

Price Signals and Group Differentiation in Agricultural Product Consumption Decisions: A Choice Experiment Analysis of Fengxian Apple Consumer Preferences

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Abstract. Price signals have the dual functions of cost constraints and quality identification in the consumption of agricultural products, and their effects are differentiated according to consumer groups. This study takes Fengxian Apple, a national geographical indication product, as an example to construct a discrete choice experiment including price, geographical indication certification, production mode, appearance level and traceability information. Based on 1080 samples, the latent class logit model is used to identify the heterogeneity of preference and estimate the willingness to pay. The results show that consumers can be divided into three classes: price-sensitive type (42%), quality trust type (33%) and certification-oriented type (25%); the price marginal utility is differentiated from -0.61 to -0.18 between groups, and the geographical indication premium is correspondingly expanded from 1.2 yuan to 4.6 yuan per catty. The quality recognition function of price signals for credence attributes such as organic and geographical indications is significantly enhanced in high-certification preference groups, providing a basis for group segmentation for differentiated pricing and accurate marketing of agricultural products.

Keywords: Price signal, Group differentiation, Choice experiment, Latent class model, Willingness to pay

1. Introduction

With the increase of residents' income and the upgrading of consumption structure, the agricultural products market is changing from quantitative satisfaction to qualitative differentiation, and consumers are increasingly concerned about safety, certification and origin information. In the market where quality information is asymmetrical, price is not only the purchase cost, but also assumes the function of quality signal: when it is difficult for consumers to directly verify the attributes of credence goods such as organic and geographical indications before purchasing, price is often used as an alternative clue to infer quality [1]. This dual attribute complicates the impact of price on consumer decision-making: rising prices not only inhibit the willingness to buy, but also may increase perceived value through quality hints.

Food safety and quality certification have become an important basis for consumers' choice, but there are systematic differences in the interpretation of quality clues by different groups [2]. As a

national geographical indication product, Fengxian Apple has both regional public brand, certification premium and mass consumption attributes. It is an ideal carrier for observing the differentiation of price signal groups. In reality, in the face of the same price change, price-sensitive consumers shrink to buy, while quality and certification-oriented consumers instead regard high prices as quality assurance, so the market presents obvious group stratification.

Existing choice experiment studies on agricultural products have mostly focused on the average effect of attribute preferences, and the portrayal of how price signals are differentiated among heterogeneous groups is still insufficient [3]. Ignoring this differentiation may not only overestimate the overall price elasticity, but also make it difficult to provide a basis for differentiated pricing. To this end, this study uses the discrete choice experiment and the latent class logit model to identify the preference classes of apple consumers in Fengxian County, quantify the group differences in price marginal utility and willingness to pay, and reveal the group heterogeneity of price signals in the quality identification function of credence attributes. The research combines price signal theory with the latent class model to provide empirical support for the precise marketing and brand pricing of regional agricultural products.

2. Literature review

2.1. Price signal and quality identification of agricultural products

Information economics distinguishes commodity attributes into search goods, experience goods and credence goods. The attributes of credence goods cannot be fully verified through pre-purchase inspection or post-purchase consumption. Consumers must rely on external clues to infer quality [1]. As the most intuitive market signal, the quality hint function of price is particularly prominent in the situation of credence goods. Grunert pointed out that food safety and quality perception are highly dependent on certification, labels and other signal carriers, and consumers' trust in signals directly affects payment behavior [2]. Recent studies have further shown that organic, green and other certification labels can significantly improve the willingness to pay, but there is a marginal decrease in certification superposition, and there is also a substitution effect between labels [4]. Under the multi-tier labeling system, the price effect of information provision on different tiers of products is also inconsistent [5], indicating that the role of price signals is highly dependent on the attribute type and information environment.

2.2. Choice experiment research on consumer preferences for agricultural products

The discrete choice experiment is widely used to estimate the marginal willingness to pay for food attributes by simulating the real purchase situation. Loureiro and Umberger found that American consumers attach more importance to food safety certification than origin labels and traceability [6]. Research on the Chinese market shows that consumers have a significant willingness to pay for organic premiums, traceability technology and green certification [7-9]; as a regional quality signal, geographical indications can create added value beyond the manufacturer's brand [10]. As far as apples are concerned, Qu et al. found that consumers have a significant premium for traceable and reduced-pesticide production information based on choice experiments, and present a price-sensitive and non-price-sensitive stratification [3].

2.3. Preference heterogeneity and consumer group segmentation

The average effect hides the structural differences in consumer preferences. The latent class model has become the mainstream method of portraying preference heterogeneity by dividing the sample into several latent classes of internal homogeneity and inter-group heterogeneity [11]. This method identifies differentiated groups such as price sensitivity and quality orientation in rice, avocado and other categories [12, 13]. However, most existing studies regard price as a unified cost variable, and rarely systematically examine the differentiation of its marginal utility between groups from the perspective of price signals. This study is working to make up for this gap.

