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RTG 1666 GlobalFood

Transformation of Global Agri-Food Systems:
Trends, Driving Forces, and Implications for Developing Countries

Georg-August-University of Göttingen

GlobalFood Discussion Papers

No. 79

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February 2016

RTG 1666 GlobalFood · Heinrich Düker Weg 12 · 37073 Göttingen · Germany
www.uni-goettingen.de/globalfood

ISSN (2192-3248)

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Feb. 15, 2016

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Abstract:

Media reports could help shape consumer attitudes towards food quality and safety. By introducing an information treatment with positive or negative media coverage, we study the impact on consumer preference for pork products. The hypothesis is tested by a hypothetical choice experiment with 788 samples in 15 cities in China. Attributes we take into account include traceability, farming style, brand and certificates, in addition to prices. The results indicate that the media coverage could significantly shape consumers' preference. A comparison of the two treatments indicates that the positive information treatment could yield smaller WTP values for all attributes related to food quality and safety.

JEL: Q13, Q18

***Keywords*:** Media coverage, , Choice experiments, Pork products, China

1 Introduction

Input pollution, market failure, and government malfunction are regarded as main factors behind the grim situation of food quality and safety (Caswell and Padberg, 1992; Zhou and Li, 2013; Resende-Filho and Hurley, 2012). A good way to tackle food safety issues is located at establishing an industry-wide quality and safety traceability system and effectively sharing information in the market (Caswell and Mojduszka, 1996; Wang and Sun, 2002; Zhou, 2006). Information sharing and risk communication are inevitably hinged to the media. In modern society, the media plays many important and complicated roles, such as informative role, educative role,

platform role, publicity role, adversarial role, and advocacy role. The media in turn could reshape consumer perception of food safety risks as a consequence of risk communication.

In the information age, the media, especially online media and social networking platforms (blogs, micro-blogs, etc.), are becoming increasingly influential because they could more easily disseminate food information, expose food safety risks, and track down the scandals (Liu et al., 2013; Men, 2012; Zhang, 2012). These media have become important supplementary channels for early warnings about vertical transmission and disclosures of market information (Jin, 2012). They have also gradually shaped consumers' expectation for the information on food quality and safety (Hoban and Kendall, 1993; Wang and Zhou, 2012; Wang et al., 2013) and can improve the efficiency of food safety risk communication. Undeniably, some media attempt to draw attention by exaggerating food safety risks or by spreading untrue rumors in order to gain more readers in an era of over-competition. These actions may cause enormous damage to public confidence in food safety and industrial development and eventually lead to public security crises (Volchkova and Zingales, 2008; Hong et al., 2014; Zhongand Kong, 2012). The interaction between media and the public is interesting and complicated.

Due to information asymmetry, consumers may make their decisions based on limited or false information, and suffer from information bias. Particularly, positive and negative media coverages have different impacts on consumer behavior. The current literature finds that negative media coverage usually has a greater impact on consumer behavior (Mizerski, 1982; Hayes et al., 2002; Morris and Shin, 2002) and, the pork market is no exception (Yan, 2015), as consumers tend to over-react to negative news.

In order to improve the efficiency of food safety traceability system, and regulate the risk communication of media, we must first precisely understand the impact of media on consumer preference under different media scenarios. It is speculated that that consumers may have different attitudes towards positive media coverage and negative media coverage. If so, careful and objective media report could increase the social welfare. Some regulation on media to prevent them from exaggerating food safety risks or from reporting untrue information is necessary.

In company with rapid income growth, meat consumption in China sees a rapid growth. Particularly, pork is the major meat consumed in China, sharing more than 60% of meat consumption (Yu and Abler 2014；Yu 2015). Hence, this paper specifically sheds light on pork products.

As the interaction between media coverage and consumer preference is widely recognized, this study tends to answer the two specific questions: (1) Is consumer preference (such as the pig farming style) different under different information scenarios (positive vs. negative media coverage) ? (2) Under different media coverage, does the law of "higher prices for better quality" hold.

In order to answer the two questions, we design a hypothetical choice experiment considering different scenarios of media coverage for consumer preferences, and estimate consumer willingness to pay for traceability pork with mixed logit models and latent class model (LCM). Such a design helps provide a quantitative base for comparison.

This study provides some insightful policy implications for consumer response to Chinese food traceability system, through better risk communication by the media.

2 Design of Choice Experiment and Survey

2.1 The design of the choice experiment

Choice experiment has been widely used for marketing and eliciting WTP values, and the design is detailed in Street and Burgess (2007), Sall (2012), and Johnson (2013). Gao, Yu and House (2010) highlighted potential bias of the design, and we must make a trade-off between information load and cognitive load. Less attributes could lead information bias, but more attributes could increase cognitive load for respondents, which make the results biased. They suggested that 5 attributes could be ideal.

