Agricultural & Rural Studies

Article

Discussion of Consumers' Preference for Food Product Traceability Information: Beijing Traceable Tomato Case Study

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Abstract: The paper exemplifies a practical application of combining MNL, RPL and LCM econometric models to study consumer preference heterogeneity in the multi-attributive setting, by analyzing a case study of information traceability preferences of Beijing consumers who buy fresh tomatoes in the post-COVID period. Methodologically, such application of different models (MNL, RPL, LCM) has initially allowed to identify general patterns in Chinese consumers' preference in the tomato traceability information, then to identify and categorize distinct groups of customers and finally to provide details to their 'marketing' profiles towards their willingness to pay. As a result, consumer groups in this study were classified around three key attributes of tomato traceability information which reflect their priorities: consumers from "Price sensitivity" group demonstrated a higher willingness to pay for information on how products were produced (production condition) and products' certification; "Testing Information Preference" group was willing to pay for the information about tomato's product quality detection, and "Official Authority Approval Preference" group has developed priority for information on production condition. Such methodological approach provides rather precise characteristics about three different consumer groups, and thus fills in the existing lacunae in the literature and can serve a guiding tool for designing a regional food safety policy. The suggested methodology is transferrable for analyzing consumers' choices for traceability information about other food products and beyond China.

Keywords: China; choice experiment; consumer preference; food supply traceability; willingness to pay

Citation: Sheng, J.; Gao, X.; Diao, M.; Gerasimova, K. Discussion of Consumers' Preference for Food Product Traceability Information: Beijing Traceable Tomato Case Study. *Agricultural & Rural Studies*, 2024, *2*, 0017. *https://doi.org/10.59978/ar02030017*

Received: 15 February 2024
Revised: 18 July 2024
Accepted: 26 July 2024
Published: 2 September 2024

1. Introduction

The recurrent food safety incidents globally, and in China specifically, are results of the existing problem of information's asymmetry, when consumers do not have access to complete information about the food products they buy. This asymmetry is embedded in inefficiency of traceability information systems which fail to collect data on the product and pass it over to consumers. The information loss can happen at different points of food supply chain (Islam et al., 2022). This issue has affected consumers' welfare and pushed the governments to introduce strict food safety regulations. If adequately managed, a food information traceability system can reduce collusive behaviors among producers and distributors, and ultimately improve safety and quality of food products (Chen et al., 2020). In the post-COVID-19 global context consumers have significantly changed their shopping and consumer behavior, paying more attention to what they buy and seeking more detailed information about food product they intend to buy (European Institute of Innovation & Technology Food, 2020). In their turn, national governments also require a nuanced understanding of the demand for food attributes in order to create an associated system of quality and safety control.

While an obvious meaning of the traceability concept can be described as tracing down information about origins of a product, there is discrepancy among existing official definitions. For example, Codex Alimentarius defines it as "the ability to follow the movement of a food through specified stage(s) of production, processing and distribution" (FAO, 2024), which represents main stages in the food chain management. A different approach is incorporated in ISO 9000's definition: "ability to trace the history, application or location of that which is under consideration" (International Standards Organisation [ISO], 2000). Olsen and Borrit (2013) noted that in the previous version of ISO's definition, the definition contained a clarification on the traceability tool – "by means of recorded identification", which was later removed. Thus, it shows that there is space for different interpretations and ambiguity.

Then it comes to consumers, they search for more data on food products to make their decisions about purchasing and consuming food, but obviously, they don't usually apply themselves high-tech methods to analyze the quality and safety of the product they buy. However, they are willing to pay for the traceability information of the product they plan to buy by choosing those products that are covered by the established schemes of certification, for example, labeling them as organic food (Janssen & Hamm, 2012).

Indeed, a traceability information system is beneficial for consumers, but there might be different pieces of the information that can produce a different impact on consumers, and in fact, different groups of consumers might develop different preferences for specific traceability information attributes. The rich empirical research has confirmed the heterogeneity of consumers' preference for attributes of traceability information on food products. Hempel and Hamm (2016) concluded that consumers' preferences should not be generalized, as they vary depending on product type and consumers' place of residence. For example, while in Germany consumers showed a clear preference for the regional origin of honey they bought (Bissinger & Herrman, 2021), in Italy consumers showed a higher degree of heterogeneity in their preference for mountain beef (Linder et al., 2022). Chinese urban consumers' willingness to pay for food correlated with the degree of their trust in the government's food safety supervision (Liu et al., 2019).

An important remark should be made that not all consumers with a preference for more detailed product information are willing to pay a high price for such traceability information (Jin et al., 2017). Many would opt out and use immediate attributes, such as price, taste, and freshness in their purchase decision-making (Zhu & Lee, 2018). Likewise, governments are seeking a more differentiated approach in managing traceability systems, for example, to distinguish current key data elements (KDEs) from linking KDEs (Gravani et al., 2023). The argument that the obligatory incorporated traceability information system will raise the costs of a whole supply chain and increase the price for traceable agricultural products in general (Liu et al., 2019) explains why no unified traceability information has been yet introduced.

