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Impacts of Delivery Charge on the Possibility of Consumers Using Online Food Delivery

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Abstract: With the maturity of the online food delivery (OFD) industry in China, the growth of the market in recent years is mainly driven by the increase of the usage frequency of existing users rather than the number of new users. The usage frequency of users is affected by various factors, with the delivery charge as one of the most significant ones. The purpose of this study is to examine the impact of delivery charge and other factors on the probability of consumers choosing to use OFD service. In this study, 391 questionnaire records from China were collected, based on which a logistic regression model was established. The results of the model show that age, occupation, monthly income, city tier of residence, location and time period of usage, and delivery charges all play a role on the probability of consumers using the service, and the delivery charge has the greatest impact. For every one yuan increase in the delivery charge, consumers will be less likely to choose "certainly" of using OFD (OR: 0.435; 95% CI: 0.415, 0.455). Sensitivity analysis shows that when the delivery charge changes between 2~5 yuan, it has the greatest impact on the probability of consumers using the service. The analysis further shows that delivery charge has different impacts under different scenarios composed of three key factors, i.e., the city tier of residence, locations of usage, and time period of usage. From a management perspective, these findings help to understand the behavior of OFD consumers and provide insights for the OFD operators to establish best pricing strategies for long-term economic sustainability.

Keywords: online food delivery; consumer behavior; delivery charge; logistic regression model

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1. Introduction

In recent years, the explosive growth of the Internet has greatly promoted the development and maturity of e-commerce and online retail in general [1–4]. More and more traditional enterprises are trying to combine with the Internet, giving birth to many new business models of "online + offline" [5,6]. People's daily lives have also changed dramatically, with the emergence of online food delivery (OFD) allowing people to gradually accept OFD as a convenient way to solve their dietary needs [7,8]. The mature development of technologies such as mobile payment, cloud computing, and same-city delivery provides a good practical application environment for OFD [9,10]. OFD is the process of preparing foods purchased by consumers online and delivering them from restaurants to consumers [11]. Compared with the traditional catering industry, OFD services can provide consumers with a rich choice and convenient dining experience [12]. People have the flexibility to choose OFD at different times and locations to meet their dietary needs [13]. More importantly, under the impact caused by COVID-19, the OFD service has shown its dominant advantage and contributed to satisfy public's demands in a safer way. According to an investigation in South Korea, findings indicate that people have increased their delivery food service for the safety's sake during the period affected by COVID-19 [14]. Meanwhile, research on Meituan Application, an OFD platform, also witnesses an increased number of orders during the postpandemic period [15]. This new type of OFD is becoming more and more popular in today's fast-paced life, especially among college students and white-collar workers, who give priority to takeaway when dining out [16,17].

The prosperity of OFD is a global trend, and the market share of OFD in many countries is showing a rapid growth trend. Among them, China's market share is in the leading position [18]. According to a report issued by the Meituan Research Institute (2020), the number of China's OFD users has reached 461 million, accounting for about 50.99% of the country's overall Internet users, and the OFD market has exceeded 650 billion yuan per year [19]. During the rapid development of OFD, large-scale OFD platforms have emerged, such as Meituan and Eleme [20]. Despite the rapid development of OFD, there are not many studies related to it, especially research on the operation of OFD platforms.

With the increasing number of competitions among various OFD platforms and the maturity of the delivery procedure of OFD orders, consumers attach higher significance on the timeliness of OFD service, thus leading to challenges for OFD platforms. Most of the OFD platforms have been at a financial loss. Only Meituan has become the first successful profitable OFD platform in 2019 with marginal profit. The difficulties for the OFD platforms to achieve profitability lie in the need to pay for the high costs of the delivery riders (the delivery staff who usually ride electric bicycles) and the limited source of income, which ultimately makes it hard to gain profits. Zhao et al. (2021) points out that the current growth of the market size of China's OFD industry is more likely to originate from the increase in the frequency of consumers' use of OFD services than the increase in the number of customers [21]. Therefore, if the OFD platform wants to remain competitive in the food service industry, it needs to pay close attention to changes in consumer preferences to consolidate its market share and continue to develop [22]. The delivery charge that consumers need to pay when using OFD has a certain impact on consumers' willingness to place orders, and the delivery charge is one of the main sources of income for the OFD platform. On one hand, a lower delivery charge tends to increase the intention of consumers to use OFD service and lead to a larger market demand for the OFD operator (the platform). On the other hand, a lower delivery charge leads to lower revenue per order (unit profit). How the optimal pricing strategy is established to ensure economic sustainability depends on the mechanism of the price impacts on demands. At present, there are few studies on the mechanism that illustrates how delivery charge applies impacts on the consumers' intention of using OFD service. Considering that, the purpose of this research is to analyze how delivery charge, together with other factors, may affect consumers' possibility of using the OFD service by establishing a consumer choice model, discuss how the effects may change under different scenarios. The results of the choice model are the possibility of potential users choosing to use the service, which can be used to estimate the market demand for the platforms and evaluate the best pricing strategies to achieve long-term economic viability.

The remainder of this paper is organized as follows. Section 2 summarizes the research background of this paper. Section 3 introduces the design of the survey, data collection, and a preliminary statistical analysis of the survey data. Section 4 constructs an ordered choice model for consumers and analyzes the results of the model. Section 5 summarizes the difference in the impacts of delivery charge under different scenarios. Finally, Section 6 presents the main conclusions of this work.

2. Literature Review

Unlike online shopping service, the goods of OFD service are more likely to be foods. While the amount of research in online shopping fields are abundant, the OFD service has only be focused in the literature in the last decade. There are some studies on the pricing of OFD platforms. However, most of the studies focus are mostly performed based on analytical models to examine the effectiveness of dynamic pricing strategies [23,24]. There is lack of studies on estimating the demand from the consumers' perspective and utilizing the choice model to investigate the relationship between intention of consumers using OFD platform and changes of delivery charges.

From the aspects of consumer's behavior, some researchers have discussed the factors affecting consumers' use of OFD, and these influencing factors mainly come from the fields of biology, society, environment, population, and psychology [25–28]. A survey on the takeaway service in British catering industry shows that the main factors influencing consumers' choice of OFD are convention, speed, and order accuracy [29]. Miura and Turrell (2014) studies the relationship between socioeconomic status and consumption of OFD, the results show that people with higher education are more inclined to choose healthier takeout food [25]. Sam et al. (2019) uses an ordered logistic regression model to test and study the relationship between consumers' working hours and the frequency of using OFD [26]. According to Zhang and Wei (2018), perceived value and service quality have a positive impact on consumers' purchase intention on fresh food e-commerce platforms, and perceived risk has a negative impact on purchase intention [27]. Chandrasekhar et al. (2019) analyzes the data of the questionnaire and the result shows that consumers pay more attention to price, quality, and delivery services [22]. Dospinescu et al. (2020) uses SPSS software to perform multiple linear regression analysis on the questionnaire data, and the results prove that there is a significant relationship between consumers' perception of reputation and food quality, food prices, menu types, food tastes, and other influencing factors [30]. After the outbreak of COVID-19 pandemic, residents have an increasing intention of OFD orders, which could provide ample data for OFD analysis. Literature on Chinese biggest OFD platform, Meituan Apps, finds that quality of online and offline service, including economy, speed, etc., contribute to the reuse intention of OFD service [15]. Study on Thailand shows that external factors consisting of trust, convenience, application quality, and satisfaction would lead the change of user behavior for OFD platform [31].

In general, there are some studies related to influencing factors of OFD users at present, and the existing studies have the following limitations:

- The influencing factors such as order prices (the sales amount of the food order excluding delivery charge) and delivery charges on consumers' willingness to use OFD are not widely considered. In real life, these factors have a great influence on consumer behavior.
- Most of the studies qualitatively analyze the relevance of various factors to consumers' willingness to use OFD, and there is a lack of quantitative analysis.
- Existing research related to pricing of OFD platforms rarely considers consumer choice behavior, and it lacks in-depth analysis on the impacts of pricing in different situations such as location and time period.

Considering these limitations, this paper divides the influencing factors into three categories: sociodemographic, characteristics of using OFD, and inherent characteristics of OFD. The used variables in our model were depicted in Table 1 with relatively references.

Table 1. Researches on factors that influence customers' online food order.