Following this principle, we specifically take into account five attributes for pork products: farming style, traceability, certificate, brand, and price. Table 1 reports a representative design.

Due to information asymmetry, pork quality and safety cannot be precisely observed, so that food labels are often used as the proxy. The first attribute which could affect pork quality and safety is the faming styles. Compared with traditional captive farming, free range offers pigs more space and outdoor activities, which could make the meat with a firmer texture and better taste. Free range can also effectively reduce the incidence of diseases, so that the use of antibiotics, fungicides, and other drugs could be substantially reduced, increasing the quality and safety of fresh pork as well (Mørkbak et al., 2010).

Second, food supply involves in many players in the supply chain, so that is difficult to identify the culprit in case of food safety accidents. Traceability provides an effective tool to identify the problem in the supply chain. Usually, a “tracing code” or “tracing mark” can be printed on a store receipt or on the package. These labels could help consumers trace back the supply chain, for instance, the name and location

of the slaughterhouse, and the farmer's information. When safety issues arise, one can use the tracing code to track down the slaughterhouse or the farmer, to see where the problem is.

Third, brand and product certification labels are important product attributes that Chinese consumers use to ensure the safety and quality of pork (Ortega et al., 2011). These two attributes hence are included as well.

Finally, price information must be included in experimental design, which can be used for calculating WTP values (Gao, Yu and House 2010). The price of pork was set based on previous studies and market real price information (Adamowiczand Wright, 2005; Medicamento et al.,2006;Mørkbak et al., 2010; Ohler et al., 2000; Tonsor et al., 2009). Weekly pork retail prices between May 2012 and June 2014 were obtained from the relevant websites of the Chinese cities where the traceability system is actually implemented. If the prices are not available in these cities, we use the price information from the corresponding provincial price bureaus.

The mean price was 12.05 yuan/500g. However, we set the base price as13 yuan/500g, which is slightly higher due to the recent pork price increase. As the traceability is very costly, we propose two high price scenarios, which are 18 yuan/500 g and 25 yuan/500g respectively. Following Hensher et al. (2005) and Loureiro and Umberger (2007), we use the JMP software to generate 12 scenarios of choice sets, which are orthogonal and efficient. They are put in random order in order to reduce the order bias. Fig.1 shows a choice scenario, in which we particularly add a non-purchase alternative, representing opt-out or status quo.

2.2Information treatment

As aforementioned, media coverage may affect consumer preference. In order to

test this hypothesis, we first use web database technology to collect the media report in the webpages, and then conduct a semantic analysis of the big data, to categorize all related news reports into two groups: positive report and negative report based on the reporting tones. It is obvious that pork prices are negatively correlated with the scale of negative media coverage（Yan, 2015）

In order to quantitatively compare the impacts of different media coverages, we set up an information treatment before the choice experiments. We prepared some cards with different media reports, and asked the respondents to randomly select a media report card, and read it before the choice experiment.

The pork product used in this study is the fresh boneless pork leg, which the most popular cut of pig meat in China. A picture of the meat product is presented during the survey (Fig. 2).

2.3 Survey design

The choice experiments are conducted in the three groups of pilot cities which implement the traceability system of meat products. The first group included Shanghai, Hangzhou, Ningbo, Chongqing, Qingdao, and Nanjing; the second group comprised of Hefei, Nanchang, and Jinan; and the third group consists of Taiyuan, Zhengzhou, Changsha, Nanning, Xi'an, and Weifang. In addition, Wuhan is selected for comparison and representative for the central China.

The respondents must be 18 years old or above and familiar with food consumption patterns of their families (Olynk et al., 2010). The survey methods combine both face-to-face interviews and online surveys. The interviewers who performed the field interviews are 16 college students recruited from Zhejiang University's School of Management whose homes are located in one of the 16 pilot cities. They had one day training before the survey. The face-to-face interviews were

conducted in supermarkets, farmers' markets, or other shops which have a large population density. The online survey was conducted by a professional survey company, SOJUMP, which provided 40 samples for each of the 16 piloting cities. 400 questionnaires were collected from the field survey, and 640 from the online survey from July 15, 2014 to September 15, 2014. The proportions of positive and negative media coverages are basically even.

