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Does dietary knowledge affect household food waste in the developing economy of China?

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ABSTRACT

Based on the China Health and Nutrition Survey (CHNS) data for 2004, 2006, and 2009, this study employs a fixed-effects model to examine the impacts of the dietary knowledge of household food decision makers on the quantity of household food waste in terms of amount and calories levels. Specifically, the interaction effect between dietary knowledge and community development is explored. The results indicate that the dietary knowledge of the household food decision maker significantly impacts food waste and calories loss. With the development of the local community, the impacts of dietary knowledge on household food waste and calories loss seem to decrease. The heterogeneous impacts of dietary knowledge on food waste and calories loss in urban and rural areas and among different income groups are also observed. The findings contribute toward a better understanding of the issues related to household food waste and calories loss in China in the context of economic development and residents' increasing dietary knowledge.

1. Introduction

Food waste refers to food appropriate for human consumption that is discarded or left to spoil in the food system (HLPE, 2014). The problem of food waste is currently increasing (Girotto et al., 2015). Globally, growing volumes of food are lost or wasted (Canali et al., 2017): one quarter to one third of all food produced is wasted (Bellemare et al., 2017). Increasing food waste has serious negative implications for food security, the global environment, the climate, water and land resources, nutritional health, and the economy (Canali et al., 2017; Conrad et al., 2018; Dorward, 2012; Garnett, 2011; Graham-Rowe et al., 2014; Hall et al., 2009; Liu et al., 2013; Munesue et al., 2015; Parizeau et al., 2015; Thyberg and Tonjes, 2016; Usubiaga et al., 2017; Venkat, 2011). Furthermore, wasting food is recognized as a rare problem affecting the achievement of economic goals in terms of food security, environmental sustainability, and farm-financial security (Garcia-Herrero et al., 2018; Richards and Hamilton, 2018; Yu and Abler, 2014, 2016).

Given the important implications of food waste, it is a topic of widespread concern for the stakeholders including researchers, policy makers, international organizations, and grassroots movements (Canali et al., 2017; Chaboud and Daviron, 2017; FAO, 2011; HLPE, 2014; Schanes et al., 2018), as it is related to food security, environmental protection, and social morality. Many studies have been conducted worldwide to seek possible methods of reducing food waste (Garrone et al., 2014; Halloran et al., 2014). Some studies have estimated and investigated food waste and the related nutrition loss in developed countries (Buzby and Hyman, 2012; Conrad et al., 2018; Garcia-Herrero et al, 2018; Secondi et al., 2015). However, uncertainty in the measurement of food waste remains a concern (Chaboud and Daviron, 2017; Koester, 2015), and the differences in statistical measures render most findings incomparable. Give to these differentiations in the measures and conclusions of food waste in existing studies, systematic reviews of a wide range of literature have also been conducted to better understand food waste (Canali et al., 2017; Girotto et al., 2015; Sheahan and Barrett, 2017).

Moreover, numerous studies have analyzed food waste for different commodities, at different stages of the food chain, the determinants and impacts thereof, and related policies (Beretta et al., 2013; Calvo-Porral

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et al., 2017; Hall et al., 2009; Halloran et al., 2014; Muriana, 2017; Visschers et al., 2016; Yu and Abler, 2014, 2016). For instance, Di Muro et al. (2016) focused on the food waste of food retailers, finding a significant impact of consumer preference for "misfit" vegetables.[1] Bremmers and Meulen (2016) reviewed the impact of legal aspects on food waste, but did not offer sufficient empirical evidences. Based on a survey of 244 Romanian consumers, Stefan et al. (2013) found that consumers' planning and shopping routines might contribute to avoiding food waste. While the impact of food waste on climate and greenhouse gas emissions attracts widespread attention (Moult et al., 2018), Bryngelsson et al. (2016) revealed that reducing food waste could lower emissions only by 1–3% and played a minor role in meeting climate targets. As global food demand continues to rise because of population and consumption growth, food waste has emerged as an important policy issue (Canali et al., 2017; Stephen and Timothy, 2019). For instance, in Italy the reform of its food waste policy includes the donation of food directly after the best-before date and significantly simplified the bureaucracy around donations (Busetti, 2019). Overall, these previous studies provide an important reference for understanding the issues related to food waste.

During different stages of economic development, the proportion of food waste varies according to food categories and along the food chain (Dou et al., 2016; FAO, 2011; Parfitt et al., 2010). For example, 25% of consumers in the EU waste cereals, against only 1% in Africa (HLPE, 2014). According to the literature, the generation of food waste along the food value chain occurs in most stages from field to fork, including in agricultural production, postharvest handling and trade, manufacture processing, food services, wholesale, retail, and final household consumption (Beretta et al., 2013; Bilska et al., 2016; Calvo-Porral et al., 2017; Di Muro et al., 2016; Girotto et al., 2015; Halloran et al., 2014; Liu et al., 2013; Muriana, 2017). In Africa, food waste mostly occurs in the processing and distribution stages, while in North America and Europe it is evident in the consumption stage (FAO, 2011; HLPE, 2014). These differences in the generation of food waste imply that the policy design to reduce it should be location-targeted and subject to the development stage.

Regarding the last stage in the food chain, previous studies have related socioeconomic development with household food waste (Garcia-Herrero et al, 2018; Liu, 2014; Stefan et al., 2013; Thyberg and Tonjes, 2016; Visschers et al., 2016). In general, household food waste occurs in the time between when food reaches the consumer and when it is eaten (Alexander et al., 2017). The sources of food and drinks consumed at home include retail as well as home-grown food and takeaways (Parfitt et al., 2010). A household's decision to waste (as opposed to the decision to save or keep food) is usually made under income constraints (Thyberg and Tonjes, 2016). Daniel (2016) found that low-income households in the United States bought less fresh high-value food than higher-income consumers, because they were more risk-averse regarding waste. High-income households were more willing to waste food in the hope that their family would eventually acquire a taste for healthier choices. In high-income countries, the food waste generated at the household level represents about half the total food waste, making this stratum one of the biggest contributors to this problem (Calvo-Porral et al., 2017; Stancu et al., 2016). It is expected that households worldwide will generate an increasing volume of food waste alongside the income growth of populations in developing countries. Despite this, there has been less attention on food waste at the household level (Ellison and Lusk, 2018), although the topic is an important policy concern (Hebrok and Boks, 2017; Richards and Hamilton, 2018).

Food waste remains poorly understood in developing countries such as China, despite growing media coverage and public concerns in recent years (Liu, 2014). China, the world's most populous country, is experiencing dramatic changes in its society because of rapid economic growth, and increasing food waste has become a widespread concern. Given the population, any changes in China's food waste can have marked consequences (Song et al., 2015). For example, if the average rice waste is 1 kg per capita per year, the total wasted rice for the country's population of 1.4 billion people will total around 1.4 million tons, almost equalling to the Philippines' rice imports from July 2018 to June 2019. Several studies on food waste in China have been conducted, most focusing on food waste at the macro level and assessing the economic and environmental effects thereof (Liu et al., 2013; Sun et al., 2018; Wen et al., 2016). However, as mentioned, little is known about the generation of food waste at the household level. For instance, Song et al. (2015) calculated the carbon, water, and ecological footprints of household food waste in China, revealing that while the food waste per capita is relatively small, the large population means that the total food waste in the country is very high. Wen et al. (2016) evaluated the economic and environmental performance of food waste treatment pilot projects in Suzhou City, China, finding that in 2013, the amount of food waste was equivalent to an average daily energy output of 27,500 m^3 of biogas and 30 tons per day of biodiesel, a daily net profit of 82,055 Chinese Yuan under normal operation. A report by Liu (2014) provided estimates of food losses and waste in China; however, these statistics relied on data published in literature and not on a direct assessment of household food waste.

Household food waste is generated from the process of food consumption at home in many ways, and consumers' dietary knowledge may play a role. Consumers may discard fresh products considered non-edible in terms of freshness and color, for example, as those who are more risk-averse tend to throw out foods close to, at, or beyond the best-before date (Ellison and Lusk, 2018). Large quantities of wholesome edible food are often unused or left over and discarded from household kitchens, especially after celebrations or festivals. This implies that consumers' dietary knowledge would be an important factor in their decision to transform inedible/edible food into food waste. Internationally, improving dietary knowledge has been shown to help people adjust their eating behavior and nutritional intake (Ren et al., 2019; Shimokawa, 2013; Zhao and Yu, 2019). Therefore, it is reasonable to assume that dietary knowledge is linked to what and how much food should go to waste (Bonaccio et al., 2013; Nayga, 2000; Wagner et al., 2016). However, as far as we know, no study has investigated the effect of consumers' dietary knowledge on household food waste.

