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Measuring consumer heterogeneous preferences for pork traits under media reports: choice experiment in sixteen traceability pilot cities, China

*Zhen Yan, Jie-hong Zhou**

School of Management, Zhejiang University, P.R. China

Abstract: An increasing number of recent media reports on pork safety problems at source have attracted great attention and thought to be a growing threat to risk perception amplification on pork safety, even leading to public panic. This paper was among the first to explore the impact of media report about potential benefits and risk of traceability on consumer utility valuation and preference heterogeneities for select pork traits. By capturing key issues from online media reports in last three years both on benefit and risk as information shock showed to interviewees, we investigate willingness to pay from 788 consumers across sixteen traceability pilot cities, China. The findings indicate that consumers value certification more than other pork traits, while only preference on farmerinfo labeling significantly imcreases in negative information group. Highly valued farmerinfo and free range labeling in same class from positive information shock, while consumer preference for free range in one class from negative group.

*Corresponding author

1 Introduction

Environmental pollution at the sources of agricultural production, market failure and government regulation failure are the important factors behind the grim situation of the quality and safety of agricultural products (Caswell and Padberg, 1992; Zhou and Li, 2013; Resende-Filho and Hurley, 2012). Therefore, the key to solving food safety problems is effective information sharing in the market (Caswell and Mojduszka, 1996; Wang and Sun, 2002; Zhou, 2006). The establishment of an industry-wide quality and safety tracing system is considered the fundamental measure needed to solve food quality and safety problems. As the main social supervisor, the media supervises public opinion and transmits information on food safety. In the information age, media, especially online media and social networking platforms (blogs, micro-blogs, etc.) are becoming increasingly influential because they significantly increase the spread of information on food quality and safety, expose food safety issues, and follow up on events (Liu, Liu and Miao, 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). These media have also gradually changed consumers' expectations concerning information on the quality and safety of agricultural products (Hoban and Kendall, 1993; Wang and Zhou, 2012; Wang, Sun, and Yang, 2013) and can improve the efficiency of food safety supervision. Undeniably, some media try to attract attention by generalizing problems and companies and by spreading rumors on the internet or through social media to promote inter-enterprise competition by converting an initially single food risk signal, which is potentially a technical risk, to a social risk and aggravating the uncertainty concerning food production, distribution and consumption. These actions will cause enormous damage to public confidence in food safety and industrial development and may eventually lead to a public safety crisis (Volchkova and Zingales, 2008; Hong, Wu and Yang, 2014; Zhong and Kong, 2012). In addition, negative and positive media coverage have different impacts on consumer behaviors: negative media coverage has a greater impact on consumer behavior (Mizerski，1982； Hayes et al.，2002； Morris and Shin, 2002). To use social forces properly in regard to food quality and safety supervision, guide the media into a positive role concerning food quality and safety supervision, and promote the creation of a food quality and safety tracing system through market incentives, this paper focuses on the following questions: (1) Is the consumer’s willingness to pay heterogeneous in the face of information (positive and negative), such as the pig farming style, on pork sources? (2) What characteristics of consumers explain the heterogeneity in their willingness to pay? (3) How does media coverage affect whether the agricultural market price can break its lemon laws to charge “higher prices for better quality” and to allocate products on the market effectively? Focusing on these three issues, we selected the key features and traits of pork quality and safety as the target, scientifically set up an experiment involving 12 traceable pork scenarios, used the mixed logit model and latent class model (LCM), fully considered the heterogeneity of different types of media coverage on consumer preferences, focused on an in-depth study of consumer preferences and consumers' willingness to pay for traceable pork with different quality and safety traits, and analyzed the sources of heterogeneity on the basis of aspects such as individual characteristics and family structure. Our study provides a valid scientific basis and reference for making decisions during the development of the policy on educating consumers about the Chinese food tracing system, improving the external media environment of the pork industry, and encouraging the government to establish a tracing system for agricultural products.

