Assessing Economic Value of Reducing Perceived Risk in The Sharing Economy: The Case of Ride-sharing Services

Full Paper

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Abstract

This study examines what types of perceived risks influence consumers' and non-consumers' willingness to pay for ride-sharing services as a representative of the sharing economy. Choice experiment models are constructed to capture consumers' and non-consumers' perceptions of the relative importance of each service attribute reducing perceived risk. Results show individuals' utility significantly increases when the service does not require private information from consumers, provides a driver-tracking system, requires a commercial driver's license from drivers, offers a driver-review system, comprehensively compensates for negative incidents, and guarantees a minimum wage and benefit plan for drivers. This research contributes to a deeper understanding of the role of perceived risk in the sharing economy, and suggests theoretical and practical implications that can assist companies and policy makers.

Keywords

Sharing economy, ride-sharing, Perceived risk theory, Willingness to pay, Choice experiment

Introduction

Sharing has existed in human communal living for a long time before the economy started to rely on monetary transactions. Recently, what is now called the "sharing economy" has entered a new phase. Web 2.0 developments and the commercialization of smartphones have helped foster businesses that allow mobile consumers to personally share and trade idle resources including natural, human, and capital resources at a low search cost based on digital platforms[1]. These third-party peer-to-peer online marketplaces where individuals trade their own goods and services or accesses to goods and services, and pay a fee to intermediaries (Sundararajan, 2013) without an employment contract is often referred to as the sharing economy, or sometimes called the peer economy, collaborative consumption, platform economy, or on-demand economy, access economy (e.g, Botsman, 2013; Weber, 2014).

The sharing economy as a new business model is playing a significant role in expanding consumers' choices and tens of millions of people worldwide consider it an alternative means of existing services. Notwithstanding its popularity mainly due to economic benefits and convenience, many individuals are still indifferent or reluctant to use such services (Ballús-Armet, Shaheen, Clonts, and Weinzimmer, 2014; PricewaterhouseCoopers, 2014). This was primarily due to three reasons: a lack of connectivity, a lack of awareness, and perceived risks, the main focus of this study. Perceived risks associated with several aspects of sharing economy services--concerns about personal information entered for transactions, flexible qualifications of service providers, a lack of comprehensive accident compensation process, and a lack of fairness in resource allocation are mainly related to perceived risks in this new segment of economy.

[1] In the field of IS, the term "platform" has been used to refer to organizational capability platforms, product family platforms, market intermediary platforms, or technology system platforms (Thomas, Autio, and Gann, 2011). Note that this study uses the term as market intermediary platforms as the term in the work of Economides and Katsamakas (2006).

Although these types of negative perceptions of the sharing economy hinder its growth by influencing the choices of both consumers and non-consumers, little is known about what kind of concerns affect participation in the sharing economy and how the value of reducing concerns can be assessed. To fill the gap in the literature, this study proposes four main perceived risks influencing consumers' and non-consumers' preferences for service features reducing perceived risk, and measures the willingness-to-pay (WTP) for the features by using discrete choice modeling. This approach allows for the estimation of the relative importance of service features for consumption decisions. If intermediaries provide a service feature to reduce perceived risk, consumers' WTP for the service increases due to the increased WTP for the service feature. Empirical data was obtained by Qualtrics panels (https://www.qualtrics.com). Qualtrics data is known for better generalizability to the population at large because Qualtrics uses by-invitation-only online panel recruitment to avoid self-selection and professional survey takers (Hagtvedt, 2011).

This study concentrates on ride-sharing services, one of the fastest growing and largest segments of the sharing economy, as well as the sector for which there has been considerable discussion of private and public concerns (Feeney, 2015). Consumers of a ride-sharing service have had opportunities to experience multiple types of perceived risks, and compare the properties of this type of service with a traditional taxi service. Moreover, these risks, in different ways, can also be sensed in other types of sharing economy services such as *Airbnb* or *Taskrabbit*.

Perceived risks are different from their actual risks. Since individuals hardly possess sufficient resources including time and skills, and strong motivations for estimating risks in most cases, what affects individuals' decision processes is perceived risks (Garbarnio and Strahilevitz, 2004). As a first study to encompass perceived barriers including private and public concerns which keep non-consumers from choosing ride-sharing services, this study describes major features of ride-sharing services pertaining to four types of perceived risks. Theoretical and empirical contributions are discussed in the conclusion section.