3 Model Design

3.1 The mixed logit model and the willingness to pay estimation

The mixed logit models and latent class models have been widely employed to capture the consumer heterogeneities in choice models. McFadden and Train (2000), Train and Sonnier (2003) considered the mixed logit model as a highly flexible model that can well approximate the random utility model. It relaxes the limitations of the standard logit model by allowing the taste parameters to vary randomly according to a parametric distribution. It also allows for unrestricted substitution patterns and correlation in unobserved factors over time (Train 2003, 2009; Hensher and Greene 2002).

Under RPL, consumer utility V_{njt} in the random utility model takes the form (Ortega, et al., 2011) of:

$$V_{njt} = \beta x_{njt} + \varepsilon_{njt}, \quad (1)$$

wherex_{njt} is a vector of the observed variables that includes the pork attributes and the socioeconomic characteristics of pork consumers; β is the corresponding parameter vector, which has the density $f(\beta|\theta)$; θ is a vector of the parameters of a continuous population distribution; and ε_{njt} is an observed random term that is assumed to be identically and independently distributed. Conditional on β, the

probability that individual n chooses alternative i in a choice set t is the conditional logit specification:

$$L_{nit}(\beta) = e^{\beta x_{nit}} / \sum_j e^{\beta x_{njt}}, \quad (2)$$

3.1.1 Mixed Logit model

The mixed logit, also called random parameters model, is defined as

$$P_{nit} = \int L_{nit}(\beta)\, f(\beta|\theta) d\beta \quad (3)$$

The coefficient β is random continuous heterogeneity following some distribution. Although a mixed logit model accounts for preference heterogeneity by allowing taste parameters to vary randomly over individuals, it is not well suitable to explain the source of heterogeneity. Instead, the latent class models are more suited to explaining the source of heterogeneity because individuals are intrinsically sorted into a number of latent classes (Boxall and Adamowicz, 2002; Ouma et al., 2007).

3.1.2 Willingness to pay

The current literature (e.g. Gao, Yu and House) shows that the WTP values for attribute k is,

$$WTP_k = -\beta_k / \beta_p, \quad (4)$$

Where β_k is an estimated parameter for the pork-specific attribute in the case of the conditional logit model and an estimated mean in the case of the mixed logit model; and β_p is the estimated price coefficient. We adopted the methods proposed by Revelt and Train (2000) to estimate individual-level parameters . A delta method is used to obtain the standard errors of the derived willingness-to-pay values (Hole, 2007). After that, the two-sample t-test is used to determine if two group's WTPs on each attribute are equal. Thus, we can test the difference of the impact of information treatment on consumer WTP values.

3.2 The latent class model (LCM)

The mixed logit though can take into account consumer heterogeneities; it can not specify the heterogeneities. An LCM can provide a more intuitive explanation for the sources of heterogeneity. It classifies respondents into groups with different preferences based on their individual and socio-economic characteristics.

When $f(\beta|\theta)$ is discrete and β represents a finite set under a particular valuation (Train and Sonnie, 2003), the members within each group have the similar preferences. These classes are computed using the probability distribution function estimated by the logit model. If a latent class q is identified within Q classes, the probability of the *n*-th consumer selecting option *i* in scenario *t* is:

$$P(nit|c) = \prod_{q=1}^{Q}[\exp(\beta_q x_{nit}) / \sum_{j=1}^{J} \exp(\beta_q x_{njt})], \quad (5)$$

Where x_{nit} is the vector of the observable quality and safety attributes of the *i*-th option; β_q is the parameter vector for different groups; and t is the number of times that the *n*-th consumer visited the experimental scenario. β_q represents the preference heterogeneity among the different groups. The probability estimate of this model is as follows:

$$P(c) = \exp(z_t'\gamma_q) / (\sum_{q=1}^{Q} exp\,(z_t'\gamma_q)). \quad (6)$$

When γ_Q=0, z_t is a series of observed characteristics that affects classification of consumer *n* into a certain latent class.

4 Results and discussion

4.1 Descriptive Statistics

After excluding incomplete responses, we obtain 429 samples with positive media coverage, and 359 for negative media coverage. That is, a total of 788

samples are used for the final econometric analysis. A descriptive statistics is presented in Table 2.

The share of female respondents is 57.8%, higher than that of male respondents. It is reasonable as food purchase in China is mainly conducted by females. The mean age falls into the category between 36 and 40years old. The mean value for education categories is 2.89, which implies that more than half of the respondents have college education. It shows that the samples might be slightly biased towards high education group, though the average education level has been significantly improved after 1980s. However, the survey was conducted in main cities in China, the education in urban areas is higher than rural areas, In addition, more than half of the samples were obtained from on-line surveys, and the population accessing to internet in China generally have better education than those without internet accessing.