2 Experimental design and data source

2.1 The design of the choice experiment

The design of a choice experiment was described by Street and Burgess (2007), Sall (2012) and Johnson (2013). First, five characteristic traits of pork were determined: farming style, traceability, certificate, brand, and price. The five labels are shown in Table 1. The quality of fresh pork is experiential and difficult to distinguish by examination; as a result, the farming style label can help the consumer determine the pork's quality. Compared with traditional captive farming, free farming gives pigs more outdoor activities and spacious pigsties supplemented with hay, wheat bran, etc., giving their meat a firmer texture and better taste. In addition, free farming can effectively reduce the incidence of disease during pig farming and, therefore, the use of antibiotics, fungicides, and other drugs, contributing to the quality and safety of the fresh pork (Mørkbak et al., 2010). A "tracing code" can be printed on a store receipt or a "tracing" mark can be printed on the packaging. These labels can include the name and location of the slaughterhouse or more details, such as the farmer's name and information about the farm. When safety issues arise, one can use the tracing code to track down the slaughterhouse or farmer that is legally accountability; brand and product certification labels are important product traits that Chinese consumers use to ensure the safety and quality of pork (Ortega et al., 2011). The price of pork was set based on previous studies (Adamowicz and Wright, 2005; Medicamento et al., 2006; Mørkbak et al., 2010; Ohler et al., 2000; Tonsor et al., 2009). Weekly pork retail prices from May 2012 to June 2014 were obtained from the websites of the Chinese cities piloting the tracing system or from the provincial price bureaus. The mean was 12.05 yuan/500g. According to the dynamic pork price report published by the Market and Economy Division of the Ministry of Agriculture, the month-to-month rise increase in pork prices is expected to be 4.9% (China Agricultural Information Network, http: //pfscnew.agri.gov.cn/). We set the base price of pork to 13 yuan/500g for the experiment based on retail price information from farmers markets, supermarkets, and specialty stores. The other two price levels were set assuming a 40% increase from the base price, i.e., 18 yuan/500 g and 25 yuan/500 g, to keep the prices in a reasonable range. Then, the minimum number of choice groups generated using the cross effect of the two attribute levels proposed by Hensher et al. (2005) and the main effects of key traits (Loureiro and Umberger, 2007) were used with the optimization capability of the JMP software package to determine the 12 attribute combinations that were used simulate the actual decision-making scenarios (Fig. 1, choice scenario). At the last step was to reduce the choice bias caused by order effects. Four different scenarios were configured and used in a random order in the choice experiment.

2.2 Information shock

To verify the effect of information on Chinese market prices, we first built a monthly dynamic evolution chart showing the quantity and ratio of topic classification, reporting tones, etc., on pork quality and safety using Web database technology and a semantic analysis of big data and then, compared it with the market prices of pork. We found that monthly changes in the amount of negative coverage corresponded to an opposing trend in the price of price, and monthly changes in the amount of positive coverage showed a consistent trend with price increases. Therefore, we asked respondents to randomly select a card containing positive or negative media coverage before the choice experiment (edited based on media coverage data collected from the internet, e.g., Fig. 2 and Fig. 3). Fresh boneless pork leg, which is the most popular cut in China, was used as subject of this research to reduce the bias of respondents caused by the appearance.

2.3 Data sources

The study areas were selected randomly from three groups of pilot cities in the Chinese meat circulation tracing system. The first group included Shanghai, Hangzhou, Ningbo, Chongqing, Qingdao, and Nanjing; the second group included Hefei, Nanchang, and Jinan; and the third group included Taiyuan, Zhengzhou, Changsha, Nanning, Xi'an, and Weifang. We included Wuhan in the experiment as a representative of the central region because of its economic level and geographic location. Respondents were 18 years of age or older and were familiar with the food consumption patterns of their families (Olynk et al., 2010). The survey methods used included field interviews and online surveys. The interviewers who performed the field interviews were 16 undergraduate and graduate students recruited from Zhejiang University’s School of Management whose homes were located in one of the 16 pilot cities; they were trained on July 9. The interviews were conducted in densely populated supermarkets, farmers’ markets, cultural squares and other locations. The online survey was commissioned from a professional survey company, SOJUMP, which conducted 40 surveys in each of the 16 pilot cities. A total of 400 questionnaires were distributed for the field survey and 640 questionnaires were distributed for the online survey from July 15, 2014 to September 15, 2014; the questionnaires on different tones of news coverage accounted for approximately 50% of the total.

3 Methodology

3.1 The mixed logit model and the willingness to pay estimation model

Mixed logit model and Latent class models have been widely employed to relax the limiting assumptions in conventional logit and probit models. McFadden and Train (2000), and Train and Sonnier (2003) describe mixed logit as a highly flexible model that can approximate and random utility model. It relaxes the limitations of standard logit 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, the deterministic component of utility V_{njt} in the random utility model takes the form of (Ortega, et al., 2011).

