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Article

Internet access and nutritional intake: Evidence from rural China

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Abstract: China has been experienced a nutrition transition and has developed the largest population of internet users. We evaluate the impacts of internet access on the nutritional intake of Chinese rural residents. An IV-Probit based propensity score matching method is used to determine the impact of internet access on nutritional intake. The data were collected from 10042 rural households existed in six provinces of China. The results reveal that the rural residents with internet access have significantly higher intakes of energy, protein, and fat than those without their counterparts. Chinese rural residents with Internet access significantly increase the intakes of energy, protein, and fat by 1.35 percent (28.62 kcal), 5.02 percent (2.61 g), and 4.33 percent (3.30 g), respectively. There is heterogeneity in the intakes of energy, protein, and fat among those in different income groups. Moreover, non-staple food consumption is the main channel through which internet access affects nutritional intake. The results stress to local population to use internet for the improvement of nutritional status.

Keywords: internet access; nutritional intake; rural China; propensity score matching

1. Introduction

Ending malnutrition is one of the main targets of the Sustainable Development Goal (SDG) [1]. China has been experienced a nutrition transition over the past four decades [2-6]. In China, both urban and rural residents are switching from low-fat traditional food, mainly based on cereals and vegetables with few animal products, to a Western-style diet that is high in saturated fat and sugar and low in fiber [7-9].

Evidence has shown that nutritional intake is determined by income [8,10,11], agricultural/food programs [12-14], agricultural commercialization [15], microcredit [16], farm production [17,18], nutrition labels and communication networks [19]. Moreover, studies have found that the internet is a new factor affecting the well-being of households, especially rural households, in both developed and developing countries/regions [20-25]. Specifically, the internet may positively affect food consumption [26-30].

In the last two decades, with the rapid development and widespread application of the internet, the China has developed the largest population of internet users in the world. According to the China Internet Network Information Center (CNNIC), by the end of 2018, the number of Chinese Internet users (netizens) had reached 829 million, and 222 million of them were rural residents [31]. It is surprising that the rural population of China connected to the internet is equal to the total population of France, Germany, the UK, and Australia. The CNNIC pointed out that the internet has already affected the lives of Chinese rural residents [31].

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The article contributes to the existing literature in three aspects. First, to the best of our knowledge, except for Parlasca, et al. [32], the previous literature has seldom investigated the relationship between internet access and nutritional intake. Using household panel data, Parlasca, et al. [32] proved that mobile phone adoption and use were positively and significantly associated with dietary diversity. Although mobile phones were the main devices by which farmers access the internet, the mobile phones could not be simply treated as a proxy variable for the internet. Moreover, the National Bureau of Statistic of China (NBSC) showed that only parts of mobile phones connect to the internet through cellular data or broadband networks (Wi-Fi) in rural areas [33]. Thus, we explore internet effects than mobile phone effects. Second, different from previous studies [22,23,29], we mainly studied the relationship between internet access and nutritional intake except for food expenditure, which can shows the effects of well-being of internet access more intuitively. Due to the nutrition transition process and nutrition-related health problems in China [34-36], it is essential to investigate the determinants of nutritional intake. Third, since there are large differences in economic development levels and diets across China, the data used in the previous studies covered relatively few areas [22-25,29].

Thus, we use a larger sample with more provinces to control for geographical heterogeneity. Therefore, the main aim of this study is to evaluate the impacts of internet access on the nutritional intake of Chinese rural residents. Particularly, the article provides answers of following questions: What is the difference in nutritional intake between rural residents with and without internet access? What is the potential mechanism by which the internet influences nutritional intake?

The remainder of the article is organized as follows. Section 2 provides the background of internet development in rural China. Section 3 introduces the PSM method. Section 4 describes the data followed by the empirical results shown in Section 5. Section 6 discusses the potential channels through which internet access affects nutritional intake. The final section provides conclusions and policy implications.

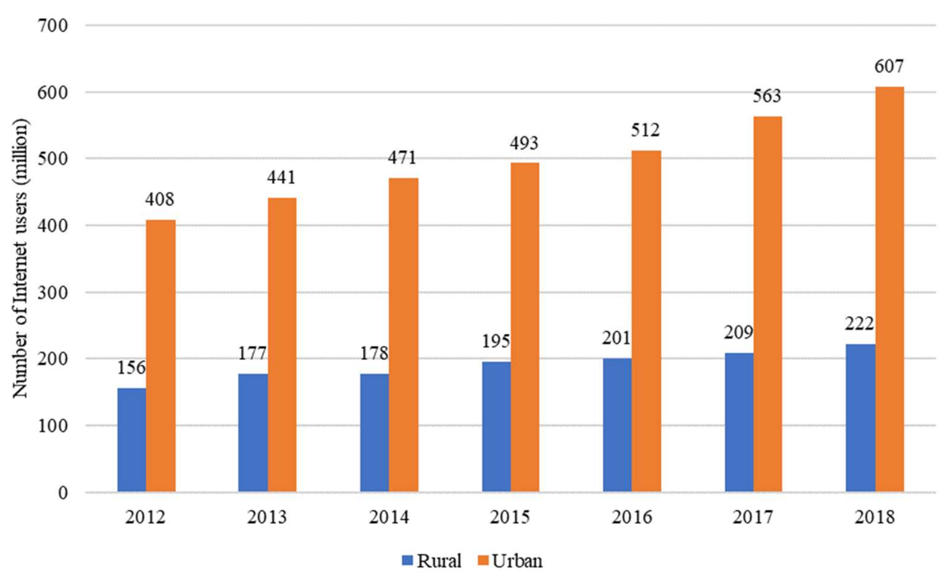

Figure 1. Internet users in rural and urban China. Source: The *Survey Report of 2012-2014 on China's Rural Internet Development* and the *34th-44th China Statistical Report on Internet Development* issued by the CNNIC.

2. The use of internet in China

The number of internet users in rural China has rapidly increased with income growth and policy support such as the "Broadband China" strategy implemented in 2013.