As shown above with the cases from the literature review, one may argue that different groups may seek different pieces of traceability information and different tools to obtain such data. Thus, it is difficult to generalize, and it would be beneficial to develop a case study methodology that can be adjusted for a specific market, a product, or a consumer group. Methodological techniques vary from the application of the best-worst scaling method (Linder et al., 2022) to combinations of logit models RPL+LCA (Wang et al., 2024) or MNL+RPL (Liu et al., 2019). In this paper, we would like to discuss the complexity of dealing with multiple preferences and provide an example of how to identify different groups of consumers of the same product based on the preference for a specific attribute of the traceability information by using a combination of MNL, RPL and LCM models. We have chosen the tomato (*Solanum lycopersicum),* which is a vegetable in culinary terms since it is a popular staple crop in China, as well as in other Asian countries, such as India (Sarkar et al., 2024).

Previous studies using empirical data to estimate consumers' preference and willingness to pay (WTP) in food consumption have certain limitations. The full characteristics of consumers and their preferences are difficult to capture, and measuring these differences is a methodological challenge. This study is not free of such limitations, but it offers a practical approach to develop a methodology that can be adjusted to further studies which could investigate more cases of preferences of specific consumers' groups in different settings. The suggested application of combining MNL, RPL, and LCM models creates a logical deductive approach: to distinguish general heterogeneity in consumers' preference and then to elaborate its further specifications. RPL or MNL models alone cannot explain sources of heterogeneity in preferences, but adding LCM addresses this limitation.

This study used traceability information for organic tomatoes being sold in Beijing as a case study based on a choice experiment (CE), in order to analyze consumers' preferences and willingness to pay (WTP) for food traceability information attributes, and to develop further knowledge on the heterogeneity of consumers in Beijing. These results enhance understanding of consumers' purchasing behavioral differences according to the food traceability information and preference patterns among different types of consumers. In its turn, such findings can improve marketing strategies for food producers and retailers and in fact, can be integrated in the general food policy formulation, at least at the Beijing city's administrative level.

The remainder of this paper is organized as follows. It explains the design of the econometric framework based on consumer utility theory, and then provides details of the experimental design, descriptive statistics and empirical analysis. Finally, we briefly summarize findings of this research.

2. Methodological Framework

Each of the selected methods contributes to a better understanding of the empirical data of this case study. First, the MNL model was used to capture general preferences for information about organic tomatoes among Beijing consumers. Then RPL model was used to calculate the specific preference of each group of consumers in the study. Finally, the LCM model was used for conducting more detailed calculations. Such progression of the used methods represents a logical process of this paper's analysis: transitioning from the MNL model to the RPL model we optimized the calculations, and by advancing from the RPL model to the MNL model we used for detailed elaboration of the results.

Paul Samuelson developed the revealed preference theory with the idea that consumers' preferences can be revealed by their purchasing behavior, and in its turn, their utility can also be affected (Samuelson, 1972). Utility theory, first developed by Lancaster (1966), provided a theoretical basis for a CE to evaluate product's attributes (Tarpey, 1973). It classifies goods according to their characteristics which, in its turn, can be measured with a utility tool (how useful they are to consumers). Following that, Lancaster assumed that since a product is a set of attributes, its characteristics and attribute quantities of product determine product's utility for consumers. Therefore, in a CE consumers' choice of goods can be translated into the choice of product's attributes, which then will reflect the consumers' preferences. In CE, consumers are required to choose from a set of optional attributes, instead of ordering or rating the traceability attributes information in a questionnaire survey, which comprehensively determines the probability of consumers' commodity selection based on attributes (Sarig, 2003).

Random utility theory (RUT) proposed by McFadden (1974) was chosen for this study as it considers choice as a discrete event. According to RUT or Random Utility Maximization (RUM), consumers are making choices about buying products following their attraction or utility, which is taken as a random variable. The model is efficient in measuring consumers' access to buy and value of goods. It fits our purpose to analyze consumers' behavior towards buying organic tomatoes.

2.1. Consumer Utility Components

According to the above theories, product's utility for consumers consists of two parts:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{1}$$

V_{nj} is the total utility of the decision maker (n) for alternative option j, which can include option attributes and personal characteristics. ε_{nj} is random and represents the factors affecting U_{nj} but not in V_{nj}. In this paper, we assume that ε_{nj} is subject to Gumbel independent identically distributed (Train, 2009).

The utility to consumers when choosing i in scenario t as:

$$U_{nit} = V_{nit} + \varepsilon_{nit} \tag{2}$$

$V_{nit} = \beta' X_{nit}$ is the deterministic combination. β' is a parameter vector of structural preference weighted by exogenous variables in determining utility; X_{nit} is the attribute vector of the alternative options i; ε_{nit} is the random term.