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

where x_{njt} is a vector of observed variables that includes the pork attributes and socioeconomic characteristics of the pork consumers. β is unobserved for each n and varies in the population with the density $f(\beta|\theta)$, θ is a vector of parameters of a continuous population distribution.ε_{njt} is an observed random term, which is assumed to be identically and independently distributed. Conditional on β the probability that individual n choose alternative i in a choice set t, is the conditional logit specification

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

Mixed Logit model (Random parameters model)

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

The coefficient β, is random continuous heterogeneity. Although mixed logit accounts for preference heterogeneity by allowing taste parameters to vary randomly over individuals, it is not well suited to explaining the source of heterogeneity. Latent class models are more suited in explaining the source of heterogeneity, since individuals are intrinsically sorted into a number of latent class (Boxall and Adamowicz, 2002; Ouma, Andulai, and Drucker, 2007).

3.2 Willingness to pay

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

where β_k is an estimated parameter of the pork-specific attribute in case of the conditional logit model, and estimated mean or standard deviation parameter in case of the mixed logit model; $\beta_p$is the estimated price coefficient. A Delta method is used to obtain the standard errors of derived willingness-to-pay values (Hole, 2007).

***3.3** The latent class model (LCM)*

An LCM can provide a more intuitive explanation for the source 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), members of each group have the same preferences, and these classes are computed using the probability distribution function estimated by the logit model. If latent class *c* is the condition, then the probability of the *n*-th consumer selecting option *i* in scenario *t* is:

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

where x_{nit} is the vector of the observable quality and safety traits of the *i*th option, β_q is the parameter vector for different groups, and t is the number of times 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:

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

When γ_Q=0, z_t is a series of observed characteristics that affects whether consumer *n* is classified into a certain latent class, is the parameter vector of the consumer group for the *q*th class variable. In the present study, each of the 12 choice scenario was a combination of different traits designed for the respondents. Repeatedly selecting a particular combination of choices showed the effect of different quality and safety traits on consumers, which can be compared with prior estimations.

4 Results and discussion

Incomplete questionnaires were excluded before the regression data analysis, resulting in 429 questionnaires on positive media coverage, 359 questionnaires on negative media coverage, and a total of 788 questionnaires for the final data processing. The variables are described in Table 2. The number of female respondents was greater than that of male respondents, accounting for approximately 57.8%, which was greater than the proportion of women over the age of 18 (49.34%) living in China, according to the results of the sixth census. This result shows that the main agricultural market buyers were women. The class mean of age was 2.55 for respondents between 36 and 40 years old. The education levels of the respondents showed that most of the respondents had an associates or college degree, which may be because the respondents in the present study were from pilot cities, and most of them were young or middle-aged internet users. As the Chinese educational system has developed, more and more young people have received higher education (Wang and Gu, 2014; CNNIC, 2014).

4.1 Respondents' willingness to pay under media coverage

The data from the 788 choice experiments included 5148 choices made with positive information and 4308 choices made with negative information. StataSE 12.0 was used for the analysis, and the parameters estimated using the mixed logit model are shown in Table 3. Among the three classes of simulation results (all samples, positive information group and negative information group), option C (opt out) had no effect. All three of the models showed negative preferences at the 1% level of significance, indicating that consumers preferred to buy pork products with labeled quality traits over other options. The coefficient of the mean purchase price was significant at the 1% level in all three models. The model showed that, given different information, consumers preferred information on farmers, free-range farming, brand, and certification. The standard deviations of the estimated random parameter coefficients were all at the 1% level, indicating that there were significant differences between the coefficients. The estimated coefficients for other quality and safety information for all three sample types were positive and significant at the 0.01 level, indicating that increasing the quality and safety information on the pork had an increased effect on consumers.

4.2 How media coverage affects the estimate of consumers' willingness to pay

A mixed logit model was used to estimate consumer preferences for pork with two types of media coverage. The mean willingness to pay shown in the first three columns of Table 4 indicated that respondents were more willing to pay for brand and certificate than for farmer information and farming style labels. Hobbs et al. (2005) came to the same conclusion in their experimental study of Canadian consumers. Consumers valued the certification label more than the farmer tracing label, indicating a low willingness to pay for farmer traceability. Comparisons of payments for the four traits with two types of media coverage indicated that negative information increased consumer willingness to pay for farmer information and free-range farming labels and decreased willingness to pay for brand and certification labels. The results confirmed the conclusion of Lee et al. (2011): information affects the amount consumers are willing to pay. The results of the present study showed that negative information had a significant effect on the respondents' willingness to pay for the farmer traceability label. The "bad news hypothesis" proposed by Swinnen et al. (2005) in a recent study of food safety information also confirmed, from another perspective, that the mass media tends to report negative events. Fundamentally speaking, consumers' understanding of implicit negative information in news magnifies the possibility and severity of the negative impact on their welfare. An economic man's estimate of the effect of negative news is far greater than the effect of positive news, a result that is in line theories of prospects and endowment effects in that the value of an economic loss is greater than that of an economic gain. Therefore, consumer valuation of food quality and safety information that explains potential health risks or consequences was greater than the valuation of general risks or positive food safety information. Nayga et al. (2006) and Roessler (2008) discussed what use policy-makers should make of public education to change consumer perceptions of traceability, improve existing tracing systems, and extend traceability from the slaughterhouse to the source (the farmer) to eliminate the influence of negative reports on the current tracing system.