In this study, we use household-level panel data to analyze household food waste in China and estimate the impacts of the dietary knowledge of the household food decision maker on the amount and calories level of food waste (Tian and Yu, 2015). Different studies adopt different definitions of food waste (Bellemare et al., 2017; Calvo-Porral et al., 2017; Ellison and Lusk, 2018; HLPE, 2014; Secondi et al., 2015; Stefan et al., 2013). FAO (2019) defined food waste as the decrease in the quantity or quality of food resulting from decisions and actions by retailers, food services and consumers, while household food waste throughout this paper is defined as the total food loss and waste happening at the final stage by consumers. Here, household food waste is measured by the quantity of the food wasted by a household over three days at home, excluding food for composting and/or for animal feed (CHNS, 1991; FAO, 2019). Furthermore, we also consider whether food waste varies significantly with the development of and changes in the socioeconomic environment proxied by the development index of local communities.

In the estimation strategy, first, a household fixed-effects model can control for unobserved factors that hardly change over a short period and can connect food waste and dietary knowledge. Second, we introduced individual, household, and community characteristics into the fixed-effects model as proxies for (at least part of) changes in unobserved time-varying food availability (as opposed to food waste). Third,

[1] "Misfit" vegetables refer to the vegetables whose appearance do not meet the best visual quality standards and are mostly wasted by retailers who assume that consumers only prefer fruits and vegetables with perfect appeal (Di Muro et al., 2016).

because consumers' characteristics may systematically differ depending on whether high-value food[2] comprises a large component of food consumption (as opposed to food waste), we examined the robustness of our estimation results by employing the subsample of the wasting of high-value food. Finally, a series of heterogeneity analyses were conducted to estimate household food waste and nutrition loss in urban and rural areas and among income groups.

The contribution to the literature on food waste in China is threefold. First, we analyze food waste at the final stage of the food supply chain, namely consumption, in China. Of the food wasted along the food chain, that in the consumption stage increases to around one third when countries moved from being low-income to middle and high-income (HLPE, 2014). Given the larger proportion of food waste at the consumption stage, better understanding the trends and determinants thereof would help policy makers design better policy portfolios to reduce this phenomenon. Second, our study used the actual food waste recorded during the consumption stage at home, providing a sound measurement thereof (Bellemare et al., 2017). Third, we obtained detailed data on food items including fresh products and the leftovers of edible food discarded from household kitchens. Thus, we could convert the mass of the food wasted into a caloric measurement, similar to the study of Hall et al. (2009). Food waste is widely measured by its quantity or value (Bellemare et al., 2017), and using nutrition loss as a result thereof enables better understanding the phenomenon in terms of the dimensions of nutritional value and food security. Finally, relatively little research assesses the dynamics of household food waste (Parizeau et al., 2015). Thus, the panel data used in this study provides insights into the trend for household food waste in China.

In the next section, we introduce the conceptual framework and econometric modeling approach. Section 3 briefly presents the data source and basic descriptive statistics, and Section 4 reports and discusses the empirical results as well as the heterogeneity analysis. The last section concludes.

2. Methodology

2.1. Household production and food waste

The theoretical framework of household food waste is usually developed based on the principles of consumer theory (Katare et al., 2017; Richards and Hamilton, 2018). We set up a theoretical model based on household production theory (Deaton and Muellbauer, 1980; Lancaster, 1966), as consumers produce an amount of calories/nutrient Z_m (m represents calories or a type of nutrient, such as protein) from N food products Q_n (n = 1….N) with the cost $C_m l$ (Deaton and Muellbauer, 1980, pp. 252-253):

$$Z_m = \sum_{n=1}^{N} b_{mn} Q_n - C_m l \tag{1}$$

where b_{mn} is the calories/nutrient component for food product Q_n, l is a scalar denoting the labor input of household production, and C_m is the corresponding production cost for nutrient Z_m.

From a nutritional perspective, calories/nutrient loss is defined by $C_m l$. Clearly, household production cost C_m depends on the dietary knowledge index (DKI) and food availability of Q_n. When there are more food choices and foods are more processed, production efficiency will be higher.

Eq. (1) can be rewritten in a matrix form:

$$Z = BQ - lC \tag{2}$$

Here, nutrient loss lC can be converted back to food Q^L, which is a household's food waste, and:

$$Q^L = l^* B^{-1} C \tag{3}$$

2.2. Three measures of food waste and loss

Eq. (3) shows the quantity of food waste in a household production framework, which can be explained as the household production costs for nutrients. We provide three measures of food waste as follows.

- Food waste rate for each product

$$r_n = \frac{Q_n^L}{Q_n} \tag{4}$$

Eq. (4) offers a measure for the food waste rate for each food product n. However, there are too many food products, and this type of measure cannot mirror the general picture of food waste and loss. If we add all quantities together regardless of product differences, the second measure is as follows:

- General food waste rate

$$r = \frac{\sum_n Q_n^L}{\sum_n Q_n} \tag{5}$$

While Eq. (5) provides a measure for general food waste, it cannot distinguish innate differences between products. Sometimes, it is not logical to add an apple to an orange. To differentiate, following Richards and Hamilton (2018), we divided food products into two broad groups: high-value foods and low-value foods.

- Nutrition loss rates

Eq. (1) from the household production framework provides a direct measure of nutrition loss. As it is difficult to unify food waste for different products in one measurement unit, we converted food waste and calories loss to provide the household production cost. We calculated the rate of nutrition loss as follows:

$$r_c = \frac{C_m l}{Z_m} \tag{6}$$

Eq. (6) provides a measure from the nutrition loss perspective. Similarly, we could measure protein, fat, and other nutrient loss as well (Tian and Yu, 2013, 2015). In this study, we specifically focus on the calories loss.

2.3. Empirical model

As mentioned, household food waste and loss, measured by household production cost C_m in Eq. (1), depends on the DKI and food availability of Q_n. Food availability depends on regional characteristics, local food supply, local facilities, and local development level, which can be defined as the urbanization and development index (UDI) of the local community. In general, compared with rural areas, food supply in urban areas is more diverse, more processed, and perhaps less fresh. DKI and UDI could have an interaction effect, as the function of dietary knowledge often depends on the social environment. Including consumers' DKI, the UDI of the local community, their interactions, and other control variables such as demographic characteristics and market prices of main food commodities, we initially specify the following estimation:

$$y_{ijt} = \alpha_0 + \alpha_1 DKI_{it} + \alpha_2 UDI_{jt} + \alpha_3 DKI_{it} \times UDI_{jt} + \gamma X_{it} + \delta Z_{jt} + \varepsilon_{ijt} \tag{7}$$

where y_{ijt} is the latent variable measuring food waste (Eq. (5)) and

[2] High-value foods refer to those that tend to be more nutritious and have shorter shelf lives than processed, shelf-stable foods (Richards and Hamilton, 2018). Here, high-value foods include meat (pork, beef, mutton, and chicken), eggs, dairy products, seafood, fruit, and fresh vegetables, while other foods were considered low-value ones.

nutrition loss (Eq. (6)) in household i in community j at year t. DKI_{it} is a score to measure the dietary knowledge of the household food decision maker i at year t, UDI_{jt} is the development index of the community j at year t, and X_{it} is a vector of control variables in household i at year t. Finally, Z_{jt} includes the market prices of six main food commodities at the community level j at year t to control for the food market effect, namely pork, cereal, chicken, beans, oil, and vegetables (Ren et al., 2019; Shimokawa, 2013). The variables of DKI_{it} and its interacted term UDI_{jt} are used to capture the impact of dietary knowledge on food waste including the heterogeneous effect of the development of the local community. The variables of $UDI_{jt}$and its interacted term DKI_{it} are used to explore the impact of the development index including the heterogeneity of the dietary knowledge of the household food decision maker on food waste. Here, the negative coefficient of the interacted term of DKI_{it} and UDI_{jt} indicates substitute effects between dietary knowledge and the development index of the community in the quantity of food waste, while the positive coefficient suggests the complementary effects. Finally, ε_{ijt} is the error term.