4.2 Estimation of Random Utility Model

The 788 respondents yield 9456 choices (788*12=9456), in which 5148 choice decisionswere made under the influence of positive media coverage and 4308 under the influence of negative media coverage.

The estimation results with the mixed logit model accounting for consumer heterogeneities are reported in Table 3. In particular, we report three different results with different samples: full sample model, only the samples with positive media coverage, and only the samples with negative media coverage.

The model fits data very well, as all parameters in all three models are statistically significant, and the magnitudes of the estimated parameters are similar except for the coefficient of farmer information. It implies that the media coverage could significantly change consumer attitude towards farmer information, but no

significant impact on other parameters, such as traceability, brand and certificate.

The coefficients for opt-out are negative and significant for all three regressions. It implies that no purchase of pork production in China actually reduce the consumer welfare. Yu and Abler (2014) pointed out that more than 60% of meat consumed in China is pork meat.

4.3 Calculating willingness to pay in mixed logit

After estimating the mixed logit model, we can calculating the willingness to pay values which could provide a quantitative benchmark for comparing the consumer preference under different media influence. The mean WTP values are reported in the first three columns of Table 4. The results indicated that respondents were willing to pay more for brand and certificate than for farmer information and farming style labels. Hobbs et al. (2005) reached the similar conclusion in their experimental study on Canadian consumers. Consumers valued the certification label more than the farmer tracing label, indicating a low WTP value for farmer traceability.

Comparisons of payments for the four attributes with two types of media coverage indicate that negative information increased consumers' WTP's for farmer information and free-range farming labels while decrease their WTP's for brand and certification labels. The results confirmed the conclusion of Lee et al. (2011): Information affects consumer preference.

The results of this study show that negative information has a significant impact on consumer WTP for the farmer traceability label (Table 4). The "bad news hypothesis" proposed by Swinnen et al. (2005) is confirmed from a different perspective. In particular, the media tend to report negative events, as the adversarial role. Fundamentally speaking, consumers understand the implicit negative

information in the news and often tend to overreact to the bad news. Information is valuable. Nayga et al. (2006) and Roessler (2008) discussed how policymakers should make use of public education system to change consumer perceptions of traceability, improve existing tracing systems, and extend traceability from the slaughterhouse to the original producer(e.g. farmers) to eliminate the influence of negative reports on the current tracing system.

4.4 Estimation of LCM

To identify the sources of the heterogeneity in different groups' WTP for pork quality and safety attributes, the results of the negative and positive information groups are separately estimated by using an LCM. The Bayesian information criterion (BIC) proposed by Boxall and Adamowicz (2002) is used to identify the number of preference groups: We find that there are four preference groups[1] both in the cases of positive and native media coverage. The final preference group classification and their corresponding parameters are reported in Table 5.

4.4.1 Consumer preference with positive media coverage

In the group with positive media coverage, respondents showed four types of preferences for traceable pork quality and safety traits: price (G1), brand (G2), source information (G3),and certificate (G4), which accounted for 28.9%,24.5%, 21.2%, and 25.4% of the treatment group, respectively. In the first group, the price coefficient is positive and statistically significant at 1% level, indicating that consumers in this class tend to “pay higher prices for better quality”. The characteristics of these respondents

[1] The BIC values were7803.10, 7560.7320, 7286.9350, and 7217.9770 for positive information groups 2, 3, 4, and 5, respectively. The BIC values were6658.22, 6502.362, 6377.502, and 6336.293 for negative information groups 2, 3, 4, and 5, respectively.

also indicate that they have a relatively high level of education and that most have family members over 65 years old. This conclusion was similar to that of Antle (2001) and Yu, Gao and Zeng (2014), who finds that when there are young children or elderly people who are more vulnerable to health risks in the family, the family are willing to pay higher prices to avoid potential food safety risks. Another characteristic of this class is that they used social networking platforms or checked online news less frequently.

The respondents in the second class, the brand preference group, are mostly middle-aged men, who were less responsible for household food procurement. Regarding community involvement, they seemed to rarely pay attention to social networking or news. Consumers in this class show a certain level of risk aversion to traceable pork quality and safety.

In the third class, the source information preference group, the coefficients for farmer tracing information and farming style information are greater than those of the other three groups and statistically significant at the 1% level. When the coefficients for individual characteristics are estimated, the respondents in the source information preference group may have the highest risk perception for pork quality and safety risks in all four groups, indicating that those in this class may be more inclined to avoid potential quality and safety risks that can lead to economic or health losses. The respondents in this class do not use social networks such as Wechat and qq frequently and rarely search for food-related or technical information. Therefore, once they were exposed to positive information, they were willing to pay slightly more for a traceable farmer information label than for a general quality label that enable slaughterhouse tracing. They show a certain degree of price sensitivity. Therefore, the mean willingness-to-pay coefficients for additional farmer information and farming style

information are only 0.215 and 0.278, respectively.

