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ZEF-Discussion Papers on
Development Policy No. 364

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Effects of using the internet on smallholder farmers' income and dietary quality in Bangladesh

Bonn, June 2025

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Fariha Farjana, Thanh Tung Nguyen, Matin Qaim, Effects of using the internet on smallholder farmers' income and dietary quality in Bangladesh, ZEF – Discussion Papers on Development Policy No. 364, Center for Development Research, Bonn, June 2025, pp. 39.

ISSN: 1436-9931

Published by:
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Acknowledgements

We gratefully acknowledge the German Academic Exchange Service (DAAD) and the Foundation Fiat Panis for funding this research.

Abstract

The internet is expanding at a rapid rate, which is true even in rural areas of low- and middle-income countries. The internet affects how people produce and consume food and other goods and services. This may also have implications for incomes and diets in smallholder farm households, where poverty and undernourishment are still commonplace. Here, we use primary data collected from 720 farm households in Bangladesh to analyze how using the internet affects agricultural production activities and food consumption choices. Potential issues of endogeneity are addressed through an instrumental variable approach and other quasi-experimental methods. Our results suggest that using the internet increases farm production diversity, commercialization, and income by improving farmers' access to markets, information, and innovative ideas. We also find positive effects on dietary diversity, even though the results depend on the concrete dietary indicators used. Strikingly, using the internet seems to encourage the production of certain nutritious and profitable foods but does not always lead to an increase in their consumption. Our results highlight the important role of the internet in enhancing farm productivity, income, and potentially also diets. At the same time, our findings also suggest that more efforts are needed to improve dietary outcomes and nutrition.

Keywords: internet, farm production activities, consumption behavior, dietary diversity, Bangladesh

JEL Codes: L86, Q120, D11, D13

1. Introduction

The internet is expanding at a rapid rate, affecting different aspects of people's daily lives, even in rural areas of low- and middle-income countries. The internet can be associated with numerous benefits by facilitating access to knowledge, information, and various types of innovations and services, thereby potentially improving productivity and income (Chang & Just, 2009; Liu et al., 2024; Nguyen et al., 2023). In addition, the internet may positively influence people's nutrition and health by providing relevant information on healthy diets and how to reduce the risk of disease (Chen & Liu, 2022; Luo et al., 2024; Pollard et al., 2015). Accordingly, it is assumed that the internet could play an important role in improving peoples' lives, including those who are often disadvantaged in terms of their access to information, markets, and services, such as smallholder farmers. However, the internet may potentially also have negative effects. For instance, it may encourage people to excessively engage in online gaming and entertainment activities, which could harm productivity, income, and health (Ayran et al., 2021; Duke & Montag, 2017; Vandelanotte et al., 2009). Furthermore, exposure to online advertising for unhealthy foods might lead to lower dietary quality (Coleman et al., 2022; Pettigrew et al., 2013). Here, we analyze the effects of using the internet on economic and dietary outcomes among smallholder farm households in Bangladesh.

A few previous studies examine effects of the internet on food consumption choices, mostly in China and with mixed results. For instance, Deng et al. (2024) and Yang et al. (2023) show that the internet contributes to an increase in the consumption of healthy foods and dietary diversity. In contrast, Ning et al. (2024) suggest that the internet promotes unhealthy dietary habits. There are also a few studies that analyze effects of the internet on farm production in different countries of Asia, generally showing improvements in farm economic performance (Kaila & Tarp, 2019; Nguyen et al., 2023; Zheng et al., 2022). However, to the best of our knowledge, there are no studies jointly analyzing effects of the internet on agricultural production and food consumption in farming households. Since smallholder farmers tend to consume a large proportion of what they produce at home, such joint analysis of production and consumption aspects, as we pursue here, is important to better understand the effects and their underlying mechanisms.

Our study has two main research objectives, namely to examine effects of using the internet (i) on smallholder food production activities and (ii) on food consumption choices. In analyzing food consumption, we also consider seasonal differences, as diets in smallholder households often deteriorate during agricultural lean seasons.

We use survey data collected in Bangladesh from randomly selected farm households, including users and non-users of the internet, and employ quasi-experimental econometric approaches for data analysis. Bangladesh is an interesting study country because the use of the internet increased rapidly over the last 10 years, from 7% of the total population in 2013 to 42% in 2023 (World Bank, 2025). In addition, undernutrition and micronutrient deficiencies remain major public health problems in Bangladesh, especially in rural areas (Dey et al., 2024; Nguyen et al., 2025; Song et al., 2023).

The subsequent sections are structured as follows: Section 2 presents a conceptual framework, illustrating possible links between using the internet and food production and consumption choices. Details about the study area, the data collection procedures, and the econometric methods are provided in Section 3. The empirical results are presented in Section 4, while Section 5 concludes with a brief summary and some policy implications.

2. Conceptual framework

Figure 1 presents the conceptual framework, illustrating the links between internet use and household food production and consumption choices.

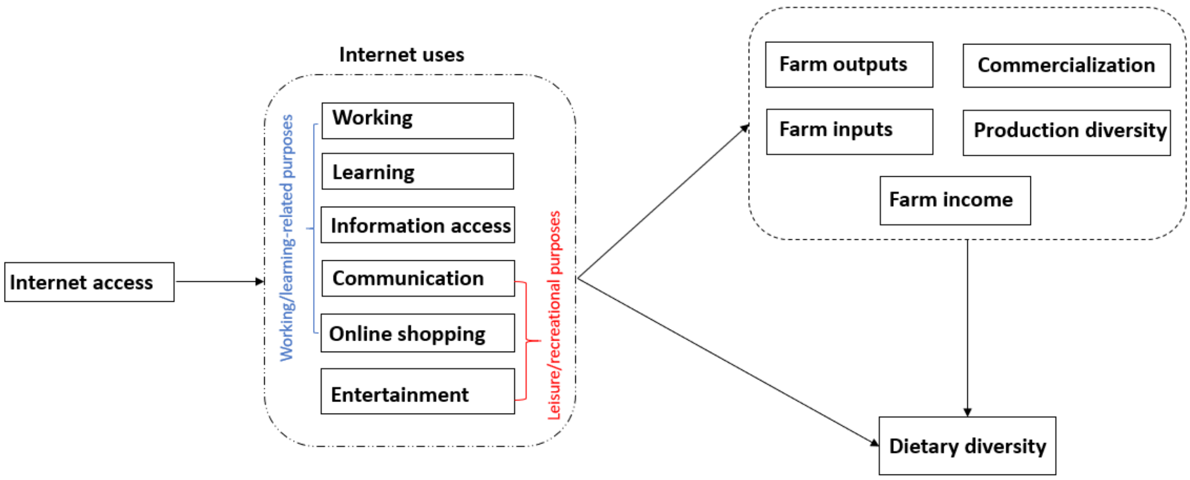

Figure 1: Conceptual framework

People use the internet for various purposes, which can be broadly categorized into working and learning-related purposes on the one hand, and leisure and recreational purposes on the other. For working and learning-related purposes, people might use the internet to search information on new farming techniques, market prices, and weather forecasts (Wei et al., 2023; Zheng et al., 2022). Farmers may also use the internet to communicate, build business networks, sell their products, and purchase agricultural inputs (Khan et al., 2022; Li et al., 2018). For leisure and recreational purposes, people may use the internet for social networking, chatting with friends, entertainment (e.g., watching movies, listening to music, playing online games), or online shopping (Chang, 2013; Ioannidis et al., 2018). Depending on the various uses of the internet, effects on farm production and dietary choices can be different.

Regarding production, if farmers primarily use the internet for working and learning-related purposes, it can lead to higher agricultural output and income (Chandio et al., 2023). Access to better farming techniques enhances efficiency, while knowledge of market prices helps in making more informed production and sales decisions. The internet also enables farmers to reduce costs by purchasing inputs at lower prices and adopting cost-effective farming methods (Rejeb et al., 2022; Zheng et al., 2021) Furthermore, internet use can promote farm commercialization by making it easier to connect with buyers and sell products beyond local markets (Birner et al., 2021; Strzębicki, 2015). Internet use may also affect production diversity—some farmers might specialize on the most profitable crops, while others may diversify based on market trends to maximize their returns. However, excessive internet use for entertainment may have negative effects if farmers become less engaged in their work, leading to inefficiencies or reduced output.

Regarding consumption, presumed that using the internet has positive effects on farm income, higher earnings can improve household diets by enabling families to afford more nutritious foods. Positive effects on farm commercialization might lead to improved dietary diversity if the income from selling farm products is used to purchase a variety of nutritious foods. However, the impact is not automatically positive. If households sell their food products but spend the earnings on less-healthy foods or non-food items, dietary diversity may decline (Ali et al., 2022). Regarding links between production and consumption diversity, if farmers diversify the foods produced, positive diet and nutrition effects may also occur through the pathway of home consumption.

The internet may also influence dietary choices more directly. For instance, in rural China it was shown that e-commerce helps to improves dietary quality by increasing households' access to diverse, nutritious foods (Shen et al., 2023). Also, diet and nutrition knowledge obtained through the internet may contribute to healthier food choices and eating habits (Deng et al., 2024; Ma & Jin, 2022; Pollard et al., 2015). Additionally, the internet could help households locate and purchase nutritious foods at better prices (Cui et al., 2024). However, exposure to online advertisements promoting unhealthy foods may negatively affect dietary choices, possibly leading to increased consumption of ultra-processed foods and snacks (Byun et al., 2021; Tsochantaridou et al., 2023).

