: the first step is assessing the utility or preference of each option and the second step is choosing the option with the highest utility or preference. The random utility theory suggests that the utilities of individuals are not known with certainty to analysts. Given the complex nature of human behaviour, the decision rule should include a probabilistic element to take into account the issue of uncertainty. The resulting model is known as a random utility model or probabilistic choice model because it outlines the choice of individuals in terms of probabilities, i.e., the model gives probabilities that each available option will be chosen, rather than predicting that a consumer will choose a particular option with certainty.

Another theory that is used to explain the choice of consumers is Lancaster's theory of consumer behaviour (Lancaster, 1966), also known as the characteristics demand theory. This theory emphasises that it is the characteristics (or attributes, hereafter) of the good or service, rather than the good or service *per se*, that conveys utilities to the consumers. In the context of choosing a cab service, a consumer's choice to use a particular cab service, i.e., traditional taxi versus ride-hailing service, may be influenced by the attributes of the service itself as well as the attributes of the service provider (the driver).

3. Insights from the Empirical Literature

In the empirical field, a growing number of studies have been carried out regarding ride-hailing service. The majority of these studies were carried out in developed countries such as the United States of America (Alemi et al., 2018; Clewlow & Mishra, 2017; Dias et al., 2016; Mitra et al., 2019; Rayle et al., 2016). Fewer studies have been carried out in developing countries such as the Philippines (Nistal & Regidor, 2016) and Vietnam (Giang et al., 2017). Most of these studies adopted a descriptive approach in their analysis. Generally, these studies explored the characteristics of ride-hailing users (Rayle et al., 2016), the reasons for using ride-hailing service (Rayle et al., 2016), the adoption and the frequency of using ride-hailing service (Alemi et al., 2018; Clewlow & Mishra, 2017), the impact of ride-hailing service on other travel modes (Alemi et al., 2018; Clewlow & Mishra, 2017), and the traditional taxi and ride-hailing users' perception towards cab service (Nistal & Regidor, 2016). Only a few empirical studies adopted an econometric approach to identify factors that affect the actual usage of ride-hailing service (Dias et al., 2016) or the frequency of using ride-hailing service (Alemi et al., 2019; Mitra et al., 2019) in the United States. Empirical studies examining factors that affect the actual uptake of ride-hailing service in a multivariate setting is very scarce in developing countries.

The empirical literature has identified various factors that may affect consumers' decision to use cab/ride-hailing service. These factors can be broadly classified into

five categories: (i) socio-demographic factors, (ii) attributes of cab service, (iii) firms' marketing strategies, (iv) mobile phone access and trust, and (v) vehicle ownership.

3.1 Socio-demographic Factors

Socio-demographic factors are important factors that may affect consumers' preferences and tastes. Age is a key factor that may affect the choice of using ride-hailing service. It has been found that the likelihood of using ride-hailing service tends to decrease with age (Dias et al., 2016). Older individuals are less familiar with technological progress and less capable of using new technological services and electronic payment methods than young people; hence, they are less likely to use ride-hailing service where digital apps are used to connect drivers with cab users to make e-payment. It is observed that ride-hailing users were generally younger than traditional taxi users, and the use of ride-hailing service was highest among young people (Rayle et al., 2016). Clewlow and Mishra (2017) also found a fairly significant gap in the usage of ride-hailing service between the youngest and oldest segments of the population. The average age of non-ride-hailing users was higher than the average age of ride-hailing users. This might be due to the digital gap between the young and old where older adults tend to face significant hurdles in using new technology. Another demographic factor is gender. It is noted that gender patterns in transportation preferences may be associated with the features of trips such as the purpose, length and frequency of trips, i.e., females often make more non-work trips, as well as more frequent and shorter trips than men do (International Finance Corporation, 2020). Rayle et al. (2016) found that more males are ride-hailing users rather than traditional taxi users. In contrast, some observed that the proportion of ride-hailing users was relatively higher among females than males (Clewlow & Mishra, 2017). The third demographic variable is marital status. Married people have greater caregiving and household management responsibility such as grocery shopping and accompanying children. They might be less likely to use cab service as frequent use of cab service may increase their trips' cost and put a strain on their limited economic resources. However, empirical studies, so far, did not find that the likelihood of using ride-hailing service differed between single and non-single persons (Dias et al., 2016).

Income is a key factor that may affect consumers' preference towards the usage of ride-hailing service. Change in income shifts the budget line. When income increases, more choices are available to consumers (Besanko & Braeutigam, 2002). Income arguably has a positive impact on the decision to use ride-hailing service. Individuals with better financial status tend to be less curtailed by financial constraints and hence more likely to use ride-hailing service. However, empirical results are mixed. In some studies (e.g., Clewlow & Mishra, 2017; Dias et al., 2016; Nistal & Regidor, 2016), it was found that high-income individuals are more likely to use ride-hailing service while others (e.g., Rayle et al., 2016) could not draw any conclusion regarding the impact of income on the use of ride-hailing service as some respondents refused to reveal their income.