Figure 1 reveals the number of rural netizens in China that were increased from 156 million in 2012 to 222 million in 2018 with an annual growth rate of 6.06% [31]. However, China's internet market is still dominated by urban areas. In 2018, the number of urban netizens increased to 607 million [31].

Given the large rural population in China, the proportion of rural netizens in the rural population was 39.4% in 2018, while the proportion of urban netizens in the urban population reached to 73% (Figure 2) [31,37]. Although mobile ownership is widely used as a proxy for internet access in China [22,25,32], a large number of mobile phones are not connected to the internet. The NBSC showed that the number of mobile phones owned per 100 rural households was 244.3 in 2016; however, only 47.8% of these mobile phones were connected to the internet [33]. Meanwhile, the number of computers owned per 100 rural households was 32.2 in 2016 [33], and the proportion of rural netizens in the rural population was 34.1% in 2016 [38]. These statistics indicate that in rural China, computer ownership is a better proxy for internet access than mobile phone ownership.

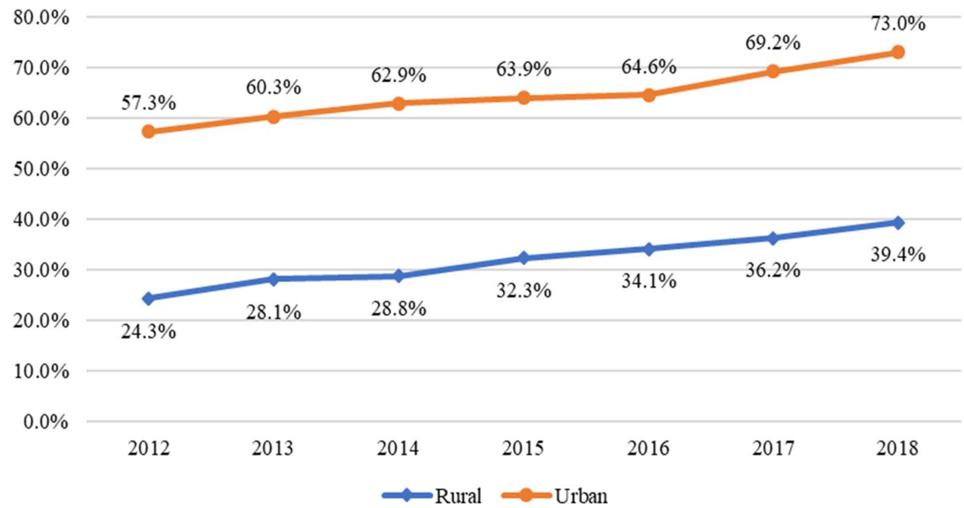

Figure 2. Proportion of netizens in China. Source: The *Survey Report of 2012-2014 on China's Rural Internet Development* and the *34th-44th China Statistical Report on Internet Development* issued by the CNNIC, and the National Bureau of Statistics of China (NBSC).

3. Materials and Methods

3.1. Data and selection of study sites

We estimated internet effects using the 2012-2018 Survey for Agriculture and Village Economy (SAVE) data collected by the Institute of Agricultural Economics and Development (IAED), Chinese Academy of Agricultural Sciences (CAAS). After data cleaning by dropping all samples that did not report their income, nutritional intake, 10042 samples from six provinces (i.e., Hebei, Jilin, Fujian, Shandong, Henan, and Yunnan) remained (Figure 3). The data include 1445 samples in 2012, 1820 samples in 2013, 1610 samples in 2014, 1471 samples in 2015, 1494 samples in 2016, 1127 samples in 2017, and 1075 samples in 2018. Therefore, the data used in this study were unbalanced panel data. Rural households with at least one computer are considered to have internet access (treatment group), and those without a computer are the control group, i.e., without internet access. The treatment group includes 3307 rural residents with internet access and 6735 rural residents without internet access.

Based on the *China Food Composition*, this study divides the food consumed by rural residents into the following ten categories: cereals, edible oil, red meat, poultry, eggs, aquatic products, dairy products, vegetables, fruits, and tubers [39]. They are converted into energy (kcal), protein (g), fat (g), and carbohydrate (g) based on the nutrition table. As cereals and tubers are both staple foods, they are combined into staple foods to analyze the quantities and prices of food consumption.

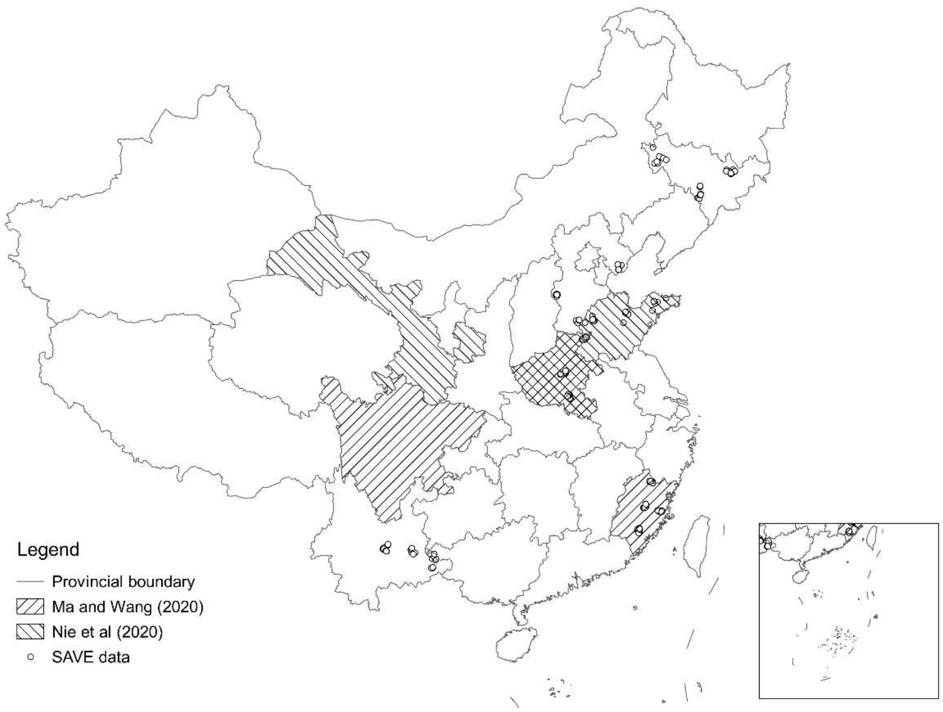

Figure 3. Location of selected areas for field survey to collect data.

