Received: 16 June 2022 | Revised: 7 March 2023 | Accepted: 8 March 2023

DOI: 10.1111/rode.12990

SPECIAL ISSUE ARTICLE

WILEY

Internet use and agricultural productivity in rural Vietnam

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Abstract

The use of the internet is growing rapidly and has become an engine for economic development. However, few studies have examined the impact of internet use on agricultural production, and the results are not yet conclusive. Employing a dataset of more than 2000 observations in rural Vietnam, our study analyses the impact of internet use on agricultural productivity using the heteroscedasticity-based instrument approach suggested by Lewbel, *Journal of Business and Economic Statistics*, 2012, 30, 67–80 and examines the heterogeneity and distribution of the impact using quantile regressions. Our results show that internet use has significant and positive effects on agricultural productivity. However, these effects are heterogeneous across population groups. The positive effects of internet use are stronger for households with a lower level of education, with a young and female head, and from ethnic minorities. The benefits are also found to be skewed towards the group of farmers at the bottom of the productivity distribution. Therefore, we propose facilitating the diffusion of the internet, since it not only boosts agricultural productivity, but also reduces productivity inequality. In addition, we recommend promoting rural education, supporting local markets, investing more in irrigation systems, and facilitating farm mechanisation as these factors are found to contribute to increasing agricultural productivity.

KEYWORDS
instrumental variable, quantile regression, rural household, Vietnam

1 | INTRODUCTION

The internet is spreading rapidly and has become an essential part of economic and human development in both developed and developing countries (World Bank, 2021a). Internet use enables households to access a wealth of information, knowledge and educational resources, expand and strengthen social networks, improve professional skills, and increase employment opportunities (Chen et al., 2022; Ma et al., 2023; United Nations, 2018). Moreover, it could reduce transaction costs, promote innovation, create new jobs, improve labour productivity, and contribute to resource conservation (FAO, 2018; Zheng & Ma, 2023). Increasing internet coverage to 75% of the population in all developing countries (up from the current level of 35% of the population) is expected to create more than 140 million jobs and contribute US$2 trillion to their collective gross domestic product (GDP) (World Bank, 2021b). The development of the internet is considered as a key factor in achieving the Sustainable Development Goals (United Nations, 2010, 2018; WBGU, 2019).

However, empirical studies show that the effects of internet use on household welfare, productivity, or poverty reduction are far more complex (Barbier, 2023; Mora-Rivera & García-Mora, 2021; Vatsa et al., 2023). On the one hand, some studies find significant and positive effects of internet use on household income, productivity, and poverty eradication (Ma & Wang, 2020; Nguyen, Nguyen, & Grote, 2022; Zheng et al., 2021). The positive impact could be stronger for marginalised and disadvantaged groups, implying an important role of internet use in reducing inequality (Kaila & Tarp, 2019; Ma, 2023; Zheng et al., 2021). On the other hand, some other studies show negligible effects or even negative effects of internet use. For example, Nguyen and Do (2022) show that using the internet for online marketplaces enhances income inequality. Due to the limited information processing capacity in the brain, the excessive amount of information can make people feel confused, stressed, have difficulty in understanding a problem or making a decision, consequently slowing down labour productivity, undermining mental health, and ruining work performance and academic success (Alheneidi, 2019; Hills, 2019; Misra et al., 2020; Sarbu, 2017).

In addition to the lack of careful reasoning and relevant knowledge, the tendency to prefer information that is more likely to be sought, understood, and compared to their perspective can lead people to accept misinformation and act accordingly (Anderson & Rainie, 2017; Pennycook & Rand, 2021). Moreover, people may be more attracted to interactive internet uses such as gaming, chatting, shopping and watching movies, and may spend more time online communicating and entertaining than study- or work-related uses (Gupta, 2017). More seriously, internet addiction is a growing problem that ruins lives by causing mental disorders, attention deficit hyperactivity disorder, depression, excessive daytime sleepiness, and social problems (Cash et al., 2012; Shrivastava et al., 2016). Besides, the development of internet networks may increase income inequality, as wealthier, more educated households may be more able to reap the benefits of internet use (Nguyen & Do, 2022). Furthermore, labour productivity could also be adversely affected (Li & Huo, 2022), for example, by an increase in adjustment costs related to the relocation of labour (Galperin & Fernanda Viecens, 2017).