Based on above models and tomato traceability information, the utility function model of consumer n for alternative options i in choice set t as:

$$U_{nit} = ASC + \beta_{1n}ENV_{it} + \beta_{2n}PFI_{it} + \beta_{3n}TSC_{it} + \beta_{4n}PTR_{it} + \beta_{5n}PC_{it} + \beta_{6n}GLP_{it} + \beta_{7n}CSP_{it} + \beta_{8n}PRI_{it} + \varepsilon_{nit} \tag{3}$$

ASC is the specific constant and represents other attributes without considering; $i = 1,2,\cdots N$ is consumers; t is the number of choice set; $n = 1,2$ is option A or B; U_{nit} is the individual utility; PRI_{it} is the price of 1 catty (0.5kg) of tomatoes in choice set t, which is in alternative options i; PPC_{it} (plant production conditions), PFI_{it} (pesticide and fertilizer information), TSC_{it} (transportation and storage conditions), PTR_{it} (product testing report), PC_{it} (product quality certificate PC), GLP_{it} (government-led platform), and CSP_{it} (companies self-built platform) are the attribute levels in alternative options j respectively. ε_{nit} is the random term.

2.2. Probability of Consumer's Choice

- Model 1: MNL model

Following the hypothesis of random term distribution and the form of utility functions (Van Wezemael et al., 2014), the Multinomial Logit (MNL) model can be used to analyze discrete choice experimental data if individual preferences are assumed to be homogeneous. This model follows the hypothesis of Independence from Irrelevant Alternatives (IIA), and the random terms follow the independent identically distributed I extremal distribution. The probability of decision maker n in alternative choosing option i is shown as Equation (4).

$$P_{ni} = \frac{\exp(V_{ni})}{\sum_{j=1}^{J} \exp(V_{nj})} = \frac{\exp(x_{ni}^{'}\beta)}{\sum_{j=1}^{J} \exp(x_{ni}^{'}\beta)} \tag{4}$$

- Model 2: RPL model

Several studies on food labeling have shown that heterogeneity needs to be considered while studying consumers' preferences (Ortega et al., 2011; Wongprawmas & Canavari, 2017). If consumers' heterogeneity is expected, a more flexible discrete choice model should be used, such as the Random Parameters Logit (RPL) model (Van Wezemael et al., 2014), which assumes that consumer's preferences are heterogeneous. In this paper, β follows the normal distribution. Then the probability of decision maker n in alternative choosing option i is shown as Equation (5).

$$P_{ni} = \int \frac{\exp x_{ni}^{'}\beta}{\sum_{j=1}^{J} \exp(x_{ni}^{'}\beta)} f(\beta) d\beta \tag{5}$$

- Model 3: LCM model

When the mixed distribution $f(\beta)$ is discrete, the Mixed Logit Model becomes the Latent Class Model (LCM). N individuals are divided into S classes, assuming that each class is composed of homogenous consumers. Equation (6) is the probability of decision maker n in alternative choosing option i.

$$P_{ni} = \sum_{s=1}^{s} \frac{\exp(x_{ni}^{'}\beta_s)}{\sum_{j=1}^{J} \exp(x_{nj}^{'}\beta_s)} R_{ns} \tag{6}$$

R_{ns} is the probability that decision-maker n in class s.

$$R_{ns} = \frac{\exp(\theta_s^{'} z_n)}{\sum_r \exp(\theta_r^{'} z_n)} \tag{7}$$

In Equation (7), z_n is a series of observable factors affecting the decision-maker types, such as sociodemographic characteristics et al., and $\theta_r^{'}$ is the parameter vector of decision makers in class S (Ortega et al., 2011).

Compared with MNL, RPL contains the consumers' heterogeneity function and does not follow the IIA hypothesis. LCM enables researchers to free the strict hypothesis of individual heterogeneity and unfounded distribution hypothesis (Greene & Hensher, 2003). This paper uses Maximum Likelihood Estimation (MLE) for analyzing parameters.

2.3. WTP Calculations

Based on the parameters estimated by the above models, we can calculate consumers' WTP. The value of WTP is a marginal rate of substitution between the non-monetary attribute and the cost. In MNL and RPL, it is a ratio of the non-monetary attribute coefficient to the monetary attribute coefficient.

$$WTP_i = -\frac{2\beta_i}{\beta_p} \tag{8}$$

i is an attribute level, β_i is the marginal utility of an attribute level relative to the reference level; p is the price attribute and β_p is the marginal utility of the price attribute. The bootstrap method proposed by Krinsky and Robb (1986) can be used to obtain the confidence interval of WTP.

3. Experimental Design and Data Description

Data collection in this study was conducted during the period from October 2019 to January 2023. The participants were randomly sampled from residents in Beijing.

3.1. Pre-Survey

To test and, if necessary, re-adjust a main questionnaire, before the formal CE, a pre-survey as market interviews were conducted on October 27–31, 2019. We randomly interviewed seven consumers at the exit of a supermarket in Haidian District, Beijing, and collected information about 9 residents through online interviews. The interviewees were residents in Beijing who used to shop at the same food supermarket.

