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E-commerce improves dietary quality of rural households in China

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Abstract

E-commerce is gaining importance in the food sector of many countries, and its potential influence on people's access to food and dietary choices is yet to be thoroughly investigated. In this study, we analyze data from a food consumption survey conducted in rural China in 2021 to examine the impact of e-commerce on individual food consumption patterns and dietary quality. Our results with instrumental variable models show that e-commerce significantly reduces the consumption of staple foods, such as cereals and potatoes, while it increases the consumption of legumes, nuts, milk, and milk products, even after controlling for income and other confounding factors. Additionally, e-commerce contributes to higher dietary diversity and dietary quality among rural households. In the face of shrinking physical markets in rural areas, it seems that rural e-commerce can serve as an important mechanism to improve food access and meet the diversifying dietary demands of rural residents.

Keywords: e-commerce; dietary patterns; dietary quality

JEL Codes: D12, I15, O33, Q13

1. Introduction

E-commerce has gained in importance for retailing in many parts of the world, including in high-, middle-, and low-income countries. In the food sector, e-commerce activities started later than in many other sectors, and the share of online sales in total food sales is still relatively small in most places. Online food sales increased significantly during the COVID-19 pandemic – a trend that will likely continue also in post-pandemic times due to new technological opportunities and changing consumer preferences (Guo et al. 2022; Tyrvainen and Karjaluoto, 2022). So far, relatively little is known about how e-commerce in the food sector may possibly influence people's food choices and nutrition. While a few studies on broader questions around online food retailing exist, concrete effects on dietary quality have not been analyzed (Meemken et al., 2022; Liu and Lin, 2020). Also, much of the existing research on e-commerce in the food sector focuses on meal-delivery services in urban environments, not on grocery sales in rural areas, probably because the e-commerce infrastructure in many rural regions is not yet very well developed. Here, we address this research gap by analyzing effects of e-commerce on peoples' diets in rural China.

China has made significant efforts to enhance the internet infrastructure in rural areas, resulting in a 59% penetration rate as of 2021, with over 99% of the rural villages connected to internet and 4G networks (CNNIC, 2022). The rate of rural internet users had reached 99.7% in 2021. Most people in rural China access the internet through their smartphones. The improvement in the network infrastructure has also fueled the rapid development of rural e-commerce, transforming consumer behavior from traditional market shopping to online shopping (Ma et al., 2021; Zhao et al., 2022). According to the National Bureau of Statistics (NBSC) (2022), China's rural online retail sales reached 2.05 trillion Chinese yuan (CNY) in 2021, with food and beverages accounting for 10.6% (MARA, 2021). The benefits of e-commerce have been well documented, with previous research highlighting the potential for welfare improvement (Li et al., 2021; Qin and Fang, 2022; Fan et al., 2018). However, previous studies looked at e-commerce in general, not at effects for food consumers. In principle, e-commerce may influence people's diets and nutrition – possibly in both positive and negative ways – but such effects have hardly been explored. Despite significant improvements in food security in China in recent decades, several diet and nutrition challenges remain, including insufficient consumption of fruits, aquatic products, and dairy, and excessive consumption of salt and edible oils (CNS, 2020).

Past research in rural China suggests that the substandard dietary quality can be attributed to various factors, including a decline in the diversity of agricultural production (Huang and Tian, 2019), the stagnation of rural food market development (Wang et al., 2017), budget constraints (Xie et al., 2022), and insufficient dietary knowledge (Lin et al., 2015). Notably, food markets have emerged as increasingly vital sources of food for rural residents over the past few decades, given the rapid decline in food subsistence production and the increasing specialization of farms (Huang and Tian, 2019).

Despite the increasing reliance on purchased foods, physical food markets in rural China have been gradually shrinking due to substantial rural-urban migration. Many rural residents, and particularly the main earners of households, have moved to urban areas for most of the year (Guo et al., 2022). Left-behind residents, mainly children and the elderly with limited or no income, have become the primary population in rural areas. Sparse population and geographic remoteness are important factors influencing household consumption; food deserts are often characterized by high food prices and low availability of heathy foods (Fan et al., 2018). In villages with large rural-urban migration rates, food retailers are increasingly likely to exit the market, as local food demand and other business activities shrink, thus further deteriorating food accessibility for the left-behind residents (Huang and Tian, 2019). In villages where local food retailers continue their business, operational costs per unit of food increase due to declining market size (Krugman, 1991), leading to fewer food choices for rural consumers. In such situations, meeting rural consumers’ rising demand for diversified diets is increasingly challenging and has become a serious bottleneck for nutritional improvements (Martin et al., 2020).

Rural e-commerce is a relatively recent phenomenon in the Chinese food sector. It has several distinctive characteristics in comparison to more traditional food markets, such as farmers' markets, grocery stores, or supermarkets. On the one hand, e-commerce significantly reduces information acquisition and search costs for consumers and provides a wider range of food choices (Pozzi, 2012; Richards et al., 2017). With the continuous investment on the logistics and distribution system at the county-township-village levels in China, the "last mile" of logistics has been connected. The shortening distance between smallholders and food markets could reduce the transaction costs of distribution and promote e-commerce development (Anderson and Anderson, 2002). On the other hand, purchasing food online increases transportation costs and creates asymmetries in food quality between consumers and sellers (Chintagunta et al., 2012; Zheng et al. 2020), which poses a greater challenge in delivering food to rural and remote areas. Despite the coverage of e-commerce sites reaching 79% in China's administrative villages in 2021 (MARA, 2022), some villages still face poor accessibility to online foods.

Existing studies on different types of information and communication technologies from various countries suggest that these technologies can augment the income of rural households through reduced transaction costs, improved market access, and better employment opportunities (Gao et al., 2018; George et al., 2016; Rajkhowa and Qaim, 2022). The use of mobile phones can also reduce uncertainty for farmers and thus help to smooth income and consumption volatility during shocks (Parlasca et al., 2020). Furthermore, studies in various countries show that mobile phones and the internet can have positive nutrition effects for rural households, mostly channeled through income gains and better access to information (Parlasca et al.; 2020; Sekabira and Qaim, 2017; Xue et al., 2021). None of these studies looks at the effects of e-commerce on peoples' food choices and diets, as we do here.

In particular, we examine the effects of e-commerce on dietary choices and dietary quality of rural households in China and also explore the possibility of e-commerce serving as a partial substitute for vanishing physical food markets in rural areas. In addition to contributing to the literature on the effects of e-commerce in the food sector, we also advance the literature on dietary patterns in rural China from a broader perspective. We use data from an own household survey conducted in 108 villages across four provinces in China in 2021. Previous studies on food consumption mainly relied on data from the China Health and Nutrition Survey (CHNS), which was last updated in 2011. Since then, significant changes in population structure and dietary patterns have occurred in rural China (Cheng et al., 2021; Zhou et al., 2022). Hence, relying on the CHNS data alone may not suffice to explain the current dietary situation of rural residents.

The remainder of this article is organized as follows. Section 2 provides a theoretical framework of potential links between the use of e-commerce and dietary quality. Section 3 describes the data and empirical methods used, including the survey data, the measurement of key variables, and the econometric models. In Section 4, the results of the analysis are presented and discussed. Finally, Section 5 concludes the article by summarizing the main findings and their implications for rural development and nutrition security.

2. Theoretical framework

The recent literature about e-commerce in the food sector describes potential negative effects on consumer nutrition and health, especially referring to meal-delivery services that have increased tremendously during the COVID-19 pandemic (Meemken et al., 2022). Meal-delivery services may be associated with more calorie-dense meal choices and less physical exercise for consumers, thus increasing the risk of obesity and related chronic diseases. However, online grocery shopping may have different effects than meal-delivery services.

Figure 1 illustrates the potential channels through which online grocery shopping may impact dietary quality. First, grocery e-commerce reduces the fixed costs associated with establishing physical stores and expands the geographic market boundary, thus improving productivity and efficiency in food supply chains (Omitola and Wills, 2018). With proper road infrastructure available, e-commerce also allows businesses to cater to consumers in remote rural areas (Wang et al., 2022).

Second, e-commerce offers the potential to provide more detailed information to consumers on aspects such as food ingredients, production, and nutrition, while also allowing suppliers to receive direct feedback. This can enhance transparency, alleviate information asymmetry, and increase consumer trust. Additionally, improved access to new services and information can increase consumers' nutrition knowledge and contribute to better dietary practices (Sekabira and Qaim, 2017).

Third, e-commerce is associated with convenience for consumers, as food purchases can be made any time from the comfort of one's own home. With just a few clicks, customers can browse through a wide range of food options and place orders online, saving time and effort. This influences food accessibility and may also change food choices, the frequency of purchases, and preferences for quality and variety.

Fourth, e-commerce and the related more efficient logistics facilitate integration of food supply chains over larger geographical regions, leading to a bigger variety of food choices, especially for consumers in remote rural locations. Through online purchases and delivery, consumers can access diverse types of foods, from traditional regional specialties to global cuisines. This may expand culinary experiences, allowing people to explore different tastes and flavors they may not have otherwise been able to enjoy.