Theoretical framework

Prior studies of perceived risk

Perceived risk has played a significant role in service purchase behavior and technology acceptance research since its introduction by Bauer's work in 1960. Types of perceived risk that were investigated have increased as the type and complexity of transactions increases. In the early stage, the perceived risk theory focused on perceived risk in physical services. Garner (1986) described social[2], financial, physical, performance, time, and psychological risk as perceived risk for services in general, and inspired many studies on perceived risk. As electronic commerce emerged and became prevalent, the focus was extended to online consumer decisions. Bhatnagar, Misra, and Rao (2000) identified three dominant perceived risks in Web shopping: product risk, financial risk, and information risk. Perceived risk was also examined as a factor in acceptance of various technology. Lee (2009) integrated the technology acceptance model and theory of planned behavior using financial, security/privacy, performance, social, and time risk and perceived benefits of online banking.

The use of sharing economy services involves both consumer purchase decisions and acceptance of innovative information technology. In addition to perceived risks examined in previous research (Ho and Victor, 1994), sharing economy service consumers face undesirable effects of the service on society. Prior research of perceived risk has focused on personal rather than social concerns although numerous studies indicate consumers' purchase decisions are affected by fairness concerns (Brown, 2000). In this light, this study attempts to integrate and re-categorize previously examined perceived risks related to the sharing economy, and incorporate a new dimension of perceived risk which has not been fully investigated.

[2] Social risk in prior studies is defined as potential loss of status in one's social group as a result of adopting a product or service, looking foolish or untrendy (Featherman and Pavlou, 2003). This risk is not related to social concerns about fairness in resource allocation and profit distribution, which is referred to as fairness risk in this study.

Deterrents of participating in the sharing economy

Whereas the motivational factors for participation (Hamari, Sjoklint, and Ukkonen, 2015), legal problems (Koopman, Mitchell, and Thierer, 2015), its potential application plans (Dillahunt and Malone, 2015) are increasingly understood, there is only limited research that would shed light on the reasons for not using sharing economy services. Gerber and Hui (2013) identify distrust of project creators' use of funds as deterrents for participation as supporters in crowdfunding. Tussyadiah (2015) finds lack of trust, lack of efficacy, and lack of economic benefits deter the use of peer-to-peer accommodation rental services. Based on a survey of *Uber* users, Ballús-Armet et al. (2014) reveal liability and trust concerns are critical barriers to participation in peer-to-peer car-sharing. Lee, Chan, Balaji, and Chong (2016) propose a benefit-cost framework to explain both motivators (enjoyment and economic reward) and deterrents (privacy and security risk) for participation in the sharing economy. However, earlier studies pay little attention to broader concerns which cause consumers to not participate in sharing economy services.

Perceived risk in the sharing economy

Consumers are exposed to perceived risk related to several aspects of sharing economy services. This study proposes the following four types of perceived risk identified through literature review: *perceived privacy risk, perceived performance risk, perceived conflict risk*, and *perceived fairness risk*. Inspired by Tiwana, Konsynski, and Bush (2010)'s framework for studying platform evolution, I categorized perceived risk (e.g., social, financial, physical, performance, time, and psychological risk) proposed in prior studies for consumer behavior and technology acceptance according to the main factor causing perceived risk. The first two perceived risks involve concerns regarding the internal performance of the sharing economy service, and the second two perceived risks involve concerns regarding the external environment, encompassing aspects such as conflict resolution processes and economic impacts of the sharing economy on society. Definitions of perceived risk are summarized in Table 1 with corresponding key attributes of ride-sharing services.

First, perceived privacy risk is relevant to concerns about intentional misuse of private information such as name, phone number, credit card information, and geolocation data generally required for using sharing economy services. Personal information may be wrongfully managed or illegally hacked, causing financial, physical, or reputational damages to consumers (Featherman and Pavlou, 2003). Second, perceived performance risk can be derived from distrust of service providers because the qualification requirements of service providers are less stringent to encourage their participation and enlarge the pool for matching supply and demand, as one of the benefits of sharing economy characteristics (Botsman, 2013). Third, perceived conflict risk is related to comprehensiveness of compensation for incidents which can occur while using the service. Consumers may be concerned about a lack of regulations promising comprehensive compensation in case of financial damages or time loss (Lee et al., 2016). Finally, consumers' decisions can be also influenced by perceived risk which involves the dynamism of markets violating one's belief or principles for distributive justice. Distributive justice is achieved from a fairness-conscious consumers' perspective when service consumers are satisfied with the outcome of resource allocation or profit distribution between intermediaries and service providers of the sharing economy (Smith, Bolton, and Wagner, 1999), similar to the concept of Fair Trade. Even if the outcome does not cause any financial or time loss directly to consumers in the short term, consumers tend to choose services which can bring fair outcomes between intermediaries and stakeholders.