The impact of the internet on agricultural production has been investigated by several studies and results are also mixed (Kaila & Tarp, 2020; Ma & Wang, 2020; Zheng et al., 2021). On the one hand, some studies show that internet use can improve overall agricultural performance (Kaila & Tarp, 2019; Zheng et al., 2021). Farmers can use the internet to get up-to-date information on weather, markets, soil and water conservation, and pest control. In addition, the use of the internet could create a more efficient and direct marketing channel, reduce transaction costs, and reduce the monopsony power of traders (Aker & Ksoll, 2016; Dzanku et al., 2021; Fafchamps & Minten, 2012; Goyal, 2010; Quandt et al., 2020). It also allows farmers to find lower prices for agricultural inputs and higher prices for agricultural products. On the other hand, internet use could help farmers find more profitable non-farm employment opportunities, motivate farmers to invest less in agricultural production or even leave the sector. For example, estimating the relationship between internet use and agricultural production in rural Viet Nam, Kaila and Tarp (2019) find that internet use significantly benefits farmers. The benefits of internet use are greater for younger households and those living in underdeveloped regions. While the study by Kaila and Tarp (2019) is a step forward, it only focuses on the impact of internet use on total agricultural revenue. The volume of total output could be improved simply by increasing the amount of inputs, which might not lead to increases in productivity or efficiency (Aragón et al., 2022; Gautam & Ahmed, 2018). Given the context in rural Vietnam, where intensive agricultural production faces multiple challenges from land degradation, overuse of fertilisers, and increasing competition for land from urbanisation and industrialisation, analysing the impact of the internet on total agricultural output value might offer less relevant policy implications than a productivity or efficiency analysis does. Moreover, the main treatment variable of internet use in Kaila and Tarp (2019) is defined at the commune level (the lowest administrative unit in Vietnam), but not at the household level. It is likely that internet access is available in a commune, but only a few households in that commune use the internet. In addition, endogeneity issues could be a potential caveat and have not yet been addressed. Ma and Wang (2020) examine the impact of internet use on the adoption of sustainable agricultural practices (SAPs) and on farm and household incomes in rural China. Their results show that internet use motivates farmers to adopt SAPs. However, the effect on farm income is insignificant. Furthermore, the effect on household income is only positive and significant for households at the middle and upper ends of the income distribution. Zheng et al. (2021) examine the impact of internet use on technical efficiency of banana farmers in China and find that internet use significantly improves the efficiency. However, unlike Ma and Wang (2020), Zheng et al. (2021) show that the positive effects of internet use are skewed towards farmers at the bottom of the income distribution, implying that internet diffusion plays an important role in reducing income inequality.

Against this background, our study has three main research objectives. First, we examine the impact of internet use on agricultural productivity using various productivity indicators. Second, we analyse the heterogeneous effects of internet use on agricultural productivity across different population groups. Third, we investigate the distributional effects of internet use. Vietnam is chosen as a case study due to: (i) a rapidly growing proportion of internet users, (ii) its economy is dependent on agriculture and a large proportion of the rural population rely on farming as its main livelihood, (iii) growth in agricultural productivity has experienced a decline in recent decades and faces numerous challenges such as climate change, land degradation and urbanisation. Our study makes several contributions to the current literature. First, few studies have examined the impact of internet use on agricultural productivity, and the results remain ambiguous. Second, while Kaila and Tarp (2019) are the pioneers in studying the impact of internet use on agricultural outputs in Vietnam, we are the first to examine the impact of internet use on agricultural productivity, and endogeneity issues are well addressed in our study. Third, our study analyses the heterogeneous and distributional effects of internet use on agricultural productivity.

The rest of the paper is organised as follows. Section 2 describes the study site and data. Section 3 presents the methods and results for the impact of the internet on agricultural productivity. Section 4 presents the methods and findings on the heterogeneous and distributional effects of internet use on agricultural productivity. Conclusion and policy implications are given in Section 5.

2 | DATA AND DESCRIPTIVE STATISTICS

2.1 | Study site and data sources

Launched publicly in Vietnam in 1997, the internet has experienced rapid growth over the past two decades, from 0.2% in 2000 to 70% in 2018 (Phan, 2019). This growth is much higher than the global average growth (7% of the world population used the internet in 2000 and this figure was 60% in 2020) (World Bank, 2022). The rapid development of the internet in Vietnam is accompanied by remarkable advances in economic development. With a total population of nearly 100 million, the country is one of the fastest-growing economies in recent decades (Le et al., 2022). Annual economic growth over the period 2000–2020 was around 6%, leading to an increase in GDP per capita from PPP$ 3000 in 2000 to PPP$ 8200 in 2019 (World Bank, 2021b). The poverty rate at US$ 1.90 per day (2011 PPP) decreased from 37% in 2002 to 1.8% in 2018. However, Vietnam's economy still depends heavily on agricultural production. According to the World Bank (2022), 62% population lived in rural areas in 2019 and 37% population worked in the agricultural sector. In recent decades, Vietnam has also achieved explosive growth in agricultural production, transforming itself from a once starving country into one of the main exporters of various crops such as rice, cassava, sweet potatoes (Amare et al., 2023). However, agricultural productivity is still low and agricultural production suffers from numerous challenges such as climate change, water scarcity, and soil degradation (FAO, 2014). In addition, the possibilities for expanding agricultural land remain limited, since arable land is mostly exploited (Duwayri et al., 2000; Grote et al., 2021). Furthermore, increasing competition for land and labour from other sectors is driving the downward trend in agricultural land use (Nguyen et al., 2021).