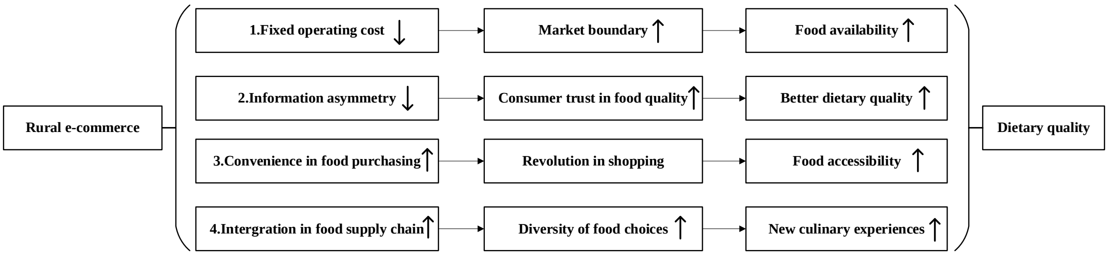

Figure1. Potential impact channels of rural grocery e-commerce on dietary quality

Based on the above analysis, we hypothesize that grocery e-commerce increases the availability and accessibility of foods for rural consumers, thus contributing to higher dietary diversity and dietary quality. Especially in situations with shrinking physical food markets, e-commerce may serve as an important market access mechanism for rural households to meet their diversifying dietary demands. We test these hypotheses with primary data from rural China.

3. Materials and methods

3.1 Household survey and data

The data used in this study were collected through a household nutrition survey from 108 villages in four Chinese provinces in the summer of 2021. The four provinces are Henan, Hubei, Shandong, and Hebei in central, eastern, and northern China, covering major agricultural production areas. We conducted surveys at the village level, the household level, and the individual level. The village questionnaire gathered data on village digital infrastructure, rural food supply and demand, prices of representative foods, and food accessibility (e.g., food markets, supermarkets, restaurants). The household and individual surveys collected in-depth information on food consumption, farming structure, market access for agricultural products, digital technology applications, and household and individual characteristics.

To ensure representative samples, a stratified sampling approach was employed. Specifically, 3-8 counties in each province and 3-11 villages in each county were randomly selected. To select households for interview, in each village a distance-based grouping method was used, where households were categorized into three groups based on the distance between their home and the office of the village committee. From each group, 5-10 households were randomly selected for study participation.

In each household, the person mainly responsible for preparing food was interviewed face-to-face. As a result, all respondents are household food decision-makers. Food consumption was captured at the individual level to increase precision. However, in rural households, meals are typically eaten together, so that we do not expect significant differences between individual-level and household-level dietary diversity.

The final sample includes 1560 households (278 in Henan, 352 in Hubei, 398 in Shandong, and 532 in Hebei). After removing questionnaires with incomplete information, we remain with 1342 observations from 108 villages. The final valid observations were 223 in Henan, 284 in Hubei, 366 in Shandong, and 469 in Hebei.

3.2 Measurement of key variables

3.2.1 Dietary patterns

We adopted the 24-hour recall method to record all food items listed in the China Food Composition Table (CFCT) 2009 (about 1500 food items) consumed by survey respondents at home and away from home, including the name of the food, the food code (showed in the CFCT 2009), any ingredients, the weight, the method of cooking, and the location and time of consumption. The individual-level food consumption data were then used to generate our dietary outcome variables.

For parts of the analysis, we classified all foods consumed by individuals into 8 groups according to the China Food Pagoda (CFP) 2022: (1) cereals and potatoes; (2) legumes (various types of beans and soy products) and nuts (melon seeds, walnuts, peanuts, pistachios, etc.);

(3) vegetables (leafy vegetables, root vegetables, eggplant and fruit, mushrooms, dried vegetables); (4) fruits (fresh fruits, dried fruits, etc.); (5) meat and poultry (beef, lamb, pork, poultry, animal offal, etc.); (6) milk and milk products (fresh milk, yogurt, cheese, milk powder, etc.); (7) eggs; (8) aquatic products (river food, seafood, mollusks, etc.). The consumption quantity for all food items was converted to grams. Figure 2 presents the dietary patterns of rural residents in relation to the recommended food quantity bounds of CFP 2022, represented by two dashed horizontal lines. The recommended food quantity bounds are set for standard adults (older than 18) with a daily calorie intake between 1600-2400 kcal (regardless of sex).

Our data reveal that all four provinces exhibit overconsumption of cereals and potatoes, as well as legumes and nuts, while fruits, milk, and milk products are under-consumed. Moreover, we find substantial variation in dietary patterns across different provinces. For instance, the average vegetable consumption falls into the corridor of recommended levels in Shandong, Henan, and Hebei, but exceeds the upper bound in Hubei. Additionally, the daily consumption of meat and poultry in Hebei is only about half of the recommended lower bound, but exceeds the recommended upper bound in the other three provinces. Furthermore, three of the four provinces (Hebei, Shandong and Henan) exhibit insufficient consumption of aquatic products, with Hubei being the only province with sufficient consumption of this food group, attributable to the strong freshwater aquaculture sector in this region. The dietary patterns for each province are also presented in Figure A1 in the online appendix.

The results show that cereals and potatoes dominate rural residents' daily diets in all four provinces, accounting for around 50% of the total quantity of consumed food, while vegetables account for around 1/3 and animal-sourced foods for only a small fraction of the daily diet quantity.

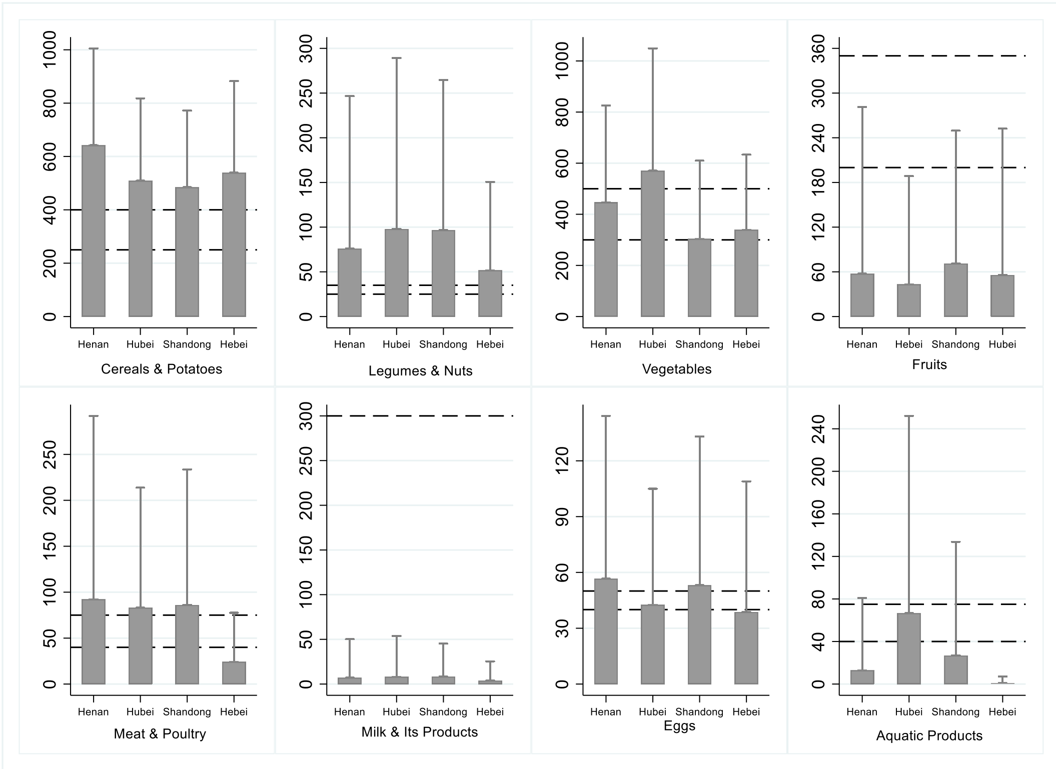

Figure 2. Dietary patterns of rural residents in four provinces of China

Notes: Horizontal dashed lines refer to the recommended consumption levels. The upper line refers to the upper bound. The lower line refers to the lower bound. The upper and lower limits for cereals and potatoes, vegetables, fruits, meat and poultry, milk and its products, eggs, aquatic products, legumes and nuts are 250/400, 300/500, 200/350, 40/75, 300/500, 40/50, 40/75, and 25/35 (g/day), respectively. The bar graph represents the average consumption of foods with standard deviations.

3.2.2 Dietary quality

Following previous literature (e.g., Xu et al., 2015; Sekabira and Qaim, 2017; Huang and Tian, 2019; Parlasca et al., 2020), we adopt two different indicators to measure dietary quality, namely dietary diversity and the Chinese Food Pagoda Score (CFPS).

(1) Dietary diversity

Dietary diversity, a widely used indicator of dietary quality (e.g., Sekabira and Qaim, 2017; Huang and Tian, 2019; Zhou et al., 2022), is assessed in this study based on the number of food groups consumed by participants within a 24-hour period. Following Chinese Dietary Guidelines 2022 (CDG 2022), we first divided the 8 food groups mentioned in CFP 2022 into 42 sub-groups. We calculated the number of sub-groups consumed in the past 24 hours, and adopted this number to measure dietary diversity. We do not take oils and fats, sugar and honey, condiments and beverages into account, as these food groups contribute little to micronutrient intakes and are sometimes negatively correlated with dietary quality (Sibhatu et al., 2015; Sekabira and Qaim, 2017). The average number of food sub-groups consumed in the sample was 6.80, which is significantly lower than the 12 food groups recommended by the CDG 2022 (refer to Table 1). Of the four provinces, rural residents in Hubei had more diversified diet than their counterparts in other provinces, while rural residents in Hebei had the lowest dietary diversity.