As for education, it is argued that individuals with higher education are more likely to have a higher propensity to use ride-hailing service since individuals with high education levels are likely to be more aware of new services and hence more likely

to use these services (Dias et al., 2016). Also, better-educated individuals have the capability to utilise new digital services such as ride-hailing given their ability to use the requisite technology. In a study in San Francisco, Rayle et al. (2016) found that a great majority of ride-hailing users have obtained at least a bachelor's degree. Clewlow and Mishra (2017) also observed that ride-hailing service adoption rate among college graduates was relatively higher than those without a college degree. It has also been found that the likelihood of using ride-hailing service was higher among respondents with at least a bachelor's degree compared to those without a degree (Dias et al., 2016). This suggests that individuals with high education levels are more likely to use ride-hailing service.

Another individual characteristic is employment status and it has been shown that employed workers are more likely to use ride-hailing service to commute from home to the workplace (Nistal & Regidor, 2016). Among individuals in the workforce, the likelihood to use ride-hailing was higher among full-time employed workers and those who were self-employed (Dias et al., 2016).

3.2 Attributes of Cab Service

A consumer's mode choice (type of cab service) may vary due to the differences in price and non-price attributes of the cab service. A consumer who derives more satisfaction from a particular cab service than its alternative may choose this specific cab service. Alemi et al. (2018) found that safety, waiting time and accessibility are key attributes that may influence a consumer's decision in the actual uptake of ride-hailing service. In a study in Malaysia, Teo et al. (2018) found that the perception of passengers with respect to price, safety, convenience and accessibility were important factors in affecting a passenger's intention to use ride-hailing service. Ubaidillah et al. (2019), in a study in Sarawak, Malaysia, found that service reliability and customer satisfaction were two key determinants of undergraduate students' intention to use Grab ride-hailing service. In another study in Kuala Lumpur, Malaysia, Chia et al. (2019) observed the presence of a positive relationship between quality of service and customer satisfaction with the intention to use ride-hailing service. Thus far, studies in Malaysia tend to focus on the factors that influence the intention to use ride-hailing service and there has not been any study that examines the relationship between the actual usage of ride-hailing service and the perception of individuals regarding the attributes of ride-hailing service *vis-à-vis* traditional taxi service, especially in a multiple variable setting.

3.3 Marketing Strategy

Firms' marketing strategies may affect consumers' preferences towards a good or service. Firms may undertake marketing strategies to differentiate their products or services from that of their competitors. Despite the efforts of firms to differentiate their products, most consumers are willing to substitute a particular brand of good or service for another. The market contains not only loyal customers but also those who are less loyal to any brand and hence may tend to switch brands when there is a change in the marketing strategy (Guadagni & Little, 1983). In the context of cab service, the service

provider may adopt marketing strategies such as advertising or promotion activities to influence consumers to use their cab service. Unlike traditional taxi drivers, ride-hailing platform providers often undertake marketing activities such as promotion pricing by offering their service at lower or discounted rates to encourage more consumers to use ride-hailing service, especially when their market penetration is low.

3.4 Mobile Phone Access and Trust

Mobile phone access may affect an individual's decision to adopt ride-hailing service. A ride-hailing platform connects ride-hailing consumers and drivers through a smartphone application. Smartphone ownership can be used as a proxy to measure the technological accessibility of ride-hailing service. A person with a smartphone is able to access ride-hailing service via a smartphone application and pay the fare without having to make a cash payment. Consumers who own smartphones are likely to have easy access to ride-hailing service and hence may be more likely to adopt ride-hailing service. Dias et al. (2016) have included smartphone ownership in the analysis of the usage of ride-hailing service and found that smartphone users have a greater likelihood of utilising ride-hailing service.

Trust is particularly important in transactions where the elements of risk and uncertainty are present (Pavlou & Gefen, 2004). Digital trust is important in understanding consumers' behaviour in undertaking online transactions. Trust in online transactions reduces the consumers' need to understand and monitor the transactions, and hence they may find online payment convenient to use (Alemi et al., 2018). It is acknowledged that it is rather challenging to build trust in mobile payment transactions (mobile trust, hereafter) which involve uncertainties and risks (Siau et al., 2004). It is observed that online trust contributes to the formation of mobile trust (Giovannini et al., 2015; Lin et al., 2011) and that users' trust in online transactions, to some extent, can be extended to transactions that involve mobile payment (Yan & Pan, 2014). Thus, users' trust in online payment may affect their tendency to use ride-hailing service which frequently involves mobile payment. A consumer who has experience in performing online payments may find ride-hailing service easy to use as it usually involves mobile payment, and thus he or she is inclined to use ride-hailing service (Giovannini et al., 2015).