Influential Factors	Variables	Related Literature
Sociodemographic factors	Income	Bates et al. [32]
	Age	Belanche [33], Chotigo et al. [31], Ma [34]
	Occupation	Das and Ghose [17], CBNData [35]
	Gender	Belanche [33], Chotigo et al. [31]
Characteristics of using OFD	Usage Frequency	Sam et al. [26]
	Time Period of Usage	Zhu and Li [36]
	Average Delivery Time	Kimes et al. [29]
	Average Amount per Order	Chandrasekhar et al. [22]
Inherent characteristics of OFD	Order Price	Chandrasekhar et al. [22]
	Delivery charge	Klein et al. [37]

3. Survey Design and Data Description

3.1. Survey Design

The survey method used in this paper is stated preference (SP) survey. The survey method has been extensively used in various fields. The ability of SP surveys enables investigators to perform preference evaluation in a set context that reduces the cognitive effort and has made it a dominant approach to study consumers' behavioral market decisions [38–40]. As our study focuses on the preference of the consumers in choosing the OFD service, the stated preference survey is considered to be appropriate to be used in this study. It can effectively obtain some data that cannot be directly measured or observed, and it is easy and flexible to handle multiple variables. According to the questions studied in this paper, the survey content is mainly divided into three parts. These are the consumer's personal information, the characteristics of using the OFD platform, and the choice results of the willingness to use under a different delivery charge. There are five variables in personal information: gender, age, occupation, monthly income, and city tier of residence. The information on using the OFD platform includes the locations where consumers often use OFD, the time period when consumers often use OFD, the frequency of using OFD each week, and the average amount spent per order. Different food prices are combined with different delivery charges. In reality, each restaurant on the OFD platform would set a minimum order price for the customer, below which the OFD service will not be provided. The minimum order price for the OFD service is typically 20 yuan for most restaurants. Some restaurants set the price up to 30 yuan but few set over 40 yuan. Thus, the three order prices in the survey are set as 20, 30, and 40 yuan. On the other hand, the delivery charges typically range from free of charge to 5 yuan per order. Accordingly, the delivery charges in the survey are set as three levels, i.e., 1 yuan, 3 yuan, and 5 yuan. In this way, a total of 9 different OFD products are formed by combining the two dimensions of order price and delivery charge. In order to observe the possibility of consumers buying OFD under these different situations, five options are provided for consumers to choose: "totally impossible (0%)", "not too possible (25%)", "neutral (50%)", "very possible (75%)", or "certainly (100%)". Each respondent needs to make a choice of purchase possibilities for the 9 OFD products in turn, so each respondent will eventually generate 9 observations. An example of the question of intention choice in a certain situation is shown in Table 2.

Table 2. Example of an intentional choice problem in situation 1.

Scenario 1		**When You Plan to Order OFD at a Price of ¥20, How Likely Is It That You Will Buy When the Delivery Charge Changes? (Choose One from 5 Options)**				
		Totally Impossible (0%)	**Not too Possible (25%)**	**Neutral (50%)**	**Very Possible (75%)**	**Certainly (100%)**
Delivery Charge (CNY)	1					✓
	3				✓	
	5		✓			

The survey method is an online questionnaire survey because online questionnaire surveys have cost advantages, and the geographical, age, occupation, and other attributes of the surveyed population are also more widely distributed. At the same time, anonymous surveys allow the surveyors to fill in the questionnaires more truthfully. Respondents to the questionnaire are OFD customers in various cities in China. We used Tencent's survey platform to establish the questionnaires and collect the data. Tencent's survey platform automatically sends the questionnaire to the users of WeChat, which is the most popular social media in China, and allows to motivate data collection process by giving certain rewards to the respondents. The link of the questionnaire (in Chinese) can be found at https://wj.qq.com/s2/7919111/e521 (accessed on 31 December 2021).

3.2. Data Description

A total of 500 questionnaires were distributed in this survey. After preliminary screening, 391 valid data samples were finally obtained. Each respondent answered 9 choice questions about the possibility of using OFD, resulting in a total of 3519 observations. This section summarizes the relevant characteristics of these sample data.

The statistical description of the main variables of the sample data is shown in Table 3. Social demographic indicators include gender, age, occupation, monthly income, and city tier of residence. The age is divided into 5 age groups: below 18, 18–24, 24–30, 30–40, and above 40. The age of the respondents is generally concentrated between 18–24, and respondents in this age group accounted for 79.5% of the total. There are 8 categories of occupations, among which students and professionals account for the largest proportion—30.4% and 19.7%, respectively. For monthly income, it is divided into 7 different segments: below 1000 yuan, 1000~2000 yuan, 2001~3000 yuan, 3001~4000 yuan, 4001~6000 yuan, 6001~8000 yuan, and above 8000 yuan. The monthly income of the respondents is evenly distributed in these seven segments, of which 2001~3000 yuan, 3001~4000 yuan, and 4001~6000 yuan are relatively more, accounting for 53.9% of the total. The city tier of residence is divided into four tiers, namely first-tier city, second-tier city, third-tier city, fourth tier cities, and below. Respondents are evenly distributed among the four cities at different tiers.

In addition to social demographic indicators, it also includes some characteristics of respondents when they use OFD: average amount spent per order, location of usage, time period of usage, usage frequency (weekly), and average delivery price per order. Average amount spent per order is divided into eight segments according to the amount of money. The first seven segments are from 10 yuan to 50 yuan with the spacing of 5 yuan, and the last one is above 50 yuan. Most of the respondents spend an average of 16–20 yuan and 21–25 yuan, which is also in line with the monthly income distribution of the respondents. For location of usage, this article mainly divides the locations into three typical urban areas, namely home, office location, and college. The respondents who often order online food in these areas accounted for 90.8% of the total. Among them, 48.1% of consumers who are accustomed to using OFD at home account for nearly half of the total. The survey also asked whether each respondent would be more accustomed to using OFD within a certain period of time in a day and what time period they usually order OFD. According to the three meals, afternoon tea and night snack, the day is divided into different time periods, such as 8 a.m. to 11 a.m. (breakfast), 11 a.m. to 2 p.m. (lunch), 2 p.m. to 5 p.m. (afternoon tea), 5 p.m. to 8 p.m. (dinner), and 8 p.m. to 11 p.m. (night snack). The specific time points are determined according to the business hours of the merchants on the OFD platform Meituan. Of the respondents, 78.5% said that they are more accustomed to using OFD during a certain period of time in a day. Among them, lunch time is 43%, accounting for the largest proportion. Second, dinner time accounted for 23.6%, which together with lunch time accounted for 66.6% of the total. Compared with formal meals such as lunch and dinner, informal meals such as afternoon tea and night snack accounted for only 10.9%.

Regarding the frequency of respondents using OFD, the survey counted the average number of times respondents use ODF per week and divided them into five different levels: 1–2, 3–4, 5–6, 7–8, and above 8. The average number of times that most of the respondents use OFD per week is 1–2 and 3–4, accounting for 66.5% of the total. This also means that for the vast majority of consumers, there may be considerable space for growth in the average number of times they use OFD per week. As for the delivery charge, the distribution of the average delivery charge of consumers is relatively concentrated, with an average value of 3.35 yuan and a variance of 2.212. The highest average delivery charge is 8 yuan and the smallest one is zero. Consumers whose delivery charges are in the range of 2~3 yuan accounted for more than half of the total, with the proportion up to 58.3%. After a preliminary statistical analysis of these data, the maximum likelihood estimation method will be used to calculate the ordered choice model, which will be discussed in detail in the next section.

Table 3. Sample characteristic (Sociodemographic variable and OFD usage variable, *n* = 391).