(2) Chinese Food Pagoda Score (CFPS)

The CFPS, which was initially proposed by Xu et al. (2015) and updated by Huang and Tian (2019), was developed to measure the overall dietary quality for each individual on the basis of the key principles of the Chinese Dietary Guidelines 2022 (CDG 2022) and the recommended consumption quantity of the Chinese Food Pagoda 2022 (CFP 2022). CFP 2022 specifies lower and upper bounds for ten food groups, which includes the eight food groups mentioned previously, as well as edible oil and salt (Table A1 in the online appendix). To calculate CFPS, we utilized the same methodology as in previous studies (Xu et al., 2015; Huang and Tian, 2019). Specifically, each food group receives a score of “1” if the real consumption is within the recommended consumption interval, “0.5” if the real consumption is 50% higher than the upper bound or 50% lower than the lower bound. If the deviation between real consumption and recommendation is larger than 50%, the score for that food group is “0”. The CFPS is then calculated by summing up the scores of eight food groups for each individual. A higher CFPS indicates a more balanced diet in accordance with the CFP 2022. Table 1 shows that the mean CFPS was only 1.22 (out of total possible score of 8), with Shandong and Hubei having slightly higher CFPS than Henan and Hebei. Consistent with previous findings (Tian et al., 2022; Huang and Tian, 2019), our results suggest that overall dietary quality is low in rural China.

Table 1 Dietary quality in four provinces of China

Variables	Total (1342)	Henan (223)	Hubei (284)	Shandong (366)	Hebei (469)
Dietary diversity	6.795(2.607)	7.013(2.903)	7.342(2.630)	6.585(2.703)	6.525(2.299)
CFPS	1.222(0.902)	0.800(0.776)	1.529(1.089)	1.281(0.899)	1.191(0.743)
Protein ratio	12.15%(0.058)	12.21% (0.048)	11.57% (0.057)	14.10% (0.065)	10.95% (0.053)
Fat ratio	11.87%(0.122)	12.22% (0.125)	11.81% (0.115)	15.42% (0.135)	8.98% (0.105)
Carbohydrates ratio	68.17%(0.214)	71.03% (0.200)	73.18% (0.181)	63.13% (0.212)	67.70% (0.227)

Notes: Chinese Food Pagoda Score (CFPS) is calculated to measure the overall dietary quality for each family on the basis of the key principles of CDG 2022 and the recommended consumption quantity of the CFP 2022. Standard deviations are in brackets.

Figure 3 presents the distribution of under-/overconsumption for each food group. We divided all individuals into five categories: moderate consumption (real consumption falls into recommendation corridor); overconsumption (real consumption is greater than the upper bound by up to 50%); heavy overconsumption (real consumption is greater than the upper bound by at least 50%); under-consumption (real consumption is less than the lower bound by up to 50%); heavy under-consumption (real consumption is less than the lower bound by at least 50%). We found that more than 70% of the rural residents over-consume cereals and potatoes. In contrast, more than 50% of the respondents have insufficient consumption of the other 7 food groups. In particular, nearly 90% of the respondents have insufficient intakes of fruits and animal products (aquatic products, meat and poultry, eggs). We further calculated the share of energy drawn from fat and protein. Results show that the fat ratio is less than 15%, which is much lower than the recommended proportion of 20-30% in CDG 2022. These data further underline that the overall dietary quality of people in rural China is low due to the over-reliance on carbohydrates and the low intakes of fat and protein.

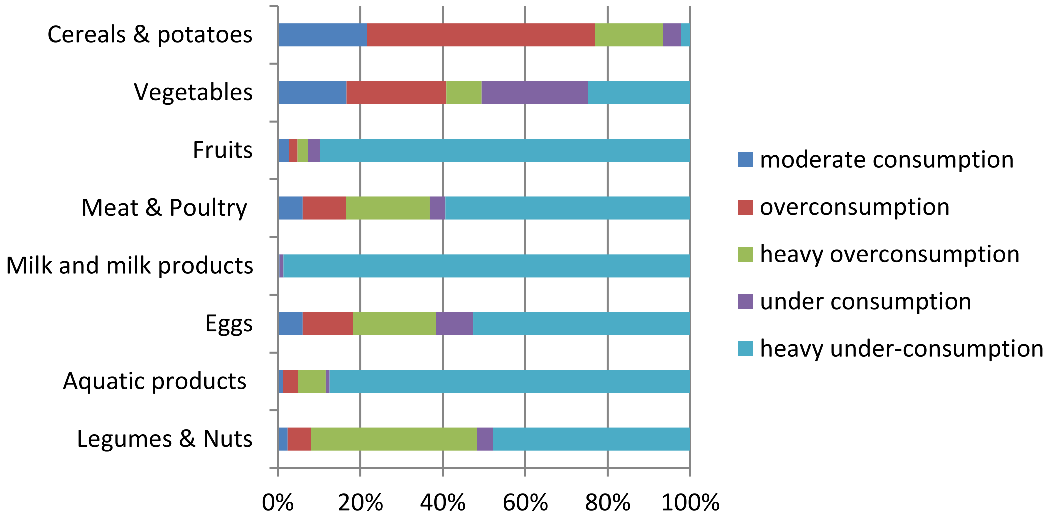

Figure 3. Consumption levels of eight food groups

Notes: moderate consumption: ≥lower bound and ≤upper bound; overconsumption: ≥upper bound by 0%-50%; heavy overconsumption: ≥upper bound by at least 50%; underconsumption: ≤lower bound by 0%-50%; heavy underconsumption: ≤lower bound by at least 50%

3.2.3 Rural e-commerce

Unlike earlier studies that analyzed e-commerce activities regardless of the specific sector of the products traded (Pantelimon et al., 2020; Wang et al., 2022), here we focus on e-commerce in the food sector. We measure e-commerce use of consumers as the monthly frequency of purchasing food online (PFO), which was reported by respondents in the survey. For respondents who purchased food online less than once in a month, we recorded their frequency in one year and converted the yearly frequency into a monthly frequency through dividing by 12.

Table 2 Rural e-commerce in four provinces of China

Variables	Total	Henan	Hubei	Shandong	Hebei
PFO	0.696(2.222)	0.913(2.490)	0.519(2.208)	0.750(1.793)	0.656(2.389)
WPF	0.254(0.436)	0.251(0.435)	0.295(0.457)	0.290(0.454)	0.203(0.402)
DFO	0.474(1.210)	0.565(1.374)	0.226(0.718)	0.667(1.416)	0.431(1.163)

Notes: PFO refers to the monthly frequency of purchasing food online. WPF refers to whether or not any online food purchase were done. DFO refers to the diversity of food groups purchased online. Standard deviations are shown parentheses.

The average frequency of purchasing food online in our sample is close to 0.70, with a considerable proportion of 75% of the households reporting to never use e-commerce to purchase food (Table 2). Around 5% of the households made more than four monthly PFO transactions, indicating a notable variation in e-commerce adoption among rural households. Regarding the regional analysis, the average PFO of households in Henan was the highest at 0.91, whereas the lowest frequency was observed in Hubei, with an average of only 0.52.

Several studies (Wang and Zhang, 2022; Zhang et al., 2018) argued that household expenditures on online food purchases may also be a good way to measure the intensity or permeation of e-commerce. However, in our survey we did not collect data on online food expenditures. As robustness checks for PFO as our main variable of interest, we look at whether or not any food was purchased online (WPF), and at the diversity of food groups purchased online (DFO), both of which are also shown in Table 2. While WPF is a dummy variable, DFO uses the eight food groups from CFP 2022, as explained above. The mean DFO is 0.474, with some regional variation. The two most frequently purchased food categories online were fruits and legumes/nuts. Conversely, eggs were the least commonly purchased online (Figure A2 in the online appendix), which may be explained by their high transport loss and accessibility through self-sufficient and local food markets.

3.2.4 Other covariates

We also collected detailed information on individual characteristics (age, gender, education, health, physical activity level, and willingness to improve dietary quality), household characteristics (household size, ratio of farming labor, share of children, share of elderly people, and per capita net income,), and village characteristics including distance to the closest tarmac road from the village council, number of bus lines passing through the village, number of delivery stations, and number of food markets in the village. Table 3 presents descriptive statistics of all covariates.

Table3 Descriptive analysis of individual, household, and village variables

	Variables	Total (1342)	Henan (223)	Hubei (284)	Shandong (366)	Hebei (469)
Individual variables	Age	53.634(11.169)	57.430(8.982)	43.011(8.591)	53.208(9.298)	58.569(10.381)
	Female	0.488(0.500)	0.520(0.501)	0.443(0.498)	0.489(0.501)	0.501(0.501)
	Education	7.746(3.255)	7.619(2.226)	7.258(3.207)	8.207(2.676)	7.742(3.599)
	Health	3.780(1.142)	3.623(1.151)	3.570(1.196)	4.254(0.887)	3.614(1.178)
	Physical activity	3.342(0.869)	2.904(0.886)	3.221(1.100)	3.659(0.615)	3.379(0.766)
	Dietary attitude	0.875(0.331)	0.892(0.311)	0.835(0.372)	0.888(0.316)	0.881(0.325)
Family variables	Household size	3.359(1.723)	3.910(1.814)	2.888(1.518)	2.940(1.384)	3.714(1.875)
	Home farming participation	78.35%(3.892)	56.26%(0.353)	71.42%(0.312)	76.32%(0.293)	94.62%(6.572)
	Elderly people ratio	23.13%(0.347)	24.13%(0.300)	2.76%(0.121)	19.98%(0.293)	37.43%(0.399)
	Children ratio	12.91%(0.184)	17.22%(0.190)	13.77%(0.197)	8.58%(0.153)	13.79%(0.188)
	Income per capita (ten thousand)	2.134(2.542)	1.652（1.770）	1.753(2.498)	3.782(3.040)	1.308(1.745)
Village var.	Road distance	0.233(1.137)	0.101(0.190)	0.574(2.345)	0.282(0.526)	0.051(0.174)
	Bus line	0.934(1.178)	0.865(0.545)	0.919(0.822)	1.399(1.883)	0.612(0.623)
	Delivery	0.626(0.484)	0.870(0.337)	0.563(0.497)	0.489(0.501)	0.654(0.476)
	Market	0.735(1.833)	0.242(0.589)	0.028(0.166)	1.713(3.030)	0.633(1.053)

Notes：Physical activity is classified based on occupation type according to the China Health and Nutrition Survey(CHNS):1 and 2 as light activity, 3 as moderate activity, and 4 and 5 as heavy activity. Household income is measured in 10000 CNY, which includes agricultural income, non-farm business income, wage income, property income, subsidies, new rural social endowment insurance, and other income. Dietary attitude refers to the desire to improve their dietary status. Standard deviations are in brackets

The data show that average respondents were above 50 years, with about half of them being female. Respondents have an average of 7.75 years of education, which is approximately 2 years lower than the national average of 9.91 years, as reported in the Seventh National Population Census in China. However, the national average refers to all adults, including younger ones who often have more education than the elderly. Noteworthy is also that better-educated adults are more likely to migrate to urban areas, at least temporarily, while our sample consists of the rural left-behinds.

