Received: 27 June 2019 | Revised: 24 October 2020 | Accepted: 29 October 2020

DOI: 10.1111/agec.12613

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE
WILEY

ORIGINAL ARTICLE

The urban–rural gap in the demand for food safety in China: The role of food label knowledge

Satoru Shimokawa[1] | **Dezhuang Hu**[2] | **Dandan Li**[3] | **Hong Cheng**[3]

[1] School of Political Science and Economics, Waseda University, Tokyo, Japan (Email: s.shimokawa@waseda.jp)

[2] School of Economics, Zhongnan University of Economics and Law, Wuhan, China

[3] Institute of Quality Development Strategy, Wuhan University, Wuhan, China

Correspondence
Hong Cheng, Institute of Quality Development Strategy, Wuhan University, Wuhan, China.
Email: 919637855@qq.com

Abstract

Despite the national promotion of food safety measures, a substantial urban–rural gap remains in the demand for food safety in China. To explain this gap, we explore the role of knowledge of food safety labels. We measure demand using the marginal willingness to pay (MWTP) for the green food label and the organic food label for rice and pork in urban and rural areas. We employ discrete choice experiments and the control function approach to control for potential endogeneity problems. The results show that the MWTP for the labels is significantly positive among people with label knowledge but insignificant or even negative among people without label knowledge, and the urban–rural gap in the MWTP is larger among the former than among the latter. These knowledge-related differences explain 8–29% of the urban–rural gap in the MWTP for the green food label. Our findings imply that improving knowledge about the green food label could potentially be effective in reducing the urban–rural gap, while our results also imply the existence of a future challenge for the government in promoting label knowledge more effectively in rural China.

KEYWORDS
China, food label, food quality, label knowledge, urban–rural gap

JEL CLASSIFICATION
D12, Q13, Q18

1 | INTRODUCTION

China—an emerging middle-income country—has been experiencing a shift in consumer demand for food quality in terms of food security (such as total calorie and protein intake), food safety and, recently, other quality aspects such as taste, appearance, and the use of additives (Gale & Huang, 2007; Guo et al., 2000; Popkin, 2006; Tian & Yu, 2013). This paper focuses on food safety, which has been aggressively promoted by the Chinese government since 2000. More specifically, the paper first considers how much of an urban–rural gap remains in the demand for food safety in China by conducting discrete choice experiments in urban and rural areas. The paper then investigates the role of consumers' knowledge regarding food safety labels. Label knowledge matters because food safety is often apparently unclear to consumers, and thus, the demand for food safety is often observed as the demand for foods with labels that certify food safety. If label knowledge is lower in rural areas than in urban areas, the demand for foods with food safety labels may be lower in rural areas than in urban areas. Therefore, this paper focuses on an urban–rural gap in knowledge of food safety labels as a key explanation for the urban–rural gap in the observed demand for food safety.

In China, food safety measures (e.g., certifications and labels) have been extended step by step from the exporting sectors to urban consumers and, recently, to rural consumers (Wang et al., 2017). Currently, the majority of the rural population purchases most of their food at wet markets or supermarkets, as many rural residents are no longer self-sufficient food producers. According to our survey, 80% of rural respondents commonly purchase rice, and 98% commonly purchase pork at a market. Due to these socioeconomic changes combined with little political attention to food safety in rural areas until recently, rural consumers currently face greater food safety problems (e.g., lack of availability of safer foods) than do urban consumers. Thus, understanding the demand for food safety among rural consumers is becoming increasingly important for policy makers.

As a key food safety measure, this paper focuses on certification labels related to chemical residuals because labeling is one of the most actively promoted measures by the government and is also comparable between urban and rural areas in China. The Chinese government has adopted three levels of certification: organic food, green food, and no harm to public food. All certifications have a specific label. Organic food is the most stringent certification and is defined by the standards and definitions equivalent to those in other countries. Green food and no-harm-to-public food are certifications used only in China. No-harm-to-public food is the least stringent certification and is defined as having levels of pesticide residues, heavy metals, and microorganisms that are lower than those outlined by the government's safety standards. Green food is certified by satisfying special standards that are more stringent than those for no-harm-to-public food but less stringent than those for organic food (Yu, Gao, & Zeng , 2014). Green food certification has been the most aggressively promoted by the government, and the number of certified products reached 25,746 in 2017 (China Green Food Development Center).

However, green foods and organic foods are still much less available in rural areas than in urban areas. Thus, if the demand for the labeled foods were increasing in rural areas, there could be a gap between the increasing demand and the low supply of labeled foods in rural areas. Such a supply-demand gap in fundamental goods such as safe foods can cause social unrest, making this an important issue for the Chinese government. At the same time, labeling is used mostly for packaged foods at supermarkets, and supermarkets are less common in rural areas than in urban areas. However, the majority of the consumers in our survey indicated that the wet market was the most common place for grocery shopping in both urban and rural areas (87% for urban and 73% for rural), and supermarkets were the second most common place in both areas (12% for urban and 14% for rural). These observations imply an increasing potential for labeled foods to be incorporated into the rural food system. Thus, it may be worthwhile to examine the potential demand for foods with safety labels not only in urban areas but also in rural areas.

To the best of our knowledge, few studies have examined China's urban–rural gap in the demand for foods with food safety labels. Most previous studies have used data from coastal urban areas or online surveys (Bai et al., 2013; Ortega et al., 2011, 2012, 2015, 2017; Shimokawa, 2016; Yin et al., 2010; Yu, Yan, & Gao, 2014; Wang, Mao, & Gale, 2008). The exceptions are Yu and Abler (2009) and Yu, Gao, and Zeng (2014), who examined the demand for food quality in rural China. Yu and Abler (2009) examined the aggregated and indirect demand for quality by using provincial-level panel data for the unit values of nine food groups. Yu, Gao, and Zeng (2014) investigated the difference in the role of green foods between a provincial capital and a county town by conducting a survey (a payment card eliciting approach) at local supermarkets in Tianjin (a large coastal city).

Our paper contributes to the previous studies in the following three ways. First, our paper offers a new explanation for the urban–rural gap in the demand for food safety (i.e., knowledge of food safety labels), while Yu and Abler (2009) and Yu, Gao, and Zeng (2014) examined the existence of the gap. Second, our paper focuses on the demand for food safety, which is a more specific aspect of food quality than the aggregated food quality examined by Yu and Abler (2009). Thus, our findings provide more convincing implications for existing safety measures. Third, our sample better represents general consumers, particularly in rural areas. In our survey, we randomly selected households from a residential list in each community and visited each of the selected households, while most previous surveys were conducted at supermarkets or online. As a result, previous findings have tended to overrepresent highly educated, higher-income, and/or younger consumers (see Wang, Mao, & Gale, 2008). For example, in the study by Yu, Gao, and Zeng (2014), the proportion of "high school graduate or above" in the rural sample was 36.5%, which is higher than the national average of 29.8% (National Bureau of Statistics of China, 2017). Considering that the national average includes both urban and rural areas, the rural sample examined by Yu, Gao, and Zeng (2014) is much more highly educated than the average population of rural areas. In our sample, the corresponding proportions are 16.6% and 49.8% for the rural and urban areas, respectively. Moreover, compared to the urban sample, our rural sample includes substantially more illiterate people, farmers, low-income people, and older people. These differences are also important for understanding the urban–rural gap in the demand for food safety.

We conducted discrete choice experiments for rice and pork by visiting 354 urban households and 357 rural households that were randomly selected from a residential list in each of 24 communities in three prefectures in Hubei Province in August 2017. We employed a hypothetical choice experiment because green foods and organic foods are not yet widely available in rural areas and even some urban areas, and thus, we could not obtain enough revealed preference data. Rice and pork were selected because they are major food products in Chinese cuisine. The questions were answered by the person who regularly goes grocery shopping for her/his household. The survey also collected basic information about a respondent and her/his household.

Using the data, we first estimate the consumers' marginal willingness to pay (MWTP) for the green food and organic food labels in both urban and rural areas. We use mixed logit models in the WTP space to estimate the MWTP, and we employ the control function approach to control for potential endogeneity in the variables related to label knowledge. Second, we further examine why demand is different between urban and rural areas, with an emphasis on the role of food label knowledge. We employ the Oaxaca–Blinder decomposition method to decompose the urban–rural differences in the MWTP for the labels into the endowment and the preference effects of label knowledge, income per household member, and other socioeconomic factors.

Our key findings are threefold. First, there was a significant urban–rural gap in the proportion of people who actually saw and knew about the green food and organic food labels, and the proportion was much lower in our sample than in previous studies. For example, the proportion of people who knew about the green food label was 48.9% in the urban areas and 37.0% in the rural areas in our sample, much lower than the 88.7% in the study by Yu, Gao, and Zeng (2014). Second, the MWTP for the labels was significantly positive only among people with label knowledge but was insignificant or even negative among people without this knowledge. Moreover, the urban–rural gap in the MWTP for the labels was larger among the former than the latter. Finally, the knowledge-related differences explain 8%–29% of the urban–rural gap in the MWTP for the green food label for rice, and this contribution is one of the largest among the eight socioeconomic factors examined. These findings imply the existence of a future challenge for Chinese agencies overseeing food safety standards (e.g., China Green Food Development Center) in more effectively promoting food safety labels in China.

