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Highlights

- Explore on-demand platform operations with hired agents.
- Consider service pricing with consumers having different risk attitudes.
- Uncover the role played by the blockchain technology.
- Compare the common pricing policy and the customized pricing policy.
- Determine the value of blockchain technology mediated customized service pricing strategy.

Optimal Pricing in On-Demand-Service-Platform-Operations with Hired Agents and Risk-Sensitive Customers
in the Blockchain Era¹

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Abstract: On-demand service platforms are popular nowadays. Many platforms hire agents to serve customers who are risk sensitive towards the waiting-time. In this paper, we apply the mean-risk theory to analytically explore how the risk attitude of customers affects the optimal service pricing decision of the on-demand platform, consumer surplus (CS) of customers, the expected profit (EP) and profit risk (PR) of the platform (and the hired service agents). In the basic model, assuming consumers are homogeneous, we find that if the customers are more risk averse (risk seeking), the optimal service price will drop (increase). Comparing among the three different risk attitudes of customers, we find that when the customers are risk seeking, the CS and the platform's EP are highest, even though the platform's PR is also highest. While the opposite happens when the customers are risk averse. In the extended model with a market including customers with different risk attitudes, the blockchain technology helps the platform assess the proportion of risk seeking, risk neutral and risk averse customers accurately. We explore the optimal service prices under both the common pricing policy and the customized pricing policy (with-respect-to customer's risk

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attitude), and derive the value of blockchain technology mediated customized service pricing strategy. We conclude by highlighting that the risk attitudes of customers play a critical role in determining the optimal on-demand service pricing, and the blockchain technology is a valuable technological tool to help.

Keywords: Behavioral OR; pricing; platform operations; mean-risk analysis; blockchain.

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1. Introduction

1.1. Background and Motivation

The on-demand economy, as a kind of the emergent sharing economy, is booming nowadays (Taylor 2018; Yu et al. 2019). It refers to the immediate and access-based provision of “on-demand” goods and services, and makes considerable revenues each year, e.g., around \$26 billion a year in 2015 (Stephany, 2015).

For on-demand services, such as many food delivery services (e.g., Deliveroo and Uber Eats across Europe, Meituan, and Ele.me in mainland China, and Instacart in the USA), consumers initiate the need and the platform will help to get the service matched and delivered. In some cases, the matching is done with respect to many independent service agents. For example, in car rental on-demand services such as taxi, the matching depends on the availability of the drivers as well as the locations. The most typical instances of such independent services are Uber in Europe and the USA. In the meantime, however, some on-demand services are not related to the presence of independent service agents. For instance, in food delivery, many platforms simply get the orders and then require the hired chefs to cook and deliver in a speedy manner. Such on-demand service is common in various world leading food-delivery markets like McDonald's and Starbucks. Similar practice can be observed in the ride-hailing industry. Didi premier in the mainland China has its own hired and well-trained drivers to offer a premium service and takes 19% in commissions on average for the actual fare riders paid⁶. In this paper, we focus on the scenario in which the service agents are hired by the platform. Examples of this type of hired-agents platform operations are summarized in Table 1.1⁷.

Uncertainties such as heavy traffics and undue orders within a period of time cause the volatility of the customer's waiting time for the on-demand service which can capture and measure the risk that the customer faces. If a customer wants to order food for a dinner, the probable delay and early arrival are all

⁶ <https://equalocean.com/auto/20190502-didi-losses-significant-money-on-its-rides> (Accessed on 2 May, 2019)

⁷ For the case with independent agents, we refer readers to Taylor (2018) for the respective study.

related to waiting time uncertainty and are treated as risk. Late delivery is obviously bad to most people (and hence constitutes “risk”). According to the findings by Instacart, customers also feel bad even for early arrivals which are earlier than expected⁸. Notice that even though intuitively, customers should tend to be “risk averse” towards the waiting time uncertainty, in this paper, we also consider the case when customers are risk neutral and risk seeking. Here, the “risk neutral” case means the customers do not pay attention to waiting time uncertainty and simply focus on the average (i.e. expected waiting time), whereas risk seeking means the customers are gamblers (Choi et al. 2018b) and enjoy the excitement when the waiting time varies. We argue that although the risk seeking behaviour is less common, it does exist in the real world (Schweitzer and Cachon 2000; Mandel 2003; Ludvig et al. 2015). For example, in cities like Hong Kong and Singapore, for the elderly, when they order the on-demand food delivery or taxi service, it is rather common that they would prepare more time for it. For example, if the expected time is 30 minutes, they will usually prepare an hour. In this case, if the variation of waiting time is higher, which means the service can arrive earlier or later with a bigger variation, these elderly customers are in fact happier because earlier arrival gives them a higher utility whereas later arrival is not too bad (as they have prepared for it). Another example of risk seeking customers can be observed in the online food delivery industry. After paying an “insurance fee” to Ele.me or Meituan about the promised arriving time (e.g., 30 minutes), some customers opportunistically hope to see that the waiting time to be longer than that for “ten times compensation” or “50% of the total amount of orders”. In this paper, we believe that including risk seeking customers in our study can provide a more complete picture and the respective analysis is also more comprehensive. It also appears that the risk seeking behaviour is important as many novel insights can be found from it. Moreover, for the situation when risk seeking is trivial, we can set the risk seeking related parameters to be very small or zero; then, our analysis will directly reduce to the situation when risk seeking is minute or gone. So, “risk seeking” behaviours are considered and kept in this paper.

Table 1.1. Real world examples of hired-agents platform services operations

⁸ Interested readers can refer to <https://blog.dominodatalab.com/data-science-instacart/> for more details. (Accessed on 15 May, 2019)

Companies	Service Types	Details	Remarks
Intracart	Grocery delivery	An American company which offers grocery delivery and retailing service. It has its own hired shoppers to pick up the ordered items and deliver for the consumers.	It offers both on-demand and scheduled services.
Deliveroo	Food ordering and delivery	The company has its "Deliveroo Editions kitchen" which has its hired agents to cook and deliver food for customers.	The company also offers other choices of restaurants.
Meituan	Food delivery	The company has hired service agents to form the Meituan Delivery Team to provide food delivery services.	The hired agents refer to the delivery part of the operations.
Ele.me	Food delivery	The company has hired service agents to form its own delivery team to provide food delivery services.	The hired agents refer to the delivery part of the operations.
Uber Eat	Food delivery	The company has hired service agents to form its own delivery team to provide food delivery services.	Uber shares and grants a proportion of delivery fee to the hired agents
Didi Premier	Taxi service	Didi has various services. Didi premier has its own hired and well-trained drivers to offer a premium service.	Some other Didi services employ independent service agents.
UberBLACK	Taxi service	Uber has various services. UberBLACK has its own hired and well-trained drivers to offer a premium service.	Some other Uber services employ independent service agents.

As a remark, the blockchain technology has been known to be useful to support platform operations. For instance, Everledger (Choi 2019) is a blockchain technology supported platform for diamond authentication. Tripago is a decentralized travel platform targeting the travel industry, which is built on top of the Ethereum blockchain technology.⁹ Fmeimei, an on-demand food delivery service platform in China, provides food safety tracing services for customers.¹⁰ In Sharon, Massachusetts, U.S., an app is used to inspect tomatoes at Wards Berry Farm.¹¹ Consumers could keep track of the source of their ordered vegetables using the mobile app. The Walmart-IBM blockchain has also been established to help with food supply chain management. Since the blockchain technology has been proposed to serve many purposes, especially with the proper use

⁹ <https://www.tripagotravel.io/> (accessed on 15 May, 2019)

¹⁰ <http://tech.sina.com.cn/i/2018-01-16/doc-ifyqrewi8641187.shtml> (accessed on 15 May, 2019)

¹¹ <https://www.forbes.com/sites/jennysplitter/2018/09/30/what-can-blockchain-really-do-for-the-food-industry/#33c203c488ef> (accessed on 15 May, 2019)

of a massive amount of trustworthy and secure data, we also explore how it can facilitate the pricing decisions in this paper.

Table 1.2 shows some features of the blockchain technology which relate to the optimal pricing of on-demand services. In particular, the blockchain technology provides the distributed ledgers so that both the on-demand service platform and the service agents can add data of services and customers in. The blockchain can keep permanent records with trustworthy data, and manipulate a massive amount of customer data ("big data"). In particular, the blockchain technology can facilitate the use of information from previous transactions to help assess individual consumers' risk attitudes and preferences. It hence helps to provide smart matching function which provides customized pricing to individual market segments, e.g., with respect to the risk attitudes of customers.