3. Materials and methods

3.1 Study area and data collection

We collected data in the south-west region of Bangladesh, particularly in the three districts of Khulna, Satkhira, and Bagerhat (Figure 2). In this study area, most households are agricultural-dependent, climate-vulnerable, and food-insecure (ADB, 2023; Shuvo et al., 2024). Rice is the major grown crop in this area, besides different types of vegetables and other crops, such as bottle gourd, bitter gourd, ladies finger, pea, potato, sweet potato, maize, and chili, among others (Hajong et al., 2021). Many of the farm households are also involved in aquaculture and livestock production.

The first internet connection in a few urban areas of Bangladesh was established in 1996 (Azam, 2007). Since 2005, mobile internet through GPRS (general packet radio service) started to spread all over the county (Islam, 2018). People in our study area in rural regions of south-west Bangladesh mainly access the internet through smartphones. Most internet users buy prepaid cellular data packages offered by different mobile network operators (e.g., Grameenphone, Robi, Banglalink, Teletalk). The supply of 4G networks by these different mobile operators ensures mobile data availability also in remote villages. Broadband internet services are hardly available in the study area.

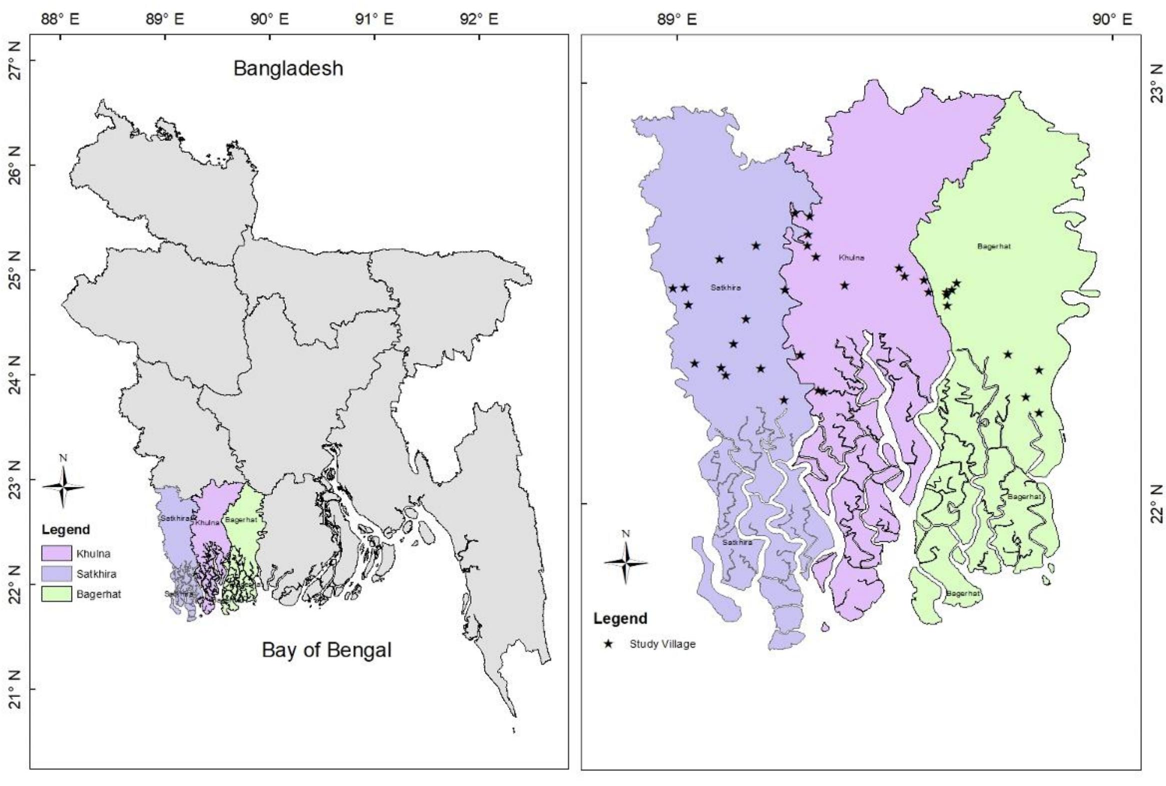

Figure 2: Map of the study area

Households for our survey were selected through a three-stage sampling procedure. First, eight Upazilas were purposively selected, proportional to the population size of each district. Second, in these eight Upazilas, 36 villages were randomly selected. Last, in each village, 20 farming households were randomly selected, resulting in a total sample of 720 households. The data were collected through personal interviews with the household heads conducted in October and November 2023.

The structured questionnaire developed for this purpose included questions on general household demographics, such as the age, sex, education levels, religion, and occupation of all household members. Agricultural production details were captured in terms of the crop, livestock, and aquaculture species produced, inputs used, production costs, harvested quantities, household consumption and sales, and market prices obtained, among others. Regarding internet use, we collected information on whether or not the household had used the internet during the last 30 days, as well as the last month internet bill (money spent).

We also collected detailed data on household food consumption, using food frequency questions. These questions were asked to the person in the household responsible for cooking. Respondents were asked about the number of times the household had consumed specific food items during the last seven days. The survey occurred during the “normal season”, when local food availability is better than during the agricultural lean season. In addition, to explore the impact of the internet on household dietary diversity during the lean season, we also collected recall data on household consumption of food items during an “average week” in the lean season. In addition to these household-level food consumption data, we collected individual-level dietary data from one male adult, one female adult, and one child in each household through separate 24-hour recalls.

3.2 Outcome variables

We analyze the effects of using the internet on various farm production and household food consumption outcomes. In this subsection, we define the outcome variables of interest and explain how they are measured.

Production outcomes

Farm output value. This is the sum of the value of all agricultural outputs the household produced in the last 12 months, including crop, livestock, and aquaculture production. Total output quantities are multiplied with the respective market prices, regardless of whether the products were sold or kept for home consumption. Farm output value is measured in thousand Bangladeshi Taka (BDT).

Farm production cost. This includes all costs associated with agricultural production activities. For crop production, we consider any costs incurred for land preparation, seeds, irrigation, pesticides, fertilizer, and hired labor. For livestock, we include the cost of livestock purchases during the last 12 months, feed, vaccination and healthcare, hired labor, among others. For aquaculture, we consider small fish and shrimp purchases, feed, pond preparation, labor, and other costs. These production costs are summed up and expressed in thousand BDT.

Farm income. This is the total farm output value minus farm production costs, expressed in thousand BDT.

Commercialization ratio. This is the value of any sales of farm output during the last 12 months divided by the total farm output value. This is the most common way of defining the level of commercialization among smallholder farmers (Ogutu & Qaim, 2019). The commercialization ratio can take values between zero and one, where zero indicates complete subsistence and one full commercialization.

Production diversity. This is defined as the number of food groups produced by the farm during the last 12 months (Nguyen & Qaim, 2025). We consider 12 different food groups, which we define in the same way as on the consumption side (see below). We calculate production diversity scores (PDS) by counting the number of different food groups produced. In addition, we also define dummy variables for each of the 12 food groups produced.

Consumption outcomes

On the consumption side, we are particularly interested in dietary quality, which we measure in terms of five different types of dietary diversity scores, as shown in Table 1. The first two of these scores are defined at the household level (FAO, 2011), namely the standard household dietary diversity score with 12 food groups (HDDS12), and an alternative household dietary diversity score with 9 food groups (HDDS9), as shown in columns (1) and (2) of Table 1. The last three food groups of the HDDS12 contain low amounts of micronutrients and therefore contribute less to healthy diets than the other 9 groups, which is why HDDS9 without these less nutritious three food groups included is often considered a better indicator of dietary quality (Parlasca et al., 2020; Sibhatu et al., 2015). These two household-level dietary diversity scores are calculated separately for the normal season and the and lean season. To get deeper insights into which food groups are being consumed in each season, we also construct separate dummies for each of the food groups considered.

In addition to the household-level metrics, we calculate individual-level dietary diversity scores to better reflect possible differences in intra-household food distribution (Verger et al., 2019). Specifically, following Agbadi et al. (2017) and Muthini et al. (2020), we calculate men’s dietary diversity scores (MDDS), women’s dietary diversity scores (WDDS), and

Table 1: Food group classifications for dietary diversity scores

Number	(1) Household dietary diversity score (HDDS12)	(2) Household dietary diversity score (HDDS9)	(3) Men dietary diversity score (MDDS)	(4) Women dietary diversity score (WDDS)	(5) Child dietary diversity score (CDDS)
1	Cereals	Cereals	Starchy staples	Starchy staples	Grains, roots, and tubers
2	White roots and tubers	White roots and tubers	Dark green leafy vegetables	Dark green leafy vegetables	Legumes and nuts
3	Vegetables	Vegetables	Other vitamin A rich fruits and vegetables	Other vitamin A rich fruits and vegetables	Dairy products (milk, yoghurt, cheese)
4	Fruits	Fruits	Other fruits and vegetables	Other fruits and vegetables	Flesh foods (meat, fish, poultry, and liver/organ meats)
5	Meat	Meat	Organ meat	Organ meat	Eggs
6	Eggs	Eggs	Meat and fish	Meat and fish	Vitamin A rich fruits and vegetables
7	Fish	Fish	Eggs	Eggs	Other fruits and vegetables
8	Legumes, nuts, and seeds	Legumes, nuts, and seeds	Legumes, nuts, and seeds	Legumes, nuts, and seeds	
9	Milk	Milk	Milk and milk products	Milk and milk products	
10	Oils and fat				
11	Sugar and sweets				
12	Spices, condiments, beverages				

Source: Based on FAO (2011) and Muthini et al. (2020).

children's dietary diversity scores (CDDS), using our individual-level 24-hour dietary recall data and the food group classifications shown in Table 1 (columns 3-5). These individual-level data are only available for the normal season.