4.3 The heterogeneity of consumer preferences under media coverage using an LCM

To identify the source of the heterogeneity of different groups' willingness to pay for pork quality and safety traits, the results of the negative and positive information groups were estimated using an LCM. The Bayesian information criterion (BIC) proposed by Boxall and Adamowicz (2002) was used to select four preference groupings[1] based on the preference classification rules proposed by Ouma, Abdulai, and Drucker (2007) and Hole (2013). The final preference heterogeneity classification and corresponding parameters are shown in Table 5.

In the positive information group, respondents showed four types of preference 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. The first group had a price coefficient that was positive and significant at the 0.001 level, indicating that consumers in this class tended to "pay higher prices for better quality" when buying pork. The characteristics of this group of respondents also indicated that these respondents had a relatively high level of education and most had family members who were at least 65 years old. This conclusion was similar to those of Antle (2001), who found that when there are young children or elderly people, who are more vulnerable to health risks, in the family, the family is willing to pay higher prices to avoid potential food safety risks. Another characteristic of this group of respondents was that they used social networking platforms or checked online news less frequently. The respondents in the second group, the brand preference group, were middle-aged men who were less responsible for household food procurement. As for community involvement, they seemed to rarely pay attention to social networking or news. This group of respondents showed a

[1]The BIC values were 7803.10, 7560.7320, 7286.9350, and 7217.9770 for positive information groups 2, 3, 4, and 5, respectively. The BIC values were 6658.22, 6502.362, 6377.502, and 6336.293 for negative information groups 2, 3, 4, and 5, respectively.

certain level of risk aversion to traceable pork quality and safety. The third group, the source information preference group, had coefficients for farmer tracing information and farming style information that were greater than those of the other three groups and significant at the 1% level. When the individual characteristic coefficients were estimated, the respondents in the source information preference group showed the highest risk estimation toward traceable pork quality and safety risks of all three groups, indicating that they may be more inclined to avoid potential quality and safety risks that can lead to economic or health losses. Respondents in this group did not use social networks such as Wechat and qq often and rarely searched for food-related or technical information. Therefore, once they were exposed to positive information, they were slightly more willing to pay for a traceable farmer information label than for a general quality label that enabled slaughterhouse tracing, and they showed a certain degree of price sensitivity. Therefore, the mean willingness to pay coefficients for additional farmer information and farming style information were only 0.215 and 0.278, respectively. To make this group a reference for the other three groups, the coefficients of the individual characteristics and the social and psychological characteristics of this group, G4, were set to zero. The certificate-preferred group primarily consisted of young families with higher incomes; a low proportion of these families included seniors who were over 65 years old, and they used Wechat and qq and paid close attention to online news and food information. They used social networks to obtain information. Information from informal channels could be transferred more efficiently and effectively and, therefore, became an important factor in decision-making. Grebitus et al. (2014) studied US consumers and found that consumers who frequently used social media to find food information were more willing to pay for cheese with an antibiotic-free label. In addition, the perception of a lower risk made them more willing to try new things, pay more attention to life quality, and, therefore, more willing to pay for the high quality guarantee of the certification label (Wu, Wang and Hu, 2014).

