Will online market help improve food safety from small suppliers? _evidence from China

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Abstract:

With the booming of e-commerce, consumers are turning to online markets for food. Among all countries, China has the largest food online buyers with 0.541 billion consumers shopping for food online. Thanks to the free services provided by multiple e-commerce and social platforms and to the developed delivery networks, farmers can sell their products online at low transition cost in China. Meanwhile, the capacities of online stores to highlight traceablity and production process and of platforms to reveal quality signals through consumer's reviewing and scoring systems, can decrease asymmetric information about food product quality and safety compared with offline markets. Thus, those special features of online market may in return to encourage farmers to change their marketing plans to sell more safe food online. Our paper uses choice experiment method to solicit farmers' different production and marketing preferences, and finds that farmers perceive higher rewards selling safer products than conventional products when using e-commerce platforms, an evidence supporting the positive impact of online market channel on the supply of safer food.

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JEL Codes: Q12, Q16

#1320

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Abstract

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Keywords: Online market, safety food supply, choice experiment

JEL codes: Q12 Q13 Q16

1. Introduction

E-commerce is booming around the world, and has brought revolutionary changes to many sectors, including food and agriculture (Lachenmeier, 2013). eMarketer (2016) has predicated the worldwide online sales will be more than double the current level to $3.578 trillion in 2020. Among all countries, China is expected to be the biggest online markets in 2019 (eMarketer, 2016). Actually, Chinese online sales has already increased from 130 billion in 2008 to 5160 billion in 2017 (Figure1). China internet networking information center (CNNIC) reported that by 2017, the number of Chinese internet shoppers had reached 0.541 billion, and 65.2% percent online business transitions happened on the e-commerce platform owned by Alibaba (CNNIC, 2017).

[Insert Figure 1 here]

Besides e-commerce platforms, with the growing popularity of social platforms like Wechat and QQ, people can also form chatting groups easily and sell products to such groups. They can choose to establish a wechat store or sell directly to their contacts by sharing related information in the chatting groups or "moments". Different from online vendors on e-commerce platforms when buyers can search products they wanted online, these wechat business mostly can be found within specific groups through friends and spread by "word of mouth". According to the report from CNNIC (2015), 87.1% percent of internet users claim that they have friends or businessmen selling products on their wechat moments. On average, people spent 2134 yuan buying commodities through social platforms in 2015, a 75.5% increase from 2014 (CNNIC,2015). From 2014 to 2016, the observed wechat business trade volume has grown from 95.3 billion to 328.77 billion (Figure2).[1]

[Insert Figure 2 here]

It is shown that 33% of online consumers have bought food/grocery online worldwide (KPMG, 2017). Among all countries, China is the one with particular high usage. For example, Jingdong, the second biggest e-commerce platform in China, once sold over 20,000 tons of fresh food within 11 days (Research JD, 2017). With the growing of online consumers, e-commerce and social platforms have given small household farmers possibility to access a nationwide or even worldwide market by simply "clicking the button". In 2016, the rural online retail sales in China achieved 894.54 billions RMB, an increase of 38.1% from 2015, and the number of rural online stores reached 8.32 millions (CIECC, 2017), many of which were direct markers for food produced from own farms.

Food is a good of credence with asymmetric information for its quality and even safety, adverse selection is usually a concerning problem resulting in the undersupply of safety and quality food (Akerlof, 1970; Nelson, 1970; Masters & Sanogo, 2002; Kawata, 2013). In traditional offline markets, sellers try to set up credible quality signal by using brands, certification systems and traceability systems. However, individual farmers are usually too small to provide credible signal quality by their brands (Moschini, Menapace & Pick, 2008), and both certification systems and traceability systems are typically too expensive for farmers in developing countries (Trienekens & Zuurbier, 2008). In theory, the large number of small online food providers may also bring challenges for governments to ensure food safety to the public. Interstingly, the appearance of online markets seems to provide a new way to provide credible quality signals at a low cost by traceability, repeat-purchasing and product reviewing and vendor scoring systems. These may help consumers to reward the high quality products and in turn encourage farmers to adopt safer production practices and to adjust their marketing strategies to supply more safety goods online.