We make the class 4 as a reference for the other three groups, the coefficients of the individual characteristics and the social and psychological characteristics for the G4 class of were set to zero. The certificate-preferring class primarily consists of young families with higher incomes; a low proportion of these families with members over 65 years old, and they frequently use Wechat and qq and paid close attention to online news and food information. They use social networks to obtain information. Information from informal channels could be disseminated more efficiently and effectively and, consequently, become an important factor in decision making. Grebitus et al. (2014) found that US consumers who frequently used social media to search for food information are willing to pay more for cheese with an antibiotics-free label. In addition, the perception of a lower risk made them more willing to try new things and pay more attention to quality of life, and, consequently, willing to pay more for the high quality guarantee of the certification label (Wu, Wang, and Hu, 2014).

4.4.2 Consumer preference with negative media coverage

The regression results of the LCM in the negative information treatment group indicate that the respondents have significantly different preferences for pork quality and safety labels than the respondents in the positive information treatment group. Class N1 has the greatest certificate coefficient. In addition, the respondents in this class prefer farmer traceability to the respondents in the other classes. The respondents in class N2 are more sensitive to price than other classes.

Class N3 has the greatest coefficient for free-range farming information in comparison with other classes. Although this coefficient was lower than those of the

other three attributes, it was substantially different from those of other three classes, consistent with the conclusions of Oglethorpe (2011) and Van Loo et al. (2014). They find that British consumers are willing to pay more for the free-range farming label than the organic label or the carbon cycle label. Vanhonacker et al. (2008) indicate that most consumers who preferred free-range farming concern about animal welfare. In China, the free-range farming label is generally used as an index of quality for most consumers. However, due to lack of a unified free-range farming standard or certificate of quality, it has not generally led to higher prices. The coefficient for brand preference is 1.096, close to that of class N1 (1.197). We believed that there might be some correlation between consumer preferences for farming style and for brand information in the actual market as 25.5% of respondents show up simultaneously in the farming style information preference class and in the brand preference class.

In class N4, the price coefficient is 0.010, statistically significant at 5% level. It indicates a weak price preference. The LCM-based analysis indicates that pork consumption habits, social networking frequency, and the frequency of internet use are the main determinants of preference heterogeneity.

The respondents in class N1 are characterized by a low level of knowledge of traceability for pork. They tend to choose pork products with certificate and farmer information labeling. The results of class N2 indicate that people who consume pork more frequently have relatively high price sensitivities, lower education levels, and low levels of risk aversion, perhaps due to a limited household expenditure budget. Families that consume more pork products could suffer from more loss of consumer surplus due to the price volatility driven caused by the negative media coverage of food safety incidence (Yu, 2014).

Compared with the characteristics of the first three classes, the fourth class has a

better understanding of pork traceability, less pork consumption, and higher risk-aversion. This group has an insignificant price coefficient, which indicates that the consumers in this class are not sensitive to price significantly. In practice, immediately after negative news coverage on food safety, consumers are more likely to buy less pork or even temporarily stop buying pork. It explains why the majority of the respondents in the negative information group prefer to buy high-quality pork with a variety of quality and safety guarantees or not to buy pork at all.

4.4.3 Comparison of WTP between positive and negative groups

In this study, the WTP values of respondents in different groups and classes are calculated based on the estimation results from LCM. The results are reported in Table 6. In the positive information group, respondents in the first class had negative preferences for free-range farming, brands, and the certificate. These families have elderly members and use social networks or follow food news less frequently, so that they have less capacity to access to food quality and safety information. Rather, they would pay a higher price for pork which they believe has higher quality and is safer. Brand is a main reference for the second's choice of traceable pork, and this class's WTP for a brand is the highest among all four classes. In the third class, the respondents' WTP's for traceability and free-range farming close to each other, and similar for the WTP's for brand and certificate , even though all WTP values are relatively low. No surprise that the certificate preference class yields the highest level of WTP for certification.

In comparison, the largest consumer WTP values in the negative information group for traceability and free range farming respectively show up in the first class (4.01) and the third class (5.66) . This result suggested that they are risk-averse. With

the stimulus of negative information, people overestimate health damage caused by the quality issues of untraceable pork, which could cause economic or emotional losses (Hu, 2010). Novemsky and Kahneman (2005) believe that there is no risk aversion to the loss of disposable money.

In addition, the largest WTP for brands occurs for the third class. According to the aforementioned LCM-based analysis, the brand information coefficient of the third class was only slightly different from the largest coefficient of the first class. The difference in WTP is cause by different magnitude of price coefficients between the two classes.

5 Conclusions and policy implications

Food safety is a key issue drawing a lot of attention in China. Particularly, the media reports help shape consumer attitudes towards to food quality and safety. By introducing different information treatment, we study the impact of different media coverage on consumer WTP for pork products, which share more than 60% of Chinese meat consumption. The hypothesis has been tested by a survey of 788 samples in 15 cities in China with hypothetical choice experiment. Attributes we take into account include traceability, farming style, brand and certificates, in addition to prices.

First, information treatment (positive vs. negative media coverage) has significant impact on consumer preference for the attributes of pork quality and quantity. In both treatment groups, the amounts of WTP for traceability and free range farming are low, while the highest WTP values occur for the certificate, followed by brand. A comparison of the two treatments indicates that the positive information treatment could yield smaller WTP values for all attributes related to food quality and

safety.

Second, according to the regression results from the LCM, there is preference heterogeneity in the WTP for pork quality and safety attributes. The respondents in the positive information group shows price preference, brand preference, source information (traceability and free-range farming) preference, and certificate preference. The negative information group shows clear preferences for mixed quality characteristics (traceability, brand, and certificate information) and free-range farming information.

Third, the major sources of heterogeneity included the frequency of internet use, the perception of food quality and safety risks, the perception of the consequences of food safety incidence, meat consumption frequency, and other individual socio-economic characteristics. When compared, the two groups have some differences in the sources of their heterogeneity. The main sources of heterogeneity for the positive information treatment group are household characteristics, the frequency of internet use, and the respondents' estimates of the consequences of food safety incidence. For the negative information group, the sources of heterogeneous preferences come from the perceived risks of pork safety incidence and the frequency of internet use.

Finally, to a certain degree, it is confirmed that people are willing to pay a "higher price for better quality" and for the safety of agricultural products. When news reports are positive, consumers are willing to pay more for safe and high-quality brands and certified products, which was conducive to the differential development of the market. When news reports are negative, consumers are willing to pay more for traceability and free-range farming labels, which helped them effectively identify the pork's source and farming

As the media could significantly shape consumer preference for the attributes of food quantity and safety, government and firms should pay attention to the media when there is a negative report. Effective risk communication is very important for reducing the impacts.

The traceability could help effectively identify the sources of food quality and safety incidents. Hence, it is necessary to expand the piloting area, and even a nation mandatory of traceability could be a good policy to increase food quality and safety subject to discussion.

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Pork label info.	**Option A**	**Option B**	**Option C**
Traceability	Farmer info	Slaughter info	Neither
Production	Captive range	Free range	A/B is
Brand	No	Yes	preferred
Certificate	Yes	No	
Price	25	13	
I would like to choose:(Please mark only one box)			

Fig. 1 Example of choice set question

Fig. 2 Fresh Hind Leg Pork Showed in Choice Experiment

Table 1 Attributes for pork products in choice experiments

Traits	Levels	Descriptions
Traceability	Binary	=1 if pork carries the label containing name of farmer, and its location
Free Range	Binary	=1 if the pork produced by free range
Brand	Binary	=1 if the pork product owns a brand
Certificate	Binary	=1 if the pork carries the label issued by government was inspected for safety standards
Price	13, 18 and 25	The price expressed in RMB(Yuan) per 500g

Table 2 Socio-demographic characteristics of the sample (*n*=788)

Variables	Description	Mean	SD
Age	1=18-25-years old; 2=26-35 years old; 3=36-45 years old; 4=46-55years old; 5=56-65years old; 6=65 or above	2.55	1.060
Gender	1=Male;0=Female	.422	.49391
Education	Uneducated or primary=1 Middle school=2; College and Undergraduate =3; Graduate or above=4	2.89	0.626
Family income	0<RMB 4000； 1>=RMB 4000	.854	14.59
No. of young members in the family	1=One or more; 0=None	.592	.4913
No. of elders in family	1=One or more; 0= None	.327	.4692
Food buyer	1=Always；0=little or never	.552	.4973
Meat consumption frequency	1=2-3times a week；0=less than that	.882	.3226
Knowledge about pork traceability	5-Liket scale, knowledge about traceable pork.	2.28	.9386
Perception of food safety risk	5-Liket scale	2.40	.8423
Perception of consequences of	5-Liket scale	2.79	.9594

food safety incidence			
Internet use frequency	1= Everyday or 2-3times a week for social networking and online news reading；0=few times than that	.817	.3866
Internet use frequency for food information	1=Everyday or 2-3times a week for search for food information online；0=fewer than that	.576	.4941