While it is difficult to find precise data on how many customers buy groceries in an average food supermarket in Beijing, an informal assessment from a shop assistant in Changping, a residential area in Beijing, suggested 400-500 people shopping daily in late 2019, and the number has visually fallen in 2022, possibly due to increasing online orders (Telephone interview with Anonymous, Hualian Supermarket, 13 January 2023).

The pre-survey result has shown that Beijing consumers did care about traceability labels for vegetables (Table 1). Ten people (7 offline and 3 online) found traceability labels very helpful in identifying high-quality food products. Four people (online respondents) thought that traceability labels were helpful. Meantime, two online respondents people acknowledged that traceability labels were not very helpful.

Table 1. Pre-Survey: Consumers' preference in traceability information.

N of respondents	Assumption about vegetable traceability labels
10	Very helpful
4	Helpful
2	Not very helpful

The main tool the respondents used to receive information about the products was scanning traceability codes from food packaging or from supermarket shelves (usually in the form of QR codes). Consumers scanned traceability codes with their mobile phones or personal computers to obtain requested food traceability information (15 people used smartphone scan codes to obtain traceability information, and only one offline respondent was using their personal computer to get such traceability information).

3.2. Questionnaire Design

3.2.1. Tomato Traceability Information

The tomato supply chain includes production, processing, product inspection, packaging, storage, and transportation, so a traceability system should provide consumers with information about the mentioned above processes. According to the National Industry Standards of the People's Republic of China – "NY/T 1993-2011 Operating rules for quality and safety traceability of Agricultural Products-Vegetables" (in Chinese "农产品质量安全追溯操作规程-蔬菜"), the information on commercially sold vegetables should contain data about origins, production, information, packaging, storage, transportation, sales and inspection. To identify key characteristics related to the production phase, we referred to International Finance Corporation (2020) handbook on food safety, which included "producing environment", "pesticide and fertilizer" and "product detection". Additional factors, such as "product certification", "transportation of tomatoes", "storage" and "qualification of the industrial entity that produced tomatoes", were added following the literature review (Jin et al., 2017; Yin et al., 2017). Thus, these six key factors were used in this study as the tomato traceability information attributes.

3.2.2. Traceability Platform Information

According to the pre-survey on agricultural retail markets in Beijing, there are mainly three types of platforms that inform about vegetables' production traceability: government-led, companies self-built, and third-party certified ones.

3.2.3. Price Information

According to the data on tomato market prices collected by the Key Agricultural Products Market Information Platform, which is supported by the Ministry of Agriculture and Rural Affairs of the People's Republic of China, the average price of tomato from June to November 2019 was 3.6 yuan/catty (supermarket price, 1catty = 0.5kg). The statistics of the Ministry of Commerce of China showed that prices for tomato in the Beijing Xinfadi agricultural market was within the range of 1.5–6 yuan/catty (Ministry of Commerce, Market Operation and Consumption Promotion Department, 2020). Referring to Gao and Schroeder's (2009) method for setting the price range of target objects, 33% and 66% upward float, and 33% downward float were taken as the price range. Considering the seasonal characteristics of Beijing tomato sales and to simplify calculations, the price attribute was set as 2.4 yuan/catty, 3.6 yuan/catty, 4.8 yuan/catty, and 6 yuan/catty.

Based on the above attributes, effect coding in the CE specified that when an attribute is selected, it is "1"; the reference attribute level is "−1" and others are "0" (Tonsor et al., 2009; Wongprawmas & Canavari, 2017). The reference levels of two attributes are "Industrial Entities

Qualification Certificate" (IEQ) and "Third-Party Certification" (TPC) respectively in this study. The attributes assignments in the CE are shown in Table 2.

Table 2. Attribute variables and assignment of quality safety traceability information.

Attribute	Variable	Assignment
Quality and safety traceability information	Plant Production Conditions (e.g., soil, air, water quality, etc., FPC)	PPC=1；PFI=0；TSC=0；PTR=0；PC=0
	Pesticide and Fertilizer Information (PFI)	PPC=0；PFI=1；TSC=0；PTR=0；PC=0
	Transport and storage conditions (TSC)	PPC=0；PFI=0；TSC=1；PTR=0；PC=0
	Product Testing Report (PTR)	PPC=0；PFI=0；TSC=0；PTR=1；PC=0
	Product Certification (PC)	PPC=0；PFI=0；TSC=0；PTR=0；PC=1
	Industrial Entities Qualification certificate (IEQ)	PPC=−1；PFI=−1；TSC=−1；PTR=−1；PC=−1
Platform types	Government-led (GLP)	GLP=1；CSP=0
	Companies self-built (CSP)	GLP=0；CSP=1
	Third-party (TPC)	GLP=−1；CSP=−1
Price	Price (PRI)	PRI1=2.4；PRI2=3.6；PRI3=4.8；PRI4=6
Control Variables	Gender (GEN)	1=male，0=female
	Age (AGE)	21.5=[18,25]，27.5=(25,30]，35=(30,40]，45=(40,50]，55=(50,60]，60=(60,+)
	Education (EDU)	12=High school and below, 15=Junior college, 16=Bachelor, 19=Master degree and above
	Income (INC)	1.5=(0,3000]，4=(3000,5000]，7.5=(5000,8000]，9=(8000,10000]，15=(10000,20000]，20=(20000 ,+)