The rest of the paper is organized as follows. Section 2 presents our conceptual framework. Section 3 illustrates our study sites and experimental design. Section 4 describes our data. Section 5 introduces our estimation methods. Section 6 presents our estimation results. Section 7 discusses the remaining limitations in our empirical analysis. Section 8 concludes with a discussion of the implications of the food safety label policies in China.

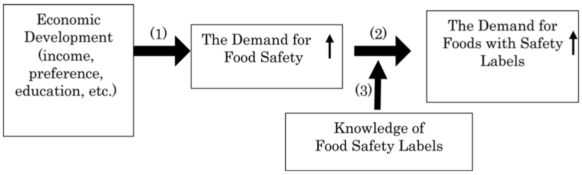

FIGURE 1 Our conceptual framework

2 | CONCEPTUAL FRAMEWORK

Figure 1 illustrates our conceptual framework. We presume that the demand for food safety increases following economic development, for example, increasing income, improving education, and changing dietary preferences (arrow (1)) (e.g., Gale & Hu, 2012; Ortega & Tschirley, 2017; Ortega et al., 2012; Yu & Abler, 2009), and an increased demand for food safety is expected to increase the demand for foods with safety labels (arrow (2)). While arrow (1) is not directly observable, previous studies have often implicitly assumed that arrow (1) is followed by arrow (2) and have estimated the demand for foods with safety labels as an approximation of the demand for food safety (e.g., Ortega et al., 2011; Wang, Mao, & Gale, 2008; Yu, Gao, & Zeng, 2014). Our conceptual framework introduces "knowledge of food safety labels" as a confounder for arrow (2). That is, arrow (1) is followed by arrow (2) only when people are sufficiently knowledgeable of food safety labels. This possibility is represented by arrow (3).

Our framework regarding the urban–rural gap in the demand for food safety indicates that the gap in demand can be explained not only by the different levels of economic development in these areas but also by a gap in the knowledge of food safety labels. Thus, to predict the demand for foods with safety labels, an important step is to take into account knowledge of food safety labels in addition to socioeconomic factors related to economic development. Overlooking the role of food label knowledge may lead to an overestimation of the influence of such socioeconomic factors (e.g., increasing income) on the demand for food safety. On the other hand, even when individuals lack knowledge of food safety labels, the labels themselves may influence demand (i.e., there may be a saliency effect). Thus, the magnitude of arrow (3) is an empirical question that will be examined in the following sections.

3 | STUDY SITES AND EXPERIMENTAL DESIGN

The data used in this paper were collected from a household survey conducted in Hubei Province in China in August 2017. We first selected three prefectures based on average annual income per capita: Wuhan (a wealthy prefecture), Xiaogan (a middle-income prefecture), and Huanggang (a poor prefecture). In each prefecture, a stratified random sampling method was adopted to select counties, towns/villages, and communities from a complete list of enumeration areas from the National Bureau of Statistics of China (NBSC). We first categorized all counties into urban and rural areas according to administrative categories and randomly selected one urban county and one rural county in each prefecture (i.e., six counties in total). We then selected two towns/villages in each sample county and two communities in each sample town/village. In total, our sample constituted 12 towns/villages and 24 communities. In each community, we randomly selected approximately 30 households from a complete list of residential households in each sample community. We visited each of the selected households to conduct our survey during August 22—27 in 2017. While visits were conducted from morning to evening, they were most often in the evening in urban areas. Choice experiments were conducted with the member of each household who regularly goes grocery shopping (if available).

Our unlabeled discrete choice experiments focused on rice and pork because they are basic food items and are expected to be consumed by all households in the surveyed communities. Table 1 summarizes the attributes of the product profiles in the experiment. For rice, the attributes include product origin (four provinces in China: Hubei, Hunan, Jiangxi, Heilongjiang), food safety labels (no label, green food label, organic food label), and product price per 5 kg (five levels). For pork, the attributes include product color (dark red, light red), fat content (lean, fatty), food safety labels, and product price per 500 g (five levels).

Notably, food items with a green food label or an organic food label are rarely found in Hubei Province, unlike in large coastal cities (e.g., Beijing and Shanghai). We found only rice and vegetables with these labels at some supermarkets in Wuhan, and rice was more frequently found with these labels than vegetables were. Additionally, the origins of most rice products are clarified, which is fitting for our experiment because product origin can be another quality signal (i.e., products from Heilongjiang are the best, while those from Hunan are the worst). Thus, our experiment included rice rather than vegetables. In contrast, we could not find pork products with a green food label or an organic food label even at the most prestigious supermarket in Wuhan.

TABLE 1 Attributes in the discrete choice experiment

Product	Attributes	Levels	Contents
Rice	Product origin	4 levels	1. Hubei
			2. Heilongjiang
			3. Hunan
			4. Jiangxi
	Price	5 levels	1. 25 yuan / 5 kg
			2. 30 yuan / 5 kg
			3. 35 yuan / 5 kg
			4. 40 yuan / 5 kg
			5. 45 yuan / 5 kg
	Food safety label	3 levels	1. No label
			2. Green food
			3. Organic food
Pork	Meat color	2 levels	1. Dark red
			2. Light red
	Fat content	2 levels	1. Lean meat
			2. Fatty meat
	Price	5 levels	1. 15 yuan / 500 g
			2. 20 yuan / 500 g
			3. 25 yuan / 500 g
			4. 30 yuan / 500 g
			5. 35 yuan / 500 g
	Food safety label	3 levels	1. No label
			2. Green food
			3. Organic food

Thus, while we set the price levels for rice based on the prices at wet markets and supermarkets in Hubei, we set the price levels for pork based on the prices at wet markets (for unlabeled pork) and at China's largest internet mall called T-mall (for labeled pork). The prices for labeled rice ranged from 38.9 to 59.9 yuan per 5 kg at supermarkets in Wuhan, and the prices for labeled pork ranged from 36 to 69 yuan per 500 g at the internet mall (we excluded prestigious brand products). Within the observed ranges, our experiment sets the highest price at a level that is low enough to be affordable for rural consumers but still higher than the price of unlabeled items. Our experiment also sets the lowest price to be the same as that observed for unlabeled items at local wet markets. We use the same price range for both urban and rural areas by assuming that the price levels for green foods and organic foods are reasonably similar in both areas. The prices of these foods cannot be much lower than the current prices regardless of selling area because the production costs needed to achieve the standards for green food or organic food cannot easily be reduced.

Each choice set comprises four hypothetical alternatives and a "do not buy" option (see Figure 2). We created

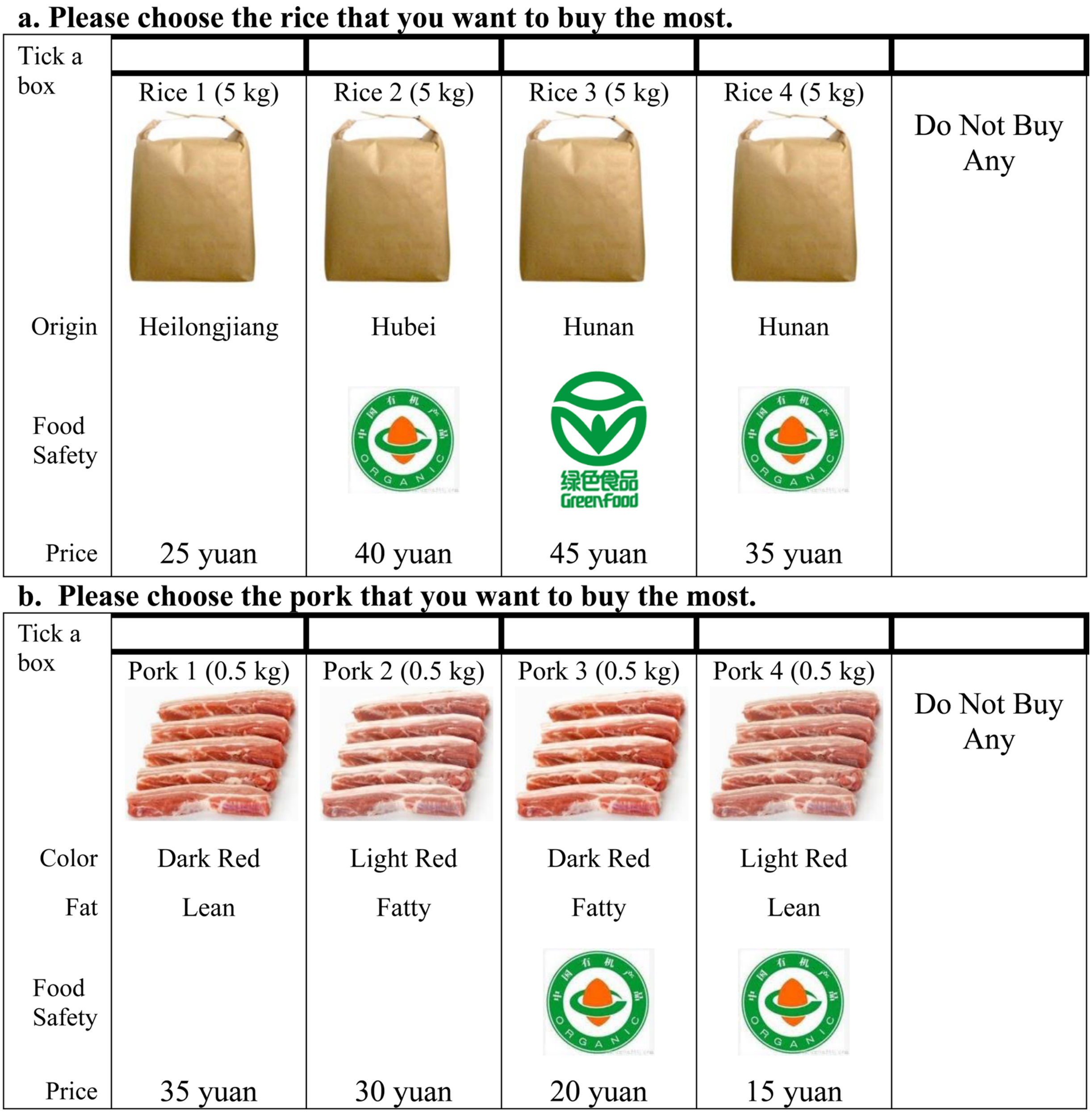

FIGURE 2 Example of a Choice Task [Color figure can be viewed at wileyonlinelibrary.com]