In order to find the effects of online market on the supply of safer food from small

[1] There exists many transitions in social platforms which are achieved directly through communications rather than through online stores. However, those transitions can not be observed by official, so the reported wechat business trading volumes does not include.

farm producers, we use choice experiment design to solicit farmers' different production and marketing preferences, considering conventional products, safer products, traditional offline market and online e-Commerce and social platforms. The paper are structured as follows. Section 2 describes the data collection process and the survey design, followed by the model description in section 3 and the empirical results in section 4. The final section concludes with a more general discussion.

2. Choice Experiment Description and Data

Choice experiments are based on Lancastrian consumer theory (Lancaster, 1966) and random utility theory (Thurston, 1927; Luce, 1959; McFadden, 1974; Hanemann, 1984). They are widely used to investigate objects' willingness to pay or to accept for a non-market attribute of a good or service (Coffie et al., 2016; Gerini et al., 2016). During the experiment, a situation of several specially designed alternatives is provided to the respondent for him/her to select the one that is mostly preferred. Each alternative contains a combination of a certain level of all considered attributes of the good or service, so that the respondent is set in a situation as in the reality to face the choices. The respondents' preference for each attribute level in terms of willingness to pay (or to accept) can be estimated from these designed alternatives and the responses. Surveys were conducted in Zhejiang province, the biggest agricultural e-commerce center in China in the summer of 2017. The "good" we choose in this experiment is the production and marketing practice for a generic crop .

2.1 Attribute specifications

After conducting focus group discussions with respondents and relevant experts, farmers' production and marketing practice was specified in four attributes: net unit profit of the product, type of products, marketing channel and marketing role. Table 1 provides a list of the attributes and their respective levels. The numbers of attributes and their levels were carefully selected to balance the task complexity and the need of the study for online market and food safety (Louviere et al.,2008).

The first attribute is net unit profit of the output. It is measured by a premium or discount percentage from the current average market level of the generic good. A level of zero means the net unit profit is right at the average market level, and -20%, -10%, 10% and 20% are all considered representing different discount and premium levels. The second attribute is safety related product type determined by the production practice, including two levels, regular of safer and environmental friendly products. China's Ministry of Agriculture (MOA) has different safety related quality standards for agricultural products, among which the Green Food AA-grade[2] means that the food is not allowed to use chemical synthetic fertilizers, pesticides, animal drugs, feed

[2] The CGFDC subsequently split Green Food certification into two grades, Grade A and Grade AA..

additives, food additives and other substances harmful to the health and the environment during production process. This is a high standard which our safer and environmental friendly product type is defined as, and products legal to market but not satisfying this standard is categorized as regular.

The third attribute relates to the marketing channel with three levels. Traditional channel refers to all off-line channels including wet markets or grocery stores. E-commerce platform channel means that the crop is sold on-line on e-commerce platforms. Farmers might own an online store and sell products they produced directly or they may sell their products to online retailers who then sell them on online stores. We also include social platform as an attribute level of marketing channel. Again, farmers may sell their crop directly or indirectly on the social platforms. The fourth attribute is the marketing role, indicating whether the farmers directly market the product to consumers or through wholesalers and retailers, indirect-marketing.

[Insert Table 1 here]

2.2 Experimental design

Experimental design is the core of all stated choice studies (Scarpa & Rose, 2010). Using "complete factorial design", the selected attributes and corresponding levels can lead to 90 possible alternatives (5×3×3×2), and 4,005 possible combinations of two-alternative choice situations (4005X4004/2). To simplify our experiments, we use the software JMP to develop a D-optimal choice design (Burgess & Street, 2003), which is widely used and proved better than random grouping and L^{MA} construction (Street, Burgess & Louviere, 2005). Main effects as well as key interactions are also allowed in the design, making it possible for us to find cross effects of key interactions such as safer and environmental-friendly products sold on e-commerce platforms.[3] Considering the trade-off between statistical efficiency and respondents' choice consistency, we choose a design of 30 choice sets, with the D-efficiency score of 95 (Louviere, 2001; Louviere et al., 2008).

To decrease the cognitive burden of respondents and the possibility of respondent fatigue, the design was blocked into six versions and randomly allocated to survey participants (Kanninen, 2002). In the end, each farmer was presented with five different situations, each involving a selection between two alternatives and an

[3] Including the interaction terms in the design results in a much large fraction of the full-choice design, however, in our cases, not including interactions terms may lead to estimation bias for interaction effects are confounded with the main effects(Johnson,Lancsar&Marshall,2013).

opt-out option, because the omission of the opt-out option could cause problems if a non-produce decision is more attractive (Hensher, Rose & Greene, 2015).