Given that panel data were used in this study and the dependent variable is characterized by the problem of zero food waste—i.e., the dependent variable is censored—the model expressed in Eq. (1) can be estimated with both random effects and fixed effects Tobit regressions. The random effects estimator assumes that DKI_{it} and UDI_{jt} are uncorrelated with any unobserved factors that may also influence the outcome variables. However, as households self-select to waste food, this assumption may be violated, which could lead to biased estimates. Therefore, in addition to the random-effects estimates, we also employed a pseudo fixed-effects estimator to control for bias that may arise from time-invariant unobserved variables. The validation of random or fixed effects was subject to a Hausman test.

2.4. Identification procedure

The overall empirical strategy for achieving the objectives of this study was threefold. First, the panel structure of the data enabled us to identify the dietary knowledge of the household food decision maker, the development index, and their interaction regarding food waste and nutrition loss. In the second part of the analysis, we checked the robustness of our main results from the following dimensions. Because the consumption trend of countries moving from being low income to being middle or high income tends to increase the component of high-value food in terms of units and nutrition, we focused on the subsample of the waste of high-value food. That is, we identified the dietary knowledge of the household food decision maker, the development index, and their interaction on high-value food waste. Third, we conducted a heterogeneity analysis by splitting the samples according to household registration and income group. We separated our sampled households into urban and rural households based on the concern of heterogeneity effects of dietary knowledge and the development index on food waste in urban and rural households. In addition, considering the possible heterogeneity of these impacts according to the distribution of household income, we identified the effect of dietary knowledge, development index, and interacted term on food waste according to the quantile distribution of household income.

3. Data and descriptive statistics

3.1. Sample

The dataset used for this study is from the China Health and Nutrition Survey (CHNS)[3], which is an international collaborative project between the National Institute of Nutrition and Food Safety at China Centers for Disease Control and Prevention and the Carolina Population Center, University of North Carolina at Chapel Hill. The CHNS is longitudinal and includes nine waves in 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, and 2015 in the nine provinces and three municipalities of China. It comprises questions about the target households, their members, and the communities. The CHNS survey team collected information on food waste only during 2004, 2006, and 2009. The modules used for food waste data collection were same among these three waves. Thus, our analysis used data from only these three waves. Finally, the unbalanced data of 12,386 households with full information were used in the estimations. Specifically, there were 4,009, 4,141, and 4,236 households in 2004, 2006, and 2009, respectively.

3.2. Food waste and nutrition loss

The CHNS collected detailed information on food consumption encompassing more than 1,500 food items consumed at home or elsewhere. To ensure the quality of the data, the CHNS enumerators recorded food consumption during a period of three consecutive days randomly selected from Monday to Sunday, and the measurements were spread over the whole week. Furthermore, for each of the food items consumed at home, the survey also recorded how much of it was wasted in grams. This enabled us to generate the two dependent variables for this study: total food waste (g) and food waste per capita per day (g).

Furthermore, we employed the food code of wasted food, along with information on the nutritional content of the diverse foods provided by the China Food Consumption Table (Tian and Yu, 2015; Yang et al., 2002) to calculate wasted food in caloric units. The nutrition content of food includes calories, protein, fat, carbohydrates, and other nutritional elements, among which calories are widely recognized as a primary nutrition metric (Tian and Yu, 2013, 2015) because it reflects the energy from food used to support body functions. A previous study argued that it was unreasonable to simply add the quantities of the various foods wasted (Koester, 2015); the calculated calories of diverse wasted foods appears to be a better indicator.

The conversion of food waste to calories loss provides a unified measure across different food products and significant policy implications for food security. Calories satisfy consumers' hunger, especially in developing economies. Tian and Yu (2015) believed that the source of calories intake was important for understanding nutrition improvement. They used the share of calories obtained from protein and fat to measure the structure of calories intake, providing an important reference for this study, as this measure can more accurately determine the nutrition loss from the component level of food wasted. However, when wasting food, in practice, it is difficult for households to delineate it into protein, fat, and carbohydrates, but easier to divide it into high-value and low-value-added food. This food quality measure is used in our study and also in other literature. In addition, during the process of development, carbohydrates are still the primary source of calories in China, on average. Thus, overall, in the current stage, focusing on the total calories loss is more practical, appropriate, and policy related, as compared to other measures of nutrition loss.

The conversion of food waste to calories loss not only gives greater weight to energy-dense foods in the calculation of food waste, but also provides an opportunity to measure the nutrition loss due to food waste. Thus, total food waste (g) and food waste per capita per day (g) were converted into the nutritional contents of this wasted food in the unit of calories. To sum up, four dependent variables were obtained to measure household food waste and calories loss, respectively.

Table 1 reports the summary statistics of the four dependent variables. On average, each household wasted about 293 g of food over the three surveyed days, resulting in a calories loss of about 294 kcal. Therefore, the food waste per capita in 3 days is about 128 g with a calories loss of 126 kcal per capita. The average quantity of food waste per capita over the three surveyed days can be converted to 15.5 kg/

[3] This study has obtained the Ethical Board Approval of Georg-August-Universität Göttingen with which one of the authors affiliates, and got the use license of community data and the data publicly available as well from CHNS.

capita/year, which is lower than the average food waste and loss of consumers in Japan the Republic of Korea, and China (73 kg/capita/year), but higher than that in south and southeast Asia (11 kg/capita/year), as estimated by FAO (2011). While the quantity of food waste in this study looks small, it is actually quite striking considering the differences in the statistical measures used, the relatively limited food supply, and the relatively higher food prices reported. First, this study only accounted for the food waste consumed at home, and did not consider that consumed away from home. In contrast, FAO (2011) reported the quantity of consumer food waste separately from postharvest losses within regional food loss and waste. Second, this study did not account for the food bought during the three surveyed days but wasted after these three days. Third, food prices related to income are still relatively higher in China than in other developed countries, and food waste is traditionally considered immoral behavior.

Table A1 also summarizes the food waste and calories loss tabulated according to urban and rural households. Unsurprisingly, the household food waste of urban residents is on average lower than that of rural residents. This is because the food in markets is usually cleaner than that just harvested, and as urban households buy most of their food in markets, rural households can produce it for themselves or buy at the wet market.

Food waste differs widely between products, as indicated in our theoretical framework of household production. A large share of household food waste is derived from fresh fruit, vegetables, meat, dairy products, and other high-value food (Conrad et al., 2018; Parfitt et al., 2010), which tend to be more nutritious and have shorter shelf lives than processed, shelf-stable foods (Richards and Hamilton, 2018). As Chinese consumers have over the past three decades tended to favor high nutritional content from high-value food, we then employed the subsample of high-value food to check the robustness of our main results. For this purpose, we categorized more than 1,500 food items in the CHNS survey into low or high-value food subject to the China Food Consumption Table. Accordingly, Table A2 summarizes the food waste and calories loss of low and high-value food. Here, high-value food includes meat (pork, beef, mutton, and chicken), eggs, dairy products, seafood, fruit, and vegetables, while other foods are considered low value.

3.3. Dietary knowledge and development index

The independent variable of interest in this study is the dietary knowledge of the household decision maker regarding food shopping and consumption. Since 2004, the CHNS has started paying attention to the dietary knowledge of residents aged over 12 years. As the household food decision maker, each respondent finished a nine-item quiz on basic dietary knowledge on food, as shown in Table A3. For each question, respondents chose from the options of "agree," "disagree," or "unknown." Based on the WHO (1998) criteria, we generated an indicator that takes the value of 1 for a correct answer, −1 for an incorrect answer, and 0 for "unknown," and constructed a summary index of these responses (Ren et al., 2019; Shimokawa 2013). The higher the DKI score is, the better is the knowledge of nutritional intake. The score ranges from −9 to 9. The results show an increasing trend of dietary knowledge from 2004 to 2009 (Table 1). It seems that the DKI of food decision makers rapidly improved after 2004, although only a slight change was evident from 2006 to 2009. Table A1 further reports the differences in the DKI of urban and rural areas, showing that urban residents have better dietary knowledge than rural ones.