3.3 Regression models

To examine the effects of using the internet on farm production and household food consumption outcomes, we use regression models of the following general type:

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 X_i + \beta_3 R_i + \varepsilon_i \tag{1}$$

where Y_i is the outcome variable of household *i* (farm production or dietary diversity, see previous subsection for details), D_i is a dummy variable indicating whether or not the household used the internet during the last 30 days, X_i is a vector of household-level controls, R_i is a vector of district fixed effects, and ε_i is a random error term. As household-level controls we include age, gender, religion, ethnicity, and education of the household head, household size, number of dependent members living in the household, land ownership, wealth in terms of the value of assets owned, as well as agroecological and market access conditions. More detailed definitions of the control variables are provided in Table A1 in the online appendix.

In equation (1), we are particularly interested in the coefficient β_1, which indicates the effect of using the internet on the particular outcome. A potential problem is that using the internet is likely endogenous. The household and its members decide themselves whether or not to use the internet based on observed and probably also unobserved factors, such as personal preferences and skills. If unobserved factors are jointly correlated with using the internet and the outcome, the estimated β_1 coefficient would be biased. We use a control function approach (CFA) to deal with such endogeneity bias. The CFA employs instrumental variables (IV) to identify causal effects (Ogutu & Qaim, 2019; Wooldridge, 2015). It offers greater flexibility in terms of functional form than traditional IV estimators.

We employ the share of households using the internet at the Upazila level (leaving out the individual household) as our IV. Similar instruments at village or neighborhood levels were used in previous studies on the impacts of the internet (Nguyen et al., 2022; Zheng et al., 2021). The share of households using the internet at the Upazila level has a positive and statistically significant coefficient in the first-stage regression (Table A2 in the online appendix), implying that our IV satisfies the relevance assumption. The internet may become more accessible and affordable with increased local adoption due to better infrastructure and lower costs. Additionally, in rural Bangladesh, households often maintain close social relationships within their communities, meaning that early adopters and users of the internet may influence others through peer effects. We also argue that our IV satisfies the exclusion restriction assumption because the internet use of others in the locality is unlikely to affect production and consumption outcomes through channels other than own internet use. This is confirmed by falsification tests for several of our outcome variables (Table A3 in the online appendix). However, in other cases, we cannot reject the null hypothesis of zero effects of the IV on the outcome, meaning that cautious interpretation is warranted.

As the IV does not seem to be valid in all our models, we additionally use propensity score matching (PSM) as an alternative approach. PSM cannot control for unobserved heterogeneity but is a common approach in the quasi-experimental literature (Do et al., 2019). We argue that obtaining consistent estimates with different approaches may add further confidence in the findings, even though a certain remaining endogeneity bias cannot be ruled out completely.

The PSM approach includes two main steps. First, we estimate a probit model of internet use to obtain the propensity scores based on a large set of exogenous variables (Table A4 in the online appendix). Second, based on the propensity scores, we use a nearest-neighbor matching (NNM) algorithm to match the treatment and control groups (with and without internet use). Here, the five nearest neighbors with common support and replacement are considered. Figure A1 in the online appendix presents the estimated propensity scores for the treatment and control groups, confirming that the common support condition is met. In addition, different quality checks indicate a considerable overlap in the common support (Tables A5 and A6 in the online appendix). Therefore, regarding the balancing of the distribution for the covariates between the treatment and control groups, the PSM is successful (Do et al., 2019).

3.4 Robustness and plausibility checks

We conduct a number of different robustness and plausibility checks to further increase the confidence in our findings. First, we implement an Oster bound test (Oster, 2019) to examine the robustness of the estimated treatment effects. Oster bounds help determine whether the estimated effects are reliable also after accounting for possible unobserved confounding variables. The results confirm that unobserved heterogeneity is unlikely to change the main conclusions (Table A7).

Second, we cross-check our results by replacing our key treatment variable, the internet use dummy, with an alternative continuous treatment variable, namely the intensity of internet use, measured as the internet bill for the last one month (30 days) prior to the survey. Regression estimates with this alternative treatment variable are shown in Tables A8-A10 in the online appendix. These estimates support the same conclusions.

Third, to test the plausibility of our estimates, we conducted several follow-up phone interviews with randomly selected sample farmers and village heads in the study area to ask more specifically for the main purposes of using the internet and discuss the main findings. Even though these were qualitative interviews and discussions with a small subsample, the feedback supports our findings and the relevance of the hypothesized underlying mechanisms.

4. Results

4.1 Descriptive statistics

Table 2 presents descriptive statistics on the production and consumption of different food groups among sample households. Almost all produce cereals (mostly rice), and many also produce eggs, meat, and fish. On the consumption side, we see some differences between the normal and lean seasons (columns 2 and 3), as expected.

Table 3 compares household characteristics between internet users and non-users. Around 43% of the sample households use the internet, while 57% do not. On average, households with internet use tend to have more household members. They are also wealthier, better educated, and more likely to belong to the ethnic majority.

Table 2: Production and consumption of different food groups

Food groups	(1) Share farms producing (%)	(2) Share of households consuming, normal season (%)	(3) Share of households consuming, lean season (%)
Cereals	99	93	100
	(0.07)	(0.25)	(0.00)
Roots and tubers	1	83	80
	(0.09)	(0.37)	(0.40)
Eggs	57	87	77
	(0.50)	(0.34)	(0.42)
Fish	53	95	94
	(0.50)	(0.22)	(0.24)
Vegetables	6	99	98
	(0.23)	(0.09)	(0.13)
Fruits	10	60	71
	(0.31)	(0.49)	(0.45)
Meat	56	56	53
	(0.50)	(0.50)	(0.50)
Legumes, nuts, and seeds	4	81	72
	(0.20)	(0.40)	(0.45)
Milk and dairy products	28	41	42
	(0.45)	(0.49)	(0.49)
Oils and fats	2	92	92
	(0.13)	(0.27)	(0.27)
Spices, condiments, and beverages	0.27	98	93
	(0.05)	(0.15)	(0.26)
Sugar and sweets	0.27	76	64
	(0.05)	(0 .43)	(0.48)
Observations	720	720	720

Notes: Standard deviations in parentheses.

Table 3: Household characteristics by internet use

Variable	Measurement units	(1) Full sample	(2) Internet non-user	(3) Internet user	(3)-(2) Difference
Household size	people	4.52	4.42	4.64	0.22*
		(1.64)	(1.62)	(1.66)	
Age head	years	50.10	50.20	49.97	-0.23
		(12.16)	(11.72)	(12.74)	
Male head	1=male; 0=otherwise	0.96	0.96	0.96	0.00
		(0.20)	(0.20)	(0.19)	
Married head	1=married; 0=otherwise	0.981	0.99	0.98	-0.01
		(0.13)	(0.12)	(0.15)	
Ethnic majority head	1=Bangladeshi; 0=otherwise	0.94	0.92	0.98	0.06***
		(0.23)	(0.28)	(0.15)	
Muslim head	1=Muslim; 0=otherwise	0.68	0.72	0.64	-0.07**
		(0.47)	(0.45)	(0.48)	
Education head	years of schooling	5.04	4.54	5.72	1.18***
		(4.31)	(4.01)	(4.61)	
No. of dependents	people	1.43	1.47	1.37	-0.11
		(1.19)	(1.19)	(1.20)	
Assets per capita	1000 BDT	10.77	9.08	13.02	3.94***
		(0.98)	(0.98)	(0.93)	
Food expenditure	1000 BDT	86.48	80.38	94.60	14.23***
		(40.33)	(33.81)	(46.47)	
Non-food expenditure	1000 BDT	96.96	81.67	117.29	35.62***
		(82.88)	(61.24)	(101.56)	
Weather shock	1=yes; 0=otherwise	0.16	0.15	0.18	0.04
		(0.37)	(0.35)	(0.39)	
Distance to market	kilometer	1.95	1.86	2.06	0.21**
		(1.30)	(1.23)	(1.39)	
Observations		720	411	309	

*Notes: *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$; standard deviations in parentheses.*

Table 4 shows farm production outcomes by internet use. Internet users have higher farm incomes, commercialization ratios, and production diversity scores than non-users.

