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The Promising Effect of a Green Food Label in the New Online Market

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Abstract: Although public interest in sustainable and safer products have steadily risen worldwide, research has shown a difference between consumer's willingness to purchase, and actual purchasing behavior, for which two main explanations exist, including a lack of accessibility and a poor knowledge of related attributes. Fortunately, the emergence of online food markets may improve this situation through convenient accessibility to sustainable food and detailed description about sustainability labels. This research uses a hedonic price analysis to compare the price premiums for the sustainability attribute in Chinese online and offline markets, using edible oil as a case. The specific objective is to test the different values of a sustainable attribute, a green food label, in two types of markets. Results show that the green food attribute could gain a price premium in the online market but not in the offline market, indicating the importance of the online channel for sustainable food sale in China. A big price mechanism difference between online and offline markets is also found, with regard to attributes of production method, variety, place of origin, packaging, and discount. These results provide a guide for firms' pricing strategies in online and offline markets.

Keywords: online market; sustainable attributes; hedonic price analysis

1. Introduction

Concerns about the environmental damage caused by conventional agricultural and food production have piqued the interests of consumers and industry for food produced in alternative ways, such as green and organic systems which are relatively less damaging to the ecosystem and are more sustainable. Such sustainable food system promotion has been popular among stakeholders in developed countries in the last century but has been controversial among policymakers in developing countries whose primary goal is feeding their population [1]. A total of 70% of the world's population is in developing countries, and the large emerging economies such as in BRICS (Brazil, Russia, India, China and South Africa) countries in particular account for a large share of world's food consumption and production. The attitudes and consumption behaviors of consumers in these countries about sustainable food will be an increasingly important factor affecting the market.

China, as the largest emerging economy with over 1/5 of the world's population, has an expanding middle-income consumer group that can afford the price premium of sustainable food. In 2017, the total retail sales of consumer goods reached 36,626 billion yuan ($5426 billion) (The exchange rate of USD to CNY is 6.75 on average in 2017.), a 10.2% increase from 2016. The retail sales of food and drink also increased by 9.7% from 2016 [2]. Meanwhile, the growing environmental concerns and continuing exposure of food safety scandals pushed up consumers' willingness to buy specially labeled food products, leading them to sustainable food consumption [3].

However, despite the fact that Chinese consumption of sustainable products has increased much in recent years, the per capita consumption is still far behind the world average level. As shown in Figure 1, Chinese organic retail sales have increased from $1012.28 million in 2012 to $6,549 million in 2016. The organic food consumption per person shows an increasing trend but is still far below the world average level. Research shows that organic and green food buyers are mainly occasional consumers and inconsistency exists between stated willingness and revealed actual purchase [4,5]. Two main explanations are the lack of accessibility and the lack of knowledge of related labels [6,7].

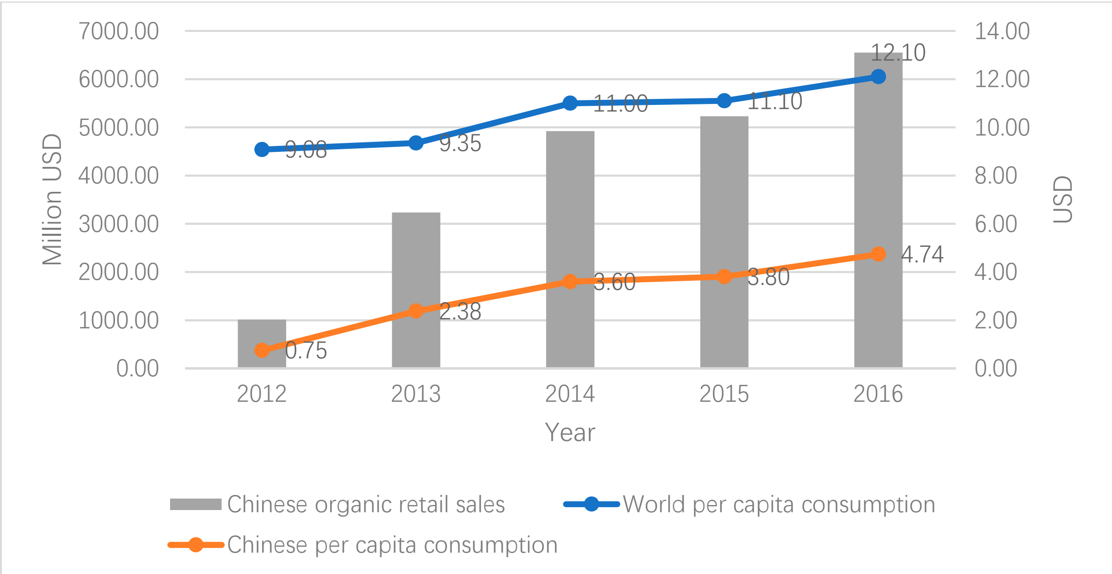

Figure 1. Chinese organic retailer sales and consumption. Source: the data is calculated and sorted by authors. (The world consumption per capita consumption data comes from annual reports of IFOAM, at https://www.ifoam.bio/en/our-library/annual-reports. The Chinese per capita consumption data comes from database set up by FIBL and statistic, at https://statistics.fibl.org/world/markets-trade-world.html?tx_statisticdata_pi1%5Bcontroller%5D=Element2Item&cHash=ceac8c85ba5fdeaff1c1be1c8f4b0ac8. Chinese per capita consumption is calculated by authors, the Chinese population data used comes from National Bureau of Statistics of China, at http://data.stats.gov.cn/easyquery.htm?cn=C01&zb=A0301&sj=2017. Exchange rate data used come from Statista, at https://www.statista.com/statistics/412794/euro-to-u-s-dollar-annual-average-exchange-rate/).