3.5 Ownership of Motor Vehicle

A consumer's driving ability may affect his/her decision to use ride-hailing service. In previous empirical studies, variables such as vehicle ownership (Clewlow, 2019; Nistal & Regidor, 2016; Rayle et al., 2016) or possession of a driving licence (Dias et al., 2016) have been used to proxy driving ability. The empirical evidence with regard to the impact of driving ability on ride-hailing usage is mixed. Alemi et al. (2018) in a study that investigated the travel pattern of young adults (18-34 years) and middle-aged adults (35-50 years old) found that the preference towards vehicle ownership and vehicle usage were important factors that limit the adoption of Uber/Lyft service among young adults. Rayle et al. (2016) found that the proportion of ride-hailing users

who did not own a vehicle (43%) in San Francisco was greater than that for the overall city population (19%). This implies that individuals who do not own a car tend to use ride-hailing service. Similarly, Clewlow (2019) observed the presence of a negative correlation between vehicle ownership and the usage of ride-hailing service. In contrast, Nistal and Regidor (2016) found that ride-hailing users tend to be those who own a car in the Philippines. Dias et al. (2016) found that the likelihood to use ride-hailing service did not differ significantly between individuals who had a driving licence and those who did not.

4. Data

This study uses primary data collected from a survey using a structured questionnaire and the survey was carried out in Penang from June till August 2017. The following Cochran's sample size formula is used to determine the appropriate sample size:

$$n_0 = \frac{z^2 pq}{e^2} \tag{1}$$

where:
e is the precision level
p is the proportion of the population that has the attribute in question
q is 1 – p
Z is the z value in the statistical table

With the maximum variability of 50%, 95% confidence level, and precision level of ±5%, the sample size required is:

$$n_0 = \frac{1.96^2 (0.5)(0.5)}{0.05^2} = 384$$

With a total population of 1.2574 million in Penang, the minimum sample size required for this study was 384 respondents to have a confidence level of 95% with a margin of error of 5%. The study targeted a larger sample size of 500 respondents to obtain more robust results. After removing observations with incomplete information, the final sample comprises 477 respondents. The targeted respondents are individuals aged 18 years old and above as the users of ride-hailing service must be at least 18 years old in order to open an account in the ride-hailing application. The sample was stratified according to the ethnic composition of Penang's population to have a representative sample to reflect Penang's multiracial society.

The questionnaire was designed to collect information on socio-demographic factors, technology-related factors, and the perception of respondents regarding cab service. Age is measured as a continuous variable, and all other factors are generally measured as categorical variables. The perception of cab service is evaluated by the degree to which the respondents agree with the given statements (for instance, 'the cab charges are fair') concerning ride-hailing service and traditional taxi service, respectively. The perception is measured using a 5-point Likert scale with (1) being 'strongly disagree' to (5) being 'strongly agree'. However, owing to fewer observations in

some cells, 'strongly agree' and 'agree' are categorised and labelled as 'agree'; similarly, 'strongly disagree' and 'disagree' are denoted as 'disagree'.

5. Methodology

In the current study, a ride-hailing user is defined as an individual who used ride-hailing service via a digital platform such as UberX, UberXL, GrabCar, and/or GrabCar+ in the six months prior to the survey; otherwise, the individual is considered as a non-user. The data is analysed using an econometric model to identify factors that affect the consumers' choice of using ride-hailing service. In terms of econometric modelling, empirical studies that examine consumers' decision to adopt ride-hailing service generally use a single decision-making model, i.e., a single discrete choice model (for instance, Dias et al., 2016). However, ride-hailing users represent a subset of cab users. As ride-hailing users are a subsample of cab users, it is likely that the subsample of ride-hailing users are not randomly selected. These ride-hailing users may have different characteristics from respondents who do not use cab service, thus giving rise to a selection bias problem. Hence, a single-equation model may not be appropriate. The sample selection bias in the analysis of correlated decisions is usually addressed by extending the single-equation model to the estimation of a multi-equation model. The decision to use ride-hailing service involves a dual decision-making process. The first decision is a consumer's decision whether to use a cab service or not, while the second decision is whether to use a ride-hailing service upon deciding to use a cab service. It is assumed that consumers first decide whether to use cab service before choosing the mode of cab service.

The consumer's decision of using of ride-hailing service may be presented by two latent equations. The first latent equation determines the decision to use a cab service which is represented by the equation below:

$$CS_i^* = \delta X_i + \gamma Z_i + v_i^* \tag{2}$$

where CS_i^*= the net benefit to the consumer who is using cab service, X_i and Z_i are the set of explanatory variables that help to determine CS_i^*, and v_i^* is the error term. Once a consumer decides to use a cab service, the consumer will then face a subsequent choice, i.e., the choice between two alternatives: ride-hailing service or traditional taxi service. This decision is described by the second latent equation:

$$RHS_i^* = \alpha X_i + \beta Y_i + \mu_i^* \tag{3}$$

where RHS_i^* = the net benefit to the consumer *i* who is using ride-hailing service, Y_i and X_i are sets of explanatory variables that help to determine RHS_i^*, and μ_i^* is the error term.