Table 4: Farm production outcomes by internet use

Variable	(1) All	(2) Internet non-users	(3) Internet Users	(3)-(2) Difference
Farm income (thsd. BDT)	77.63	50.99	113.06	62.07***
	(172.67)	169.36	170.92	
Production cost (thsd. BDT)	117.54	125.27	107.26	-18.01*
	(129.47)	(130.74)	(127.23)	
Farm output value (thsd. BDT)	195.17	176.26	220.31	44.05**
	(239.56)	(232.04)	(247.36)	
Commercialization ratio	0.57	0.55	0.60	0.04**
	(0.283)	(0.288)	(0.276)	
PDS9	4.36	4.19	4.59	0.40***
	(1.73)	(1.67)	(1.78)	
PDS12	3.91	3.68	4.20	0.52***
	(1.85)	(1.72)	(1.98)	
Observations	720	411	309	

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; standard deviations in parentheses; PDS9, production diversity score with 9 food groups; PDS12, production diversity score with 12 food groups.*

Table 5: Dietary diversity outcomes by internet use

Variable	(1) All	(2) Internet non-users	(3) Internet users	(3)-(2) Difference
Normal season				
HDDS9	6.95	6.75	7.21	0.46***
	(1.53)	(1.57)	(1.45)	
HDDS12	9.61	9.39	9.89	0.50***
	(1.81)	(1.83)	(1.75)	
MDDS	3.88	3.73	4.08	0.35***
	(1.30)	(1.31)	(1.27)	
WDDS	3.92	3.72	4.18	0.46***
	(1.32)	(1.25)	(1.37)	
CDDS	3.91	3.82	4.03	0.21
	(1.21)	(1.11)	(1.33)	
Lean season				
HDDS9	6.87	6.69	7.11	0.42***
	(1.65)	(1.61)	(1.68)	
HDDS12	9.36	9.10	9.69	0.59***
	(2.01)	(1.94)	(2.06)	
No. of observations	720	411	309	

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1; standard deviations in parentheses. HDDS9, household dietary diversity score with 9 food groups; HDDS12, household dietary diversity score with 12 food groups; MDDS, men's dietary diversity score; WDDS, women's dietary diversity score; CDDS, child dietary diversity score.*

Table 5 shows various dietary diversity indicators by internet use. All household- and individual-level dietary diversity scores are higher among the internet-users than among the non-users, and these differences are statistically significant, except for children. Whether these differences also hold after controlling for confounding factors is analyzed in the following.

4.2 Effects of using the internet on food production and consumption

Table 6 shows the estimated effects of using the internet on farm production outcomes, after controlling for confounding factors. Panel A illustrates the estimates from the CFA models, while panel B shows results from PSM. Results obtained with both econometric approaches suggest that using the internet has significantly positive effects on farm income, commercialization, and production diversity.

Table 6: Effects of using the internet on farm production outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Farm income	Production cost	Farm output value	Commercialization ratio	PDS9	PDS12
Panel A: Estimates from CFA models						
Internet use	56.789***	-27.381***	29.408	0.049**	0.528***	0.513***
	(13.988)	(9.562)	(18.837)	(0.023)	(0.138)	(0.141)
Panel B: Estimates from PSM models						
Internet use	65.943***	-9.93	56.013***	0.057**	0.761***	0.736***
	(13.988)	(9.562)	(18.837)	(0.023)	(0.138)	(0.141)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses. CFA, control function approach; PSM, propensity score matching (average treatment effects); PDS9, production diversity score with 9 food groups; PDS12, production diversity score with 12 food groups.*

The estimates suggest that using the internet helps to double net farm incomes (column 1 of Table 6). These big effects can be explained as farmers may use the internet to get up-to-date information on new farming techniques, market prices, and weather forecasts, which helps to increase outputs and decrease production costs (see columns 2 and 3 of Table 6). Similar effects of farmers using the internet were also shown in previous studies (Lio & Liu, 2006; Ma et al., 2020). Moreover, the follow-up phone interviews, in which we discussed our estimates with farmers and village heads, confirm that our results are plausible. For example, one farmer stated:

'Yes, the internet helps us increase production in several ways. We get knowledge on high-yield seeds, improved irrigation, and disease control through online resources like Krishi Math (farmer's field school). This year our crop production is more, and we make profit. My son gave

us information about the weather in advance, which helped a lot! We harvested the crop a bit earlier, knowing about the storm, and thus reduced our crop losses.'

The results in Table 6 also suggest that using the internet increases the farm commercialization ratio by 5-6 percentage points (column 4). This is reasonable given that farmers have better real-time information about market prices, which may help them negotiate better deals. Additionally, the internet facilitates networking with agricultural extension officers, other farmers, and traders, possibly encouraging more market-oriented behavior. A follow-up telephone interview with a farmer and village head revealed the following:

'… We mainly use the internet to know about the current market price of the product in the capital city; then we contact the wholesaler so that he (the wholesaler) cannot ask for a low price. We also use the internet to sell livestock on social networking platforms for Eid-ul-Adha (a religious festival of the Muslim community for which slaughtering cows or goats is a ritual). As homegrown animals are more organic and healthy, people are interested in these livestock for consumption. Besides, young people in our villages also use the internet to sell fish and shrimps to retail markets to a diverse array of customers through online platforms besides selling to local markets.'

Columns (5) and (6) of Table 6 show the effects of using the internet on farm production diversity scores. These are also positive and statistically significant, which is plausible with better access to information about profitable crop, livestock, and aquaculture species. In a previous study in China, Zheng et al. (2022) also showed that using the internet leads to the adoption of additional crop species and varieties. A follow-up phone interview with a farmer from our sample revealed:

'…internet use enables me to cultivate diverse fish and livestock due to quick access to new farming concepts through online platforms. Internet use helps me learn about diverse paddy, fish, and poultry breeds. This knowledge makes me confident to attempt new farming methods. From YouTube, I also learned a lot about better cultivation of diverse crops, such as mustard, lentils, and vegetables. I have observed that the diversity of farm production increases financial success in my village. People have started to cultivate multiple fruits and vegetables for home consumption and sales.'

Table 7 illustrates the estimated effects of using the internet on household- and individual-level dietary diversity scores. Again the two econometric approaches, CFA and PSM, lead to consistent results. The internet has significantly positive effects on household dietary diversity during the normal season and the lean season, and for both indicators, HDDS9 and HDDS12. This finding is consistent with Cui et al. (2024), who found positive effects of using the internet on household-level dietary quality in rural China.

Table 7: Effects of using the internet on dietary diversity scores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	HDDS9	HDDS12	HDDS9 (lean)	HDDS12 (lean)	MDDS	WDDS	CDDS
Panel A: Estimates from CFA models							
Internet use	0.304***	0.347**	0.297**	0.454***	0.103	0.239**	0.101
	(0.117)	(0.141)	(0.130)	(0.159)	(0.096)	(0.102)	(0.137)
Panel B: Estimates from PSM models							
Internet use	0.279**	0.353**	0.259*	0.454**	0.187	0.285**	0.228
	(0.14)	(0.165)	(0.149)	(0.182)	(0.125)	0.122	0.178

*Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses. CFA, control function approach; PSM, propensity score matching (average treatment effects). All dietary diversity scores refer to the normal season, except for those where lean season is specified.HDDS9, household dietary diversity score with 9 food groups; HDDS12, household dietary diversity score with 12 food groups; MDDS, men's dietary diversity score; WDDS, women's dietary diversity score; CDDS, child dietary diversity score.*

Interestingly, however, the effects on HDDS shown in Table 7 are smaller than the effects on PDS shown in Table 6, meaning that not all additional food groups produced are also consumed by household members. For the individual-level dietary diversity scores in Table 7, we find positive effects of using the internet, but these are also relatively small and statistically significant only for women.

Table 8 presents the effects of using the internet on the production and consumption of specific food groups. The results suggest that using the internet increases the likelihood of producing fish, meat, and legumes, nuts, and seeds. As mentioned, access to better information increases farmers' openness to adopt additional species and aquatic breeds (Ragkos et al., 2019). Apart from general information, many farmers also share personal success stories and videos of producing new species and breeds through local social media platforms, which encourages other households with internet access to also try those species. In a follow-up phone interview, one sample farmer stated:

'Definitely, the internet helps me to increase the production of different things. This works in different ways: by getting expert knowledge, learning about high-yield seeds, good livestock and aquatic breeds, improved fertilizers, cost-effective irrigation methods, and pest control……. I do mainly fish farming, and a bit of crops and livestock. Online platforms motivate me to produce more fish, as these have good market prices…… Through YouTube videos, I acquired knowledge about efficient methods of fish farming, including feeding practices and disease prevention; this knowledge minimizes my farming expenses. ……. improved fish cultivation methods …. lead to higher production and income……If I can manage everything, in the near future, I will expand my business more.'