Table 3 Simulated maximum likelihood estimates from mixed logit model

	Full Sample		Positive Media		Negative Media	
	Mean coef.	SD coef.	Mean coef.	SD coef.	Mean coef.	SD coef.
Price	-0.0636***	NA	-0.0603***	NA	-0.0670***	NA
	(-17.43)		(-12.28)		(-12.34)	
Opt-out	-1.821***	NA	-1.810***	NA	-1.833***	NA
	(-24.89)		(-18.29)		(-16.93)	
Traceability	0.122***	0.138***	0.0862***	0.0475	0.164***	0.196***
	(6.76)	(3.40)	(3.69)	(0.35)	(5.88)	(4.15)
Freerange	0.207***	0.213***	0.190***	0.176***	0.223***	0.236***
	(11.23)	(7.24)	(7.82)	(4.03)	(8.04)	(5.50)
Brand	0.490***	0.311***	0.485***	0.277***	0.490***	0.328***
	(22.28)	(10.96)	(16.68)	(6.89)	(14.92)	(7.90)
Certificate	0.822***	0.652***	0.815***	0.675***	0.813***	0.598***
	(26.39)	(21.53)	(18.71)	(16.20)	(18.64)	(13.98)
No. of obs	28368		15624		12924	
Log likelihood at start values	-8055.7747		-4341.708		-3708.69	
Simulated log likelihood at convergence	-7778.3373		-4173.8581		-3599.5693	
LR chi2(4)	641.27***		381.81***		259.07***	

Notes: ***, **, * represent significant variables at 1%, 5% and 10% levels, respectively. T-values are in parentheses..

Table 4 WTP means across the information treatments

Attribute	Full Sample (n=788)	Positive Media (n=429)	Negative Media (n=359)	Mean WTP differences (P and N)	t-value	df
Traceability	1.91[a][1.35[1], 2.48[2]]	1.43[0.67, 2.19]	2.43[1.60, 3.29]	-1.02	-16.64**	786
Freerange	3.25[2.64, 3.86]	3.12[2.30, 4.00]	3.35[2.45, 4.22]	-0.19	-2.26**	786
Brand	7.70[6.66, 8.74]	8.05[6.53, 9.56]	7.34[5.66, 8.74]	0.74	3.90***	786
Certificate	12.92[11.34, 14.51]	13.57[1.16, 15.89]	12.20[10.03, 14.22]	1.39	2.25**	796

[a] Marginal willingness to pay estimates of pork attributes in RMB yuan from Mixed Logit Models
[1] Maximum: lower 95% confidence interval level
[2] Minimum: upper 95% confidence interval level
** Indicate WTP values statistically significant at 5% level.
*** Indicate WTP values statistically significant at 1% level.

Table 5 Maximum likelihood estimates of pork quality attributes from LCM

Variables	Positive Media				Negative Media			
	G1	G2	G3	G4	N1	N2	N3	N4
Utility function coefficients								
choice3	-1.802***	0.189	-6.755***	-3.191***	-5.410***	-7.677***	0.563	-1.807***
	(-7.02)	(0.44)	(-10.19)	(-6.11)	(-5.60)	(-9.98)	(1.71)	(-8.42)
Price	0.0342***	-0.0708***	-0.303***	-0.0420**	-0.165***	-0.356***	-0.0492**	0.0101
	(3.77)	(-3.57)	(-9.42)	(-2.05)	(-3.73)	(-8.51)	(-3.06)	(1.07)
Traceability	0.0628	0.137*	0.213**	-0.0430	0.663**	0.286**	0.0554	0.199***
	(1.65)	(2.08)	(3.23)	(-0.36)	(3.01)	(2.87)	(0.76)	(5.11)
Freerange	0.184***	0.170**	0.274***	0.0999	0.205*	0.159	0.279***	0.261***
	(5.25)	(2.73)	(3.74)	(0.91)	(2.03)	(1.55)	(4.16)	(7.12)
Brand	0.320***	1.251***	0.376***	0.659***	1.224***	0.368***	1.070***	0.286***
	(9.12)	(12.45)	(5.43)	(5.40)	(5.03)	(3.73)	(12.14)	(8.28)
Certificate	0.143***	1.500***	0.583***	1.733***	2.331***	0.724***	1.452***	0.227***
	(3.52)	(16.56)	(4.67)	(11.37)	(6.86)	(5.27)	(14.10)	(6.41)
Class membership coefficients								
Gender	0.241	-0.738**	-0.0788		0.417	0.406	-0.298	
	(0.72)	(-2.05)	(-0.22)		(1.18)	(0.86)	(-0.90)	
Age	0.0979	0.773***	0.427*		0.0862	0.202	0.140	
	(0.39)	(3.37)	(1.71)		(0.46)	(0.94)	(0.81)	
Edu	0.611**	0.564*	-0.439		-0.243	-0.731**	-0.135	
	(2.05)	(1.90)	(-1.53)		(-0.77)	(-1.98)	(-0.46)	
Income	-0.175	-0.856*	0.00781		-0.00665	-0.610	-0.281	
	(-0.38)	(-1.86)	(0.02)		(-0.01)	(-1.01)	(-0.57)	
No. of young members in the family	0.133	0.653*	-0.557		-0.444	0.0574	0.172	