Sociodemographic Variable	Characteristic	Frequency	Percentage (%)	OFD Usage Variable	Characteristic	Frequency	Percentage (%)
Gender	Male	57	14.6	Average amount spent per order (CNY)	10–15	65	16.6
	Female	334	85.4		16–20	140	35.8
Age	below 18	52	13.4		21–25	90	23.0
	18–24	311	79.5		26–30	39	10.0
	24–30	22	5.6		31–35	22	5.6
	30–40	4	1		36–40	19	4.9
	above 40	2	0.5		41–50	3	0.8
Occupation	Student	119	30.4		50 or more	13	3.3
	Public functionary	16	4.1	Location of usage	Home	188	48.1
	Professional	77	19.7		Office location	88	22.5
	Worker	44	11.3		University	79	20.2
	Management	30	7.7		Else	36	9.2
	Freelancer	69	17.6	Time period of usage	Breakfast	4	1.0
	Unemployed	16	4.1		Lunch	168	43.0
	Else	20	5.1		Afternoon tea	17	4.3
Monthly income (CNY)	below 1000	64	16.4		Dinner	92	23.6
	1000–2000	66	16.9		Night snack	26	6.6
	2001–3000	71	18.2		Else	84	21.5
	3001–4000	68	17.4	Usage frequency (weekly)	1–2	143	36.6
	4001–6000	72	18.3		3–4	117	29.9
	6001–8000	25	6.4		5–6	66	16.9
	above 8000	25	6.4		7–8	31	7.9
City tier of residence	First-tier city	99	25.3		above 8	34	8.7
	Second-tier city	111	28.4	Average delivery charge per order (CNY)	0–1	100	25.6
	Third-tier city	97	24.8		2–3	228	58.3
	Fourth tier cities and below	84	21.5		4–5	56	14.3
					above 5	7.0	1.8

4. Model Construction and Results

This section constructs an ordered choice model to research the impact of delivery charges and other factors on the possibility of consumers using OFD. The obtained behavior model can estimate the usage probability of consumers under different delivery charges, which can provide a certain theoretical basis for the delivery charge pricing of the OFD platform. The choice to use the behavior model is due to its two advantages: it can be used to obtain an estimate of the consumer's response to changes in the delivery charge and the interaction between various independent variables can be studied. After constructing the behavior model, the questionnaire survey data described in Section 3 is brought into the model to calculate the parameters of the model, and the result of the final model can be obtained result. Sensitivity analysis of marginal effect and elasticity to the variables are developed in the final model.

4.1. Model Construction

The dependent variable of the model is the probability of consumers using OFD, which is ordinal. The level of possibility is represented by a digital scale between 0 and 4, where 0 means the least possibility and 4 means the highest possibility. The independent variable is composed of the personal attributes of consumers, the characteristics of using OFD, and the attributes of OFD, including order price and delivery charge. Since there is an order of priority among the dependent variables, an ordered choice model is used. The ordered choice model was first proposed by Aitchison and Silvey (1957) and presented in a new form through Zavoina and McKelvey (1975) [41,42]. The ordered choice model is suitable for research fields such as social sciences and economics. Now this model had been applied in a large number of literatures and is increasing rapidly.

Since each respondent in the survey had made a choice for different situations, in order to deal with the risk of similarity in the unobserved attributes of the respondent, a logical model with random effects is chosen. According to the random utility theory [43], assuming that N samples are observed, the choice of the nth sample is determined by the utility U_n. The utility U_n of the nth sample is composed of a fixed term V_n and a random term ε_n. The equation is as follow:

$$U_n = V_n + \varepsilon_n \tag{1}$$

The value of the determination term V_n is related to multiple independent variables and has a linear relationship. The equation is as follows:

$$V_n = \sum_{k=1}^{K} \beta_k X_{nk} \tag{2}$$

where K in Equation (2) is the number of independent variables, and β_k is the parameter corresponding to the kth independent variable. X_{nk} is the kth independent variable of sample n, such as age, gender, monthly income, and other variables. In the ordered choice model, the utility U_n is defined as a hidden variable $y_n{}^*$, and its calculation formula is shown below:

$$y_n{}^* = \sum_{k=1}^{K} \beta_k X_{nk} + \varepsilon_n \tag{3}$$

The dependent variable y_n has the following relationship with the hidden variable

$$y_n = \begin{cases} 0, & y_n{}^* \le \gamma_1 \\ 1, & \gamma_1 < y_n{}^* \le \gamma_2 \\ 2, & \gamma_2 < y_n{}^* \le \gamma_3 \\ \ldots & \ldots \\ m, & \gamma_m < y_n{}^* \end{cases} \tag{4}$$

where γ_m, $(i = 1, 2, \ldots, m)$ is called the selection threshold. In this research model, $m = 4$, which means there are 5 categories. $y_n = 0,\ 1,\ 2,\ 3,\ 4$ represents the different levels of the possibility of consumers using OFD, namely "totally impossible", "not too possible", "neutral", "very possible", and "certainly".

Assuming that the random term ε_n obeys the logistic distribution, this model is then called an ordered logit model. The cumulative probability expression of the dependent variable y_n is as follow:

$$P(y_n \leq m) = P({y_n}^* \leq \gamma_m) = \frac{e^{\gamma_m - V_n}}{1 + e^{\gamma_m - V_n}} \tag{5}$$

According to Equation (5), the calculation formulae for the probability that the consumer's choice of probability of using OFD is a certain category are as follows:

$$P(y_n = 0) = \frac{e^{\gamma_1 - \sum_{k=1}^{K} \beta_k X_{nk}}}{1 + e^{\gamma_1 - \sum_{k=1}^{K} \beta_k X_{nk}}} \tag{6}$$

$$P(y_n = j) = P(y_n \leq j) - P(y_n \leq j-1) = \frac{e^{\gamma_{j+1} - \sum_{k=1}^{K} \beta_k X_{nk}}}{1 + e^{\gamma_{j+1} - \sum_{k=1}^{K} \beta_k X_{nk}}} - \frac{e^{\gamma_j - \sum_{k=1}^{K} \beta_k X_{nk}}}{1 + e^{\gamma_j - \sum_{k=1}^{K} \beta_k X_{nk}}}, j = 1, 2, 3 \tag{7}$$

$$P(y_n = 4) = 1 - P(y_n \leq 3) = 1 - \frac{e^{\gamma_4 - \sum_{k=1}^{K} \beta_k X_{nk}}}{1 + e^{\gamma_4 - \sum_{k=1}^{K} \beta_k X_{nk}}} \tag{8}$$

The sum of the probabilities of each result category satisfies:

$$P(y_n = 0) + P(y_n = 1) + \cdots + P(y_n = 4) = 1 \tag{9}$$

4.2. Modeling Results

IBM SPSS Statistics 25 software is used to estimate the parameters of the model based on a total of 3519 questionnaire observation data mentioned in Section 3. The final model is obtained by adopting backward-stepwise selection method. After the preliminary analysis of the model results, the sensitivity analysis of the variables in the model is further carried out.

4.2.1. Preliminary Analysis of Model Results

The final model is determined by a backward-stepwise selection method. First, all relevant variables are considered in the ordered logistic regression model, and the result is shown in Table 4 under the title of Model 1. Among them, delivery charge, order price, average amount per order, age average delivery time, and usage frequency (weekly) are all continuous variables, and the remaining variables are all binary variables. It can be seen that the P-values of more variables in the initial model 1 are obvious greater than 0.1, such as order price, student and unemployed categories in the occupation variable, and office location category in the location of usage variable, etc. After removing insignificant variables, the ordered logistic regression is performed again. After many iterations of optimization, the final determined model is obtained, which is called model 2. The log-likelihood of model 2 is -4544.227 and the pseudo-R^2 is 0.412, which indicate that the fitting effect of model 2 is better and the goodness of fit and accuracy are higher. In Model 2, there are few variables whose P-values are greater than 0.1. Since these variables are related to the research focus of this paper and may have indirect effects on the dependent variables, they are reserved for further analysis. The final variables related to consumer characteristics left in Model 2 are age, occupation, monthly income, and city tier of residence. The location of usage and time period of usage that describe the characteristics of consumers' use of OFD are left in the final model. Delivery charge, related to OFD attributes, is maintained in final model. For the order price variables in the OFD attribute, the coefficients of variables show no statistical significance with small value, which indicates that the impact of order price on consumer intention for OFD can be ignored.

Table 4. Parameter calibration results of ordered logit model.