Table 8: Effects of using the internet on food production and household food consumption choices

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Cereals	Roots and tubers	Eggs	Fish	Vegetables	Fruits	Meat	Legumes nuts, and seeds	Milk and dairy	Oils and fats	Spices and condiments	Sugar and sweets
Panel A. Estimates from CFA models											
Food production choices											
0.052	0.000	0.034	0.152***	0.037*	0.019	0.104***	0.114***	0.016	-0.004	-0.007	-0.005
(0.070)	(0.007)	(0.038)	(0.053)	(0.021)	(0.024)	(0.037)	(0.035)	(0.035)	(0.012)	(0.005)	(0.003)
Food consumption in normal season											
-0.001	0.033	-0.003	0.051***	0.011*	0.118***	0.051	0.021	0.024	0.041*	0.011	-0.009
(0.017)	(0.031)	(0.027)	(0.017)	(0.006)	(0.038)	(0.040)	(0.032)	(0.040)	(0.021)	(0.011)	(0.033)
Food consumption in lean season											
-	0.000	0.033	0.034	0.058***	0.001	0.063*	0.085**	-0.016	0.041	0.060***	0.061***
-	(0.000)	(0.033)	(0.033)	(0.020)	(0.010)	(0.034)	(0.039)	(0.036)	(0.039)	(0.020)	(0.020)
Panel B. Estimates from PSM models											
Food production											
0.055	-0.011	0.081***	0.004	0.066	0.053	-0.014	0.024	0.082***	0.08***	0.033	0.055
(0.037)	(0.039)	(0.023)	(0.012)	(0.042)	(0.046)	(0.042)	(0.046)	(0.026)	(0.025)	(0.045)	(0.037)
Food consumption in normal season											
0.018	0.036	0.00	0.066***	0.005	0.101**	0.051	0.003	-0.003	0.064**	0.016	-0.007
(0.022)	(0.035)	(0.032)	(0.022)	(0.009)	(0.045)	(0.046)	(0.037)	(0.046)	(0.026)	(0.014)	(0.04)
Food consumption in lean season											
-	0.055	-0.011	0.081***	0.004	0.066	0.053	-0.014	0.024	0.082***	0.08***	0.033
-	(0.037)	(0.039)	(0.023)	(0.012)	(0.042)	(0.046)	(0.042)	(0.046)	(0.026)	(0.025)	(0.045)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses. CFA, control function approach; PSM, propensity score matching. Consumption of food groups based on 7-day recall data at the household level. The models on cereal consumption during the lean season could not be estimated because all households consumed cereals.*

In Table 8, we also see more fish consumption among internet users, but the effects are smaller than on the production side. This further underlines that some of the species are primarily produced for market sales and not for home consumption. On the consumption side, we also hardly see any positive effects for meat, legumes, nuts, and seeds, especially not in the normal season. On the other hand, we see that using the internet increases the likelihood of consuming fruits, vegetables, and oils and fats.

5. Discussion and conclusion

Using recent primary data from 720 farm households in rural Bangladesh and quasi-experimental econometric techniques, we have analyzed effects of using the internet on farm production and food consumption patterns. We make novel contributions to the literature in that we are the first to examine effects of the internet on smallholder farmers by jointly capturing production and consumption decisions and by considering seasonal differences in household dietary quality.

Regarding the production side, our results suggest that using the internet has positive effects on farm output values, income, and commercialization. We also show that using the internet increases the number of different food groups produced on the farm, especially in terms of increasing the likelihood of producing fish, meat, and legumes, nuts, and seeds. These food groups are particularly nutritious and therefore potentially improve dietary quality in the local context.

Regarding the consumption side, our findings suggest that using the internet increases household dietary diversity in both the normal and lean seasons. However, the effects on dietary diversity are relatively small and smaller than the effects on farm production diversity. Using individual-level food consumption data, we find positive effects of using the internet on women's dietary diversity scores, whereas the effects on men's and children's dietary diversity scores are not statistically significant. Our estimates reveal that using the internet increases the likelihood of fish consumption, but not the likelihood of consuming meat, legumes, nuts, and seeds, even though these food groups were found to be increased on the production side. Obviously, some of the additional food groups are primarily produced for market sales and not for home consumption.

Based on our findings, we provide a few policy recommendations. First, since using the internet clearly improves farm outputs, market orientation, and incomes, internet adoption should be facilitated through appropriate action. So far, less than half of the farm households in the study area use the internet, so there is much potential for further enhancement. Public and private sector interventions to increase adoption should include improvements in the internet infrastructure, such as supplying 4G or 5G networks also in remote rural areas, as this enables people to use various apps efficiently. Our results show that farmers do not only benefit from standard websites but also from using social media and video platforms for learning about new farming techniques. In addition, offering affordable internet use and data packages will likely boost internet adoption, as will the development of user-friendly apps in local languages that are tailored to the needs of smallholder farmers (e.g., infos on relevant farming innovations, market data, and weather forecasts). Training programs to increase the digital literacy of farmers, including those with lower levels of formal education, may also help to increase the use of the internet and its benefits.

Second, the positive effects of the internet on smallholder household diets are welcome but could be further increased. Suitable interventions may include the provision of locally-relevant online and social media contents on healthy food and nutrition habits, including cooking shows and workshops with the promotion of healthy recipes. While we did not collect detailed data on who in the household uses the internet, field observations and follow-up discussions suggest that there is a certain bias towards male household members, whereas women are often those making decisions of what foods to use and prepare. Hence, improving women's access to the internet may help to further improve the diet and nutrition outcomes. Needless to say that other interventions unrelated to the internet are also important to improve nutrition, such as enhancing the efficiency of local markets for nutritious foods.

In closing, we acknowledge a few limitations of our study. First, while we collected some information on how people use the internet in qualitative follow-up interviews, our quantitative survey data lack details on who in the households exactly used the internet, how often, and for what concrete purposes. Second, we use cross-section observational data, which means that we are not perfectly able to deal with all possible sources of endogeneity. Third, our study refers to one specific area in Bangladesh. While some of the findings may also be applicable to other contexts, broad generalizations are likely not appropriate. Follow-up research with more comprehensive data from different contexts may help to further increase the internal and external validity of our findings.

References

Agbadi, P., Urke, H. B., & Mittelmark, M. B. (2017). Household food security and adequacy of child diet in the food insecure region north in Ghana. *PLOS ONE*, *12*(5), e0177377. https://doi.org/10.1371/journal.pone.0177377

Ali, M., Raihan, M. J., Siddiqua, T. J., Haque, M. A., Farzana, F. D., Ahmed, S. M. T., Rahman, S., Naz, F., Faruque, A. S. G., & Ahmed, T. (2022). Factors associated with low and medium household dietary diversity compared with high dietary diversity among marginalised households in rural Bangladesh: Findings from a Suchana baseline survey. *BMJ Open*, *12*(11), e062143. https://doi.org/10.1136/bmjopen-2022-062143

ADB. (2023). *Bangladesh's agriculture, natural resources, and rural development sector assessment and strategy*. https://www.adb.org/sites/default/files/institutional-document/864661/bangladesh-agriculture-sector-assessment-strategy.pdf

Ayran, G., Süleyman, Z., Avcı, Ü., & Arık, U. (2021). The effect of internet addiction on eating attitude and body image in university students. *Journal of Child and Adolescent Psychiatric Nursing*, *34*(3), 199–205. https://doi.org/10.1111/jcap.12320

Azam, S. (2007). Internet adoption and usage in Bangladesh. *Japanese Journal of Administrative Science*, *20*(1), 43–54. https://doi.org/10.5651/jaas.20.43

Birner, R., Daum, T., & Pray, C. (2021). Who drives the digital revolution in agriculture? A review of supply-side trends, players and challenges. *Applied Economic Perspectives and Policy*, *43*(4), 1260–1285. https://doi.org/10.1002/aepp.13145

Byun, D., Kim, R., & Oh, H. (2021). Leisure-time and study-time internet use and dietary risk factors in Korean adolescents. *The American Journal of Clinical Nutrition*, *114*(5), 1791–1801. https://doi.org/10.1093/ajcn/nqab229

Chandio, A. A., Gokmenoglu, K. K., Khan, I., Ahmad, F., & Jiang, Y. (2023). Does internet technology usage improve food production? Recent evidence from major rice-producing provinces of China. *Computers and Electronics in Agriculture*, *211*, 108053. https://doi.org/10.1016/j.compag.2023.108053

Chang, C. C. (2013). Examining users' intention to continue using social network games: A flow experience perspective. *Telematics and Informatics*, *30*(4), 311–321. https://doi.org/10.1016/j.tele.2012.10.006

Chang, H., & Just, D. R. (2009). Internet access and farm household income – Empirical evidence using a semi-parametric assessment in Taiwan. *Journal of Agricultural Economics*, *60*(2), 348–366. https://doi.org/10.1111/j.1477-9552.2008.00189.x

Chen, L., & Liu, W. (2022). The effect of internet access on body weight: Evidence from China. *Journal of Health Economics*, *85*, 102670. https://doi.org/10.1016/j.jhealeco.2022.102670.