We choose to present the situations with specific pictures to make it easier for respondents to understand. The definitions of attributes and attribute levels are provided prior to the choice sets to help respondents understand the choice sets.

[Insert Figure 3 here]

Hypothetical bias is a significant problem when using stated preference methods, and one of the most popular ex-ante approaches to reduce this bias is "cheap talk" (Cummings & Taylor, 1999; Pallab & Robert, 2007; Landry & List, 2010). We have adopted the script of Cummings & Taylor (1999) in the questionnaire.

2.3 Survey procedure and data

We choose Zhejiang province as a representative because it is the most active internet business center where Alibaba located, and has sold over 8 billion yuan agricultural products through e-commerce in 2015, ranked first among other provinces (AliResearch, 2016).

To ensure the sample to be random and representative of Zhejiang rural areas, we used the sample households that China Rural Household Panel Survey (CRHPS) and China Household Finance Survey (CHFS) programs selected in 2017. They are national-wide survey programs which have a very strict sampling procedure to select the sample so that it can be representative at both province and country level (Zhang et al., 2014). 17 counties including Chunan, Tonglu, Yiwu , Yongkang, Longquan, Beilun, Cixi, Xianju and Luqiao are selected in the sample (Figure 3), each selected rural household is paid a house visit and interviewed by the CRHPS survey teams composed of carefully trained student enumerators knowing the local dialects from Zhejiang University after strict training procedure. The survey was conducted during summer of 2017 which lasted for nearly 5 weeks. 561 valid samples were collected for analysis.

[Insert Figure 4 here]

Face-to-face interviews were conducted to ensure the quality of the questionnaire. Because many respondents at home are older farmers who are the heads of the households and agricultural producers while online market are often run by their younger family members (Lin, Xie & Lv, 2016), the enumerators were asked to patiently explain each scenario to the respondents until they truly understand. They were asked to explain the definitions and read the "cheap talk" script, and to make sure each decision was made after serious considerations. Before answering the questions, each respondent is told that the answer should be based on family choice rather than personal decision， and s/he needs to tell the enumerator why a particular choice is made in the first choice situation to ensure s/he did understand the experiment.

The whole questionnaire contains three parts, the first part is demographic questions as warm-ups, the second part is the choice experiment, and the last part is attribute importance rankings.

Table 2 shows the description of demographic variables. 62.05% of respondents are males and the average age is 59.78, showing a population aging situation in rural areas. Most of the respondents are educated and can read by themselves. Phones are widely used by farmers, with an owning rate of 92.00%. Nearly half of the households own a computer at home. 15.96% households have bought goods online a month before surveying, while 3.52% families have bought food online. The average farm size represented by land operated is 2.24 mu, while the average number of separate plots is 2.85.

[Insert Table 2 here]

2.4 Questionnaire coding

Because we have included an opt-out option in each situation, we adopted effect coding technique instead of the traditional dummy coding for qualitative attribute variables to differentiate cases when the attribute is not taking a particular level, negative one valued variable, from when the attribute is not relevant in opt-out, zero valued variable. Table 3 shows the coding of the variables.

[Insert Table 3 here]

3. Method description

3.1 Econometric framework

According to the Lancastrian consumer theory (Lancaster, 1966) and random utility theory (Thurston, 1927; Luce, 1959; McFadden, 1974; Hanemann,1984), in the context of our study， farmers choose one production and marketing practice from available alternatives to reach their utility maximization, and the utility is not derived from the practice itself but from the characteristics/attributes of the practice such as net unit profit, product type, marketing channel, and marketing role. Although conventional production theory uses profit maximization as the starting point to analyze producer's behavior, literature has shown a stream to use utility model to analyze farmers' preferences (Ortega et al., 2014; Ortega et al., 2016; Coffie et al., 2016; Pröbstl, 2016; Waldman et al., 2017).Considering our analysis involves food safety issues which might result in farmer's extra utilities, we followed their steps.