Variable	Model 1		Variable	Model 2	
	Coefficient	p-Value		Coefficient	p-Value
Delivery charge	−0.834	0.000	Delivery charge	−0.833	0.000
Order price	0.028	0.151	Average amount per order	0.350	0.000
Average amount per order	0.346	0.000	Age	0.147	0.028
Age	0.143	0.033	Occupation		
Gender			Public functionary	0.457	0.036
Male	−0.163	0.092	Professional	0.502	0.002
Female	0 [a]		Management	0.342	0.081
Occupation			Freelancer	0.353	0.033
Student	−0.009	0.958	**Monthly income (CNY)**		
Public functionary	0.466	0.033	Income below 1000	−0.603	0.000
Professional	0.506	0.002	Income between 1000 and 2000	−0.300	0.033
Worker	0.292	0.097	Income between 2001 and 3000	−0.285	0.023
Management	0.348	0.075	Income between 3001 and 4000	−0.297	0.014
Freelancer	0.362	0.029	**City tier of residence**		
Unemployed	−0.010	0.964	First-tier city	−0.101	0.301
Else	0 [a]		Second-tier city	−0.226	0.018
Monthly income (CNY)			Third-tier city	0.086	0.370
Income below 1000	−0.606	0.000	**Location of usage**		
Income between 1000 and 2000	−0.307	0.030	Home	0.312	0.009
Income between 2001 and 3000	−0.290	0.022	University	0.383	0.008
Income between 3001 and 4000	−0.309	0.011	**Time period of usage**		
Income between 4001 and 6000	−0.179	0.127	Lunch	0.046	0.606
Income above 6000	0 [a]		Afternoon tea	0.353	0.049
City tier of residence			Dinner	0.135	0.168
First-tier city	−0.104	0.292	Night snack	0.457	0.002
Second-tier city	−0.243	0.011	**Parameters**		
Third-tier city	0.077	0.426	γ_1	−2.161	0.000
Fourth tier cities and below	0 [a]		γ_2	−0.773	0.008
Location of usage			γ_3	0.163	0.578
Home	0.325	0.007	γ_4	1.130	0.000
Office location	−0.020	0.881	Pseudo-R^2	0.412	
University	0.374	0.010	Log-likelihood	−4544.227	
Time period of usage			n	3519	
Breakfast	0.003	0.992			
Lunch	0.044	0.622			
Afternoon tea	0.347	0.053			
Dinner	0.136	0.164			
Night snack	0.460	0.002			
Average delivery time	0.054	0.213			
Usage frequency (weekly)	0.011	0.636			
Parameters					
γ_1	−2.057	0.000			
γ_2	−0.669	0.028			
γ_3	0.267	0.379			
γ_4	1.234	0.000			
Pseudo-R^2	0.395				
Log-likelihood	−4591.092				
n	3519				

[a] This parameter is set to zero because it is redundant. p-Value is the significance coefficient of the independent variable. When $p < 0.1$, the regression result of the independent variable is considered to be significant.

The signs and sizes of the coefficients of each variable in Model 2 are in line with expectations. The delivery charge has a negative effect on the possibility of consumers using OFD, that is, the greater the delivery charge, the lower the probability of consumers using OFD. The specific explanation is that when the delivery charge decreases, the probability that consumers choose “certainly” use OFD will be reduced (OR: 0.435; 95% CI: 0.415, 0.455). When faced with the same OFD product, consumers who spend more per order on average are more likely to choose “certainly” to use OFD than those who spend less. This also means that the acceptance of consumers who spend more per order on average on delivery charge is higher than that of consumers who spend less. With regard to occupational factors, the probability that consumers who are professionals choose “certainly” to use OFD is higher than that of other occupations. From the perspective of monthly income, when faced with the same OFD products, consumers with higher monthly incomes are more likely to choose "certainly" to use OFD products. At the same time, it can be found that consumers with higher monthly incomes can accept higher delivery charges than those with lower monthly incomes. This may be because consumers with higher monthly income pay more attention to other factors such as delivery time and service level. For consumers who often use OFD at university, the probability of choosing "certainly" to use OFD is 1.074 times that of consumers who often use OFD at home. It may be because students at university need more discounted OFD, while consumers at home can have alternatives to cook their own meals. Regarding the time period when consumers often use OFD, when faced with the same delivery charge, consumers who often order afternoon tea and night snack are more likely to use OFD than those who frequently use OFD during lunch and dinner. This is because there are fewer businesses operating during informal meals time periods, and consumers can find fewer alternatives to meet their dining needs during these time periods, so even if the delivery charge is higher, consumers are willing to place orders.

After preliminary analysis of the influence of different factors on the possibility of consumers using OFD, a separate study is carried out on the delivery charge variable with the greatest impact. The population with the same attribute characteristics and the largest proportion is selected as the calculation case. The specific attributes are female, 18–24 years old, living in a second-tier city, student at university, with a monthly income of 3001~4000 yuan, often using OFD at home, often using OFD at lunchtime, average amount per order is 16~20 yuan. The corresponding variables are assigned according to these attributes and fixed. The delivery is charged from 0 to 8 yuan to calculate the probability of choosing different results for the sample of consumers in turn. The calculation result is shown in Figure 1. It can be clearly found that as the delivery charge increases, the probability of choosing "totally impossible" increases rapidly. When the delivery charge is 8 yuan, the probability of choosing "totally impossible" is close to 100%, which means that the consumers are most likely reject to use OFD. For the curve choosing "certainly", as the delivery charge increases, the probability of it being selected will first decrease rapidly, and then the decreasing trend will slow. If it is considered that the one with the highest probability of being selected among the five results is the final choice of the consumer, then as the delivery charge increases, the consumer will first choose "certainly". Specifically, the lines that depict "certainly" and "not too possible" interact at the point of 1.4 yuan, which can be seen as the break-even point for the two options. It means that when the delivery charge is larger than 1.4 yuan, the possibility for a customer choosing "certainly" is smaller than the possibility of choosing "not too possible". On the other hand, when the delivery charge is smaller than 1.4 yuan, the possibility for a customer choosing "certainly" is greater than the possibility of choosing "not too possible". Nonetheless, the break-even point of 1.4 yuan is only illustrative and may change according to gender, age, city tier, etc. When the delivery charge increases to more than 3 yuan, the result of the consumer's choice is "totally impossible". The analysis of the calculation results shows that when the delivery charge is at a lower level, the option with a higher probability of consumers using OFD is more likely to be selected. As the delivery charge increases, it gradually changes to the option with a lower probability. This also means that by reducing the delivery charge, there is a high possibility that consumers who choose "totally impossible" will be converted into three options with the middle degree of possibility. On the whole, as the delivery charge continues to increase, the possibility of consumers using OFD will continue to decrease.

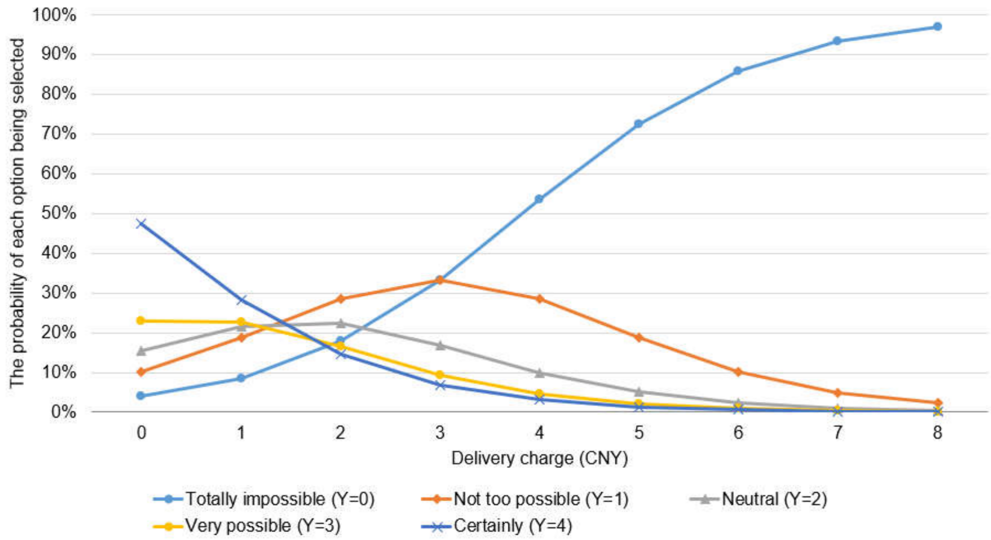

Figure 1. The selection probability of each result as the delivery charge changes.