Coleman, P. C., Hanson, P., Van Rens, T., & Oyebode, O. (2022). A rapid review of the evidence for children's TV and online advertisement restrictions to fight obesity. *Preventive Medicine Reports*, *26*, 101717. https://doi.org/10.1016/j.pmedr.2022.101717

Cui, Y., Zhao, Q., Glauben, T., & Si, W. (2024). The impact of internet access on household dietary quality: Evidence from rural China. *Journal of Integrative Agriculture*, *23*(2), 374–383. https://doi.org/10.1016/j.jia.2023.11.014

Deng, X., Peng, J., & Wan, C. (2024). The impact of internet use on land productivity: Evidence from China land economy survey. *Land*, *13*(2), Article 2. https://doi.org/10.3390/land13020262

Dey, M. M., Spielman, D. J., Haque, A. M., Rahman, M. S., & Valmonte-Santos, R. (2013). Change and diversity in smallholder rice–fish systems: Recent evidence and policy lessons from Bangladesh. *Food Policy*, *43*, 108-117. https://doi.org/10.1016/j.foodpol.2013.08.011

Do, T. L., Nguyen, T. T., & Grote, U. (2019). Nonfarm employment and household food security: Evidence from panel data for rural Cambodia. *Food Security*, *11*(3), 703–718. https://doi.org/10.1007/s12571-019-00929-8

Duke, É., & Montag, C. (2017). Smartphone addiction, daily interruptions and self-reported productivity. *Addictive Behaviors Reports*, *6*, 90–95. https://doi.org/10.1016/j.abrep.2017.07.002

FAO. (2011). *Guidelines for measuring household and individual dietary diversity*. https://openknowledge.fao.org/items/9bb3c3ce-66cf-4b00-b460-de29822bbd75

Hajong, P., Ahammad, K., Islam, M., & Rahman, S. (2021). Study on scope and existing cropping pattern at south-western saline region of Bangladesh. *Journal of Science Technology and Environment Informatics*, *27*, 2278–2286. https://doi.org/10.18801/jbar.270221.277

Ioannidis, K., Treder, M. S., Chamberlain, S. R., Kiraly, F., Redden, S. A., Stein, D. J., Lochner, C., & Grant, J. E. (2018). Problematic internet use as an age-related multifaceted problem: Evidence from a two-site survey. *Addictive Behaviors*, *81*, 157–166. https://doi.org/10.1016/j.addbeh.2018.02.017

Islam, M. Z. (2018, August 20). Mobile data leads to internet boom. *The Daily Star*. https://www.thedailystar.net/news/business/telecom/mobile-data-service-leads-to-internet-boom-in-bangladesh-1623310

Kaila, H., & Tarp, F. (2019). Can the internet improve agricultural production? Evidence from Vietnam. *Agricultural Economics*, *50*(6), 675–691. https://doi.org/10.1111/agec.12517

Khan, N., Ray, R. L., Zhang, S., Osabuohien, E., & Ihtisham, M. (2022). Influence of mobile phone and internet technology on income of rural farmers: Evidence from Khyber Pakhtunkhwa Province, Pakistan. *Technology in Society*, *68*, 101866. https://doi.org/10.1016/j.techsoc.2022.101866

Li, H., Li, J., Shen, Y., Zhang, X., & Lei, Y. (2018). Web-based irrigation decision support system with limited inputs for farmers. *Agricultural Water Management*, *210*, 279-285 https://doi.org/10.1016/j.agwat.2018.08.025

Lio, M., & Liu, M. C. (2006). ICT and agricultural productivity: Evidence from cross-country data. *Agricultural Economics*, *34*(3), 221–228. https://doi.org/10.1111/j.1574-0864.2006.00120.x

Liu, W., Xiao, W., Li, Y., & Westlund, H. (2024). How internet access impacts rural households' income in China: Evidence from the China family panel survey. *Applied Economics*, 1–16. https://doi.org/10.1080/00036846.2024.2331423

Luo, X., Pu, H., Wang, S., Zhong, D., Liu, F., & Li, Z. (2024). Influence of internet use on Chinese residents' health: The mediating role of health knowledge. *Technology in Society*, *76*, 102413. https://doi.org/10.1016/j.techsoc.2023.102413

Ma, B., & Jin, X. (2022). Does internet use connect us to a healthy diet? Evidence from rural China. *Nutrients*, *14*(13), Article 13. https://doi.org/10.3390/nu14132630

Ma, W., Nie, P., Zhang, P., & Renwick, A. (2020). Impact of internet use on economic well-being of rural households: Evidence from China. *Review of Development Economics*, *24*(2), 503–523. https://doi.org/10.1111/rode.12645

Muthini, D., Nzuma, J., & Qaim, M. (2020). Subsistence production, markets, and dietary diversity in the Kenyan small farm sector. *Food Policy*, *97*, 101956. https://doi.org/10.1016/j.foodpol.2020.101956

Nguyen, T. T., & Qaim, M. (2025). Local and regional food production diversity are positively associated with household dietary diversity in rural Africa. *Nature Food*, *6*(2), 205–212. https://doi.org/10.1038/s43016-024-01096-6

Nguyen, T., Nguyen, T. T., & Grote, U. (2023). Internet use and agricultural productivity in rural Vietnam. *Review of Development Economics*, *27*(3), 1309–1326. https://doi.org/10.1111/rode.12990

Nguyen, T. T., Nguyen, T.T., & Grote, U. (2022). Internet use, natural resource extraction and poverty reduction in rural Thailand. *Ecological Economics*, *196*, 107417. https://doi.org/10.1016/j.ecolecon.2022.107417

Ning, K., Zhu, Z., Xu, Z., Liu, H., & Lu, M. (2024). Internet use, dietary habits and adolescent obesity: Evidence from China. *International Journal of Health Economics and Management*, *24*(4), 517–535. https://doi.org/10.1007/s10754-024-09386-z

Ogutu, S. O., & Qaim, M. (2019). Commercialization of the small farm sector and multidimensional poverty. *World Development*, *114*, 281–293. https://doi.org/10.1016/j.worlddev.2018.10.012

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, *37*(2), 187–204. https://doi.org/10.1080/07350015.2016.1227711

Parlasca, M. C., Mußhoff, O., & Qaim, M. (2020). Can mobile phones improve nutrition among pastoral communities? Panel data evidence from Northern Kenya. *Agricultural Economics*, *51*(3), 475–488. https://doi.org/10.1111/agec.12566

Pettigrew, S., Tarabashkina, L., Roberts, M., Quester, P., Chapman, K., & Miller, C. (2013). The effects of television and internet food advertising on parents and children. *Public Health Nutrition*, *16*(12), 2205–2212. https://doi.org/10.1017/S1368980013001067

Pollard, C. M., Pulker, C. E., Meng, X., Kerr, D. A., & Scott, J. A. (2015). Who uses the internet as a source of nutrition and dietary information? An Australian population perspective. *Journal of Medical Internet Research*, *17*(8), e4548. https://doi.org/10.2196/jmir.4548

Ragkos, A., Koutouzidou, G., Koutsou, S., & Roustemis, D. (2019). *A new development paradigm for local animal breeds and the role of information and communication technologies* (A. Theodoridis, A. Ragkos, & M. Salampasis, Eds.). Springer International Publishing.

Rejeb, A., Rejeb, K., Abdollahi, A., Al-Turjman, F., & Treiblmaier, H. (2022). The interplay between the internet of things and agriculture: A bibliometric analysis and research agenda. *Internet of Things*, *19*, 100580. https://doi.org/10.1016/j.iot.2022.100580

Shen, J., Zhu, Z., Qaim, M., Fan, S., & Tian, X. (2023). E-commerce improves dietary quality of rural households in China. *Agribusiness*, *39*, 1495–1511. https://doi.org/10.1002/agr.21864

Shuvo, S. D., Hasan, M. M., Das, T. K., Hossain, M. E., Aktar, T., Riazuddin, M., & Hasan, M. S. (2024). Food insecurity and its contributing determinants among rural households in the south-western region of Bangladesh, 2021: A cross-sectional study. *Public Health in Practice (Oxford, England)*, *8*, 100514. https://doi.org/10.1016/j.puhip.2024.100514

Sibhatu, K. T., Krishna, V. V., & Qaim, M. (2015). Production diversity and dietary diversity in smallholder farm households. *Proceedings of the National Academy of Sciences*, *112*(34), 10657–10662. https://doi.org/10.1073/pnas.1510982112

Song, P., Adeloye, D., Li, S., Zhao, D., Ye, X., Pan, Q., Qiu, Y., Zhang, R., & Rudan, I. (2023). The prevalence of vitamin A deficiency and its public health significance in children in low- and middle-income countries: A systematic review and modelling analysis. *Journal of Global Health*, *13*, 04084. https://doi.org/10.7189/jogh.13.04084

Strzębicki, D. (2015). The development of electronic commerce in agribusiness–The polish example. *Procedia Economics and Finance*, *23*, 1314–1320. https://doi.org/10.1016/S2212-5671(15)00573-0

Tsochantaridou, A., Sergentanis, T. N., Grammatikopoulou, M. G., Merakou, K., Vassilakou, T., & Kornarou, E. (2023). Food advertisement and dietary choices in adolescents: An overview of recent studies. *Children*, *10*(3), 442. https://doi.org/10.3390/children10030442

Vandelanotte, C., Sugiyama, T., Gardiner, P., & Owen, N. (2009). Associations of leisure-time internet and computer use with overweight and obesity, physical activity and sedentary behaviors: Cross-sectional study. *Journal of Medical Internet Research*, *11*(3), e1084. https://doi.org/10.2196/jmir.1084

Verger, E. O., Ballard, T. J., Dop, M. C., & Martin-Prevel, Y. (2019). Systematic review of use and interpretation of dietary diversity indicators in nutrition-sensitive agriculture literature. *Global Food Security*, *20*, 156–169. https://doi.org/10.1016/j.gfs.2019.02.004