The regression results of LCM from the negative information group indicated that the respondents had significantly different preferences for pork quality and safety labels than respondents in the positive information group. Group N1 had the greatest certificate coefficient. In addition, respondents in this group preferred farmer traceability more than respondents in other groups. Respondents in group N2 had a relatively greater sensitivity to price. In addition, group N3 had the highest level of recognition for free range farming information. Although this coefficient was lower than those of the other three traits, it was significantly different from those of the respondents in the other 3 groups, which was inconsistent with the conclusions of Gadema and Oglethorpe (2011) and Van Loo et al. (2014). They found that, for poultry, the British were significantly more willing to pay for the free range farming label than for the organic label or the carbon cycle label. Vanhonacker et al. (2008) explained that most consumers who preferred free range farming were concerned about animal welfare, and animals have more outdoor space in free range farming (due to its lower housing density and more freedom in activities). In China, the free range farming label is generally used as evidence of quality; however, due to the lack of a unified free range farming standard and certificate of quality, it has not generally led to higher prices. The brand preference coefficient was 1.096, which was close to that of group N1 (1.197). We believed that there was a certain association between the preferences for farming style and brand information of the respondents, which might have been because, in the actual market, a portion of what people pay for free range pork was transferred to the brand, and 25.5% of respondents were in both the farming style information preference group and brand preference group. In group N4, the price coefficient of 0.010 was significant at the 0.05% level, indicating a weak price preference. The LCM-based analysis indicated that pork eating habits, social networking frequency, and online news reading frequency were the main sources of preference heterogeneity in respondents' preference for pork quality and safety. The respondents in group N1 were characterized by their low levels of knowledge about traceable pork and risk; they tended to choose certificate and prefer farmer information. Group N2's results indicated that people who consumed pork daily were had relatively high price sensitivities, lower education levels and low levels of risk aversion. This might be due to a constraint on the percentage of the total household expenditure that was on food (rather than the impact of total household income, which was not significant in the present study). Families that preferred pork were more concerned about the consumer surplus decline due to the fluctuations in prices and production caused by negative news about food safety. Compared to the characteristics of the first three classes, the fourth group had a better understanding of pork traceability, consumed less pork, and was highly risk-averse. This group did not have a particularly strong preference for any of the four trait types but did have an insignificant price preference. In practice, for some time after negative news coverage of food safety, they were more likely to less pork or temporarily stopped buying pork, which also explained why the majority of the respondents in the negative information group preferred to buy high-quality pork that came with a variety of quality and safety guarantees or not to buy pork at all.

In summary, when the news was positive, income, whether there were elderly members in the family, perceptions of the severity of the consequences of the risk, frequency of finding food information online, and technological information provided the main basis for classifying consumer preferences for pork quality and safety. When there was a negative news report, education level, pork eating habits, level of perception about the risks, use of social networks, and level of attention to online news provided the main basis for classifying consumers' preference for pork quality and safety.

5 Conclusions and policy implications

By allowing two types of media-reported information, positive and negative information, we introduced a mixed logit model and LCM to estimate and analyze

Chinese consumers' preferences for pork quality and safety traits, its heterogeneity, and sources of heterogeneity. The twelve choice experiment scenarios were based on five characteristics: traceable information, farming style, brand, certificate, and price. Experiments were conducted on 788 respondents selected from three groups of traceable pork pilot cities in China. The results showed the following:

First, there were differences in respondents' preferences for quality and safety traits between the positive and negative information groups. In both groups, the amounts paid for the farmer information and free range farming labels were low, and the highest amount was paid for certificate followed by brand. A comparison of the two groups indicated that, in the positive information group, the respondents' willingness to pay for farmer traceability was the lowest of all of the traits. In the negative information group, the respondents were more willing to pay for farmer information than for a farming style label.

Second, according to the regression results from LCM, there was preference heterogeneity in the respondents' willingness to pay for pork quality and safety traits. Respondents in the positive information group showed price preference, brand preference, source information (farmer information and free range farming) preference, and certificate preference. The negative information group showed clear preferences for mixed quality characteristics (farmer, brand, and certificate information) and free range farming information.

Third, the major sources of heterogeneity consumers' willingness to pay for traceable pork included the frequency with which a respondent checked online and food-related news, the risk probability, and the respondent's perception of the consequences, eating habits, and other individual socio-economic characteristics. When compared, the two groups had some differences in the sources of their heterogeneity. The main sources of heterogeneity for the positive information group were household characteristics, frequency of checking online and food-related news, and the respondents' estimates of the consequences. For the negative information group, the sources of heterogeneous preferences for pork quality and safety were the respondents' estimates of the probability of incidents due to pork safety issues and the frequency with which they checked online news.

On the basis of these findings, we make the following recommendations for policies that will improve pork quality and safety.

Because of the online information platform, enterprises and producers should pay attention to the timeliness of the information disclosed when there are negative reports. When it is established, the tracing system should be vigorously extended to the sources and companies should be encouraged to voluntarily, with support from the government, establish a complete tracing system that covers the entire process. Farmers at the source should be included in the ripple effects that are fully traceable, and production information should be archived in the terminal market because this can help mitigate the social amplification of risk. Source information that combines traceability and farming styles can effectively improve consumers' willingness to pay for pork quality and safety and is encourages consumers to pay a "higher price for better quality" in the primary agricultural market. In the early stages of a full tracing system, the government can enhance its fiscal policy to support the establishment of farmer archives, encourage the promotion and popularization of production behavior recording, and focus on establishing unified farming technology standards and norms.