4.2.2. Sensitivity Analysis of Marginal Effects

After the preliminary analysis of the calculation results of the ordered choice model, the sensitivity analysis of the ordered choice model is further carried out. The sensitivity analysis part includes marginal effect sensitivity analysis and elastic sensitivity analysis. For the marginal effect calculation of the noncontinuous variable X_k, it only needs to calculate the $P(y_n = j)$ when the variable takes the value 1 and the value 0, and the difference obtained by subtraction is the marginal effect of the variable X_k on $y_n = j$. For a continuous variable X_k, it needs to find the partial derivative of X_k for $P(y_n = j)$ to get the marginal effect of variable X_k on $y_n = j$. The calculation equations are:

$$
\begin{aligned}
\frac{\partial P(y_n=j)}{\partial X_k} &= \frac{\partial[P(y_n\le j)-P(y_n\le j-1)]}{\partial X_k} \\
&= \frac{\partial\left[\frac{e^{\gamma_{j+1}-\Sigma_{k=1}^{K}\beta_k X_{nk}}}{1+e^{\gamma_{j+1}-\Sigma_{k=1}^{K}\beta_k X_{nk}}}\right]}{\partial X_k} - \frac{\partial[e^{\gamma_j-\Sigma_{k=1}^{K}\beta_k X_{nk}}/(1+e^{\gamma_j-\Sigma_{k=1}^{K}\beta_k X_{nk}})]}{\partial X_k} \\
&= \frac{-\beta_k e^{\gamma_{j+1}-\Sigma_{k=1}^{K}\beta_k X_{nk}}}{\left(1+e^{\gamma_{j+1}-\Sigma_{k=1}^{K}\beta_k X_{nk}}\right)^2} - \frac{-\beta_k e^{\gamma_j-\Sigma_{k=1}^{K}\beta_k X_{nk}}}{\left(1+e^{\gamma_j-\Sigma_{k=1}^{K}\beta_k X_{nk}}\right)^2} \\
&= -\beta_k P(y_n \le j)[1-P(y_n\le j)] + \beta_k P(y_n \le j-1)[1-P(y_n \le j-1)] \\
&= \beta_k\left[P^2(y_n\le j) - P^2(y_n \le j-1)\right] - \beta_k P(y_n = j)
\end{aligned}
\tag{10}
$$

According to Equation (10), the marginal effect of the calculation example in Section 4.2.1 when the delivery charge is 1 yuan is calculated, and the results of the calculation are shown in Table 5. It can be seen that the marginal effects of the delivery charge variables at Y = 0, 1, 2, 3, and 4 are 0.0657, 0.1002, 0.0423, −0.0393, and −0.1690, respectively. This means that when the delivery charge increases by 1 yuan on the basis of 1 yuan, the probability of the consumers choosing different results will change. It can be found that when the delivery charge increases, the probability of consumers choosing "very possible" and "certainly" both decreases. For the average amount per order, its marginal effects at Y = 0, 1, 2, 3, and 4 are −0.0276, −0.0421, −0.01778, 0.0165, and 0.0710, respectively. It can be considered that the higher the average amount per order of consumers, the probability of choosing "very possible" and "certainly" will increase; meanwhile, the probability of choosing the other options will decrease.

Table 5. Variable marginal effects of ordered logit model.

Variable	Totally Impossible (Y = 0)	Not too Possible (Y = 1)	Neutral (Y = 2)	Very Possible (Y = 3)	Certainly (Y = 4)
Delivery charge	0.0657	0.1002	0.0423	−0.0393	−0.1690
Average amount per order	−0.0276	−0.0421	−0.0178	0.0165	0.0710
Age	−0.0116	−0.0177	−0.0075	0.0069	0.0298
Occupation					
Public functionary	−0.0299	−0.0514	−0.0306	0.0109	0.1010
Professional	−0.0322	−0.0559	−0.0342	0.0107	0.1117
Management	−0.0234	−0.0392	−0.0217	0.0102	0.0741
Freelancer	−0.0241	−0.0405	−0.0226	0.0104	0.0768
Monthly income (CNY)					
Income below 1000	0.0609	0.0734	0.0128	−0.0418	−0.1053
Income between 1000 and 2000	0.0268	0.0368	0.0111	−0.0179	−0.0568
Income between 2001 and 3000	0.0253	0.0350	0.0107	−0.0169	−0.0541
Income between 3001 and 4000	0.0207	0.0343	0.0184	−0.0096	−0.0639
City tier of residence					
First-tier city	0.0083	0.0123	0.0047	−0.0052	−0.0201
Second-tier city	0.0162	0.0264	0.0135	−0.0081	−0.0479
Third-tier city	−0.0065	−0.0102	−0.0047	0.0037	0.0177
Location of usage					
Home	−0.0280	−0.0383	−0.0113	0.0188	0.0588
University	−0.0258	−0.0436	−0.0248	0.0106	0.0836
Time period of usage					
Lunch	−0.0037	−0.0055	−0.0022	0.0022	0.0092
Afternoon tea	−0.0241	−0.0404	−0.0226	0.0104	0.0767
Dinner	−0.0101	−0.0160	−0.0076	0.0055	0.0282
Night snack	−0.0299	−0.0514	−0.0306	0.0109	0.1010

For the occupation factors in discrete variables, the marginal effect of the professional variable at Y = 4 is 0.1117, which means that the probability of consumers whose occupations are professionals choose “certainly” is 0.1117 higher than that of other occupations. For the three options that Y = 0, 1, 2, the probability that consumers whose occupations are professionals choose these options is lower than that of other occupations. For the influencing factors of the city tier of residence, the marginal effect of the third-tier city variable at Y = 4 is 0.0177, indicating that the probability of consumers living in third-tier city choosing “certainly” is 0.0177 higher than that of consumers in other tier of cities. For the factors of location of usage, the marginal effects of home and university variables at Y = 3 and Y = 4 are both greater than zero, which indicates that consumers who often use OFD at home and university are more likely to choose “certainly” than those who use OFD at other places. For the influencing factors of time period of usage, the marginal effect of the night snack variable at Y = 4 is 0.1010, which means that the probability of consumers who often use OFD during the night snack time period choosing “certainly” is 0.1010 higher than that of consumers ordering ODF during other time periods.

The variable value of the calculation case is fixed, and then the value of the delivery charge variable is set to change from 0 to 8 yuan and its marginal effect is calculated in turn. The calculation results are shown in Table 6 and Figure 2. It can be seen that the marginal effect curve of “totally impossible” is always positive. It means that along with the increasing of delivery charge, more and more people think it is “totally impossible” to order OFD with the set delivery charge. When the delivery charge reaches 4 yuan, the largest number of people will switch their intention of using OFD service and the marginal effect curve reaches the peak value. After the peak value, the marginal effect curve remains positive but decreases. It is due to that when the delivery charge is greater than 4 yuan, the majority of consumers had changed to “totally impossible” to use OFD service. The number of people change their intention of OFD service will decrease along with the increasing of delivery charge. For the option “certainly”, the marginal effect of the delivery charge variable is gradually increasing and always less than 0. This means that as the delivery charge increases, the number of consumers using OFD will first decline rapidly and then slowly decline. For the three options “not too possible”, “neutral”, and “very possible”, the marginal effect of the delivery charge variable is first positive, and gradually negative as the delivery charge increases.

Table 6. The marginal effect of delivery charge at different values.

Delivery Charge (CNY)	Totally Impossible (Y = 0)	Not too Possible (Y = 1)	Neutral (Y = 2)	Very Possible (Y = 3)	Certainly (Y = 4)
0	0.0316	0.0695	0.0724	0.0344	−0.2078
1	0.0657	0.1002	0.0423	−0.0393	−0.1690
2	0.1222	0.0851	−0.0289	−0.0744	−0.1040
3	0.1851	−0.0001	−0.0710	−0.0604	−0.0537
4	0.2073	−0.0852	−0.0619	−0.0349	−0.0253
5	0.1659	−0.1002	−0.0370	−0.0173	−0.0114
6	0.1010	−0.0694	−0.0186	−0.0079	−0.0050
7	0.0518	−0.0375	−0.0086	−0.0035	−0.0022
8	0.0243	−0.0180	−0.0038	−0.0016	−0.0010

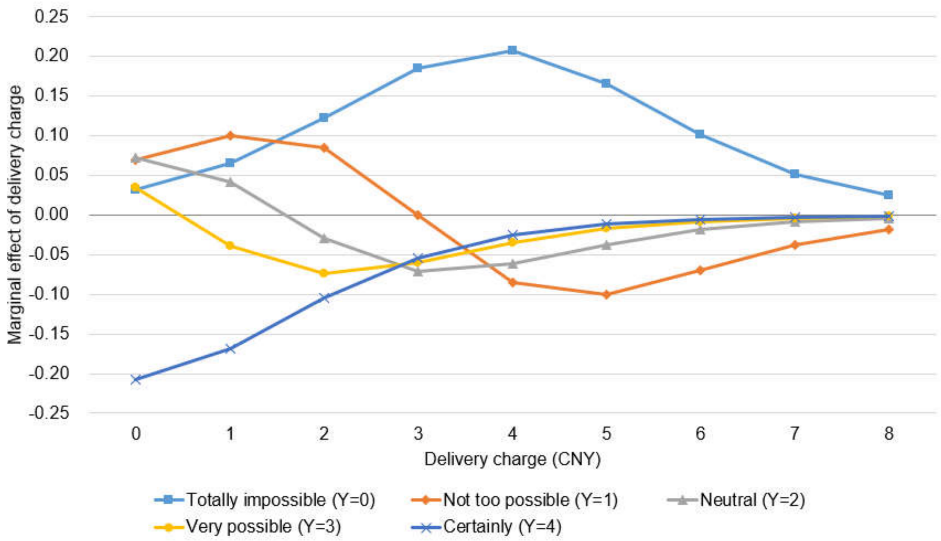

Figure 2. The marginal effect of delivery charge at different values.