Latent variables, CS_i^* and RHS_i^* capture the likelihood of using a hired cab service and the likelihood of using ride-hailing service, respectively. Both CS_i and RHS_i are the observed counterparts for CS_i^* and RHS_i^*, respectively. RHS_i^* is a linear function of X set of explanatory variables (including the constant term) and Y set of explanatory variables, while CS_i^* is a linear function of both X set of explanatory variables (including the constant term) and Z set of variables which act as instruments for the selection. As the

observed variables are binary choice variables, the variance of the error terms cannot be identified as they are often normalised to one in the probit model. The error terms are assumed to follow a bivariate normal distribution as follows:

$\mu_i \sim N(0,1)$
$v_i \sim N(0,1)$
$corr(\mu_i, v_i) = \rho$

Error terms μ_i and v_i capture the effect of unobserved variables that affect the likelihood of using ride-hailing service and using cab service, respectively. To test for the interdependency of dual-choice decisions, i.e., (a) the decision to use cab service and (b) the decision to use ride-hailing service, the relationship between the error terms for the two equations is examined through the parameter rho (ρ) (Heckman, 1976, 1978). The parameter ρ captures the correlation between the unobserved variables that affect the likelihood of using cab service with the unobserved variables that affect the likelihood of using ride-hailing service. When the value of rho (ρ) is significantly different from 0, the sign of rho shall indicate the direction of the endogeneity bias (Makinen et al., 2011). A positive value of rho indicates that the unobserved variables are positively correlated with one another, while a negative value of rho suggests that the unobserved variables are negatively correlated. Hence, the estimates will be biased without correction. One way to solve this is to model both choice decisions using the Heckman probit selection model (Heckman, 1976, 1979). The model is identified given that the variances are equal to one [var[μ] = var [v] = 1] and as long as there is at least one identifying variable which is not in the outcome equation (Maddala, 1983). In the event the parameter ρ is not statistically significant, this indicates that the unobserved variables in the cab service equation (2) are not related to the unobserved variables in ride-hailing service equation (3). This suggests that the decision to use cab service [equation (2)] does not affect the decision to use ride-hailing service [equation (3)]. Thus, both decisions can be estimated independently using two separate probit/logit models.

5.1 Formulation of the Empirical Model

The consumer's decision on the choice of using ride-hailing service depends on observed characteristics as well as unobserved characteristics of the respondents. Many consumers may choose not to use cab service, so any data on the use of cab service is subjected to considerable self-selection. The selection equation is associated with the consumer's decision to use a cab service. The decision is modelled as a probit model where the dependent variable will take a value of 1 if a respondent reported using cab service, and 0 otherwise. This decision is represented by the cab service usage equation. Upon deciding to use a cab service, the second decision is to choose between traditional taxi service and ride-hailing service. This decision is modelled as a probit model where the dependent variable will take a value of 1 if a respondent is a ride-hailing user. A ride-hailing user is defined as a respondent who has reported using ride-hailing service in the six months prior to the survey. This equation is represented by the ride-hailing service usage equation. Both equations are modelled using the Heckman probit selection model which simultaneously estimates cab service usage and ride-hailing service usage decisions.

The estimated coefficients in a non-linear model reveal the direction of an effect but not its magnitude. Long (1997) cautions that it is difficult to use the estimated coefficients for non-linear models to offer information about marginal effects of the independent variables on the dependent variable. Given that the probit parameter estimates of the explanatory variables have little practical appeal, the discussion of the results is based on the predicted marginal effect of statistically significant explanatory variables. The discussion on marginal effects in this study draws on the explanations given by Hoffman and Kassouf (2005), Viego and Temporelli (2017), and Williams (2012). It is noted that the marginal effect for a dummy explanatory variable is evaluated for the discrete change of the dichotomous variable from 0 to 1, *ceteris paribus*. In the current study, the marginal effect reflects the difference in the adjusted predicted probability of using cab service (or ride-hailing service) for a particular group compared to the reference group, for example, males compared to females (being the reference group).

5.2 Explanatory Variables in Cab Service Usage and Ride-Hailing Service Usage Equations

The explanatory variables are selected *a priori* based upon their role in the decision process as discussed in the theoretical and empirical literature. The explanatory variables are categorised into four main groups: socio-demographic characteristics, attributes of cab service, technological capability and other factors. The list of explanatory variables included in the cab service usage equation is slightly different from those in the ride-hailing service usage equation. Socio-demographic variables namely age, education, gender, employment status, marital status, income and ethnicity are included in both equations. Other variables that may influence the decision to use cab service are the respondents' evaluation or ranking of the attributes of cab service. In terms of ranking, the data revealed that four attributes of cab service, i.e., cost (fare), safety, accessibility and waiting time, were frequently reported as either the most or second most important factor that affects the decision to use cab service. Each characteristic is entered into the regression as a dummy variable which is given a value of one if the respondent ranked the characteristic as either the most or second most important attribute in the decision to use a cab service.