Companies should pay attention to the importance of labels that enable tracing, especially the collection of farmer information. From the perspective of product positioning and promotion, young target groups in social media and social platforms deserve more attention. The construction of a tracing system should be encouraged and integrated with brand building and the certification system to promote strategies that differentiate, diversify and personalize agricultural products to meet new demands in the new economic normal.

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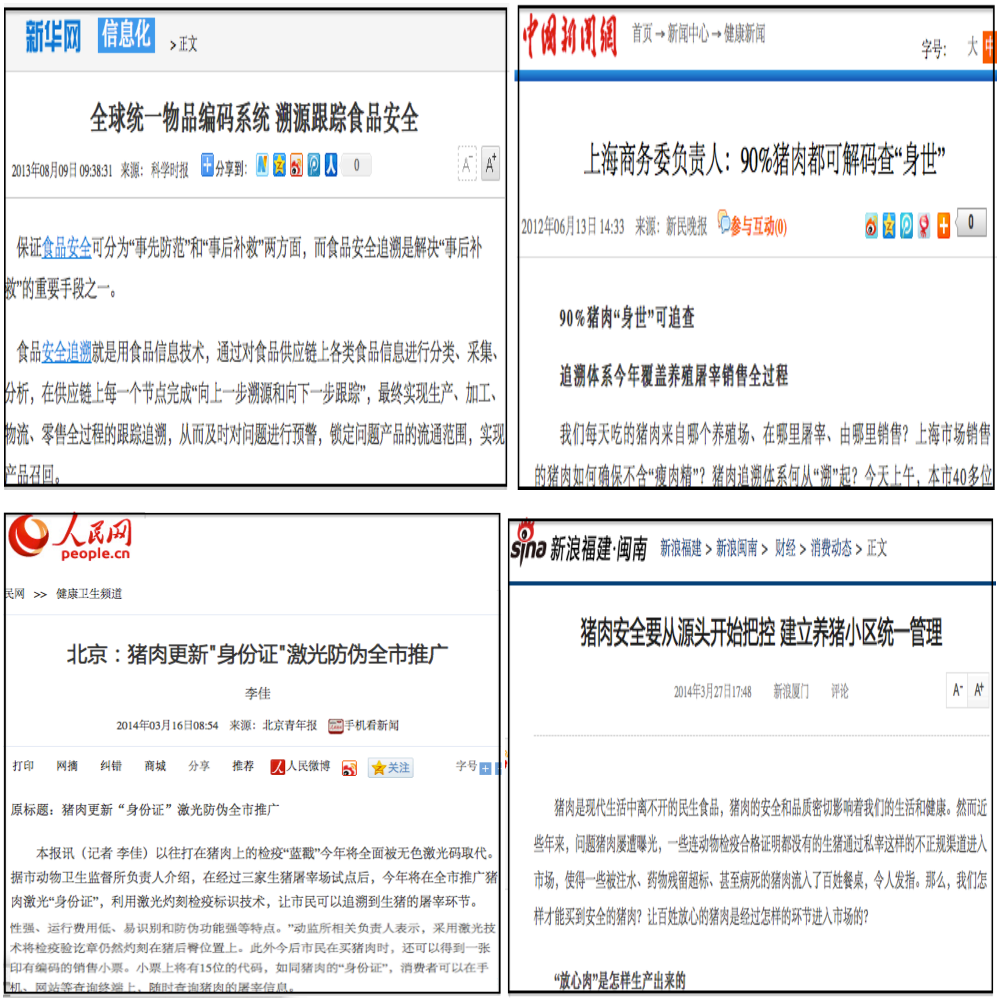
Pork label info.	**Option A**	**Option B**	**Option C**
Traceability	Farmer info	Slaughter info	Neither A/B
Production	Captive range	Free range	is preferred
Brand	No	Yes	
Certification	Yes	No	
Price	25	13	
I would like to Choose: (Please mark only one box)	□	□	□