Table 1.2. Features of the blockchain technology for on-demand services.

Features	Details
Big data	The blockchain can keep a massive amount of data regarding customers (demographic details as purchasing/servicing history).
Permanent record	The information stored in the blockchain is permanent, which cannot be changed easily by any parties.
Trustworthy data	The stored data in the blockchain are trustworthy, which can be verified any time in the future.
Distributed ledgers	Data can be added by the related parties anywhere. This facilitates the addition and sharing of information between the platform and service agents.
Risk attitude assessment and smart matching	With big data of previous transaction data, the blockchain technology can assess the risk attitudes of individual consumers as well as their risk sensitivities (Choi et al. 2019). After that, customized pricing can be offered to individual market segments (e.g., with respect to risk attitudes).

1.2. Research Questions and Major Findings

Motivated by the popularity of on-demand service platform operations and the probable risk attitudes possessed by the customers and the platforms, we build stylized analytical models in this paper to explore the following important research questions:

1. How would the risk attitudes of the customers affect the optimal on-demand service pricing, the consumer surplus, the profitability and profit risk of the platform and the hired service agents?
2. For the number of hired service agents and effective demand arrival rate, how would they affect the optimal on-demand service pricing, the consumer surplus, the profitability and profit risk of the platform and the hired service agents?
3. In the market with different kinds of risk sensitive customers, if the blockchain technology is present to help identify different kinds of risk sensitive customers, what will be the optimal service price if only a common flat price can be offered? If the customized service pricing is offered to each type of risk sensitive customers, what will be the respective benefit to the platform, the service agents and the consumers?

By addressing the above important research questions, we generate several important insights. For example, in the basic model when we assume the market only includes homogeneous customers with the same type of risk attitude: If the customers are more risk averse, then the optimal service price will drop. The opposite appears for the risk seeking case in which the optimal service price will increase if the customers are more risk seeking. Comparing among the three different risk attitudes of the customers, we find that when the customers are risk seeking, the consumer surplus (CS) level and the expected profits of platform and service agents are highest, even though the profit risks of the platform and service agents are also highest. While the opposite happens when the customers are risk averse. Under the basic model, we conclude by uncovering that the risk attitudes of customers play a critical role in shaping the optimal service pricing for on-demand services. In the extended model with a market including customers having different risk attitudes, with the blockchain technology, we first argue that the platform can assess the proportion of risk

seeking, risk neutral and risk averse customers accurately and then offer the optimal price. For the scenario when the platform offers one flat price to all customers (irrespective of their risk attitude) and the scenario when the platform offers customized price to customers with respect to their risk attitude, we derive the respective optimal service prices. Comparing between these two scenarios yields the value of customized service pricing (which is made possible with the use of blockchain technology). The loss brought by ignoring risk preferences of customers is further evaluated. We find that the blockchain technology is a useful technological tool to improve the optimal service pricing for on-demand services platforms.

1.3. Contribution Statements and Organization

To the best of our knowledge, this is the first paper which examines on-demand service platform operations with the considerations of hired agents and customers with different risk attitudes (based on the mean-variance theory). The findings advance our knowledge towards the on-demand service platform as well as the impacts brought by customers with different risk attitudes. In addition, this paper uncovers the role played by the blockchain technology and determines the value of blockchain technology mediated customized service pricing strategy. Both novel academic and managerial insights are hence generated.

The rest of this paper is arranged as follows. We present the literature review in Section 2. We present the basic model in Section 3, where the on-demand service operations are highlighted. We explore the impacts of risk attitudes on the optimal service pricing in Section 4. We extend the analysis to the case with the considerations of market segmentation by using the blockchain technology in Section 5. We conclude this paper in Section 6. All proofs are placed in Appendix (A4) [Online Supplementary Appendix].

2. Literature Review

2.1. Platform Service Operations

Platform operations are especially useful in the sharing economy (Cui and Hu 2018). As a matter of fact, the most convenient way of facilitating sharing among individuals and/or companies is to employ technology based platforms (Tian et al. 2017; Jiang and Tian 2018; Tian and Jiang 2018). In the literature, a number of platform related OM studies have been published. For example, Bhargava et al. (2013) study the optimal versioning and establishment timing for the platform technology. Anderson et al. (2014) report the investment in platform operations with the network externalities considerations. Chen et al. (2015) explore how platform based peer-to-peer know-how sharing can benefit farmers. Van Astyne et al. (2016) discusses new strategic issues for platform operations. Bellos et al. (2017) investigate the car sharing operations and highlight the role played by product line design. Jiang et al. (2017) examine the peer-to-peer platform marketplace with consumers possessing uncertain valuation. Benjaafar et al. (2018) examine product sharing under the peer-to-peer platform scenario and uncover how social welfare is affected. Parker and Van Alstyne (2018) investigate the timely issues on the relationship between innovation and the open-code proposal for platform development.

Some studies focus on exploring the pricing decisions for platform services. For instance, Banerjee et al. (2015) explore the optimal pricing decisions in the platform for ride-sharing services. Wang et al. (2016) study the optimal pricing policies for platforms supporting taxi-hailing services. Cachon et al. (2017) look into the surge pricing policies on a platform when the service capacity is under self-scheduling control. Kung and Zhong (2017) derive the optimal pricing policy for a two-sided platform service. Taylor (2018) studies the optimal supply demand matching in on-demand service platforms with independent service agents, and considers the optimal service pricing decision. Bai et al. (2018) explore the optimal pricing problem for the on-demand service platform with impatient consumers. The authors use data from Didi to conduct numerical testing of the results. Bai and Tang (2018) study the case when two on-demand service platforms compete. They highlight the situations when both platforms can be profitable under such a duopoly competitive setting. Choi and He (2019) investigate the optimal pricing decision for the peer-to-peer

platform service for fashion products' rental operations. Most recently, Sun et al. (2019) analytically study the pricing problem in platform operations with ride-sourcing. The authors uncover that the customers will become worse-off if the closest drivers are chosen.

Similar to the above examined studies, this paper also explores platform service operations. In particular, we also focus on studying the optimal pricing decision for the on-demand service. However, different from all of the reviewed papers, we focus on uncovering the impacts brought by risk attitudes of customers, and we also focus on the scenario when the service agents are hired by the platform.

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2.2. Blockchain Technologies

Established with the development of bit-coins, blockchain technologies have emerged as a critical technological advance in recent years (Iansiti and Lakhani 2017). In operations management, Babich and Hilary (2018) examine how blockchain technologies can help improve operations in different topical areas, which include information and data sharing, risk management in supply chain operations, automated smart contracting, etc. Chod et al. (2018) analytically study how blockchain technologies may help to show the operational capabilities of a firm. The authors uncover that blockchain technologies can help firms better-get some more desirable terms in finance and enjoy a smaller signalling expense. Choi et al. (2019) review the literature and propose the use of blockchain technology in conducting mean-variance analysis in global supply chains with air logistics. Most recently, Shi and Choi (2019) analytically explore how blockchain technologies can be used to enhance food safety in supply chains. The authors highlight how information visibility can facilitate the recall of poor quality or contaminated food products. Following the footsteps of the above papers, this paper also employs blockchain technologies in the analysis. However, the focal points are totally different as this paper focuses on on-demand service pricing with hired agents.

2.3. Risk Sensitive Decision Makers

Risk aversion for decision making has been a popular topic in operational research for over a decade. For example, Choi et al. (2008) study the returns contract in a two-echelon supply chain when agents are risk averse. Asian and Nie (2014) investigate risk aversion in supply chains with disruptions. Chiu et al. (2015) explore the supply chain with multiple risk averse retail buyers. Ray and Jenamani (2016) study the supply chain sourcing problem with disruptions using the mean-variance risk analysis method for risk aversion. Zhao et al. (2018) extend Choi et al. (2008) and examine the use of options contract in a two-echelon supply chain. Consumers are commonly risk sensitive. In the literature, Fay and Xie (2010) compare the probabilistic selling scheme and the advance selling scheme. In their extended analysis, they reveal how risk aversion of

consumers may affect the result. Leider and Sahin (2014) explore contracts and consumption of access services. The authors uncover how consumers' risk aversion would affect their consumption for access services. Gallego et al. (2015) investigate the extended warranty services in the presence of risk averse strategic consumers. They find the conditions in which their proposed residual value warranty would outperform the traditional warranty. Lee et al. (2015) explore loss averse and forward looking consumers in supply chain systems. The authors propose the use of quick response for firms to deal with this consumer behaviour. Karaz et al. (2016) study the risk averse preference of consumers in medicine supply chains. Baucells and Hwang (2016) study the case when consumers have reference price in mind and they highlight how loss aversion affects mental accounting for consumers.