Wei, X., Liu, Y., & Liu, Y. (2023). Study on the impact of internet usage, aging on farm household income. *Sustainability*, *15*(19), 14324. https://doi.org/10.3390/su151914324

Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human Resources*, *50*(2), 420–445. https://doi.org/10.3368/jhr.50.2.420

World Bank. (2025). *Bangladesh—Individuals Using The Internet (% Of Population)—2025 Data 2026 Forecast 1990-2023 Historical*. https://tradingeconomics.com/bangladesh/individuals-using-the-internet-percent-of-population-wb-data.html

Yang, M., Zhang, Z., & Wang, Z. (2023). Does internet use connect smallholder farmers to a healthy diet? Evidence from rural China. *Frontiers in Nutrition*, *10*, 1122677. https://doi.org/10.3389/fnut.2023.1122677

Zheng, H., Ma, W., Wang, F., & Li, G. (2021). Does internet use improve technical efficiency of banana production in China? Evidence from a selectivity-corrected analysis. *Food Policy*, *102*, 102044. https://doi.org/10.1016/j.foodpol.2021.102044

Zheng, Y., Zhu, T., & Jia, W. (2022). Does internet use promote the adoption of agricultural technology? Evidence from 1449 farm households in 14 Chinese provinces. *Journal of Integrative Agriculture*, *21*(1), 282–292. https://doi.org/10.1016/S2095-3119(21)63750-4

Online Appendix

Effects of using the internet on smallholder farmers' income and dietary quality in Bangladesh

Table A1: Definition of control variables

Name	Measurement unit	Definition
Internet use	Dummy (1=yes, 0=otherwise)	At least one household member uses the internet
Household size	People	Total number of household member
Age head	Years	Age of the household head
Male head	Dummy (1=male, 0=female)	Sex of the household head is male
Married head	Dummy (1=married, 0=otherwise)	Marital status of the household head
Muslim head	Dummy (1=Muslim, 0=otherwise)	Religion of the household head
Education head	Years	Years of schooling of the household head
No. of dependent	People	Number of dependent people in the household
Tenant farmer	Dummy (1=yes, 0=no)	It the household head is tenant farmer=1, 0=otherwise
Asset per capita	BDT	Value of key assets owned by the household in per capita terms (log-transformed)
Weather shock	Dummy (1=yes, 0=no)	If the households experienced flood or drought or both during the last 12 months
Distance	Kilometer	Distance between house to the local market
District	District dummy1 District dummy2	District dummy 1 (1=Bagerhat, 0=otherwise) District dummy 2 (1= Khulna, 0=otherwise)

Table A2: First-stage regression model

Variables	Internet use
Share of households using the internet in the Upazila	0.020***
	(0.005)
Household size	0.178***
	(0.044)
Age head	0.001
	(0.005)
Male head	-0.094
	(0.244)
Married head	-0.190
	(0.383)
Ethnic majority head	1.305***
	(0.291)
Muslim head	-0.316***
	(0.122)
Education head	0.027**
	(0.013)
No. of dependents	-0.136**
	(0.060)
Tenant dummy	-0.060
	(0.105)
Asset per capita (ln)	0.338***
	(0.057)
Weather shock dummy	-0.076
	(0.136)
Distance to market	0.032
	(0.039)
Bagerhat	0.081
	(0.132)
Khulna	0.140
	(0.129)
Constant	-5.669***
	(0.828)
Observations	720
Wald chi2	96.99
P-value	0.00

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses*

Table A3: Falsification tests

Variables	Share of households using the internet in the Upazila	Std. error
Farm production activities		
Total farm income	0.183	(0.611)
Total cost	0.045	(0.430)
Farm output value	0.875	(0.712)
Total commercialization	-0.003***	(0.001)
PDDS12	0.013**	(0.005)
PDDS9	0.014**	(0.005)
Household consumption outcome		
HDDS12	-0.014**	(0.006)
HDDS12lean	-0.012*	(0.007)
HDDS9	-0.011**	(0.005)
HDDS9 lean	-0.015***	(0.005)
MDDS	0.013***	(0.005)
WDDS	0.015***	(0.005)
CDDS	-0.001	(0.009)
Household food consumption choices in normal season		
Cereals	0.005***	(0.001)
Roots and tubers	-0.001	(0.001)
Eggs	-0.003**	(0.001)
Fish	0.001*	(0.001)
Vegetables	0.000	(0.000)
Fruits	-0.003**	(0.002)
Meat and organ meat	-0.004**	(0.002)
Legumes, seeds and nuts	-0.003**	(0.001)
Milk and dairy	-0.002	(0.002)
Oils and fats	0.000	(0.001)
Spices and condiments	-0.000	(0.001)
Sweets	-0.004**	(0.002)
Household food consumption choices in lean season		
Cereals	0.000	(0.000)
Roots and tubes	-0.001	(0.001)
Eggs	-0.004**	(0.001)
Fish	0.000	(0.001)
Vegetables	-0.000	(0.001)
Fruits	0.004**	(0.001)
Meat and organ meat	-0.006***	(0.002)
Legumes, seeds and nuts	-0.002	(0.002)
Milk and dairy	-0.006***	(0.002)
Oils and fats	0.001	(0.001)
Spices and condiments	0.003***	(0.001)
Sweets	-0.002	(0.002)

Household food production choices		
Cereals	-0.005*	(0.003)
Roots and tubes	-0.001*	(0.000)
Egg	0.009***	(0.002)
Fish	0.012***	(0.002)
Vegetables	-0.002**	(0.001)
Fruits	-0.006***	(0.001)
Meat and organ meat	0.013***	(0.002)
Legumes, seeds and nuts	-0.003***	(0.001)
Milk and dairy	-0.003**	(0.001)
Oils and fats	-0.000	(0.000)
Spices and condiments	-0.000	(0.000)
Sweets	-0.000	(0.000)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses*

Table A4: Propensity score estimation (probit regression of internet use)

Variables	Coefficient	Standard error
Household size	0.167***	0.046
Age head	0.001	0.004
Male head	-0.098	0.256
Married head	-0.262	0.379
Ethnic majority head	1.361***	0.260
Education head	0.027**	0.013
Muslim head	-0.362***	0.119
No. of dependents	-0.137**	0.061
Tenant dummy	-0.063	0.105
Asset per capita	0.329***	0.056
Weather shock	-0.029	0.136
Distance to market	0.049	0.039
Bagerhat	0.075	0.134
Khulna	0.138	0.128
Constant	-4.660***	0.773
Observations		720
Log likelihood		-433.58
LR chi2		96.47
Prob. > chi^2		0.000
Pseudo R^2		0.098

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

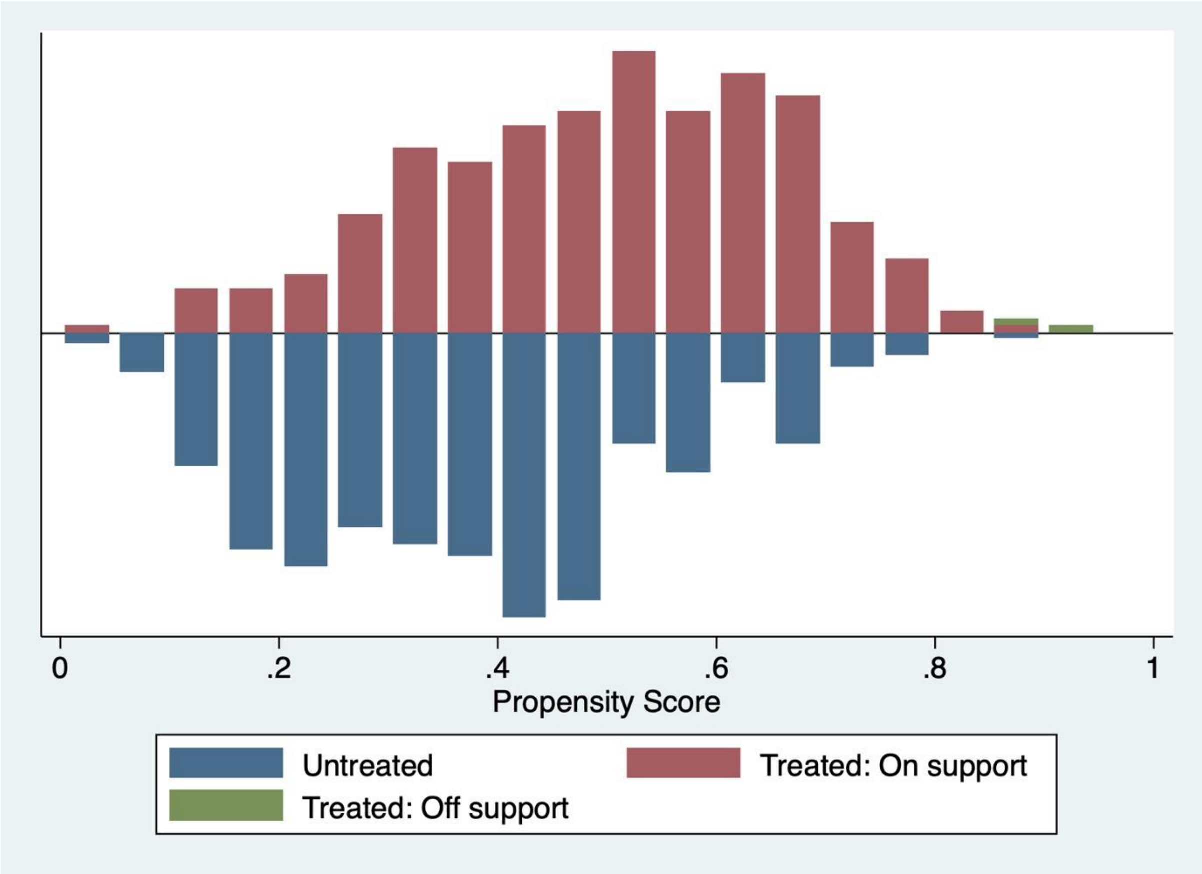

Figure A1: Propensity score distribution and common support for propensity score estimation by groups

Notes: "Treated: on support'' presents the households using the internet that have a suitable match, while ''Treated: off support'' presents the households using the internet that do not have a suitable match; "Untreated" presents the households without internet use.