30 different choice sets using a D-optimal design created from the full-factorial candidate set using a modified Federov search algorithm. To reduce the probability of respondent fatigue, the choice tasks were split into five orthogonal blocks of six choice tasks each. Before respondents started the experiment, we employed a cheap-talk strategy to mitigate hypothetical bias and informed respondents that people tend to act differently when they face hypothetical decisions.

After conducting the choice experiments, we examined the respondents' understanding of each of the green food and organic food labels. The following three questions were asked: (1) Have you ever seen the label? (2) Do you know the meaning of the label? and (3) What is the meaning of the label? For question (3), respondents could choose one of the following four choices: (i) No use of pesticides, chemical fertilizers, and other chemical inputs; (ii) Limited use of pesticides, chemical fertilizers, and other chemical inputs; (iii) Nutritional contents within food are above government standards and are healthier for consumers; and (iv) Levels of pesticide residues, heavy metals, and microorganism contents within the food are below those outlined by government standards and are safe for consumers. (i), (ii), and (iv) are the definitions of organic food, green food, and no-harm-to-public food, respectively. There is no official label for (iii).

At the end of the survey, we also collected the following background information: sex, age, household size,

TABLE 2 Key characteristics of our sample

	Urban (n = 351)		Rural (n = 356)		Difference
	Mean (1)	SD	Mean (2)	SD	(2) – (1) (3)
Age (years)	50.5	14.8	55.9	14.6	5.3***
Female (1 = female, 0 = male)	0.6	0.5	0.4	0.5	−0.2***
Married (1 = married, 0 = ow)	0.9	0.3	0.9	0.3	0.0
Household size (persons)	3.7	1.9	4.1	2.1	0.4***
With children under 18 (1 = yes, 0 = ow)	0.58	0.03	0.53	0.03	−0.05
Per capita annual income(1,000 RMB/year)	11.0	9.1	8.1	6.3	−2.9***
Shopping every day (1 = yes, 0 = ow)	0.69	0.02	0.23	0.02	−0.47***
Mainly use a supermarket (1 = yes, 0 = ow)	0.12	0.02	0.13	0.02	0.01
Occupations (%)	(n = 207)		(n = 202)		
Managers	14.4%		5.5%		−9.0***
Professionals and technicians	10.1%		8.4%		−1.6
Clerks	9.6%		3.0%		−6.6***
Commercial and service workers	26.0%		11.9%		−14.1***
Agriculture, forestry, husbandry, and fishery producers	6.7%		44.1%		37.3***
Production and transportation workers	13.9%		13.4%		−0.6
Cannot be specified	19.2%		13.9%		−5.4
Education level (%)	**Urban**	**Rural**	**Difference (Rural–Urban)**		**CSY 2017 National**
Illiterate	4.0%	9.0%	5.0***		5.3%
Elementary School	16.3%	32.7%	16.3***		25.6%
Junior High School	29.9%	41.7%	11.6***		38.8%
High School	23.1%	12.4%	−10.7***		12.8%
Professional School	9.1%	1.7%	−7.4***		11.1%
University or Above	17.7%	2.5%	−15.1***		6.0%

Note: ow = otherwise; CSY = China Statistical Yearbook.
***and ** indicate the 1% and 5% significance level, respectively.

household demography, education level, annual household income, who regularly goes grocery shopping, frequency of grocery shopping, shopping sites, average monthly food expenditures per person, and self-production of rice and pork.

4 | DATA AND DESCRIPTIVE ANALYSIS

Our data set contains 711 households, but four households were excluded from our analysis due to missing values and invalid answers. Thus, our analytical sample contains 707 households. When available, we interviewed the household member who regularly goes grocery shopping. Response rates varied from 80% to 50% across communities, and they tended to be lower in urban areas, particularly in Wuhan.

Table 2 presents the key characteristics of our sample and shows that our rural sample is substantially different from the samples examined in previous studies, while our urban sample is similar to those in previous studies. In particular, compared to that of previous studies, the distribution of education levels (the last panel) in our sample more closely resembles the nationally representative data from the China Statistical Yearbook in 2017 (the column named "CSY 2017"). For example, the illiteracy rates in our sample were 9% in rural areas and 4% in urban areas. These data are consistent with the data from CSY 2017, which reported that the average illiteracy rates in 2016 were 5.4% at the national level and 6.0% in Hubei Province. Our enumerator read the questionnaire out loud for illiterate respondents.

Table 2 also shows that the average per capita annual income is 36% higher in urban areas (10,996 RMB) than in rural areas (8,072 RMB). According to the CSY 2017, the average per capita income was 18,283 RMB in urban areas and 10,849 RMB in rural areas in Hubei in 2015. Thus, our sample is, on average, poorer than the NBSC sample in both areas, particularly in urban areas because one-third of

TABLE 3 Knowledge of food safety labels

	All (1)	Urban (2)	Rural (3)	(2)–(3) (4)
Knowledge of the green food label				
Saw and knew the green food label	42.9%	48.9%	37.0%	11.9%**
Among the people who knew the label:				
Correctly understood green food	18.0%	18.5%	17.4%	1.1%
Misunderstood green food as organic	39.3%	37.6%	41.7%	4.1%
Misunderstood green food as nutritious	10.2%	11.0%	9.1%	1.9%
Misunderstood green food as no-harm-to-public food	32.5%	32.9%	31.8%	1.1%
Never saw the green food label	46.1%	36.2%	56.0%	−19.9%***
Knowledge of the organic food label				
Saw and knew the organic food label	16.5%	19.2%	13.7%	5.5%**
Among the people who knew the label:				
Correctly understood organic food	41.0%	36.8%	46.9%	−10.2%
Misunderstood organic as green food	12.0%	13.2%	10.2%	12.0%
Misunderstood organic as nutritious	12.8%	11.8%	14.3%	−12.8%
Misunderstood organic as no-harm-to-public food	34.2%	38.2%	28.6%	−9.7%
Never saw the organic food label	73.1%	67.5%	78.7%	−11.2%***

Note: We tested whether (2)–(3) is zero or nonzero in column (4).
***and ** indicate the 1% and 5% significance level, respectively.

our sample is from one of the poorest prefectures (Huanggang) and because higher-income households were more difficult to interview in Wuhan. Consequently, the urban–rural gap in income is smaller in our sample than in the NBSC sample. However, our sample still has enough variation in per capita income levels to capture most general consumers, and the Gini coefficient is 0.39.

The occupation structure was also substantially different between urban and rural areas (the second panel in Table 2). In terms of occupation, the share of agricultural, forestry, husbandry, and fishery producers was much higher in rural areas (44%) than in urban areas (6.7%); in contrast, the share of commercial and service workers was much higher in urban areas (26.0%) than in rural areas (11.9%). The average household size and respondent age were slightly higher in rural areas than in urban areas. The household size was 4.1 persons and 3.7 persons in rural and urban areas, respectively. The average age was 55.9 and 50.5 years old in rural and urban areas, respectively. Approximately 70% of our sample was people who regularly buy food for their households. The time needed for respondents to complete the questionnaire was approximately 30 min in both the urban and rural areas.

While urban–rural differences in other factors are expected (e.g., shopping patterns and farming), we need a more in-depth explanation for the average age in our sample, which is much higher than the national average. This is because we interviewed the people who commonly purchase groceries for their household. Even though there were younger people in the interviewed households, we interviewed an older person who tended to go grocery shopping for her/his household. Based on the data on the age groups of household members, 58% of the people in the interviewed households were between 20 and 59 years old, and 22% of them were aged 60 or above. According to the CSY 2017, the proportion of people between 20 and 59 years old was 61% and that of people aged 60 or above was 17%. Thus, the proportion of older people was slightly higher in our sampled households compared to the national average, and this difference is much smaller than the difference in the average age.

Table 3 describes the knowledge of the green food and organic food labels for the participants in our entire sample and in our urban and rural samples (columns 1, 2, and 3, respectively). Column (4) presents the difference between urban and rural areas. On average, 42.9% of our sample said that they saw and knew about the meaning of green food labels, while only 16.5% of them saw and knew about the meaning of organic food labels. The proportion of people who knew about the labels was much lower in rural areas (37% and 13.7% for green food and organic food, respectively) than in urban areas (48.9% and 19.2% for green food and organic food, respectively), and the urban–rural differences were statistically significant at the 5% level.