4.2.3. Elastic Sensitivity Analysis

The elastic value is the degree of change of this variable which is caused by the change of another one. Divide the rate of change of these two variables to get the elasticity value of the variable to the other variable, denoted by E. For the continuous variable X_k, the calculation equation for the elasticity of $y_n = j$ is:

$$E_{X_{nk}}^{P(y_n=j)} = \frac{\partial P(y_n = j)}{P(y_n = j)} / \frac{\partial X_{nk}}{X_{nk}} = \frac{\partial P(y_n = j)}{\partial X_{nk}} \times \frac{X_{nk}}{P(y_n = j)} \tag{11}$$

Substitution Equation (10) for calculation, Equation (11) is expressed as:

$$\begin{aligned} E_{X_{nk}}^{P(y_n=j)} &= \frac{\beta_k X_{nk}\left[P^2(y_n \le j) - P^2(y_n \le j-1)\right]}{P(y_n=j)} - \beta_k X_{nk} \\ &= \beta_k X_{nk}\left[\frac{P^2(y_n \le j) - P^2(y_n \le j-1)}{P(y_n \le j) - P(y_n \le j-1)} - 1\right] \\ &= \beta_k X_{nk}[P(y_n \le j) + P(y_n \le j-1) - 1] \end{aligned} \tag{12}$$

The delivery charge that can be adjusted by the OFD platform is calculated flexibly. The calculation cases and variable values are the same as those in Section 4.2.1. The value of the delivery charge is set to change from 1 yuan to 8 yuan, and the flexibility of each option when the delivery charge changes can be calculated. The calculated results are shown in Table 7 and Figure 3. It can be seen from Figure 3 that, except for the "total impossible" option, the curve trend of elasticity of other options, along with the change of delivery charge, is roughly the same. Along with the increase of delivery charge, the elasticity curves of "not too possible", "Neutral", "Very possible", and "Certainly" all decrease. The flexibility of the "total impossible" option increases first and then decreases with the growth of the delivery charge, but the value of elasticity is always positive. The maximum value of elasticity appears when the delivery charge is between 2~4 yuan. At this time, the change of the delivery charge has a great influence on the choice probability of the "total impossible" option. The elasticity of "certainly" options is always negative and the absolute value increases along with the increase of delivery charge. As the delivery charge increases, the absolute value of the elasticity of the option representing the high probability of consumers using OFD is greater, which indicates that the change of the delivery charge has a great impact on the option representing the high probability of consumers using OFD.

Table 7. Elasticity values of delivery charge.

Delivery Charge (CNY)	Totally Impossible (Y = 0)	Not too Possible (Y = 1)	Neutral (Y = 2)	Very Possible (Y = 3)	Certainly (Y = 4)
1	0.7613	0.5326	0.1954	−0.1735	−0.5976
2	1.3690	0.5936	−0.2577	−0.9050	−1.4227
3	1.6666	−0.0004	−1.2576	−1.9170	−2.3264
4	1.5501	−1.1882	−2.4769	−2.9669	−3.2283
5	1.1427	−2.6641	−3.6582	−3.9596	−4.1082
6	0.7054	−4.0969	−4.7231	−4.8897	−4.9689
7	0.3887	−5.3416	−5.6898	−5.7765	−5.8170
8	0.2006	−6.4138	−6.5942	−6.6378	−6.6580

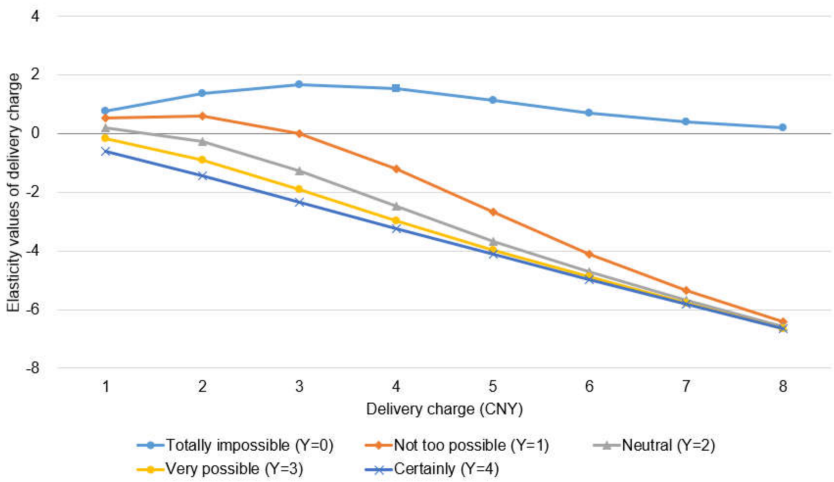

Figure 3. Elasticity values of delivery charge.

5. Comparison of the Impact of Delivery Charges under Different Scenarios

After analyzing the impact of delivery charges on consumer choice results in the previous section, this section further explores the impact of delivery charges on the probability of consumers using OFD under different scenarios. The different situations of the three factors of city tier of residence, location of usage, and time period of usage are composed to construct different scenarios. The advantage of this analysis is that these different scenarios are consistent with the current division of OFD platform operations in cities, regions, and time, which makes the OFD platform easier to utilize the results and implement different delivery charge pricing strategies for different scenarios. The probability of consumers using OFD under a certain scenario will be affected by changes of delivery charge and can be reflected in the final use expectations. The calculation formula is as follow:

$$E_{order} = \sum_{j=0}^{4} P(y_n = j) Prob_j \tag{13}$$

where

- E_{order} is the expectation of consumers using OFD.
- $P(y_n = j)$ is the probability that the consumer chooses the *j*th option.
- $Prob_j$ is the usage probability represented by the *j*th option; from the smallest probability "totally impossible" to the largest "certainly" option, the probabilities are 0%, 25%, 50%, 75%, and 100%, respectively.

The basic attributes of the case selected for calculation are: female, 18–24 years old, occupation is a student, with a monthly income of 3001~4000 yuan, average amount per order is 16~20 yuan. Values to the corresponding variables are assigned according to the attributes. For the city tier of residence, location of usage, and time period of usage, different values are taken to form a variety of scenarios, and the delivery charge will be changed from 0 to 6 yuan in each scenario to calculate the consumer's use expectations. The calculation results are shown in Table 8. It can be clearly found that changes in delivery charges have the greatest impact on consumer's use expectations. Taking the scenarios of first-tier city, home, and lunch time as examples, when the delivery charge increases from 0 to 6 yuan, the expected probability of consumers using OFD drops from 76.9% to 5.6%. This also shows that the OFD platform can greatly change the expected probability of consumers using OFD by changing the delivery charge. In addition, if the OFD platform sets an expected probability for consumers to use OFD, it can get the most appropriate delivery charges in different scenarios so as to achieve its goal.

Except for the difference in the impact of the delivery charge under different scenarios, it can be found that the consumer's use expectations will also be greatly influenced by the location of usage changes. The time period of usage also applies impact on consumer's use expectations, while the city tier of residence shows less influence on expectations. This means that consumers living in cities of different tiers have less sensitivity to delivery charges. After a preliminary interpretation of the calculation results, a detailed discussion about the effects of delivery charges on user's expectations with respects to different city tiers of residence, different location of usage, and different time period of usage is generated. Some opinions and suggestions for the delivery charge pricing of the OFD platform are also provided.