To measure the value of reducing perceived risks and compare the relative importance of different types of perceived risks, the following six key features of a ride-sharing service were chosen through a thorough literature review and interviews with consumers, non-consumers, and an expert: *Privacy*, *License*, *Review, Tracking*, *Conflict*, and *Fairness*. Considering survey participants' limited capacity to compare various combination of features, this study chose six most frequently recurring features from the literature and interviews.

Origin	Attributes	Primarily related perceived risk	Description-Definition of perceived risk
Internal environ-ment	Requiring private information from consumers (*Privacy*)	Privacy risk	The possibility of consumers' personal information being misused
	Commercial taxi driver's license	Performance risk	The possibility of products or services not delivering the

	(*License*)		advertised and expected benefits
	Driver-rating system (*Review*)		
	Driver-tracking system (*Tracking*)		
External environment	Proper accident compensation (*Conflict*)	Conflict risk	The possibility of conflicts between firms and consumers not being properly resolved from a consumer perspective
	Minimum wage and benefit plan for drivers (*Fairness*)	Fairness risk	The possibility of resources and profits not being fairly allocated or distributed between firms and stakeholders

Table 1. Summary of attributes and related perceived risk

First, with regard to perceived privacy risk, the feature of requiring private information from consumers was chosen because one way to fundamentally block information misuse is not to provide personal information. When consumers have to enter their private information, concerns about consumer information management or protection may increase perceived privacy risk and decrease the WTP for the service. Second, three features, *License*, *Review*, and *Tracking*, were selected as features reducing perceived performance risk: licensed drivers can lower consumers' perceived performance risk because they are more likely to be trained and serious drivers; a driver-rating system can reduce perceived performance risk if consumers can find it before a ride; and a tracking system enabling consumers to identify drivers' location around them and know when they will arrive can decrease perceived performance risk. Since a taxi driver's license and driver-rating system could provide information about drivers' general performance, these two features are expected to a substitute of each other. Third, in terms of conflict risk, whether the service provides proper conflict resolution processes is chosen to be examined. Since the pace of legislation is typically slower than the speed with which various disputes associated with the new business models of the sharing economy arise, consumers may have a higher level of perceived conflict risk compared to other services which have existed for a long time. Lastly, working conditions for drivers was included because of its influence on perceived fairness risk. Perceived fairness risk can be sensed basically due to the new structures of the sharing economy labor markets. Sharing economy platforms generally treat service providers as independent contractors, not as employees. As fair trade products are preferred by many consumers, fairness-conscious consumers may not want their service choice to contribute to worsening workers' long-term working conditions such as no guaranteed minimum wage, and a lack of health and retirement benefits. Thus, I develop the following hypotheses (see Table 2): that requiring private information from consumers is negatively associated with the WTP for ride-sharing services; all the other aforementioned features are expected to be positively associated with the WTP for ride-sharing services; and a commercial driver's license and rating system about individual drivers are substitutable to some extent.

Method and Data

Method

This study employs a choice experiment (CE) to analyze consumers' risk perception for service attributes by calculating the WTP for each attribute (Train, 2003). The CE is rooted in Lancastrian consumer theory (Lancaster, 1966) and random utility theory (McFadden, 1974). The Lancastrian approach to consumer theory assumes that utility is derived from the characteristics of goods rather than from the goods themselves. Models based on random utility theory assume that decision makers choose one of the mutually exclusive alternatives, which provides the highest utility in their choice set.

The CE enables researchers to estimate the WTP for product or service attributes that are not directly traded in markets because the estimation does not require survey participants to answer the WTP for each attribute directly. To measure risk perception in terms of monetary values is beneficial because attributes that influence the WTP for ride-sharing services are not traded individually, and for respondents, judging the WTP for each attribute separated from each other attribute is not straightforward.

Individual n's utility associated with the choice of an alternative i from a finite set of J alternatives included in choice set C_{nt} in situation t can be written as in equation (1).