The appearance of an online food market in recent years has seemingly helped to help boost the consumption of sustainable food through increased availability and information which generates knowledge online. Compared with the offline market, many sellers and consumers participated in the online market, which has led to a great variety of products with different labels or claims. That is, the market has become highly differentiated and consumers can easily switch among various products. At the same time, online shopping in China provides benefits beyond convenience. Compared with traditional offline consumption, consumers received a higher satisfaction online [8]. By selling online, store owners can also introduce more information, including the difference between organic, green food cultivation, and conventional food. Consumers can know the details of where and how the product is produced through viewing the videos or pictures on the webpage. Thus, it is interesting to find out whether the online market is a better market venue than the traditional offline market in terms of selling sustainable food in China.

Eco-friendly or sustainable attributes have always been a hot topic, generating a vast literature [9–11]. Many of them such as Young, et al. [12], Yin, et al. [13], D'Souza, et al. [14] and Grunert, et al. [15] use traditional offline markets in developed countries with stated preferences from surveys, while some are for an emerging economy such as Zheng, Wang and Lu [11], and a few use hedonic analysis with revealed market data [16]. Regarding criticism about the discrepancy between stated and revealed preferences for food attributes, Resano-Ezcaray, et al. [17] identify the need for research using actual market data to reveal consumers' value of the sustainability attributes. Revealed preference analysis of online market is limited and the very few works use data from developed countries, such as Roheim, Asche and Santos [16], Carlucci, et al. [18], Roselli, et al. [19]. The only revealed preference for online food study conducted in emerging countries we found is Wang, et al. [20], which does not address sustainable attributes. Although the literature indicates that shoppers derive utility from online shopping [21,22] and thus it reflects on the price through their willingness to pay, to our knowledge, there is virtually no revealed preference research providing a comparison of sustainable attribute valuation between online and offline channels in emerging countries. Further, no study provides price formation comparisons between online and offline market channels, which are important for marketers and for the government in promoting sustainable development.

We choose to use the green food label as a representative of sustainable attributes based on two reasons, although organic labels are also often used in the literature. First, it is the first certification trademark designed by Chinese Ministry of Agriculture to promote environmentally-friendly cultivation and achieve sustainable development [23]. Generally, "Green Food stands for edible produce and processed products produced in a sound environment and under technical standards with wholesome quality control, non-pollution, safety, quality, and special logo" [24]. Second, compared with an organic label, the green food label has a longer history and is more popular among Chinese consumers. Green food sales in China has increased from 386.6 billion yuan ($ 57.30 billion) in 2016 to 403.4 billion yuan ($ 59.76 billion) in 2017 [25,26].

In this paper, we estimate the market price premium for the green food label from the new online market and the traditional market, compare the difference, and identify attributes that contribute to the price difference, if any, between online and offline markets, using the case of edible oil in China. Our contribution to the literature is to use actual market data to determine the revealed preference of consumers in the new online market, and identify its advantage over the traditional offline market. Edible oil is chosen for three reasons. First, it can be easily differentiated by a large number of attributes [27]; second, edible oil has a long shelf life and is easy for transportation, making it suitable to sell both online and offline; and third, edible oil is an important dietary component for Chinese consumers, which is mostly for family use.

The paper is structured as follows. Section 2 summarizes the Chinese online food market development, followed by a description of the data and methods in Section 3. The results are shown in Section 4. The final section presents the conclusion.

2. Background of Online Food Market Development in China

The online market is growing rapidly and becoming increasingly important for food sellers. The world e-commerce giant, Amazon, bought Whole Foods in 2017, starting a challenge to the traditional food retail industry [28]. Actually, two years earlier in 2015, the second biggest e-commerce company in China, Jingdong (JD.com) announced its collaboration with Yonghui supermarket, which sold 36.7 billion yuan ($5.9 billion) the year before [29].

eMarketer [30] has predicted that worldwide online sales will reach $3.578 trillion in 2019, more than double the 2015 level. Among all countries, China is expected to be the biggest online market in 2019 [30]. In 2017, Chinese online sales has reached 7.2 trillion yuan ($1.07 trillion), with 533 million online shoppers [31]. Among all business to consumer e-retailers in China, Alibaba's Tmall owns the biggest market share, 65.2%; followed by Jingdong with the percentage of 23.2, the third giant is Suning, taking account of 5.3% [32].

The Chinese online food market has experienced a long exploration period, and started to boom in 2012. Since 2012, the government has released several policy documents encouraging the online market development of agricultural products. The participation of e-commerce giants such as Alibaba and Jingdong has also accelerated the online food market development. In 2016, the trading volume of agricultural products in Chinese online markets reached 220 billion yuan ($31.84 billion), up from 150 billion yuan ($23.11 billion) in 2015, and already triple that of 2013 [33]. As shown in Figure 2, the agricultural product sales on Alibaba has grown from 3.04 billion dollars in 2012 to 14.47 billion dollars in 2016. The food sales in Jingdong kept an average of annual 150% growth rate from 2013 to 2017 [34], while the rate was accelerating at 330% during the last year [35].

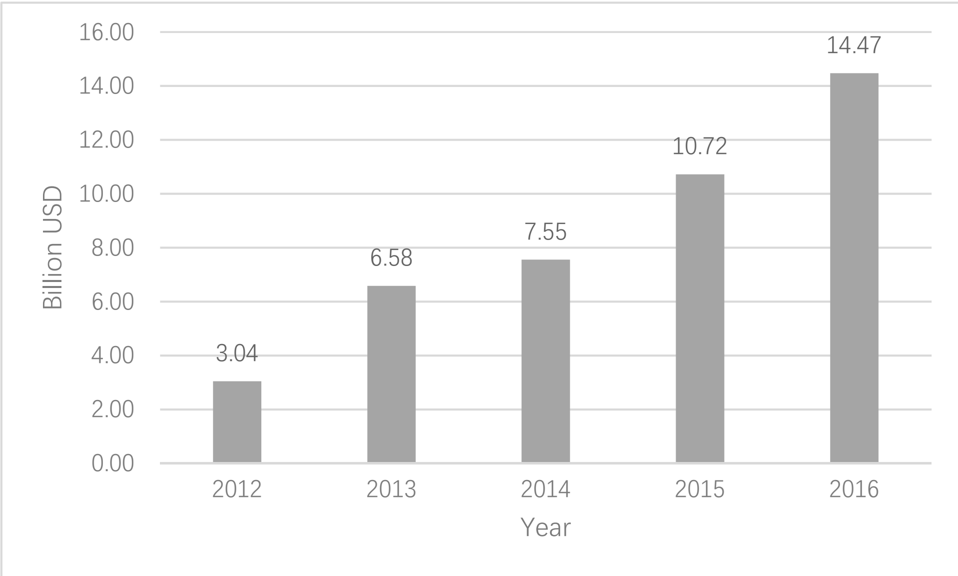

Figure 2. Trading volume of agricultural products in Alibaba. (In the annual report, the statistical caliber for trading volume of agricultural products changed since 2014.) (Source: 2012,2013,2014,2015,2016 "Agricultural Products E-commerce Whitepaper" report of Aliresearch.).

3. Data and Methodology

3.1. Hedonic Theory

Hedonic theory was first formally represented by Lancaster [36], and other contributors include Court [37] and Rosen [38]. Hedonic theory assumes a market with many producers and consumers, and thus individuals do not have any market power to influence the price. Further, consumers are aware of the attributes of products and zero cost is needed for product conversion. Under these assumptions, consumers' utility is derived from the characteristics of products rather than the product itself, and the price of a product is a function of the implicit prices of its quality attributes. For product i, its price, P_i, is determined by its attributes $z_1, z_2, \ldots, z_n$:

$$P_i = f_i(z_1, z_2, z_3, \ldots, z_n) \tag{1}$$

Different from the stated preference method, we apply the hedonic analysis using real market observed data to avoid any hypothesis bias. However, there are also some restrictions. The implicit prices of attributes can only be interpreted as a lower bound of the willingness-to-pay for consumers who bought the product [39], and are decided by both sellers' costs and consumers' willingness-to-pay [40]. In this paper, our main focus is the difference of the price premium of sustainable attributes in online and offline markets. Because production costs do not vary for the same product in two marketing channels except a small retail cost, the revealed attribute premiums can be explained by the difference of consumers' willingness-to-pay from the two channels.

The hedonic theory is widely used to estimate the implicit prices of food attributes. Referring to the cooking oil study, a few studies have analyzed market values of olive oil attributes under different market conditions, such as in producing countries [41], in developing countries [27], or through an e-commerce channel alone in developed countries [18]. However, the difference between the online market and the traditional offline market in emerging countries has not been systematic analyzed. As Mikalef et al 2012 [22] and 2013 [21] point out, browsing websites for product attributes brings consumers different utility values compared to when they look in offline stores based on utilitarian motivated shoppers; in this paper we focus on the differences between the two types of markets.

3.2. Data

The online and offline data are from the same period—February to March of 2018—and come from online and offline supermarkets. Since products in the online market are for consumers nationwide, we try to collect offline data to also be representative of Chinese traditional offline markets nationally. As shown in Figure 3, the offline sample is collected in 8 randomly chosen cities from 8 provinces in China, including Chengdu from Sichuan province, Jinan from Shandong province, Hangzhou from Zhejiang province, Guiyang from Guizhou province, Lanzhou from Gansu province, Guangzhou from Guangdong province, Wuhan from Hubei province, and Suihua from Heilongjiang province. In each city, two supermarkets, a big one such as Walmart and a small one, are chosen to record the details of the product. The edible oil online data is collected from the online supermarkets Tmall, Jingdong and Suning. Because many product attributes are shown in pictures on websites instead of via text, we choose to record the online data manually instead of using codes such as python. The search term used was "edible oil" in chaoshi.tmall.com, chaoshi.jd.com, chaoshi.suning.com. To avoid bias caused by never-sold products, only products with transactions are recorded. We use the products' cumulative monthly sales and buyer comments as the identifiers to screen. Because our main interest is the specific green food label, we only include domestic products from China. After data cleaning, there are 444 valid offline samples and 922 valid online samples.

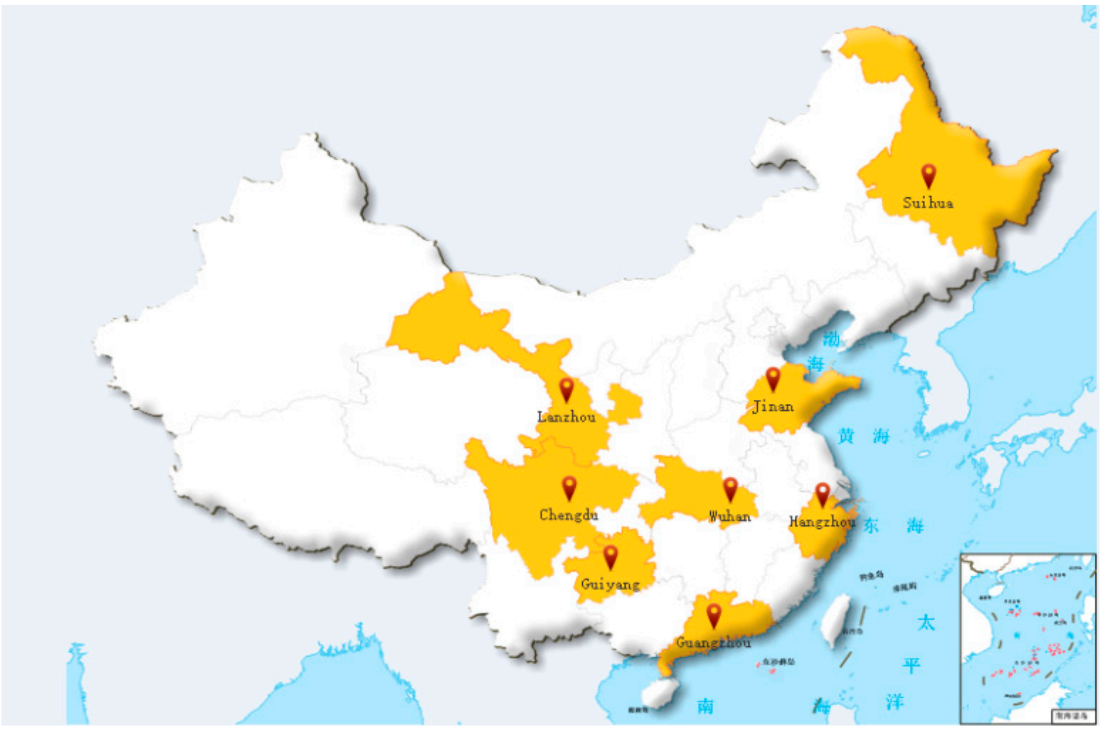

Figure 3. Map of offline sample collection sites.

The variables are chosen based on the existing literature about edible oil and the comparable characteristics of edible oil in the Chinese online and offline supermarket. Final attributes are set to include place of origin, variety, packaging, production method, extraction method, whether or not with a sale promotion claim in the form of discount.

Table 1 shows the summary statistics for the edible oil. The data shows that the online edible oil market varies a lot from the offline market, with more varieties and higher percentage of green labeled products. The average market price of edible oil is 46.92 yuan per liter, with a large range and high standard deviation of 80.35. The online market price is nearly two times bigger than that of the offline sample. The cause could be that products sold online are generally more diversified with more desired attributes such as a green label, non-genetically modified (non-GM), smaller size, gift pack, glass bottle, as well as consumers' willingness-to-pay for convenience. While the green labeled edible oil products are still few in the market, the online market generally has more compared with that of offline. The characteristics of online supermarket make the green food easier to access. Non-GM products account 1.49% point lower in the offline market than in the online market.

Table 1. Descriptive statistics of edible oil.

		All Sample	**Online Sample**	**Offline Sample**
	Price (RMB/L)	46.92 (80.35)	58.11 (94.41)	20.60 (20.23)
Production method	With green food label (%)	2.86%	3.25%	2.03%
	No green food label (%)	97.14%	96.75%	97.97%
Genetically-modified	With genetically modified ingredients (%)	7.10%	6.62%	8.11%
	Non-genetically modified ingredients (%)	92.90%	93.38%	91.89%
Product size	Volume (L)	3.63 (2.41)	3.43 (2.69)	4.05 (1.61)
Extraction method	Leaching (%)	17.94%	13.12%	27.93%
	Pressing (%)	82.06%	86.88%	72.07%
Variety	Soybean oil (%)	7.69%	3.80%	15.77%
	Peanut oil (%)	16.62%	17.46%	14.86%
	Rapeseed oil (%)	18.81%	17.03%	22.52%
	Sunflower seed oil (%)	6.95%	6.07%	8.78%
	Olive oil (%)	1.98%	1.74%	2.48%
	Sesame oil (%)	1.46%	2.06%	0.23%
	Corn oil (%)	15.89%	15.84%	15.99%
	Camellia oil (%)	5.78%	8.46%	0.23%
	Linseed oil (%)	5.86%	7.92%	1.58%
	Canola oil (%)	0.73%	0.76%	0.68%
	Rice oil (%)	1.46%	1.95%	0.45%
	Grapeseed oil (%)	0.22%	0.33%	0.00%
	Tea seed oil (%)	0.07%	0.11%	0.00%
	Wheatgerm oil (%)	0.15%	0.22%	0.00%
	Walnut oil (%)	0.22%	0.33%	0.00%
	Perilla oil (%)	0.15%	0.22%	0.00%
	Pumpkin seed oil (%)	0.22%	0.33%	0.00%
	Sue seed oil (%)	0.07%	0.11%	0.00%
	Hemp seed oil (%)	0.51%	0.76%	0.00%
	Blend oil (%)	15.16%	14.50%	16.43%

Table 1. *Cont.*

		All Sample	Online Sample	Offline Sample
Place of origin	North-east China (%)	7.61%	3.90%	15.32%
	North-west China (%)	11.86%	8.57%	18.69%
	North China (%)	5.93%	3.47%	11.04%
	South-west China (%)	3.07%	1.84%	5.63%
	Central China (%)	33.16%	30.91%	37.84%
	South China (%)	9.66%	11.17%	6.53%
	East China (%)	7.47%	9.44%	3.38%
	Unspecified (%)	21.24%	30.70%	1.57%
Container material	Plastic (%)	87.04 %	82.32%	96.85 %
	Glass (%)	10.76%	15.29%	1.35%
	Tin can (%)	2.20%	2.39%	1.80%
	Number of colors printed on container	2.25 (0.74)	2.41 (0.59)	1.90 (0.89)
	Packaged with a giftbox (%)	3.59%	4.99%	0.68%
	With discount claim (%)	34.04%	42.41%	16.67%
Observations	Number of products	1366	922	444

The average product size of edible oil online is 0.62 L smaller than in the offline market. Most, 82.06%, of edible oil still uses traditional pressing methods for extraction. The data also shows that the online market provides consumers with more options. Among the 20 different varieties of edible oil, 8 kinds of edible oil could only be found online, such as grapeseed oil, tea seed oil, wheatgerm oil, etc. A third of the edible oil originates from Chinese central areas. Interestingly, online market sells relatively more oil from the developed area in China than the offline market, the East and the South, while the offline market sells more from the less developed area of China—the West and the North. The packaging of the product also varies across the two markets: 96.85% of products in the offline market uses a plastic container, while in the online market the percentage is 82.32, with glass container making up the difference.

Packaging in the online market tends to be more colorful than offline, with an average of 2.41 kinds of colors for the container. The percentage of products packaged with an extra giftbox is also higher online: 4.99% compared with 0.68% in the offline supermarket. All the above attribute statistics consistently show that the online market seems to attract higher end customers with higher quality products.

3.3. Emprical Model

Various models have been used to support hedonic analyses in the literature, and the general conclusion is to choose a suitable model specification based on the objective and data of research [40]. However, it is expected that the hedonic price function is non-linear and many studies use a logarithmic transformation of the dependent variable for estimation [42–44]. Considering that some origins may be well known for certain oil products, we add interaction terms between variety and origin variables in the equation, of which the variables and their coefficients are also vectors. In the context of our research, equation 1 becomes,

$$\begin{aligned} \ln P = \beta_0 + \beta_1 green + \beta_2 gm + \beta_3 \ln volume + \beta_4 leaching + \zeta_0 variety \\ + \eta_0 origin + \beta_5 plastic + \beta_6 \ln color + \beta_7 giftbox + \beta_8 discountclaim + \theta_0 variety * origin + \zeta \end{aligned} \tag{2}$$

A description of the variables is shown in the Appendix A. The final price is used, which is calculated after any claimed discount. To make the data more comparable, we drop those varieties that are observed online only as shown in Table 1, which eliminated 22 observations (The average price for 22 dropped samples is 256.10 yuan per liter. After elimination, the average price for total sample is 42.48 yuan per liter). Thus, in the estimation, we actually use 900 online samples and 444 offline samples. Many variables used for estimation are dummy variables, including categorical variables such as variety and place of origin. Notice that the variety, origin, and the interaction term between variety and origin are vector variables, and so are their corresponding coefficients. We only have two cardinal regressors, volume and color. The logarithmic transformation of them is chosen based on estimation results via R-squared.

To test for a structural difference of attributes between online and offline markets, we pool the online and offline samples together, then add interaction terms for all attributes with an online dummy variable using Equation (3),

$$\begin{aligned} \ln P = \beta_0 + \beta_1 green + \beta_2 gm + \beta_3 ln\ volume + \beta_4 leaching + \zeta_0 variety + \eta_0 origin + \beta_5 plastic \\ + \beta_6 ln\ color + \beta_7 giftbox\ \beta_8 discountclaim + \theta_0 variety * origin + [\beta_9 + \beta_{10} green \\ + \beta_{11} gm + \beta_{12} \ln volume + \beta_{13} leaching + \zeta_1 variety + \eta_1 origin \\ + \eta_{14} plastic + \eta_{15} \ln color + \eta_{16} giftbox + \eta_{17} discountclaim + \theta_1 variety * origin] * online + \zeta \end{aligned} \quad (3)$$

In addition to Equation (3), we also use a quantile regression model as a supplement to OLS to take a closer look at the interactive effect of green label attributes and the online market. Equation (3) then becomes:

$$\begin{aligned} \ln P = \beta_0^\tau + \beta_1^\tau green + \beta_2^\tau gm + \beta_3^\tau ln\ volume + \beta_4^\tau leaching + \zeta_0^\tau variety + \eta_0^\tau origin + \ \beta_5^\tau plastic + \beta_6^\tau ln\ color + \\ \beta_7^\tau giftbox + \beta_8^\tau discountclaim + \theta_0^\tau variety * origin + \\ \left[\begin{array}{c} \beta_9^\tau + \beta_{10}^\tau green + \beta_{11}^\tau gm + \beta_{12}^\tau \ln volume + \beta_{13}^\tau leaching + \zeta_1^\tau variety \eta_1^\tau origin + \ \beta_{14}^\tau plastic + \beta_{15}^\tau ln\ color + \\ \beta_{16}^\tau giftbox + \beta_{17}^\tau discountclaim + \theta_1^\tau variety * origin \end{array} \right] * \\ online + \zeta; \tau \in (0,1) \end{aligned} \quad (4)$$

where $\ln P^\tau$ represents the logarithmic transformation of (predicted) price at the τ^{th} quantile of the distribution. Different from the ordinary least squares method, the quantile regression estimates the parameter by directly minimizing the sum of absolute residuals [45], and can thereby avoid any estimation bias caused by extreme values. The quantile approach helps us analyze the edible oil attribute market value across different products' price levels. Quantile regression has been used in several hedonic analysis studies, such as Costanigro, et al. [46], and Wen, Gui, Tian, Xiao and Fang [44].

4. Results and Discussion

Table 2 shows the OLS estimation results for the pooled sample for Equation 3. The four columns in the left panel of the table are the coefficient estimates for the offline market, and those in the right panel are for the interaction with online market. In each part, the first column shows the coefficient estimates, the second column shows the standard errors, and the third and fourth columns show the calculated percentage change of price and marginal implicit price (MIP) for the dummy variables, separately.

Table 2. OLS estimation results.

					Online Interactive Coefficients			
Variables	**Coef.**	**SE**	**% of Price**	**MIP**	**Coef.**	**SE**	**% of Price**	**MIP**
Green	−0.08	0.07	−7.82	−3.32	0.22 **	0.10	24.61	10.45
GM	−0.37 ***	0.06	−31.20	−13.25	−0.05	0.09	−4.74	−2.01
Ln(volume)	−0.26 ***	0.03	−23.05		0.00	0.04		
Leaching	−0.24 ***	0.05	−21.49	−9.13	−0.06	0.08	−5.57	−2.37
Soybean oil	−0.21	0.14	−18.94	−8.05	−0.02	0.16	−1.77	−0.75
Peanut oil	0.52 ***	0.11	68.37	29.04	−0.41 ***	0.13	−33.37	−14.17
Rapeseed oil	−0.32 ***	0.11	−27.53	−11.69	−0.03	0.13	−2.63	−1.12
Sunflower seed oil	−0.08	0.08	−7.30	−3.10	−0.29 **	0.12	−25.32	−10.76
Olive oil	0.59 ***	0.12	79.50	33.77	−0.02	0.21	−1.99	−0.85
Corn oil	−0.11	0.07	−10.15	−4.31	−0.31 ***	0.10	−26.51	−11.26
Linseed oil	0.57 ***	0.21	76.83	32.63	−0.13	0.23	−12.01	−5.10
Northeast China	−0.24 **	0.12	−21.65	−9.20	0.07	0.19	7.62	3.23

Table 2. *Cont.*

Variables	Coef.	SE	% of Price	MIP	Online Interactive Coefficients			
					Coef.	SE	% of Price	MIP
East China	−0.16	0.13	−14.62	−6.21	−0.04	0.14	−3.56	−1.51
North China	−0.36 ***	0.11	−30.51	−12.96	0.32 *	0.18	38.13	16.19
Central China	0.04	0.10	4.48	1.90	0.28 **	0.13	31.78	13.50
South China	−0.12	0.12	−10.86	−4.61	0.20	0.16	22.51	9.56
Southwest China	−0.20	0.15	−17.96	−7.63	0.41	0.29	50.08	21.27
Northwest China	−0.27 ***	0.08	−23.89	−10.15	0.48 **	0.21	61.93	26.31
Plastic	−0.50 ***	0.13	−39.47	−16.76	−0.46 ***	0.16	−36.93	−15.69
Ln(color)	−0.06	0.04	−6.04		-0.07	0.08		
Giftbox	−0.20	0.18	−18.29	−7.77	0.89 ***	0.21	143.27	60.85
Discount claim	−0.10 ***	0.03	−9.27	−3.94	0.20 ***	0.04	22.63	9.61
Soybean oil * Northeast China	0.07	0.16	7.27	3.09	−0.11	0.26	−10.15	−4.31
Soybean oil * Central China	−0.23	0.17	−20.47	−8.69	−0.32	0.20	−27.31	−11.60
Peanut oil * Central China	−0.33 **	0.14	−27.75	−11.79	−0.02	0.17	−1.67	−0.71
Peanut oil * South China	−0.30 *	0.18	−26.21	−11.13	0.17	0.21	18.29	7.77
Rapeseed oil * North China	0.57 ***	0.13	76.83	32.63	−0.70 ***	0.21	−50.19	−21.32
Rapeseed oil * Central China	0.07	0.14	6.88	2.92	−0.30	0.21	−26.14	−11.10
Rapeseed oil * Southwest China	0.34 *	0.18	40.49	17.20	−0.73 **	0.31	−51.86	−22.03
Rapeseed oil * Northwest China	0.30 ***	0.11	34.58	14.69	−0.61 ***	0.22	−45.39	−19.28
Sunflower seed oil * Central China	−0.18	0.12	−16.47	−7.00	−0.11	0.17	−10.68	−4.54
Corn oil * Northeast China	−0.01	0.12	−1.40	−0.59	0.15	0.21	16.07	6.82
Corn oil * Central China	−0.18 *	0.10	−16.14	−6.85	−0.05	0.14	−4.95	−2.10
Corn oil * South China	−0.17	0.16	−15.97	−6.78	0.12	0.20	12.64	5.37
Constant	3.97 ***	0.16			0.61 ***	0.18		
Observations	1344							
R-squared	0.82							

Note: (1) ***, **, and * represent the 1%, 5%, and 10% significance levels, respectively. (2) For dummy variable, % of price is calculated using 100*[exp(coefficient)-1]. MIP is calculated using the estimated percentage change of price and products' mean price. In estimation, the average price for total sample is 42.48 yuan per liter.

Results show that the online market and offline edible oil market differ largely and should be considered as separate markets. Significant differences exist in consumers' preferences for the green food label, oil variety, packaging, and place of origin attributes. The interactive effects of variety and place of origin also vary across the two markets. The result for the discount claim attribute is also different, showing companies' different promotion strategies.

In the online market, the price premium of each attribute depends on its own coefficient as well as the coefficients of its related interaction terms. First the "constant" term is significant, which means the default oil sold online is more expensive than offline. The green food label is significantly positive in the online market, and it has a price premium of 24.61% or 10.45 yuan per liter. The coefficient for GM is significantly negative, indicating that non-GM food is preferred, which is consistent with the literature [47]. The GM effect is very strong with GM oil 31% lower priced than non-GM oil. The parameter on volume is significantly negative, as expected: a product's unit price drops by 0.26% with a 1% increase in the size by volume. The negative and significant parameter for leaching could be explained by a difference in production costs: the cost when using leaching for extraction is generally lower compared with traditional pressing methods. Results also reveal that price is strongly related to oil variety and place of origin attributes, while the interactive effects of certain varieties and place of origin are also significant. Soybean oil, which is a common staple oil in northern China, is priced similarly as other varieties only, and compared with them, olive oil and linseed oil have significantly positive price premiums while corn oil, rapeseed oil, and sunflower seed oil are priced lower. Edible oil comes from northeast and northern China, and has a lower price compared to undefined products. Plastic container affects price negatively compared with glass bottles and tin cans. The coefficient for color is not significant, suggesting that the amount of color printed on the container does not significantly influence a product's price premium. Also, a higher price is associated with the product packaged as a giftbox, and with regards to the discount claim, unexpectedly the coefficient is positive, suggesting that products with a discount claim are actually more expensive in the online market. Recall that in Table 1 the descriptive statistics of discount claims in the online market is 42.41%, while the percentage is 16.67 in the offline market. Those together indicate that the discount claim in the online market possibly work as a strategy to attract consumers' attention and incentivize purchase, rather than simply being a price markdown.

The price formation of edible oil in the offline market can be revealed by the coefficients of attributes directly, except for variety and place of origin variables. Different from the online market, the green food certification fails to make a difference in price, which highlights the role of the online market for green labeled edible oil, a sustainable food product. Consumers show a similar negative attitude for GM food as their online counterparts. Also similar to the online market, volume, leaching extraction method, and plastic container adversely affect price formation. The price premiums vary across varieties as well as across place of origin. The number of colors in container and giftbox attribute show no significant influence in price formation. As expected, the products with a discount claim are significantly lower in the offline market.

The significance of the reported coefficient for any interaction term between an attribute and the online dummy, using the offline market as the baseline, means that the price premium for that attribute is statistically different between the two market channels. Results show that the green food label is positively significant, indicating a significant difference in price premium for the green food label between the online and offline markets. The price premium difference contributed by the green label between the two markets is 10.45 yuan per liter. The new online market is a good channel by which to market sustainable food where the green label can receive a price premium of nearly 10 yuan per liter, provided that all other attributes remain the same. The reasons that can explain this effect include the online market providing more information either with language descriptions, pictures and/or videos to promote such attributes, and that the online market can attract consumers who already prefer such attributes but do not have local access via offline markets.

In terms of GM, volume, extraction method, and the number of colors printed on container attributes, our results suggest that there is no significant difference between online and offline markets. It is interesting to notice that although GM and sustainable attributes are often related, Chinese consumers care more about GM for the reasons of food safety and consumers' own health than for environmental sustainability. The former is already reflected in the traditional offline market, but not yet in the latter. Besides production method, results show that variety, place of origin, packaging, discount claim attributes, and the interaction effects of place of origin and variety account for the different price formation between the online and offline markets. To be more specific, price premiums for peanut oil, rapeseed oil from the north, southwest, and northwest China, sunflower oil, and corn oil are higher offline compared with the online market. Products that come from central China gain a higher implicit price offline than online compared with undefined areas. Results also reveal that consumers value giftboxes more in the online market.

Table 3 shows the estimation results for green food labels from the quantile regression model for pooled data, using Equation 4. It describes the impact of the green food label on edible oil prices across quantiles. The results confirm that the green food certification attribute shows no significant influence on edible oil in all price levels for the offline market. However, in the online market, the coefficient is insignificant either below the 10th percentile or above the 70th percentile. Results suggest that the green food attribute is valued online especially for medium priced edible oil products. Remember that the online oil price has very high variation with different quality products that attract different types of consumers from price seeking to quality seeking ones. The extremely low-priced products attract consumers who care about price more than quality and it is hard for these consumers to trust the quality. Both of these reasons prevent buyers from paying a high price premium for the green food label. On the other hand, for high price categories, the insignificant effects can be explained as that the products tend to be gift packaged products and/or the costly olive oil; in this category, consumers value other attributes more than green labels.

Table 3. Quantile estimation results of green food label.

			Interactive Effects	
Green food	**Coef.**	**SE**	**Coef.**	**SE**
q10	0.00	0.09	0.26	0.19
q20	−0.06	0.08	0.24 **	0.11
q30	−0.07	0.08	0.31 ***	0.11
q40	−0.10	0.07	0.33 ***	0.10
q50	−0.06	0.07	0.25 **	0.10
q60	−0.08	0.08	0.24 **	0.11
q70	−0.09	0.10	0.20	0.13
q80	−0.10	0.12	0.20	0.15
q90	0.06	0.16	0.00	0.23

Note: Standard errors were calculated by bootstrapping, of which five hundred random draws were taken.

5. Conclusions

The online market has expanded quickly for food products, especially in emerging countries such as China. The proliferation of the online market brings revolutionary opportunities for the food industry. The online market is different from the offline market in many aspects. In terms of sustainable food consumption, the online market has more differentiated products and detailed product descriptions to educate consumers, and consumers can have access without time and space limitations. Those together would possibly increase consumers' willingness-to-pay for sustainable product. This paper uses national level real market data to compare values of the green food label in Chinese online and offline markets. This study aims to broaden the knowledge of the difference between online and offline markets, especially for sustainable food marketers.

Our results suggest that the market value of the green food label is about 10.45 yuan per liter higher in the online market than in the offline market. In the offline market, the green food label shows no significant influence on price. This may imply a failure of the offline edible oil market for green food differentiation, and more efforts are needed to promote the sustainability concept in traditional markets. In the online market, the situation is quite different. The average price premium of the green food label is about 24.61% of the price, and for products from the 20th to 60th quantile price level, the green food label provides an even higher price value. Without consumer information, we cannot identify if there exists any systematic differences between online and in-store shoppers nor tell if these differences are the causes for preference of sustainable attributes. However, the high online price variation and the quantile effects do imply that consumers who buy products online care more about the sustainability attributes and less about cost relative to others. Further, observing stores in both markets, we believe that the online product description is effective for highlighting the sustainability attribute. The new online market provides a more effective channel to sell sustainable food than the traditional offline market.

This study also shows that a great difference exists between online and offline markets. To begin with, with other factors being equal, the average price online is significantly higher. Second, in the online edible oil market, products with a discount claim are more expensive than those without, while in the offline market, the sign of the coefficient is negative. This indicates that different promotion strategies are used by e-sellers and offline sellers. Third, packaging plays an important role in online marketing: the results show that compared with the traditional offline market, consumers are willing to pay more (a higher price premium) for a giftbox online, and less for products with a plastic container. These results can help sellers to develop efficient price marketing for the online market.

Due to data limitations, this research is not able to provide insight into how consumers' demographic variables or hedonic motivations affect the differences between the online and offline markets. Future research would benefit from the use of household scanner data, taking products' attributes, consumers' characteristics, as well as behavioral motivations into consideration. The potential marketing role of social media could also be considered in a further study [21,22].

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Appendix A

Table A1. Description of variables.

Variables	Type	Description
Dependent variable		
Price	Continuous	Yuan per liter after claimed discount
Independent variables		
Green	Dummy	With green food label = 1, otherwise = 0
Gm	Dummy	With genetically modified ingredient = 1, otherwise = 0
Volume	Continuous	Volume of product
Leaching	Dummy	Using leaching method for extraction = 1, otherwise = 0
Variety1	Dummy	Soybean oil = 1, otherwise = 0
Variety2	Dummy	Peanut oil = 1, otherwise = 0
Variety3	Dummy	Rapeseed oil = 1, otherwise = 0
Variety4	Dummy	Sunflower seed oil = 1, otherwise = 0
Variety5	Dummy	Olive oil = 1, otherwise = 0
Variety6	Dummy	Corn oil = 1, otherwise = 0
Variety7	Dummy	Linseed oil = 1, otherwise = 0
-	Dummy	Other varieties = 1, otherwise = 0 (baseline)
Origin1	Dummy	Northeast China = 1, otherwise = 0
Origin2	Dummy	East China = 1, otherwise = 0
Origin3	Dummy	North China = 1, otherwise = 0
Origin4	Dummy	Central China = 1, otherwise = 0
Origin5	Dummy	South China = 1, otherwise = 0
Origin6	Dummy	South-west China = 1, otherwise = 0
Origin7	Dummy	North-west China = 1, otherwise = 0
-	Dummy	Unspecified = 1, otherwise = 0 (baseline)
Plastic	Dummy	Container's material is plastic = 1, otherwise = 0
Color	Continuous	Number of colors in container
Giftbox	Dummy	Packaged with a giftbox = 1, otherwise = 0
Discount claim	Dummy	With discount claim = 1, otherwise = 0
Online	Dummy	Online market = 1, offline = 0

Note: Discount claims are made by the sellers, who claim there is a price discount. Sometimes, sellers first increase the sticker price then drop the price to claim a discount.

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