	(0.37)	(1.86)	(-1.50)	(-1.26)	(0.13)	(0.50)
No. of elders in family	0.834**	-0.653*	-0.493	-0.401	-0.467	-0.317
	(2.45)	(-1.70)	(-1.13)	(-1.15)	(-1.11)	(-0.99)
Meat consumption frequency	0.141	-0.699**	-0.0677	0.579	-0.286	-0.204
	(0.41)	(-1.96)	(-0.17)	(1.49)	(-0.60)	(-0.57)
Food buyer	0.160	-0.310	-0.496	-0.0538	2.113*	-0.460
	(0.32)	(-0.64)	(-0.96)	(-0.11)	(1.70)	(-1.02)
Knowledge about pork traceability	-0.0003	-0.152	-0.116	-0.338*	0.0202	-0.124
	(-0.00)	(-0.83)	(-0.56)	(-1.78)	(0.09)	(-0.70)
Perception of food safety risk	0.293	-0.361	-0.565**	-0.723***	-1.024***	-0.274
	(1.38)	(-1.54)	(-2.10)	(-2.80)	(-3.06)	(-1.19)
Perception of consequences of food safety incidence	0.169	0.464**	0.539**	0.179	0.225	0.135
	(0.82)	(2.30)	(2.30)	(0.81)	(0.81)	(0.66)
Internet use frequency	-1.040*	-1.357**	-0.0508	0.721	0.741	0.796*
	(-1.93)	(-2.18)	(-0.09)	(1.32)	(1.19)	(1.57)

Internet use frequency for food information	-0.138	0.733*	-1.162***		0.104	-0.333	0.0644	
	(-0.39)	(1.72)	(-3.07)		(0.23)	(-0.66)	(0.15)	
Constant	-2.617	-1.343	1.829		1.303	0.663	0.486	
	(-1.79)	(-0.92)	(1.22)		(0.89)	(0.35)	(0.38)	
N	15300				12564			
Latent class probability	0.289	0.245	0.212	0.254	0.236	0.169	0.255	0.340
Log likelihood	-3443.4364				-2994.6007			
No. of groups	429				359			

Notes: ***, **, * represent significant variables at 1%, 5% and 10% levels, respectively. t-values are in parentheses.

Table 6 WTP for pork attributes from LCM under different media coverage（rmb/500g）

Attribute	Class1	Class2	Class3	Class4
Positive media info.				
Traceability	-	1.93*	0.70***	-
		[-1.96, 4.07]	[0.25, 1.15]	
Freerange	-5.40***	2.39**	0.90***	-
	[-9.28, -1.52]	[0.19, 4.60]	[.42, 1.39]	
Brand	-9.37***	17.67***	1.23***	15.69*
	[-14.59, -4.15]	[6.75, 28.59]	[0.75, 1.73]	[-1.37, 32.75]
Certificate	-4.18**	21.18***	1.92***	41.28**
	[-7.54, -8.15]	[10.00, 32.36]	[1.13, 2.71]	[2.30, 80.25]
Negative media info.				
Traceability	4.01***	0.80***	-	-
	[2.69, 5.32]	[0.27, 1.33]		
Freerange	1.24**	-	5.66*	-
	[0.13, 2.33]		[1.34, 9.99]	
Brand	7.40***	1.03***	21.74***	-
	[4.10, 10.69]	[0.55, 1.52]	[7.23, 36.25]	
Certificate	14.09***	2.03***	29.52***	-
	[9.25, 18.92]	[1.37, 2.69]	[11.03, 48.02]	

Notes: ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively. "–" indicates that the estimated coe□cient is not statistically significant, and the WTP value is not calculated. [] represents Interval at 95% Conf..