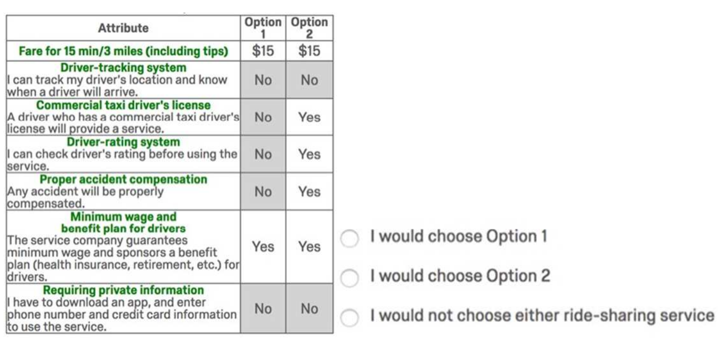
$U_{nit} = V_{nit} + \varepsilon_{nit}$ (1)
where V_{nit} is a deterministic component of utility and ε_{nit} is a Gumbel-distributed random error component. The Gumbel distribution is characterized by the scale parameter μ_n and the variance of $\mathrm{Var}(\varepsilon_{nit}) = \mu_n^2(\pi^2/6)$. When $U_{nit} > U_{njt}$ for all $j \neq i$, alternative i is chosen by consumer n. Thus, the probability that a consumer selects alternative i can be described as:
$P_{nit} = P(U_{nit} > U_{njt};\ \forall j \in C_{nt},\ \forall\ j \neq i)$ (2)
Unlike the traditional conditional logit model, a random parameter logit (RPL) allows heterogeneity as a continuous function of the random parameters underlying the distribution of the surveyed population. Using RPL, heterogeneity in preferences is estimated since individuals' preferences for service features are not assumed homogeneous. Thus, equation (1) can be re-written as:
$U_{nit} = \alpha_n p_{nit} + \boldsymbol{\theta_n}'\boldsymbol{z}_{nit} + \varepsilon_{nit}$ (3)
p_{nit} is a price or cost variable, and $\boldsymbol{z}_{nit}$ is a vector of other non-price attributes. α_n is assumed to be a constant parameter and $\boldsymbol{\theta_n}$ is assumed to be a vector of normally distributed random parameters that are consumer specific, relying on the central limit theorem. Due to the ordinal property of the utility function, individual behavior is not affected when dividing equation (3) by the scale parameter μ_n, and equation (4) becomes scale-free with the constant variance of ε_{nit}, after the division.
$U_{nit} = (\alpha_n/\mu_n)p_{nit} + (\boldsymbol{\theta_n}/\mu_n)'\ \boldsymbol{z}_{nit} + \varepsilon_{nit}$ (4)
Equation (4) can be simplified as:
$U_{nit} = \boldsymbol{\beta_n}'\boldsymbol{x}_{nit} + \varepsilon_{nit}$ (4′)
$\boldsymbol{\beta_n}$ is a vector of parameters corresponding to the vector of attributes $\boldsymbol{x}_{nit}$ including a price or cost variable so that the probability of selecting alternative i from choice set C_{nt} is represented by
$P_{nit} = \int [\exp(\boldsymbol{\beta_n}'\boldsymbol{x}_{nit}) / \sum_j \exp(\boldsymbol{\beta_n}'\boldsymbol{x}_{njt})]\ f(\boldsymbol{\beta_n}) d\boldsymbol{\beta_n}$ (5)
where $f(\boldsymbol{\beta_n})$ is the distribution of the random parameters (Train, 2003).
Given utility's non-cardinal nature, utility coefficients are usually transformed into more meaningful WTP values or implicit prices for each of the attributes. Traditionally, WTP is simply calculated as the ratio of the coefficient on marginal utility of an attribute to the price coefficient, which is typically assumed to be nonrandom. However, directly specifying the distribution of WTP allows a variation in a price variable (Ortega, Wang, Wu, and Olynk, 2011), and a consumer n's utility can be written as:
$U_{nit} = \lambda_n p_{nit} + (\lambda_n \boldsymbol{w}_n)'\ \boldsymbol{z}_{nit} + \varepsilon_{nit}$ (6)
where the utility coefficients are parameterized as $\lambda_n = (\alpha_n/\mu_n)$ and $\boldsymbol{w_n} = (\boldsymbol{\theta_n}/-\alpha_n)$. The estimated price coefficient λ_n is assumed to follow a truncated triangular distribution spanning negative values, considering positive values of price and reducing a step for calculation of the WTP. $\boldsymbol{w_n}$ (the vector WTP coefficients) is assumed to be normally distributed, relying on the central limit theorem. By estimating $\boldsymbol{w_n}$, the WTP for each feature can be estimated and compared. Alternatively, a latent class approach can be used when heterogeneity in parameters is assumed. A latent class logit model (LCM) allows for the sorting of heterogeneous respondents into a number of S distinct latent classes composed of homogeneous individuals (Boxall and Adamowicz, 2002). The probability of selecting i given choice situation t takes the form of
$P_{nit} = [\sum_{s=1}^{S} \exp(\boldsymbol{\beta_s}'\boldsymbol{x}_{nit}) / \sum_j \exp(\boldsymbol{\beta_s}'\boldsymbol{x}_{njt})] R_{ns}$ (7)
where $\boldsymbol{\beta_s}$ is the specific parameter vector for class s, and R_{ns} is the probability of individual n falling into class s. R_{ns} can be modelled as
$R_{ns} = \exp(\theta_s{}'z_n) / \sum_r \exp(\theta_r{}'z_n)$ (8)
where θ_s is the parameter vector for members in class s and z_n is a set of characteristics that influence individual n in the class.

Experiment design

Seven features of ride-sharing service, their levels, and corresponding hypotheses are described in Table 2. Fare for three miles as an average distance of a trip was also added in the experiment to estimate the WTP for comparison. A full factorial experimental design which includes all possible combinations of the seven attributes and with two alternatives to choose between would require the use of $(5\times2\times2\times2\times2\times2\times2)^2$ choice sets. Because of this practically infeasible number of choice sets, I use a fractional factorial design through the OPTEX procedure in SAS 9.3. Sixteen choice scenarios and a D-optimal design that allowed for the estimation of all main and two-way interaction effects are chosen (see an example choice set in Figure 1). I incorporate 16 simulated ride-sharing service selecting scenarios into a survey where I collected data on consumers' socio-economic demographics, commuting habits, and risk perceptions. The hypotheses are proposed based on the assumption that perceived risk decreases consumers' and non-consumers' utility.

Service Attribute	Attribute Levels	Descriptions	Hypotheses (Test result)	
Fare for 3 miles ($; including tips; *Fare*)	7, 9, 12, 15, 17			
Requiring private information (*Privacy*)	Yes	A passenger has to download an app, and enter personal information including credit card information to use services	H1: Requiring private information from consumers is negatively associated with the utility of the service. (Supported for non-consumer group only)	
	No	No need to download or provide any personal information to platform providers		
Commercial taxi driver's license (*License*)	Yes	A driver who obtained a commercial taxi driver's license provides the service	H2a: Requiring a commercial taxi driver's license is positively associated with the utility of the service. (Supported)	H2d: A commercial taxi driver's license as a driver's requirement and the availability of a rating system about individual drivers are complements for each other. (Supported for non-consumer group only)
	No	A driver who does not have a commercial taxi driver's license provides the service		
Driver-rating system (*Review*)	Yes	A passenger can check an individual driver's and application's rating before rides. Only highly rated drivers can drive and the application is being highly rated by large number of consumers	H2b: Availability of a rating system about individual drivers is positively associated with the utility of the service. (Supported)	
	No	A rating system is not available		
Driver-tracking system (*Tracking*)	Yes	A passenger can track a driver' location and know when the driver will come	H2c: Availability of a driver-tracking system is positively associated with the utility of the service. (Supported)	
	No	No tracking system		
Proper accident compensation (*Conflict*)	Yes	Any accidents will be properly compensated	H3: An improper compensation process is negatively associated with the utility of the service. (Supported)	
	No	Some accidents may not be properly compensated		
Minimum wage and benefit plan for drivers (*Fairness*)	Yes	The service company guarantees minimum wage and sponsors a benefit plan such as health insurance and retirement for drivers	H4: Guaranteeing a minimum wage and sponsoring a benefit plan for drivers are negatively associated with the utility of the service. (Supported)	
	No	The service company does not contribute to minimum wage and a benefit plan for drivers		

Table 2. Attributes and hypotheses



Attribute	Option 1	Option 2
Fare for 15 min/3 miles (including tips)	$15	$15
Driver-tracking system I can track my driver's location and know when a driver will arrive.	No	No
Commercial taxi driver's license A driver who has a commercial taxi driver's license will provide a service.	No	Yes
Driver-rating system I can check driver's rating before using the service.	No	Yes
Proper accident compensation Any accident will be properly compensated.	No	Yes
Minimum wage and benefit plan for drivers The service company guarantees minimum wage and sponsors a benefit plan (health insurance, retirement, etc.) for drivers.	Yes	Yes
Requiring private information I have to download an app, and enter phone number and credit card information to use the service.	No	No

I would choose Option 1
I would choose Option 2
I would not choose either ride-sharing service

Figure 1. An example choice set

Participants face travelling decision making scenarios between hypothetical service options composed of different attribute combinations. 400 valid surveys yielded a statistical sample of 19,200 individual observations (400 observations with 16 choice sets and 3 choices). To control for other factors that may influence the level of perceived risk, a hypothetical scenario is assumed and stated to participants. The statement describes that the service application was downloaded more than 1 million times by other consumers to consider the "critical-mass" phenomenon on service usage and to reflect a reality in which adopting ride-sharing service is pervasive. I also assume a situation where vehicles are the same.