Table 3 also shows whether people understood the labels correctly, and the patterns of misunderstanding were similar between urban and rural areas. Among the people who knew the labels, only 18.0% and 41.0% correctly understood the green food label and the organic food label, respectively. The percentage of people who knew the green food label but misinterpreted the label as an organic food was 39.3%. Similarly, 10.2% misinterpreted the green food label as indicating nutritious food, and 12.8% misinterpreted the organic food label as indicating nutritious food. Additionally, more than 30% misinterpreted the green food and the organic food labels as being no-harm-to-public food labels.

In sum, Table 3 shows that the key urban–rural difference in the knowledge of the green food and organic food labels is the proportion of those who "saw and knew the label" rather than how correctly people understood the labels. Thus, as a measure of label knowledge, we focus on whether a person saw and knew the label. More specifically, in our analysis, having label knowledge means people understand the label as a good safety signal, and people who have only seen the label were not considered as having label knowledge. In the following sections, we will examine how these differences between urban and rural areas are associated with the MWTP for food safety labels.

5 | ESTIMATION METHOD

We first present our estimation method for MWTP for nonprice attributes and the effect of label knowledge on the MWTP for the food safety labels. Second, we illustrate the control function approach to controlling for potential endogeneity in the variables related to label knowledge. Last, estimating individual-level MWTP for the label, we decompose the observed urban–rural gap in the MWTP for the labels into endowment and preference components and further decompose into the contribution of each socioeconomic factor.

5.1 | Estimation of MWTP

Based on the random utility theory (Hanemann, 1984; Mcfadden, 1974), respondents are assumed to choose the rice and pork that provide them the maximum utility. When respondent i chooses alternative j in question t, the utility obtained from the choice is:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}, \tag{1}$$

where V_{ijt} is the deterministic part of utility and ε_{ijt} is the unsolvable component. The selected alternative provides the largest utility compared to the utility provided by other available alternatives in the question.

In our experiments, the factors determining V_{ijt} are prices, food labels, and origins or color and fat content), and all the factors are randomly assigned across respondents. The unsolvable components ε_{ijt} may include respondents' socioeconomic backgrounds and other unobservable factors. Because the deterministic part is randomly assigned, V_{ijt} is uncorrelated with ε_{ijt} in our experiment. Thus, the coefficient estimators in V_{ijt} should be consistent (i.e., there should be no significant endogeneity bias). The basic form of the deterministic part for rice V^r_{ijt} and that for pork V^p_{ijt} can be defined as:

$$V^r_{ijt} = \alpha_{r1}\, Green_{ijt} + \alpha_{r2} Org_{ijt} + \alpha_{r3}{}' Origins_{ijt} + \alpha_{r4} Optout_{ijt} + \lambda_{ri} price_{ijt}, \tag{2}$$

$$V^p_{ijt} = \alpha_{p1}\, Green_{ijt} + \alpha_{p2} Org_{ijt} + \alpha_{p3} Color_{ijt} + \alpha_{p4} Lean_{ijt} + \alpha_{p5} Optout_{ijt} + \lambda_{pi} price_{ijt}, \tag{3}$$

where $Green_{ijt}$ and Org_{ijt} are indicators for the green food label and the organic food label, respectively. In (2), $Origins_{ijt}$ is a vector of indicators for the four product origins (Hubei is excluded). In (3), $Color_{ijt}$ is the indicator for a dark red color, and $Lean_{ijt}$ is the indicator for lean meat. In both equations, $Optout_{ijt}$ is the indicator for choosing the opt out alternative, and $price_{ijt}$ is price in yuan. Thus, $-\lambda_{fi}$ is the price coefficient for product $f = \{r, p\}$, and the αs are the MWTP for nonprice attributes. Hereafter, we refer to these models as the basic models.

Next, while V_{ijt} and ε_{ijt} are uncorrelated in Equation (1), respondents' socioeconomic background may influence their decisions through treatments such as food labels. In other words, the effect of food labels may be heterogeneous across respondents. To investigate this possibility, we introduce interaction terms between the label indicators and respondents' key characteristics into the basic models. Because the treatments are randomly assigned, the interaction terms are not correlated with the error term ε_{ijt}.

We start investigating the role of food label knowledge by introducing the interaction terms between the label indicator and the indicator for "know the label" (e.g., the green food label indicator*the indicator for knowing the green food label) into the basic models as follows:

$$V^r_{ijt} = \beta_{r1}\, Green_{ijt} + \beta_{r2} Org_{ijt} + \beta_{r3} Green_{ijt} * Know\_Gr_i + \beta_{r4} Org_{ijt} * Know\_Or_i + \beta_{r5}{}' Origins_{ijt} + \beta_{r6} Optout_{ijt} + \lambda_{ri} price_{ijt}, \tag{4}$$

$$V^p_{ijt} = \beta_{p1}\, Green_{ijt} + \beta_{p2} Org_{ijt} + \beta_{p3} Green_{ijt} * Know\_Gr_i + \beta_{p4} Org_{ijt} * Know\_Or_i + \beta_{p5} Color_{ijt} + \beta_{p6} Lean_{ijt} + \beta_{p7} Optout_{ijt} + \lambda_{pi} price_{ijt}, \tag{5}$$

where $Know\_Gr_i$ and $Know\_Or_i$ are the indicators for knowing the green food label and the organic food label, respectively. Thus, $Green_{ijt} * Know\_Gr_i$ and $Org_{ijt} * Know\_Or_i$ are the interaction terms between the label indicators and the label knowledge indicators. The coefficients on the interaction terms represent how differently individuals who know the label respond to the label compared to individuals who do not know the label. Hereafter, we refer to these models as the knowledge models.

Moreover, to control for the influence of other important socioeconomic factors, we add interaction terms between the label indicator and each of the indicators for high income (higher than the median), high education level (graduated high school or above), old age (older than the median), and farming.

$$\begin{aligned} V^r_{ijt} &= \gamma_{r1}\ Green_{ijt} + \gamma_{r2}Org_{ijt} + \gamma_{r3}Green_{ijt}{*}Know\_Gr_i \\ &+ \gamma_{r4}Org_{ijt}{*}Know\_Or_i + \gamma_{r5}{}'Green_{ijt}{*}X_{ijt} \\ &+ \gamma_{r6}{}'Org_{ijt}{*}X_{ijt} + \gamma_{r7}{}'Origins_{ijt} + \gamma_{r8}Optout_{ijt} + \lambda_{ri}price_{ijt}, \end{aligned} \tag{6}$$

$$\begin{aligned} V^p_{ijt} &= \gamma_{p1}\ Green_{ijt} + \gamma_{p2}Org_{ijt} + \gamma_{p3}Green_{ijt} * Know\_Gr_i \\ &+ \gamma_{p4}Org_{ijt} * Know\_Or_i + \gamma_{p5}{}'Green_{ijt} * X_{ijt} \\ &+ \gamma_{p6}{}'Org_{ijt} * X_{ijt} + \gamma_{p7}Color_{ijt} \\ &+ \gamma_{p8}Lean_{ijt} + \gamma_{p9}Optout_{ijt} + \lambda_{pi}price_{ijt}, \end{aligned} \tag{7}$$

where X_{ijt} is a vector of other control variables, including the indicators for high income, high education level, old age, and farming. Thus, $Green_{ijt} * X_{ijt}$ and $Org_{ijt} * X_{ijt}$ are the interaction terms between the label indicators and each of the control variables. These models are hereafter referred to as the full models.

To estimate Equations (2)–(7), there are at least three potential and feasible estimation methods: a conditional logit model, mixed logit model in preference space, and mixed logit model in WTP space. We will employ the mixed logit model because it relaxes the independence of irrelevant alternatives (IIA) assumption of conditional logit models, allowing coefficients to vary randomly over individuals by assuming a particular continuous heterogeneity distribution for coefficients a priori (McFadden & Train, 2000). Another attractive feature of the mixed logit model is that it enables us to account for heterogeneity in preferences that are unrelated to observed characteristics.

Among the two types of the mixed logit model, we employ the model in WTP space proposed in Train and Weeks (2005) and estimate the direct WTP measure from the coefficients. Although the model in preference space is also widely used to estimate WTP, previous studies have shown that the estimation in preference space may produce unrealistic estimates (Meijer & Rouwendal, 2006; Scarpa et al., 2008). This is because, in the model in preference space, the WTP for an attribute is given by the ratio of the attribute coefficient to the price coefficient, and thus, the WTP distributions are heavily skewed and may not even have defined moments. To address this potential problem, the price coefficient is often fixed in the model in preference space. However, it is often unreasonable to assume that all individuals have the same preferences for price (Meijer & Rouwendal, 2006). In contrast, the model in WTP space involves estimating the distribution of WTP directly by reformulating the model in such a way that the coefficients directly represent the WTP measures. This approach has been found to produce more realistic WTP estimates in applications than the model in preference space.

In our model, the price coefficient $-\lambda_i$ is given a log-normal distribution. The coefficients associated with other attributes are normally distributed. The WTPs are assumed to be uncorrelated across attributes. We estimated all the models separately between urban and rural areas.