This study used a 2-year panel dataset collected in 2016 and 2017 as part of the rural research programme 'Poverty dynamics and sustainable development: A long-term panel project in Thailand and Vietnam (TVSEP)'. The surveys in Vietnam were conducted in three provinces, namely Ha Tinh, Thua Thien Hue, and Dak Lak. These provinces are generally characterised by heavy reliance on agriculture and high poverty rates (Hartwig & Nguyen, 2023). The TVSEP project was conducted in Vietnam from 2007 to 2017, but the information on internet use of the surveyed households was only available from the two surveys in 2016 and 2017. Therefore, we used data collected in these two waves, 2016 and 2017. The original sample was around 1800 households per year, but for the purpose of our study, which focused on agricultural productivity and efficiency, we excluded non-crop farmers and farmers who did not harvest crops during the survey period. In this regard, our final sample included the observations from 2003 households (1106 households in 2016 and 997 households in 2017).

Two structured questionnaires (for households and villages) were used for data collection. The household questionnaire contains different sections on demographics, health, education, land, farming, extraction of natural resources, off-farm wage employment, non-farm self-employment, consumption, borrowing, assets, shocks and risks, insurance, and public transfers. The household questionnaire also has a separate subsection asking households if they have used the internet in the last 12 months, the main devices for internet connection and the main purposes of internet use. Another subsection in the household questionnaire concerns agricultural activities, in which households report crop varieties, cultivated area, crop outputs and revenue, and expenses for seeds and seedlings, land preparation, pesticides, fertilisers, harvesting, and labour hours. The village questionnaire was used to collect information about the geography, economy and infrastructure conditions in the villages. All interviewers were carefully selected and intensively trained before the surveys. Each interview was conducted at households' homes and lasted around 2 hours. After the interview, each completed questionnaire was checked for consistency and plausibility by another interviewer and then by the team leaders. If the collected information was implausible or contradictory, the responsible interviewers had to collect the information again by telephone or by visiting the households again.

2.2 | Descriptive statistics

Table 1 compares household and village characteristics between two groups of households who use and do not use the internet. The average age of the household heads in the group of internet users is around 53 years, while the average age in the other group is 56 years. This makes sense given that older persons are more reluctant to innovate and less likely to use the internet for entertainment purposes (Penard et al., 2015). Internet users also have a higher level of education. This could be because people with lower educational levels are not well equipped with information technology (IT) skills or have difficulty reading comprehensive texts (Močnik & Širec, 2010). Penard et al. (2015) also show that younger and better educated people are more likely to use the internet. In terms of gender, the share of male-headed households is 84% in the group of internet users, around 5% higher than in the group of internet non-users. Regarding ethnicity, the share of ethnic minority households in the group of internet non-users is around 27%, and thus 11% higher than in the other group. This implies that Kinh households (the majority ethnic group) are more likely to use the internet than ethnic minority households. This is plausible as ethnic minority households are often characterised by lower levels of education and living conditions compared to Kinh households and they tend to live in remote regions with underdeveloped infrastructure conditions. Households with internet use also have a larger household size and a lower share of children and old people. This is plausible given that in working age there is a greater demand to use the internet to seek employment, learn and expand social networks. Internet users also have more land and assets than non-users. Accordingly, wealthier households are more likely to use the internet because they can afford to buy devices such as computers or smartphones and pay subscription fees to connect to the internet. Regarding shocks, internet users are less likely exposed to shocks. The share of internet users who experience a health shock is around 17%, whereas 22% of internet non-users experience at least one health shock. Likewise, 25% of the internet non-users suffer from weather shocks, while these are around 22% of internet users. It is likely that updated information on weather forecasts, health care, and preventive measures from the internet could help households to prevent and recover from climate-related disasters and diseases.

TABLE 1 Household and village characteristics by internet use status.