In order to evaluate levels of physical activity, a system based on occupational type was utilized with values ranging from 0 to 5 (0= no physical activity; 1= very light physical activity, working in a sitting position like office worker or watch repairer; 2= light physical activity, working in a standing position such as sales person or teacher; 3= moderate physical activity like student or driver; 4= heavy physical activity such as farmer or dancer; and 5= very heavy physical activity such as loader, logger, or miner). We classified 1 and 2 as light activity, 3 as moderate activity, and 4 and 5 as heavy activity. The data in Table 3 reveals that a significant proportion of rural residents is still engaged in heavy physical activity, primarily related to agricultural production. Furthermore, our data show that nearly 88% of the respondents expressed a desire to improve their dietary status.

The annual per capita household income was 21338 yuan, slightly higher than the reported national average in rural areas (18931) published by the National Bureau of Statistics (NBSC). In terms of village-level variables, 95% of the surveyed villages have access to a tarmac road within a 1 km distance and over 60% have direct access to at least one bus line. In contrast, 73% of the villages have no food markets, supermarkets, or restaurants, confirming the limited availability and accessibility of traditional food retailers in rural China.

3.3 Econometric models

We employ the following econometric model to assess the impact of e-commerce on dietary patterns in rural China:

$$PFC_{ik} = \beta_0 + \beta_1 PFO_i + \beta_2 lnincome_i + \beta_3 X_i + \beta_4 V_i + u_{ik} \tag{1}$$

Where PFC_{ik} is individual i's consumption quantity of food group k. According to the China Food Pagoda 2022, food items were categorized into eight groups. PFO_i is the monthly frequency of purchasing food online, $\ln income_i$ is the logarithm of per capita income, and X_{in} is a vector of other covariates, such as age, education, health status, employment, physical activity, dietary attitude, and household size. We also include a vector of village dummy variables, V_i, to account for potential heterogeneity in terms of food prices, infrastructure, consumer preferences, and other regional characteristics.

In addition to the quantities of individual food groups consumed, we also use two dietary quality indicators, as explained above, namely dietary diversity and CFPS. Effects of PFO_i on these dietary quality indicators, Y_i, are estimated with the following model:

$$Y_i = \delta_0 + \delta_1 PFO_i + \delta_2 lnincome_i + \delta_3 X_i + \delta_4 V_i + u_i \tag{2}$$

The main challenge in the estimation process is the potential endogeneity resulting from rural e-commerce. Individuals and households choose themselves whether or not to use e-commerce options based on both observed and unobserved characteristics. Unobserved heterogeneity in particular can lead to biased estimates when the coefficients of interest are estimated with OLS. To address this challenge, we employ and instrumental variable (IV) model, as follows:

$$\begin{gathered} PFO_i = \sigma_0 + \sigma_1 Z_i + \sigma_2 X_i + \sigma_3 V_i + r_i \\ Y_i = \alpha_0 + \alpha_1 P\hat{F}O_i + \alpha_2 lnincome_i + \alpha_3 X_i + \alpha_4 V_i + u_i \end{gathered} \tag{3}$$

As instrument for PFO_i, we employed the average frequency of purchasing food online by other households in the same village. The use of mean values of other households within a village as an IV is a widely used empirical strategy (e.g., Rozelle et al., 1999; Harvey, 2003; Caillavet et al., 2015; Khonje et al., 2022; Mastenbroek et al., 2020). According to peer group effect theory (Evans et al., 1992; Zhao et al., 2022), an individual's action (in our case the individual's frequency of purchasing food online) can be impacted by others in their village because people living in the same setting tend to be influenced by each other (peer effects). When many households in the village choose to purchase food online on a regular basis, the individual himself/herself will also be more likely to adopt this behavior. Therefore, we expect that our IV is strongly correlated with the respondent's frequency of purchasing food online. Moreover, since our IV only considers the frequency of purchasing food online by other households within the village (not the individual himself/herself), we do not expect a direct effect of the IV on the individual's dietary quality. Finally, our IV meets the exogeneity assumption. We will test the validity of our IV in the next section.

As explained, rural e-commerce may – to some extent – also substitute for the shrinking physical food market infrastructure in rural China. To test this substitution effect, we estimate our models separately for villages with and without traditional food markets. If rural e-commerce increases dietary quality in both types of villages, but the effect is stronger in villages without traditional food markets, we can conclude that rural e-commerce is a partial substitute for traditional physical food markets.

4. Results and discussion

4.1 Baseline results

Table A3 in the online appendix shows the first-stage regression results for our IV model. The instrument is highly significant, as expected, and the Kleibergen-Paap LM test rejects the null hypothesis of a weak instrument (Chi^2=333.22). The Durbin-Wu-Hausman（DWH）test, which is shown in the last column of Table 4, suggests that purchasing food online is endogenous in some of the outcome equations, while the exogeneity hypothesis cannot be rejected in others. The OLS and IV models mostly show similar results, but for consistency, we mainly rely on the IV models for interpretation. The effects of purchasing food online are summarized in Table 4. Full model results with all covariates included are presented in Tables A3 and A4 in the online appendix.

The estimates suggest that purchasing food online decreases the consumption of cereals and potatoes, as well as vegetables, while it increases the consumption of milk and milk products, and legumes and nuts. Each unit of increase in the frequency of online purchases leads to a 17.6-gram decrease in the daily intake of cereals and potatoes and an 18.3-gram decrease in the daily intake of vegetables. Conversely, milk and milk product intake is increased by 1.2 grams and legume and nut intake by 8.7 grams. Relative to mean consumption levels, these point estimates represent changes of between 3% and 13% of the different food groups.

The negative impact of PFO on cereals and potatoes aligns with Bennett's law, which suggests that – with rising living standards and improved food accessibility – consumers will shift from starchy staples to a more diversified diet that includes meat, dairy, and fruits. As stipulated in the theoretical framework, e-commerce improves food availability and accessibility and can also contribute to higher nutrition knowledge, all factors that work in the direction of better dietary quality. Of note in rural China is that legumes and nuts are already over-consumed in many households, so that more consumption is not necessarily positive for nutrition and health.

We further investigate the impact of rural e-commerce on our two scores of dietary quality. Results are summarized in the lower part of Table 4 (full results in Table A4). Consumers with more frequent online purchases have a higher dietary diversity, although this results is only statistically significant in the OLS model. Moreover, we find that rural e-commerce leads to a significantly higher CFPS. Each unit of increase in the frequency of online purchases increases the CFPS quality score by 0.043, which is equivalent to a 3.5% increase relative to the sample mean value. We conclude that e-commerce contributes to improvements in dietary quality in rural China.

Table 4 Impact of rural e-commerce on food consumption and dietary quality

		OLS		IV		DWH test
dietary pattern	Cereals and potatoes	-5.350*	(2.860)	-17.626***	(6.131)	7.400***
	Vegetables	-4.212	(3.191)	-18.298**	(7.598)	6.365**
	Fruits	-0.765	(1.652)	-6.188	(4.656)	2.047
	Meat and poultry	0.154	(1.146)	-3.788	(2.782)	3.086*
	Milk and milk products	0.828*	(0.462)	1.171*	(0.624)	1.435
	Eggs	-0.453	(0.641)	-0.431	(1.315)	0.001
	Aquatic products	-0.948	(1.621)	-1.655	(2.330)	0.669
	Legumes and nuts	5.725***	(2.767)	8.720**	(3.698)	4.022**
diet quality	Diversity	0.124***	(0.041)	0.042	(0.063)	3.185
	CFPS	0.017*	(0.011)	0.043***	(0.015)	8.342***

Notes: Food consumption data based on individual-level 24-h recalls. *, **, *** refer to significance at the 10%, 5%, and 1% level, respectively. CFPS is the China Food Pagoda Score (see table A1). Standard error are shown in parentheses.

4.2 Robustness check

To test the robustness of our findings, we conducted additional analyses using two alternative indicators of e-commerce, namely whether or not any food online purchases were done (WPF) and the diversity of food groups purchased online (DFO). The results are summarized in Table 5 (full results in Tables A5 and A6). The direction of the results is identical to those with the PFO indicator, even though the estimates in most of the individual food group regressions are not statistically significant. However, the estimates for the dietary quality indicators (dietary diversity and CFPS) are positive and statistically significant in both cases, confirming that e-commerce contributes to improved dietary quality in China also when alternative indicators of e-commerce are being used.

Table 5 Impact of rural e-commerce (robustness checks with alternative e-commerce indicators)

		WPF		DFO	
dietary pattern	Cereals and potatoes	-31.610	(20.265)	-10.362*	(5.759)
	Vegetables	-7.575	(21.448)	-1.839	(6.716)
	Fruits	14.793	(15.884)	0.623	(4.692)
	Meat and poultry	9.851	(9.204)	1.692	(2.916)
	Milk and milk products	2.751	(2.642)	0.162	(0.732)
	Eggs	3.841	(5.114)	-0.869	(1.539)
	Aquatic products	-1.727	(7.117)	-0.119	(2.167)
	Legumes and nuts	3.841	(12.126)	3.655	(3.145)
dietary quality	Diversity	0.737***	(0.202)	0.308***	(0.076)
	CFPS	0.047	(0.059)	0.030*	(0.019)

Notes: Food consumption data based on individual-level 24-h recalls. *, **, *** refer to significance at the 10%, 5%, and 1% level, respectively. CFPS is the China Food Pagoda Score (see table A1). WPF refers to whether any food was purchased online. DFO refers to diversity of food online purchases. Standard errors are shown in parentheses.

4.3 Heterogeneity analysis

In this section, we test the hypothesis that e-commerce options partly substitute for missing or shrinking traditional physical food markets in rural China. Our survey data reveal that 79 of 108 villages do not have a traditional food market. To test the hypothesis, we conduct regressions separately for villages with and without traditional food markets. Results are summarized in Table 6 (full results in Tables A7 and A8 in the online appendix).

Overall, the coefficients are less significant than those for the full sample models, which is likely due to the smaller sub-samples. Specifically, we only observe a significantly negative impact of e-commerce on the consumption of cereals and potatoes in villages with a traditional food market. Conversely, we only observe a significantly positive impact of e-commerce on the consumption of legumes and nuts in villages without a traditional food market. Furthermore, e-commerce significantly increases dietary diversity in both types of villages. These results suggest that households in both types of villages benefit from e-commerce, but the substitution hypothesis, which would imply larger e-commerce effects in villages without a traditional food market, is not really confirmed. This results may possibly change with further rising frequencies of online food purchases.

Table 6 Heterogeneous impact in villages with and without traditional food market

		With traditional market		Without traditional market	
dietary pattern	Cereals and potatoes	-10.458*	(5.323)	-2.051	(3.674)
	Vegetables	-6.747	(4.691)	-2.998	(4.412)
	Fruits	-2.984	(2.393)	0.644	(2.226)
	Meat and poultry	0.339	(1.528)	0.356	(1.515)
	Milk and milk products	0.271	(0.169)	1.106	(0.707)
	Eggs	0.871	(1.072)	-1.068	(0.830)
	Aquatic products	0.141	(1.056)	-1.551	(2.466)
	Legumes and nuts	2.780	(2.446)	7.430*	(3.885)
dietary quality	Diversity	0.169***	(0.065)	0.095**	(0.048)
	CFPS	0.025*	(0.014)	0.011	(0.015)

Notes: CFPS is the China Food Pagoda Score (see table A1). *, **, *** refer to significance at the 10%, 5%, and 1% level, respectively. Standard errors are shown in parentheses. Results estimated using OLS.

5. Conclusion

While e-commerce has gained in importance for food retailing in many countries, very little is known yet about the effects of e-commerce on consumers' food choices, dietary quality, and nutrition. In this article, we have analyzed the effects of e-commerce on food consumption and diets in rural China. Rural China is particularly interesting for this analysis, not only because of the strong and rapid recent development of its internet infrastructure, but also because e-commerce is rising at a time when the physical infrastructure of traditional retailing is gradually vanishing. Along with the large rural-urban migration of economically active population groups in China, many traditional food retailers are exiting rural village locations, with the result that food accessibility for left-behind rural residents is declining.

We have used survey data from rural households collected in four provinces of China in 2021 and have estimated effects of the frequency of purchasing food online on people's dietary patterns. Our results with instrumental variable models show that e-commerce significantly reduces the consumption of staple foods, such as cereals and potatoes, while it increases the consumption of legumes, nuts, milk, and milk products, even after controlling for income and other confounding factors. Additionally, e-commerce contributes to higher dietary diversity and dietary quality among rural households. In the face of shrinking physical markets in rural areas, it seems that rural e-commerce can serve as an important mechanism to improve food access and meet the diversifying dietary demands of rural residents.

A few limitations of our analysis should be mentioned. First, e-commerce and its use by households can be measured in different ways. As our main indicator, we used the frequency of online food purchases. Alternatives would be to look at online expenditures, but such data were not collected in our survey. Second, dietary patterns and the role of different types of retailers may vary across seasons, which is not captured with our data collected only during the summer season. Particularly in northern China, traditional food supplies may be limited during the winter months due to adverse weather conditions. E-commerce may possibly play a more important role in ensuring food accessibility during the winter months. Third, rigorous causal inference and also the analysis of trends is difficult with the cross-section data used here. Follow-up research with panel data could lead to additional insights.

Nevertheless, our study contributes to the literature by presenting the first empirical evidence of the potential role of e-commerce for peoples' food security and dietary quality, especially in rural areas of emerging economies. Our results suggest that the rise in grocery e-commerce may have positive nutrition effects, and that these effects may be different from those of meal-delivery services. Important to note is that equitable access to e-commerce options requires proper network and road infrastructure. These conditions are largely met in rural China but not in rural areas of many other middle- and low-income countries. Public investment in rural infrastructure may therefore be needed in many places before the potentials of e-commerce can be harnessed at scale.

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Appendix

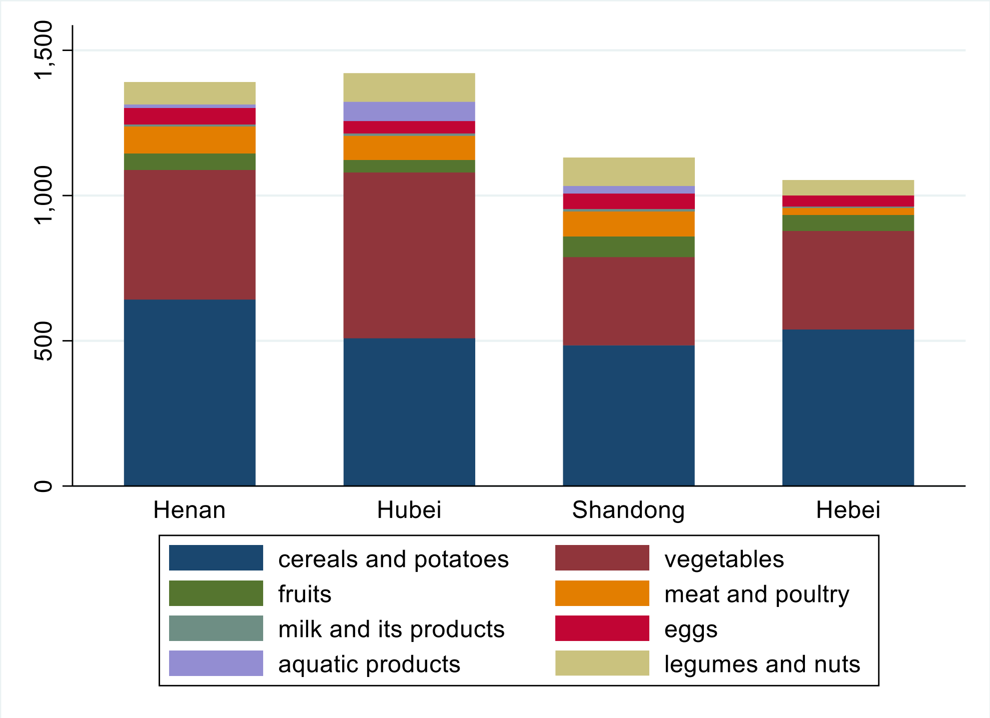

Figure A1 Dietary pattern for each province.

Notes: These values are mean daily food consumption measured by gram using a 24-h recall method.

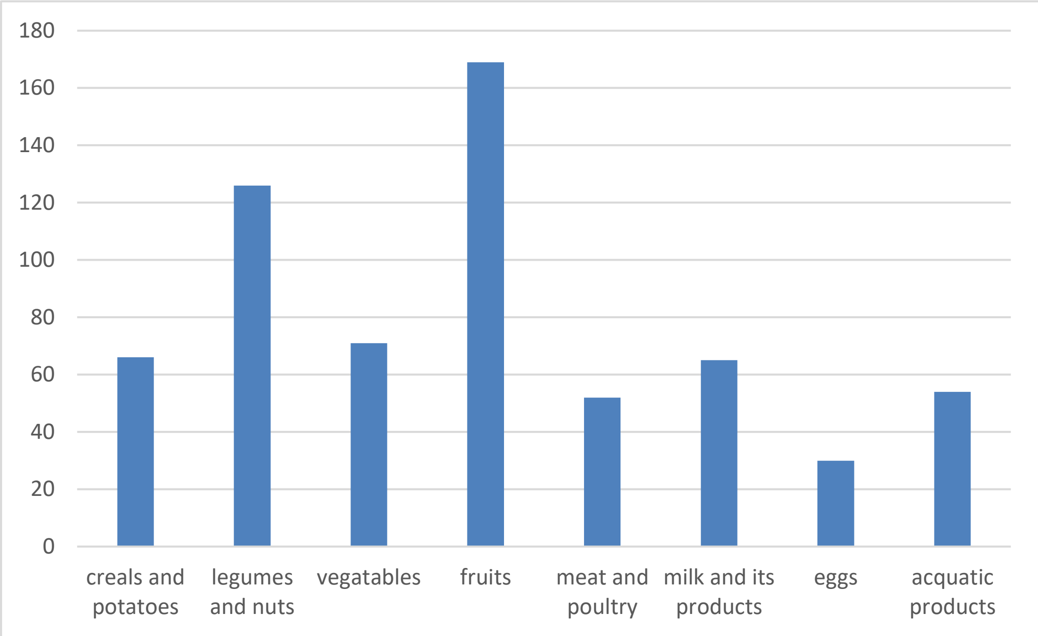

Figure A2 A descriptive statistic about the food categories purchased online

Table A1 Calculation of Chinese Food Pagoda Score (CFPS)

Food group	1600kcal	1800kcal	2000kcal	2200kcal	2400kcal	2600kcal	2800kcal	Dietary guidelines
Cereal & potato(g)								250-400
Score as “1”	175–225	200–250	225–275	250–300	275–325	325–375	350–400	
Score as “0.5”	88–175	100–200	113–225	125–250	138–275	163–325	175–350	
Score as “0.5”	225–338	250–375	275–413	300–450	325–488	375–563	400–600	
Vegetables (g)								300-500
Score as “1”	⩾300	⩾400	⩾450	⩾450	⩾500	⩾500	⩾500	
Score as “0.5”	150–300	200–400	225–450	225–450	250–500	250–500	250–500	
Fruits (g)								200-350
Score as “1”	⩾200	⩾200	⩾300	⩾300	⩾350	⩾350	⩾400	
Score as “0.5”	100–200	100–200	150–300	150–300	175–350	175–350	200–400	
Meat & poultry (g)								40-50
Score as “1”	15–65	25–75	25–75	50–100	50–100	50–100	75–125	
Score as “0.5”	8–15	13–25	13–25	25–50	25–50	25–50	38–75	
Score as “0.5”	65–98	75–113	75–113	100–150	100–150	100–150	125–188	
Eggs(g)								40-75
Score as “1”	40–50							
Score as “0.5”	20–40							
Score as “0.5”	50–75							
Aquatic products(g)								40-75
Score as “1”	⩾40	⩾50	⩾50	⩾75	⩾75	⩾75	⩾100	
Score as “0.5”	20–40	25–50	25–50	38–75	38–75	38–75	50–100	
Milk and its products (g)								300-500
Score as “1”	300–500							
Score as “0.5”	500–750							
Score as “0.5”	150–300							
Legumes & nuts(g)								25-35
Score as “1”	15–25	15–25	15–25	25–35	25–35	25–35	25–35	
Score as “0.5”	8–15	8–15	8–15	13–25	13–25	13–25	13–25	
Score as “0.5”	25–38	25–38	25–38	35–53	35–53	35–53	35–53	
Edible oil (g)								25-30
Score as “1”	⩽25				⩽30			
Score as “0.5”	25–38				30–45			
Salt (g)								<6
Score as “1”	⩽6							
Score as “0.5”	6–9							

Note: The energy level is the upper bound for each interval. For instance, individuals with energy intake lower than or equal to 1600 kcal is classified into the group “1600.”

Table A2 Impact of rural e-commerce on food consumption using OLS

Variables	Cereals and potatoes	Vegetables	Fruits	Meat and poultry	Milk and its products	Eggs	Aquatic products	Legumes and nuts
PFO	-5.350*	-4.212	-0.765	0.154	0.828*	-0.453	-0.948	5.725**
	(2.860)	(3.191)	(1.652)	(1.146)	(0.462)	(0.641)	(1.621)	(2.767)
lnincome	-0.299	3.738	8.395	7.522**	1.156	2.810*	0.562	-3.913
	(8.763)	(9.714)	(6.027)	(3.502)	(0.939)	(1.689)	(3.142)	(6.584)
Age	0.534	0.207	-0.922	-1.010*	0.212	-0.546**	-0.934*	0.767
	(1.077)	(1.132)	(0.731)	(0.523)	(0.178)	(0.248)	(0.532)	(0.566)
Gender	-0.170	5.491**	0.624	0.587	0.463*	-0.647	1.183*	1.844
	(2.874)	(2.662)	(1.325)	(1.232)	(0.255)	(0.808)	(0.706)	(1.378)
Education	-8.278	-19.198**	5.691	6.805**	-0.862	0.879	2.444	-1.977
	(8.024)	(9.185)	(4.853)	(3.091)	(0.777)	(2.023)	(2.156)	(4.161)
Health	-21.786*	-31.171**	-4.632	1.577	-1.020	-2.787	0.997	6.945
	(11.408)	(13.800)	(6.003)	(4.507)	(1.103)	(2.359)	(2.832)	(5.225)
Physical activity	-1.817	-10.414	12.915	7.789	-4.266	9.535	8.877	10.832
	(26.803)	(28.395)	(11.104)	(12.036)	(3.058)	(5.873)	(8.834)	(12.458)
Dietary attitude	-21.719***	-18.261***	-10.194***	1.267	-0.950*	-4.318***	0.705	-6.312**
	(5.674)	(6.223)	(3.695)	(2.718)	(0.553)	(1.310)	(1.266)	(3.174)
Household size	-0.487	0.205	0.273	0.155	0.020	-0.057	0.351***	0.105
	(0.641)	(0.566)	(0.167)	(0.183)	(0.034)	(0.123)	(0.099)	(0.371)
Agriculture share	16.797	31.435	2.433	21.844	-6.476	-1.248	12.672	-21.025
	(37.853)	(40.129)	(18.598)	(15.458)	(4.010)	(8.128)	(11.831)	(18.494)
Elderly ratio	65.813	-88.568	89.035**	55.112**	6.910	7.968	-10.081	-2.071
	(55.960)	(63.571)	(42.061)	(25.890)	(6.531)	(11.380)	(13.830)	(26.317)
Children ratio	-227.901	-655.191	373.862**	-118.288	-27.142	190.125	47.861	-221.613
	(795.253)	(720.553)	(162.242)	(628.675)	(26.452)	(123.499)	(77.528)	(340.593)
Village dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	761.913***	738.638***	-53.467	20.412	2.472	31.214	24.268	120.081
	(220.798)	(217.241)	(79.968)	(153.053)	(14.284)	(38.841)	(32.699)	(107.519)
Observations	1,342	1,342	1,342	1,342	1,342	1,342	1,342	1,342
R-squared	0.245	0.296	0.138	0.214	0.143	0.186	0.231	0.172

Notes: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors. PFO refers to purchase food online frequency.

Table A3 Impact of rural e-commerce on food consumption using IV

First-stage regression：

Variables	PFO
IV	-5.662***(0.849)
lnincome	0.0148(0.065）
Age	-0.225***(0.008)
Gender	-8.984(16.316)
Education	-0.0080.0136)
Health	0.028(0.045)
Physical activity	-0.018(0.049)
Dietary attitude	0.225**(0.107)
Household size	0.085*(0.046)
Agriculture share	-0.004*(0.002)
Elderly ratio	0.050(0.161)
Children ratio	-0.151(0.300)
Road	3.413(0.115)
Bus	5.880*(3.546)
Market	1.719*(0.963)
Constant	-0.876(3.419)
Observations	1,340
R-squared	0.516

Second-stage estimation：

Variables	Cereals and potatoes	Vegetables	Fruits	Meat and poultry	Milk and its products	Eggs	Aquatic products	Legumes and nuts
PFO	-17.626***	-18.298**	-6.188	-3.788	1.171*	-0.413	-1.655	8.720**
	(6.131)	(7.598)	(4.656)	(2.782)	(0.624)	(1.315)	(2.330)	(3.698)
lnincome	1.070	5.086	8.810	7.925**	1.128	2.803*	0.640	-3.946
	(8.523)	(9.433)	(5.806)	(3.351)	(0.909)	(1.646)	(2.989)	(6.319)
Age	-0.147	-0.599	-1.054	-1.252**	0.202	-0.559**	-0.964*	0.778
	(1.046)	(1.102)	(0.693)	(0.501)	(0.175)	(0.248)	(0.510)	(0.561)
Gender	-0.338	5.201**	1.009	0.504	0.428*	-0.602	1.197*	1.672
	(2.755)	(2.546)	(1.307)	(1.183)	(0.241)	(0.773)	(0.668)	(1.304)
Education	-8.018	-18.744**	4.617	6.818**	-0.869	0.738	2.494	-2.047
	(7.623)	(8.798)	(4.607)	(2.931)	(0.744)	(1.937)	(2.046)	(3.966)
Health	-22.788**	-32.039**	-4.744	1.313	-1.037	-2.869	0.920	6.747
	(10.936)	(13.277)	(5.932)	(4.327)	(1.050)	(2.265)	(2.703)	(4.970)
Physical activity	3.290	-3.538	16.394	10.084	-4.210	9.777*	8.983	10.105
	(25.813)	(27.303)	(11.248)	(11.551)	(2.908)	(5.613)	(8.402)	(11.869)
Dietary attitude	-18.667***	-15.254**	-9.664***	1.994	-1.004*	-4.439***	0.864	-6.732**
	(5.548)	(6.005)	(3.428)	(2.739)	(0.517)	(1.300)	(1.184)	(3.072)
Household size	-0.556	0.126	0.252	0.135	0.023	-0.054	0.348***	0.125
	(0.617)	(0.554)	(0.167)	(0.180)	(0.033)	(0.118)	(0.093)	(0.356)
Agriculture share	24.211	37.642	-0.685	22.623	-6.688*	-2.550	13.049	-21.757
	(36.166)	(38.390)	(17.702)	(14.752)	(3.758)	(7.790)	(11.242)	(17.489)
Elderly ratio	61.440	-100.363*	83.108**	48.285*	5.572	4.198	-10.127	-8.054
	(53.891)	(60.198)	(38.819)	(25.151)	(5.739)	(11.032)	(13.104)	(24.126)
Children ratio	-511.248***	-214.525	-68.217	-15.283	-15.000	-2.012	9.323	-71.557*
	(123.102)	(140.824)	(72.932)	(44.923)	(11.672)	(42.237)	(9.507)	(40.919)
Village dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	740.955**	855.396*	517.798	39.391	-11.122	91.419	-60.721	-87.405

	(334.796)	(464.409)	(418.964)	(233.587)	(15.971)	(116.220)	(50.836)	(95.586)
Observations	1,342	1,342	1,342	1,342	1,342	1,342	1,342	1,342
R-squared	0.230	0.282	0.120	0.201	0.138	0.177	0.231	0.166

Notes: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors. PFO refers to purchase food online frequency.

Table A4 Impact of rural e-commerce on dietary quality

	OLS		IV	
	(1)	(2)	(3)	(4)
Variables	Diversity	CFPS	Diversity	CFPS
PFO	0.124***	0.017*	0.042	0.043***
	(0.041)	(0.011)	(0.063)	(0.015)
lnincome	0.285***	-0.017	0.296***	-0.019
	(0.076)	(0.022)	(0.074)	(0.021)
Age	-0.017*	0.000	-0.022**	0.002
	(0.010)	(0.003)	(0.010)	(0.003)
Gender	0.078***	-0.001	0.077***	-0.000
	(0.022)	(0.007)	(0.021)	(0.007)
Education	0.125*	0.031	0.129**	0.030
	(0.067)	(0.020)	(0.064)	(0.019)
Health	-0.039	0.010	-0.050	0.012
	(0.080)	(0.031)	(0.077)	(0.030)
Physical activity	0.454**	-0.057	0.484***	-0.070
	(0.185)	(0.071)	(0.176)	(0.068)
Dietary attitude	0.206***	0.021	0.220***	0.016
	(0.059)	(0.015)	(0.058)	(0.015)
Household size	0.008	0.004***	0.007	0.004***
	(0.005)	(0.001)	(0.005)	(0.001)
Agriculture share	0.155	-0.055	0.174	-0.065
	(0.283)	(0.092)	(0.270)	(0.088)
Elderly ratio	0.885*	-0.114	0.749	-0.099
	(0.509)	(0.156)	(0.486)	(0.148)
Children ratio	0.124***	0.017*	0.042	0.043***
	(0.041)	(0.011)	(0.063)	(0.015)
Village dummy	Yes	Yes	Yes	Yes
Constant	12.053***	0.759	1.705	0.505
	(1.615)	(0.597)	(1.808)	(0.365)
Observations	1,342	1,342	1,342	1,342
R-squared	0.206	0.308	0.188	0.302

Notes: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively. Calculation of CFPS is given in Table A1. Values in parentheses are standard errors. PFO refers to purchase food online frequency.

Table A5 Robustness test of rural e-commerce and dietary pattern

Variables	(1) Cereals and potatoes	(2) Vegetables	(3) Fruits	(4) Meat and poultry	(5) Milk and its products	(6) Eggs	(7) Aquatic products	(8) Legumes and nuts	(9) Diversity	(10) CFPS
WPF	-31.610	-7.575	14.793	9.851	2.751	3.729	-1.727	3.841	0.773***	0.047
	(20.265)	(21.448)	(15.884)	(9.204)	(2.643)	(5.114)	(7.117)	(12.126)	(0.202)	(0.059)
lnincome	0.551	3.934	7.989	7.254**	1.083	2.707	0.607	-4.004	0.264***	-0.018
	(8.831)	(9.823)	(5.918)	(3.505)	(0.962)	(1.715)	(3.229)	(6.605)	(0.078)	(0.022)
Age	0.471	0.309	-0.762	-0.931*	0.203	-0.496**	-0.911*	0.572	-0.015	-0.000
	(1.084)	(1.144)	(0.707)	(0.532)	(0.181)	(0.250)	(0.534)	(0.575)	(0.010)	(0.003)
Gender	-0.055	5.432**	0.473	0.506	0.463*	-0.693	1.170	1.981	0.075***	-0.001
	(2.878)	(2.666)	(1.320)	(1.232)	(0.254)	(0.813)	(0.712)	(1.392)	(0.022)	(0.007)
Education	-7.720	-19.177**	5.305	6.573**	-0.897	0.772	2.449	-1.850	0.111	0.031
	(8.025)	(9.145)	(4.816)	(3.120)	(0.782)	(2.021)	(2.114)	(4.186)	(0.068)	(0.020)
Health	-22.100*	-31.142**	-4.368	1.729	-1.005	-2.711	1.003	6.802	-0.031	0.010
	(11.406)	(13.813)	(6.001)	(4.487)	(1.106)	(2.362)	(2.830)	(5.284)	(0.079)	(0.031)
	-2.548	-11.714	12.002	7.436	-4.063	9.205	8.585	12.869	0.469**	-0.053
Physical activity	(26.788)	(28.385)	(11.024)	(11.999)	(3.044)	(5.870)	(8.853)	(12.520)	(0.185)	(0.071)
Dietary attitude	-21.729***	-18.787***	-10.774***	1.000	-0.884	-4.510***	0.587	-5.404*	0.205***	0.023
	(5.747)	(6.258)	(3.652)	(2.706)	(0.555)	(1.325)	(1.395)	(3.149)	(0.060)	(0.016)
Household size	-0.503	0.218	0.299*	0.168	0.020	-0.049	0.354***	0.078	0.008*	0.004***
	(0.640)	(0.563)	(0.168)	(0.180)	(0.035)	(0.123)	(0.100)	(0.369)	(0.005)	(0.001)
Agriculture share	14.589	30.520	3.036	22.333	-6.236	-1.131	12.465	-20.089	0.208	-0.050
	(37.863)	(40.140)	(18.488)	(15.420)	(4.023)	(8.118)	(11.685)	(18.573)	(0.281)	(0.093)
Elderly ratio	65.890	-89.274	88.192**	54.714**	6.992	7.691	-10.239	-0.826	0.882*	-0.112
	(55.939)	(63.617)	(42.221)	(25.961)	(6.564)	(11.409)	(13.875)	(26.378)	(0.509)	(0.156)
Children ratio	-17.475	-598.188	282.722	-180.468	-46.264	167.734	60.830	-258.571	-36.743***	1.418
	(804.357)	(731.116)	(184.418)	(632.318)	(33.084)	(126.171)	(94.375)	(328.028)	(5.743)	(2.314)
Village dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	697.232***	716.755***	-30.320	37.272	8.889	36.483	19.305	138.996	13.620***	0.876
	(224.192)	(221.291)	(79.590)	(154.434)	(16.179)	(39.983)	(36.696)	(106.676)	(1.681)	(0.613)
Observations	1,342	1,342	1,342	1,342	1,342	1,342	1,342	1,342	1,342	1,342
R-squared	0.246	0.295	0.139	0.214	0.142	0.186	0.231	0.167	0.208	0.307

Notes: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively. Calculation of CFPS is given in Table A1. Values in parentheses are standard errors. WPF refers to whether rural households purchase food online.

Table A6 Robustness test of rural e-commerce and dietary pattern

Variables	(1) Cereals and potatoes	(2) Vegetables	(3) Fruits	(4) Meat and poultry	(5) Milk and its products	(6) Eggs	(7) Aquatic products	(8) Legumes and nuts	(9) Diversity	(10) CFPS
DFO	-10.362*	-1.839	0.623	1.692	0.162	-0.869	-0.119	3.655	0.308***	0.030
	(5.759)	(6.716)	(4.692)	(2.916)	(0.732)	(1.539)	(2.167)	(3.145)	(0.076)	(0.019)
lnincome	0.271	3.902	8.326	7.399**	1.134	2.931*	0.523	-4.151	0.266***	-0.019
	(8.798)	(9.765)	(6.001)	(3.509)	(0.951)	(1.708)	(3.169)	(6.588)	(0.078)	(0.022)
Age	0.603	0.343	-0.879	-0.990*	0.182	-0.548**	-0.893*	0.594	-0.017*	-0.000
	(1.079)	(1.131)	(0.714)	(0.517)	(0.179)	(0.248)	(0.518)	(0.575)	(0.010)	(0.003)
Gender	-0.045	5.394**	0.595	0.554	0.488*	-0.660	1.172	1.929	0.074***	-0.001
	(2.869)	(2.655)	(1.307)	(1.227)	(0.258)	(0.809)	(0.726)	(1.390)	(0.022)	(0.007)
Education	-7.913	-19.178**	5.591	6.686**	-0.856	0.992	2.365	-2.011	0.110	0.030
	(8.024)	(9.163)	(4.865)	(3.091)	(0.787)	(2.017)	(2.157)	(4.172)	(0.068)	(0.020)
Health	-21.970*	-31.312**	-4.480	1.721	-0.995	-3.033	1.163	7.020	-0.026	0.011
	(11.455)	(13.821)	(6.041)	(4.504)	(1.121)	(2.362)	(2.810)	(5.291)	(0.079)	(0.031)
	-2.032	-11.718	12.517	7.553	-3.974	9.502	8.542	12.389	0.447**	-0.056
Physical activity	(26.720)	(28.377)	(11.049)	(12.044)	(3.056)	(5.869)	(8.757)	(12.504)	(0.187)	(0.071)
Dietary attitude	-22.037***	-18.858***	-10.388***	1.174	-0.821	-4.302***	0.517	-5.542*	0.208***	0.022
	(5.707)	(6.234)	(3.640)	(2.708)	(0.554)	(1.321)	(1.367)	(3.170)	(0.059)	(0.016)
Household size	-0.491	0.222	0.280*	0.160	0.017	-0.059	0.357***	0.085	0.008*	0.004***
	(0.638)	(0.564)	(0.168)	(0.183)	(0.035)	(0.124)	(0.100)	(0.370)	(0.005)	(0.001)
Agriculture share	14.956	30.864	2.317	21.977	-6.389	-1.213	12.421	-19.991	0.200	-0.050
	(37.919)	(40.144)	(18.609)	(15.473)	(4.033)	(8.115)	(11.773)	(18.554)	(0.282)	(0.093)
Elderly ratio	67.337	-89.165	88.703**	54.709**	7.083	8.031	-10.245	-1.620	0.833*	-0.118
	(55.873)	(63.750)	(42.561)	(25.832)	(6.543)	(11.410)	(13.889)	(26.368)	(0.502)	(0.156)
Children ratio	-71.433	-617.287	365.615**	-143.339	-31.868	206.147	49.932	-287.260	-36.263***	1.291
	(810.302)	(720.580)	(177.659)	(632.572)	(27.576)	(126.067)	(83.032)	(322.571)	(5.769)	(2.285)
Village dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	713.103***	722.228***	-52.613	27.114	5.008	26.313	22.179	146.260	13.455***	0.905
	(223.759)	(217.714)	(81.103)	(154.615)	(15.486)	(39.399)	(33.802)	(104.701)	(1.684)	(0.605)
Observations	1,341	1,341	1,341	1,341	1,341	1,341	1,341	1,341	1,341	1,341
R-squared	0.245	0.295	0.138	0.214	0.142	0.187	0.231	0.167	0.213	0.307

Notes: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively. Calculation of CFPS is given in Table A1. Values in parentheses are standard errors. FCO refers to food categories purchased online.