5.2 | Control function approach

A key remaining concern in estimating Equations (4)–(7) is the potential endogeneity in the interaction terms with the indicators for knowing the food safety labels.[1]Because label knowledge is interacted with randomly assigned labels, it may influence consumer choices only through the randomly assigned labels in our experiments, and thus, the influences of selection bias and reverse causality are expected to be minimized. However, there may still be some omitted variables that are correlated with the interaction terms, such as unobserved attributes of food markets, advertisements, and available information about food labels. To mitigate the influence of such unobserved attributes, we apply the control function approach (Petrin & Train, 2010; Train, 2009) to the interaction terms.

For explanatory purposes, we rearrange Equation (1) as follows:

$$U_{ijt} = \beta_1\ L_{ijt} * KnowL_i + \beta_X{}'X_{ijt} + \beta_q q_{ijt} + e_{ijt}, \tag{8}$$

where $L_{ijt} * KnowL_i$ is the interaction term between the randomly assigned label (L_{ijt}) and the indicator of

[1] We also examined the endogeneity of prices by using community indicators as exogenous variables in the first stage. Because the results are similar to those in the base models, we did not include the results, which are available upon request.

knowing the label ($KnowL_i$), X_{ijt} is a vector of other observed attributes in V_{ijt}, q_{ijt} is a vector of unobserved attributes that are correlated with the interaction term, and e_{ijt} is the exogenous error term. Given equation (8), the error term in Equation (1), ε_{ijt}, contains both q_{ijt} and e_{ijt}. Additionally, the interaction term $L_{ijt} * KnowL_i$ can be expressed as:

$$L_{ijt} * KnowL_i = \theta_0 + \theta_z Z_{ijt} + \theta_q q_{ijt} + \varphi_{ijt}, \quad (9)$$

where Z_{ijt} is a vector of exogenous variables that explain the interaction term and consist of X_{ijt} and excluded instruments z_{ijt}, while q_{ijt} is the unobserved attributes that are correlated with the interaction term. φ_{ijt} is an exogenous error term.

Suppose we estimate Equation (9) using only the observed variables Z_{ijt} and denote the residuals from the estimation as δ_{ijt}. Then, δ_{ijt} contains both q_{ijt} and φ_{ijt}. Thus, replacing q_{ijt} in Equation (8) with a proper estimator for δ_{ijt} ($\hat{\delta}_{ijt}$), we obtain:

$$U_{ijt} = \tilde{\beta}_1 L_{ijt} * KnowL_i + \tilde{\beta}'_X X_{ijt} + \beta_\delta \hat{\delta}_{ijt} + \tilde{e}_{ijt.} \quad (10)$$

In Equation (10), $\hat{\delta}_{ijt}$ explicitly controls for the unobserved factors q_{ijt} that caused the endogeneity in the interaction term in Equation (8). Thus, in Equation (10), the interaction term is not correlated with the error term $\tilde{e}_{ijt}$, and we can obtain consistent estimators for $\tilde{\beta}_1$ and other coefficients.

To obtain the residual $\hat{\delta}_{ijt}$, we specify Equation (9) using Ordinary Least Squares (OLS) estimation. This procedure is called the first stage, as in two-stage least squares estimation. In Equations (4)–(7), there are two endogenous interaction terms (i.e., interactions with knowing the green food label and with knowing the organic food label). For each interaction term, we estimate the residual $\hat{\delta}_{ijt}$ (i.e., there will be two residual terms). As the excluded instruments z_{ijt}, we employ indicators for the 24 geographic communities (i.e., the smallest geographic unit in our sample). The community indicators are expected to proxy for the unobserved attributes of food markets, advertisements, and the available information about food labels within a geographic market, and such attributes may be correlated with the effect size of label knowledge through the food label. Additionally, in the context of our experiment, we may reasonably assume that people's residential communities are predetermined and thus externally given in the short run. The statistical validity of the excluded instruments is further examined in the next paragraph.

The first stage results show that our excluded instruments are significantly correlated with the interaction terms for knowing the labels (see Supporting Information Appendix Table A1). The partial F statistic of the excluded instruments ranges from 4.27 to 6.99 and is jointly statistically significant at the 1% level in all models. We also conduct the modified refutability test (Guevara, 2018) to assess the exogeneity of the instruments, which is the overidentification test for discrete choice models. We cannot employ the test directly to the mixed logit model because the model is not designed to include so many variables (i.e., 23 community indicators). Thus, we conduct the test based on logit models. The chi-squared test statistic with 25 degrees of freedom ranges from 17.8 (p-value = 0.85) to 19.3 (p-value = 0.78) in our models, and we fail to reject the null hypothesis that the instruments are exogenous in all models. Although the results do not guarantee exogeneity, we at least did not find any evidence against using the instruments. Thus, we employ the instruments to mitigate the potential endogeneity bias in estimating Equations (4)–(7).

In the second stage, after obtaining the residual estimates $\hat{\delta}_{ijt}$ from the first stage, we add them to each of Equations (4)–(7). We then estimate the equations by employing the mixt logit model in WTP space.

5.3 | Decomposition of an urban–rural gap in the MWTP for food safety labels

We further estimate individual-level WTP for food safety labels, β_i^{FQL}, for the basic models following Revelt and Train (2001). Using the individual-level MWTP for the labels, we decompose the urban–rural gap in the estimates into the influences of differences in endowments and preferences. We employ the MWTP rather than the parameter coefficients from the mixed logit model because they cannot be compared if the scale parameters are not controlled for (e.g., Gao & Schroeder, 2009; Lusk & Schroeder, 2004; Train, 2009). We examine the influences of label knowledge, per capita income, and other socioeconomic factors by employing the Oaxaca–Blinder decomposition method (Jann, 2008; Oaxaca & Ransom, 1999). All explanatory variables are standardized to make their influence comparable across different measurement units.

$$\beta^{FSL,\,rural} - \beta^{FSL,\,urban} = \Delta x \left\{ D \cdot \alpha^{rural} + (1 - D) \cdot \alpha^{urban} \right\} + \Delta\alpha \left\{ (1 - D) \cdot x^{rural} + D \cdot x^{urban} \right\}, \quad (11)$$

where $\beta^{FSL,\,j}$ is the MWTP for food safety labels in area j, x^j is a vector of explanatory variables in area j, α^j is a vector of the OLS coefficient estimates on the variables x^j obtained from regressing $\beta^{FSL,\,j}$ on x^j in area j, Δx is a vector of the differences between the mean of x^{rural} and the mean of x^{urban}, $\Delta\alpha$ is a vector of the differences between α^{rural} and α^{urban}, and D is a weight between urban and rural areas. In our model, x includes knowledge of food safety labels, per capita household income, education level, age, gender, marital status, and household size.

Note that $\beta^{FSL,\,j}$ represents the effect induced only by food labels in our experiment, and socioeconomic factors were already determined before the labels were assigned in the experiment. Thus, we can reasonably assume that the explanatory variables x are predetermined when we estimate α^j (i.e., there is no reverse causality). Moreover, taking the mean difference between urban and rural areas for each variable, we can control for province-level unobserved factors that are common between urban and rural areas on average (e.g., dietary culture, geographic and historical background). This mitigates the potential influence of omitted variables.

In Equation (11), the first term measures the contribution of the urban–rural gap to the average levels of the explanatory variables, and the second term measures the contribution of the urban–rural gap to the coefficients on the explanatory variables (i.e., to what extent preferences are influenced by the explanatory variables). Hereafter, the first term and the second term will be referred to as the endowment effect and the preference effect, respectively. We evaluate the contributions of each explanatory variable for two cases, $D = 1$ (i.e., using the coefficients for rural areas) and $D = 0$ (i.e., using the coefficients for urban areas).

In our estimation, we used Stata MP 14. Specifically, we used the *mixlogitwtp* command to estimate mixed logit models. To obtain the MWTP at the individual level, we used the *mixlbeta* command. The Oaxaca decomposition was conducted by using the *oaxaca* command.

6 | ESTIMATION RESULTS

The coefficient estimates were obtained from estimating Equations (2)–(7). Table 4 presents the results for rice, and Table 5 presents the results for pork. Tables 4 and 5 summarize the MWTP for food safety labels and the interaction terms between the label and the label knowledge; the results for the other explanatory variables are suppressed. The full results are presented in the Supporting Information Appendix (Tables A2 and A3). In Tables 4 and 5, the first panel shows the results for the basic models (Equations (2) and (3)), the second panel shows the results for the knowledge models (Equations (4) and (5)), and the third panel shows the results for the full models (Equations (6) and (7)). We also separately present the results for all samples and for two subsamples: urban and rural areas. For the knowledge and the full models, we also present the results of the control function approach (controlling for potential endogeneity) in addition to the baseline results.

Overall, the results demonstrate that the MWTP for the green food label and the organic food label are substantially different between urban and rural areas. First, the results for the basic models (the first panel in Tables 4 and 5) show that while the MWTP for the labels are positive for both rice and pork in all areas, the mean and SD of the MWTP is much higher in urban areas than in rural areas for both products. For example, in the case of rice, the mean MWTP for the green food label is 19.8 RMB in all samples, 33.8 RMB (SD = 26.6) in urban areas and 9.3 RMB (SD = 14.4) in rural areas. Additionally, the mean MWTP is consistently higher for the green food label than for the organic food label, even though the standard for organic food is stricter than that for green food. For example, in the case of rice, the mean MWTP for the green food label for all samples is 19.8 RMB, while that for the organic food label is 11.3 RMB. This is possibly because many people did not understand the exact meaning of the green food label, and a more familiar label was better appreciated (see Table 3).