In the sample selection model, at least one or more identifying variable(s) is (are) required to be included in the cab service usage equation. The identifying variable(s) should have an impact on the choice to use cab service, and the variable(s) is not associated with the choice to use traditional taxi service or ride-hailing service, in the ride-hailing usage equation. In this study, vehicle ownership is used as the identifying variable. The ownership of vehicles may affect a consumer's decision whether to use a cab service or not, but it will not affect the decision about the mode of cab service, i.e., ride-hailing or traditional taxi service, once the consumer has decided to use a cab service.

In the ride-hailing usage equation, consumer's comparative satisfaction with ride-hailing and taxi service may affect the type of cab service they choose. Some analysts simply account for customers' satisfaction towards the ride-hailing service *per se*. Others take into account consumers' comparative satisfaction of the two options, i.e.,

ride-hailing and traditional taxi service. This study adopted the latter option to account for differences in consumers' satisfaction towards ride-hailing and taxi service in terms of various attributes such as price, safety, driver's attitude, vehicle's condition and waiting time. Respondents were asked to give their rating from (1) strongly disagree to (5) strongly agree for various statements about the attributes of both traditional taxi and ride-hailing service. For each attribute, the comparative rating of both types of cab service is represented by a dummy variable which takes a value of 1 if a respondent reported a higher rating in favour of ride-hailing service compared to traditional taxi service for the attribute in question.

Other dummy variables included in the ride-hailing service usage equation are the engagement in online-payment transactions and firms' promotion activities. Conducting online payments is considered as a proxy of trust in the security of *e*-payment systems. Having confidence in the security of e-payment systems may affect a consumer's decision on the type of cab service adopted. Consumers who have experience in performing online payments or transactions may be more likely to use ride-hailing service that usually involves a mobile-payment system. Finally, consumers' decision to use a particular mode of cab service may be driven by the marketing strategy especially in terms of price promotion. The price promotion variable is entered as a dummy variable in the ride-hailing service equation; it is given a value of 1 if the respondent identified promotions such as cash rebate and promotion code as a factor that affected his or her decision to use ride-hailing service.

6. Results and Discussion

6.1 Descriptive Results

The traditional taxi service existed in Penang before the advent of ride-hailing service, but the data indicates that the former is losing its appeal among cab users. This current study observed that more than 74% of the respondents preferred to use ride-hailing service instead of traditional taxi service (Table 1). An online survey conducted by the Land Public Transport Commission (SPAD) Malaysia revealed that over 80% of the public prefer using ride-hailing service such as Uber and Grabcar over regular taxis in Malaysia (Premananthini, 2016).

The sample used in this study was equally weighted between males and females. This distribution of surveyed respondents is similar to the gender profile of Penang's population, i.e., 50.29% male and 49.71% female (Department of Statistics Malaysia, 2017). Out of 477 respondents, 51% of them indicated that they had used cab service at least once in the six months prior to the survey. Among cab service users, 42 respondents used only traditional taxi service. Among the 200 ride-hailing users, 124 respondents used only ride-hailing service, and 76 respondents used both ride-hailing and traditional taxi service. Out of the 242 cab users, about 83% are ride-hailing users. Among ride-hailing users, the majority (62%) are rare users, a quarter of them are occasional users, and the remaining 12.5% are frequent users.

Table 2 displays the descriptive statistics of the variables for users and non-users of ride-hailing service. The overall sample is fairly distributed between males and females. It is worth noting that the proportion of males is lower among ride-hailing users (42%)

Table 1. Preferred choice and actual uptake of cab service

Type of cab service	Preference of cab service	
	Number of respondents	Percentage
Taxi	121	25.4
Ride-hailing	354	74.2
Don't know	2	0.4
Total	477	100.0
Type of cab service	Actual uptake of cab service	
	Number of respondents	Percentage
Cab users		
Taxi users only	42	8.8
Ride-hailing users	200	41.9
Non-cab users	235	49.3
Total	477	100.0

than non-users of ride-hailing service (56%). As for ethnicity, 55% of the respondents are non-Malays (Chinese, Indian and others). More than 60% of ride-hailing users are non-Malays and this proportion is much higher than the corresponding proportion of non-Malays among non-users of ride-hailing service (50%). This shows that the use of ride-hailing service is less prevalent in the Malay community than among the non-Malays. In terms of marital status, more than half of the total sample (52%) are married, and there exists a higher proportion of married persons among ride-hailing users (37%) than non-users of ride-hailing service (64%). In terms of education, half of the respondents attained tertiary education or higher. The proportion of individuals with tertiary education is higher among ride-hailing users (67%) than non-users of ride-hailing service (39%). This shows that the demand for ride-hailing service is higher among tertiary-educated individuals.