3.2. Propensity score matching

An access of rural residents to the internet is a self-selection process. It could be affected by some unobserved attributes, including social networks and innate abilities and motivation that may be correlated with their nutritional intake [40-42]. According to Crown, these problems may cause selection bias and produce endogeneity [43]. This study, thus, adopts a PSM method, which is a semiparametric technique and widely used to solve the problem of selection bias and endogeneity [42,44-47]. In fact, PSM method estimates the treatment effects between the treatment group and matched control group of observed characteristics based on propensity scores [48-50]. The propensity score may define as it is the conditional probability of assignment to a particular treatment given a vector of observed covariates [46]. In this study, the rural residents with internet access are the treatment group. Those without internet access are the control group, and a Probit model is constructed to estimate the propensity scores. The Probit model is given as:

$$\mathrm{p}(x_i) = \mathrm{prob}(Y_i = 1|x_i) = \int_{-\infty}^{\beta_i x_i} \phi(t)\mathrm{d}t = \Phi(\beta_i x_i) \quad (1)$$

where $\mathrm{p}(x_i)$ is the probability that rural resident (i) has internet access; $Y_i = 1$ indicates rural resident *i* accesses the internet and $Y_i = 0$ indicates that without internet access. The x_i are the relevant factors that affect internet access and mainly include the individual characteristics of rural residents such as the gender of the household heads (HHs). It also includes the characteristics of rural households such as per capita annual income. β_i are the vectors of parameters that are need to be estimated.

There are potential endogeneity due to the unobservable characteristics and simultaneity bias, which leads to the major limitation of the PSM. An access to internet can in-

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crease the income of rural residents [23], and in contrast, the income level of rural residents can affect internet access. Therefore, we use instrumental variables (IVs), including "the location relationship between villages and towns" and "the per capita annual income of the village", to construct an IV-Probit model to solve such problems [51,52]. The two variables were used as instruments because they correlate with the per capita annual income of rural residents and because they do not affect the internet access of rural residents. Although rural residents in the same county have similar internet access levels, the level of internet development can be similar or different between different counties. Thus, we clustered the data by county to obtain robust standard errors.

To further obtain robust matching results, this study uses three common matching algorithms, i.e., the five-nearest neighbor matching algorithm, the kernel matching algorithm, and the radius matching algorithm. By controlling the selection bias and circumventing the endogenous problem, the unbiased estimation of the ATT is obtained. The ATT for nutritional intake is given as:

$$\mathrm{ATT} = \mathrm{E}(Y_i^T - Y_i^C | T = 1) = \mathrm{E}(Y_i^T | T = 1) - \mathrm{E}(Y_i^C | T = 1) \quad (1)$$

where Y_i^T and Y_i^C represent the nutritional intake of the treatment and control groups, respectively.

4. Results

4.1. Summary statistics of basic variables

The descriptive statistics of the sample data are given in Table 1. The treatment group has significantly lower consumption of staple foods than the control group and significantly higher consumption of the other eight food categories. Compared with the NBSC (Table A1), the quantities of household food consumption of staple foods, red meat, poultry, aquatic products, dairy products, vegetables, and fruits are lower than the NBSC standard, while edible oil and eggs are higher. The results reveal that the daily energy intake is 2142.55 kcal in the treatment group and it is significantly higher than that (i.e., 2079.89 kcal) in the control group. The daily intakes of protein and fat in the treatment group are 54.65 g and 79.66 g, respectively, and both are significantly higher than those (51.40 g and 73.45 g) in the control group. The daily intake of carbohydrate is not different between the two groups. Furthermore, it is found that the internet access may significantly promote the intake of protein, fat and energy.

Table 1. Summary statistics of basic variables.

Variables	Description	Full sample		Treatment		Control		Diff.
		Mean	SD	Mean	SD	Mean	SD	
Household heads (HHs) characteristics								
Gender	1=Male, 0=Female	0.95	0.22	0.96	0.20	0.94	0.23	0.01**
Age	Years	51.43	10.32	49.83	9.14	52.22	10.77	-2.39***
Years of education		7.73	2.40	8.30	2.26	7.45	2.42	0.86***
Occupation: only engaged in agriculture	1=Yes; 0=No	0.65	0.48	0.62	0.49	0.66	0.47	-0.04***
Agricultural training	1=Yes; 0=No	0.31	0.46	0.36	0.48	0.28	0.45	0.08***
Household characteristics								
The proportion of children under the age of 14	%	11.22	16.09	12.50	15.78	10.59	16.21	1.90***
The proportion of seniors above the age of 65	%	10.22	24.63	5.35	14.48	12.61	28.01	-7.26***
Income (per capita per annum)	1000 yuan	11.04	10.78	13.43	12.48	9.87	9.63	3.56***
Village characteristics								
Income (per capita per annum per village)	1000 yuan	8.47	5.51	9.79	6.14	7.83	5.04	1.96***
Located in the town	1=Yes; 0 =No	0.14	0.35	0.15	0.36	0.14	0.34	0.02*
Nutritional intake (per capita per day)								
Energy	kcal	2100.53	786.07	2142.55	806.74	2079.89	774.95	62.66***
Carbohydrate	g	307.43	119.06	306.29	121.57	307.99	117.81	-1.70
Fat	g	75.50	48.42	79.66	48.30	73.45	48.34	6.20***
Protein	g	52.47	20.74	54.65	21.80	51.40	20.12	3.24***