Assuming there is a choice set C which contains j alternatives, where ξ_{ijt} is a residual, unsolvable component, when farmer i chooses alternative j in a situation t, the utility he obtains is,

$$U_{ijt} = V_{ijt} + \xi_{jt} \quad (1)$$

In the present context, V_{ijt} ,the deterministic part of U_{ijt}, can be defined as,

$$V = \beta_1 Pro + \beta_2 Safe + \beta_3 Soc + \beta_4 Ecom + \beta_5 Dir + \beta_6 Safe * Soc$$
$$+ \beta_7 Safe * Ecom + \beta_8 Dir * Soc + \beta_9 Dir * Ecom + \beta_{10} Safe * Dir + \beta_{11} Optout$$

(2)

where , *Pro* refers to the net profit per jin of product sold, *Safe* is a binary variable indicating the product sold has followed the safe production practice or not, *Soc* and *Ecom* refers to the marketing channel is social platforms and e-commerce platforms, respectively. *Dir* is also a binary variable indicating the product is sold through direct-marketing or not, while the *Safe*Soc, Safe*Ecom, Dir*Soc, Dir*Ecom, Safe*Dir* are the two-way interactions we included.

Generally, the farmer will choose alternative j if $U_{ijt} > U_{izt}, \forall j \neq z$,the probability for farmer n to choose i in situation t is,

$$P_{ijt} = Prob(\xi_{ijt} - \xi_{izt} > V_{izt} - V_{ijt}, \forall z \neq j) \quad (3)$$

The conditional logit model (Mcfadden, 1974) assumes that alternatives are irrelevant (IIA), and ξ_{ijt} are independent and identically distributed Gumbel variables, and δ is normalized to 1, then utility weight (β_{ijt}) for a given attribute will be given as,

$$\beta_{ijt} = \beta \, . \quad (4)$$

The random parameter logit (RPL) (Mcfadden & Tran, 2000) model keeps the assumption of error term and scale variable, while relaxes the IIA assumption of conditional logit, allowing coefficients to vary randomly over individuals by assuming some continuous heterogeneity distribution a priori, then the probability becomes,

$$P_{ijt} = \int \frac{\exp(V_{ijt})}{\sum_j \exp(V_{izt})} f(\beta) d(\beta) \quad (5)$$

where f(.) is the distribution of the random parameter, the non-price parameters is random parameters, following a standard normal distribution.

Sometimes, discrete distribution might be better than continuous distribution assumption in which heterogeneity across classes exists. Then there comes latent class logit model, which captures preference heterogeneity in distinct classes (Boxall & Adamowicz, 2002; Greene & Hensher, 2003). βi then becomes,

$$\beta_i = \beta_q \text{ with probability } w_{iq} \text{ for } q = 1,...,Q,$$
$$\text{where } \sum_q w_{iq} = 1, w_{iq} > 0, w_{iq} = \exp(h'\gamma_q) / \sum_{q=1}^{Q} \exp(h'\gamma_q); q = 1,...,Q, \gamma_1 = 0. \quad (6)$$

However, some researchers have argued that preference heterogeneity may be better described as "scale" heterogeneity (Louviere et al., 1999; Louviere et al. , 2002; Louviere & Eagle; Louviere et al., 2008). This has led to the development of scaled multinomial logit (S-MNL) model, allowing the scale of errors vary across individuals (Fiebig et al., 2010). And the generalized multinomial logit model (G-MNL) nests the S-MNL, MIXL models, accommodating both preference and scale heterogeneity (Fiebig et al., 2010), and the β_i can be specified as,

$$\beta_i = \sigma_i \beta + [\gamma + \sigma_i(1-\gamma)]\Gamma \eta_i \quad (7)$$

where σ_i is the individual-specific scale of the idiosyncratic error term, γ is a scalar parameter, $\Gamma \eta_i$ varies with scale.

Our empirical methodology is based on using experimental choice modeling methods to analyze farmer's marketing preferences among a series of alternatives. We first estimate a basic mixed logit model without interactions, then add attribute interactions to model 2. In model 3, we used GMNL model to see if the scale heterogeneity exists.