The other independent variable of interest pertains to the urbanization and development level of the community in which the household is located. During the CHNS, at the community level, municipal officials were interviewed in each wave and relevant data on issues like infrastructure, population density, local labor markets, and service availability are collected. Following Jones-Smith and Popkin (2010) and Van de Poel et al. (2009), this study therefore relied on a broader definition of development, which embraces various other community characteristics believed to co-determine urbanization and development levels (Tafreschi, 2015). The CHNS data include a comprehensive and one-dimensional index of community development (UDI), which was computed for all communities in all survey waves. Using 12 components from the domains population density, economic activity, traditional and modern market availability, transportation, sanitation, communication, housing, education, health infrastructure, social services, and diversity, scaling procedures from the psychometric literature were utilized to generate and evaluate the resulting index (for a detailed discussion see Jones-Smith and Popkin (2010)). Each of the 12 components is allowed to have a maximum score of 10, and the index was scaled from 0 to 120 with lower values reflecting lower levels of urbanization and development. To clarify the degree of variation in the data, Table 1 shows the trend of the index over time, and Table A1 shows the evolution of the UDI for urban or rural communities. The overall average indicates that communities made continuous progress in the late 2000 s (Table 1), and the index seems to discriminate well between geographic areas (Table A1). As discussed earlier, urban areas exhibit higher levels of development throughout the time span under consideration.

Figs. A1–A2 show the correlations between DKI, UDI, and food waste. DKI and UDI are treated in five quantiles, respectively. However, no obvious differences are evident for the average food waste and nutrition loss among these quantile groups. To further detect the impact of DKI and UDI on food waste and nutrition loss, multivariate regressions are needed to control for other variables that may affect these

Table 1
. Statistics for key variables.

Symbol	Variable definition	Mean			
		Full sample	2004	2006	2009
Dependent variables					
HFW	Quantity of household food waste over 3 days (g)	292.93	330.06	276.77	273.90
		(479.32)	(538.24)	(447.76)	(432.17)
PFW	Quantity of household food waste per capita over 3 days (g)	127.67	152.56	116.80	115.32
		(204.58)	(239.04)	(187.99)	(179.31)
HCL	Household calories loss over 3 days (kcal)	293.95	346.76	253.16	283.92
		(647.86)	(766.38)	(545.44)	(608.38)
PCL	Calories loss per capita over 3 days (kcal)	125.97	156.92	105.82	116.66
		(275.38)	(342.65)	(225.06)	(242.61)
Independent variables of interest					
DKI	Dietary knowledge index	4.15	1.59	5.28	5.44
		(2.86)	(1.56)	2.47	(2.55)
UDI	Urbanization and development index of a community	65.10	63.04	64.54	67.68
		(20.06)	(20.11)	(20.29)	(19.50)

Data source: Authors' calculation based on the CHNS data (2004–2009).

Table 2
Statistics for other control variables.

Symbol	Variable definition	Mean	SD
Characteristics of the food decision maker			
Gender	Gender of the household food decision maker (1 = Male; 0 = Female)	0.22	0.41
Age	Age of the household food decision maker (Years)	50.15	13.89
Hukou	Household Registration (1 = Urban; 0 = Rural)	0.42	0.49
Education	Years of education (Years)	7.61	4.02
Work status	Whether working (1 = Yes; 0 = No)	0.55	0.50
Working intensity			
Light	1 = Yes; 0 = No	0.52	0.50
Moderate	1 = Yes; 0 = No	0.13	0.33
Heavy	1 = Yes; 0 = No	0.35	0.48
No working ability	1 = Yes; 0 = No	0.01	0.11
Food preference	Preference index for unhealthy foods	−2.53	1.71
Family characteristics			
Demographic structure			
Age 14	Proportion of family members aged 14 years and less	9.62	14.44
Age 15–39	Proportion of family members aged 15–39 years	37.95	23.31
Age 40–59	Proportion of family members aged 40–59 years	31.95	28.06
Age 60	Proportion of family members aged 60 years and older	20.48	31.87
Family size[a]	Number of household members	2.42	0.84
Log(income)	Natural logarithm of family income per capita inflated to 2015 (Yuan)	8.84	2.11
Food prices in community			
Beans	Price of beans at the community level (Yuan/Jin[b])	4.81	1.68
Chicken	Price of chicken at the community level (Yuan/Jin)	17.77	5.84
Pork	Price of pork at the community level (Yuan/Jin[b])	21.29	4.17
Vegetables	Price of vegetables at the community level (Yuan/Jin[b])	1.30	0.57
Oil	Price of oil at the community level (Yuan/Jin[b])	6.73	1.33
Cereal	Price of cereal at the community level (Yuan/Jin[b])	4.15	0.87
Observations		n = 12386	

[a] The first adult in the household has a weight of 1. Each additional adult aged 14 years and more has a weight of 0.5. Each child aged less than 14 years has a weight of 0.3.
[b] 1 Jin = 0.5 kg.
Source: Authors' calculation using the CHNS data (2004–2009).

parameters.

3.4. Other control variables

Table 2 statistically describes another set of independent variables. First, this study included information on numerous variables. Individual characteristics for the food decision maker include gender, age, educational attainment, and employment record. Furthermore, the household food decision makers' food preference was generated from five questions concerning the consumption of fast food, salty snack foods, fruits, vegetables, soft drinks, and sugared fruit drinks. For each question, respondents were asked to report their preference, like, or dislike of a specific food. We assigned the value of −1 for liking a healthy preference, 1 for liking an unhealthy preference, and 0 for "neutral," and calculated a summary index of these responses. A higher score indicates an unhealthier food consumption preference. Table A4 provides more detail regarding these questions. Family characteristics include equivalent family size and the proportion of family members by age for the following cohorts: less than 14, 15–39, 40–59, and 60 years and older. We also controlled for the net income per capita at the 2015 constant price, and employed the logarithm form of net income in the empirical study to control for potential heteroscedasticity of the income variable. Other control variables were prices at the community level for six groups of food, namely beans, chicken, pork, vegetables, oil, and cereal. Table A1 further presents the summary statistics of these variables independent of the interest and control variables for urban and rural households.

4. Estimation results

Following the empirical model and estimation procedure described above, Eq. (5) was step-wisely estimated through both random-effects and fixed-effects Tobit regressions. Thereafter, Hausman tests were conducted to justify the selection of the random and fixed effects models. As Tables 3 and 4 show, the results of all Hausman tests indicate that the fixed-effects models are more suitable for the estimates for food waste and calories loss. The fixed effects Tobit regression does not only address the problem of zero waste in the identification of the empirical specifications, but also controls for potential bias from time-invariant unobserved variables. Thus, Tables 3 and 4 only report the estimation results of the fixed-effects Tobit models.[4]

4.1. Impact of DKI on household food waste

Table 3 presents the estimation results of household food waste by step-wisely including the variables of DKI, UDI, and their interactive terms. First, the estimates for household food waste indicate that DKI does not have a significant impact until the UDI and their interaction term is further controlled. This implies a significant interaction effect between the dietary knowledge and development level, and that the marginal effect of DKI on food waste depends on the community development level.

Specifically, the last column suggests that the mean marginal effect of DKI is undefined ($0.2341–0.0039*UDI_{jt}$) and changes with the size of the *UDI* (Eq. (5) and Fig. 1). The calculated results indicate that when UDI < 60.03, i.e., when community development level is low, increasing dietary knowledge will increase food waste and decrease the marginal effect. When UDI = 60.03, changes in dietary knowledge do not impact

[4] The results of the random effects Tobit regressions can be provided upon request.

Table 3
Estimation results of the fixed effects model for household food waste.

Variables	FE (1)	FE (2)	FE (3)	FE (4)
Log(HFW)				
DKI	−0.0125		−0.0214	0.2341***
	(0.03)		(0.03)	(0.08)
UDI		0.0306***	0.0300***	0.0417***
		(0.01)	(0.01)	(0.01)
DKI*UDI				−0.0039***
				(0.00)
Control variables	YES	YES	YES	YES
N	12,386	12,386	12,386	12,386
Chi^2	297.22***	310.15***	313.07***	318.81***
Hausman Test (Chi^2)	237.61***	240.57***	261.76***	249.43***
Log(PFW)				
DKI	−0.0110		−0.0101	0.1339***
	(0.03)		(0.03)	(0.04)
UDI		0.0267***	0.0232***	0.0206***
		(0.01)	(0.01)	(0.01)
DKI*UDI				−0.0022***
				(0.00)
Control variables	YES	YES	YES	YES
N	12,386	12,386	12,386	12,386
Chi^2	247.24***	282.09***	267.78***	210.71***
Hausman Test (Chi^2)	221.13***	225.64***	252.25***	183.99***

Note: Standard errors in parentheses; significance level * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.010$.