Quantities of food consumption (per capita per annum)								
Staple food	kg	138.12	51.88	135.43	51.01	139.44	52.25	-4.01***
Edible oil	kg	14.50	8.78	14.97	8.67	14.26	8.83	0.71***
Red meat	kg	25.27	24.09	27.96	25.16	23.95	23.44	4.01***
Poultry	kg	4.76	6.61	4.99	6.82	4.64	6.51	0.35*
Eggs	kg	10.36	12.35	11.83	12.96	9.64	11.98	2.19***
Aquatic products	kg	6.74	8.94	7.91	9.64	6.16	8.51	1.75***
Dairy products	kg	4.80	13.20	5.52	13.13	4.44	13.22	1.08***
Vegetables	kg	65.02	66.08	67.45	67.91	63.83	65.14	3.62*
Fruits	kg	23.15	25.10	25.93	28.34	21.78	23.22	4.15***
Number of observations		10042		3307		6735		

Notes: *** p<0.01, ** p<0.05 and * p<0.1; incomes were deflated with the consumer price index (CPI) provided by the NBSC (2012=100); in 2018, 1 USD=6.62 yuan.

4.2. Results of PSM

We used an IV-Probit model to estimate propensity scores, and the results are given in Table A1. Firstly, the result of the Wald test for exogeneity rejected the null hypothesis of no endogeneity. Secondly, the F statistic value of the first stage of the IV-probit model is 99.56 which is greater than 10. It indicates that the null hypothesis of weak IVs is rejected [53].

The effects of internet access on nutritional intake are estimated using the PSM method based on the five-nearest neighbor matching algorithm (Table 2). The results showed that the daily intakes of protein and fat in the treatment group were significantly higher by 5.02% (2.61 g) and 4.33% (3.30 g) than those in the control group. Additionally, the intake of energy in the treatment group is significantly higher by 1.35% (28.62 kcal) than that in the control group. However, the daily intake of carbohydrate is not different between the two groups.

The estimated results proved that the internet access increased the proportion of protein and fat intake that is significantly higher than the proportion of energy intake. This result may be explained by the fact that the energy was supplied mainly from carbohydrate. The carbohydrate reaches 55-65%; in contrast, for fat, it reaches only 20-30% [8]. Therefore, the increases in the intakes of protein and fat did not caused the same level of increase in energy. Finally, the internet access significantly improved the intake main nutritional components (i.e., protein and fat) of rural residents.

Table 2. Effects of internet access on food intake.

Daily intake of nutrition	PSM[1]						PSM[2]		OLS
	NN5 matching[a]		Kernel matching[b]		RD matching[c]		NN5 matching[a]		
	Change	Change (%)	Change	Change (%)	Change	Change (%)	Change	Change (%)	Change (%)
Energy (kcal)	28.62*	1.35*	32.50**	1.54**	61.36***	2.95***	29.47*	1.40*	1.91
Carbohydrate (g)	−2.90	−0.94	−1.58	−0.51	−1.77	−0.57	−3.39	−1.09	−0.73
Fat (g)	3.30***	4.33***	3.13***	4.09***	6.10***	8.29***	3.46***	4.55***	6.90*
Protein (g)	2.61***	5.02***	2.70***	5.20***	3.22***	6.27***	2.88***	5.55***	5.77**

Notes: *** p<0.01, ** p<0.05 and * p<0.1; [1] the propensity scores calculated by the IVs-Probit model; [2] the propensity scores calculated by the Ordinary Probit model; [a] results of matching using five-nearest neighbor algorithm; [b] results of matching using kernel algorithm; [c] results of matching using radius algorithm.

4.3. Balancing, sensitivity and robustness tests

To ensure that the matching estimators correctly identify the treatment effects, the matching balancing condition and the conditional independence condition must be satisfied [46]. The matching balance is tested based on three alternative algorithms. Table 3 shows no significant differences between the treatment group and the control group after matching, and the five-nearest neighbor matching algorithm is preferred over the other algorithms.

Table 3. The test of matching balance.

Variables	Percentage of bias after

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	NN5 matching[a]	Kernel matching[b]	RD matching[c]
Gender of HHs (1=Male, 0=Female)	3.9	4.4*	5.5**
Age of HHs	−2.8	−2.3	−22.3***
Square of age of HHs	−3.0	−2.6	−24.5***
Years of education of HHs	0.1	1.6	35.0***
Occupation of HHs: only engaged in agriculture (1 = Yes, 0 = No)	−0.1	1.1	−8.2***
Agricultural training (1 = Yes, 0 = No)	−0.7	−0.1	16.5***
The proportion of children under the age of 14	−1.4	−2.1	11.4***
The proportion of seniors above the age of 65	0.3	−0.2	−29.7***
Per capita per annual income (Yuan)	−0.4	−0.1	23.2***
Pseudo-R2	0.001	0.001	0.045

Notes: *** p<0.01, ** p<0.05 and * p<0.1; [a] matching using five-nearest neighbor algorithm; [b] matching using kernel algorithm with bandwidth of 0.06; [c] matching using radius algorithm with caliper of 0.05.

Although it's difficult to directly test the conditional independence condition, the Rosenbaum bounds test is used to assess the sensitivity of the PSM method to unobserved variables [47]. The results of Rosenbaum bounds test are shown in Table A2. It is found that the matching results were not sensitive to unobserved factors, except for protein. However, the IV-Probit procedure partly fixed the endogeneity problem caused by the omitted variables. There are reasons to believe that our results in Table 2 are reliable.

We compared the results of different estimation techniques to test the robustness of the estimated ATTs (Table 2). The results of the robustness test showed that the signs and magnitudes of energy, protein, fat, and carbohydrate are consistent with different estimation method, Probit models, and the PSM algorithms. The results in Table 2 suggested that the PSM results are robust. The results estimated by the OLS method and the ordinary Probit model based on PSM method are biased due to ignoring the problems of endogeneity (Table 3). Compared with the PSM method, the OLS method overestimated the results of protein and fat. While the estimated ATTs of energy, protein, and fat obtained by the Ordinary Probit model based PSM method are higher than those obtained by the IV-Probit based on PSM method.