3.2 Willingness-to-change space

We define the monetary attribute as m_{njt}, and the non-monetary attributes as x_{njt}, then the function becomes,

$$U_{ijt} = \alpha_i m_{ijt} + \beta'_i x_{ijt} + \xi_{ijt} / \sigma_i \quad (8)$$

Willingness to change (WTC) captures both willingness to pay (WTP) and willingness to accept (WTA) (Schulz & Tonsor, 2010; Ortega et al., 2014). A positive

WTC is WTP, which identifies the premium producers would sacrifice to obtain a preferred attribute, while WTA identifies how much producers would accept when providing a not favored attribute. While most literature used the preference model to estimate WTC (Schulz & Tonsor, 2010; Ortega et al., 2014; Permadi et al, 2017; Jin et al., 2017), literature has shown that preference space estimation may produce unrealistic estimates (Meijer & Rouwendal, 2006; Scarpa, Thiene & Train, 2010). We have followed the way of WTP space to reformulate the model to get the direct-marketing WTA measures from coefficients (Train & Weeks, 2005). We compared the results of two estimations.

4. Results

4.1 Standard models

Table 4 has shown the estimation results of basic models. Model 1 has shown the estimation results of RPL without interactions, while model 2 shows the results with two-way interactions, and model 3 considers both preference heterogeneity and scale heterogeneity. Model 4 and model 5 are special cases of full generalized model, they are included to check if the results are robust.

[Insert Table 4 here]

In mode 1, all attributes are significant except direct-marketing. The positive sign on *net unit profit* shows that higher utility associated with higher levels of net unit profit, which is consistent with the theory. While the results also show that farmers prefer to sell safe products rather than regular products, for farmers in China usually own small farm business and sell what they produce, it reflects the motivation to pursue food safety. This result is consistent with many literature, which shows that farmers value profit and food safety as main targets (Nweke & Akorhe, 1983; Coffie et al., 2016). The negative sign of e-commerce platforms and social platforms reflects that farmers usually prefer offline traditional channel, which they are more familiar with. The parameter of direct-marketing is insignificant, which shows direct-marketing or not is indifferent for farmers.

In model 2, the direction and significance of coefficients of main attributes stay the same with model 1. Among the two-way interactions, only *e-commerce platforms*safe product* is significant and has a positive value, which indicates that there exists a positive interactive effect. Specifically, if the marketing channel is e-commerce, and all other factors stays the same, farmers will get higher utility from selling safe products compared with regular products.

The results of generalized models indicate that farmers put a positive value on *net unit profit*, *safe product*, *e-commerce platforms*safe product* and negative value on *e-commerce platforms*, and *social platforms*. Most of the results of standard deviations of coefficients are significant, indicating that parameters are heterogeneous. The scale parameter is only significant in GMNL-1, indicating the exists of scale heterogeneity of model 4. Comparing the results of basic models, we can also see that the results are consistent.

4.2 Preference Space and WTC Space Estimates

We reported the WTC space and preference space estimates side by side in Table 5. The directions of estimated parameters are consistent across two models. Standard deviations of WTC space is smaller than preference model, showing that the results of has WTC space has less variation, thus more reliable. The following explanation is based on results of WTC space.

[Insert Table 5 here]

Since we have used effect coding, given other attributes stay the same, the WTC for social channels shall be 2 times of estimation results, which becomes -0.5. It means that to encourage farmers to change to social platforms as marketing channel for agricultural business from the traditional channel, the profit premium needs to be 0.5 percent above the average net profit per product. Farmers will have some learning cost and expected to be compensated by higher sales price to change to new online market. For there exists a significant interactive effect between *safe product* and *e-commerce platforms*, the WTC for *safe product* then depends on the value of *e-commerce platforms*, vice versa. To be more specific, when selling safe product, farmers shall accept 0.5 percent average net profit subsidy to be willing to turn to use e-commerce platforms as marketing channel. When farmers are selling regular product, willingness to accept from the traditional channel to e-commerce platforms becomes 0.9 percent of net unit profit, much higher than 0.5 percent. If the farmer is marketing through e-commerce channels, they are willing to sacrifice 1.4 percent of net unit profit to sell safe products instead of regular products. If farmers are using social platforms or traditional channels as marketing channels, the willingness to sacrifice then becomes the same as the average net unit profit of market, much lower than 1.4.