Table A5: Balancing test

		Mean			
Variable		Treated	Control	Difference	p-value
Household size	Unmatched	4.64	4.42	0.22*	0.07
	Matched	4.61	4.65	-0.04	0.76
Age head	Unmatched	49.97	50.20	-0.23	0.80
	Matched	49.95	50.16	-0.21	0.83
Male head	Unmatched	0.96	0.96	0.00	0.87
	Matched	0.96	0.96	0.00	0.87
Married head	Unmatched	0.98	0.99	-0.01	0.42
	Matched	0.98	0.99	-0.01	0.26
Ethnic majority	Unmatched	0.98	0.92	0.06***	0.00
	Matched	0.98	0.98	0.00	0.87
Education head	Unmatched	5.72	4.54	1.18***	0.00
	Matched	5.70	5.70	0.00	0.99
Muslim head	Unmatched	0.64	0.72	-0.07**	0.03
	Matched	0.64	0.65	-0.01	0.81
No. of dependents	Unmatched	1.37	1.47	-0.11	0.24
	Matched	1.36	1.34	0.01	0.91
Tenant farmer	Unmatched	0.50	0.56	-0.06*	0.09
	Matched	0.50	0.49	0.01	0.75
Asset per capita	Unmatched	9.10	8.64	0.45***	0.00
	Matched	9.09	9.08	0.01	0.85
Weather shock	Unmatched	0.18	0.15	0.04	0.20
	Matched	0.18	0.20	-0.02	0.44
Distance to market	Unmatched	2.06	1.86	0.21**	0.04
	Matched	2.05	2.03	0.02	0.83
Bagerhat	Unmatched	0.25	0.25	0.00	0.90
	Matched	0.25	0.27	-0.01	0.70
Khulna	Unmatched	0.39	0.39	0.00	0.98
	Matched	0.39	0.36	0.03	0.50

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses*

Table A6: Quality test for propensity score matching (NNM)

Type of statistic		Value
Pseudo R^2	Before matching	0.098
Pseudo R^2	After matching	0.004
LR test (p-value)	Before matching	0.000
LR test (p-value)	After matching	0.999
Mean standardized bias	Before matching	13.5
Mean standardized bias	After matching	2.8
Percent bias reduction		79.26%

Table A7: Oster bound test on robustness of significantly estimated effects to unobservables

Farm production activities	Coef.	Std. err.	Delta	Beta
Total farm income	57.840***	(14.54)	7.798	[62.068; 57.840]
Total farm cost	-26.709***	(9.37)	-12.381	[-26.709; -29.870]
Farm output value	31.131*	(18.833)	5.024	[31.131; 26.330]
Total commercialization	0.037*	(0.022)	7.428	[0.037; 0.035]
Household production diversity scores for 12 food groups	0.539***	(0.137)	20.418	[0.540; 0.546]
Household production diversity scores for 9food groups	0.557***	(0.134)	19.274	[0.564; 0.557]
Household consumption outcome				
HDDS9	0.260	(0.116)	2.638	[0.260; 0.177]
HDDS12	0.286	(0.140)	2.718	[0.286; 0.198]
LeanHDDS9	0.233*	(0.013)	2.487	[0.233; 0.153]
LeanHDDS12	0.394**	(0.158)	3.334	[0.394; 0.307]
MDDS	0.159	(0.098)	2.067	[0.159; 0.087]
WDDS	0.2978***	(0.103)	3.538	[0.2978; 0.233]
CDDS	0.1008	(0.139)	2.457	[0.1008; 0.062]
Household food production choices				
Cereals	0.0249	(0.070)	3.261	[0.025; 0.0181]
Roots and tubers	-0.0026	(0.007)	7.121	[-0.0026; -0.0023]
Egg	0.0652*	(0.038)	5.568	[0.0652; 0.0568]
Fish	0.19633***	(0.053)	-6.883	[0.1963; 0.2181]
Vegetables	0.02776	(0.021)	-6.255	[0.0278; 0.0325]
Fruits	-0.0065	(0.024)	1.007	[-0.0065; -0.00004]
Meat and organ meat	0.1519***	(0.037)	27.750	[0.1519; 0.1561]
Legumes, seeds and nuts	0.0976***	(0.032)	18.839	[0.0976; 0.0985]
Milk and dairy	0.0030	(0.035)	0.320	[-0.0067; 0.0030;]
Oils and fats	-0.0044	(0.012)	2.463	[-0.0044; -0.0028]
Spices and condiments	-0.0072	(0.005)	-8.086	[-0.0072; -0.0081]
Sweets	-0.0061	(0.004)	-19.730	[-0.0061; -0.0066]
Household food consumption choices in normal season				
Cereals	0.0161	(0.017)	1.735	[0.0161; 0.0072]
Roots and tubers	0.0289	(0.030)	3.583	[0.0222; 0.02890]
Egg	-0.0127	(0.027)	-1.341	[-0.01272; -0.0225]
Fish	0.0547***	(0.017)	4672.662	[0.0547; 0.0577]
Vegetables	0.0116*	(0.007)	18.542	[0.0116; 0.0117]
Fruits	0.1040***	(0.038)	5.393	[0.1040; 0.0938]
Meat and organ meat	0.03411	(0.039)	2.784	[0.03411; 0.0233]
Legumes, seeds and nuts	0.0072	(0.031)	0.615	[-0.0047; 0.0072]
Milk and dairy	0.0160	(0.039)	0.886	[-0.0022; 0.0160;]
Oils and fats	0.0402*	(0.022)	9.647	[0.0401; 0.0382]
Spices and condiments	0.0092	(0.012)	9.676	[0.0092; 0.0087]
Sweets	-0.0234	(0.033)	-13.540	[-0.0234; -0.026]

Household food consumption choices in lean season				
Cereals	---	---	---	----
Roots and tubers	0.0257	(0.032)	2.849	[0.0258; 0.0177]
Egg	0.0167	(0.033)	1.351	[0.0168; 0.0046]
Fish	0.0573***	(0.020)	7.394	[0.0573; 0.0555]
Vegetables	-0.0006	(0.010)	-1.275	[-0.0006; -0.0011]
Fruits	0.07557**	(0.034)	5.404	[0.07557; 0.0663]
Meat and organ meat	0.0618	(0.039)	4.930	[0.0618; 0.0531]
Legumes, seeds and nuts	-0.0226	(0.035)	-1.802	[-0.0226; -0.0363]
Milk and dairy	0.0195	(0.039)	1.117	[0.0195; 0.0021]
Oils and fats	0.0621	(0.021)	11.051	[0.0621; 0.0606]
Spices and condiments	0.0717***	(0.021)	85.340	[0.0717; 0.0750]
Sweets	0.0269	(0.036)	7.293	[0.0269; 0.0243]

*Notes: *** p < 0.01, **p < 0.05, * p < 0.1, Robust standard error in parentheses*

Table A8: Impact of internet bill on farm production activities

	Farm income	Total production cost	Farm output value	Commercialization ratio	PDS9	PDS12
CFA	0.103***	-0.000	0.102	0.000*	0.002***	0.002***
	(0.029)	(0.052)	(0.067)	(0.000)	(0.000)	(0.000)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses*

Table A9: Impact of internet bill on household production and consumption diversity score

	HDDS9	HDDS12	HDDS9 lean	HDDS12 lean	MDDS	WDDS	CDDS
CFA	0.001***	0.001***	0.001***	0.001***	0.000*	0.001***	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses*

Table A10: Impact of internet bill on food production and households food consumption choices

	Cereals	Roots and tubers	Egg	Fish	Vegetables	Fruits	Meat and organ meat	Legumes, seeds and Nuts	Milk and dairy	Oils and fats	Spices, condiments and beverages	Sweets
Food production												
	0.000*	0.000	0.000***	0.000***	0.000	0.000	0.000***	0.000***	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Food consumption in normal season												
	0.000	0.000**	0.000	0.000***	0.000**	0.000***	0.000**	0.000	0.000	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Food consumption in lean season												
	0.000	0.000*	0.000	0.000***	0.000	0.000**	0.000**	0.000	0.000*	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses*