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Uncovering merchants' willingness to wait in on-demand food delivery markets

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Abstract: While traditional on-demand food delivery services help restaurants reach more customers and enable doorstep deliveries, they also come with drawbacks, such as high commission fees and limited control over the delivery process. White-label food delivery services have emerged as an alternative, ready-to-use platform for restaurants to arrange delivery for customer orders received through their applications or websites, without the constraints imposed by traditional on-demand food delivery platforms or the need to develop an in-house delivery operation. Although several studies have investigated consumer behavior when using traditional on-demand food delivery services, there is limited research on merchants' behavior when adopting white-label food delivery services. In this research, we develop a non-parametric survival model to estimate merchants' willingness to wait when using white-label food delivery services and examine how various factors, such as delivery fees, the number of placed orders, and average waiting time, affect merchants' willingness to wait, drawing on a dataset of both delivered and canceled orders from a crowd-sourcing delivery platform in Singapore. The empirical results show that merchants' willingness to wait has a non-linear relationship with their average waiting time; it initially increases and then decreases with average waiting time. Moreover, the relationship between merchants' willingness to wait during the pick-up stage and their average waiting times in the matching stage follows a similar non-linear trend. Merchants who have experienced lengthy waiting times on average in the matching stage tend to be less patient in the pick-up stage. This research sheds light on the stage-specific dynamics of merchants waiting behavior in white-label delivery service and provides insights for delivery platforms to optimize their operational strategies and enhance user experiences.

Keywords: Food delivery, On-demand services, Waiting time, Willingness to wait

1. Introduction

Advancements in transportation and logistics, along with developments in city infrastructure and technologies, have paved the way for innovative on-demand services such as ride-hailing, grocery delivery, food delivery, and household services (Wang, 2022). Travel behavior changes at the individual level during the COVID-19 pandemic have accelerated the rapid expansion of on-demand services (Parady et al., 2020). Facilitated by third-party platforms, these transportation-enabled on-demand services establish efficient connections between customers/users, service/product producers, and drivers/couriers (Liang et al., 2023). For example, online platforms of food delivery services, such as DoorDash, UberEats, and Meituan connect customers who place food orders online, merchants who prepare the food, and drivers[1] who are responsible for food pick-up and delivery. Beyond catering to individual customers, these third-party platforms also provide white-label delivery services to merchants. For example, DoorDash and Uber not only provide food delivery and ride-hailing services for individual customers but also provide white-label food delivery services (i.e., DoorDash Drive and Uber Direct) for merchants. When using white-label delivery services, customers place orders on merchants' own sales channels (e.g., website or app) and interact with merchants only. Merchants then seek delivery services from third-party platforms and pay delivery fees for each order, thus avoiding the high labor costs of building their own logistics network. Whether for individual customers or merchants, these third-party delivery platforms prioritize user[2] experience as their core advantage.

[1] In Asia, many food delivery drivers are riders, who mainly use motorcycles or bicycles to deliver meals to customers.
[2] Both merchants and customers can be users of the delivery service provided by third-party platforms. When customers use third-party platforms (e.g., DoorDash and Meituan) for food ordering and delivery, the term "users" refers to customers. When merchants use white-label delivery services provided by third-party platforms, the term "users" refers to merchants.

and pay delivery fees for each order, thus avoiding the high labor costs of building their own logistics network. Whether for individual customers or merchants, these third-party delivery platforms prioritize user[2] experience as their core advantage. Among the various factors that contribute to user satisfaction, waiting time is particularly important (Hernandez and Monzon, 2016). A shorter waiting time can attract more users (Kremer and Debo, 2016), while long waits may result in dissatisfaction and user attrition (Lu et al., 2013). Therefore, understanding users' waiting behavior is crucial for improving service quality and ensuring a positive user experience.

Users generally expect prompt and efficient delivery service with minimal waiting time. However, challenges such as too few idle drivers or excessive demand can make it difficult for platforms to meet these expectations. This mandates a comprehensive understanding of their willingness to wait, which allows the platform to mitigate user dissatisfaction and enhance system efficiency through appropriate operational strategies. Prior research often simplifies users' willingness to wait (also known as wait tolerance) as a fixed value for the sake of modeling convenience (Yang et al., 2020; Qin et al., 2021). However, this assumption is inaccurate, since users' willingness to wait can vary significantly among individuals and is influenced by various factors, such as personal preferences, urgency of need, and previous experiences on the platform (Kuzu et al., 2019; Liu et al., 2022). By understanding the distribution of users' willingness to wait under different circumstances, platforms can optimize pricing strategies to balance profitability and user experience.

Although waiting behavior-related studies have been conducted for years, our study distinguishes itself from previous research in three key respects. First, many studies have primarily focused on identifying the factors that impact users' waiting time, with little attention paid to their willingness to wait (Yang et al., 2021; Brown, 2023). Users' waiting time represents the objective duration they spend waiting for a service, while willingness to wait signifies individuals' subjective attitudes towards acceptance of waiting. A few studies have attempted to measure users' waiting tolerance through stated preference (SP) surveys (Fan et al., 2016; Rahimi et al., 2019). Although survey data can provide valuable insights into users' attitudes towards waiting, they may not truly reflect users' patience during waiting due to recall bias, social desirability bias, and bias caused by the survey context (Murphy et al., 2005; Hensher, 2010). In contrast, we directly use the real-world operational dataset from a crowd-sourcing delivery platform, which includes both delivered orders and canceled orders, to estimate the willingness to wait. Specifically, we first employ the non-parametric survival model, the Kaplan–Meier estimator, to estimate the survival function for different merchants, and then use numerical integration techniques to estimate their willingness to wait.

Second, users' willingness to wait is affected by diverse factors and varies from user to user. In this paper, we focus on understanding how the delivery fee, number of orders, and average waiting time influence merchants' willingness to wait because these factors play crucial roles in shaping their overall experience with the delivery service. The delivery fee paid by merchants directly affects their perception of value and cost-effectiveness as users often measure the quality of service against the monetary cost they make (Seo et al., 2020; Hu et al., 2021). Moreover, merchants who have handled a higher number of orders through the platform, and consequently have frequent interaction with it, may have different expectations for waiting time (Bemelmans et al., 2015). Also, users' average waiting time is a critical factor affecting their willingness to wait. On one hand, excessive waiting times can result in frustration, impatience, and even abandonment of the wait (Allon et al., 2011; Lu et al., 2013). On the other hand, merchants with longer average waiting times become accustomed to prolonged waits and treat the longer waiting time as the norm; thus, they tend to develop greater tolerance (Emadi and Swaminathan, 2018). The two opposing forces may lead to a non-linear relationship between average waiting time and willingness to wait. However, it is unclear how users' average waiting time influences their subjective willingness to wait. Drawing from previous theoretical and empirical work, we propose several hypotheses to explore how merchants' willingness to wait is affected by the average waiting time and other factors, such as delivery fee and the number of orders.

Third, in on-demand urban services, fulfilling a user's order typically entails multiple steps. For instance, in on-demand food delivery services, platforms initially match users with drivers, and subsequently, the matched drivers will collect and deliver meals. Users may encounter waiting time during both the online matching phase (from the time an order is placed until it is accepted by a driver) and the physical pick-up stage (from the order acceptance until the driver collects the order). Prior studies have focused on investigating the waiting time within a specific stage (Wang et al., 2019; Liu et al., 2022) or analyzing the overall waiting time (Yang et al., 2021). Few studies have examined users' waiting behaviors in the two stages separately and their interactions. In this study, we explore the waiting behaviors of merchants, i.e., users of white-label delivery services, in both the online matching and physical pick-up stages, and examine the interrelationships between merchants' waiting behaviors across these stages.

Using over a year's order data from an on-demand food delivery platform in Singapore[3] that provides white-label delivery services for merchants, we first estimate merchants' willingness to wait in both the matching and pick-up stages, and then test the proposed hypotheses using empirical analysis. The results show that merchants using the delivery service provided by this platform are predominantly willing to wait for 10 to 30 min during the matching stage. However, during the pick-up stage, their patience level greatly increases, with most merchants willing to wait for more than 50 min. Our empirical analysis also yields several additional findings. First, our analysis reveals that merchants' willingness to wait is negatively impacted by delivery fee in the matching stage and is positively influenced by the number of orders in both the matching and pick-up stages. Second, we observe that the correlation between the average waiting time and merchants' willingness to wait is not linear, demonstrating a threshold effect. As the average waiting time increases, merchants' willingness to wait first increases and then decreases beyond a certain turning point. Moreover, these turning points differ significantly across the matching and pick-up stages. Last, our empirical findings shed light on the interactions between stages. Specifically, merchants who encounter short waiting times on average in the online matching stage demonstrate greater patience in the physical pick-up stage, whereas those experiencing prolonged waiting times in the matching stage exhibit lower willingness to wait in the pick-up stage. These findings can guide service providers in effectively managing and reducing waiting time, particularly in the matching stage, in order to maintain higher levels of user willingness to wait and enhance overall customer satisfaction.

The paper is organized as follows. Section 2 reviews the relevant literature. Section 3 outlines the estimators and formulates the hypotheses. Section 4 describes the dataset and estimates of willingness to wait. Section 5 introduces the variables and regression models. Section 6 discusses the regression results, robustness checks, and the managerial implications. Section 7 presents the conclusion.

2. Literature review

Waiting is an inevitable process when using transportation services, and it plays a crucial role in shaping user satisfaction and loyalty (Pruyn and Smidts, 1998). The experience of waiting can evoke a range of negative emotions, such as frustration, boredom, and even anger (Taylor, 1994; Hui and Tse, 1996). When the wait is perceived as too long or unbearable, individuals may give up waiting and choose not

[3] The name of the investigated platform is withheld at the request of the data contributor.

to receive service, leading to business loss and negative customer evaluations (Janakiraman et al., 2011; Lu et al., 2013). However, the effects of waiting are not always negative (Friman, 2010). According to Ülkü et al. (2020), customers who wait longer in queues tend to consume more during the service. In the context of transportation services, existing research has mainly focused on the waiting behavior of transit passengers, exploring how transit waiting affects overall service satisfaction (Tyrinopoulos and Antoniou, 2008; Monsuur et al., 2021; Echaniz et al., 2022) and identifying key factors that shape transit passengers' attitudes towards waiting (Wang et al., 2021; Cheng and Tsai, 2014; Shaw et al., 2021). For example, Rahimi et al. (2019) find that transit users who have used ridesharing services have lower waiting tolerance during a disruption, based on survey data from transit users in the Chicago metropolitan area. Cheng and Tsai (2014) reveal that passengers' tolerance of waiting during train delays varies significantly across individual characteristics, such as gender and age. Despite extensive studies on the waiting behavior of transit passengers, less attention has been paid to the waiting behavior of users of on-demand delivery services. Unlike the waiting experience of passengers in public transportation, waiting for on-demand delivery services involves multiple stages, such as waiting for matching, pickup, and delivery, all of which are heavily influenced by the algorithms of the delivery platform. Consequently, the factors affecting users' waiting behavior in on-demand delivery services may differ substantially from those in traditional transportation service contexts.

Although users' waiting time is often recognized as a crucial aspect for improving on-demand services in general, the specific behavior of users while waiting for the service has received relatively less attention. Among these, Wang et al. (2019) model passengers' cancelation of confirmed orders as the result of mode switching when passengers encounter empty taxis while waiting for ride-hailing vehicles. They propose a non-linear equation system that effectively describes the interaction between the two markets at equilibrium. By analyzing the number of canceled orders for each merchant on an on-demand food delivery platform, Xu et al. (2021) find that the factors leading to user cancelations include price, waiting time in different operational processes, merchant location, category, and popularity. Based on queuing theory, Wang et al. (2024) propose a spatial matching model which specifically considers the characteristics of passenger abandonment behavior while waiting for drivers. Their model can help ride-hailing platforms in designing a matching policy that adapts to time-varying demand. Liu et al. (2022) investigate passengers' willingness to wait for a ride-sourcing platform's response to a vehicle dispatch request, a stage analogous to the matching stage in our research. They design a dynamic reward system based on delay announcements and incorporate it into a time-dependent survival model to examine passengers' abandonment decisions.

Our paper differs from the above in the following respects. First, we study the impact of average waiting time on users' willingness to wait in the context of food delivery services. In addition, instead of assuming independent waiting behaviors in different stages, we note that users' waiting experiences encompass two interrelated stages and explore their interaction. Specifically, our empirical findings demonstrate that short waiting in the matching stage positively influences users' waiting patience in the subsequent pick-up stage, but prolonged waiting for matching has a significant negative impact on users' willingness to wait for pick-up.

3. Estimators and hypotheses

3.1. Order fulfillment process

The general order fulfillment process for on-demand delivery services is illustrated in Fig. 1. The process starts when a user initiates a delivery service request via the platform, which marks the creation of an order. The delivery service requested by a user could be a ride from a specific location to a desired destination or food delivery from a particular restaurant to a specified address. Following this, the platform sends the delivery request to multiple available drivers simultaneously until one of them accepts the request. The driver who accepts the request then comes to the specified location to pick up the order (a meal for food delivery service or a passenger for ride-hailing) and subsequently delivers it to the user's desired destination. Typically, the delivery order fulfillment process can be divided into three stages: matching, pick-up, and delivery, as shown in Fig. 1.

In the matching stage, users may experience long waiting time if there are few idle drivers on the platform, particularly during peak hours. In such cases, the user may stop waiting and use another platform. Therefore, the matching stage begins when the order is created and ends when the driver accepts the delivery request or the user cancels the order. In the pick-up stage, if the driver takes a long time to pick up the order, the user may lose patience and cancel the order. The beginning of the pick-up stage is when a driver accepts the delivery request, and the endpoint is when the driver picks up the order or the user cancels the order. Once the order is successfully picked up by the driver, almost no user will cancel the order.[4] Therefore, we exclude the delivery stage from our analysis.

In this paper, "users" refer to merchants who use white-label delivery services provided by a crowd-sourcing delivery platform in Singapore. On the investigated platform, merchants, upon receiving customers' orders through their websites or applications, initiate the order fulfillment process by requesting delivery services from the platform. Merchants inform the platform of their expected pick-up time when requesting delivery services, but the platform does not provide merchants with estimated or remaining waiting time during the order fulfillment process. The decision to wait or not (i.e., cancel the order) for delivery is made by merchants.

3.2. Willingness to wait

3.2.1. Definition of willingness to wait

Willingness to wait is a crucial aspect of merchants' waiting behavior and significantly influences whether an order can be successfully fulfilled. Willingness to wait refers to the maximum amount of time a merchant can tolerate during the waiting period. Specifically, it is the time span from the initial start of waiting until the merchant decides to give up waiting and cancel the order. Therefore, for orders canceled by merchants, the waiting time accurately reflects their willingness to wait. However, for non-canceled orders, the observed waiting time before the order is accepted by a driver in the matching stage, or the observed waiting time before the order is picked up in the pick-up stage, is shorter than merchants' actual willingness to wait. This is because merchants would continue to wait for a certain additional time if the order was not successfully accepted or picked up by a driver. In essence, these non-canceled orders can be regarded as instances of right-censoring.[5] Although they are right-censored observations, these non-canceled orders still offer valuable information for estimating merchants' willingness to wait. By considering both canceled and non-canceled orders, more comprehensive and accurate estimation of willingness to wait can be achieved.

Moreover, it is important to analyze merchants' willingness to wait in the matching and pick-up stages separately due to the different levels of uncertainty and decision-making processes involved in each

[4] As reported by the dataset, less than 0.01% of orders are canceled during the delivery stage.

[5] Right-censoring occurs when a subject leaves the study before an event occurs or the study ends before the event has occurred. For example, in a study on cancer survival rates, right-censoring would occur if some participants are still alive at the end of the study period or are lost to follow-up before dying of cancer.

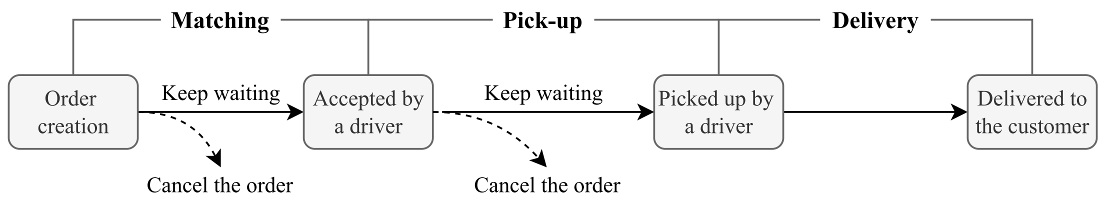


Fig. 1. The order fulfillment process.

Table 1
Relationship between waiting time and willingness to wait.

Stage	Order status	Waiting time	Willingness to wait
Matching stage	Non-canceled orders	order create time - request accept time	>waiting time
	Canceled orders	order create time - order cancel time	= waiting time
Pick-up stage	Non-canceled orders	request accept time - driver pick-up time	>waiting time
	Canceled orders	request accept time - order cancel time	= waiting time

stage. In the matching stage, merchants face greater uncertainty about whether drivers are available to accept their orders, as they do not have information on driver availability. The cost of switching to alternative delivery platforms is also relatively low in the matching stage. In contrast, the waiting context in the pick-up stage is significantly different from that in the match stage. Merchants have already received a commitment from the platform that drivers will pick up their orders and, therefore, face lower uncertainty. Additionally, the cost of switching to an alternative delivery platform at this stage is significantly higher, as they would need to undergo another matching process with high uncertainty regarding driver availability. As noted by Kuzu et al. (2019), individuals will adjust their patience based on the specific context of waiting. Consequently, merchants' waiting behavior in the pick-up stage differs substantially from that in the matching stage.

Table 1 shows the relationship between waiting time and willingness to wait for canceled and non-canceled orders in the matching stage and pick-up stage.

3.2.2. Derivation of willingness to wait

Similar to Brown et al. (2005) and Mandelbaum and Zeltyn (2013), survival analysis is employed to define and estimate merchants' willingness to wait. Specifically, we use T to denote the waiting time until the merchant cancels the order. Let T be a non-negative random variable with probability density function $f(t)$. The merchant's willingness to wait (μ) is represented by the expectation of T:

$$\mu = \int_0^\infty t f(t) dt. \tag{1}$$

The survival function $S(t)$ represents the probability that the merchant does not cancel the order until the duration t:

$$S(t) = P(T > t) = 1 - \int_0^t f(x)dx = \int_t^\infty f(x)dx. \tag{2}$$

It is apparent that the derivative of $S(t)$ equals $-f(t)$, and $S(t)$ is subject to boundary conditions $S(0) = 1$ and $S(\infty) = 0$. According to the integration by parts rule, we have:

$$\mu = \int_0^\infty -tS(t)'dt = (-tS(t))|\, t = 0^{t=\infty} - \int_0^\infty -t'S(t)dt = \int_0^\infty S(t)dt. \tag{3}$$

In essence, the merchant's willingness to wait is inferred to be the integral of the survival function. After estimating the merchants' survival function with respect to waiting time, it becomes feasible to estimate their willingness to wait.

3.2.3. Kaplan–Meier estimator

Survival analysis provides a variety of methods for estimating the survival function, including nonparametric, semiparametric, and parametric models. While semiparametric and parametric models are more efficient and have better interpretability than nonparametric models, they require a much larger sample size and more assumptions about the data. Also, they may not be as robust to outliers as nonparametric models. Therefore, we opt for the widely used non-parametric model, the Kaplan–Meier (KM) estimator (Kaplan and Meier, 1958), to estimate the survival function.

An order can be in one of three states at any given moment. During the matching stage, the three states are waiting to be matched, canceled, and accepted by a driver. In the pick-up stage, the states are waiting to be picked up, canceled, and picked up by a driver. The event of interest is the cancelation of the order, while the order being accepted or picked up by a driver serves as right-censoring. Let $t_1 < t_2 < \cdots < t_j < \cdots < t_K$ be the waiting times until cancelation of orders belonging to the same user, arranged in ascending order, where K represents the total number of distinct waiting times until cancelation for that user. Assume $t_0 = 0$, we have $S(t_0) = P(T > t_0) = 1$, because no order is canceled when waiting time is zero. Suppose n_j denotes the number of orders for which the waiting time to be matched or picked up exceeds t_{j-1}, and m_j represents the number of orders that are canceled in the interval $(t_{j-1}, t_j]$. Then, given that the user waits beyond time t_{j-1}, the probability of the merchant continuing to wait until time t_j is:

$$P(T > t_j | T > t_{j-1}) = \frac{n_j - m_j}{n_j}. \tag{4}$$

More generally, the unconditional probability of waiting until t_j (i.e., the survival function) is equal to the product of the conditional probabilities in each time interval before t_j:

$$\begin{aligned} P(T > t_j) &= P(T > t_j | T > t_{j-1}) P(T > t_{j-1}) \\ &= P(T > t_j | T > t_{j-1}) P(T > t_{j-1} | T > t_{j-2}) P(T > t_{j-2}) \\ &\ \ \vdots \\ &= P(T > t_j | T > t_{j-1}) P(T > t_{j-1} | T > t_{j-2}) \cdots P(T > t_1 | T > t_0) \\ &\quad \times P(T > t_0). \end{aligned} \tag{5}$$

By substituting Eq. (4) into Eq. (5), we obtain the KM estimator of the survival function:

$$\hat{S}(t) = \prod_{j | t_j \le t} \left(\frac{n_j - m_j}{n_j} \right). \tag{6}$$

3.2.4. Numerical integration

By integrating the KM estimator of the survival function, we can get an estimate of the willingness to wait for different merchants. However, when censoring is present, the KM estimator of the survival function relies on ranking the observed event times (i.e., $t_1 < t_2 < \cdots < t_j < \cdots < t_K$), rather than on a closed-form expression that can be integrated analytically. Therefore, we have to use numerical integration to get the approximation of willingness to wait.

There are several numerical integration techniques, such as the trapezoidal rule, Simpson's rule, and Gaussian quadrature. One advantage of the trapezoidal rule is that it is well-suited for integration over irregularly spaced data points and requires only the function values at the endpoints of each subinterval. As illustrated in Eq. (6), the KM estimator of the survival function is stepwise, equal to the joint product of the conditional probabilities at different event time intervals. These event times are unevenly spaced, which makes the trapezoidal rule a suitable choice for numerical integration. Therefore, by using the trapezoidal rule to integrate the KM estimator of the survival function, we can get the estimator of willingness to wait:

$$\hat{\mu} = x \sum_{j=2}^{K} \frac{t_j - t_{j-1}}{2} \left[\hat{S}(t_{j-1}) + \hat{S}(t_j) \right]. \tag{7}$$

By combining Eqs. (6) and (7), we find that $\hat{\mu}$ is mainly determined by the waiting time of canceled orders (t_j and t_{j-1}), the number of canceled orders (m_j) and non-canceled orders (n_j) in the defined time interval. Unlike directly using the average waiting time of only canceled orders as merchants' willingness to wait (Xu et al., 2021), the estimates of willingness to wait in this study consider both canceled and non-canceled orders of a merchant. As a result, the estimator of willingness to wait (i.e., $\hat{\mu}$) acknowledges that merchants' waiting behaviors are reflected not only by the time they are willing to wait before canceling but also by the instances in which they choose not to cancel.

3.3. Hypotheses

3.3.1. The influence of delivery fee and the number of orders on merchant's willingness to wait

A higher delivery fee elevates merchants' monetary costs, leading them to expect higher-quality services, such as more prompt matching and pick-up, and hence causing a decrease in their patience to wait (Seo et al., 2020; Hu et al., 2021). Moreover, merchants often compare delivery fees across different platforms. They tend to opt for a more cost-effective alternative if faced with a higher delivery fee, resulting in reduced willingness to wait on the current platform. Therefore, we propose the following hypothesis:

Hypothesis 1. Merchants who pay a higher fee for food delivery services are less willing to wait.

Merchants that have handled a larger number of orders may have developed more efficient operational strategies, such as flexible order bundling (Yildiz and Savelsbergh, 2019; Ulmer et al., 2021), which allows them to manage longer waiting times and maintain operational efficiency, thus exhibiting more patience while waiting for delivery service from the platform. Moreover, in the context of on-demand delivery services, there are often peak hours when the demand for delivery drivers is higher than the supply of available drivers (e.g., lunch and dinner times). Merchants with experience in handling higher order volumes might be more accustomed to these supply–demand dynamics and, therefore, are more patient when waiting for a suitable driver. Therefore, we propose the following hypothesis:

Hypothesis 2. Merchants who have placed a higher number of orders have a higher willingness to wait.

3.3.2. The effect of average waiting time on merchants' willingness to wait

The average waiting time can have a dual impact on merchants' willingness to wait, driven by two opposing forces. On the one hand, increased waiting time may result in negative emotions, including frustration, impatience, and dissatisfaction (Allon et al., 2011; Lu et al., 2013). If a merchant repeatedly experiences long waiting times, they may perceive that the delivery service is slow or inefficient. This negative perception could decrease the merchant's willingness to wait and may even result in abandoning the wait, as they link the long waiting time to a poor service quality (Maister et al., 1984; Tereyağoğlu et al., 2018). On the other hand, merchants who consistently experience longer waiting times might have developed a higher tolerance for waiting (Watkins et al., 2011). Moreover, merchants who experience longer waiting times are likely to adjust their expectations regarding waiting (Emadi and Swaminathan, 2018). As a result, they anticipate longer waiting periods as a norm rather than an exception.

Following Janakiraman et al. (2011), we expect the above two opposite forces will drive an inverted U-shaped relationship between the average waiting time and willingness to wait. Initially, merchants' willingness to wait increases with their average waiting time. However, once the average waiting time exceeds a certain threshold, excessively long waiting times start to negatively impact merchants' willingness to wait. This gives rise to the following hypothesis:

Hypothesis 3. Merchants' willingness to wait exhibits an inverted U-shaped relationship with their average waiting time.

3.3.3. Impact of average waiting time in the matching stage on merchants' willingness to wait for pick-up

It is essential to acknowledge that successful matching is the prerequisite for the pick-up stage. Therefore, when analyzing waiting behavior in the pick-up stage, we cannot overlook the influence of the matching stage. To capture the sequential nature of waiting experiences, we discuss the carry-over effect from the matching stage to the pick-up stage. Similar to the previous hypothesis, the carry-over effect is also driven by two opposing forces. On the one hand, merchants might anchor their expectations for the waiting time in the pick-up stage based on their waiting experience in the matching stage (Weinberg, 2000). If their average waiting time during the matching stage is long, they might interpret this as a sign of busy times for the platform. Consequently, they may have a higher willingness to wait during the pick-up stage.

On the other hand, when merchants have encountered prolonged waiting time during the matching stage, they may become more impatient and less tolerant of further delays during the subsequent pick-up stage. The frustration and impatience caused by extended matching waiting time can erode their willingness to wait for an additional period before their orders are picked up. This aligns with findings in queuing literature, which suggests that customers who wait too long before entering the service may lose trust in the system (Robinson, 1996; Lewicki et al., 2006), register more complaints (Bearden and Teel, 1983), or request additional compensatory services (Oliver and Swan, 1989). By viewing waiting for matching as waiting in the queue and waiting for pick-up as receiving service, it is reasonable to expect that longer waiting time during the matching stage will result in lower willingness to wait in the pick-up stage. When the average waiting time in the matching stage is relatively low, merchants are less likely to feel frustration or impatience and the anchoring effect dominates, leading to an increase in willingness to wait in the pick-up stage. Once merchants' average waiting time in the matching stage exceeds a certain threshold, the frustration/impatience effect gains prominence, resulting in a decline in willingness to wait for pick-up. Therefore, we propose the following hypothesis:

Hypothesis 4. Merchants' willingness to wait in the pick-up stage exhibits an inverted U-shaped relationship with their average waiting time in the matching stage.

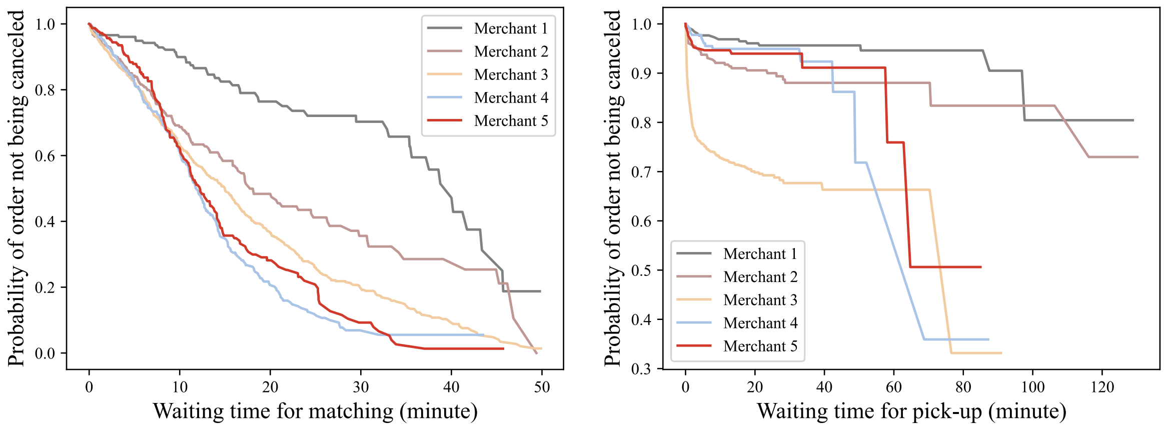


Fig. 2. Estimated survival functions for five different merchants in both the matching and pick-up stages.

Table 2
Explanation of order data.

Attribute	Definition
Order ID	Unique identifier of the order.
Merchant ID	Unique identifier of the Merchant who placed the order.
Merchant location	Physical address of the merchant who placed the order.
Order create time	Time the order was created.
Order accept time	Time the order was successfully accepted by a driver.
Driver pick-up time	Time the order was actually picked up by the driver.
Order cancel time	Time the order was canceled by the merchant.
Delivery fee	Total amount of delivery fee paid by the merchant.

4. Data and estimates of willingness to wait

4.1. Data description

To estimate merchants' willingness to wait and test our hypotheses, we use data from a crowd-sourcing delivery platform in Singapore that provides white-label food delivery services to merchants. This dataset contains detailed processing timestamps for both delivered and canceled orders from November 21, 2020, to February 21, 2022. Table 2 shows the detailed information recorded for each order. Missing values of order accept time, order pick-up time, and order cancel time mean that the order was not successfully accepted by a driver, the driver did not pick up the order, and the order was not canceled by the merchant, respectively.

4.2. Estimates of willingness to wait

In this section, we present estimates of merchants' willingness to wait for matching and pick-up, which are denoted as $Will2WaitMatch$ and $Will2WaitPick$, respectively. Based on data for more than 140,000 food delivery orders from 400 merchants, $Will2WaitMatch$ and $Will2WaitPick$ are estimated using the method described in Section 3.2. Fig. 2 illustrates the estimated survival functions of five different merchants in both the matching stage and the pick-up stage. The survival function provides the probability of an order not being canceled as the waiting time changes. We can observe that the shapes of the survival functions vary notably among different merchants, indicating differences in their willingness to wait.

Fig. 3 shows histograms of the estimated willingness to wait for matching and pick-up. The x-axis denotes the duration of willingness to wait (in minutes) and the y-axis denotes the number of merchants falling within each corresponding interval. We observe a significant difference in merchants' willingness to wait between the matching stage and the pick-up stage. Most merchants are willing to wait for 10 to 30 min during the matching process. However, their patience level increases considerably during the pick-up stage, with a majority willing to wait for more than 50 min. This may be because merchants understand that drivers might require time to reach the pick-up location, and they also need time to prepare and package meals.

We present the correlation between merchants' willingness to wait during the matching stage and pick-up stages in Fig. 4, where each point represents a merchant. We note that there is not a clear linear relationship between merchants' willingness to wait for matching and their willingness to wait for pick-up. Although the waiting time of canceled orders directly reflect merchants' willingness to wait, information contained in non-canceled orders is also essential; neglecting such information may induce bias and hinder the comprehensive understanding of merchants' willingness to wait. Fig. 5 illustrates the relationship between the estimated willingness to wait and the average waiting time of canceled orders. We find that merchants' willingness to wait for matching shows a positive correlation with the average matching waiting time of canceled orders. However, there is no apparent linear relationship between their willingness to wait for pick-up and the average pick-up waiting time of canceled orders. This observation suggests that the estimated willingness to wait is a more comprehensive measure of merchants' willingness to wait than relying solely on the waiting time of canceled orders.

5. Models and variables

5.1. Variable description

Taking each merchant as an individual sample point, we create a new dataset to test our hypotheses, in which the two dependent variables are the merchant's willingness to wait for matching and for pick-up (i.e., $Will2WaitMatch$ and $Will2WaitPick$). Our independent variables include the merchants' paid delivery fee and the number of orders they placed, which are denoted as $MeanFee$ and $NumOrder$, respectively. The variable $MeanFee$ represents the average fee paid by the merchant to the platform, and the variable $NumOrder$ is the number of orders placed by the merchant on the platform. The histograms of $MeanFee$ and $NumOrder$ are shown in Fig. 6. Moreover, we use the average matching waiting time and the average pick-up waiting time of all non-canceled orders for a merchant as two independent variables, denoted as $WaitTimeMatch$ and $WaitTimePick$.

When estimating merchants' willingness to wait, we consider both canceled and non-canceled orders, as both types of orders provide insights into merchants' subjective waiting behavior. Canceled orders directly reflect merchants' waiting tolerance, while non-canceled orders reveal that merchants are willing to wait beyond a certain time. When calculating merchants' average waiting time, we only consider non-canceled orders due to two concerns. First, we intend to use merchants' average waiting time to capture their typical waiting experience, which is primarily influenced by platform operations. However, the waiting

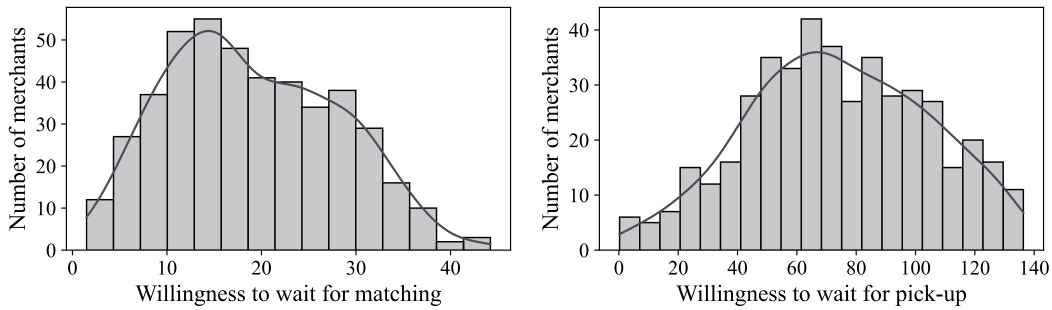


Fig. 3. Histogram of willingness to wait for matching and pick-up.

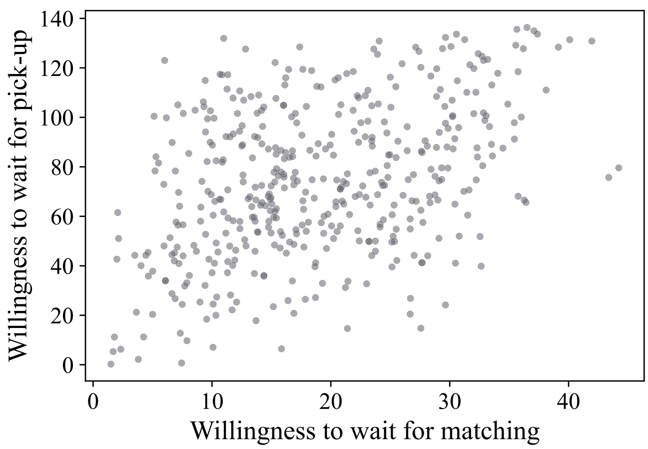


Fig. 4. Relationship between merchants' willingness to wait for matching and willingness to wait for pick-up.

time of canceled orders can be affected by the subjective preferences of merchants rather than by platform operations. For example, some merchants may cancel orders due to personal impatience rather than the efficiency of the platform. We acknowledge that orders canceled immediately after a driver accepts them are more likely to result from order errors or random last-minute changes. These immediate cancellations may provide misleading information about willingness to wait. We have conducted a robustness check in Section 6.2.2 by excluding these immediate cancellations when estimating willingness to wait.

Second, as willingness to wait estimator is a function of the waiting time of canceled orders,[6] including canceled orders when calculating waiting time will undermine the reliability of the relationship between average waiting time and willingness to wait revealed by regression analysis.

In addition, we introduce two control variables, i.e., $RatioShort$ and $RatioLong$ to account for variations in delivery distance distribution across different merchants. $RatioShort$ represents the ratio of orders with short delivery distance (less than 5 km), while $RatioLong$ represents the proportion of orders with long delivery distance (more than 12.5 km). These two variables control for the impact of the varying delivery distance distributions on the mean fee a merchant paid during the study period.[7] To control for the effect of food types on merchants' willingness to wait, we include a control variable, denoted as $FastFood$, indicating whether a merchant is a fast food restaurant or not. This information is obtained by using the Places API provided by Google Maps to query the location of the merchant. Table 3 presents descriptive statistics for each variable.

5.2. Models

Our study examines the impact of delivery fee, the number of placed orders, and average waiting time on merchants' willingness to wait in both the matching and pick-up stages (Hypotheses 1, 2, and 3). Also, we explore the relationship between merchants' average waiting time for matching and their willingness to wait in the pick-up stage (Hypothesis 4). To test our hypotheses, we propose the following multiple linear regression models:

$$\begin{aligned} Will2WaitMatch_i = &\alpha_0 + \alpha_1 MeanFee_i + \alpha_2 \log(NumOrder_i) \\ &+ \alpha_3 WaitTimeMatch_i \\ &+ \alpha_4 WaitTimeMatch_i^2 + \alpha_5 RatioShort_i \\ &+ \alpha_6 RatioLong_i \\ &+ \alpha_7 FastFood_i + \epsilon_i, \end{aligned} \tag{8}$$

$$\begin{aligned} Will2WaitPick_i = &\beta_0 + \beta_1 MeanFee_i + \beta_2 \log(NumOrder_i) \\ &+ \beta_3 WaitTimePick_i \\ &+ \beta_4 WaitTimePick_i^2 + \beta_5 WaitTimeMatch \\ &+ \beta_6 WaitTimeMatch^2 \\ &+ \beta_7 FastFood_i + \beta_8 RatioShort_i + \beta_9 RatioLong_i + \epsilon_i, \end{aligned} \tag{9}$$

where i represents the ith merchant and ϵ_i is the error term. The quadratic terms $WaitTtimeMatch$ and $WaitTtimePick$ are included to capture the non-linear pattern and potential threshold effect of average waiting time on merchants' willingness to wait. We also take the logarithm of $NumOrder$ to reduce the impact of extreme values.

6. Results and implications

6.1. Regression results

Table 4 shows the regression results for willingness to wait for matching under different model specifications. Column (1) only considers $MeanFee$, $NumOrder$, $RatioShort$, and $RatioLong$. The results align with Hypotheses 1 and 2. The coefficients suggest that merchants having placed a larger number of orders are willing to wait longer, while an increase in delivery fee may decrease their willingness to wait. The results are consistent in column (4) when other variables are added in the model. Other than the direction and statistical significance of coefficients, their magnitudes are also important (Parady and Axhausen,

[6] Upon revisiting the willingness-to-wait estimator, specified by Eqs. (6) and (7) it is apparent that the estimation of willingness to wait relies on the waiting time for canceled orders, the number of canceled orders, and the number of non-canceled orders within designated time intervals.

[7] The platform charges delivery fees based on the delivery distance. Orders with a delivery distance of less than 5 km incur a fixed basic fee. Beyond 5 km and within 12.5 km, the fee increases by 0.5 $S\$$ per additional kilometer, and by 0.3 $S\$$ per additional kilometer beyond 12.5 km.

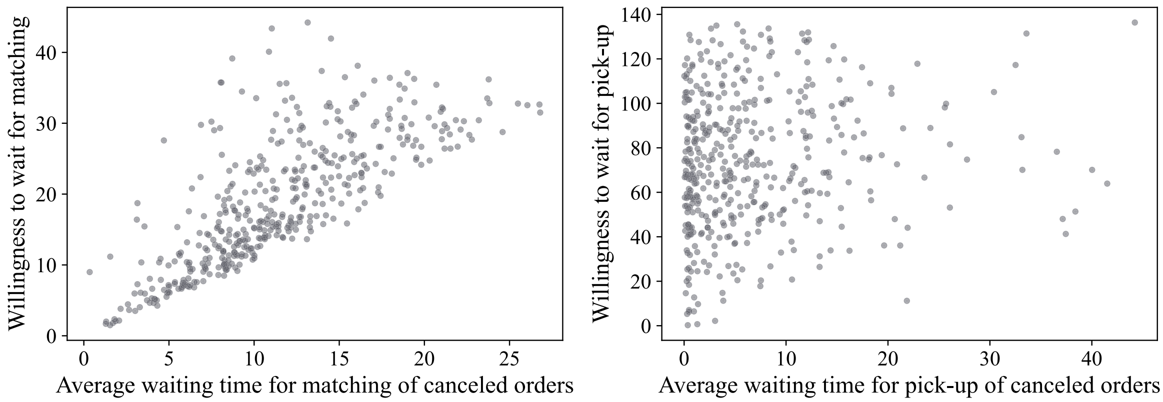


Fig. 5. Relationship between merchants' willingness to wait and their average waiting time of canceled orders.

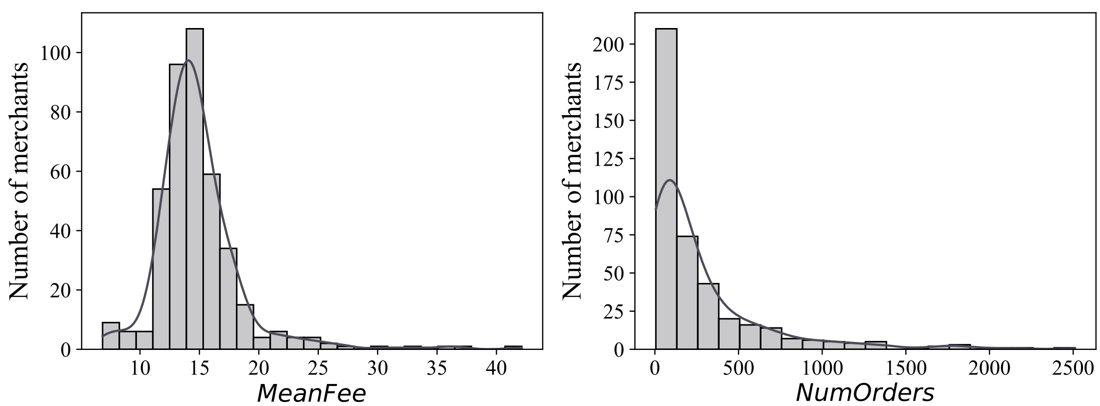


Fig. 6. Histograms of $MeanFee$ and $NumOrder$.

Table 3
Descriptive statistics.

Variable	Definition	Mean	S.D.
$Will2WaitMatch$	Estimated willingness to wait of the merchant in the matching stage	19.000	8.677
$Will2WaitPick$	Estimated willingness to wait of the merchant in the pick-up stage	77.339	29.422
$MeanFee$	Average delivery fee paid by a merchant to the platform (S$)	14.892	3.739
$NumOrder$	Number of orders placed by a merchant	271.978	371.583
$WaitTimeMatch$	Average waiting time for matching of all non-canceled orders for a merchant (min)	6.544	3.344
$WaitTimePick$	Average waiting time for pick-up of all non-canceled orders for a merchant (min)	29.047	8.237
$RatioShort$	Ratio of orders under 5 km delivery distance for a merchant	0.383	0.227
$RatioLong$	Ratio of orders over 12.5 km delivery distance for a merchant	0.230	0.162
$FastFood$	Whether the merchant is a fast food restaurant (1) or not (0)	0.303	0.460

2023). According to column (4), a merchant's willingness to wait for matching decreases by 0.373 min with each unit increase in the mean delivery fee. This supports Hypothesis 1 that merchants who pay a higher fee are less willing to wait due to their expectations for faster service. Moreover, the significantly positive coefficient of $\log NumOrder$ suggests that merchants' willingness to wait for matching is expected to increase by 0.013 min associated with a 1% increase in order quantities placed by them.

Column (2) includes the average waiting time for matching. We find that the variable $WaitTimeMatch$ is statistically significant and positive, indicating that an increase in average waiting time renders merchants more patient and elevates their willingness to wait. Given the existence of opposing forces, we further investigate whether the relationship between $WaitTtimeMatch$ and $Will2WaitMatch$ is non-linear. The square term of $WaitTimeMatch$ is added in column (3). The primary term's coefficient is significantly positive, and the coefficient of the quadratic term is significantly negative. This implies a nonlinear relationship between merchants' average waiting time and their willingness to wait in the matching stage, with a turning point at 16.6 min ($-0.5\hat{\alpha}_3/\hat{\alpha}_4$, derived from the estimates in column (4)). Fig. 7(a) illustrates variations in the willingness to wait with the average waiting time during the matching stage, confirming an inverted U-shaped relationship between $Will2WaitMatch$ and $WaitTimeMatch$ (in support of Hypothesis 3). The results are consistent when $FastFood$ is controlled in column (4).

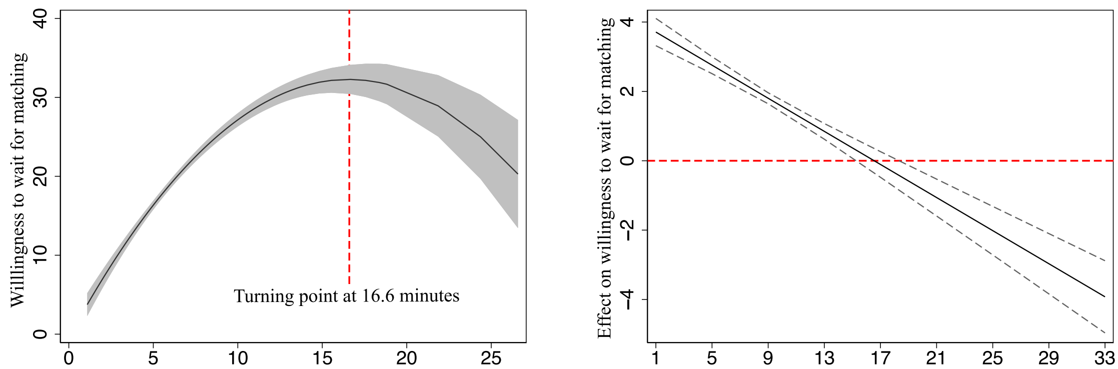
Initially, an increase in the average waiting time leads to a higher willingness to wait due to merchants' psychological adaptation and expectation adjustments. However, longer waiting time can also trigger negative emotions among merchants about waiting. When the accumulated negative emotions cannot be offset by the psychological adaptation and expectation adjustments, merchants' willingness to wait begins to decrease. As shown in Fig. 7(b), during the matching stage, the marginal effect of average waiting time on willingness to wait exhibits a notable decreasing trend and turns from positive to negative once the threshold of 16.6 min is surpassed. This implies that further increases in average waiting time lead to a decline in merchants' willingness to wait.

Table 5 reports the regression results for willingness to wait for pick-up. $WaitTimePick$ and its quadratic term are included in column

Table 4
Regression results for merchants' willingness to wait for matching.

Variables	$Will2WaitMatch$			
	(1)	(2)	(3)	(4)
$MeanFee$	−0.323*** (0.113)	−0.367*** (0.083)	−0.404*** (0.073)	−0.373*** (0.072)
log $NumOrder$	1.236*** (0.322)	1.925*** (0.238)	1.353*** (0.216)	1.324*** (0.213)
$WaitTimeMatch$		1.749*** (0.093)	4.010*** (0.223)	3.950*** (0.220)
$WaitTimeMatch^2$			−0.122*** (0.011)	−0.119*** (0.011)
$RatioShort$	−1.155 (2.530)	4.209** (1.874)	5.789*** (1.657)	5.369*** (1.633)
$RatioLong$	3.573 (3.506)	5.704** (2.569)	7.788*** (2.272)	6.494*** (2.259)
$FastFood$				−2.259*** (0.585)
$Constant$	17.469*** (2.695)	0.776 (2.162)	−5.220*** (1.984)	−4.126** (1.971)
R^2	0.062	0.498	0.612	0.625
$Adj.R^2$	0.052	0.492	0.606	0.619

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Numbers in parentheses are standard errors.



(a) $WaitTimeMatch$ (b) $WaitTimeMatch$

Fig. 7. The inverted U-shaped relationship between $WaitTimeMatch$ and $Will2WaitMatch$ (a), and Average marginal effect of $WaitTimeMatch$ on $Will2WaitMatch$ (b). Note: The gray area and the dotted lines depict 95% confidence intervals.

Table 5
Regression results for merchants' willingness to wait for pick-up.

Variables	$Will2WaitPick$			
	(1)	(2)	(3)	(4)
$MeanFee$	−0.086 (0.292)	−0.465* (0.239)	−0.526** (0.237)	−0.451* (0.236)
log $NumOrder$	14.551*** (0.830)	15.871*** (0.678)	15.498*** (0.691)	15.391*** (0.686)
$WaitTimePick$		4.721*** (0.486)	4.172*** (0.508)	3.959*** (0.509)
$WaitTimePick^2$		−0.046*** (0.007)	−0.039*** (0.007)	−0.036*** (0.007)
$WaitTimeMatch$			2.664*** (0.746)	2.612*** (0.740)
$WaitTimeMatch^2$			−0.119*** (0.038)	−0.117*** (0.038)
$RatioShort$	−3.104 (6.525)	1.740 (5.265)	4.082 (5.267)	2.934 (5.233)
$RatioLong$	27.536*** (9.042)	23.594*** (7.279)	26.004*** (7.215)	22.950*** (7.223)
$FastFood$				−5.548*** (1.891)
$Constant$	3.104 (6.949)	−93.883*** (10.335)	−94.282*** (10.446)	−87.945*** (10.572)
R^2	0.456	0.651	0.662	0.669
$Adj.R^2$	0.451	0.646	0.655	0.662

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Numbers in parentheses are standard errors.

(2). We further add the waiting time in the matching stage and its quadratic term in column (3). Column (4) includes all the variables. The coefficients on $logNumOrder$ are positive and significant at the 0.01 level across all columns, suggesting a significant positive impact of the number of placed orders on merchants' willingness to wait for pick-up. For every 1% increase in the number of orders, the willingness to wait for pick-up increases by about 0.15 min. While the coefficients on the average delivery fee continue to be negative, they are significant only at the 10% level after adding other controls.

Results in column (2) verify the inverted U-shaped relationship between the average waiting time for pick-up and the willingness to wait in the pick-up stage, as Fig. 8(a) plots (in support of Hypothesis 3). The turning point is 55.0 min ($-0.5\hat{\beta}_3/\hat{\beta}_4$, derived from the estimates in column (4)), which is much higher than that in the matching stage (i.e., 16.6 min). The higher threshold of waiting time in the pick-up stage could be triggered by multiple reasons. First, in the pick-up stage, merchants have already received the platform's commitment that drivers will pick up their orders. This guarantee may foster a sense of reliability and lead to higher willingness to wait. Second, merchants understand that drivers require a certain travel time to reach the pick-up location, thereby being more tolerant of waiting. Furthermore, compared with the matching stage, merchants have already waited for a longer time in the pick-up stage and tend to perceive the costs associated with canceling an order or switching to another delivery platform as higher. Therefore, the sunk cost effect may drive merchants to keep waiting and result in a higher waiting threshold in the pick-up stage.

Results in column (3) reveal an inverted U-shaped relationship between merchants' average waiting time in the matching stage and their willingness to wait for pick-up. (in support of Hypothesis 4). As shown in Fig. 8(b), the turning point is at 11.2 min ($-0.5\hat{\beta}_5/\hat{\beta}_6$, derived

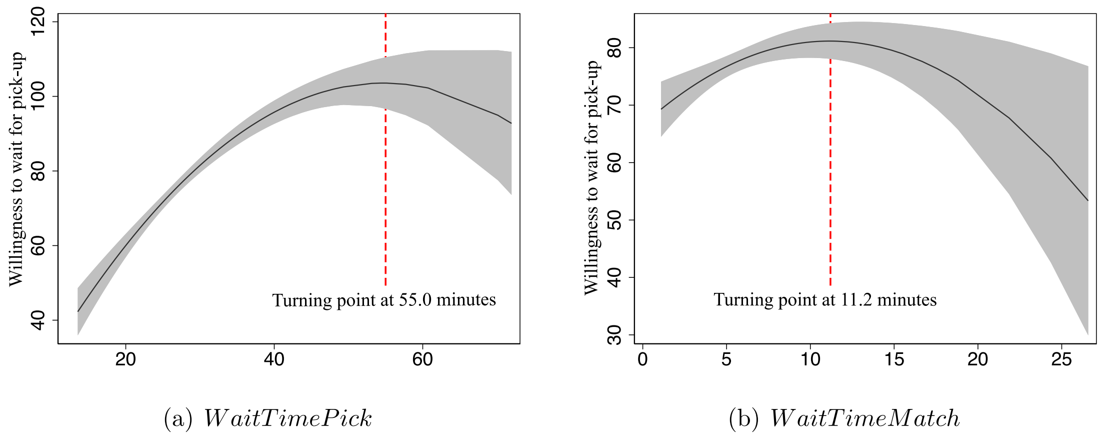


Fig. 8. Inverted U-shaped relationship between $WaitTimePick$ and $Will2WaitPick$ (a), and the inverted U-shaped relationship between $WaitTimeMatch$ and $Will2WaitPick$ (b). Note: The gray area and the dotted lines depict 95% confidence intervals.

Table 6
First-stage instrumental variable regression in the matching and pick-up stages.

Variables	log $NumOrder$	
	Matching stage	Pick-up stage
$PopDensity$	0.063*** (0.012)	0.059*** (0.012)
$WaitTimePick$		−0.030 (0.036)
$WaitTimePick^2$		0.000 (0.000)
$MeanFee$	0.013 (0.016)	0.018 (0.017)
$WaitTimeMatch$	0.180*** (0.049)	0.189*** (0.051)
$WaitTimeMatch^2$	−0.012*** (0.002)	−0.012*** (0.003)
$RatioShort$	−0.611* (0.368)	−0.622* (0.369)
$RatioLong$	−0.451 (0.509)	−0.399 (0.509)
$FastFood$	−0.079 (0.132)	−0.113 (0.133)
$Constant$	3.890*** (0.404)	4.469*** (0.720)
R^2	0.159	0.166
$Adj.R^2$	0.144	0.147

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Numbers in parentheses are standard errors.

from the estimates in column (4)), beyond which the $WaitTimeMatch$ has a negative effect on merchants' willingness to wait for pick-up. In other words, when the average waiting time in the matching stage exceeds 11.2 min, it starts to erode merchants' willingness to wait for their orders to be picked up.

These results highlight the significant impact of waiting experience during the matching stage on merchants' willingness to wait in both matching and pick-up stages. If the waiting time during the matching stage is below 11.2 min, it positively influences merchants' willingness to wait in both matching and pick-up stages. However, when the average waiting time for matching falls between 11.2 and 16.6 min, its marginal effect on merchants' willingness to wait for matching decreases, yet remains positive, while the prolonged waiting time in the matching stage starts to negatively impact merchants' willingness to wait for pick-up. Once the average waiting time in the matching stage exceeds 19.4 min, it exerts an adverse influence on merchants' willingness to wait in both stages.

6.2. Robustness checks

6.2.1. Discussion of the potential endogeneity issue

When examining the impact of the number of orders placed by merchants on their willingness to wait, there is potential reverse causality considering that merchants who are willing to wait longer may also be likely to use the platform more frequently, resulting in higher order quantities. Thus, $NumOrder$ may be an endogenous variable. Ignoring the endogeneity issue may lead to biased estimates.

To address the endogeneity concern, we use population density around the merchant[8] (denoted as $PopDensity$) as the instrumental variable for the number of orders placed by merchants. $PopDensity$ satisfies both the relevance condition and the exclusion condition (Wooldridge, 2010). On one hand, areas with higher population densities typically exhibit greater demand for food delivery services. Merchants operating in these locations are likely to receive more food delivery requests from customers, resulting in an increased number of orders. On the other hand, merchants' willingness to wait is more closely related to platform operational factors such as order fulfillment efficiency and delivery fees. Population density, as an external environmental factor, does not have a direct effect on the waiting behavior of merchants. Table 6 reports the first stage of the instrumental variable regression. It shows a significant correlation between $PopDensity$ and the endogenous variable (i.e., $NumOrder$) at the 1% level. However, the Hausman endogeneity test (Hausman, 1978) shows no significant differences between the second stage IV regression results and OLS regression results. The p-values of the tests are 0.330 in the matching stage and 0.520 in the pick-up stage, suggesting no evidence of endogeneity issue in either stage. This is reasonable as merchants placing more orders can be due to various factors such as business growth, customer demand, and overall satisfaction with the platform's delivery efficiency rather than merely willing to wait longer. Therefore, the reverse causality effect may not be a significant concern.

6.2.2. Alternative specifications of willingness to wait for pick-up

The delivery platform allows orders to be canceled without charge within a short time window after being accepted by the driver. As a result, we can observe that in the first few minutes of the pick-up stage, many orders are canceled. These cancelations are primarily driven by factors such as merchants placing incorrect orders or finding better options on other platforms. The estimated willingness to wait for pick-up ($Will2WaitPick$) may be biased if these canceled orders are included in the model. To address this issue, we test the sensitivity of our results to different specifications of $Will2WaitPick$. Specifically, we exclude orders canceled within the first one, two, and three minutes after matching, when estimating merchants' willingness to wait for pick-up. The regression results for different specifications of $Will2WaitPick$ are presented in Table 7.

This robustness check suggests that the main results remain consistent when excluding orders canceled within the first three minutes after matching. The significance level and sign of the coefficients

[8] Demographic data are derived from the Singapore Census of Population 2020 https://www.singstat.gov.sg/publications/reference/cop2020/cop2020-sr1.

Table 7
Regression results under different specifications of $Will2WaitPick$.

Variables	$Will2WaitPick$ ≤3 min	$Will2WaitPick$ ≤2 min	$Will2WaitPick$ ≤1 min	$Will2WaitPick$
$MeanFee$	−0.416 (0.260)	−0.404 (0.254)	−0.268 (0.241)	−0.451* (0.236)
log $NumOrder$	15.036*** (0.776)	15.184*** (0.751)	15.059*** (0.728)	15.391*** (0.686)
$WaitTimePick$	3.555*** (0.645)	3.489*** (0.631)	3.644*** (0.595)	3.959*** (0.509)
$WaitTimePick^2$	−0.027*** (0.009)	−0.026*** (0.009)	−0.028*** (0.009)	−0.036*** (0.007)
$WaitTimeMatch$	2.439*** (0.909)	2.367*** (0.877)	2.104*** (0.787)	2.612*** (0.740)
$WaitTimeMatch^2$	−0.116** (0.048)	−0.116** (0.046)	−0.110*** (0.039)	−0.117*** (0.038)
$RatioShort$	2.035 (5.551)	2.438 (5.448)	2.285 (5.315)	2.934 (5.233)
$RatioLong$	19.567** (8.046)	20.130** (7.789)	19.677** (7.618)	22.950*** (7.223)
$FastFood$	−7.941*** (2.154)	−7.822*** (2.086)	−8.347*** (2.016)	−5.548*** (1.891)
$Constant$	−78.260*** (12.677)	−78.257*** (12.439)	−81.292*** (11.865)	−87.945*** (10.572)
R^2	0.681	0.687	0.675	0.669
$Adj.R^2$	0.672	0.678	0.667	0.662

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Numbers in parentheses are standard errors.

Table 8
Regression results under different specifications of $WaitTimeMatch$ in the matching stage.

Variables	$Will2WaitMatch$			
	Median	75th Percentile	90th Percentile	Average
$MeanFee$	−0.454*** (0.093)	−0.344*** (0.079)	−0.357*** (0.071)	−0.373*** (0.072)
log $NumOrder$	1.758*** (0.266)	1.219*** (0.232)	0.935*** (0.213)	1.324*** (0.213)
$WaitTimeMatch$	3.498*** (0.269)	2.282*** (0.157)	1.370*** (0.125)	3.950*** (0.220)
$WaitTimeMatch^2$	−0.119*** (0.014)	−0.047*** (0.006)	−0.016*** (0.003)	−0.119*** (0.011)
$RatioShort$	4.016* (2.082)	5.274*** (1.787)	4.073** (1.590)	5.369*** (1.633)
$RatioLong$	7.373** (2.895)	6.591*** (2.472)	4.317* (2.214)	6.494*** (2.259)
$FastFood$	−2.258*** (0.744)	−1.991*** (0.639)	−2.164*** (0.572)	−2.259*** (0.585)
$Constant$	4.620* (2.397)	0.162 (2.093)	0.578 (1.899)	−4.126** (1.971)
R^2	0.396	0.554	0.641	0.625
$Adj.R^2$	0.385	0.546	0.635	0.619

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Numbers in parentheses are standard errors.

for key independent variables, e.g., $NumOrder$, $WaitTimeMatch$, and $WaitTimePick$, remain consistent. Moreover, it shows that excluding these orders when estimating $Will2WaitPick$ enhances the model's goodness of fit compared to the original analysis. It indicates that cancelations occurring very shortly after matching are influenced by various factors which are not captured by the model.

6.2.3. Alternative specifications of average waiting time

In our main analysis, we use the average waiting time of all non-canceled orders for a merchant as the measure of the merchant's typical waiting experience. To assess the robustness of our findings, we employ three alternative specifications for the measures of $WaitTimeMatch$ and $WaitTimePick$: median waiting time, 75th percentile waiting time, and 90th percentile waiting time. Tables 8 and 9 report regression results under different specifications of $WaitTimeMatch$ and $WaitTimePick$ in the matching stage and the pick-up stage, respectively.

Across different measures of merchants' waiting time, the significance level and sign of the coefficients for $NumOrder$ remain unchanged both in the matching stage and pick-up stage. Similarly, the sign of the coefficient on $MeanFee$ remains negative in the matching and pick-up stages, with the significance level at 1% level in the matching stage, consistent with our main analysis. Moreover, under the three alternative specifications, the coefficients of $WaitTimeMatch$ and $WaitTimePick$ remain significantly positive, and the coefficients of their quadratic terms remain significantly negative. This aligns with our main analysis (i.e., using average waiting time), demonstrating the robustness of our conclusions regarding the influence of merchants' waiting experience on their willingness to wait.

Although the significance level and sign of the coefficients are consistent across different measures of merchants' waiting time, R^2 values and coefficient magnitudes for $WaitTimeMatch$ and $WaitTimeMatch^2$ differ significantly across different specifications in Table 8. The differences in the magnitudes of these coefficients indicate that the curvature of the inverted U-shaped relationships between merchants' willingness to wait and waiting time changes with different specifications of waiting time. The coefficient magnitudes for $WaitTimeMatch$ and $WaitTimeMatch^2$ are both largest when using the average waiting time, implying both a steeper initial increase and a subsequent more pronounced decline in willingness to wait beyond the turning point as average waiting time increases. This signifies a stronger curvature of the inverted U-shaped relationship and a more distinct turning point. The absolute values of both coefficients are smaller when using median waiting time and decrease when using the 75th percentile of waiting time. For the 90th percentile of waiting time, the coefficient magnitudes for $WaitTimeMatch$ and $WaitTimeMatch^2$ are the smallest. The decreasing magnitudes of the two coefficients indicate a less pronounced curvature of the inverted U-shaped relationship when using higher percentiles of waiting time. Despite this, the R^2 value increases for higher percentiles. The R^2 values are larger for the 90th percentile and average waiting time. This implies that the variations in willingness to wait are explained more by the extreme and average waiting times than median and 75th percentile waiting times. Considering that the average waiting time accounts for the average distribution of waiting time and exhibits a more pronounced curvilinear effect on willingness to wait, it is used as the baseline measure in our main analysis.

6.2.4. Alternative time periods

Our research is conducted at the aggregate level, where both dependent and independent variables are measured by aggregating data over a specific period of time. This approach raises a concern that our findings may be exclusive to the time period under investigation. To alleviate this concern, we conduct a robustness check by changing the time periods.

Table 9
Regression results under different specifications of $WaitTimeMatch$ and $WaitTimePick$ in the pick-up stage.

Variables	$Will2WaitPick$			
	Median	75th Percentile	90th Percentile	Average
$MeanFee$	−0.406 (0.272)	−0.348 (0.253)	−0.436* (0.226)	−0.451* (0.236)
$\log NumOrder$	15.690*** (0.772)	14.822*** (0.734)	14.211*** (0.669)	15.391*** (0.686)
$WaitTimePick$	2.440*** (0.453)	2.161*** (0.400)	1.585*** (0.268)	3.959*** (0.509)
$WaitTimePick^2$	−0.021*** (0.006)	−0.015*** (0.004)	−0.006*** (0.002)	−0.036*** (0.007)
$WaitTimeMatch$	2.117*** (0.803)	1.666*** (0.512)	1.025** (0.406)	2.612*** (0.740)
$WaitTimeMatch^2$	−0.105** (0.043)	−0.053*** (0.019)	−0.024** (0.011)	−0.117*** (0.038)
$RatioShort$	1.420 (5.980)	2.122 (5.623)	−2.299 (4.987)	2.934 (5.233)
$RatioLong$	27.063*** (8.304)	23.148*** (7.781)	13.633* (6.976)	22.950*** (7.223)
$FastFood$	−7.441*** (2.143)	−6.791*** (2.026)	−5.763*** (1.818)	−5.548*** (1.891)
$Constant$	−50.360*** (10.442)	−58.948*** (10.475)	−54.151*** (8.675)	−87.945*** (10.572)
R^2	0.571	0.618	0.694	0.669
$Adj.R^2$	0.562	0.609	0.688	0.662

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Numbers in parentheses are standard errors.

Table 10
Regression results for different time periods in the matching stage.

Variables	$Will2WaitMatch$			
	6 months	9 months	12 months	15 months
$MeanFee$	−0.434*** (0.079)	−0.447*** (0.076)	−0.371*** (0.072)	−0.373*** (0.072)
$\log NumOrder$	1.358*** (0.253)	1.310*** (0.222)	1.264*** (0.214)	1.324*** (0.213)
$WaitTimeMatch$	4.088*** (0.307)	3.804*** (0.288)	4.101*** (0.237)	3.950*** (0.220)
$WaitTimeMatch^2$	−0.122*** (0.018)	−0.113*** (0.017)	−0.129*** (0.012)	−0.119*** (0.011)
$RatioShort$	4.329** (1.799)	5.397*** (1.703)	4.577*** (1.636)	5.369*** (1.633)
$RatioLong$	2.878 (2.696)	4.577* (2.389)	5.318** (2.300)	6.494*** (2.259)
$FastFood$	−2.412*** (0.652)	−2.151*** (0.609)	−2.189*** (0.585)	−2.259*** (0.585)
$Constant$	−3.437 (2.236)	−1.805 (2.076)	−3.790* (1.977)	−4.126** (1.971)
R^2	0.660	0.625	0.628	0.625
$Adj.R^2$	0.652	0.618	0.621	0.619

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Numbers in parentheses are standard errors.

Table 11
Regression results for different time periods in the pick-up stage.

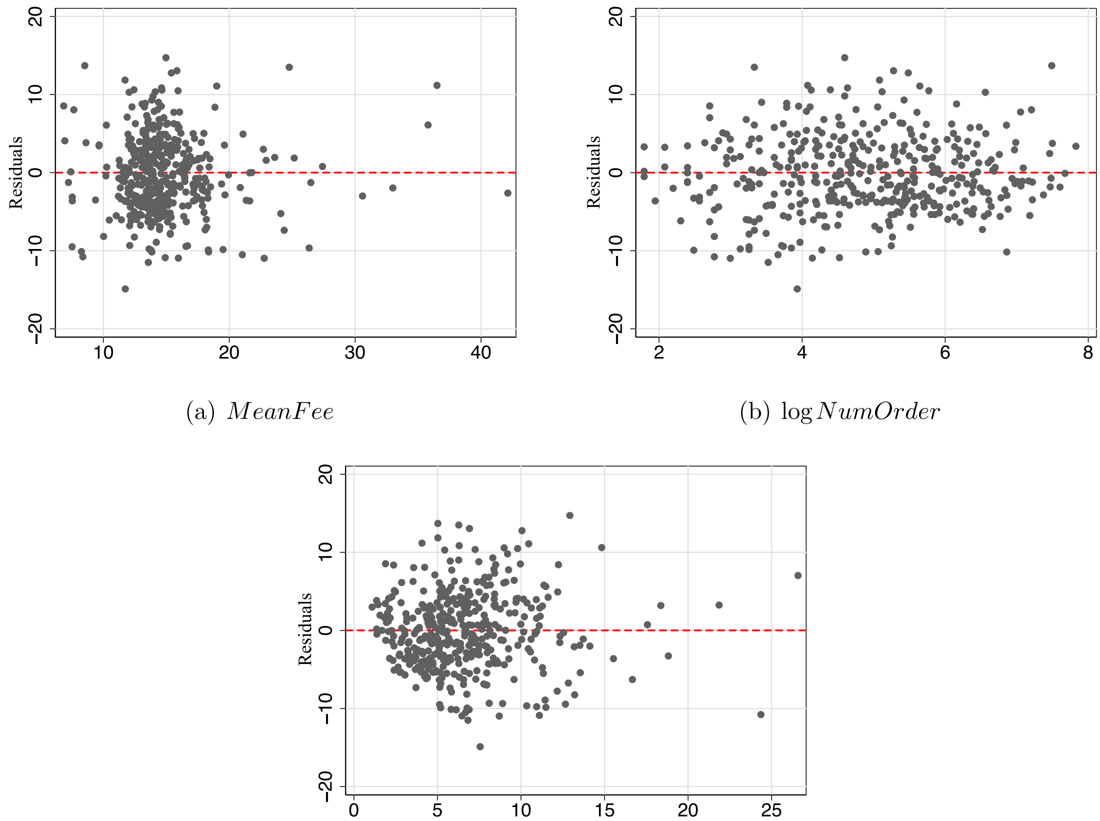
Variables	$Will2WaitPick$			
	6 months	9 months	12 months	15 months
$MeanFee$	−0.590** (0.278)	−0.693*** (0.250)	−0.455* (0.237)	−0.451* (0.236)
$\log NumOrder$	15.718*** (0.877)	15.227*** (0.725)	15.388*** (0.691)	15.391*** (0.686)
$WaitTimePick$	3.716*** (0.594)	4.069*** (0.541)	3.942*** (0.517)	3.959*** (0.509)
$WaitTimePick^2$	−0.033*** (0.008)	−0.038*** (0.008)	−0.036*** (0.007)	−0.036*** (0.007)
$WaitTimeMatch$	2.959*** (1.071)	2.603*** (0.945)	2.667*** (0.782)	2.612*** (0.740)
$WaitTimeMatch^2$	−0.133** (0.061)	−0.111** (0.055)	−0.119*** (0.041)	−0.117*** (0.038)
$RatioShort$	2.605 (6.194)	3.881 (5.499)	3.487 (5.260)	2.934 (5.233)
$RatioLong$	17.216* (9.269)	19.010** (7.693)	22.700*** (7.364)	22.950*** (7.223)
$FastFood$	−4.726** (2.296)	−5.553*** (2.001)	−5.496*** (1.897)	−5.548*** (1.891)
$Constant$	−80.423*** (12.308)	−84.084*** (11.161)	−87.941*** (10.752)	−87.945*** (10.572)
R^2	0.652	0.668	0.669	0.669
$Adj.R^2$	0.642	0.660	0.662	0.662

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Numbers in parentheses are standard errors.

We re-estimate merchants' willingness to wait and all independent variables for four different time spans during our study period, i.e., within 6, 9, 12, and 15 months before February 1, 2022. Then, we conduct regression analyses for each of these time spans. The regression results for the matching stage and pick-up stage are shown in Tables 10 and 11, respectively. The significance levels and signs of the coefficients of key independent variables ($MeanFee$, $NumOrder$, $WaitTimeMatch$, and $WaitTimePick$) remain consistent across all time spans. Notably, the magnitude of the coefficient of $MeanFee$ in the pick-up stage is relatively larger in the results for 6-month and 9-month time spans compared to the results for 12-month and 15-month time spans, indicating that the impact of $MeanFee$ on merchants' willingness to wait for pick-up is greater in the first 9 months than in the last 6 months during the study period. In addition, the magnitudes of coefficients of $NumOrder$, $WaitTimeMatch$, and $WaitTimePick$ do not change significantly across the four periods, demonstrating that the impacts of these variables on merchants' willingness to wait are consistent across the study period.

6.3. Managerial implications

Our findings provide crucial management insights for food delivery service platforms. First, the negative effect of mean delivery fees and the positive impact of the ratio of long-distance orders on merchants' willingness to wait highlight the importance of a well-designed pricing mechanism. When designing the pricing structure for delivery fees, platforms are suggested to consider charging a lower delivery fee to increase merchants' willingness to wait when it requires a longer time to process the order request due to various reasons, such as system failure, limited available drivers, severe traffic congestion, and bad weather. In addition, platforms can offer delivery fee discounts for long-distance orders to attract merchants with more long-distance orders, as they have a higher willingness to wait. Second, as merchants who place a larger number of orders exhibit a higher willingness to wait, it is critical for platforms to foster relationships with their frequent users and increase their loyalty to the platform. For example, platforms can design incentives to encourage repeat business, such as offering



(a) $MeanFee$

(b) $\log NumOrder$

(c) $WaitTimeMatch$

Fig. 9. Residuals against the predicted $Will2WaitMatch$ and different independent variables.

rewards or price discounts for merchants who have used the platform for a certain number of times within a specific period.

Third, the presence of a threshold effect, i.e., merchants' willingness to wait declines beyond certain waiting time thresholds, in both the matching and pick-up stages suggests that platforms should establish optimal waiting time targets below these identified thresholds to ensure high merchant satisfaction and engagement. Platforms should continuously monitor merchants' waiting times and make necessary operational adjustments. Specifically, maintaining an average waiting time for matching below 11.2 min will circumvent the negative effect of waiting on merchants' willingness to wait in both the matching and pick-up stages, enhancing overall user satisfaction and reducing cancellations. Conversely, if the average waiting time for matching exceeds 16.6 min, platforms should take immediate measures to expedite the matching process, as prolonged waiting at this stage negatively impacts merchants' willingness to wait in both matching and pickup stages. In addition, if a merchant has waited for over 11.2 min during the matching stage and tends to have a lower willingness to wait for pick-up, the platform can devise strategies to counteract the negative impacts of prolonged waiting in the matching stage, such as providing discounts to merchants and reducing the waiting time in the pickup stage by changing drivers' delivery sequence. For the pickup stage, the platform should keep the waiting time below 55 min to avoid a decrease in merchants' willingness to wait due to extended waiting.

7. Concluding remarks

Using both delivered and canceled orders from an on-demand food delivery platform, we estimate willingness to wait of merchants (users of this platform) by integrating the survival function of merchants' waiting time. We then investigate how various determinants, including the delivery fee, number of placed orders, and the average waiting time, shape merchants' willingness to wait at different stages. In particular, we examine the non-linear effect of average waiting time on willingness to wait within each stage, as well as the influence of average waiting time in the matching stage on the willingness to wait in the pick-up stage.

The empirical evidence suggests that merchants with higher order volumes show higher willingness to wait in both the matching and pick-up stages, while higher fees for delivery services only negatively impact merchants' willingness to wait for matching. Notably, this study reveals an inverted U-shaped relationship between average waiting time and the willingness to wait in both the matching and pick-up stages. The identified thresholds serve as important references for platform operations. Although our study focuses on food delivery service, the theoretical mechanisms and empirical findings are likely applicable to other on-demand service environments, such as ride-hailing services and grocery delivery services. Additionally, our findings indicate a similar inverted U-shaped relationship between merchants' average waiting time on average in the matching stage and their willingness to wait in the pick-up stage. Such a carry-over effect urges the platform to enhance merchants' waiting experience in the matching stage. Maintaining merchants' waiting time for matching within a specific threshold will yield a positive impact on merchants' willingness to wait in both the matching and pick-up stages.

It is important to acknowledge the limitations of our study and consider potential avenues for future research. First, our research primarily concentrates on aggregated data and does not capture temporal changes in users' willingness to wait. Users' preferences, expectations, and behaviors may change over time due to various factors such as market dynamics, service improvements, or external events. Future research could explore the dynamics of willingness to wait by examining

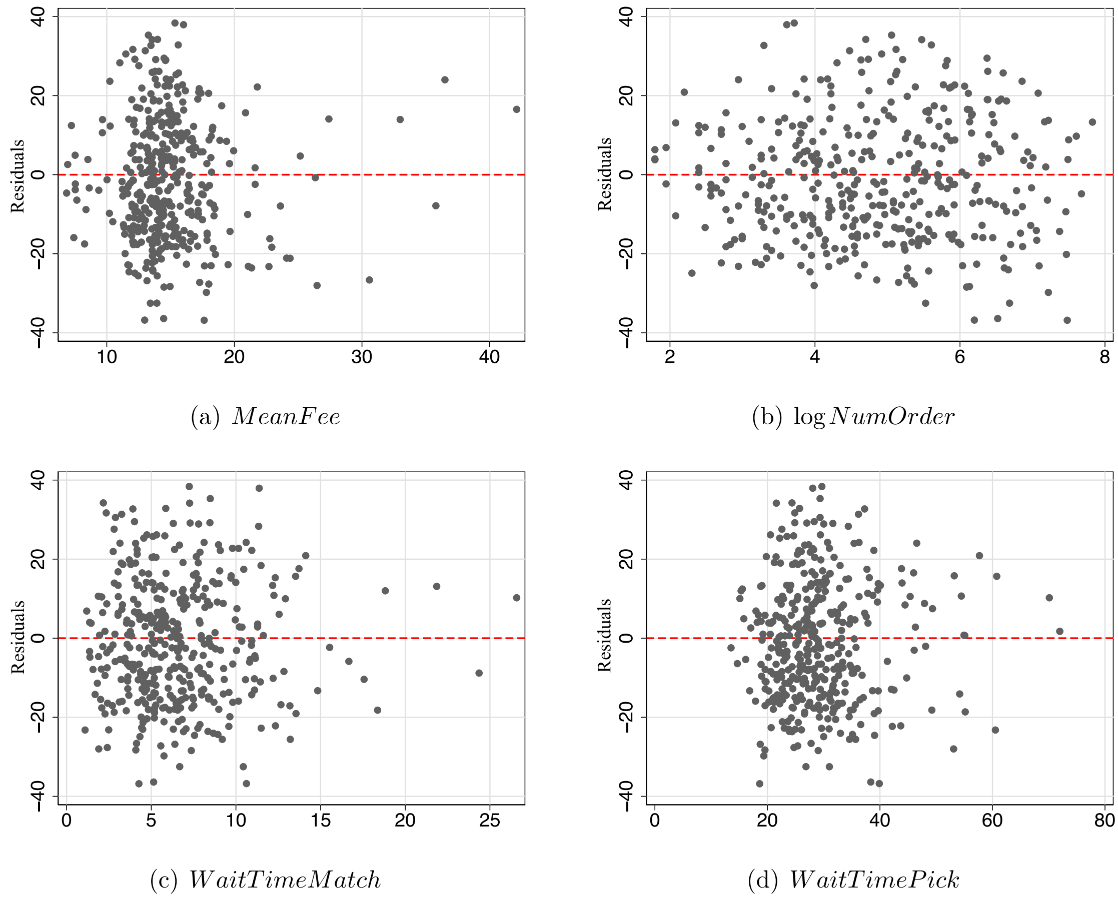


Fig. 10. Residuals against the predicted $Will2WaitPick$ and different independent variables.

how it changes across time or capturing temporal variations in users' preferences. Furthermore, our study primarily examines aggregated data to provide insights into the overall behavior of users. However, an individual-level analysis could provide deeper understanding of heterogeneity in users' willingness to wait. Exploring individual-level factors, such as user characteristics or past waiting experiences, may help identify subgroups with distinct waiting preferences and behaviors. Second, the generalizability of our findings may be confined to the specific characteristics of the platform under investigation. When extending our findings to other on-demand delivery platforms with different business models, differences in operational processes and control mechanisms may confound the results. To enhance generalizability, future research could examine other types of on-demand delivery service providers with different business models to examine the robustness and applicability of our findings. Lastly, establishing a causal relationship between average waiting time and merchants' willingness to wait is challenging. Future research could consider experimental or quasi-experimental designs, such as randomized controlled trials or natural experiments, to further investigate the impact of average waiting time on merchants' willingness to wait.

CRediT authorship contribution statement

Jian Liang: Writing – original draft, Software, Methodology, Investigation, Data curation, Conceptualization. **Ya Zhao:** Writing – review & editing, Software, Methodology, Investigation, Conceptualization. **Hai Wang:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Zuopeng Xiao:** Writing – review & editing. **Jintao Ke:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix. Residuals plots

The residuals against the predicted willingness to wait and key independent variables for the matching stage and the pick-up stage are presented in Figs. 9 and 10, respectively.

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