Data

This study analyzes 6,382 choice sets with 19,146 options obtained from 400 survey participants. Participants were recruited through *Qualtrics* online survey panels in February 2017. 18 choice sets were excluded because of missing values. Samples are limited to people who currently live or work in six large cities, New York, Los Angeles, Chicago, San Francisco, Boston, and Washington D.C. where the six largest number of *Uber* drivers are active.

Variable	Consumers	Non-consumers	Total
Number of participants	251	149	400
Number of observations	4,000	2,382	6,382
Age (mean)	39.55	50.42	43.60
Female (%)	65.34	69.13	66.75
Education (%)			
Primary	1.59	8.05	4.00
Secondary	36.65	49.66	41.50
Associate	24.70	26.17	25.25
Undergraduate	23.11	5.37	16.50
Graduate/professional	13.55	9.40	12.00
Other	0.40	1.34	0.75
Household annual income (%)			
< 15,000	5.98	8.05	6.50
15,000-25,000	8.37	11.41	9.50
25,000-50,000	21.51	30.20	24.75
50,000-75,000	29.48	28.86	29.25
75,000-100,000	11.55	10.07	11.00
100,000-125,000	6.37	1.34	4.50
125,000-150,000	4.38	3.36	4.00
>150,000	12.35	6.71	10.25
Frequency of taxi/ride-sharing service use (%)			
< 5 Times/Year	10.36	58.39	28.25
5-11 Times/Year	11.16	12.75	11.75
1-2 Times/Month	21.12	13.42	18.25
3-4 Times/Month	32.67	6.71	23.00
> Once/Week	24.70	8.72	18.75

Table 3. Socio-demographic statistics

Results

Table 4 contains the estimated coefficients from the RPL models. Overall, both consumers and non-consumers consider a tracking system, a commercial drivers' license, the availability of a driver review system, proper accident compensation, and drivers' fair working conditions to be valuable. However, the need to make personal information available to the intermediary does not significantly influence the consumer group. The insignificant coefficient on the interaction term shows a commercial taxi driver's license and driver review system are not significantly substitutable nor complementary to each other for both consumers and non-consumers.

Variable	Consumers		Non-consumers		Total sample	
Fare	-0.182***	(0.012)	-0.117***	(0.016)	-0.151***	(0.009)
Privacy	-0.018	(0.035)	0.424***	(0.065)	0.143***	(0.034)
Tracking	0.536***	(0.043)	0.365***	(0.048)	0.455***	(0.031)
License	0.356***	(0.050)	0.425***	(0.078)	0.409***	(0.042)
Review	0.298***	(0.045)	0.442***	(0.067)	0.329***	(0.036)
Conflict	0.235***	(0.034)	0.436***	(0.057)	0.292***	(0.030)
Fairness	0.434***	(0.036)	0.312***	(0.051)	0.369***	(0.029)
License × Review	0.042	(0.065)	-0.075	(0.110)	0.026	(0.056)
Opt Out	-2.992***	(0.148)	-1.532***	(0.183)	-2.342***	(0.112)
STDEV(Privacy)	0.255***	(0.060)	0.629***	(0.073)	0.449***	(0.041)
STDEV(Tracking)	0.453***	(0.049)	0.211***	(0.077)	0.326***	(0.042)
STDEV(License)	0.331***	(0.054)	0.506***	(0.070)	0.383***	(0.046)
STDEV(Review)	0.279***	(0.060)	0.342***	(0.078)	0.259***	(0.053)
STDEV(Conflict)	0.258***	(0.057)	0.454***	(0.070)	0.348***	(0.040)
STDEV(Fairness)	0.285***	(0.054)	0.354***	(0.065)	0.292***	(0.039)
N	251		149		400	
Log-likelihood	-3323		-1896		-5439	
Adj.pseudo R-squared	0.241		0.240		0.208	

AIC/N	1.690	1.709	1.753

Notes: *, **, and *** denote statistical significance at the .10, .05, and .01 level, respectively. Standard errors are reported in parentheses. Parameters were estimated using NLOGIT 6.