Next, we introduce the interaction terms between the label indicators and the label knowledge indicators in the knowledge models and the full models (the second and third panels in Tables 4 and 5). We present the baseline results, and the control function (CF) results that control for the potential endogeneity in the interaction terms. Both the baseline results and the CF results are consistent between the knowledge models and the full models, which indicates that the results are robust to the inclusion of additional control variables.[2] A key difference between the baseline and the CF results is the MWTP for food safety labels among people without label knowledge, where the MWTP is positive in the baseline results while negative in the CF results. Consequently, the coefficient estimates on the interaction terms, which measures the gap in the MWTP between people with and without label knowledge, become substantially larger in the CF results than in the baseline results. Because we expect that the CF results are more likely to be consistent than the baseline results, we hereafter focus on interpreting the CF results for the full models. At the same time, some coefficients for the organic food labels are unreasonably large. This may be due to a low correlation between our regional instruments and the knowledge about organic food labels (i.e., a small denominator in the 2SLS estimator), and the magnitudes should be interpreted with caution.

[2] We also examined other combinations of socioeconomic factors including shopping frequency, supermarket use, household size, and living with children. Due to technical limitations, we could not include all the factors at once. Although the results are not reported, the influence of label knowledge on the MWTP for the labels is robust in all the models.

TABLE 4 Estimation results for rice (RMB / 5 kg)

Sample	All				Urban				Rural			
Est. App.	Base		CF		Base		CF		Base		CF	
	WTP Mean	WTP SD	WTP Mean	WTP SD	WTP Mean	WTP SD	WTP Mean	WTP SD	WTP Mean	WTP SD	WTP Mean	WTP SD
Basic Models												
Green Label	19.8***	21.2***			33.8***	26.6***			9.3***	14.4***		
Organic Label	11.3***	6.1***			22.4***	5.9			2.9***	1		
Likelihood	−5082				−2634				−2365			
Knowledge Models												
Green Label	10.8***	11.4***	−61.9***	22.1***	26.1***	15.4***	−26.8	20.1***	4.4**	11.0***	−53.9***	21.7***
Organic Label	10.0***	1.7	−30.0***	16.1***	32.5***	2.9	4.5	16.2***	1.5	0.1	−31.1***	10.1***
Green*Know	15.2***	18.7***	175.0***	12.7***	28.2***	21.4*	131.9***	27.6***	9.0***	9.9**	143.1***	20.9***
Organic*Know	2.3	2.7	238.8***	13.4**	−11.3*	1.2	113.6*	1.6	7.5**	7.0**	226.0***	15.7**
Likelihood	−5080		−5866		−2621		−2774		−2362		−2855	
Full Models												
Green Label	15.1***	14.8***	−20.6	14.9***	29.7***	14.3***	−30.3	0.2	11.3***	2.4	−33.8*	16.4***
Organic Label	13.1***	3.6**	−17.6**	15.9***	29.0***	12.4***	11.7	17.7***	7.5***	1.2	−8.2	9.7***
Green*Know	11.8***	12.9***	86.0***	31.8***	23.8***	33.6***	132.1**	29.8***	7.2**	13.4***	104.1**	19.0***
Organic*Know	−0.3	0.5	160.8***	0.9	−9.2	5.1	60.6	2.4	6.4**	6.5	108.8	25.6***
Likelihood	−5041		−5850		−2613		−2758		−2355		−2854	
Observations	21230		21230		10550		10530		10700		10700	

Note: All models include product origins, price, and an optout dummy. In full models, as other control variables, Green and Organic are interacted with each of the indicators of high income, high education level, above the median age, female, and farming. The full results are available in the Supporting Information Appendix. Est. App. = Estimation approach; and CF = Control function approach.

***, **, * indicate the 1%, 5%, and 10% significance levels, respectively.

TABLE 5 Estimation results for pork (RMB / 500 g)

Sample	All				Urban				Rural			
Est. App.	Base		CF		Base		CF		Base		CF	
	WTP Mean	WTP SD	WTP Mean	WTP SD	WTP Mean	WTP SD	WTP Mean	WTP SD	WTP Mean	WTP SD	WTP Mean	WTP SD
Basic models												
Green label	11.4***	10.5***			54.7***	28.3***			3.4***	3.3***		
Organic label	9.0***	10.1***			41.7***	23.8**			3.6***	3.8***		
Likelihood	−5490				−2680				−2711			
Knowledge models												
Green label	5.6***	2.5**	−61.2***	10.6***	38.9***	16.1*	−121.7**	11.7	2.8***	2.8***	−45.2***	7.7***
Organic label	7.0***	5.8***	−32.0**	12.8***	39.1***	13.8	−53.4**	21.8***	3.2***	1.1	−27.2***	12.2***
Green*Know	11.7***	17.0***	188.8***	14.0***	21.3**	42.8***	383.3***	50.7***	10.3***	19.2***	134.6***	13.5***
Organic*Know	6.5**	11.7***	273.4***	6.6	22.0*	5.6	545.9**	8.9	7.2***	7.8***	208.9***	0.3
Likelihood	−5469		-5816		−2679		−2841		−2687		−2901	
Full models												
Green label	11.4***	1.7	−35.1**	0.1	46.5***	18.2	−110.7**	30.3***	8.9***	5.3***	−29.4*	7.4***
Organic label	11.0***	4.5***	−35.7***	13.0***	45.7***	18.9*	−62.3**	16.1*	5.4***	0.8	−44.1***	12.0***
Green*Know	8.0***	10.9**	139.3***	26.5***	15.3	38.2**	334.5***	27.7*	4.7***	3.7***	101.1***	15.6***
Organic*Know	7.6**	0.8	305.4***	0.9	19.7	16.6	590.7***	10.3	4.2**	6.7***	297.9***	2.0
Likelihood	−5458		−5824		−2673		−2823		−2684		−2894	
Observations	21230		21220		10550		10520		10700		10700	

Note: All models include product origins, price, and an optout dummy. In full models, as other control variables, Green and Organic are interacted with each of the indicators of high income, high education level, above the median age, female, and farming. The full results are available in Appendix. Est. App. = Estimation approach; and CF = Control Function Approach.
***, **, * indicate the 1%, 5%, and 10% significance levels, respectively.

Overall, the mean MWTP for the labels is significantly positive among people with label knowledge, while the mean MWTP is insignificant or even negative among people without such knowledge. Moreover, the urban–rural gap in the mean MWTP for the labels is larger among people with label knowledge compared to people without label knowledge. In terms of rice (Table 4), the mean MWTP for the green food label is significantly positive among people with label knowledge in both areas, and it is much higher in urban areas (101.8 RMB = 132.1–30.3) than in rural areas (70.3 RMB = 104.1–33.8). In contrast, the mean MWTP for the green food label is negative among people without label knowledge in both areas (−30.3 RMB in urban and −33.8 RMB in rural) although it is statistically significant only in rural areas. The mean MWTP for the organic food label is statistically insignificant regardless of the label knowledge in both areas.

In terms of pork (Table 5), similar to the case of rice, the mean MWTP for the green food label is significantly positive among people with label knowledge in both areas, and it is much higher in urban areas (223.8 RMB = 334.5–110.7) than in rural areas (71.4 RMB = 101.1–29.4). In contrast, the mean MWTP for the green food label is significantly negative among people without label knowledge in both areas (−110.7 RMB in urban and −29.4 RMB in rural). The mean MWTP for the organic food label is also significantly positive among people with label knowledge in both areas, while it is significantly negative among people without label knowledge in both areas.

The standard deviations (SDs) of the MWTP tend to become larger in the CF results than in the baseline results, although the difference between the SDs is much smaller than that between the mean MWTPs. In the CF results, the urban–rural gap in the SDs of the MWTP tends to be larger for the green food label than for the organic food label. This may be because green foods are more widely available than organic foods, and thus consumers' preferences for and knowledge about the green food label are more heterogeneous.

Last, we decompose the observed urban–rural differences in the individual-level MWTP for the food labels into two parts: the endowment effect and the preference effect. Each of these two effects is further decomposed into the contributions of each of the eight explanatory variables. All explanatory variables are standardized to make the contributions comparable across different measurement units. Tables 6 and 7 show the decomposition results for rice and pork, respectively. There are three key findings. First, the urban–rural gap in the mean MWTP for the food labels is statistically significant for all cases, and the largest gap is observed for the green food label for rice. The largest gap is equally attributable to the preference and the endowment effects. That is, the urban–rural gap in the MWTP for the green food label for rice is explained by urban–rural differences in the responsiveness to socioeconomic changes and urban–rural differences in the levels of socioeconomic factors equally well. Second, in the case of the MWTP for the green food label for rice, label knowledge tends to be the largest contributor to both the endowment and preference effect (8%–29%). Third, in the other three cases (i.e., green food labels for pork and organic labels for rice and pork), the preference effect is much larger than the endowment effect, and most of the preference effect is explained by the constant term (i.e., a difference in intercepts) rather than the examined socioeconomic factors. Label knowledge has a significant endowment effect only for pork with a green food label when $D = 1$, and it contributes negligibly in all other cases.