Similar to the above studies, we also examine the impacts of risk attitudes of consumers. However, different from all of them, we include in our analysis all probable risk attitudes of consumers, namely risk neutral, risk averse, and risk seeking. We also focus on investigating how risk attitudes of consumers affect the on-demand service pricing which has never been explored in the current literature. Moreover, we argue that with the blockchain technology, the platform is able to understand the risk preference of consumers better and hence more sophisticated pricing can be provided. This is in line with the proposal developed by Choi et al. (2019).

3. Basic Model

Consider a platform which offers an on-demand service such as quick food delivery. Demand comes when a customer has a need which requires immediate or relatively quick service fulfillment. The platform hires n service agents (e.g., chefs, drivers) and jobs will be assigned to them evenly and randomly¹². Observing that

¹² Taylor (2018) assumes that each agent has an opportunity cost K per unit time, which can be observed by the platform in the hired agent mode. By considering the agents' opportunity costs, the platform assigns jobs to the agents who act as followers and will proceed to take them. We explicitly do not consider the fixed salary (i.e., nK) for the service agents, which covers their opportunity costs because it will not affect any results and insights qualitatively.

Didi shares 81% of the fare and grants it to the drivers and Uber Eats shares about 20%-25% of the delivery fee and provides to the hired agents¹³, we assume that the service agents are compensated by receiving a share of the revenue. To be specific, the platform signs a revenue sharing contract with the agents where the agents get $1 - \alpha$ proportion of the total revenue and the platform gets α proportion.

It is well-known that customers have concerns on the waiting time. We follow Taylor (2018) in formulating the expected waiting time for the customers. We consider the situation that the service needs from customers follow a Poisson process and the service times are exponentially distributed. The effective demand arrival rate is r and the average service rate is m . The customer's expected waiting time in this $M/M/n$ queueing system at the steady state is given as follows (Taylor 2018):

$$T(n, r) = \left(\frac{(r/m)^n}{n!(1-R)^2 mn} \right) \left/ \left(\sum_{i=0}^{n-1} \frac{[r/m]^i}{i!} + \frac{[r/m]^n}{n!(1-R)} \right) \right., \quad (3.1)$$

where $R = r/nm < 1$.

Note that in the basic model, different from the literature in which they consider the matching between agents and customers, we only focus on how the waiting time (its expected value and volatility) would affect the customer's demand for the on-demand service. Thus, we define the scaled expected waiting time (which can be put together into the customer's valuation to decide if the on-demand service is needed or not) as follows where $\eta > 0$ is a positive constant:

$$t = \eta T(n, r). \quad (3.2)$$

The customer's valuation towards the service is v , which follows a uniform distribution $U(0,1)$. In this paper, we consider the case when the customers are risk sensitive. For the analysis purpose, in the basic model, we consider a homogeneous market in which all customers exhibit the same risk attitude. This is for the sake of closed-form analysis to highlight the impact brought by different risk attitudes. In the extended

¹³ <https://www.thezebra.com/insurance-news/5623/on-demand-food-delivery-services/> (accessed on 23 March, 2018)

model, we investigate the more general and realistic case when customers in the market possess different risk attitudes.

To model the customer's risk attitude towards waiting time volatility, we follow the standard mean-variance theory concept (Kouvelis et al. 2018) and a larger variation of waiting time implies a higher level of risk¹⁴. The mean-variance approach has been well-established and widely adopted in the OR/OM literature (see Zhao et al. 2018; Choi et al. 2019).

Table 3.1. Meanings of different risk attitudes of customers

Risk Attitudes of Customers	Meanings
Risk averse	The risk averse customers prefer a lower waiting time volatility
Risk neutral	The risk neutral customers only focus on the expected waiting time and have no preference for waiting time volatility
Risk seeking	The risk seeking customers prefer a higher waiting time volatility

Table 3.1 displays the meanings of different risk attitudes of consumers. We include a disutility $\hat{\beta}\sigma_T$ in the analysis, where (i) $\hat{\beta}$ is the customer's risk sensitivity coefficient towards waiting time volatility; it is positive if the customer is risk averse, 0 if the customer is risk neutral, and negative if the customer is risk seeking; (ii) σ_T is the standard deviation of the waiting time.

For a notational purpose, we have (3.3) and present Lemma 3.1.

$$\hat{\beta}\sigma_T = \beta. \quad (3.3)$$

¹⁴ The MV approach is not the only approach in capturing risk sensitivity. For example, VaR (Kouvelis and Li 2018) is another measure. However, we use the MV approach as it is an intuitive and implementable measure.

Lemma 3.1. (a) $\sigma_T = \left[T(n, r) \cdot \left(\frac{2}{mn - r} - T(n, r) \right) \right]^{\frac{1}{2}}$. (b) It is increasing in r and $T(n, r)$, while it is decreasing in n .

Lemma 3.1 is a very important finding which shows the analytical closed-form expression for the waiting time's standard deviation, and summarizes how it relates to the expected waiting time, the effective arrival rate and the number of service agents.

Since $t + \beta$ is a very important parameter, we call it the *total waiting time disutility* (TWTD). Define an important threshold in the following:

$$\tilde{\beta} = \frac{\eta \left[T(n, r) \cdot \left(\frac{2}{mn - r} - T(n, r) \right) \right]^{\frac{1}{2}}}{\left(T(n, r) - \frac{1}{mn - r} \right)}.$$

Proposition 3.1. (a) When the customers are risk averse or risk neutral (i.e. when the customer's risk sensitivity towards waiting time volatility $\hat{\beta}$ is nonnegative): TWTD (i.e. $t + \beta$) is increasing in the customer's expected waiting time (i.e. $T(n, r)$) and effective demand arrival rate (i.e. r), while decreasing in the number of service agents (i.e. n). (b) When customers are risk seeking (i.e. $\hat{\beta}$ is negative): TWTD (i.e. $t + \beta$) decreases in the customer's expected waiting time if $\hat{\beta} < \tilde{\beta}$; otherwise, TWTD is increasing in the expected customer's waiting time.

Proposition 3.1 shows some important results. In particular, depending on the risk attitude of customers, the relationships between TWTD and the expected waiting time, the effective demand arrival rate and the number of service agents are different. We can see that a change of risk attitude will revert the relationships, which highlights the critical importance of risk attitude in deciding the impacts brought by the key problem parameters such as the effective arrival rate and the number of service agents. For the reasons explaining this situation, we can observe that TWTD depends on β , which in turn depends on the waiting time volatility. For the risk averse customers, waiting time volatility is bad whereas it is treasured by the risk

seeking customers. When the effective arrival rate, the number of service agents and the expected waiting time are changed in a way which favors the risk averse customers (i.e., reducing the waiting time volatility), the risk seeking customers will be unhappy as the effect to them is just the opposite. For the risk neutral customers, β plays no role and the findings follow the impacts brought by a change of parameters on the expected waiting time t .

The customer will adopt the service if her valuation is higher than the service price (p), minus the scaled expected waiting time (t), and the risk threshold (β). Note that the service price refers to the fare/ logistics and service fee in the ride-hailing/food delivery industry. If the market size is \tilde{N} , where \tilde{N} is a random variable with a mean N and standard deviation σ_N , then we have the following profit function for the platform and the agents:

$$\begin{aligned}\tilde{\Pi}_{PF}(p) &= \alpha \tilde{N} p \int_{p+t+\beta}^1 f(v) dv \\ &= \alpha \tilde{N} p (1 - F(p+t+\beta));\end{aligned}\tag{3.4}$$

$$\begin{aligned}\tilde{\Pi}_{AG}(p) &= (1-\alpha) \tilde{N} p \int_{p+t+\beta}^1 f(v) dv \\ &= (1-\alpha) \tilde{N} p (1 - F(p+t+\beta)).\end{aligned}\tag{3.5}$$

It is easy to find that the expected profits and standard deviation of profits of the platform and the agents are shown as follows:

$$\bar{\Pi}_{PF}(p) = \alpha p N (1 - F(p+t+\beta)),\tag{3.6}$$

$$S_{PF}(p) = \alpha p (1 - F(p+t+\beta)) \sigma_N,\tag{3.7}$$

$$\bar{\Pi}_{AG}(p) = (1-\alpha) p N (1 - F(p+t+\beta)),\tag{3.8}$$

$$S_{AG}(p) = (1-\alpha) p (1 - F(p+t+\beta)) \sigma_N.\tag{3.9}$$

Define the objective for the platform:

$$\max_p \bar{\Pi}_{p_F}(p). \quad (3.10)$$

Note that as the service agents have no decision making power in this paper, their risk preference does not affect any decisions involved in the analysis and hence we do not consider them in this paper.

We have Lemma 3.2.

Lemma 3.2. (a) $\bar{\Pi}_{p_F}(p)$ is a concave function of p in the basic model in which all customers are homogeneous and exhibit the same risk attitude. (b) The optimal service price which maximizes $\bar{\Pi}_{p_F}(p)$ is:

$$p^* = \frac{1-t-\beta}{2}. \quad (3.11)$$

Note that Lemma 3.2(a) shows the nice structural property of $\bar{\Pi}_{p_F}(p)$ which facilitates the derivation of the unique optimal service price, which is shown in Lemma 3.2(b). From Lemma 3.2(b), we easily see that the optimal service charge is a linear function of the expected waiting time t , and the consumer's risk attitude parameter β . In particular, since the effective arrival rate is exogenous and not affected by the pricing policy, when the expected waiting time t increases, the optimal service price drops which follows the standard tradeoff between speed and price where a higher speed (lower waiting time) would yield a higher price. For the impacts brought by the risk attitude, we will discuss them in Section 4.

4. Impacts of Risk Attitudes

4.1. Notation

We first define some notation. We use subscripts RAC, RNC, RSC to represent risk-averse-customers¹⁵, risk-neutral-customers, and risk-seeking-customers, respectively. Table 4.1 shows the list of notation.

Table 4.1. Abbreviations for different risk attitudes and notation of optimal prices

Notation	Meaning
RA	Risk averse
RN	Risk neutral
RS	Risk seeking
p_{RAC}^*	The optimal price when the customers are risk averse
p_{RNC}^*	The optimal price when the customers are risk neutral
p_{RSC}^*	The optimal price when the customers are risk seeking

4.2. Customers' Risk Attitudes¹⁶

From Section 3, we have already derived the optimal service fee for the platform. We now present Proposition 4.1 which shows that the customers' risk attitude would affect the optimal service pricing decision.

Proposition 4.1. *Under the mean-risk framework, the optimal service pricing decision of the platform is largest when the customers are risk seeking, followed by the case when the customers are risk neutral and it is smallest when the customers are risk averse, i.e. $p_{RAC}^* < p_{RNC}^* < p_{RSC}^*$.*

¹⁵ In this paper, unless otherwise specified, we use the term "customer" and "consumer" interchangeably.

¹⁶ For the case when the platform (or more precisely, its operations manager) is risk sensitive, see Appendix (A1) for the respective result.

Proposition 4.1 shows a neat result regarding the optimal service pricing decision when the customers exhibit different risk attitude. To be specific, among all risk attitudes of the customers, if the customers are risk seeking, the platform will charge the highest optimal on-demand service price, followed by the risk neutral customer case, and then the risk averse customer case.

For the customers in the market, we derive the consumer surplus $CS_{\beta}(p)$ as follows:

$$\begin{aligned}
 CS_{\beta}(p) &= \int_{p+t+\beta}^1 (v - (p+t+\beta))f(v)dv \\
 &= \int_{p+t+\beta}^1 (v - (p+t+\beta))dv \\
 &= \frac{1}{2}[1 - p - t - \beta]^2.
 \end{aligned} \tag{4.1}$$

Define:

$$\bar{\Pi}_{PF,RAC}^* = \bar{\Pi}_{PF}(p_{RAC}^*); \bar{\Pi}_{PF,RNC}^* = \bar{\Pi}_{PF}(p_{RNC}^*); \bar{\Pi}_{PF,RSC}^* = \bar{\Pi}_{PF}(p_{RSC}^*);$$

$$CS_{RAC}^* = CS_{\beta}(p_{RAC}^*); CS_{RNC}^* = CS_{\beta}(p_{RNC}^*); CS_{RSC}^* = CS_{\beta}(p_{RSC}^*).$$

$$S_{PF,RAC}^* = S_{PF}(p_{RAC}^*); S_{PF,RNC}^* = S_{PF}(p_{RNC}^*); S_{PF,RSC}^* = S_{PF}(p_{RSC}^*);$$

With the result of Proposition 4.1, we derive Proposition 4.2.

Proposition 4.2. *Under the mean-risk framework: (a) The consumer surplus is largest when the customers are risk seeking, followed by the case when the customers are risk neutral and it is smallest when the customers are risk averse, i.e. $CS_{RAC}^* < CS_{RNC}^* < CS_{RSC}^*$. (b) For the platform's expected profit: $\bar{\Pi}_{PF,RAC}^* < \bar{\Pi}_{PF,RNC}^* < \bar{\Pi}_{PF,RSC}^*$. (c) The platform's profit risk is largest when the customers are risk seeking, followed by the case when the customers are risk neutral and it is smallest when the customers are risk averse (i.e. $S_{PF,RAC}^* <$*

$S_{PF,RNC}^* < S_{PF,RSC}^*$). (d) For the agents, the impacts of customers' risk attitude on their expected profit and profit risk follow the same pattern as the platform's.

Proposition 4.2 presents the results on how the customers' risk attitude affects the consumer surplus, the expected profit of the platform, the expected profit of the agents, the profit risk of the platform as well as the profit risk of the agents. Comparing among the three different risk attitudes of the customers, we find that when the customers are risk seeking, the consumer surplus level and the expected profits of platform and service agents are highest, even though the profit risks of the platform and service agents are also highest. When the customers are risk neutral, the consumer surplus level and the expected profits of platform and service agents are higher than the case when the customers are risk averse but lower than the case when the customers are risk seeking, the profit risks of the platform and service agents follow the same pattern. Proposition 4.2 gives an interesting finding which is very neat: For the platform and the agents, if the customers are risk seeking, they will enjoy the best profitability (measured by expected profit) but also face the highest level of profit risk (measured by standard deviation of profit). For the consumers, the same pattern appears in which consumer surplus is highest when the consumers are risk seeking, followed by risk neutral and then risk averse.

4.3. Effects of n and r

Now we turn our attention to the effects brought by the number of hired service agents (n) and the effective arrival rate (r). From Lemma 3.2, we know that p^* decreases in TWTD (i.e. $t + \beta$). Based on the results in Lemma 3.1 and note that the expected waiting time $T(n, r)$ decreases in the number of service agents (i.e., n) and increases in the effective arrival rate (i.e., r), respectively, we have Corollary 4.1.

Corollary 4.1. (a) Under the mean-risk framework, when the consumers are risk-averse and risk-neutral, the optimal service price increases in the number of agents and decreases in the effective arrival rate. (b) When

the consumers are risk seeking and $\hat{\beta} < \tilde{\beta}$, the optimal service price decreases in the number of agents and increases in the effective arrival rate; otherwise it follows the pattern in the risk-averse and risk-neutral scenarios.

Similar results hold for the optimal profit and consumer surplus.

Corollary 4.2. (a) Under the mean-risk framework, when the consumers are risk-averse and risk-neutral, the optimal profit and consumer surplus increase in the number of agents and decrease in the effective arrival rate. (b) When the consumers are risk seeking and $\hat{\beta} < \tilde{\beta}$, the optimal profit and consumer surplus decrease in the number of agents and increase in the effective arrival rate; otherwise they follow the pattern in the risk-averse and risk-neutral scenarios.

Corollary 4.1 and Corollary 4.2 highlight two things: (i) The risk attitude of customers plays a critical role in affecting the impacts brought by the number of service agents and the effective arrival rate. (ii) For the risk seeking case, there exists a threshold on β which governs the results. For the second finding, note that in the customer's utility, TWTD includes the expected waiting time t and β ; when the customers are risk seeking, β is being treasured while β is increasing in t . As a result, there are two "counting forces" in the utility function. The effect of risk seeking hence depends on how strong each force is relative to the other, which is mathematically determined by the condition $\hat{\beta} < \tilde{\beta}$.

Based on the results in Proposition 4.2 and observing the effect of TWTD (i.e., $t + \beta$) on the optimal service price, we have the following results.

Corollary 4.3. When the consumers are risk seeking (but not overly risk seeking; i.e., $\hat{\beta} < \tilde{\beta}$): The gap between the optimal service prices p_{RSC}^* and p_i^* ($i=RAC, RNC$) decreases in the number of service agents and increases in the effective arrival rate.

Based on the results in Corollary 4.3 and observing the effect of TWTD (i.e., $t + \beta$) on the consumer surplus and the optimal profit, we have the following results.

Corollary 4.4. *When the consumers are risk seeking (but not overly risk seeking; i.e., $\hat{\beta} < \tilde{\beta}$): (a) The gap between the consumer surplus CS_{RSC}^* and CS_i^* ($i=RAC, RNC$) and (b) the gap between optimal profits of the platform $\bar{\Pi}_{PF,RSC}^*$ and $\bar{\Pi}_{PF,i}^*$, both decrease in the number of agents and both increase in the effective arrival rate, respectively.*

Explanations for the findings from Corollary 4.3 and Corollary 4.4 follow the same logic as the ones for Corollary 4.1 and Corollary 4.2. However, it is interesting to observe from Corollary 4.3 and Corollary 4.4 that compared to the scenario with risk seeking customers, the differences in terms of consumer surplus and optimal platform's profits for the scenarios with risk neutral and risk averse follow a clear pattern (with respect to the number of service agents and the effective arrival rate), and are also analytically tractable.

5. Extended Model: Heterogeneous Risk Attitude

In Section 3 and Section 4, we consider the case when the customers in the market exhibit the same risk attitude, i.e. being homogeneous in risk attitude. This is obviously a limiting and unrealistic situation. In this section, we consider the case when the market includes certain proportions of risk averse, risk neutral and risk seeking customers, i.e. the case with heterogeneous customers in terms of risk attitude. In reality, these proportions can be learnt by the platform using its data from the previous transactions.

In particular, we know that the blockchain technology serves as a distributed ledger and can keep track of all data of customer transactions' history. If the platform has implemented the blockchain technology based distributed database system, it will be easy for the platform to capture and manipulate the customer data and employ them to conduct market segmentation, e.g., identify the risk attitudes of customers. This is commonly done by what we called "big data analytics" nowadays (Choi et al. 2018a).

Thus, in this paper, we assume that the platform has implemented the efficient distributed database system supported by the blockchain technology. As such, the platform can know the proportion of each kind of risk sensitive customers in the market. Notice that the fixed cost of the blockchain technology is substantial but it is viewed as a sunk cost, which is omitted in real operations afterwards. In addition, its per unit cost is usually negligibly small, hence we do not include the cost of the blockchain technology in this section. We do explore the case when the blockchain technology is associated with non-trivial costs in Appendix (A2)¹⁷, which shows that our results in the basic model (Section 3) and the extended model (Section 5) remain robust.

In the following two sub-sections, we divide the analysis into two parts, where the first part refers to the case without implementing the blockchain technology to identify customers' risk sensitivities. Under this scenario, the platform can only offer a common price to all customers, irrespective of their risk attitude; the second part refers to the case when the platform can offer a tailored price to each customer group with respect to the customers' risk attitude. Table 5.1 shows the proportion of each kind of customers and the corresponding parameters.

Table 5.1. Parameters related to different risk attitudes

<i>Risk Attitude</i>	<i>Proportion</i>	<i>Value of β</i>
Risk averse	a	u
Risk neutral	b	0
Risk seeking	c	$-l$

5.1. Common Pricing

¹⁷ We sincerely thank an anonymous reviewer for advising us to enrich our study with this extended consideration.

In the extended model, it is easy to find that the expected profits and standard deviation of profits of the platform and the agents are shown as follows.

$$\bar{\Pi}_{PF,COM}(p) = \alpha p N(1 - p - t + cl - au), \quad (5.1)$$

$$S_{PF,COM}(p) = \alpha p(1 - p - t + cl - au)\sigma_N, \quad (5.2)$$

$$\bar{\Pi}_{AG,COM}(p) = (1 - \alpha)p N(1 - p - t + cl - au), \quad (5.3)$$

$$S_{AG,COM}(p) = (1 - \alpha)p(1 - p - t + cl - au)\sigma_N. \quad (5.4)$$

Define the objective for the platform:

$$\max_p \bar{\Pi}_{PF,COM}(p). \quad (5.5)$$

With (5.5), we have Lemma 5.1.

Lemma 5.1. (a) $\bar{\Pi}_{PF,COM}(p)$ is a concave function of p . (b) In the extended model with common pricing for all customers, the optimal service price which maximizes $\bar{\Pi}_{PF,COM}(p)$ is

$$p^{COM*} = \frac{1 + cl - t - au}{2}. \quad (5.6)$$

Lemma 5.1 shows the optimal on-demand service price if the market contains different types of risk sensitive customers as depicted in Table 5.1. In addition, with (5.6), we can derive the following:

$$\bar{\Pi}_{PF,COM*} = \bar{\Pi}_{PF,COM}(p^{COM*}) = \alpha N \left(\frac{1 + cl - t - au}{2} \right)^2, \quad (5.7)$$

$$S_{PF,COM*} = S_{PF,COM}(p^{COM*}) = \alpha \sigma_N \left(\frac{1 + cl - t - au}{2} \right)^2, \quad (5.8)$$

$$\bar{\Pi}_{AG,COM*} = \bar{\Pi}_{AG,COM}(p^{COM*}) = (1 - \alpha) N \left(\frac{1 + cl - t - au}{2} \right)^2, \quad (5.9)$$

$$S_{AG,COM^*} = S_{AG,COM}(p^{COM^*}) = (1-\alpha)\sigma_N \left(\frac{1+cl-t-au}{2} \right)^2. \quad (5.10)$$

We have conducted the analytical sensitivity analysis (see Table A3 in the Appendix) to show how an increase of each major parameter affects the optimal on-demand service price under the common pricing scenario, and the respective expected profits and standard deviation of profits for the platform and the service agents. It is interesting to observe from the sensitivity analysis that if the market has more risk averse customers, then the optimal on-demand service price under the common pricing scenario, and the respective expected profits and standard deviation of profits for the platform and the service agents will all drop. The opposite result appears for the risk-seeking case. It is also important to note that the scaled expected waiting time (t) plays a role in which a smaller t will lead to a raise of the optimal on-demand service price under the common pricing scenario due to better service with the reduction of waiting time and its variance, and the respective expected profits and standard deviation of profits for the platform and the service agents.

Furthermore, we can derive the consumer surplus under the extended model with common pricing to be the following:

$$CS_{COM}(p) = a \left[\frac{1}{2} (1-p-t-u)^2 \right] + b \left[\frac{1}{2} (1-p-t)^2 \right] + c \left[\frac{1}{2} (1-p-t+l)^2 \right].$$

Thus, we have:

$$CS_{COM^*} = CS_{COM}(p^{COM^*}) = \frac{a}{8} [1-t-(2-a)u-cl]^2 + \frac{b}{8} [1-t+au-cl]^2 + \frac{c}{8} [1-t+au+(2-c)l]^2. \quad (5.11)$$

From (5.11)¹⁸ and Table 5.2, we have Proposition 5.1.

¹⁸ For the interested readers, please refer to Table A2 in Appendix (A3) for more details of the detailed sensitivity analysis on the consumer surplus under the common pricing scheme.

Proposition 5.1. *When the scaled expected waiting time (t) is sufficiently small¹⁹: Under the extended model with common pricing, if the scaled expected waiting time (t) increases (decreases), the optimal on-demand service price, and the respective expected profits and standard deviation of profits for the platform and the service agents, and consumer surplus will all decrease (increase).*

Proposition 5.1 indicates one important fact on the impact of the scaled expected waiting time. When it is bigger, it brings harm to the profitability of the platform and service agents, and also hurts consumers. From these perspectives, it is wise and important to reduce the expected waiting time. As a remark, since the standard deviation of profits for the platform and service agents will decrease when the expected waiting time increases, it also implies that the platform and service agents will face a lower profit risk when the expected waiting time drops. This also indicates a tradeoff between profitability and profit risk, with respect to the probable increase or decrease of the expected waiting time.

5.2. Blockchain Supported Market-Segment Customized Pricing

Now, suppose that the platform has implemented the smart technology by blockchain in which the risk preference of customers can be identified easily and accurately. In this case, the platform can offer customized price to consumers in each risk sensitive market segment separately. In this situation, we have Lemma 5.2.

Lemma 5.2. *Under the extended model with customized pricing, the optimal service price for each market segment is listed as follows:*

¹⁹ It refers to the case when $t < 1 - au + cl$. Notice that this is a reasonable and valid condition here since in real world practices, the platform which offers an on-demand service always has a time promise. Some typical examples are the “Everything 30min” promise in Ele.me (see <https://en.wikipedia.org/wiki/Ele.me>), the “Within 30 minutes” promise in Uber Eats (see <https://la.eater.com/2015/5/4/8545731/uberfresh-rebrand-ubereats-expansion-deliverywire-uber>), and the “As little as 1 hour” promise in Instacart (see <https://www.instacart.com/try-express>) in the food delivery industry.

$$p_{RSC}^{CUS*} = \frac{1-t+l}{2}. \quad (5.12)$$

$$p_{RNC}^{CUS*} = \frac{1-t}{2}. \quad (5.13)$$

$$p_{RAC}^{CUS*} = \frac{1-t-u}{2}. \quad (5.14)$$

With Lemma 5.2, we can derive the following:

$$\bar{\Pi}_{PF,CUS*} = \alpha N \xi^{CUS*}, \quad (5.15)$$

where

$$\xi^{CUS*} = \frac{1}{4} [a(1-t-u)^2 + b(1-t)^2 + c(1-t+l)^2], \quad (5.16)$$

$$S_{PF,CUS*} = \alpha \sigma_N \xi^{CUS*}, \quad (5.17)$$

$$\bar{\Pi}_{AG,CUS*} = (1-\alpha) N \xi^{CUS*}, \quad (5.18)$$

$$S_{AG,CUS*} = (1-\alpha) \sigma_N \xi^{CUS*}. \quad (5.19)$$

Furthermore, it is easy to derive the consumer surplus at the optimal customized prices to be the following:

$$CS_{CUS*} = \frac{a}{8} [1-t-u]^2 + \frac{b}{8} [1-t]^2 + \frac{c}{8} [1-t+l]^2. \quad (5.20)$$

Similar to the case under the common pricing scheme, if the scaled expected waiting time (t) is sufficiently small²⁰, the consumer surplus under the market-segment customized price scheme will also decrease (increase) with the increase (decrease) in the scaled expected waiting time (t). Please refer to Table

²⁰ $t < 1 - au + cl$.

A2 (Appendix A3) for more details of the sensitivity analysis on the consumer surplus under the customized pricing scheme.

Note that in real world implementation, to avoid complaints by individual customers who may find that they pay more or less, the platform can mention that it is offering customized services with respect to individual members (and hence the service charges may vary, based on their specific previous purchasing history and records, etc.). In addition, the platform should provide some favourable offers such as “discount coupons” (to be used for future services) to the customers who are charged “more” (e.g., because they are risk seeking). For instance, in the USA, Instacart has incorporated manufacturer coupons into its on demand food delivery service, and consumers can find them either through the “Deals that Delight” section in its official website or through the “Coupons” tab on its app.²¹ Another on demand service platform Ele.me from China also provides opportunities to its consumers collect “energy points,” which are the scores that can be translated to cash allowances for shopping on Tmall.²² Granting coupons incurs a low cost for the platform to promote business, while it is something positive to the customers. The platform might also consider offering free promotional souvenirs/gifts to help. For example, if we look at the case with food delivery services, free gifts can be new dishes for trial, soft drinks, salad, fruit, etc. Food delivery platforms also offer a kind of “insurance fee” to stimulate risk seeking customer to pay more and speculate the waiting time to be longer than promised. Ele.me compensates the customers who have paid additional fee for delivery “insurance” if the deliveries are delayed more than 15 minutes than the expected waiting time, although the situation is rare²³. It is also an easy approach to separate the market-segment with the use of blockchain to keep track of all the transactions histories of customers.

²¹ More information can be found in <https://www.instacart.com/#nvrl-hero>, <https://www.policygenius.com/blog/7-ways-to-save-on-instacart/> and <https://www.couponchief.com/instacart>. (Accessed on Nov, 2018)

²² See <https://www.alizila.com/ele-me-now-delivering-24-7-for-alibaba-health/>. (Accessed on 15 Nov, 2018)

²³ See <https://alltechasia.com/5-popular-food-delivery-apps-china/>. (Accessed on 12 Feb, 2019)

5.3. Values of Blockchain Supported Market-Segment Customized Pricing (VMCP)

With the results from Sections 5.1 and 5.2, we now proceed to explore VMCP for the platform, service agents and customers, which are denoted by $VMCP_{PF*}$, $VMCP_{AG*}$, and $VMCP_{CS*}$ respectively. Note that these “value terms” capture the *expected* values of blockchain supported market-segment customized pricing scheme. This “concept” actually comes from the decision analysis literature (see Pratt et al, 1995). We formally define them as follows and then present Lemma 5.3

$$VMCP_{PF*} = \Delta \bar{\Pi}_{PF,CUS-COM*} = \bar{\Pi}_{PF,CUS*} - \bar{\Pi}_{PF,COM*}, \quad (5.21)$$

$$VMCP_{AG*} = \Delta \bar{\Pi}_{AG,CUS-COM*} = \bar{\Pi}_{AG,CUS*} - \bar{\Pi}_{AG,COM*}, \quad (5.22)$$

$$VMCP_{CS*} = \Delta CS_{CUS-COM*} = CS_{CUS*} - CS_{COM*}, \quad (5.23)$$

$$\Delta S_{PF,CUS-COM*} = S_{PF,CUS*} - S_{PF,COM*},$$

$$\Delta S_{AG,CUS-COM*} = S_{AG,CUS*} - S_{AG,COM*}.$$

Lemma 5.3. (a) $VMCP_{PF*} = \frac{\alpha NH}{4}$, and $VMCP_{AG*} = \frac{(1-\alpha)NH}{4}$ where $H = a(1-a)u^2 + c(1-c)l^2 + 2auctl > 0$.

(b) $\Delta S_{PF,CUS-COM*} = \frac{\alpha \sigma_N H}{4}$ and $\Delta S_{AG,CUS-COM*} = \frac{(1-\alpha) \sigma_N H}{4}$. (c) $\Delta CS_{CUS-COM*} > 0$ if and only if $cl > au$.

Lemma 5.3 gives the analytical closed-form expressions for VMCP and many other important terms. From them, we can observe that when u and l increase, $VMCP_{PF*}$, $VMCP_{AG*}$, $\Delta S_{PF,CUS-COM*}$ and $\Delta S_{AG,CUS-COM*}$ all increase. This observation highlights the impacts brought by the risk averse and risk seeking behaviors of customers on the VMCP as well as profit risk differences (i.e., $\Delta S_{PF,CUS-COM*}$ and $\Delta S_{AG,CUS-COM*}$).

Define:

$$\text{Significance of risk averse customers in the market: } SIG_{RAC} = au, \quad (5.24)$$

$$\text{Significance of risk seeking customers in the market: } SIG_{RSC} = cl. \quad (5.25)$$

Note that by definition, SIG_{RAC} can capture how significant the risk averse customers in the market are because it includes both the proportion of risk averse customers in the market as well as the respective degree of risk aversion. Similarly, SIG_{RSC} captures the significance of risk seeking customers in the market.

From Lemma 5.3, we can directly derive Proposition 5.2.

Proposition 5.2. *In the extended model: Customized pricing is good for profit improvement for both the platform and the service agents, but it also leads to higher risk but whether it is good for the consumers depends on the significance of risk averse and risk seeking customers in the market. To be specific, consumers are benefitted by the customized pricing scheme if and only if the significance of risk seeking customers in the market (SIG_{RSC}) is higher than the significance of risk averse customers (SIG_{RAC}) in the market.*

Proposition 5.2 has revealed several interesting results. In particular, it uncovers the fact that customized pricing outperforms the common pricing in yielding higher profits for both the platform and the service agents. However, the profit risks are also higher. As such, the customized pricing policy does not dominate the common pricing strategy from the mean-risk “two-dimensional” perspective. Regarding consumer surplus, it is important to note that whether consumers are benefitted by the customized pricing depends on the significance of risk seeking customers and the significance of risk averse customers in the market. If the risk seeking customers are more significant, the consumers will be benefitted by the customized pricing scheme because consumer surplus will be higher.

6. Ignoring Risk Preferences: Losses

We have established in the above sections that consumers can exhibit different risk preferences towards waiting times for on-demand services. In Section 5, we have explored the optimal pricing with the common price and customized price scenarios when the platform has implemented the efficient distributed database system supported by the blockchain technology. Now, a natural question arises: What if we ignore the risk preferences? What are the losses? In this section, we analytically explore them under both the common and customized pricing scenarios (with the blockchain technology). Here, “ignoring risk preferences” refers to the case when the platform makes the pricing decisions simply by assuming that the whole market is full of risk neutral consumers and do not consider the presence of consumers with other risk attitudes.

With the results from Sections 4.1, 5.1 and 5.2, we now proceed to explore the losses of the platform, service agents and customers under both a common price scheme and a market-segment customized price scheme, which are denoted by LCP_{PF^*} , LCP_{AG^*} , LCP_{CS^*} , and $LMCP_{PF^*}$, $LMCP_{AG^*}$, $LMCP_{CS^*}$, respectively. The profit risk differences are denoted as $\Delta S_{PF,COM^*-(p_{RNC}^*)}$, $\Delta S_{AG,COM^*-(p_{RNC}^*)}$, and $\Delta S_{PF,CUS-(p_{RNC}^*)}$, $\Delta S_{AG,CUS-(p_{RNC}^*)}$, respectively. All detailed definitions are shown in Table 6.1. We have Lemma 6.1.

Table 6.1. Definitions

$LCP_{PF^*} = \Delta \bar{\Pi}_{PF,COM^*-(p_{RNC}^*)} = \bar{\Pi}_{PF,COM^*} - \bar{\Pi}_{PF}(p_{RNC}^*)$	$LMCP_{PF^*} = \Delta \bar{\Pi}_{PF,CUS-(p_{RNC}^*)} = \bar{\Pi}_{PF,CUS^*} - \bar{\Pi}_{PF}(p_{RNC}^*)$
$LCP_{AG^*} = \Delta \bar{\Pi}_{AG,COM^*-(p_{RNC}^*)} = \bar{\Pi}_{AG,COM^*} - \bar{\Pi}_{AG}(p_{RNC}^*)$	$LMCP_{AG^*} = \Delta \bar{\Pi}_{AG,CUS-(p_{RNC}^*)} = \bar{\Pi}_{AG,CUS^*} - \bar{\Pi}_{AG}(p_{RNC}^*)$
$LCP_{CS^*} = \Delta CS_{COM^*-(p_{RNC}^*)} = CS_{COM^*} - CS(p_{RNC}^*)$	$LMCP_{CS^*} = \Delta CS_{CUS-(p_{RNC}^*)} = CS_{CUS^*} - CS(p_{RNC}^*)$
$\Delta S_{PF,COM^*-(p_{RNC}^*)} = S_{PF,COM^*} - S_{PF}(p_{RNC}^*)$	$\Delta S_{PF,CUS-(p_{RNC}^*)} = S_{PF,CUS^*} - S_{PF}(p_{RNC}^*)$
$\Delta S_{AG,COM^*-(p_{RNC}^*)} = S_{AG,COM^*} - S_{AG}(p_{RNC}^*)$	$\Delta S_{AG,CUS-(p_{RNC}^*)} = S_{AG,CUS^*} - S_{AG}(p_{RNC}^*)$

Lemma 6.1. (a) If $cl > au$, then: i) $LCP_{PF^*} > 0$, $LCP_{AG^*} > 0$, $\Delta S_{PF, COM^*-(p_{RNC}^*)} > 0$ and $\Delta S_{AG, COM^*-(p_{RNC}^*)} > 0$; ii) $LMCP_{PF^*} > 0$, $LMCP_{AG^*} > 0$, $\Delta S_{PF, CUS-(p_{RNC}^*)} > 0$, and $\Delta S_{AG, CUS-(p_{RNC}^*)} > 0$. (b) If $t > \frac{(2-a)u + cl}{2}$, then $\Delta CS_{COM^*-(p_{RNC}^*)} > 0$ and $\Delta CS_{CUS-(p_{RNC}^*)} > 0$.

Lemma 6.1 gives the market conditions when ignoring the risk preferences of the consumers in the market will lead to losses from the perspectives of the platform, service agents and customers under both a common price scheme and a market-segment customized price scheme. From Lemma 6.1, we have Proposition 6.1.

Proposition 6.1. When the significance of risk seeking customers in the market (SIG_{RSC}) is higher than the significance of risk averse customers (SIG_{RAC}) in the market (i.e., $cl > au$), considering the risk preferences of the consumers is good for profit improvement for both the platform and the service agents, although it also leads to a higher level of risk. While whether it is good for the consumers depends on the scaled expected waiting time. To be specific, if the scaled expected waiting time is sufficiently large (i.e., $t > \frac{(2-a)u + cl}{2}$), consumers are benefited when their risk preferences are considered.

Proposition 6.1 has highlighted the significance of considering risk preferences of the consumers in the market. Specifically, it indicates the fact that when the significance of risk seeking customers in the market is higher than the significance of risk averse customers in the market, considering the risk preferences of the consumers is always good for profit improvement for both the platform and the service agents, no matter whether the platform only provides a common price for all consumers or adopts a market-segment customized pricing scheme. In the meantime, regarding consumer surplus, it is important to note that whether consumers are benefitted depends on the scaled expected waiting time. If the scaled expected waiting time is sufficiently high, the consumers will also be benefited from the considerations of their risk preferences.

The findings in Proposition 6.1 are especially important when the average waiting time of the on demand platform increases. Didi, for example, after a new Beijing government policy²⁴ went into effect on July 1, 2018, the average waiting time in Beijing now exceeds 40 minutes instead of the initial five minutes only in the past.²⁵ Under such case, considering the preferences of consumers can not only benefit the consumers, but also the platform when the significance of risk seeking customers in the market is sufficiently high.

7. Conclusion

7.1. Concluding Remarks and Managerial Insights

In the sharing economy, platform operations for on-demand services (e.g., food delivery) are very popular nowadays. For typical on-demand service platforms, customers are waiting-time-sensitive and they may also possess a certain risk attitude. In this paper, motivated by the importance of on-demand service platform operations, we have applied the mean-risk theory and analytically explored how the risk attitudes of customers would affect the optimal service pricing decision, consumer surplus of customers in the market, and the expected profit and profit risk of the platform and the (hired) service agents. Our analysis has generated many important insights.

In the basic model (when we assume that the market only includes homogeneous customers with the same type of risk attitude), under the mean-risk theory, we have found that if the customers are more risk averse, then the optimal service price will drop. The opposite appears for the risk seeking case in which the

²⁴ To enhance the overall of online ride-hailing services, transport officials in at least seven major Chinese cities—including Beijing, Shanghai, Shenzhen and Hangzhou—has issued car-hailing regulations as a response to China's Ministry of Transport's July guidelines. Didi therefore, has restricted its private "taxis" to native Beijing residents only under the pressure of the governmental policies in these cities.

²⁵ See <https://supchina.com/2018/07/08/long-wait-on-didi-blame-beijings-july-1-crackdown-on-private-taxi-drivers/> and <https://www.forbes.com/sites/ywang/2016/10/12/why-china-is-proposing-strict-rules-on-the-ride-hailing-market/#33dc28817871>. (Accessed on 10 December, 2018)

optimal service price will increase if the customers are more risk seeking. Comparing among the three different risk attitudes of the customers, we have shown that when the customers are risk seeking, the consumer surplus level and the expected profits of platform and service agents are highest, even though the profit risks of the platform and service agents are also highest. While the opposite happens when the customers are risk averse.