3.3. Simplifying the Questionnaire

In this study, each choice set contains two options: "Choice" and "No Choice". In order to ensure that respondents can only maximize their utility by showing their preferences (Penn, et al. 2014), respondents are required to make choices in forced-choice sets in experiments, that is, respondents must choose one in every choice set, and the choice sets do not include "Not making a choice" item. There are three attributes under each option in questionnaires from the above attribute levels setting, and each attribute has at least three attribute levels. In the case of two options, a total of $(6 \times 3 \times 4)^2 = 5184$ different attribute levels will be theoretically generated.

In order to simplify calculation (Mukerjee & Wu, 1999; Loeppky, 2012), based on the condition that the products attributes have been defined, this study applies the fractional factorial design method and orthogonal design to obtain choice sets. Orthogonal design means that using orthogonal code to make the sum of inner product in choice sets any two columns is zero. In order to get a smaller orthogonal design, we used Ngene 1.1.1 software to select 36 choice sets with different attribute levels, and then generate 9 different "blocks", namely 9 different questionnaire versions, so that respondents only need to make 4 choices in each questionnaire. According to the D-error offered by software, the efficiency of orthogonal design can be reflected. D-error of orthogonal questionnaire is 0.0413 in this study, which proves that our simplification is scientific and efficient. Following Wongprawmas and Canavari (2017), this study uses the method of combining pictures and words.

One of the simplified choice sets as Table 3. Each participant was given 5 choice sets (including a repeat scenario) before they were told that the tomatoes differed only in three attributes, and other attributes were the same.

Table 3. Choice Set Example Scenario 1: Which tomatoes would you buy?

	A	**B**
		
Quality and safety traceability information	Pesticide and fertilizer information	Industrial entities qualification certificate
Platform types	Government-led	Third-party
Price	3.6 yuan/ catty	4.8 yuan/ catty

3.4. Formal CE

The formal CE was from January 17–31, 2020. Due to COVID-19 in China, we conducted experiments on consumers by online questionnaires. The surveyed group was a random sample of consumers who have purchased in "Freshippo" APP during the above period. Freshippo is a retail chain for groceries and fresh goods in China. It exemplifies the creation of a new shopping experience through complimenting online and offline operations in retail stores, warehouses, and the online orders department. As of March 31, 2022, we had 273 self-operated Freshippo stores, primarily located in tier-one and tier-two cities in China.

It is common that online questionnaires can be prone to such problems, as sampling frame error, no answer error, and response bias (Couper, 2000; Lessler & Kalsbeek, 1992). However, as the target group investigated in this study consisted of consumers who intended to buy traceable food, these consumers had to scan QR codes or entered traceable codes on the web to get traceability information, so they must have been able to use smartphones or other electronic equipment. Therefore, the sampling frame error in this online survey is relatively low.

In addition, all questions in questionnaires were forced choice sets, and the multiple-choice questions were strictly regulated. The respondents could only submit the questionnaire answers after they had answered all questions, which reduced the number of errors caused by incomplete answers. The online questionnaire was designed to set the minimum finishing time for each page in order to increase the attention of respondents in this study. Besides, the research team also ran three times manual sampling tests and eliminated obviously unreasonable answers. Validation questions, repeated questions, and small probability event questions were used to control the questionnaire answers (Gao et al., 2015).

In the process of filling in questionnaires, the randomness and validity of samples were strictly controlled. For randomness, respondents selected in the experiments were consumers who intended to buy traceable food. The questionnaires were set as "Are you more willing to buy food with traceability information than ordinary food?" to filtrate eligible samples. For validity, respondents were required to use electronic equipment, such as smartphones or computers to fill in questionnaires, and the survey location was limited to Beijing by IP address. Finally, we got 597 valid questionnaires, and the sample statistical characteristics are shown in Table 4.

Table 4. Statistical characteristics of the investigated samples.

Variables	Options	Samples	Proportion (%)
Gender	male	273	45.73
	female	324	54.27
Age	[18–25)	87	14.57
	[26–30)	144	24.12
	[31–40)	219	36.68
	[41–50)	108	18.09
	[51–60)	30	5.03
	[61, +)	9	1.51
Education	High school and below	24	4.02
	Junior college	93	15.58
	Bachelor	411	68.84
	Master degree and above	69	11.56
Income	(0,3000]	30	5.03
	(3000,5000]	81	13.57
	(5000,8000]	132	22.11
	(8000,10000]	144	24.12
	(10000,20000]	159	26.63
	(20000, +)	51	8.54
With children aged below 0–12 or old people older than 65	Only child	144	24.12
	Only old man or woman	57	9.55
	None	165	27.64
	Both	231	38.69

4. Empirical Results

4.1. Consumers' Preference for Tomato Traceability Information and WTP

In our RPL model, we assume that the random utility is normally distributed, and Halton draws 1000 times for estimating. The results are shown in Table 5.