7 | LIMITATIONS

Three limitations are worth noting. First, there may be measurement error in the perception of the food safety labels in the experiment, which may influence the relationship between the demand for food safety and the demand for foods with safety labels (i.e., arrow (2) in Figure 1). This point is particularly concerning in rural areas where most people have not even seen the labels before. Similarly, it is also possible that respondents may associate other characteristics with the food labels—for example, some people suspect cheating and do not trust the labels. Yin et al. (2010) and Sirieix et al. (2011) find that urban consumers do not have a high level of trust in food safety systems such as the organic food certification system in China. If the green food label and the organic food label are not considered valid signals of food safety or quality, our conclusions based on observed preferences for the labels can be misleading.

Moreover, trust and label knowledge may be correlated, and we expect that consumers with more label knowledge are likely to have a lower level of trust in food safety labels in China. In this case, the effect of label knowledge on the MWTP for the labels would be insignificant. This possibility may partially explain why we found insignificant effects for the organic food label. Additionally, the effect of the label and of label knowledge are different between urban and rural areas. This urban–rural gap in effects can be due not only to a difference between levels of label knowledge but also to a difference in the relationship between trust and label knowledge. For example, knowledgeable rural consumers may trust food safety labels more than the corresponding urban consumers do. Thus, the contribution of label knowledge to the urban–rural gap in the MWTP for the label (Tables 6 and 7) may be overestimated. Additionally, such an urban–rural difference in trust may

TABLE 6 Oaxaca–Blinder decomposition of the MWTP for food safety labels for rice

(Rural–Urban)	Green Food						Organic Food					
	D = 0	*p*	Contr	D = 1	*P*	Contr	D = 0	*p*	Contr	D = 1	*p*	Contr
Total difference	−3.12	0.00		−3.12	0.00		−0.27	0.02		-0.27	0.02	
Endowment effect	−1.44	0.13	46%	−1.55	0.02	50%	0.13	0.27	−47%	0.01	0.94	−2%
Preference effect	−1.67	0.21	54%	−1.57	0.18	50%	−0.39	0.01	147%	-0.27	0.04	102%
Endowment Effects												
Knew the label	−0.92	0.01	29%	−0.25	0.23	8%	0.03	0.12	−11%	0.00	0.83	1%
Per capita income	−0.19	0.49	6%	−0.06	0.88	2%	0.01	0.83	−3%	0.00	0.96	−1%
High education level	−0.14	0.73	4%	−0.71	0.04	23%	0.07	0.16	−27%	-0.01	0.84	3%
Age	−0.04	0.89	1%	−0.23	0.43	7%	−0.06	0.11	22%	-0.05	0.09	20%
Female	0.07	0.77	−2%	−0.25	0.32	8%	−0.02	0.46	9%	0.03	0.24	−11%
Married	−0.01	0.85	0%	−0.01	0.85	0%	0.00	0.85	0%	0.00	0.85	0%
Household size	0.31	0.13	−10%	−0.02	0.89	1%	0.01	0.63	−4%	0.04	0.08	−14%
Farming	−0.54	0.47	17%	−0.02	0.95	1%	0.09	0.35	−33%	0.00	0.94	1%
Preference Effects												
Knew the label	−0.33	0.08	10%	−0.35	0.08	11%	−0.02	0.24	6%	0.02	0.27	−6%
Per capita income	0.06	0.77	−2%	−0.07	0.77	2%	0.00	0.92	1%	0.00	0.92	−1%
High education level	−0.28	0.28	9%	0.29	0.27	−9%	−0.04	0.21	14%	0.04	0.20	-15%
Age	−0.10	0.64	3%	0.10	0.64	−3%	0.00	0.89	−1%	0.00	0.89	1%
Female	−0.16	0.37	5%	0.16	0.37	−5%	0.03	0.21	−10%	-0.03	0.21	10%
Married	0.00	0.95	0%	0.00	0.97	0%	0.00	0.98	0%	0.00	0.98	0%
Household size	−0.17	0.26	5%	0.17	0.24	−5%	0.01	0.39	−5%	-0.01	0.38	5%
Farming	0.26	0.53	−8%	−0.26	0.53	8%	−0.04	0.37	17%	0.04	0.37	−17%

Note: D = weight on rural areas; p = p-value; and contr = contribution. All explanatory variables are standardized.

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE

TABLE 7 Oaxaca–Blinder decomposition of the MWTP for food safety labels for pork

(Rural – Urban)	Green Food						Organic Food					
	D = 0	*p*	Contr	D = 1	*P*	Contr	D = 0	*p*	Contr	D = 1	*p*	Contr
Total difference	−0.95	0.01		−0.95	0.01		−0.57	0.08		−0.57	0.08	
Endowment effect	0.02	0.94	−2%	−0.29	0.23	30%	−0.17	0.57	31%	−0.13	0.52	24%
Preference effect	−0.97	0.04	102%	−0.66	0.10	70%	−0.39	0.37	69%	−0.43	0.26	76%
Endowment Effects												
Knew the label	−0.07	0.27	7%	−0.21	0.02	22%	−0.05	0.26	8%	−0.03	0.43	6%
Per capita income	0.09	0.32	−10%	0.15	0.23	−16%	−0.19	0.05	34%	−0.11	0.38	19%
High education level	0.02	0.88	−2%	−0.01	0.90	2%	0.14	0.31	−24%	0.00	0.99	0%
Age	−0.08	0.43	8%	−0.21	0.05	23%	−0.15	0.13	27%	−0.06	0.56	10%
Female	−0.06	0.47	7%	−0.08	0.36	8%	0.03	0.72	−5%	0.06	0.43	−11%
Married	−0.01	0.85	1%	0.00	0.86	0%	0.01	0.85	−1%	0.00	0.86	0%
Household size	0.02	0.78	−2%	0.04	0.47	−4%	0.05	0.43	−9%	0.03	0.63	−5%
Farming	0.11	0.67	−12%	0.03	0.76	−4%	−0.01	0.98	1%	−0.03	0.79	5%
Preference Effects												
Knew the label	−0.07	0.21	7%	−0.07	0.21	7%	−0.01	0.81	1%	−0.01	0.82	1%
Per capita income	0.03	0.70	−3%	−0.03	0.71	3%	0.04	0.55	−8%	−0.04	0.56	8%
High education level	−0.02	0.85	2%	0.02	0.85	−2%	−0.07	0.43	12%	0.07	0.43	−12%
Age	−0.07	0.36	7%	0.07	0.36	−7%	0.05	0.49	−8%	−0.05	0.49	8%
Female	−0.01	0.89	1%	0.01	0.89	−1%	0.02	0.77	−3%	−0.02	0.77	3%
Married	0.01	0.83	−1%	0.00	0.96	0%	−0.01	0.83	1%	0.00	0.96	0%
Household size	0.01	0.77	−1%	−0.01	0.77	1%	−0.01	0.77	2%	0.01	0.77	−2%
Farming	−0.04	0.78	4%	0.04	0.78	−4%	−0.01	0.93	2%	0.01	0.93	−2%

Note: D = weight on rural areas; p = p-value; and contr = contribution. All explanatory variables are standardized.

also be observed for consumers with a higher age, higher income, and higher education level. Thus, the contributions of these factors to the urban–rural gap in the MWTP for the labels can also be overestimated. Therefore, it is unclear how omitting trust would affect the ordering of contribution sizes across the socioeconomic factors.

Second, while we employed the cheap talk strategy to mitigate hypothetical bias, hypothetical bias still remains in our WTP estimates. As shown in previous studies (e.g., De-Magistris et al., 2013; Penn & Hu, 2018), hypothetical bias is more likely to cause upward bias in the MWTP estimates for desirable food labels. Thus, hypothetical bias potentially weakens our findings on the positive MWTP for food labels among consumers who knew about the labels, while it may have little influence on the insignificant or negative MWTP for food labels among consumers without label knowledge. Although it is unclear how hypothetical bias influences our findings on the urban–rural gap in the MWTP for food labels, we expect that the influence is relatively small because hypothetical bias would not be systematically different between urban and rural consumers after we control for key socioeconomic characteristics.

Third, our mixed logit model relies on the assumption that the unobserved factors' distribution is normal or lognormal. However, if the unobserved factors are not normally distributed in the real world, such differences may be erroneously attributed to the distribution of the MWTP for observed attributes such as safety labels and product origins. To mitigate the limitations from using the same distribution for unobserved factors, we segmented our sample between rural and urban areas. For other characteristics besides residential area, it was more difficult to set thresholds and segmentation criteria. It is also difficult to predict the direction of potential bias for the urban–rural gap in the MWTP.

8 | CONCLUSIONS

We explored the role of knowledge about food safety labels in the urban–rural gap in the demand for food safety in China by using data from discrete choice experiments conducted in urban and rural areas in Hubei Province in China in 2017. The experiments were designed to measure the MWTP for the green food label and the organic food label for rice and pork, and mixed logit models and the control function approach were used to estimate the MWTP. Moreover, using the Oaxaca–Blinder decomposition method, we decomposed the urban–rural gap in the MWTP for the labels into the endowment and preference effects of label knowledge, income per household member, and other key socioeconomic factors.