Table 4
Estimation results of the fixed effects model for household calories loss.

Variables	FE(1)	FE(2)	FE(3)	FE(4)
Log(HCL)				
DKI	−0.0005		0.0089	0.2172***
	(0.03)		(0.03)	(0.08)
UDI		0.0309***	0.0287***	0.0454***
		(0.01)	(0.01)	(0.01)
DKI*UOI				−0.0033***
				(0.00)
Control variables	YES	YES	YES	YES
N	12,386	12,386	12,386	12,386
Chi^2	275.84***	280.33***	283.30***	302.72***
Hausman Test (Chi^2)	215.82***	229.87***	223.70***	239.58***
Log(PCL)				
DKI	0.0069		0.0065	0.1221***
	(0.02)		(0.02)	(0.04)
UDI		0.0145***	0.0144***	0.0209***
		(0.01)	(0.01)	(0.01)
DKI*UOI				−0.0018***
				(0.00)
Control variables	YES	YES	YES	YES
N	12,386	12,386	12,386	12,386
Chi^2	169.09***	178.27***	177.99***	188.05***
Hausman Test (Chi^2)	124.84***	172.84***	169.00***	243.56***

Note: Standard errors in parentheses; significance level * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.010$.

food waste. Finally, when UDI > 60.03, increasing dietary knowledge decreases food waste, but the marginal effect increases with development level.

$$Marginal\ \ Effect\ \ of\ \ DKI = \begin{cases} > 0 & if\ \ UDI < 60.03 \\ = 0 & if\ \ UDI = 60.03 \\ < 0 & if\ \ UDI > 60.03 \end{cases} \tag{8}$$

This shows that promoting dietary knowledge does not help to reduce food waste in less developed regions, although it will work when the community development level passes some hurdle (e.g., UDI = 60.03 in this study). In less developed communities mainly in rural areas, foods are often not diverse and not well processed, as many are home produced. Thus, more dietary knowledge will lead consumers to further process and increase their waste, increasing waste and loss in household production. However, in urban areas, most food products are well processed and there are more food choices. Consumers are able to choose more suitable and processed foods for home production, and less waste and loss ensues. In addition, in well-developed regions, consumers care more about the environment, and more dietary knowledge leads to less food waste and loss.

The mean marginal effect of UDI (0.0417–0.0039*$DKI_{it} > 0$, as DKI < 9) is positive, indicating that in more developed areas, consumers waste more food. This is consistent with the results obtained when employing the macro data (HLPE, 2014) (but still more DKI helps reduce waste and loss). In an affluent society where food is not scarce, consumers released from hunger tend to pursue the taste and nutrition, and more food loss seems a rational behavior (Yu and Abler, 2009, 2016).

However, the interaction impact of DKI and UDI on household food waste is negative and statistically significant, suggesting that more knowledge in less developed areas may result in more food waste, while in contrast, in more developed areas, more knowledge could result in less food waste. In other words, with the development of the local community, the positive impact of DKI on household food waste will be attenuated. Thus, there seems to be an offsetting effect between DKI and UDI.

Second, the estimation results for food waste per capita in a household are almost consistent with the results for household food waste. Fig. 2 shows the marginal effect of DKI on the log of per capital food waste. The results for the fixed-effects models 2, 3, and 4 jointly confirm that rapid urbanization and development of the local community results in more food waste per capita (Thyberg and Tonjes, 2016). Parfitt et al. (2010) argued that urbanization requires an extension of food supply systems, leading to diet diversification and a disconnection from food sources, which may ultimately increase food waste. Although the improved DKI may increase food waste per capita in a household in less developed areas, this driving effect will decrease with the urbanization and development of the local community. Finally, the mean marginal effect of DKI on food waste per capita in a household is negative.

4.2. Impact of DKI on household calories loss

Table 4 reports the FE Tobit estimation results for calories loss. The impact of DKI is only significant in the columns of fixed-effects model 4. These results are consistent with those for food waste and loss in Table 3. It also indicates that our results are robust.

Considering the interaction between DKI and UDI, the results suggest that the marginal effect of DKI for household calories loss (HCL) is 0.2172–0.0033*UDI. If the UDI < 65.82, the marginal effect of DKI is positive, implying that a lower DKI is positively correlated with calories loss in less developed communities. If the UDI = 65.82, the marginal effect of DKI is zero, and if > 65.82, the marginal effect of DKI is negative. This implies that a lower DKI may reduce calories loss in well-developed communities. The relationship is shown in Fig. 3.

$$MarginalEffectofDKI = \begin{cases} > 0 & if\ \ UDI < 65.82 \\ = 0 & if\ \ UDI = 65.82 \\ < 0 & if\ \ UDI > 65.82 \end{cases} \tag{9}$$

We also found that the marginal effect of UDI on nutrition loss is 0.0452–0.0033*DKI > 0 as DKI < 9. This indicates that well-developed communities have higher food waste and loss, and increasing dietary knowledge may offset the marginal effect of UDI. In addition, the results for per capita calories loss (PCL) are consistent. Fig. 4 shows the marginal effect of KDI. These consistent results also indicate the robustness

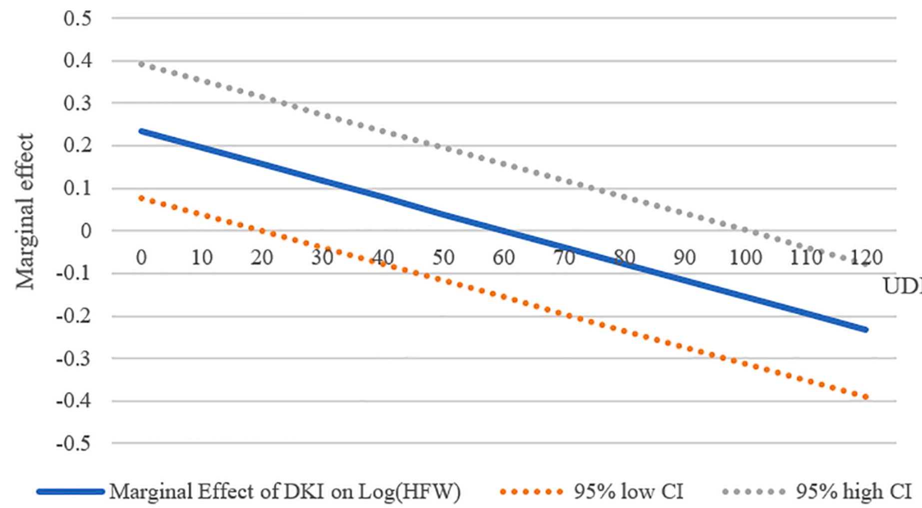

Fig. 1. . The marginal effect of *DKI* on log (HFW) with the change of *UDI*.

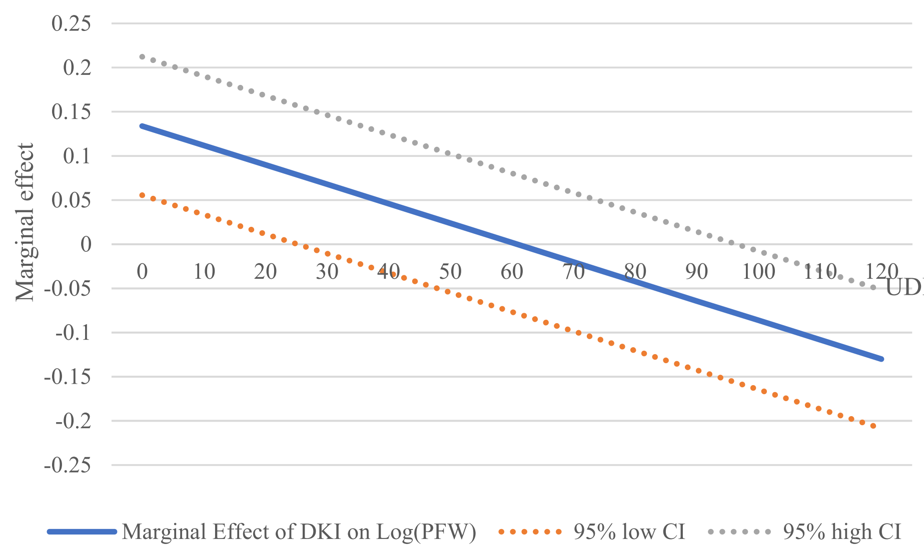

Fig. 2. . The marginal effect of *DKI* on log (PFW) with the change of *UDI*.

of our findings.