Table 5. MNL and RPL model estimation results.

	MNL		RPL	
Variables	Mean	SE	Mean	SE
ASC	0.246***	0.056	0.253***	0.085
Plant Production Conditions (e.g., soil, air, water quality, etc., FPC)	0.481***	0.090	0.572***	0.155
Pesticide and Fertilizer Information (PFI)	−0.291***	0.096	−0.388**	0.170
Transport and Storage Conditions (TSC)	−0.566***	0.086	−1.017***	0.148
Product Testing Report (PTR)	0.507***	0.087	0.927***	0.170
Product Certification (PC)	−0.008	0.085	0.071	0.139
Price (PRI)	−0.521***	0.032	−1.324***	0.170
Government-led Platform (GLP)	0.677***	0.065	1.241***	0.158
Companies Self-built Platform (CSP)	−0.327***	0.058	−0.586***	0.107
STDEV (FPC)	/	/	0.775***	0.259
STDEV (PFI)	/	/	0.938***	0.273
STDEV (TSC)	/	/	0.486*	0.286
STDEV (PTR)	/	/	0.895***	0.231
STDEV (PC)	/	/	0.345	0.287
STDEV (GLP)	/	/	0.809***	0.171
STDEV (CSP)	/	/	0.480***	0.161
STDEV (PRI)	/	/	1.454***	0.202
Number of respondents	597			
Sample size was observed	2388			
Log likelihood	−991.16		−856.98	
AIC	1998.32		1745.97	
BIC	2042.25		1833.82	

Notes: (1) "*", "**" and "***" represent significance at the statistical level of 10%, 5%, and 1%; (2) The price unit is yuan/ catty (0.5kg).

There is a similarity between the MNL model and the RRL model, which not only reflects the characteristics of traceability information attributes but also indicates that estimation results are robust. Among the five attribute levels of traceability information, the means of FPC and PTR are positive and statistically significant, indicating that these two attribute levels are relative to the reference attribute level (IEQ) to provide positive marginal utility to consumers.

In contrast, the means of PFI and TSC are negative and statistically significant, indicating that these two attributes brought more negative marginal utility to consumers than at the reference attribute level. The means of PC are not statistically significant, indicating that there is no significant difference between the utility brought by PC and the reference attribute.

Differences in traceability information platforms also produced different impacts on consumers. For the traceability information platform, the means of GLP are positive and statistically significant, indicating that this attribute level brings more positive marginal utility to consumers than the reference attribute level (TPC). The means of CSP are negative and statistically significant, indicating that this attribute level brings more negative marginal utility to consumers than TPC. The mean of price is negative, indicating that it brings negative marginal utility to consumers.

Comprehensively, the marginal utilities of six attribute levels in traceability information were ranked: PTR > PPC > IEQ ≈ PC > PFI > TSC. Thus, the results showed that consumers were concerned about tomato planting conditions and detection situations, and consumers' preference for product certification was not significant. In addition, consumers showed a low preference for pesticide and fertilizer information. The marginal utility of three attribute levels of traceability platform was in the following order as: GLP > TPC > CSP.

This result shows that consumers trust the authority of a Government-Led platform. It is consistent with the conclusions of Liu et al. (2019) and Wu et al. (2019) on the Chinese apples' traceability labels.

According to the RPL model, the WTP for premiums (relative to a reference level) of tomato traceability information attributes were estimated to obtain means and standard errors. The bootstrap method proposed by Krinsky and Robb (1986) was used to obtain a confidence interval. The results of WTP are shown in Table 6.

Table 6. Estimated results of WTP.

Attributes	Mean	SE	Confidence Interval
Plant Production Conditions (FPC)	0.864	0.250	[0.476,1.316]
Pesticide and Fertilizer Information (PFI)	−0.586	0.260	[−1.038, −0.160]
Transport and Storage Conditions (TSC)	−1.536	0.244	[−2.008, −1.168]
Product Testing Report (PTR)	1.400	0.262	[0.984, 1.890]
Product Certification (PC)	0.106	0.210	[−0.246, 0.462]
Government-led Platform (GLP)	1.874	0.242	[1.516, 2.322]
Companies self-built Platform (CSP)	−0.886	0.168	[−1.192, −0.626]

Notes: (1) 95% confidence interval in Table V; (2) The unit of willingness to pay is yuan/catty (0.5kg); (3) The reference level of Attribute 1 is Industrial Entities Qualification Certificate, and the reference level of Attribute 2 is the Third-Party platform.

Among the six attribute levels of the tomato traceability information, consumers have the highest WTP premium for PTR, which is 1.400 yuan/catty (0.5kg). The second preferred attribute is the FPC, 0.864 yuan/catty (0.5kg). Among the three traceability information platforms, consumers have the highest WTP premium for GLP, which is 1.874 yuan/catty (0.5kg).