The respondents were categorised into three groups according to their monthly income: low-income (RM3,499 and below), middle-income (RM3,500–RM6,499), and high-income (RM6,500 & above) groups. Out of 477 respondents, 70% of them are in the low-income group, 26% in the middle-income group, and 4% in the high-income group. A similar income distribution is observed among the ride-hailing service users. The proportion of respondents who fall into the middle-income category is slightly higher among non-users of ride-hailing than users of ride-hailing, while the reverse is seen for the high-income group. In terms of age, the average age of respondents in the sample is 34 years old. A comparison of the age profile of ride-hailing users and non-users of ride-hailing shows that the former is relatively younger than the latter, i.e., the majority (57%) of ride-hailing users are below the age of 30 and the corresponding figure is 35% for non-users of ride-hailing.

The choice to use ride-hailing service may be related to mobile payment access and trust. In terms of smartphone ownership, more than 95% of the total number of

Table 2. Descriptive statistics of the variables

Variable	Non-users of ride-hailing		Ride-hailing users		Total	
	Responses	%*	Responses	%*	Responses	%*
Age						
18 – 19	18	6.50	19	9.50	37	7.76
20 – 29	79	28.52	94	47.00	173	36.27
30 – 39	81	29.24	54	27.00	135	28.30
40 – 49	41	14.80	26	13.00	67	14.05
50 – 59	37	13.36	6	3.00	43	9.01
60 & above	21	7.58	1	0.50	22	4.61
Gender						
Female	121	43.68	116	58.00	237	49.69
Male	156	56.32	84	42.00	240	50.31
Ethnicity						
Malay	139	50.18	75	37.50	214	44.86
Chinese	108	38.99	103	51.50	211	44.23
Indian & others	30	10.83	22	11.00	52	10.90
Marital Status						
Not married	101	36.46	126	63.0	227	47.59
Married	176	63.54	74	37.0	250	52.41
Education						
Primary education & below	12	4.33	1	0.50	13	2.73
Secondary education	157	56.68	65	32.50	222	46.54
Tertiary education & higher	108	38.99	134	67.00	242	50.73
Income						
Low-income (RM3499 & below)	194	70.04	140	70.00	334	70.02
Middle-income (RM3500–RM6499)	74	26.71	50	25.00	124	26.00
High-income (RM6500 & above)	9	3.25	10	5.00	19	3.98
Smartphone ownership						
Non-owner	20	7.22	3	1.50	23	4.82
Owner	257	92.78	197	98.50	454	95.18
Online payment transaction						
Non-online payment user	113	40.79	21	10.50	134	28.09
Occasional online payment user	87	31.41	70	35.00	157	32.91
Frequent online payment user	77	27.80	109	54.50	186	38.99
Ownership of motor vehicle						
Non-owner	22	7.94	37	18.50	59	12.37
Owner	255	92.06	163	81.50	418	87.63

Note: * as column percentage.

respondents owned a smartphone. There is no apparent difference in the proportion of individuals owning smartphones irrespective of whether they are users or non-users of ride-hailing service. However, consumers who have experience in performing online payment transactions may find themselves more adept at using ride-hailing service because it usually involves mobile payment. The adoption of online payments is markedly different for ride-hailing users and non-users of ride-hailing. The proportion of individuals who have experience in performing online transactions was higher among ride-hailing users than non-users of ride-hailing. Among ride-hailing users, 89.5% of the respondents are familiar with online payments and only 10.5% have never made any online payments. In contrast, 41% of non-users of ride-hailing have never done online payments. Therefore, familiarity with online payments seems to be positively related to the use of ride-hailing service.

Finally, it is interesting to examine the relationship between motor vehicle ownership and the use of cab service. Most respondents in the sample own motor vehicles such as motorcycles or cars. The large majority of respondents in the subsamples of non-users of ride-hailing and users of ride-hailing own a motor vehicle, i.e., 92% and 82%, respectively. Given that 82% of ride-hailing users own a motor vehicle may imply that ride-hailing is regarded as a convenient mode of transport even for those who own a vehicle.

6.2 Econometric Results

Table 3 shows the estimated results of the Heckman probit selection model and the marginal effects of explanatory variables. The LR test rejected the null hypothesis that both cab service usage and ride-hailing usage equations are independent (i.e., $\rho = 0$) at the 5% level of significance, thus implying the presence of selection bias. This suggests that it is necessary to account for selectivity bias with the Heckman probit selection model. Due to differences in the modelling and measurement of variables (especially the attributes of cab service), the results of this study are not directly comparable to the findings of previous studies.

6.2.1 Usage of Cab Service

Out of the eleven factors considered for the cab service usage equation, seven factors are statistically significant in affecting the probability of using cab service. Five of these factors (i.e., age, gender, education, income and marital status) are socio-demographic variables, highlighting the importance of socio-demographic factors in affecting consumers' decision to use cab service. This result is consistent with the finding of Alemi et al. (2019) who adopted an ordered probit model in their analysis which showed that socio-demographic factors such as income, education and age were important in determining the use of ride-hailing service.