4.3. Impact of DKI on household food waste and calories loss for high-value food

With economic growth, residents in China tend to increase their consumption of high-value food such as meat, seafood, fruit, and so on (Yu and Abler, 2009). In general, the food waste of high-value food is higher than that of other food. To better understand the issues related to food waste in the future, the waste and calories loss of high-value food must be explored.

Using the subsample of high-value food, the FE Tobit regressions for food waste and calories loss were estimated. Table 5 shows that the results are almost the same as those in Tables 3 and 4. DKI, UDI, and their interaction term have significant impacts on the quantities of food waste and calories loss. Therefore, less waste of high-value foods will occur for households with improved dietary knowledge. However, the improved dietary knowledge of the food decision maker will increase the food wasted in terms of calories. Again, for high-value food, with the development of the local community, the amount and calories of food waste will also increase. The coefficient of the interactive term of dietary knowledge and development of the community are always negative, suggesting again the existence of offsetting effects of dietary knowledge and community development. The marginal effect of community development will be attenuated by the dietary knowledge of consumers. Thus, overall, the results from the subsample of high-value food are consistent with those from the full sample, confirming the robustness of our main findings.

4.4. Heterogeneity analysis

Table 6 presents the heterogeneous impacts of DKI on food waste and calories loss for urban and rural households separately. Interestingly, in addition to the positive effect of DKI on household calories loss in urban

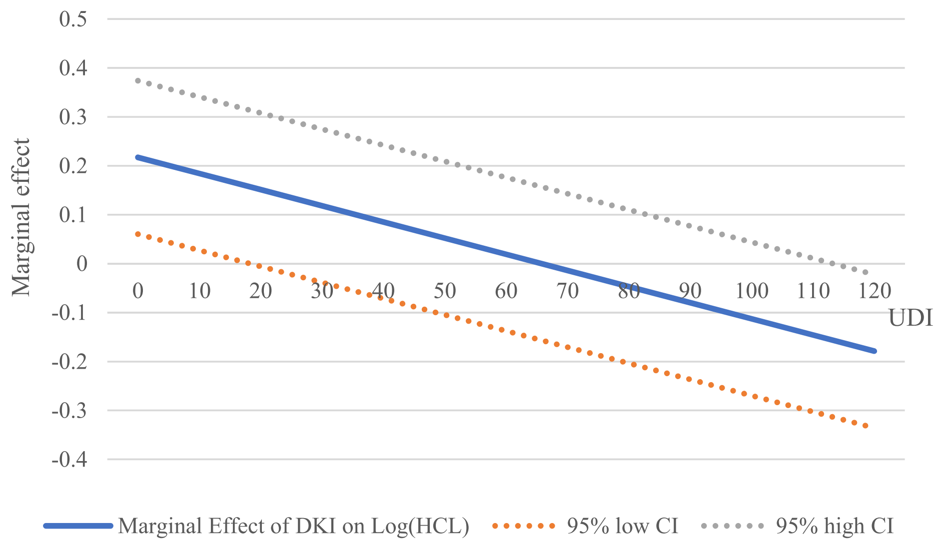

Fig. 3. . The marginal effect of *DKI* on log (HCL) with the change of *UDI*.

areas, it has insignificant impacts on all food waste and calories loss measures in urban regions (as most of the estimated parameters are not significant). In contrast, the coefficient of DKI on the quantity of food waste was always significantly positive in rural areas, and the interaction effects of DKI and UDI on food waste were significant and negative. This is consistent with the whole sample. The attenuation effect of dietary knowledge for the marginal effect of community development is once again observed for food waste and loss in rural China. Similar results are observed for the calorie loss per capita as most parameters are significant for rural areas, and not for urban area. As such, heterogeneity exists in the impacts of DKI on the food waste and calories loss of urban and rural areas. With the urbanization and development of the community in which the household is located, the impacts of DKI on food waste and calories loss are changing, and become less significant.

The results in Tables A5 and A6 further reveal the heterogeneity of the impacts of DKI on food waste and calories loss subject to the quantile of household income at the 20th, 40th, 60th, and 80th percentile distribution. Specifically, we look at the interactive term between DKI and UDI, which is negative and mostly significant for the 1st, 2nd, and 3rd quantiles, and turns positive for the 4th and 5th quantiles. It implies that the offsetting effect between DKI and UDI only exists for the relatively low-income groups, and disappears for the high-income groups. As the interaction term for the 5th quantile is positive and significant, it implies that the impacts of dietary knowledge increases with the marginal effect of community development levels for both calories loss and food waste and loss for the highest income group.

4.5. Policy implications

The challenge of reducing food waste is a complex social, economic, and environmental problem (Ponis et al., 2017; Yu and Abler, 2014, 2016). Thus, multiple policies should be designed and implemented to realize the objective of food waste reduction. The specific policy implications of this study are summarized as follows. First, food waste policies must be urgently designed to minimize food waste at the household level in China. Given the heterogeneity of the quantity of food waste among different populations, one policy to reduce food waste should target rural or low-income households.

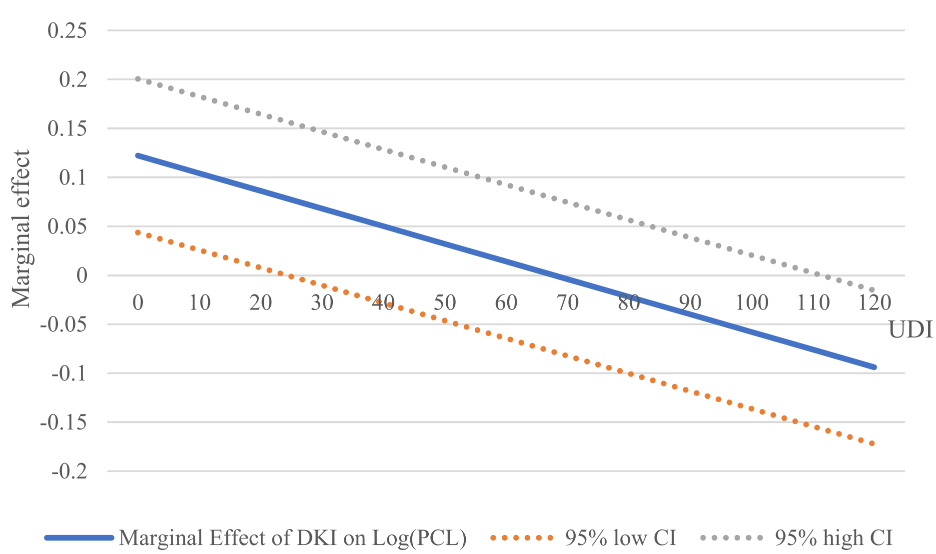

Fig. 4. . The marginal effect of *DKI* on log (PCL) with the change of *UDI*.

Table 5
Estimation results of the fixed effects model for high-value food waste and calories loss.

Variables	Food waste		Calories loss	
	Log(HFW)	Log(PFW)	Log(HCL)	Log(PCL)
DKI	0.2214**	0.2864***	0.1970***	0.1754***
	(0.09)	(0.08)	(0.05)	(0.04)
UDI	0.0326***	0.0378***	0.0163***	0.0124**
	(0.01)	(0.01)	(0.01)	(0.01)
DKI*UDI	−0.0041***	−0.0046***	−0.0027***	−0.0024***
	(0.00)	(0.00)	(0.00)	(0.00)
Control variables	YES	YES	YES	YES
N	12,386	12,386	12,386	12,386
Chi^2	278.12***	283.71***	170.6***	164.29***
Hausman Test (Chi^2)	228.27***	243.56***	84.58***	102.83***

Note: Standard errors in parentheses; significance level * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.010$.

Table 6
Estimation results of the fixed effects models for food waste and calories loss for urban and rural households.

	Urban		Rural	
	Log(HFW)	Log(PFW)	Log(HFW)	Log(PFW)
DKI	0.3718	0.3250	0.3219**	0.2082*
	(0.26)	(0.24)	(0.13)	(0.12)
UDI	−0.0057	−0.0005	0.0582***	0.0523***
	(0.02)	(0.02)	(0.01)	(0.01)
DKI*UDI	−0.0041	−0.0035	−0.0058**	−0.0041*
	(0.00)	(0.00)	(0.00)	(0.00)
Control variables	YES	YES	YES	YES
N	5193	5193	7193	7193
Chi^2	218.15***	204.92***	308.95***	227.90***
	Urban		Rural	
	Log(HCL)	Log(PCL)	Log(HCL)	Log(PCL)
DKI	0.4331*	0.2187	0.1839	0.2786**
	(0.26)	(0.25)	(0.13)	(0.12)
UDI	0.0058	−0.0036	0.0517***	0.0498***
	(0.02)	(0.02)	(0.01)	(0.01)
DKI*UDI	−0.0043	−0.0022	−0.0033	−0.0050**
	(0.00)	(0.00)	(0.00)	(0.00)
Control variables	YES	YES	YES	YES
N	5193	5193	7193	7193
Chi^2	167.00***	163.97***	273.54***	218.20***

Note: Standard errors in parentheses; significance level * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.010$.

Second, food waste is linked to many factors, although this study focused only on the dietary knowledge of the household food decision maker. However, the study provides solid evidence that more dietary knowledge may play different roles in communities at different levels of development. When the development level of a community is low, dietary knowledge may increase food waste and loss at the household level, but when it is high, dietary knowledge will decrease food waste and loss. This implies that the effect of promoting nutrition knowledge on food waste and loss depends on the level of community development.

Third, the offsetting effect between dietary knowledge and community development levels are the key message here. Though food waste will increase with the community development level, but the marginal effect could be attenuated by increasing dietary knowledge.

In addition, the effect of dietary knowledge on food waste is only statistically significant for residents in rural areas. Though previous studies indicated that food waste in rural areas could be easily used in a far less impacting way (Moult et al., 2018), we argue that reducing food waste makes more sense than searching for a method to reuse it. Thus, in order to reduce food waste in China at the consumption level, a clear message for policy makers is to promote dietary knowledge among household food decision makers, of whom the majority are women (Zhao and Yu, 2019).

Similarly, implementing food waste education programs such as providing information about the negative effects of food waste in landfills (Qi and Roe, 2017) may be an effective intervention to reduce the amount of food waste. However, a program aiming to reduce food waste by improving the dietary knowledge of food decision makers should be implemented according to the actual development level of the target region. Improving dietary knowledge may be an efficient way to reduce food waste and calories loss in somewhat developed areas, but may lead to more food waste in less developed regions.

5. Conclusions

This study investigated household food waste in China and the resulting calories loss by focusing on the impacts of dietary knowledge. The results reveal that improving food decision makers' dietary knowledge could significantly influence food waste and calories loss. Furthermore, dietary knowledge has significant interaction effects with urbanization and community development on food waste and calories loss. That is, there is an offsetting effect between dietary knowledge and community development. This is the key message of this study.

Similar impacts of dietary knowledge also occur for the food waste and calories loss of high-value food. Compared with urban households, dietary knowledge plays a more significant role in the food waste and calories loss of rural households. Finally, the heterogeneity in the impacts of dietary knowledge on food waste and calories loss among the different income groups was also investigated. The negative impacts of dietary knowledge on food waste and calories loss were only significant for the richest residents. The interaction effect between dietary knowledge and community development on food waste is negative for the low-income groups but becomes positive for the richest residents.

The findings of this study provide a better understanding of food waste in China in the context of rapid economic development and urbanization as well as of the increasing dietary knowledge of food decision makers. With further economic development and urbanization in China in the future, food waste will continue to increase, which will exacerbate the negative implications for food security, nutrition health, and the environment, especially for households currently in rural areas or those in a relatively low-income group. However, improving the nutrition knowledge of food decision makers in China can help reduce food waste overall, although this may also unfortunately result in greater calories loss. Nevertheless, with the development of the community to a certain level, improved dietary knowledge will help to reduce both food waste and calories loss.

The findings of this study not only contribute to the literature on food waste, but also have important policy implications to further reduce this phenomenon in China. Considering China's rapid development in recent years, the level of development and urbanization is much higher than that ten years ago. As such, promoting the dietary knowledge of food decision makers is expected to play an important role in reducing food waste and calories loss. Given that reducing food waste can be an effective way to combat hunger, improve food security, and make better use of natural resources (Beretta et al., 2013; Munesue et al., 2015), this study also provides a reference for research and policy design related to food waste in other developing countries in the process of urbanization.

Finally, we highlight two major limitations of this study. The analysis was based on data from the CHNS collected in 2004, 2006, and 2009, with information on 12,386 households. Firstly, while the employed data provided a good opportunity to explore food waste in China, it is quite old, and thus is acknowledged as a major limitation here. Nevertheless, the findings based the old data still contribute to a better understanding of the role of dietary knowledge in household food waste in the context of rapid economic development and urbanization in China. Secondly, the study may underestimate the quantity of household food waste, as the CHNS data did not account for the food waste from the food consumed away from home and the leftover foods that might be wasted after the recorded three days. In future studies, updated data are needed to investigate the recent trend of food waste in China.

CRediT authorship contribution statement

Shi Min: Conceptualization, Methodology, Software, Visualization, Investigation, Formal analysis, Writing - original draft. **Xiaobing Wang:** Conceptualization, Methodology, Supervision, Validation, Writing - review & editing. **Xiaohua Yu:** Data curation, Methodology.

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Appendix A

See Figs. A1 and A2 and Tables A1–A6.

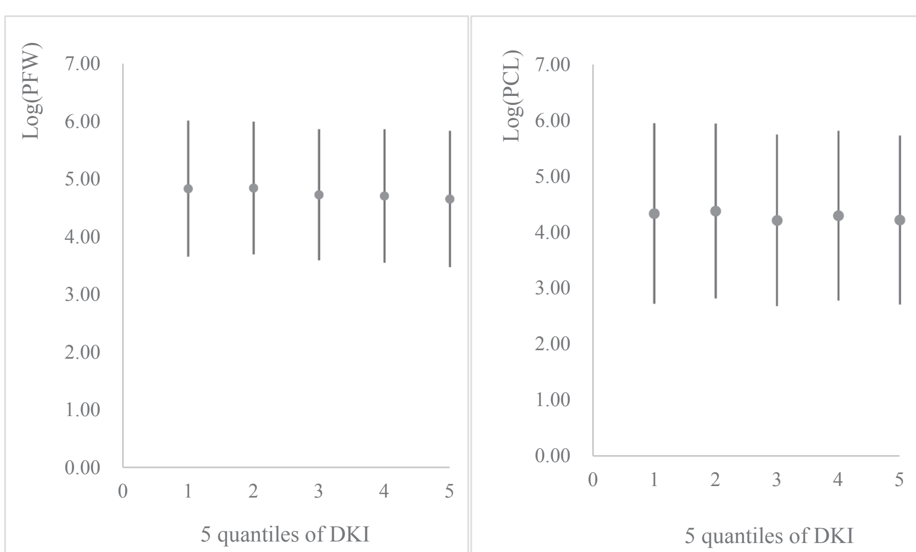

Fig. A1. Relation between food waste and DKI.

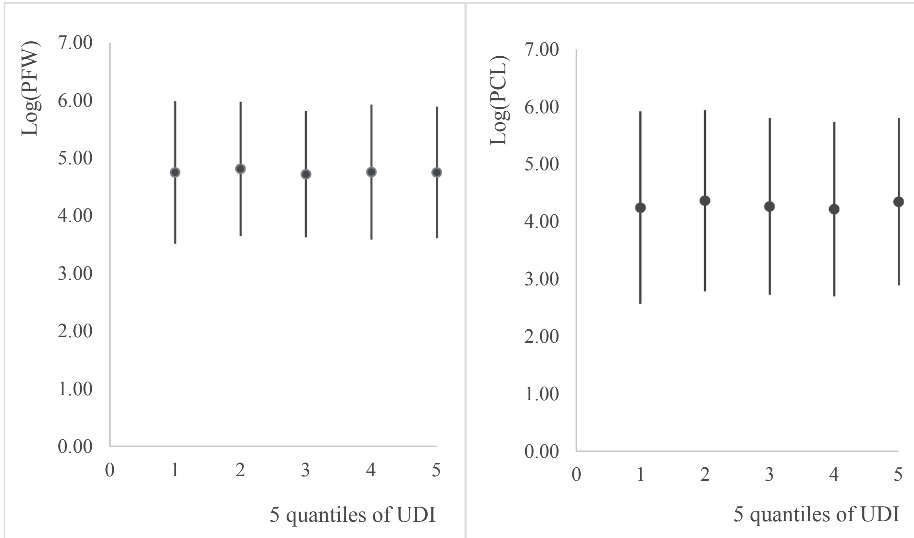

Fig. A2. Relation between food waste and UDI.