4.4. *Test of heterogeneity*

To further analyze the heterogeneity of the matching results, this study investigates the impacts of internet access on the nutritional intake of rural residents with different incomes based on the five-nearest neighbor matching algorithm. First, this study divides the per capita annual income of rural residents into three quantiles: 1) those with an upper limit of 4887.59 yuan (low-income group); 2) those with an upper limit of 12233.90 yuan (medium-income group), and 3) those with an upper limit of 65911.20 yuan (high-income group).

Compared with the results of whole sample, the impacts of internet access on the nutritional intake of those in the different income groups have different features (Table 4). Specifically, in the low-income group, internet access significantly affects the intakes of energy, protein, and fat, with incensement of 3.52%, 7.40%, and 10.42%, respectively. These figures are higher than those of the full sample and the other two income groups. In the medium-income group, the intakes of protein and fat are affected by internet access with increase of 5.82% (higher than the full sample) and 3.79% (lower than the full sample). In contrast, energy and carbohydrate are not affected. In the high-income group, only the protein intake is significantly affected with an increase of 2.59%. However, it is lower than full sample.

Furthermore, the results revealed that the internet access primarily affects the intakes of protein and fat in the low- and medium-income groups. The intake of energy is affected only in the low-income group. Moreover, for the high-income group, only the protein intake is affected by internet access, but the impact is less than that of the other two groups. Besides, the intake of carbohydrate in the three groups is not affected by internet access which is consistent with the full sample.

Table 4. Effects of internet access on nutritional intake for different income level.

Daily nutritional intake	Change (%)			
	Full sample	Low-income group	Medium-income group	High-income group
Energy (kcal)	1.35*	3.52**	1.28	0.16
Carbohydrate (g)	−0.94	−0.43	−0.78	−1.17
Fat (g)	4.33***	10.42***	3.79*	1.59
Protein (g)	5.02***	7.40***	5.82***	2.59**
N	10042	3348	3347	3347

Notes: *** p<0.01, ** p<0.05 and * p<0.1.

5. Discussions

The impacts of internet access on expenditure and food consumption have been proved to be significant [23,29]. It is suggested that the expenditure and food consumption can be the channels of the impacts of internet access on nutritional intake [54]. First, the internet can break the constraints of market access and connect the closed rural areas with the market [35]. Thus, the rural residents with internet access may have a stronger willingness to consume both food and other goods, even at the same income level. Second, one of the biggest advantages of online shopping is the low prices. Although the price elasticities for nutrients were negative [55], low prices may lead to an increase in nutritional intake. Unlike to urban residents, the rural residents were also food producers, mainly staple food producers.

5.1. The channel of expenditure

The impacts of internet access on various consumption expenditure items are shown in Table 5. The internet access significantly increases the total consumption expenditure of rural residents by 8.90% (483.18 yuan), which is in line with the conclusions of Ma et al [23]. Specifically, the internet access significantly increased consumption expenditures on food by 6.35% (188.97 yuan), suggested that the internet access affects nutritional intake by increasing the expenditure of rural residents on food. The consumption expenditures on clothing, residence, household facilities, articles and services (HFAS), transport and communication, education, culture and recreation (ECR), and miscellaneous goods and services (MGS) are also significantly increased with the internet access, while expenditure on HCMS significantly decreased.

Table 5. The channels of internet access affect nutritional intake.

Channels of expenditure	Consumption expenditure per capita per annum		Channel of food consumption	Quantities of food consumption		Prices of food consumption	
	Change (yuan)	Change %		Change (kg)	Change%	Change (yuan/kg)	Change %
Food	188.97***	6.35***	Staple food	−3.28*	−2.36*	−0.05	−1.29
Clothing	77.97***	12.90***	Edible oil	0.43**	2.93**	−0.12	−0.97
Residence	22.17*	16.17*	Red meat	1.52***	5.74***	0.12	0.46
HFAS	26.23**	19.68**	Poultry	0.05	1.08	−0.48*	−2.80*
Transport and communication	112.13***	23.36***	Eggs	2.10***	21.53***	−0.12	−1.29
ECR	33.18*	5.03*	Aquatic products	1.01***	14.55***	0.66**	4.29**
HCMS	−27.13*	-9.35*	Dairy products	1.05***	23.35***	0.13	1.16
MGS	49.66***	33.79***	Vegetables	2.07	3.16	0.16**	3.64**
Total	483.18***	8.90***	Fruits	3.32***	14.70***	0.14	1.75

Notes: *** p<0.01, ** p<0.05 and * p<0.1; HFAS=household facilities, articles and services; HCMS=health care and medical services. MGS=miscellaneous goods and services; ECR= education, culture and recreation.

5.2. The channel of food consumption

The impacts of internet access on the quantities and prices of food consumption are shown in table 5. In terms of the quantities of food consumption, the internet access has significant positive impacts on the consumption of non-staple foods that are favored by people such as edible oil, red meat, eggs, aquatic products, dairy products, and fruits [6]. In contrast, the internet access has negative impacts on the consumption of staple foods and no effects on poultry and vegetables.

Regarding the consumption of nonstable foods by rural residents, the internet access has significant impacts on the consumption of red meat, eggs, aquatic products, dairy products, and fruits, with incensement of 5.74% (1.52 kg), 21.53% (2.10 kg), 14.55% (1.01 kg), 23.35% (1.05 kg), and 14.70% (3.32 kg), respectively. However, it has little impact on edible oil consumption, increasing it by only 2.93% (0.43 kg). The internet access increased the food access channels of rural residents to a certain extent, for example, by fostering the development of e-commerce in rural areas, and more food access channels can improve the dietary quality of rural residents [56,57].

In terms of the prices of food consumption, the internet access significantly affects the prices of only poultry, aquatic products, and vegetables that have no effects on the prices of other foods. In most of the studies on price data in China, the price data are not the actual prices of food. Rather, they reflect the unit value of food, i.e., they comprehensively reflect the quality of food such as the appearance, nutrient content, flavor, and taste of food [58]. When the food consumption expenditure of rural residents increased, they may consume more high-quality food, leading to a non-significant impact of internet access on the prices of the most expensive foods.