3. Methodology

3.1. Theoretical framework

This research is based on characteristic demand theory, random utility theory and price signal theory. Lancaster proposed that the utility of a commodity comes from its combination of attributes rather than the commodity itself, and consumers maximize utility through attribute trade-offs [14]. McFadden's random utility framework represents individual choice as the sum of observable utility and random terms, laying the foundation for discrete choice modeling [15]. The price signal theory emphasizes that under credence attributes, price plays a dual role of both cost and quality hint. Accordingly, consumers' choice of Fengxian apples depends on the combined utility of price and various quality attributes, and the price marginal utility may vary depending on the group's dependence on quality signals. Figure 1 shows the overall analysis framework from the dual function of price signals to group differentiation.

3.2. Choice experiment design

According to literature and pre-research, five types of attributes are selected to portray Fengxian apples: price (6/9/12/15 yuan per catty), geographical indication certification (with/without), production mode (organic/green/conventional), appearance level (high-quality/ordinary) and traceability information (blockchain traceable/none). The attribute levels refer to the actual price range and mainstream certification types of the Fengxian apple market to ensure that the situation is close to real decision-making. The D-optimal design is used to generate choice sets, taking into account orthogonality and parameter identification efficiency. Each respondent completes several groups of "three-choice-one" tasks, each group contains two product profiles and one non-purchase option to approach the real purchase situation.

3.3. Data sources and samples

The data comes from the questionnaire survey of apple consumers in Fengxian County and surrounding cities in 2024. Intercept sampling combined online and offline, and 1,080 valid samples were obtained after eliminating invalid questionnaires. The questionnaire includes the choice experiment tasks and socio-economic characteristics of the respondents (gender, age, income, education, health concern). In order to reduce the hypothetical bias, budget constraints are suggested before the experiment and the incentive compatibility situation is emphasized [16]. The gender and age structure of the sample are basically the same as the regional consumer population.

3.4. Latent class logit model

When the consumer n belongs to the latent class c , the utility of choosing alternative j is:

$$U_{njc} = \beta'_c X_{nj} + \varepsilon_{njc} \quad (1)$$

where X_{nj} is the attribute vector, β_c is the class-specific preference parameter, and ε_{njc} follows an independently and identically distributed extreme value distribution. The class membership probability is determined by socio-economic characteristics Z_n :

$$\pi_{nc} = \frac{\exp(\gamma'_c Z_n)}{\sum_{s=1}^C \exp(\gamma'_s Z_n)} \quad (2)$$

The probability that an individual chooses alternative j is the weighted sum of the conditional choice probabilities of each class:

$$P_{nj} = \sum_{c=1}^C \pi_{nc} \frac{\exp(\beta'_c X_{nj})}{\sum_{k \in J} \exp(\beta'_c X_{nk})} \quad (3)$$

The marginal willingness to pay for attribute a is the negative ratio of its coefficient to the price coefficient:

$$WTP_c^a = -\frac{\beta_c^a}{\beta_c^{price}} \quad (4)$$

The model determines the optimal number of classes by the Akaike information criterion and the Bayesian information criterion, and uses the expectation maximization algorithm to solve iteratively. Compared with the mixed logit assumption that the parameters follow a specific distribution, the latent class model can portray the heterogeneity of discrete groups without the distribution assumption [17]. The variance inflation factor of each explanatory variable is less than 5, and the potential heteroscedasticity is controlled by robust standard errors.

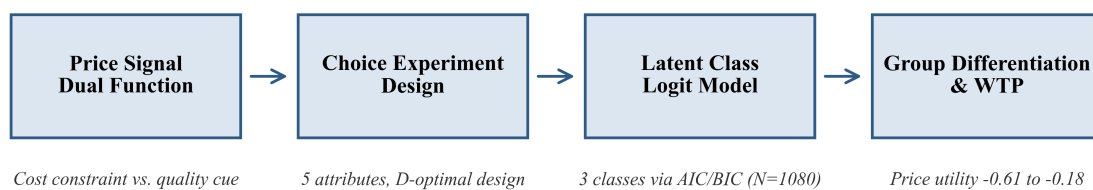


Figure 1. Research framework

4. Results

4.1. Latent class identification and preference structure

The comparison of information criteria shows that the three-class model fits optimally. Accordingly, apple consumers in Fengxian are divided into three latent classes: price-sensitive (42%), quality trust (33%) and certification-oriented (25%). Figure 2 reports the utility coefficients and confidence intervals of the key attributes of each class, and the preference structure of the three groups shows

obvious differentiation. The price-sensitive type has the largest absolute value of the price coefficient and has a lower sensitivity to certification and appearance; the quality trust type assigns the highest utility to organic and appearance levels; the certification-oriented type has the strongest response to geographical indications and traceability information. The analysis of socio-economic characteristics shows that certification-oriented consumers have higher income and health concern, while price-sensitive consumers are mainly middle- and low-income and price comparers.