Given that the coefficients of the probit model do not measure the magnitude of the impact of a change in the predictor variables on the dependent variable, this study uses the marginal effects for the explanatory variables to show the partial effects of each independent variable on the probability that the observed dependent variable is equal

Table 3. Estimated results for Heckman probit selection model and marginal effects

Variables	Cab service coefficient (1)	Ride-hailing service coefficients (2)	Marginal effects: Probability of using cab service (3)	Marginal effects: Conditional Probability of using ride-hailing service (4)
Socio-demographic				
AGE	-0.0145**	0.0129	-0.005	0.016
	(0.0072)	(0.0102)		
MALE	-0.3300**	0.3128*	-0.111	0.043
	(0.1328)	(0.1756)		
NON-MALAY	-0.0168	0.1630	-0.006	0.055
	(0.1301)	(0.1912)		
TERTIARY	0.6139***	-0.3039	0.215	0.016
	(0.1348)	(0.2073)		
MARRIED	-0.3657*	-0.1330	-0.126	-0.120
	(0.1919)	(0.2757)		
MID-INCOME	0.2255	0.1241	0.075	0.088
	(0.1674)	(0.2517)		
HIGH-INCOME	0.7057**	-0.5385	0.224	-0.064
	(0.3339)	(0.3695)		
The importance of service attribute (ranking)				
RANK_COST	0.4237***		0.143	
	(0.1419)			
RANK_SAFETY	-0.2165[a]		-0.072	
	(0.1335)			
RANK_ACCESSIBILITY	0.1517		0.050	
	(0.1600)			
RANK_WAITING TIME	-0.1629		-0.055	
	(0.1466)			
Ownership of motor vehicle				
OWN_VEHICLE	-0.4542**		-0.150	
	(0.2069)			
Online payment transaction				
ONLINE		0.3107		0.122
		(0.2350)		
Marketing				
PROMOTION		0.0949		0.034
		(0.1834)		
Comparative perception towards service attributes				
COMPARE_PRICE (FARE)		-0.1546		-0.053
		(0.1997)		

Table 3. Continued

Variables	Cab service coefficient (1)	Ride-hailing service coefficients (2)	Marginal effects: Probability of using cab service (3)	Marginal effects: Conditional Probability of using ride-hailing service (4)
COMPARE_VEHICLE CONDITION		0.0588 (0.2052)		0.021
COMPARE_POLITE ATTITUDE		0.5043** (0.2367)		0.169
COMPARE_SAFETY		0.2331 (0.2476)		0.081
COMPARE_WAITING TIME		0.5049*** (0.1912)		0.190
CONSTANT	0.7937** (0.2866)	0.2710 (0.4341)		
Log-pseudolikelihood	-370.9328			
Wald chi-square statistic	34.32***			
Wald test of independent equations: ρ=0	6.89***			

Notes: ***, **, * denote significance at the 1%, 5% and 10% levels, respectively. Standard errors are in parentheses.

[a] denotes significance at the 11% level.

to one. The subsequent discussion shall focus on the marginal effects of explanatory variables based on the results displayed in Table 3. The marginal effects of explanatory variables on the probability of using cab service are shown in the third column, while the marginal effects on the conditional probability of using ride-hailing service are shown in the fourth column. The conditional probability of using ride-hailing service is relevant to individuals who use ride-hailing service upon deciding to use cab service.

Age is statistically significant and negatively related to the likelihood of using cab service. The probability of using cab service will decrease marginally by 0.5 percentage points with every 1-year increase in age. Similarly, gender is statistically significant and adversely associated with the likelihood of using cab service. Being male decreases the probability of using cab service by 11.1 percentage points. This is probably due to gender differences in terms of purpose and frequency of rides or trips. In comparison to men, women often take more frequent and short trips especially for non-work purposes as they need to handle more household management activities such as grocery shopping (International Finance Corporation, 2020). Meanwhile, the probability of using cab service increases by 21.5 percentage points for individuals with tertiary education compared to those with lower education levels. Being married decreases the probability of using cab service by 12.6 percentage points. Being in the high-income bracket increases the probability of using cab service by 22.4 percentage points. In

terms of ethnicity, there is no significant difference in the probability of using cab service between Malay and non-Malay respondents. Ownership of vehicles significantly reduces the probability of using cab service by 15 percentage points. This indicates that individuals who do not own any private vehicle are more likely to use cab service. This differed from the finding of Dias et al. (2016) which showed that the likelihood of using ride-sourcing service did not differ significantly between individuals who have a driving licence and those who do not. This is probably because the possession of a driving licence (i.e., driving ability) is not tantamount to owning a car (i.e., having a car at one's disposal). In Penang, private motor vehicles have been frequently used by residents as a means of transportation as it is easily accessible and able to provide a point-to-point transportation. Some Penangites opine they prefer to drive if they have a car (Tan, 2019). This also probably contributes partly to the relatively low usage of public transport in Penang. Only 20% of the respondents reported travelling by bus.