Table 4. Parameter estimates from Random Parameters Models

The significance of the standard deviation of features in Table 4 implies significant group heterogeneity which can be identified in the LCM. Table 5 presents that the probability that a randomly selected consumer belongs to Class 1a, 1b, or 1c is 68%, 11%, 21%, respectively. The probability that a randomly selected non-consumer belongs to Class 2a, 2b, or 2c is 42%, 29%, 28%, respectively. All consumer groups show significant coefficients for *Fare*, which implies that consumer groups are sensitive to fare. Class 1a generally regards all key attributes as valuable except *Privacy*. Class 1b puts a high value on not providing their private information compared to the other two consumer groups. For Class 1b, while a commercial driver's license and a rating system of drivers do not significantly influence consumers' utility when provided alone, they increase consumers' utility when provided with each other; these two features are complements to each other (significant positive value on the interaction terms). Class 1b shows a relatively high *Conflict* coefficient value relative to the coefficients on the other features, meaning comprehensive compensation processes are important to this group. Class 1c presents a relatively low price coefficient in absolute value relative to the coefficient values on the other features; however, their values on *Tracking* and *Review* are relatively high, and surprisingly, their utility decreases when they do not provide their private information. These values imply Class 1c appreciates the distinctive features of ride-sharing services more than consumers in the other groups. A tracking system is one distinctive benefit of ride-sharing services, and a rating system for drivers is a major tool to reduce perceived risk. Class 1c seems to understand the advantages of providing private information such that by entering their credit card information, they can utilize a more convenient payment system without cash and by providing their personal information, they may think they can contribute to construct a credible system from both service consumers and providers' sides.

Class 2a shows generally significant coefficients on features similar to Class 1a, but considers not providing private information to the service company valuable. Class 2a places the highest value on *License*. The significant negative coefficient on the interaction term indicates *License* and *Review* features are substitutable to some extent in this class. Non-consumers' choices in Class 2b are significantly influenced by features of performance risk (*Tracking*, *License*, *Review*), conflict risk (*Conflict*), and fairness risk (*Fairness*). Class 2c is differentiated from other classes in terms of their privacy sensitivity. Their utility is significantly increased when the service does not require to download an app or enter their personal information. All six classes exhibit statistical significance for the *Conflict* and *Fairness* coefficients.

Variable	Consumers						Non-consumers					
	Class 1a		Class 1b		Class 1c		Class 2a		Class 2b		Class 2c	
Fare	-0.292***	(0.020)	-0.332***	(0.059)	-0.058**	(0.026)	-0.276***	(0.061)	0.023	(0.031)	-0.193***	(0.040)
Privacy	-0.027	(0.039)	0.566***	(0.126)	-0.125*	(0.065)	0.410***	(0.107)	0.089	(0.082)	0.809***	(0.118)
Tracking	0.453***	(0.040)	0.562***	(0.136)	0.789***	(0.078)	0.322***	(0.070)	0.487***	(0.081)	0.136	(0.109)
License	0.396***	(0.051)	-0.363	(0.198)	0.403***	(0.126)	0.517***	(0.091)	0.390***	(0.142)	0.202	(0.176)
Review	0.354***	(0.050)	-0.134	(0.161)	0.699***	(0.123)	0.472***	(0.091)	0.649***	(0.143)	0.217	(0.158)
Conflict	0.214***	(0.038)	0.531***	(0.132)	0.325***	(0.070)	0.396***	(0.071)	0.486***	(0.083)	0.497***	(0.104)
Fairness	0.486***	(0.038)	0.449***	(0.133)	0.417***	(0.069)	0.385***	(0.065)	0.300***	(0.094)	0.333***	(0.103)
License × Review	-0.063	(0.062)	0.602**	(0.239)	0.008	(0.146)	-0.259**	(0.119)	0.242	(0.167)	0.312	(0.207)
Opt Out	-6.664***	(0.329)	-1.347**	(0.587)	-0.274	(0.318)	-7.391***	(1.137)	0.263	(0.372)	0.068	(0.438)
Class prob.	0.679		0.107		0.214		0.423		0.293		0.284	
N	251						149					
Log-likelihood	-2929						-1693					
Adj.pseudo R-squared	0.331						0.321					
AIC/N	1.485						1.518					

Notes: *, **, and *** denote statistical significance at the .10, .05, and .01 level, respectively. Standard errors are reported in parentheses. Parameters were estimated using NLOGIT 6.