Fig. 1 Example of choice set question



新华网 信息化 > 正文

全球统一物品编码系统 溯源跟踪食品安全

2013年08月09日 09:38:31 来源：科学时报 分享到： 0

保证食品安全可分为"事先防范"和"事后补救"两方面，而食品安全追溯是解决"事后补救"的重要手段之一。

食品安全追溯就是用食品信息技术，通过对食品供应链上各类食品信息进行分类、采集、分析，在供应链上每一个节点完成"向上一步溯源和向下一步跟踪"，最终实现生产、加工、物流、零售全过程的跟踪追溯，从而及时对问题进行预警，锁定问题产品的流通范围，实现产品召回。

中国新闻网 首页→新闻中心→健康新闻 字号：大 中

上海商务委负责人：90%猪肉都可解码查"身世"

2012年06月13日 14:33 来源：新民晚报 参与互动(0) 0

90%猪肉"身世"可追查

追溯体系今年覆盖养殖屠宰销售全过程

我们每天吃的猪肉来自哪个养殖场、在哪里屠宰、由哪里销售？上海市场销售的猪肉如何确保不含"瘦肉精"？猪肉追溯体系何从"溯"起？今天上午，本市40多位

人民网 people.cn

民网 >> 健康卫生频道

北京：猪肉更新"身份证"激光防伪全市推广

李佳

2014年03月16日08:54 来源：北京青年报 手机看新闻

打印 网摘 纠错 商城 分享 推荐 人民微博 关注 字号

原标题：猪肉更新"身份证"激光防伪全市推广

本报讯（记者 李佳）以往打在猪肉上的检疫"蓝戳"今年将全面被无色激光码取代。据市动物卫生监督所负责人介绍，在经过三家生猪屠宰场试点后，今年将在全市推广猪肉激光"身份证"，利用激光灼刻检疫标识技术，让市民可以追溯到生猪的屠宰环节。

性强、运行费用低、易识别和防伪功能强等特点。"动监所相关负责人表示，采用激光技术将检疫验讫章仍然灼刻在猪后臀位置上。此外今后市民在买猪肉时，还可以得到一张印有编码的销售小票。小票上将有15位的代码，如同猪肉的"身份证"，消费者可以在手机、网站等查询终端上，随时查询猪肉的屠宰信息。

sina 新浪福建·闽南 新浪福建 > 新浪闽南 > 财经 > 消费动态 > 正文

猪肉安全要从源头开始把控 建立养猪小区统一管理

2014年3月27日17:48 新浪厦门 评论 A- A+

猪肉是现代生活中离不开的民生食品，猪肉的安全和品质密切影响着我们的生活和健康。然而近些年来，问题猪肉屡遭曝光，一些连动物检疫合格证明都没有的生猪通过私宰这样的不正规渠道进入市场，使得一些被注水、药物残留超标、甚至病死的猪肉流入了百姓餐桌，令人发指。那么，我们怎样才能买到安全的猪肉？让百姓放心的猪肉是经过怎样的环节进入市场的？