We found that the proportion of consumers who knew about the green food label and/or the organic food label was much smaller in our sample (17%–43%) than in previous studies of China's coastal areas (e.g., 89%). The MWTP for the green food label was substantially higher among consumers who knew about the label, and the knowledge effect was larger in urban areas than in rural areas. Among consumers without label knowledge, the MWTP was insignificant or even negative in both areas. The MWTP for the organic food label for rice tended to be smaller and less robust than that for the green food label. Moreover, knowledge-related differences explained 8%–29% of the urban–rural gap in the MWTP for the green food label, and the gap was equally attributable to differences in both consumer preferences and socioeconomic endowments. The urban–rural differences in the effects of label knowledge may be explained by different levels of trust in the labels or different price expectations for green foods and organic foods. We leave the investigation of which factors explain the urban–rural difference in the effects of label knowledge to future research.

Our findings imply that the demand for green foods will not increase unless more consumers recognize the green food label in both areas. In addition, even if consumers recognize the labels, the labels will not be effective when consumers have a low level of trust in the food safety system in China. In our results, this possibility was implied by the insignificant effect of label knowledge on the MWTP for the organic food label for rice. A similar problem was also observed for the certifications of infant formulas in China (Hanser & Li, 2015). Moreover, Ding et al. (2018) examined the food safety problem from the producer side and showed that apple farmers in China simply follow the directions of their farm-based leaders without understanding the meanings of food safety standards and certifications.

A fundamental problem for recent food safety measures in China may be that the measures have been promoted too rapidly for consumers and farmers to understand or trust safety standards and certifications. For example, although the China Green Food Development Center has been actively promoting the expansion of green food production on its website, we found that very little green food was available even in Wuhan (the largest city in Hubei Province), and many rural consumers have never seen green foods. On the other hand, once consumers know about green foods, their MWTP should be substantially higher. These findings suggest that the China Green Food Development Center needs to disseminate information about green foods more effectively in rural areas. In urban areas, improving trust in the food safety system and the safety labels is necessary for making the labels more effective.

ACKNOWLEDGMENTS

We gratefully acknowledge funding for this research from JSPS KAKENHI Grant Number JP16H06203. We also thank Dr. Lianfa Luo and other staff members and graduate students at the Wuhan University Institute of Quality Development Strategy for their support in conducting household surveys.

REFERENCES

Bai, J., Zhang, C., & Jiang, J. (2013). The role of certificate issuer on consumers' willingness-to-pay for milk traceability in China. *Agricultural Economics*, *44*(4-5), 537–544.

De-Magistris, T., Gracia, A., & Nayga, R. M. (2013). On the use of honesty priming tasks to mitigate hypothetical bias in choice experiments. *American Journal of Agricultural Economics*, *95*(5), 1136–54.

Ding, J., Moustier, P., Ma, X., Huo, X., & Jia, X. (2018). Doing but not knowing: how apple farmers comply with standards in China. *Agriculture and Human Values*, *36*, 61–75.

Gale, H. F., & Hu, D. (2012). Food safety pressures push integration in China's agricultural sector. *American Journal of Agricultural Economics*, *94*(2), 483–488.

Gale, H. F., & Huang, K. (2007). Demand for food quantity and quality in China. Working Paper (USDA Economic Research Report No. 32). United States Department of Agriculture, Economic Research Service

Gao, Z., & Schroeder, T. C. (2009). Consumer responses to new food quality information: are some consumers more sensitive than others? *Agricultural Economics*, *40*(3), 339–346.

Guevara, C. A. (2018). Overidentification tests for the exogeneity of instruments in discrete choice models. *Transportation Research Part B*, *114*, 241–253.

Guo, X., Mroz, T. A., Popkin, B. M., & Zhai, F. (2000). Structural change in the impact of income on food consumption in China, 1989–93. *Economic Development and Cultural Change*, *48*(4), 737–760.

Hanemann, W. M. (1984). Discrete/continuous models of consumer demand. *Econometrica*, *52*(3), 541–561.

Hanser, A., & Li, J. C. (2015). Opting out? Gated consumption, infant formula and China's affluent urban consumers. *The China Journal*, *74*, 1324–9347.

Jann, B. (2008). The Blinder-Oaxaca decomposition for linear regression models. *The Stata Journal*, *8*(4), 453–479.

McFadden, D. L. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Eds.), *Frontiers in econometrics* (pp. 105–142). Academic Press.

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Economics*, *15*(5), 447–470.

Meijer, E., & Rouwendal, J. (2006). Measuring welfare effects in models with random coefficients. *Journal of Applied Economics*, *21*(2), 227–244.

National Bureau of Statistics of China. (2017). *China statistical yearbook*. China Statistics Press.

Lusk, J. L., & Schroeder, T. C. (2004). Are choice experiments incentive compatible? A test with quality differentiated beef steaks. *American Journal of Agricultural Economics*, *86*(2), 467–82.

Ortega, D. L., & Tschirley, D. L. (2017). Demand for food safety in emerging and developing countries: A research agenda for Asia and Sub-Saharan Africa. *Journal of Agribusiness in Developing and Emerging Economies*, *7*(1), 21–34.

Ortega, D. L., Wang, H. H., Wu, L., & Olynk, N. J. (2011). Modeling heterogeneity in consumer preferences for select food safety attributes in China. *Food Policy*, *36*(2), 318–324.

Ortega, D. L., Wang, H. H., Olynk, N. J., Wu, L., & Bai, J. (2012). Chinese consumers' demand for food safety attributes: A push for government and industry regulations. *American Journal of Agricultural Economics*, *94*(2), 489–495.

Ortega, L. D., Wang, H. H., Wu, L., & Hong, S. J. (2015). Retail channel and consumer demand for food quality in China. *China Economic Review*, *36*, 359–366.

Ortega, L. D., Chen, M., Wang, H. H., & Shimokawa, S. (2017). Emerging markets for US pork in China: Experimental evidence from mainland and Hong Kong consumers. *Journal of Agricultural and Resource Economics*, *42*(2), 275–290.

Oaxaca, R. L., & Ransom, M. R. (1999). Identification in detailed wage decompositions. *The Review of Economics and Statistics*, *81*(1), 154–157.

Penn, J. M., & Hu, W. (2018). Understanding hypothetical bias: An enhanced meta-analysis. *American Journal of Agricultural Economics*, *100*(4), 1186–206.

Petrin, A., & Train, K. (2010). A control function approach to endogeneity in consumer choice models. *Journal of Marketing Research*, *47*(1), 3–13.

Popkin, M. B. (2006). Global nutrition dynamics: the world is shifting rapidly toward a diet linked with noncommunicable diseases. *The American Journal of Clinical Nutrition*, *84*(2), 289–298.

Revelt, D., & Train, K. (2001). Customer-specific taste parameters and mixed logit: Households' choice of electricity supplier. Munich, Germany: University Library of Munich. Working Paper (Econometrics 0012001),

Scarpa, R., Thiene, M., & Train, K. (2008) Utility in willingness to pay space: A tool to address confounding random scale effects in destination choice to the Alps. *American Journal of Agricultural Economics*, *90*(4), 994–1010.

Shimokawa, S. (2016). Why can calorie posting be apparently ineffective? Roles of two conflicting learning effects. *Food Policy*, *64*, 107–120.

Sirieix, L., Kledal, P. R., & Sulitang, T. (2011). Organic food consumers' trade-offs between local or imported, conventional or organic products: a qualitative study in Shanghai. *International Journal of Consumer Studies*, *35*(6), 670–678.

Train, K., & Weeks, M. (2005). Discrete choice models in preference space and willingness-to-pay space. In R. Scarpa & A. Alberini (Eds.), *Applications of simulation methods in environmental and resource economics* (pp. 1–16). Netherlands: Springer.

Tian, X., & Yu, X. (2013). The demand for nutrients in China. *Frontiers of Economics in China*, *8*(2), 186–206.

Train, K. (2009). *Discrete choice methods with simulation* (2nd ed.). Cambridge University Press.

Wang, Z., Mao, Y., & Gale, F. (2008). Chinese consumer demand for food safety attributes in milk products. *Food Policy*, *33* (1), 27–36.

Wang, Z., Fan, Y., Zhang, Z., & Godefroy, S. (2017). Food safety standards. In J. J. Jen & J. Chen (Eds.), *Food safety in China: science,* *technology, management and regulation* (pp. 363–380). John Wiley & Sons Ltd.

Yin, S., Wu, L., Du, L., & Chen, M. (2010). Consumers' purchase intension of organic food in China. *Journal of the Science of Food and Agriculture*, *90*(8), 1361–1367.

Yu, X., & Abler, D. (2009). The demand for food quality in rural China. *American Journal of Agricultural Economics*, *91*(1), 57–69.

Yu, X., Gao, Z., & Zeng, Y. (2014). Willingness to pay for the 'green food' in China. *Food Policy*, *45*(1), 80–87.

Yu, X., Yan, B., & Gao, Z. (2014). Can willingness-to-pay values be manipulated? Evidence from an organic food experiment in China. *Agricultural Economics*, *45*(s1), 119–127.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

How to cite this article: Shimokawa S, Hu D, Li D, Cheng H. The urban–rural gap in the demand for food safety in China: The role of food label knowledge. *Agricultural Economics*. 2021;1–19. https://doi.org/10.1111/agec.12613