In addition to socio-demographic factors, there are some interesting findings concerning service attributes that affect consumers' choice of using cab service. The importance of service attributes such as cost and safety[1] significantly affect the probability of using cab service. The probability of using cab service among individuals who rank cost of cab service (i.e., cab fare) as an important factor in affecting their decision to use cab service is 14.3 percentage points higher than those who do not. In contrast, the probability of using cab service among individuals who rank safety as an important factor is 7.2 percentage points lower than those who do not. Other attributes such as waiting time and accessibility to cab service do not significantly affect the probability of using cab service. The findings highlight the importance of cost and safety attributes in affecting a consumer's decision to use cab service.

6.2.2 Usage of Ride-hailing Service

Out of the thirteen factors considered, three factors are statistically significant in affecting the probability of using ride-hailing service upon deciding to use cab service (i.e., the conditional probability of using ride-hailing service). Among all the socio-demographic factors, gender is the only factor that significantly influences the conditional probability of using ride-hailing service. The conditional probability of using ride-hailing service is higher among men than women, i.e., subsequent to the decision to use cab service. It is interesting to note that the effect of the gender variable in the ride-hailing service equation is the reverse of the result in the cab service equation which shows a higher probability of using cab service among women instead. A plausible explanation for the relatively lower likelihood of women using ride-hailing service may be associated with the concern for safety. The ride-hailing service in Malaysia was subject to negligible government regulations (particularly at its inception) in comparison to the traditional taxi service, and this gives rise to the issue of women being wary of their safety when using ride-hailing service.

An individual's decision to use ride-hailing service may depend on whether an individual is familiar with making online payments since the payment for ride-hailing is

[1] The coefficient for RANK_SAFETY was statistically significant at 11% level.

usually done online. The result shows that individuals with online payment transactions experience do not exhibit a significantly different probability of using ride-hailing service compared to those without such experience. Nonetheless, the positive value of the marginal effect appears to indicate that having experience in performing online payments will enhance the conditional probability of using ride-hailing service. The result also suggests that service providers' promotion activity is not an important factor that significantly affects a consumer's choice of using ride-hailing service once he or she decides to use cab service.

The results pointedly show that it is the consumers' comparative rating of selected attributes of ride-hailing and traditional taxi service which affect their choice of cab service. Among the five key attributes of cab service, drivers' politeness (COMPARE_POLITE ATTITUDE) and waiting time (COMPARE_WAITING TIME) are statistically significant in affecting the cab-users' decision to use ride-hailing service. Individuals who reported a higher rating for drivers' politeness in favour of ride-hailing service over traditional taxi service have a 16.9 percentage points higher conditional probability of using ride-hailing service. Similarly, individuals who gave a higher rating for waiting time in favour of ride-hailing service over traditional taxi service have a 19 percentage points higher conditional probability of using ride-hailing service. The results suggest that the likelihood of using ride-hailing service is higher among respondents who rate driver's politeness and waiting time to be better for ride-hailing service providers in comparison to taxi service providers. Other attributes such as safety, price and vehicle condition were not significantly important in affecting the cab-users' mode choice decision, i.e., the decision to use ride-hailing versus traditional taxi service once they decided to use cab service.

7. Conclusion and Implications

With the entrance of Uber into the land transportation industry, ride-hailing service has gained popularity and changed the way people travel in urban areas in Malaysia such as Penang and Kuala Lumpur. Nearly two-fifths of the respondents in this study were ride-hailing services users and most of these ride-hailing users were occasional users. The higher rating for ride-hailing *vis-à-vis* traditional taxi in terms of characteristics such as driver's disposition and waiting time were found to be significant predictors that affect the probability of using ride-hailing service. The following are some policy implications based on the findings of this study. The first is with regard to the higher likelihood of men using ride-hailing service as compared to women. Companies in the sharing economy such as ride-hailing service can expand their pool of users by understanding what women are gaining (or not gaining) from the service provided. One possible reason women are less likely to use cab service is the lack of female drivers. The results have highlighted that cost and safety of cab service are two key factors that may affect an individual's decision to use cab service. Women are generally security-conscious, particularly in shared spaces, for instance in a cab. Providing more security is an effective strategy that ride-hailing companies could undertake to better serve women. The key to encouraging more women to use ride-hailing service is to attract more female drivers which will increase the demand for ride-hailing among women, which in

turn will increase the demand for female drivers, thereby giving rise to a virtuous cycle. The analysis on the role of comparative features of ride-hailing and traditional taxi service shows that the higher rating for ride-hailing compared to traditional taxi service with respect to driver's politeness and waiting time significantly increase the likelihood of using ride-hailing service. This suggests that consumers choose ride-hailing service over traditional taxi service due to their relatively higher satisfaction with respect to these attributes. In other words, in order to compete with the providers of ride-hailing service, the providers of traditional taxi service need to improve in these two aspects, namely drivers' politeness and waiting time. Hence, relevant policies should be formulated to assist traditional taxi service providers to sustain their competitiveness and to promote healthy competition in the cab service industry given that the growing demand for ride-hailing service has adversely affected the livelihood and earnings of traditional taxi providers.

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