4.2. Analysis of the Heterogeneity of Consumer Preference

According to the difference in the standard error of WTP, consumers are also characterized by heterogeneity due to differences in their preferences for the attributes of traceable agricultural products. Therefore, this study further introduces covariates such as age, gender, education, and monthly income per capita to the LCM model for analysis.

The statistically significant preference heterogeneity in the RPL model can be translated into different classes (Class) in the LCM model, in order to identify distinct consumer groups (Table 7). It shows that the consumers' preference for price (PRI) in Class 1 (33.1%) is significantly higher than for other attributes (absolute value). As this consumer group is concerned more about products' prices, we define it as the "Price Sensitivity" (PS) Class. Class 2 (26.1%) shows that the second identifiable consumer group obtained the highest level of utility from the PTR, and the TSC is the lowest, so we entitled this class as the "Testing Information Preference" (TIP) Class. Compared with above two classes, the preference of consumers in Class 3 (40.8%) for GLP is higher than other attributes (absolute value), indicating that this consumer group has the highest preference for traceability information provided by GLP. We called them an "Official Authority Approval Preference" (OAAP) Class. Further analysis of age (AGE), gender (GEN), education (EDU), and income (INC) relative to the PS Class indicated that male consumers with higher education and lower per capita monthly income are more likely to be in TIP Class. Younger women are more likely to represent the OAAP Class.

Table 7. LCM Model Estimation Results.

Variables	Class 1	Class 2	Class 3
ASC	−0.193 (0.387)	0.096 (0.254)	0.128 (0.097)
Plant production Conditions (PPC)	2.111*** (0.574)	−0.924** (0.422)	0.432*** (0.167)
Pesticide and Fertilizer Information (PFI)	−0.350 (0.600)	0.664** (0.298)	−0.484*** (0.169)
Transport and Storage Conditions (TSC)	−1.494*** (0.463)	−2.499*** (0.494)	−0.331** (0.160)
Product testing report (PTR)	0.931** (0.416)	3.750*** (0.870)	0.022 (0.151)
Product certification (PC)	−0.862 (0.734)	0.432 (0.308)	0.155 (0.141)
Government-led (GLP)	1.690** (0.796)	0.911*** (0.205)	0.769*** (0.102)
Companies self-built (CSP)	−1.280** (0.571)	−0.928*** (0.215)	−0.225** (0.097)
Price (PRI)	−3.819*** (0.882)	−1.236*** (0.268)	0.001 (0.053)
Age (AGE)	/	−0.010** (0.004)	−0.025*** (0.004)
Gender (GEN)	/	0.347** (0.147)	−0.236* (0.124)
Education (EDU)	/	0.651*** (0.161)	−0.059 (0.123)
Income (INC)	/	−0.380*** (0.147)	0.060 (0.123)
Probability	0.331	0.261	0.408
Number of respondents		597	
Sample size was observed		2388	
Log likelihood		−821.66	
AIC		1717.32	
BIC		1920.47	

Notes: (1) the figures in brackets are SE. of the estimated coefficients. (2) "*", "**" and "***" represent significance at the statistical level of 10%, 5%, and 1% respectively. (3) The price unit is yuan/catty (0.5kg). (4) When the samples were divided into three categories, AIC and BIC were the smallest ones. (5) The reference level of Attribute 1 is the Industrial Entities Qualification Certificate, and the reference level of Attribute 2 is the Third-Party platform.

5. Conclusions

In this paper, we analyzed the preference of consumers in Beijing for tomato traceability information attributes based on a choice experiment (CE) and measured their willingness to pay for such data (WTP). Meanwhile, the heterogeneity of consumers was also estimated.

Since the consumers' answers to price in the questionnaires are discrete data, this paper used the "discrete choice model" to estimate the consumers' willingness to pay. First, the MNL model, which is the basic type of Logit model, was applied to analyze the data. However, the MNL model can be used for estimating average preferences and cannot identify inter-individual heterogeneity. The most commonly used model for data heterogeneity analysis is the RPL model. The MNL model satisfies the assumption that the random error term follows the strict IID (Independent Identical

Distribution), while the RPL model relaxes this restriction and allows parameters to vary randomly between individuals. The heterogeneity of individuals can be described by the distribution of model parameters (mean value, standard deviation), and the heterogeneity can be studied better. Further, the LCM model is a statistical analysis technique that combines latent variable theory with categorical variables and can analyze potential categorical variables that may exist other than categorical variables with statistical correlation. Unlike MNL and RPL models, LCM is a semi-parametric model that does not require preselection of specific assumptions about the distribution of parameters between individuals (Greene & Hensher, 2003). In LCM, groups are composed of a limited number of identifiable individuals with the same preferences, and preferences are heterogeneous among groups. One of the advantages of LCM over RPL is that it can shed light on systemic causes of preference changes (Tabi & del Saz-Salazar, 2015), that is, whether there may be potentially unobservable heterogeneity.