5.1. Comparison under Different City Tiers

This section studies the sensitivity to the change of delivery charge of consumers living in different tiers of cities. The attributes are the same as the value set in calculating Table 8. The city tiers are set as first-tier city, second-tier city, third-tier city, and fourth-tier city and below, and the delivery charge varies from 0 to 8 yuan. The expected probabilities of consumers using OFD when the delivery charge changes under each city tier are calculated in turn.

The result of the calculation is shown in Figure 4. It can be seen that consumers living in different tiers of cities have basically the same changing trend of expected probabilities. As the delivery charge increases from 0 to 8 yuan, the expected probability decreases from the range of 70~80% to less than 5%. When the delivery charge is set as the same level, the expected probabilities, ranking from smallest to largest, are in the order of second-tier city, first-tier city, fourth-tier city and below, and third-tier city. For the OFD platform, when setting a probability of consumers' use of OFD, different delivery charges can be concluded from our analysis for different tiers of cities. For example, when the expected probability of consumers using OFD is 70%, the delivery charges for first-tier city, second-tier city, third-tier city, and fourth-tier city and below should be set as 0.4 yuan, 0.6 yuan, 0.7 yuan, and 0.8 yuan, respectively. However, on the whole, there is little difference of the expected possibilities to OFD service of consumers from different tiers of cities, which is also consistent with the report content released by big data platform Trustdata (2019) [44].

Table 8. The impact of delivery charge on the possibility of consumers using OFD in various scenarios.

City Tier of Residence	First-Tier City			Second-Tier City			Third-Tier City			Fourth Tier Cities and below		
Location of Usage	Home	Office Location	University	Home	Office Location	University	Home	Office Location	University	Home	Office Location	University
Lunch												
0	76.9%	72.0%	77.9%	75.0%	70.0%	76.1%	79.5%	75.0%	80.5%	78.3%	73.6%	79.3%
1	63.0%	57.3%	64.3%	60.8%	55.0%	62.1%	66.4%	60.8%	67.6%	64.8%	59.2%	66.1%
2	47.6%	41.9%	48.9%	45.3%	39.7%	46.6%	51.1%	45.3%	52.4%	49.5%	43.7%	50.8%
3	32.9%	27.9%	34.0%	30.8%	26.0%	32.0%	36.0%	30.8%	37.2%	34.6%	29.4%	35.8%
4	20.4%	16.6%	21.4%	18.8%	15.2%	19.7%	22.9%	18.8%	23.9%	21.8%	17.8%	22.7%
5	11.3%	8.8%	11.9%	10.3%	7.9%	10.8%	13.0%	10.2%	13.7%	12.2%	9.6%	12.9%
6	5.6%	4.3%	6.0%	5.1%	3.8%	5.4%	6.6%	5.1%	7.1%	6.2%	4.7%	6.6%
Afternoon tea												
0	81.2%	76.8%	82.1%	79.5%	74.9%	80.5%	83.5%	79.5%	84.3%	82.5%	78.3%	83.3%
1	68.4%	62.9%	69.6%	66.3%	60.7%	67.5%	71.6%	66.3%	72.7%	70.2%	64.8%	71.3%
2	53.3%	47.5%	54.7%	51.0%	45.2%	52.3%	56.8%	51.0%	58.1%	55.2%	49.4%	56.5%
3	38.1%	32.8%	39.4%	36.0%	30.7%	37.2%	41.4%	35.9%	42.7%	39.9%	34.5%	41.2%
4	24.7%	20.4%	25.7%	22.9%	18.8%	23.9%	27.4%	22.9%	28.5%	26.2%	21.7%	27.2%
5	14.2%	11.3%	15.0%	13.0%	10.2%	13.7%	16.3%	13.0%	17.1%	15.3%	12.2%	16.1%
6	7.4%	5.6%	7.8%	6.6%	5.0%	7.0%	8.6%	6.6%	9.1%	8.0%	6.1%	8.5%
Dinner												
0	78.2%	73.4%	79.2%	76.3%	71.4%	77.4%	80.7%	76.3%	81.7%	79.6%	75.0%	80.6%
1	64.6%	59.0%	65.9%	62.4%	56.7%	63.7%	67.9%	62.4%	69.1%	66.4%	60.8%	67.7%
2	49.3%	43.5%	50.6%	47.0%	41.3%	48.3%	52.8%	47.0%	54.1%	51.2%	45.4%	52.5%
3	34.4%	29.2%	35.6%	32.3%	27.3%	33.5%	37.6%	32.3%	38.8%	36.1%	30.9%	37.3%
4	21.6%	17.6%	22.6%	20.0%	16.2%	20.9%	24.2%	20.0%	25.2%	23.0%	18.9%	24.0%
5	12.1%	9.5%	12.8%	11.0%	8.6%	11.6%	13.9%	11.0%	14.7%	13.1%	10.3%	13.8%
6	6.1%	4.6%	6.5%	5.5%	4.1%	5.8%	7.2%	5.5%	7.6%	6.7%	5.1%	7.1%
Night snack												
0	82.5%	78.3%	83.4%	80.9%	76.5%	81.8%	84.7%	80.9%	85.5%	83.7%	79.7%	84.6%
1	70.2%	64.8%	71.4%	68.1%	62.6%	69.3%	73.3%	68.1%	74.4%	71.9%	66.6%	73.0%
2	55.3%	49.5%	56.6%	53.0%	47.2%	54.3%	58.7%	52.9%	60.1%	57.2%	51.4%	58.5%
3	39.9%	34.5%	41.2%	37.8%	32.4%	39.0%	43.3%	37.7%	44.6%	41.8%	36.3%	43.0%
4	26.2%	21.7%	27.3%	24.4%	20.1%	25.4%	29.1%	24.4%	30.2%	27.7%	23.1%	28.8%
5	15.4%	12.2%	16.1%	14.0%	11.1%	14.8%	17.5%	14.0%	18.3%	16.5%	13.2%	17.3%
6	8.0%	6.2%	8.5%	7.2%	5.5%	7.7%	9.4%	7.2%	9.9%	8.7%	6.7%	9.3%

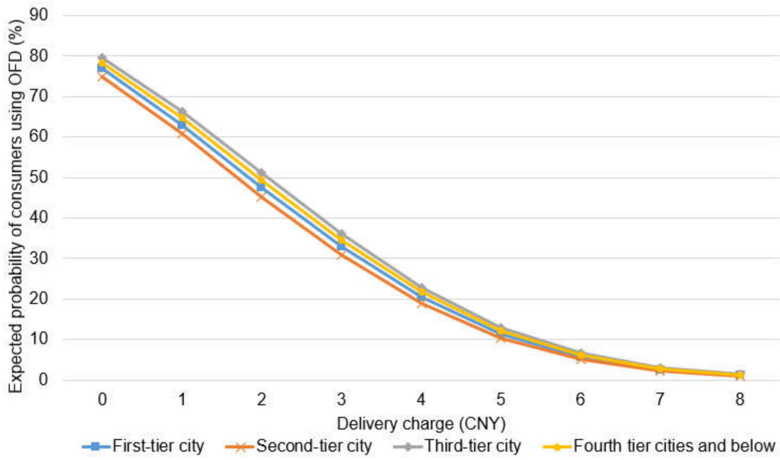

Figure 4. The impact of delivery charge on the possibility of consumers using OFD in different city tier.

5.2. Comparison under Different Urban Area

This section analyzes the sensitivity to the change of delivery charge of consumers in different urban areas. The locations where consumers often use OFD include home, office location, and universities. These three locations represent the most typical areas in each city, which are residential areas, office areas (office buildings, etc.), and university areas. The attributes are set as the same value as the case used in calculating Table 8, but the locations of usage are set as home, office location, and universities, and the delivery charge varies from 0 to 8 yuan. The expected probabilities of consumers using OFD when the delivery charge changes under each urban area are calculated in turn.

It can be seen from Figure 5 that the expected probability of consumers at home, office location, and university has basically the same trend of change. With the continuous increase of delivery charges, the expected probability of consumers at home and colleges using OFD drops from 75% to less than 5%, and the expected probability of consumers in the office location area using OFD decreases from 70% to close to 0%. When the delivery charge is set as the same level, the expected probabilities of consumers using OFD at home and colleges are almost the same, and both are higher than those at the office location. This may be because consumers in the office area do not want to spend time waiting for OFD because they have few breaks at work and might directly choose to eat in restaurants around the office. Therefore, the demand of OFD is lower than that of consumers in other locations. For the OFD platform, if consumers are expected to use OFD with an expected probability of 60%, the delivery charges that need to be set in residential areas, office areas, and university areas should be 0.6 yuan, 1.1 yuan, and 1.2 yuan, respectively.