5. Conclusion and discussion

Our main interests are the positive coefficient of the interactions of *safe product*e-commerce platforms*, which shows that using e-commerce platforms as marketing channels, and selling safe products give farmers extra utility compared with regular products. A number of possibilities might explain this observation: First, as mentioned in the beginning, food is a consumption of credence, quality and trust account a lot in online business (Henson & Traill, 1993; Latvala & Kola, 2002; Li, 2010). In Asia-Pacific, 59% online consumers cite quality as driver of grocery store switching (4% higher than global level). Besides, one important driver for Chinese online food consumption is “food safety concerns have driven consumers in search of high-quality goods” (Nielsen, 2015). News also shows that online food stores’ profits rely much on repeat-purchasing. For the model in the paper only includes one period analysis, the positive coefficient of *safe product*e-commerce platforms* could be explained as a motive to pursue profits of the next period. More specifically, farmers may believe that selling safe products instead of regular products online could earn more profit in the long run through current profit is given in the experiment. Second, for our survey is conducted in Zhejiang province, where farmers are usually doing well. They might have more motivation for self-fulfillment rather than net profits. The online shops often need to describe their products using pictures, words and even videos, selling which kind of products online might relates to farmer’s self-esteem, then, safe products might give much satisfaction compared with regular products.

We shall notice that the result shows that farmers prefer to sell better quality of food on e-commerce platforms, but it does not grantee that the food bought on e-commerce platforms is of better quality. We may aware that the quality/safety of food does not only depend on itself, but also relevant to other processes such as transportation. Arguments exist that online food shopping might cause higher risks, for instance, there exists higher microbiological risks if cooling chain is broken during transport (Gianfaldoni & Guidi, 2008; Grunert & Ramus, 2004).