"放心肉"是怎样生产出来的

Fig. 2 Positive Information Card of Media Coverage

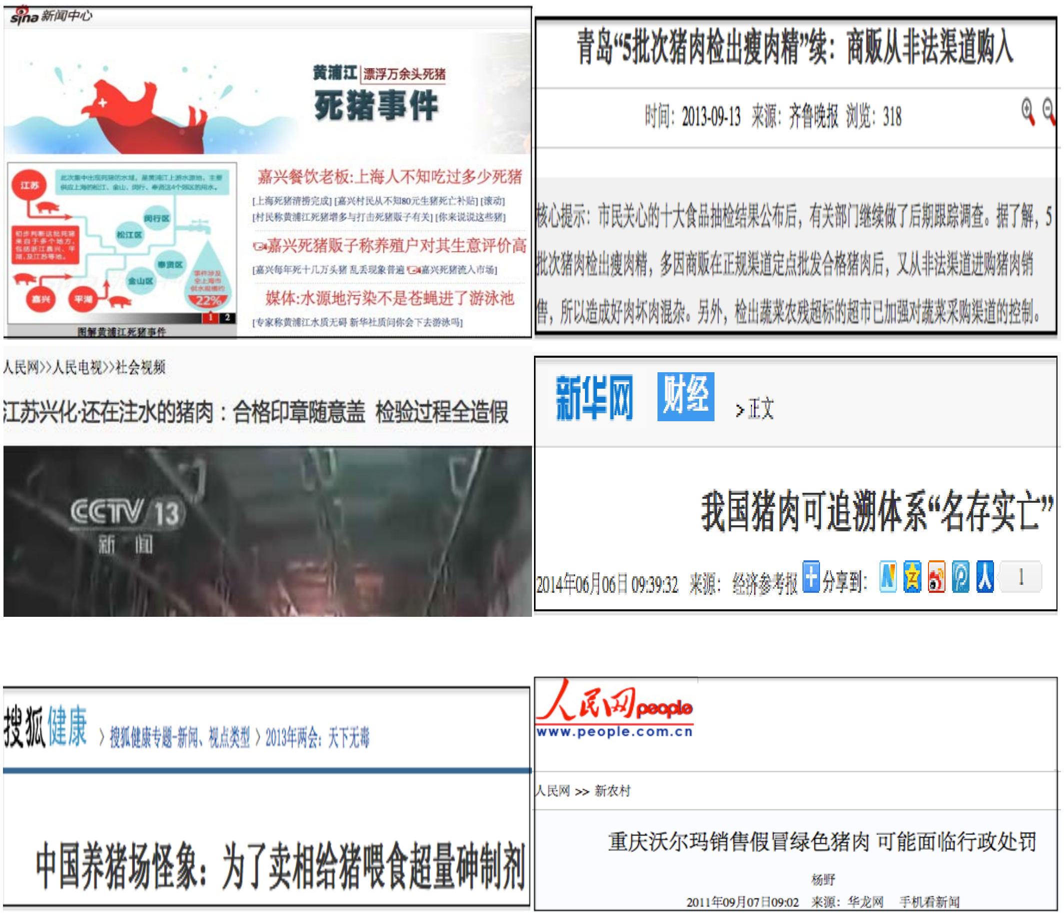


Fig. 3 Negative Info. Card of Media Coverage

Table 1 Traits and trait level of pork in choice experiments

Traits	**Levels**	**Descriptions**
Traceability	Binary	=1 if pork carries the label containing name of farmer, and its location
Production	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 in family	1=One or more; 0=None	.592	.4913
No. of aged in family	1=One or more; 0= None	.327	.4692
Household buyer	1=Always; 0=little or never	.552	.4973
Eating habit	1=2-3times a week; 0=less than that	.882	.3226
knowledge	5-Liket scale, knowledge about traceable pork.	2.28	.9386
Perception of risk prob.	5-Liket scale	2.40	.8423
Perception of	5-Liket scale	2.79	.9594

risk			
Tqnews	1= Everyday or 2-3times a week for social networking and online news reading; 0=few times than that	.817	.3866
Tqfnews	1= Everyday or 2-3times a week for finding food information online; 0=fewer than that	.576	.4941

Table 3 Simulated maximum likelihood estimates from mixed logit model

	Total		Positive		Negative	
	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)	
outopt	-1.821***	NA	-1.810***	NA	-1.833***	NA
	(-24.89)		(-18.29)		(-16.93)	
farmerinfo	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	Pooled (n=788)	Post. Info. (n=429)	Negt. Info. (n=359)	Mean WTP differences (P and N)
farmerinfo	1.91	1.43	2.45	-1.02
Freerange	3.25	3.14	3.33	-0.19
Brand	7.70	8.05	7.31	0.74
certificate	12.92	13.52	12.13	1.39

Note: Implicit price estimates of pork attributes in RMB yuan from Mixed Logit Models

Table 5 Maximum likelihood estimates of pork quality attributes from LCM

Variables	Positive info. group				Negative info. group			
	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)
farmerinfo	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. young	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. aged	0.834**	-0.653*	-0.493		-0.401	-0.467	-0.317	
	(2.45)	(-1.70)	(-1.13)		(-1.15)	(-1.11)	(-0.99)	
Eating habit	0.141	-0.699**	-0.0677		0.579	-0.286	-0.204	
	(0.41)	(-1.96)	(-0.17)		(1.49)	(-0.60)	(-0.57)	
Tbuy	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	-0.0003	-0.152	-0.116		-0.338*	0.0202	-0.124	
	(-0.00)	(-0.83)	(-0.56)		(-1.78)	(0.09)	(-0.70)	
Risk prob.	0.293	-0.361	-0.565**		-0.723***	-1.024***	-0.274	
	(1.38)	(-1.54)	(-2.10)		(-2.80)	(-3.06)	(-1.19)	
Risk reslt.	0.169	0.464**	0.539**		0.179	0.225	0.135	
	(0.82)	(2.30)	(2.30)		(0.81)	(0.81)	(0.66)	
Tqnews	-1.040*	-1.357**	-0.0508		0.721	0.741	0.796*	
	(-1.93)	(-2.18)	(-0.09)		(1.32)	(1.19)	(1.57)	
Tqfnews	-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.