Table 5. Parameter estimates from Latent Class Models

Table 6 shows the WTP for each service feature. The WTP for *Privacy*, *License*, *Review*, and *Conflict* in the non-consumer group is higher compared to the consumer group. In particular, the WTP for *License* (\$3.01) and *Conflict* (\$2.80) is much higher in the non-consumer group, meaning that non-consumers demand a higher qualification and a more comprehensive compensation process for accidents than consumers. Non-consumers show the highest WTP for *License*, and consumers show the highest WTP for *Tracking*. The WTP for *Privacy* is not statistically significant in the consumer group. The hypothesis test results are summarized in Table 2. The test result of H2d indicates that an increase in non-consumers'

WTP for the service caused by one of two features is positively affected by the availability of the other feature.

Variable	Consumers		Non-consumers		Total sample	
Privacy	0.12	[-0.10, 0.34]	1.51***	[2.05, 0.96]	0.51***	[0.33, 0.70]
Tracking	2.35***	[2.03, 1.91]	1.29***	[3.70, 0.93]	1.85***	[1.64, 2.07]
License	1.53***	[1.15, 1.89]	3.01***	[3.26, 2.33]	1.75***	[1.43, 2.07]
Review	1.54***	[1.20, 1.22]	2.62***	[3.27, 1.97]	1.79***	[1.51, 1.56]
Conflict	0.97***	[0.72, 2.09]	2.80***	[1.85, 2.33]	1.40***	[1.24, 1.72]
Fairness	1.80***	[1.50, 0.34]	1.50***	[2.05, 1.14]	1.53***	[1.34, 0.70]
License × Review	0.21	[-0.68, 0.26]	-1.18***	[-1.90,-0.47]	0.19	[-0.67, 0.07]
N	251		149		400	
Log-likelihood	-3323		-1896		-4882	
Adj.pseudo R-squared	0.241		0.240		0.289	
AIC/N	1.690		1.709		1.567	

Table 6. Willingness-to-pay, mean [95% confidence interval]

Conclusion

This study contributes to a deeper understanding of consumers' choice in an innovative segment of the economy, the sharing economy. This study examines the role of perceived risk in the acceptance of ride-sharing. In order to assess perceived risk, this study estimates the WTP for service attributes reducing perceived risks. The following findings are added to the existing literature: a) both consumers and non-consumers consider service providers' working conditions as much as the other attributes which offer more direct benefits to consumers; b) the influence of requiring downloading an app and entering private information including credit card information on a majority of consumers and some non-consumers' ride-sharing service purchase decisions is not significant; c) non-consumers tend to have the higher WTP for a commercial drivers' license and comprehensive conflict resolution process than consumers; and d) a majority of consumers and non-consumers prefer distinctive technical benefits (e.g., *Tracking*) which originated from the sharing economy service sector, and a rating system (e.g., *Review*) to decrease perceived risk and secure mutual trust considering the purchase process of the sharing economy.

This study extends the theory of perceived risk in technology acceptance by incorporating social concerns which have received limited attention in previous literature on the sharing economy. Compared to prior studies considering perceived risks which could directly damage consumers only, this study adds the dimension of social justice, which reflects consumers' concerns about proper functioning of sharing economy services in society. This paper also contributes to the literature of the sharing economy. I classified both consumers' and non-consumers' salient perceived risks in the sharing economy, manifesting the framework for studying platform evolution presented by Tiwana et al. (2010).

The CE results suggest several practical implications beyond one type of service or city. To continuously expand their market segments, sharing economy companies need to understand how both consumers and non-consumers regard service providers' working conditions, a certificate proving their skills based on an existing system, and comprehensive compensation for negative uncertainties as important factors when choosing a service. Policy makers should monitor companies to prevent misuse of consumers' private information because many respondents show low concerns about downloading apps and entering their private information to the apps. To decrease perceived risks, policy makers can also draft legislation to induce this innovative service sector to reduce uncertainties when launching the service.

This study proposes the CE as a methodological tool to assess service feature values of other sharing economy services. Researchers can categorize consumers and non-consumers' concerns into four types of perceived risks in the sharing economy. After identifying major service features which can influence sharing service-acceptance processes by reducing perceived risks, researchers can construct the CE to present a new perspective on platform-centric ecosystems. Researchers can also consider a separated (adaptive) dual response method for WTP estimation when designing choice sets (Schlereth and Skiera, 2016). Given the fast growth of the sharing economy, future studies exploring new emerging issues of perceived risks and alternative experimental designs of the CE would be welcome.

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