Table A1
. Statistics for variables by household registration.

Variables	Urban		Rural		Difference[1]
	Mean	SD	Mean	SD	(Rural-Urban)
Dependent Variables					
HFW	255.80	410.60	319.90	514.40	64.11***
PFW	124.70	196.30	130.20	209.30	5.50
HCL	236.60	523.00	335.50	719.60	98.87***
PCL	113.30	247.20	135.40	292.90	22.09***
Independent Variables of interest					
DKI	4.65	2.80	3.78	2.85	−0.88***
UDI	82.39	12.53	52.67	14.45	−29.72***
Characteristics of the food decision maker					
Gender	0.22	0.42	0.22	0.41	−0.01
Age	52.68	13.83	48.33	13.65	−4.36***
Education	9.05	4.18	6.57	3.54	−2.48***
Work status	0.39	0.49	0.67	0.47	0.27***
Working intensity					
Light	0.83	0.38	0.29	0.46	−0.54***
Moderate	0.10	0.31	0.14	0.35	0.04***
Heavy	0.05	0.21	0.56	0.50	0.51***
No working ability	0.02	0.14	0.01	0.07	−0.01***
Food preference	−2.83	1.70	−2.32	1.69	0.51***
Family characteristics					
Demographic structure					
Age 14	7.24	12.69	11.34	15.35	4.11***
Age 15–39	31.88	23.51	42.33	22.16	10.45***
Age 40–59	34.53	30.37	30.09	26.11	−4.44***
Age 60	26.35	35.67	16.24	28.05	−10.12***
Family size	2.18	0.73	2.59	0.87	0.41***
Log(income)	9.18	2.12	8.59	2.06	−0.59***
Food prices in community					
Beans	4.75	1.69	4.85	1.68	0.10***
Chicken	17.05	5.52	18.28	6.00	1.23***
Pork	20.71	4.17	21.71	4.12	1.00***
Vegetables	1.33	0.56	1.27	0.57	−0.05***
Oil	6.39	1.26	6.98	1.32	0.60***
Cereal	4.11	0.85	4.18	0.89	0.73***
Observations	$n = 5193$		$n = 7193$		

Source: Authors' calculation using the CHNS data (2004–2009); Note: 1 results of the t test.

Table A2
Food waste and calories loss of high and low-value products.

Food category	HFW (g)	PFW (g)	HCL (kcal)	PCL (kcal)
All samples	292.93	127.67	293.95	125.97
	(479.32)	(204.58)	(647.86)	(275.38)
High-value products[a]	223.00	97.83	121.83	53.92
	(392.58)	(169.71)	(309.91)	(139.49)
Low-value products[a]	69.93	29.85	172.11	72.05
	(198.64)	(82.47)	(538.75)	(223.61)

[a] High-value products are vegetables, fruit, meat, poultry, eggs, fish, shellfish, and mollusk; the others are low-value products.

Table A3
Questions concerning dietary knowledge in the CHNS.

Dietary knowledge: Do you strongly agree, agree, are neutral, disagree, or strongly disagree with this statement?	True/ False
**Please note that the question is not asking about your actual habits.*	
Q1: Choosing a diet with a lot of fresh fruit and vegetables is good for one's health	T
Q2: Eating a lot of sugar is good for one's health	F
Q3: Eating a variety of foods is good for one's health	T
Q4: Choosing a diet high in fat is good for one's health	F
Q5: Choosing a diet with a lot of staple foods (rice and rice products and wheat and wheat products) is not good for one's health	T
Q6: Consuming a lot of animal products daily (fish, poultry, eggs, and lean meat) is good for one's health	F
Q7: Reducing the amount of fatty meat and animal fat in the diet is good for one's health	T
Q8: Consuming milk and dairy products is good for one's health	T
Q9: Consuming beans and bean products is good for one's health	T
Index rules: "1" point was given for a correct answer, "-1" point for an incorrect answer, and "0" points for the other answers.	

Source: The dietary knowledge questionnaire is from the official website of the China Health and Nutrition Survey (CHNS) (http://www.cpc.unc.edu/projects/china).

Table A4
Questions concerning food preferences in the CHNS.

Food Preference: How much do you like this food: Like very much, like, am neutral, dislike, or dislike very much?	Healthy (H)/ Unhealthy (U)
Q1: Fast food (KFC, pizza, hamburgers, etc.)	U
Q2: Salty snack foods (potato chips, pretzels, French fries, etc.)	U
Q3: Fruit	H
Q4: Vegetables	H
Q5: Soft drinks and sugared fruit drinks	U
Index rules: "1" point was given for liking an unhealthy preference, "-1" point for liking an healthy preference, and "0" points for neutral.	

Source: The dietary knowledge questionnaire is from the official website of the China Health and Nutrition Survey (CHNS) (http://www.cpc.unc.edu/projects/china).

Table A5
Estimation results of the fixed effects models for food waste by quantiles of income.

	Log(HFW)				
	1st Q	2nd Q	3rd Q	4th Q	5th Q
DKI	0.1406	0.3256	0.4081	−0.4429	−0.9658**
	(0.23)	(0.26)	(0.27)	(0.32)	(0.39)
UDI	0.0389	0.0414	0.1423***	0.0188	−0.0619
	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)
DKI*UDI	−0.0024	−0.0102**	−0.0070	0.0071*	0.0096*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Control variables	YES	YES	YES	YES	YES
N	2478	2477	2478	2476	2477
Chi^2	63.14***	68.81***	58.31***	45.22***	91.34***
	Log(PFW)				
	1st Q	2nd Q	3rd Q	4th Q	5th Q
DKI	0.1763	0.3445	0.3762	−0.3173	−1.1047**
	(0.25)	(0.23)	(0.26)	(0.31)	(0.46)
UDI	0.0635*	0.0416	0.1238***	−0.0017	−0.0610
	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)
DKI*UDI	−0.0029	−0.0100***	−0.0058	0.0054	0.0113**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Control variables	YES	YES	YES	YES	YES
N	2478	2477	2478	2476	2477
Chi^2	61.82***	59.80***	56.33***	47.96**	71.05***

Note: Standard errors in parentheses; significance level * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.010$.

Table A6
Estimation results of the fixed effects models for calories loss by quantiles of income.

	Log(HCL)				
	1st Q	2nd Q	3rd Q	4th Q	5th Q
DKI	0.4430*	0.2472	0.3750	−0.2968	−0.8247**
	(0.25)	(0.26)	(0.28)	(0.33)	(0.41)
UDI	0.0594	0.0334	0.1352***	0.0276	−0.0240
	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)
DKI*UDI	−0.0071*	−0.0086**	−0.0066	0.0050	0.0078
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Control variables	YES	YES	YES	YES	YES
N	2478	2477	2478	2476	2477
Chi^2	57.77***	52.26***	57.93***	44.56***	95.08***
	Log(PCL)				
	1st Q	2nd Q	3rd Q	4th Q	5th Q
DKI	0.5198**	0.4678*	0.5776*	−0.2518	−0.8633**
	(0.25)	(0.26)	(0.34)	(0.31)	(0.41)
UDI	0.0928**	0.0454	0.1530***	0.0116	−0.0650
	(0.04)	(0.03)	(0.05)	(0.03)	(0.05)
DKI*UDI	−0.0070*	−0.0110**	−0.0103*	0.0046	0.0096*
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Control variables	YES	YES	YES	YES	YES
N	2478	2477	2478	2476	2477
Chi^2	40.90**	43.58***	42.56**	37.21**	65.36***

Note: Standard errors in parentheses; significance level * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.010$.

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