The results showed that compared with the reference level of preference for tomatoes provided with industrial entity's qualification certificates, Beijing consumers were more willing to pay higher premiums for retrieving information about the production environment and product quality detection, which have been calculated at 1.400 yuan/catty and 0.864 yuan/catty respectively. They were not willing to pay higher premiums for pesticide and fertilizer information, transportation, and storage conditions. The influence of product certification was almost the same as the reference level. In general, the marginal utility brought to consumers by the six attributes of traceability information has been ranked from high to low as: Product testing report > plant production conditions > industrial entity qualification certificate ≈ product certification > pesticide and fertilizer information> transportation and storage conditions.

As for analyzing the preference for three traceability information platforms, compared with the reference level of a third-party platform, consumers were more willing to pay a higher premium of 1.874 yuan/catty for a government-led platform, but are not willing to pay a premium for a private companies' internal reporting platform. In general, the marginal utility brought to consumers by the three attributes of traceability platforms are ranked from high to low as: Government-led platform > third-party platform > companies' internal platform.

In addition, differences in consumers' characteristics such as gender, age, education, and monthly income, determine that consumers have produced different preferences for tomato traceability information. Through the LCM model, consumer groups in this study were classified around three key attributes of tomato traceability information which reflect their priorities: "Price sensitivity", "Testing Information Preference" and "Official Authority Approval Preference". The "Price Sensitivity" group has a higher WTP for information on tomatoes' production condition and product certification of tomatoes they buy. The "TIP" group developed the highest WTP in the information about tomato's product quality detection, and the second priority was information about pesticides and fertilizers usage. The "OAAP" group only has a higher WTP for information on production conditions. All three groups preferred to receive the traceability information from government-led platforms.

The findings in this paper are in line with the previous research on consumers' preferences and willingness to pay for food products traceability information, showing heterogeneity of consumers' preferences. However, the suggested combination of research methods, such as obtained sample data by CE method, and using MLP estimation method to analyze MNL, RPL, and LCM models under the two consumer conditions of homogeneity and heterogeneity, has allowed to draw patterns in these preferences and classify consumers into three groups based on their priorities. This, on one hand, matches the theory of revealed preference, and on the other, gives concise information about the key priorities for these groups that can be beneficial in updating a marketing strategy for food enterprises.

Moreover, according to the characteristics of relevant research on WTP, previous studies on WTP were aimed at a hypothetical commodity that did not appear in the market and then calculated the price to be paid by consumers. This study abstracts a conceptualized "traceable tomato" by starting from the real traceable tomato in the market and further integrating other food attributes. The results obtained not only meet the technical requirements of WTP measurement but also are more credible (Perni et al., 2021). The choice experiments that we have designed included many traceable tomato' attributes, which addressed consumers' concerns. However, all these attributes cannot be fully reflected upon during the moment of purchase. Therefore, adding these attributes into the choice experiment as "attribute information" is not only useful to study the WTP of consumers but also shows that calculated WTP is matching the "attribute" that consumers care about, so findings are credible.

Food safety is an integral part of the Chinese national food security policy. Integrating a whole traceability information system into the food supply chains might not be feasible cost-wise, neither through public or private funds, at least in the near future. The application of AI and new technologies, such as Blockchain Technology (BT) can potentially provide a base for a comprehensive food information traceability system (Feng et al., 2020). However, to reap the full benefits of BT, technological advancement should be accompanied with “the right managerial effort to improve the consumers’ WTP” (Brusset et al., 2024).

Since this research is embedded in the local context (the Beijing area) and a specific product, the exact findings cannot be extended to other areas and other food products, but the chosen methodology can be used as an example of how to approach the heterogeneity of consumers’ preference regarding food product traceability information. The suggested methodological approach can be replicated for future research on other food products, and in different geographical contexts, and thus, it will be useful for further methodological discussions in the food study field.

One of the key issues for Chinese food consumers is trust, since they have less trust in internal (corporate) traceability in food enterprises, as our study has shown, and as previous studies showed, sometimes doubt official food control certification (Liu et al., 2019). Thus, better knowledge of consumers’ priorities can be used together with the application of advanced technologies to enhance communication and trust between consumers and corporate and state actors, and as a result to improve national strategy for food security and system of food control in China. With the key priorities of consumers being clearly identified, in addition to managing obligatory controlling measures on food safety, policymakers can organize additional testing in the most efficient manner, while food producers can apply this detailed knowledge of marketing portfolios to maintain customers’ satisfaction and increase sales.

CRediT Author Statement: Jiping Sheng: Conceptualization, Methodology, Investigation; **Xiaoge Gao:** Conceptualization, Methodology, Data curation, Writing-original draft, Software, Validation; **Mengyao Diao:** Conceptualization, Methodology, Data curation, Writing-original draft; **Ksenia Gerasimova:** Conceptualization, Methodology, Data curation, Writing-original draft, Investigation, Writing-review & editing.

Data Availability Statement: Data is not available.

Funding: This work was supported by Research on the Tracking of Public Consumption Demand for Green Food (High-Quality Green Agricultural Products) (GFJY20240027), and Research on the Potential of Diversified Food Supply and Related Policies in China (RKX2024007) for Jiping Sheng.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Acknowledgments: Not applicable.

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