In the extended model with a market including customers having different risk attitudes, for the scenario when the platform offers one flat price (called “common price”) to all customers (irrespective of their risk attitude), we have derived the optimal on-demand servicing pricing decision and also revealed that if the scaled expected waiting time (t) increases (decreases), the optimal on-demand service price, and the respective expected profits and standard deviation of profits for the platform and the service agents, and consumer surplus will all decrease (increase). For the scenario when the platform offers a customized price to each customer with respect to her risk attitude (see Section 5.2), we have also derived the respective optimal service price. Comparing between the two scenarios under the extended model yields the value of customized service pricing (which is made possible with the use of blockchain technology). Comparing between the common pricing scheme and the customized service pricing scheme, we have proven that the customized pricing scheme is good for profit improvement for both the platform and the service agents, but it also leads to higher risk; whether it is good for the consumers depends on the significance of risk averse and risk seeking customers in the market. To be specific, consumers are benefited by the customized pricing scheme if and only if the significance of risk seeking customers in the market is higher than the significance of risk averse customers in the market. We have also explored the loss if the platform ignores the risk preferences of the customers. We have found that this can lead to losses to both the customers and the platform and the loss of profit for the platform will be especially prominent if the significance of risk seeking customers in the market is higher than the significance of risk averse customers in the market.

We thus conclude by highlighting the importance of exploring customer risk attitude in deciding the optimal on-demand service price and the use of blockchain technology can enhance the profitability of the

platform and the service agents by employing the customized pricing scheme, even though customers may or may not be benefited.

7.2. Future Research

In this paper, we explore the optimal service pricing decision for the platform under an exogenous revenue sharing mechanism with hired agents. Future research can be conducted to include the logistics arrangement and operations with consideration of endogenous costs such as agent wage design and investment on blockchain technology applications (Hua et al. 2012, Taylor 2018). More research efforts can also be put on the cost saving aspect in real world implementation of the on-demand services. For example, machine learning and AI technology based models can be utilized to optimize the delivery route to reduce cost and delivery time to better satisfy customers. Smart contracting applications to meet the win-win situation of platforms and service providers and delivery logistics companies can be explored more as well. How to use the smart process of blockchain to solve the dispute of the two sides or three sides, and how the payment method in blockchain affect the supply chain efficiency all deserve deeper exploration. In addition, we assume that the effective arrival rate is exogenous in this paper. It is interesting to consider the case in which the effective arrival rate is affected by customer utility and the pricing decision. New interesting insights can be derived after exploring the respective equilibrium. Furthermore, we highlight the three different types of risk preferences of consumers, which are common in the literature (e.g., see Choi et al. 2018b). It is interesting to consider further differentiation of consumers, such as the one feels bad for late arrivals while prefers early arrivals that cause different waiting costs, in future research.

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Appendix (A1): Platform's Risk Attitudes

From Section 3, we can see that the optimal service fee set by the risk sensitive platform is independent of the platform's risk sensitivity. As such, the platform's risk attitude does not affect its way of making the optimal service pricing decision. We have Proposition A1.

Proposition A1. *Under the mean-risk framework, the optimal service pricing decision of the platform depends on scaled waiting time t and the customer's risk sensitivity and attitude, but it is independent of the platform's risk attitude. Thus, we have: $p_{RAPF}^* = p_{RNPF}^* = p_{RS PF}^* = p^*$.*

Proposition A1 is a bit surprising. With it, we know that no matter the platform is risk seeking, risk averse or risk neutral, the same optimal price will be set. This implies that in the following sections, we do not need to focus on the platform's risk attitude in deciding the respective optimal on-demand service price.

Appendix (A2): Extended Model with Implementation Costs of Blockchain Technology

Define the fixed cost for the implementation of blockchain technology as F , which is sufficiently large as a sunk cost. Let f be the variable cost of the blockchain technology application for per unit order. In the basic model, the expected profits and standard deviation of profits of the platform become as follows:

$$\bar{\Pi}_{PF}(p) = (\alpha p - f)N(1 - F(p + t + \beta)) - F, \quad (A1)$$

$$S_{PF}(p) = (\alpha p - f)(1 - F(p + t + \beta))\sigma_N, \quad (A2)$$

Note that the fixed cost of the fixed cost for the implementation of blockchain technology (F) does not affect the optimal service price. It is easy to show that $\bar{\Pi}_{PF}(p)$ is still a concave function of p in the basic model. The optimal service price which maximizes $\bar{\Pi}_{PF}(p)$ is:

$$p^* = \frac{f + \alpha(1 - t - \beta)}{2\alpha}. \quad (A3)$$

When the consumers are homogeneous in risk attitude, we have Lemma A1.

Lemma A1. *Under the extended model with customized pricing and blockchain technology cost consideration, the optimal service price for each market segment and the optimal expected profit and its variance are listed as follows:*

$$p_{RSC}^{CUS*} = \frac{\alpha(1 - t + l) + f}{2\alpha}. \quad (A4)$$

$$p_{RNC}^{CUS*} = \frac{\alpha(1 - t) + f}{2\alpha}. \quad (A5)$$

$$p_{RAC}^{CUS*} = \frac{\alpha(1 - t - u) + f}{2\alpha}. \quad (A6)$$

$$\bar{\Pi}_{PF,CUS*} = N\xi^{CUS*} - F, \quad (A7)$$

$$\text{where } \xi^{CUS*} = \frac{1}{4\alpha} \left[a(\alpha(1-t-u)-f)^2 + b(\alpha(1-t)-f)^2 + c(\alpha(1-t+l)-f)^2 \right], \quad (\text{A8})$$

$$S_{PF,CUS*} = \sigma_N \xi^{CUS*}. \quad (\text{A9})$$

From Lemma A1, the variable cost of the blockchain technology application does not affect the structure of either the optimal prices or expected profit and its variance. This shows that our results in the basic model (Section 3) and the extended model (Section 5) remain robust.

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Appendix (A3)

Table A1. Sensitivity analysis.

Parameters	Meanings	Impacts				
		p^{COM*}	$\bar{\Pi}_{PF,COM*}$	$S_{PF,COM*}$	$\bar{\Pi}_{AG,COM*}$	$S_{AG,COM*}$
$a \uparrow$	The proportion of risk averse customers increases	↓	↓	↓	↓	↓
$b \uparrow$	The proportion of risk neutral customers increases	—	—	—	—	—
$c \uparrow$	The proportion of risk seeking customers increases	↑	↑	↑	↑	↑
$u \uparrow$	Significance of risk aversion increases	↓	↓	↓	↓	↓
$l \uparrow$	Significance of risk seeking behavior increases	↑	↑	↑	↑	↑
$t \uparrow$	Scaled expected waiting time increases	↓	↓	↓	↓	↓
$\alpha \uparrow$	Revenue share proportion for the platform increases	—	↑	↑	↓	↓
$N \uparrow$	The expected number of customers increases	—	↑	—	↑	—
$\sigma_N \uparrow$	Standard deviation of the number of customers increases	—	—	↑	—	↑

Table A2. Sensitivity analysis results on the consumer surplus under both the common pricing scheme and the market-segment customized price scheme.

Parameters	Meanings	Impacts	
		CS_{COM}^*	CS_{CUS}^*
$a \uparrow$	The proportion of risk averse customers increases	\uparrow if $t < 1 - au + cl$	\uparrow
$b \uparrow$	The proportion of risk neutral customers increases	\uparrow	\uparrow
$c \uparrow$	The proportion of risk seeking customers increases	\uparrow if $t > 1 - au + cl$	\uparrow
$u \uparrow$	Significance of risk aversion increases	\uparrow if and only if $t > 1 - 4u + 3au - 3cl$	\uparrow if and only if $t > 1 - u$
$l \uparrow$	Significance of risk seeking behavior increases	\uparrow if and only if $t < 1 + 3au + 4l - 3cl$	\uparrow if and only if $t < 1 + l$
$t \uparrow$	Scaled expected waiting time increases	\uparrow if and only if $t > 1 - au + cl$	\uparrow if and only if $t > 1 - au + cl$
$\alpha \uparrow$	Revenue share proportion for the platform increases	—	—
$N \uparrow$	The expected number of customers increases	—	—
$\sigma_N \uparrow$	Standard deviation of the number of customers increases	—	—