Tables and Figures

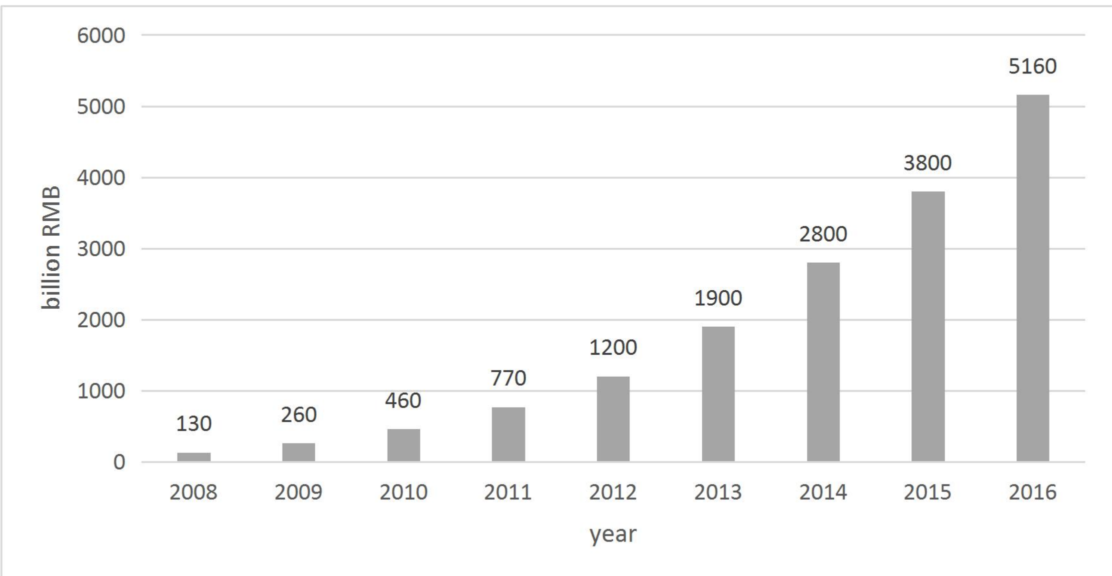

Figure1. Online retail sales from 2008 to 2016 in China

Source: National Bureau of Statistics of China

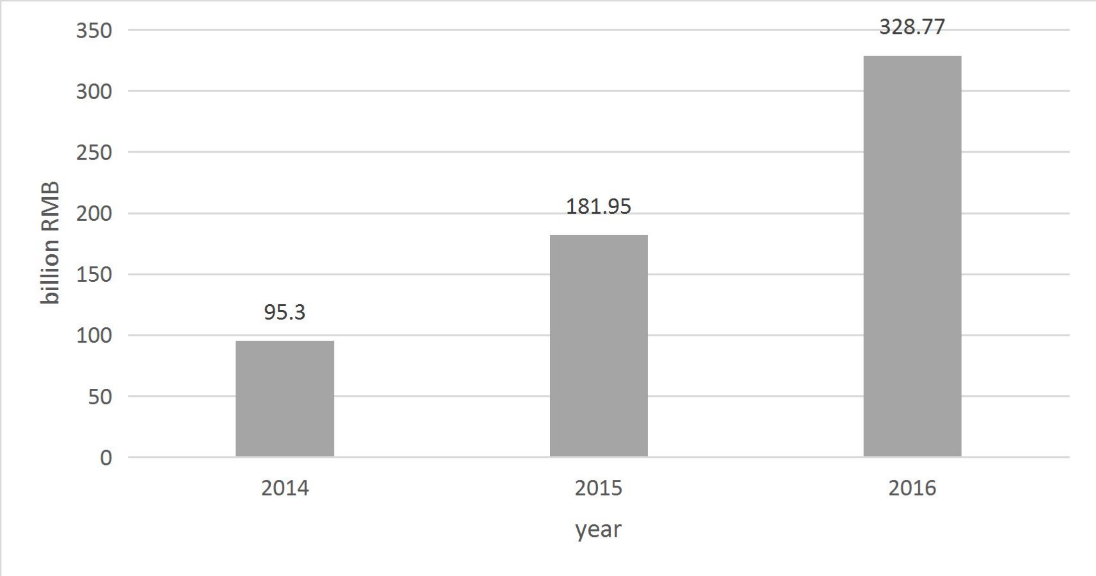

Figure2. Wechat business trading volume from 2014 to 2016.

Source: Iiyiou

	MARKETING SYSTEM A	MARKETING SYSTEM B	Opt Out C
Net Unit Profit	 Same with market	 10% higher than market	NONE: I would not choose A or B.
Product Type	 Safe Product	 Regular Product	
Marketing Channel	 Traditional Channel	 Social Platforms	
marketing role	 direct-marketing	 direct-marketing	
I PREFER	☐	☐	☐

Figure3.Sample choice set

Figure 4. Map of study area indicating survey sites

Table1. Attribute and attribute levels used in the choice experiment

Attributes	Levels
Net unit profit	-20%,-10%,0,10%,20%
Product type	Safer and environmental friendly products, regular products
Marketing channel	Traditional channels, e-commerce platforms, social platforms
marketing role	direct-marketing, indirect-marketing

Table2. Demographic description

Variables	Means	Standard deviation
Characteristics of respondents		

Male(%)	62.05%	--
Age in years	59.78	13.13
Uneducated(%)	17.90%	--
Household and farm characteristics		
With phones(%)	92.00%	--
With computers(%)	45.65%	--
Have bought goods online	15.95%	
Have bought food online	3.52%	--
Land owned(mu)	2.24	1.97
Number of plots	2.85	1.88

Table3.Variables and coding

Variables	Coding
Net unit profit	Numerical values as in table1
Safe product	1=for a safer product,-1=for a regular product,0=opt-out
E-commerce platforms	1=by e-commerce platforms , -1=by social platforms, -1=by off-line/traditional channel,0=opt-out
Social platforms	1=by social platforms, -1=by e-commerce platforms, -1=by off-line/traditional channel,0=opt-out
direct-marketing	1=by direct-marketing, -1=not by direct-marketing, 0=opt-out

Table4.Estimation results of RPL and GMNL

	RPL without interactions	RPL with interactions	Full GMNL	GMNL-1	GMNL-2
Choice	Coef.	Coef.		Coef.	Coef.
Mean					
net unit profit	3.98***	4.18***	4.55***	4.37***	4.20***