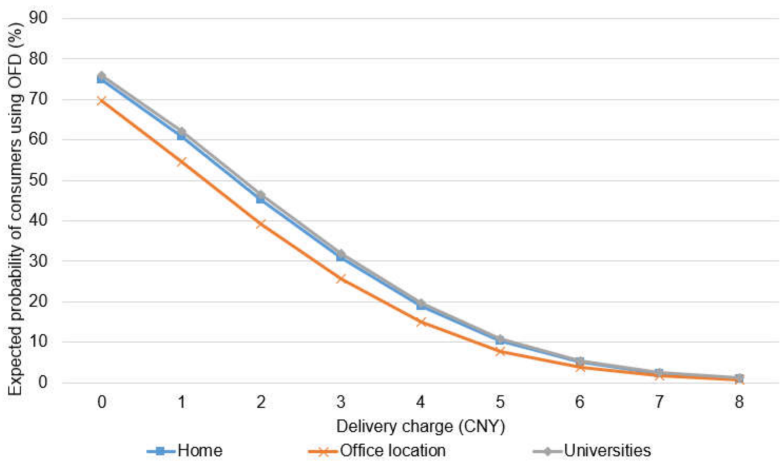

Figure 5. The impact of delivery charge on the possibility of consumers using OFD in different urban area.

5.3. Comparison under Different Time Period

This section analyzes the sensitivities to the change of delivery charge of consumers in different time periods. The period of usage of consumers' ordering OFD service is accumulated, including lunch, afternoon tea, dinner, and night snack, which is consistent with the business hours division of merchants on the current OFD platform. Among them, lunch and dinner are considered as formal meals, while afternoon tea and supper are considered as informal meals. The attributes are set as the same value as the case used in calculating Table 8, but the time periods of usage are set as lunch, afternoon tea, dinner, and night snack, and the delivery charge varies from 0 to 8 yuan. The expected probabilities of consumers using OFD when the delivery charge changes under each time period are calculated in turn.

It can be seen from Figure 6 that with the continuous increase of delivery charges, the expected probability of consumers using OFD during the time period for afternoon tea and night snacks drops from 80% to less than 5%. The expected probability of consumers using OFD during the time period for lunch and dinner time decreases from 75% to close to 0%. When the delivery charge is set as the same level, there is almost no difference in the expected probability value of consumers during formal mealtime, and there is also almost no difference in informal mealtime. Consumers in informal mealtime have a higher expected probability of using OFD than consumers in formal mealtime. Possible reason for this discrepancy includes that many restaurants will close during informal mealtime; thus, it provides less alternatives for consumers to choose from. Under the circumstance, in order to meet the demands of meals, it is easier for consumers during informal mealtime to pay higher delivery charge than the situation during formal mealtime. For the OFD platform, if consumers are expected to use OFD with an expected probability of 50%, the delivery charges for lunch, afternoon tea, dinner, and night snack should be 1.7 yuan, 2.1 yuan, 1.8 yuan, and 2.2 yuan, respectively.

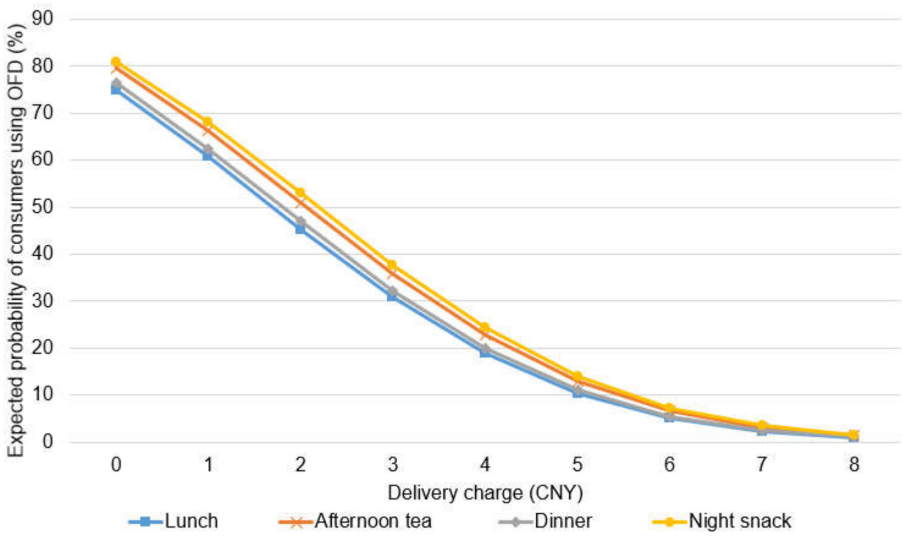

Figure 6. The impact of delivery charge on the possibility of consumers using OFD in different used time period.

6. Conclusions

In this research work, the impact of delivery charges on the possibility of consumers using OFD under different scenarios was studied. A total of 391 valid samples were obtained in China through online questionnaire surveys, with a total of 3591 observation data. Then build an ordered choice model, the dependent variable of the model is the likelihood of consumers using OFD. According to the survey data, the final model is determined by the backward-stepwise selection method. The results show that age, occupation, monthly income, city tier of residence, location of usage, time period of usage, and delivery charges all have an effect on the likelihood of consumers using OFD. Among them, the delivery charge has the greatest impact. Along with the increase of delivery charge, the probability of consumers choosing "certainly" option will be reduced (OR: 0.435; 95% CI: 0.415, 0.455). Taking a certain group of people as a case analysis, the results show that consumers have the greatest probability of choosing the "certainly" option when the delivery charge is in the range of 0~1.4 yuan. In the range of 1.4~3 yuan, consumers have the greatest probability of choosing "not too possible" option. When the delivery charge exceeds 3 yuan, the probability of consumers choosing "totally impossible" is the greatest.

The sensitivity analysis of variables is also carried out in this case. The result shows that among the five options, the probability of the "totally impossible" option being selected is most likely to be affected by the delivery charge. At the same time, when the delivery charge changes between 2 yuan and 5 yuan, the impact on the probability of consumers using OFD is the greatest. In the range of 0~2 yuan and above 6 yuan, the impact on consumers is relatively small. Furthermore, the expected probability of consumers using OFD under multiple different scenarios composed of city tier of residence, urban area, and time period for using OFD are calculated. The results show that the OFD platform can greatly change the expected probability of consumers using OFD by changing the delivery charge. At the same time, it is also found that there are certain differences between the impact of delivery charges on the probability of consumers using OFD under different scenarios. The difference of the impact of delivery charges in different urban areas is the largest, followed by the time period for using OFD. There is no obvious difference in the effect of delivery charges between different city tiers. These conclusions have provided certain guiding suggestions for the delivery charge pricing of the OFD platform in different situations.

The main contributions of this study are as follows. First of all, the existing literatures do not explicitly consider factors such as delivery charge and their impacts on customers' preference of using the OFD service, while these factors are critical to affect the choice of customers. By making a detailed analysis on the fees concerning OFD service including order price and delivery price, the factors considered in the study are comprehensive and in line with the real-life situations, which enable the platform to better understand the customers' behavior and choices. Furthermore, various studies have investigated how other factors influence the decision on the usage of OFD service, but relevant quantitative research are rare. Results from quantitative analysis in this study contributes to predict and analyze the effects that delivery charges apply on customers' choices and provide suggestions for pricing strategies of the OFD platform.

The impacts of delivery charge on customers' intention to use OFD service are obtained. Based on the results, the intention of customers to use OFD service is quite sensitive to the delivery charge when the charge is relatively small (1~2 yuan). Furthermore, the impacts of delivery changes differ in cities of different sizes (tiers), locations of different types, and different periods.

The OFD platforms can utilize the findings on the price impacts mechanism in this study, together with information on operational cost and potential market size, to establish the optimal pricing models for different situations. Based on the pricing models, the optimal tradeoff between the market demand and unit profit margin can be obtained to maximize the overall profit of the platform. Such pricing models for the OFD platforms, which form the future research direction, are critical for the OFD platforms to achieve long-term economic sustainability.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

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