6. Conclusion and policy implications

In the current study, the PSM method was used to explore the effects internet access on the nutritional intake of rural residents using the SAVE data from 2012 to 2018. We also conducted various robustness tests and analyzed the heterogeneity across different income levels of rural residents in China. Furthermore, we found that how the internet access can affect the nutritional intake on rural residents.

The results reveal that the Chinese rural residents with internet access significantly increased the intake of energy, protein, and fat by 1.35 percent (28.62 kcal), 5.02 percent (2.61 g), and 4.33 percent (3.30 g), respectively. The internet access significantly improved the nutritional status of Chinese rural residents. There is heterogeneity in the intakes of energy, protein, and fat among those in different income groups, while there is no such heterogeneity in the intake of carbohydrates. For the low-income group, residents with internet access significantly increased the intake of protein and fat by 7.40 percent and 10.42 percent, respectively. For the high-income group, only the intake of protein is affected by the internet access. The food consumption is the main channel through the internet access affects nutritional intake, mainly by increasing the quantities of non-staple food consumption to improve the nutritional intake of rural residents.

The findings of the study have important implications for policymakers. The positive effects of internet access suggest that it is important to speed up the construction of rural telecommunications infrastructure to ensure that most rural residents in China can access the internet. It is likely that the nutritional status of the Chinese rural residents can be improved. Although the nutritional status of low-income group benefits the most from the internet access, reducing the cost of the internet use in the rural area should be an important goal in the process of implementing the "rural vitalization strategy".

Our study, however, has two limitations. First, we use computer ownership as the proxy for the internet access subject to the questionnaire design. Though the proportion of computer ownership is similar to the current rural internet access rates, there is still a gap between computer ownership and the internet access. Second, the SAVE data only contains data on food at home consumption. As food consumed away from home growing faster than at home counterparts in China [59], further studies may provide new insights into that issue.

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Appendix A

Table A1. The results of the IV-Probit model.

Variables	Coefficients	Robust Standard Error
Per capita per annual income (Yuan)	0.68***	0.13
Gender of HH (1=Male, 0=Female)	0.14	0.13
Age of HHs	0.05*	0.03
Square of age of HHs	−0.00*	0.00
Years of education of HHs	0.04**	0.02
Occupations of HHs: only engaged in agriculture (1 = Yes; 0 = No)	0.40***	0.11
Agricultural training (1 = Yes; 0 = No)	0.17***	0.06
The proportion of children under the age of 14	0.59***	0.23
The proportion of seniors above the age of 65	0.29	0.33
Dummy of year (Year=2013)	0.13	0.10
Dummy of year (Year=2014)	0.13	0.09
Dummy of year (Year=2015)	0.27**	0.12
Dummy of year (Year=2016)	0.23	0.20
Dummy of year (Year=2017)	0.16	0.21
Dummy of year (Year=2018)	0.31	0.20
Constant	−8.37***	1.17
Log likelihood	−22033.97	
N	10042	
Wald test of exogeneity	5.23**	
F (1410027)	99.56	

Notes: *** p<0.01, ** p<0.05 and * p<0.1; robust standard errors are obtained by clustered at the county level.

Table A2. The hidden bias test based on Rosenbaum bounds.

Variables	Γ
Energy	1.23−
Carbohydrate	1.23−
Fat	1.15−
Protein	1.02−

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Notes: Rosenbaum bounds are tested based on five-nearest neighbor matching; Γ is the sensitivity parameter when p-value reaches the 0.05 threshold; - indicates the p-value is on lower bound.

References

1. The United Nations. *The Sustainable Development Goals Report 2020*; United Nations Publications: New York, NY, 2020.
2. Popkin, B.M. The nutrition transition and obesity in the developing world. *J. Nutr.* **2001**, *131*, 871s-873s.
3. Fan, S.; Yosef, S.; Pandya-Lorch, R. Linking agriculture to nutrition: the evolution of policy. *China Agric. Econ. Rev.* **2020**, *12*, 595-604, doi:10.1108/CAER-03-2020-0040.
4. Chen, K.; Liu, C.; Liu, X.; Wang, Z.; Luo, R.; Li, S.; Yu, Y.; Alderman, H. Nutrition, Cognition, and Social Emotion among Preschoolers in Poor, Rural Areas of South Central China: Status and Correlates. *Nutrients* **2021**, *13*, 1322.
5. Ren, Y.; Castro Campos, B.; Peng, Y.; Glauben, T. Nutrition Transition with Accelerating Urbanization? Empirical Evidence from Rural China. *Nutrients* **2021**, *13*, 921.
6. Tian, X.; Yu, X. Using semiparametric models to study nutrition improvement and dietary change with different indices: The case of China. *Food Policy* **2015**, *53*, 67-81, doi:10.1016/j.foodpol.2015.04.006.
7. Wang, Q.; Jensen, H.H.; Johnson, S.R. China's nutrient availability and sources, 1950–1991. *Food Policy* **1993**, *18*, 403-413, doi:10.1016/0306-9192(93)90063-h.
8. Gao, Y.; Zheng, Z.H.; Henneberry, S.R. Is nutritional status associated with income growth? Evidence from Chinese adults. *China Agric. Econ. Rev.* **2020**, *12*, 507-525, doi:10.1108/Caer-11-2019-0216.
9. Wang, L.; Wang, H.; Zhang, B.; Popkin, B.M.; Du, S. Elevated Fat Intake Increases Body Weight and the Risk of Overweight and Obesity among Chinese Adults: 1991–2015 Trends. *Nutrients* **2020**, *12*, 3272.
10. Liu, Y.; Renwick, A.; Fu, X. Off-farm income and food expenditure of rural households in China. *Br. Food J.* **2019**, *121*, 1088-1100, doi:10.1108/BFJ-07-2018-0475.
11. Colen, L.; Melo, P.C.; Abdul-Salam, Y.; Roberts, D.; Mary, S.; Paloma, S.G.Y. Income elasticities for food, calories and nutrients across Africa: A meta-analysis. *Food Policy* **2018**, *77*, 116-132, doi:10.1016/j.foodpol.2018.04.002.
12. Lentz, E.C.; Barrett, C.B. The economics and nutritional impacts of food assistance policies and programs. *Food Policy* **2013**, *42*, 151-163, doi:10.1016/j.foodpol.2013.06.011.
13. Reimer, J.J.; Weerasooriya, S. Macroeconomic Impacts of U.S. Farm and Nutrition Programs. *J. Agric. Resour. Econ.* **2019**, *44*, 624–645.
14. Rossi, L.; Ferrari, M.; Martone, D.; Benvenuti, L.; De Santis, A. The Promotions of Sustainable Lunch Meals in School Feeding Programs: The Case of Italy. *Nutrients* **2021**, *13*, 1571.
15. Ogutu, S.O.; Gödecke, T.; Qaim, M. Agricultural Commercialisation and Nutrition in Smallholder Farm Households. *J. Agric. Econ.* **2019**, *71*, 534-555, doi:10.1111/1477-9552.12359.
16. You, J. The role of microcredit in older children's nutrition: Quasi-experimental evidence from rural China. *Food Policy* **2013**, *43*, 167-179, doi:10.1016/j.foodpol.2013.09.005.
17. Zeng, D.; Alwang, J.; Norton, G.W.; Shiferaw, B.; Jaleta, M.; Yirga, C. Agricultural technology adoption and child nutrition enhancement: improved maize varieties in rural Ethiopia. *Agric. Econ.* **2017**, *48*, 573-586, doi:10.1111/agec.12358.
18. Ecker, O. Agricultural transformation and food and nutrition security in Ghana: Does farm production diversity (still) matter for household dietary diversity? *Food Policy* **2018**, *79*, 271-282, doi:10.1016/j.foodpol.2018.08.002.
19. Jäckering, L.; Gödecke, T.; Wollni, M. Agriculture–nutrition linkages in farmers' communication networks. *Agric. Econ.* **2019**, *50*, 657-672, doi:10.1111/agec.12516.
20. Chang, H.H.; Just, D.R. Internet Access and Farm Household Income - Empirical Evidence using a Semi-parametric Assessment in Taiwan. *J. Agric. Econ.* **2009**, *60*, 348-366, doi:10.1111/j.1477-9552.2008.00189.x.
21. Chang, H.H.; Lambert, D.M.; Mishra, A.K. Does participation in the conservation reserve program impact the economic well-being of farm households? *Agric. Econ.* **2008**, *38*, 201-212, doi:10.1111/j.1574-0862.2008.00294.x.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 13 May 2021 doi:10.20944/preprints202105.0289.v1

22. Ma, W.; Grafton, R.Q.; Renwick, A. Smartphone use and income growth in rural China: empirical results and policy implications. *Electron. Commer. Res.* **2020**, *20*, 713–736, doi:10.1007/s10660-018-9323-x.
23. Ma, W.; Nie, P.; Zhang, P.; Renwick, A. Impact of Internet use on economic well‐being of rural households: Evidence from China. *Rev. Dev. Econ.* **2020**, *24*, 503-523, doi:10.1111/rode.12645.
24. Ma, W.; Wang, X. Internet Use, Sustainable Agricultural Practices and Rural Incomes: Evidence from China. *Aust. J. Agr. Resour. Econ.* **2020**, *64*, 1087-1112, doi:10.1111/1467-8489.12390.
25. Nie, P.; Ma, W.; Sousa-Poza, A. The relationship between smartphone use and subjective well-being in rural China. *Electron. Commer. Res.* **2020**, 10.1007/s10660-020-09397-1, doi:10.1007/s10660-020-09397-1.
26. Hitt, L.; Tambe, P. Broadband adoption and content consumption. *Inf. Econ. Policy* **2007**, *19*, 362-378, doi:10.1016/j.infoecopol.2007.04.003.
27. Beuermann, D.W.; McKelvey, C.; Vakis, R. Mobile Phones and Economic Development in Rural Peru. *J. Dev. Stud.* **2012**, *48*, 1617-1628, doi:10.1080/00220388.2012.709615.
28. Nakasone, E.; Torero, M. A text message away: ICTs as a tool to improve food security. *Agric. Econ.* **2016**, *47*, 49-59, doi:10.1111/agec.12314.
29. Hou, J. Does computer usage change farmers' production and consumption? Evidence from China. *China Agric. Econ. Rev.* **2018**, *Volume 11*, 387-410, doi:10.1108/caer-09-2016-0149.
30. Mishra, A.K.; Kumar, A.; Joshi, P.K.; D'Souza, A.; Tripathi, G. How can organic rice be a boon to smallholders? Evidence from contract farming in India. *Food Policy* **2018**, *75*, 147-157, doi:10.1016/j.foodpol.2018.01.007.
31. CNNIC. *The 44th China Statistical Report on Internet Development*; China Internet Network Information Center (CNNIC): Beijing, China, 2019.
32. Parlasca, M.C.; Mußhoff, O.; Qaim, M. Can mobile phones improve nutrition among pastoral communities? Panel data evidence from Northern Kenya. *Agric. Econ.* **2020**, *51*, 475-488, doi:10.1111/agec.12566.
33. NBSC. *Statistical communiqué on the third national agricultural census (No.4)*; Available online: http://www.stats.gov.cn/tjsj/tjgb/nypcgb/qgnypcgb/201712/t20171215_1563634.html, accessed on 10 January 2021.
34. Ren, Y.J.; Li, H.; Wang, X.B. Family income and nutrition-related health: Evidence from food consumption in China. *Soc. Sci. Med.* **2019**, *232*, 58-76, doi:10.1016/j.socscimed.2019.04.016.
35. Yuan, M.; Seale, J.L.; Wahl, T.; Bai, J.F. The changing dietary patterns and health issues in China. *China Agric. Econ. Rev.* **2019**, *11*, 143-159, doi:10.1108/Caer-12-2017-0254.
36. Gao, C.; Xu, J.; Liu, Y.; Yang, Y.X. Nutrition Policy and Healthy China 2030 Building. *Eur. J. Clin. Nutr.* **2021**, *75*, 238-246, doi:10.1038/s41430-020-00765-6.
37. NBSC. *China Statistical Yearbook 2019*; China Statistics Press: Beijing, China, 2019.
38. CNNIC. *The 39th China Statistical Report on Internet Development*; China Internet Network Information Center (CNNIC): Beijing, China, 2017.
39. Yang, Y.X.; Wang, G.Y.; Pan, X.C. *China Food Composition, 2nd ed. Book 1*; Peking University Medical Press: Beijing, China, 2009.
40. Elahi, E.; Abid, M.; Zhang, L.; ul Haq, S.; Sahito, J.G.M. Agricultural advisory and financial services; farm level access, outreach and impact in a mixed cropping district of Punjab, Pakistan. *Land Use Pol.* **2018**, *71*, 249-260, doi:10.1016/j.landusepol.2017.12.006.
41. Elahi, E.; Weijun, C.; Zhang, H.; Nazeer, M. Agricultural intensification and damages to human health in relation to agrochemicals: Application of artificial intelligence. *Land Use Pol.* **2019**, *83*, 461-474, doi:10.1016/j.landusepol.2019.02.023.
42. Han, X.; Yang, S.; Chen, Y.; Wang, Y. Urban segregation and food consumption. *China Agric. Econ. Rev.* **2019**, *11*, 583-599, doi:10.1108/CAER-07-2018-0153.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 13 May 2021 doi:10.20944/preprints202105.0289.v1

43. Crown, W.H. Propensity-score matching in economic analyses: comparison with regression models, instrumental variables, residual inclusion, differences-in-differences, and decomposition methods. *Appl. Health Econ. Health Policy* **2014**, *12*, 7-18, doi:10.1007/s40258-013-0075-4.
44. Paudel, G.P.; Krishna, V.V.; McDonald, A.J. Apparent Gains, Hidden Costs: Examining Adoption Drivers, Yield, and Profitability Outcomes of Rotavator Tillage in Wheat Systems in Nepal. *J. Agric. Econ.* **2020**, *71*, 199-218, doi:10.1111/1477-9552.12333.
45. Mayen, C.D.; Balagtas, J.V.; Alexander, C.E. Technology Adoption and Technical Efficiency: Organic and Conventional Dairy Farms in the United States. *Am. J. Agr. Econ.* **2010**, *92*, 181-195, doi:10.1093/ajae/aap018.
46. Rosenbaum, P.R.; Rubin, D.B. The central role of the propensity score in observational studies for causal effects. *Biometrika* **1983**, *70*, 41-55, doi:10.1093/biomet/70.1.41.
47. Rosenbaum, P.R. *Observational Studies*; Springer Verlag: New York, NY, 2002.
48. Tian, X.; Wang, H. The Impact of Having One Parent Absent on Children' Food Consumption and Nutrition in China. *Nutrients* **2019**, *11*, 3077.
49. Hosseini, S.H.; Jones, J.M.; Vatanparast, H. Association between Grain Intake, Nutrient Intake, and Diet Quality of Canadians: Evidence from the Canadian Community Health Survey–Nutrition 2015. *Nutrients* **2019**, *11*, 1937.
50. Giannini, S.; Passeri, G.; Tripepi, G.; Sella, S.; Fusaro, M.; Arcidiacono, G.; Torres, M.O.; Michielin, A.; Prandini, T.; Baffa, V., et al. Effectiveness of In-Hospital Cholecalciferol Use on Clinical Outcomes in Comorbid COVID-19 Patients: A Hypothesis-Generating Study. *Nutrients* **2021**, *13*, 219.
51. Rotondi, V.; Stanca, L.; Tomasuolo, M. Connecting alone: Smartphone use, quality of social interactions and well-being. *J. Econ. Psychol.* **2017**, *63*, 17-26, doi:10.1016/j.joep.2017.09.001.
52. Wellalage, N.; Locke, S. Access to credit by SMEs in South Asia: do women entrepreneurs face discrimination. *Res. Int. Bus. Financ.* **2017**, *41*, 336-346, doi:10.1016/j.ribaf.2017.04.053.
53. Staiger, D.; Stock, J.H. Instrumental Variables Regression with Weak Instruments. *Econometrica* **1997**, *65*, 557-586, doi:10.2307/2171753.
54. Nemecek, T.; Jungbluth, N.; i Canals, L.M.; Schenck, R. Environmental impacts of food consumption and nutrition: where are we and what is next? *Int. J. Life Cycle Assess.* **2016**, *21*, 607-620, doi:10.1007/s11367-016-1071-3.
55. Lokuge, M.N.; Zivkovic, S.; Lange, K.; Chidmi, B. Estimation of a censored food demand system and nutrient elasticities: a cross-sectional analysis of Sri Lanka. *Int. Food Agribus. Manag. Rev.* **2019**, *22*, 717-729, doi:10.22434/ifamr2019.0031.
56. Huang, Y.; Tian, X. Food accessibility, diversity of agricultural production and dietary pattern in rural China. *Food Policy* **2019**, *84*, 92-102, doi:10.1016/j.foodpol.2019.03.002.
57. Wang, O.; Somogyi, S. Consumer adoption of online food shopping in China. *Br. Food J.* **2018**, *120*, 2868-2884, doi:10.1108/BFJ-03-2018-0139.
58. Yu, X.; Abler, D. The Demand for Food Quality in Rural China. *Am. J. Agr. Econ.* **2009**, *91*, 57-69, doi:10.1111/j.1467-8276.2008.01159.x.
59. Bai, J.; Seale Jr, J.L.; Wahl, T.I. Meat demand in China: to include or not to include meat away from home? *Aust. J. Agr. Resour. Econ.* **2020**, *64*, 150-170, doi:10.1111/1467-8489.12362.