safe product	0.57***	0.65***	0.67***	0.65***	0.65***
social platforms	-0.27***	-0.29***	-0.29***	-0.28***	-0.29***
e-commerce platforms	-0.34***	-0.37***	-0.38***	-0.37***	-0.37***
direct-marketing	0.04	0.03	0.02	0.02	0.02
opt-out	0.4	0.56	0.79	0.78	0.58
safe product*e-commerce platforms		0.12***	0.12***	0.12***	0.12***
direct-marketing*social platforms		-0.06	-0.06	-0.06	-0.06
direct-marketing*e-commerce platforms		-0.04	-0.04	-0.04	-0.04
direct-marketing*safe product		-0.04	-0.05	-0.04	-0.04
SD					
safe product	0.31***	0.30***	0.29***	0.29***	0.30***
social platforms	0.38***	0.38***	0.39***	0.38***	0.38***
e-commerce platforms	0.44***	0.44***	0.43***	0.42***	0.44***
direct-marketing	0.33***	0.34***	0.36***	0.34***	0.35***
Optout	2.23***	2.26***	2.11***	2.04***	2.26***
safe product*e-commerce platforms		-0.19	-0.22*	-0.21*	-0.19*
direct-marketing*social platforms		-0.06	-0.04	-0.05	-0.06
direct-marketing*e-commerce platforms		0.08	0.08	0.08	0.08

direct-marketing*safe product		-0.24**	-0.25**	-0.23**	-0.24**
Tau			0.33	0.24**	0.05
Gamma			0.69		
P>chi	0	0	0	0	0
N	8415	8415	8415	8415	8415

Notes: *, **, *** denote significance at the 0.1, 0.05, and 0.01 level, respectively.

Table 5. Estimation results of GMNL-2 using PS and WS[4]

	WTC Space				Preference Space			
choice	Coef.	P>z	[95% Conf.	Interval]	Coef.	P>z	[95% Conf.	Interval]
Mean								
net unit profit	4.20***	0.00	3.39	5.02	1.00			
optout	0.58	0.24	-0.38	1.53	-2.54***	0.00	-3.14	-1.94
safe product	0.65***	0.00	0.54	0.76	0.60***	0.00	0.50	0.71
social platforms	-0.29***	0.00	-0.36	-0.21	-0.25***	0.00	-0.32	-0.18
e-commerce platforms	-0.37***	0.00	-0.47	-0.27	-0.35***	0.00	-0.44	-0.26
direct-marketing	0.02	0.59	-0.06	0.11	0.05	0.22	-0.03	0.13
safe product*social platforms	0.03	0.36	-0.04	0.11	0.05	0.11	-0.01	0.12
safe product*e-commerce platforms	0.12***	0.01	0.03	0.21	0.10***	0.01	0.02	0.18
direct-marketing*social platforms	-0.06	0.10	-0.13	0.01	-0.06	0.10	-0.13	0.01
direct-marketing*e-commerce platforms	-0.04	0.28	-0.12	0.04	-0.04	0.32	-0.11	0.04

[4] We choose to report the results of GMNL-2 model because the information indicator has shown it performed better, as shown in appendix.

direct-marketing*safe product	-0.04	0.28	-0.12	0.03	-0.02	0.54	-0.09	0.05
SD								
optout	2.26***	0.00	1.76	2.76	2.21***	0.00	1.74	2.67
safe product	0.30***	0.00	0.12	0.48	0.22	0.10	-0.04	0.48
social platforms	0.38***	0.00	0.24	0.52	-0.34***	0.00	-0.47	-0.20
e-commerce platforms	0.44***	0.00	0.26	0.61	-0.40***	0.00	-0.57	-0.22
direct-marketing	0.35***	0.00	0.16	0.54	-0.21*	0.06	-0.43	0.01
safe product*social platforms	0.05	0.56	-0.13	0.24	0.00	0.97	-0.15	0.16
safe product*e-commerce platforms	-0.19	0.12	-0.42	0.05	-0.14	0.26	-0.38	0.10
direct-marketing*social platforms	-0.06	0.48	-0.21	0.10	-0.02	0.88	-0.27	0.23
direct-marketing*e-commerce platforms	0.08	0.34	-0.09	0.26	0.02	0.75	-0.13	0.18
direct-marketing*safe product	-0.24**	0.03	-0.45	-0.03	-0.17	0.22	-0.44	0.10
tau	0.05	0.85	-0.49	0.59	0.06	0.76	-0.30	0.42

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Appendix

	Full GMNL	GMNL-1	GMNL-2
N	8415	8415	8415
Ll(model)	-2103.65	-2105.37	-2103.76
Df	23	22	22
AIC	4253.29	4254.73	4251.53
BIC	4415.16	4409.56	4406.36