Table A7 Heterogeneous impact in villages with traditional food market

Variables	(1) Cereals and potatoes	(2) Vegetables	(3) Fruits	(4) Meat and poultry	(5) Milk and its products	(6) Eggs	(7) Aquatic products	(8) Legumes and nuts	(9) Diversity	(10) CFPS
PFO	-10.458*	-6.747	-2.984	0.339	0.271	0.871	0.141	2.780	0.169***	0.025*
	(5.323)	(4.691)	(2.393)	(1.528)	(0.169)	(1.072)	(1.056)	(2.446)	(0.065)	(0.014)
lnincome	12.084	7.627	7.177	5.691	1.117	6.745*	0.939	5.459	0.304**	-0.033
	(14.020)	(13.248)	(16.774)	(4.126)	(1.222)	(3.723)	(1.572)	(11.341)	(0.128)	(0.035)
Age	-0.241	-2.401	-0.322	-0.387	0.136	-0.317	-0.173	1.029	-0.014	-0.001
	(1.631)	(1.993)	(1.585)	(0.740)	(0.115)	(0.377)	(0.287)	(0.870)	(0.018)	(0.005)
Gender	-10.480	10.639	-28.064	-11.718	2.150	-1.860	-10.619	3.929	-0.175	-0.015
	(24.600)	(25.261)	(20.151)	(10.574)	(2.026)	(5.490)	(9.967)	(12.135)	(0.247)	(0.080)
Education	-1.134	4.673	0.737	1.596	0.364	-1.059	-0.208	0.045	0.085**	-0.000
	(4.256)	(4.497)	(2.553)	(1.779)	(0.313)	(0.880)	(0.636)	(1.892)	(0.038)	(0.012)
Health	-9.583	-19.211	12.203	9.280	0.213	1.252	1.256	5.205	0.298**	0.006
	(13.980)	(14.384)	(8.708)	(6.235)	(0.992)	(3.072)	(2.154)	(6.501)	(0.117)	(0.037)
	-23.393	-39.486*	1.501	3.203	0.056	-2.019	-2.159	-4.162	0.188	0.031
Physical activity	(18.633)	(23.585)	(13.511)	(7.664)	(0.819)	(4.668)	(3.361)	(7.302)	(0.162)	(0.053)
Dietary attitude	46.587	12.034	33.638*	-1.635	-2.537	21.418***	11.252*	-13.046	0.522*	-0.045
	(38.513)	(31.980)	(18.677)	(14.033)	(4.719)	(7.936)	(5.828)	(18.883)	(0.273)	(0.102)
Household size	-10.945	-7.554	-15.866*	6.491	-1.677	-2.646	0.339	-9.302*	0.077	-0.017
	(9.798)	(12.748)	(9.047)	(4.047)	(1.162)	(2.093)	(0.948)	(4.807)	(0.094)	(0.025)
Agriculture	10.359	142.749**	-49.124	-6.888	-7.431	-1.019	27.062**	-3.263	0.126	0.186
share	(54.291)	(63.480)	(55.923)	(18.138)	(8.372)	(11.432)	(13.363)	(22.634)	(0.472)	(0.161)
Elderly ratio	24.579	87.378	-4.245	-0.211	-5.078	-7.294	2.208	-20.580	0.088	-0.029
	(51.843)	(56.656)	(30.954)	(21.072)	(4.009)	(11.607)	(14.960)	(30.996)	(0.458)	(0.163)
Children ratio	59.685	55.917	132.660	-10.743	2.679	15.895	2.636	7.144	1.572*	0.353
	(86.126)	(103.802)	(94.105)	(34.561)	(4.887)	(14.530)	(13.489)	(32.239)	(0.861)	(0.287)
Village dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	518.220**	417.107**	36.593	-40.995	-8.528	-5.119	6.273	2.136	0.915	1.436***
	(202.954)	(210.228)	(120.414)	(67.077)	(10.082)	(45.986)	(40.749)	(131.171)	(1.797)	(0.538)
Observations	431	431	431	431	431	431	431	431	431	431
R-squared	0.217	0.192	0.133	0.147	0.138	0.264	0.135	0.211	0.173	0.260

Notes: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively. Calculation of CFPS is given in Table A1. Values in parentheses are standard errors. PFO refers to purchase food online frequency.

Table A8 Heterogeneous impact in villages without traditional food market

Variables	(1) Cereals and potatoes	(2) Vegetables	(3) Fruits	(4) Meat and poultry	(5) Milk and its products	(6) Eggs	(7) Aquatic products	(8) Legumes and nuts	(9) Diversity	(10) CFPS
PFO	-2.051	-2.998	0.644	0.356	1.106	-1.068	-1.551	7.430*	0.095**	0.011
	(3.674)	(4.412)	(2.226)	(1.515)	(0.707)	(0.830)	(2.466)	(3.885)	(0.048)	(0.015)
lnincome	-4.393	5.246	9.088	6.862	1.113	1.695	-0.178	-7.501	0.298***	-0.006
	(11.006)	(12.531)	(6.121)	(4.521)	(1.180)	(1.944)	(4.142)	(7.986)	(0.092)	(0.027)
Age	0.902	1.670	-1.145	-1.287*	0.268	-0.637*	-1.311*	0.612	-0.016	0.001
	(1.402)	(1.424)	(0.809)	(0.703)	(0.263)	(0.332)	(0.778)	(0.746)	(0.012)	(0.004)
Gender	18.556	38.742	11.594	-6.554	-5.114*	-4.479	-12.851**	-2.210	-0.121	0.060
	(22.691)	(25.999)	(11.773)	(8.841)	(2.848)	(5.206)	(5.407)	(10.766)	(0.167)	(0.055)
Education	0.390	5.359	0.633	0.413	0.543	-0.502	1.721*	2.725	0.070***	-0.003
	(3.724)	(3.278)	(1.567)	(1.608)	(0.339)	(1.110)	(0.998)	(1.814)	(0.026)	(0.009)
Health	-6.881	-20.947*	4.673	6.701*	-1.416	1.114	3.576	-5.263	0.065	0.042*
	(9.999)	(11.841)	(6.078)	(3.808)	(1.003)	(2.630)	(2.928)	(5.429)	(0.083)	(0.024)
	-21.571	-30.593*	-4.987	0.522	-1.045	-2.525	1.899	10.770	-0.085	0.001
Physical activity	(13.871)	(16.575)	(6.954)	(5.465)	(1.433)	(2.759)	(3.614)	(6.592)	(0.092)	(0.037)
Dietary attitude	-24.910	-25.821	6.897	11.879	-4.794	5.258	8.020	22.274	0.466*	-0.063
	(34.970)	(38.872)	(14.340)	(16.283)	(3.931)	(7.808)	(12.896)	(16.121)	(0.242)	(0.093)
Household size	-26.390***	-19.147***	-9.059**	-1.029	-0.823	-4.736***	1.926	-5.536	0.281***	0.045**
	(7.287)	(7.256)	(4.052)	(3.689)	(0.721)	(1.714)	(1.690)	(4.116)	(0.075)	(0.019)
Agriculture	-0.446	-0.235	0.288*	0.253	0.051	-0.006	0.418***	0.109	0.005	0.003**
share	(0.659)	(0.606)	(0.152)	(0.206)	(0.042)	(0.130)	(0.113)	(0.394)	(0.005)	(0.001)
Elderly ratio	12.639	-1.785	6.530	31.280	-7.181	2.305	17.701	-20.271	0.211	-0.060
	(50.455)	(54.279)	(24.727)	(20.645)	(5.593)	(10.769)	(15.816)	(23.200)	(0.363)	(0.113)
Children ratio	75.192	-118.312	54.657	79.633**	7.153	5.707	-10.510	-5.438	0.657	-0.290
	(73.815)	(82.206)	(48.467)	(34.964)	(9.650)	(15.590)	(19.628)	(36.126)	(0.626)	(0.193)
Village dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	795.815***	765.594***	-55.034	31.285	4.882	30.555	34.249	171.260	11.844***	0.650
	(257.300)	(259.648)	(85.463)	(175.190)	(17.926)	(45.335)	(41.826)	(127.017)	(1.847)	(0.697)
Observations	909	909	909	909	909	909	909	909	909	909
R-squared	0.250	0.301	0.149	0.233	0.146	0.167	0.262	0.169	0.225	0.335

Notes: *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively. Calculation of CFPS is given in Table A1. Values in parentheses are standard errors. PFO refers to purchase food online frequency.