4.2. Group differentiation of price marginal utility and willingness to pay

Table 1 reports the coefficient estimation and marginal willingness to pay of the latent class logit model. The price marginal utility between the three groups decreased from price-sensitive -0.61 and quality-trust -0.34 to certification-oriented -0.18, and the price elasticity difference is more than three times. Accordingly, the willingness to pay for geographical indication certification has expanded from 1.2 yuan for the price-sensitive type to 4.6 yuan per catty for the certification-oriented type; the premium of organic attributes is as high as 5.3 yuan per catty in the certification-oriented group. This shows that the quality identification function of the price signal for credence attributes is amplified with the enhancement of group certification preferences: certification-oriented consumers are more inclined to interpret higher prices as quality assurance, and the inhibitory effect of price is partially offset by quality hints. Traceability information also presents a similar pattern of group differentiation.

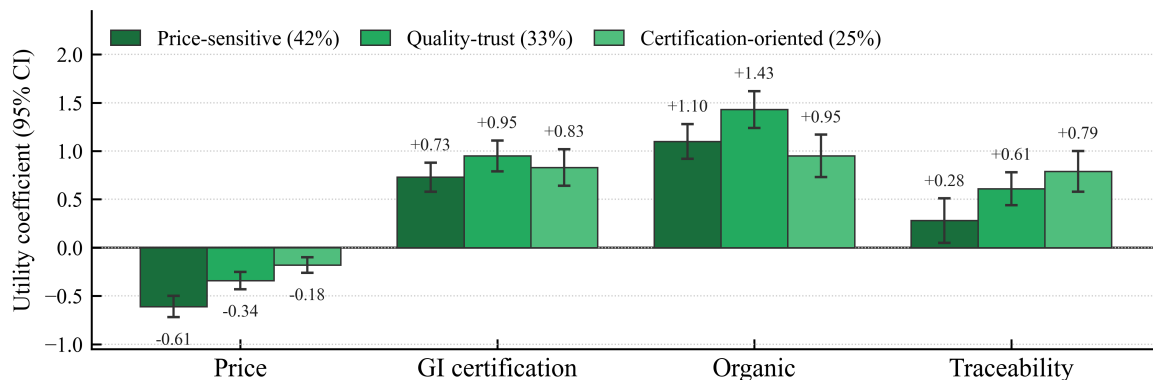


Figure 2. Main results

Table 1. Latent class logit estimates and marginal WTP (yuan/catty, in parentheses). Asterisks denote significance at the 1%, 5% and 10% levels (three, two and one asterisk, respectively)

Attribute	Price-sensitive (42%)	Quality-trust (33%)	Certification-oriented (25%)
Price (yuan/catty)	-0.61***	-0.34***	-0.18***
GI certification	0.73*** (1.2)	0.95*** (2.8)	0.83*** (4.6)
Organic	1.10*** (1.8)	1.43*** (4.2)	0.95*** (5.3)
Green certification	0.52*** (0.9)	0.71*** (2.1)	0.48** (2.7)
High-quality appearance	0.44** (0.7)	0.88*** (2.6)	0.31* (1.7)
Traceability	0.28* (0.5)	0.61*** (1.8)	0.79*** (4.4)

5. Discussion

The research results reveal the duality of price signals in the consumption of agricultural products and their group differentiation mechanism. For price-sensitive consumers, price mainly plays a role in cost constraints, and purchasing decision-making is highly dependent on the price level; while for certification-oriented consumers, the price is more responsible for the function of quality signals, forming mutual verification with geographical indications, organic and other credence attributes, thus weakening the negative effect of price. This differentiation explains why unified price elasticity estimates obscure the real market structure.

The above findings have clear marketing and policy implications. For enterprises, differentiated pricing and precise layered marketing are more effective: price-sensitive groups should focus on cost-effectiveness and promotion, while certification-oriented groups should strengthen geographical indications and traceability endorsements to consolidate high-end positioning with price signals. For regional public brand governance, stable certification quality and reliable traceability system are the prerequisites for maintaining the effectiveness of price signals, otherwise it is difficult to convert high prices into quality trust.

There are limitations in this research. The choice experiment is a stated preference approach, which may deviate from the real purchasing behavior; the sample is concentrated in a specific area, and the external validity needs to be tested. The interaction mechanism between price signals and brand reputation and consumption experience is worth deepening.

6. Conclusion

This study takes Fengxian Apple, a national geographical indication product, as an example. Using the discrete choice experiment and the latent class logit model, it systematically examines the group differentiation effect of price signals on the consumption decision-making of agricultural products. The study concluded three points: first, consumers can be steadily divided into three latent classes: price-sensitive type, quality trust type and certification-oriented type, accounting for 42%, 33% and 25% respectively; second, the price marginal utility is differentiated from -0.61 to -0.18 between groups, the willingness to pay for geographical indications and organic attributes has expanded significantly, and the difference in price elasticity is more than three times; third, the quality identification function of price signals for credence attributes is significantly enhanced in high-certification preference groups, and the cost effect and signal effect of price rise and fall between different groups. The research provides a new perspective for understanding the price stratification mechanism of the agricultural market, and also provides a basis for group segmentation for differentiated pricing and accurate marketing of regional brands. In the future, the robustness and boundary of the effect can be tested in combination with real transaction data.

Author contribution

Kun Yang conceived the study, designed the choice experiment, conducted the empirical analysis, and wrote the manuscript.

Declaration of interest

The author declares no conflict of interest.

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