	Whole sample	Internet users	Internet non-users
Age head (years)	55.26	53.43***	56.30***
	(11.99)	(9.82)	(12.95)
Ethnic minority (%)	23.59	16.43***	27.65***
	(42.46)	(37.08)	(44.74)
Male head (%)	81.60	84.49**	79.96**
	(38.76)	(36.22)	(40.05)
Years of education	7.14	8.31***	6.48***
	(2.85)	(2.74)	(2.69)
Child share (%)	16.29	15.08**	16.98**
	(19.14)	(17.43)	(20.03)
Old share (%)	14.14	6.80***	18.31***
	(27.73)	(15.08)	(32.07)
Household size (people)	3.91	4.12***	3.78***
	(1.64)	(1.47)	(1.72)
Asset value per capita (PPP$)	1018	1502***	744***
	(1403)	(1822)	(999)
Tractor (numbers)	0.22	0.26**	0.20**
	(0.48)	(0.53)	(0.45)
Land per capita (ha)	0.30	0.33**	0.27**
	(0.66)	(0.70)	(0.63)
Irrigated land area (ha)	0.45	0.54***	0.40***
	(0.61)	(0.68)	(0.56)
Plot size (ha)	0.23	0.25*	0.22*
	(0.46)	(0.55)	(0.39)
Distance to plots (km)	0.98	0.97	0.98
	(0.92)	(0.88)	(0.95)
Weather shock (%)	24.44	22.47***	25.56***
	(42.98)	(41.77)	(43.64)
Health shock (%)	20.54	17.87**	22.06**
	(40.41)	(38.34)	(41.48)
Enterprises (numbers)	0.35	0.43***	0.30***
	(0.99)	(1.06)	(0.95)
Distance to market (km)	3.69	2.90***	4.14***
	(6.33)	(4.78)	(7.03)
Mountain (%)	45.89	40.34***	49.03***
	(49.84)	(49.09)	(50.01)

TABLE 1 (Continued)

	Whole sample	Internet users	Internet non-users
River (%)	42.70	42.18	43.00
	(49.48)	(49.42)	(49.53)
No. of observations	2003	761	1342

Note: Standard errors in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

TABLE 2 Internet use and main devices.

Main use purposes by users[a]	**(%)**	**No. of households having this purpose**
Entertainment	89	671
Contacting friends/relatives	66	498
Learning	37	277
Searching information and doing businesses	30	227
No. households having information of main purposes	752[b]	
Main device for connecting to internet	**(%)**	**No. of households having this device**
Smartphone/tablet	83	628
Computer	15	116
Others (from internet cafes)	2	17
No. households having information of main devices	752[b]	

[a]Households are asked to report multiple main purposes of using internet;
[b]The number of households using the internet is 761 households, but some households have missing information on main purposes and devices to connect to the internet.

Village characteristics show that internet users live in villages with more enterprises and closer to markets. Internet non-users, on the other hand, tend to live in mountain regions. This is understandable as in remote villages, the internet infrastructure can be underdeveloped, connections slow and unstable. Moreover, markets and non-farm employment opportunities could help people become more prosperous, thereby enabling and motivating them to use the internet.

Table 2 provides more details on the devices that rural households use to connect to the internet and the purposes of internet use. The internet was mainly used for entertainment (89%), followed by social contacts (66%). The purposes of 'learning' and 'searching information' account for 37% and 30%, respectively. The main devices used for connecting to the internet are smartphones or tablets (83%). The percentage of households using computers to connect to the internet is 15%, while this figure through internet cafes is 2%.

3 | IMPACTS OF INTERNET USE ON AGRICULTURAL PRODUCTIVITY

The first step of our empirical analysis was to estimate the impact of internet use on agricultural productivity. We use five indicators of agricultural productivity, including (1) production efficiency, (2) crop revenue per harvested land area (per ha), (3) crop income per ha, (4) crop revenue per family labour hour (per hour), (5) crop income per hour. The indicator of production efficiency (1) is used to evaluate the overall performance of farmers and was estimated by a True Random Effects Stochastic Frontier approach (TRE) with a Translog Frontier Production Function (see results of the estimation in Appendix SA2). The indicators (2) and (3) (crop revenue per ha and crop income per ha) are commonly used to measure land productivity, whereas the indicators (4) and (5) (crop revenue per hour and crop income per hour) represent labour productivity. The selection of these indicators are based on previous studies on production efficiency (Gautam & Ahmed, 2018; Nguyen et al., 2021; Yang et al., 2016). Regarding land and labour productivity, existing studies use either crop revenue or crop income per unit of land or labour. For example, Djido and Shiferaw (2018) and Zhang et al. (2021) use crop income per unit of labour, while Dubbert (2019) and Ghimire and Kapri (2020) use crop revenue per unit of labour. Amare et al. (2018) use crop income per unit of land, while Muyanga and Jayne (2019) use crop revenue per unit of land. We use both crop revenue and crop income. Crop income is calculated by subtracting variable costs of crop production from crop revenue. They are then divided by the total harvested land area or total hours of labour used for crop production of the household in the year that data were collected to provide crop revenue per ha or per hour and crop income per ha or per hour. Since 90% of the labour hours in crop production of the surveyed households are from family labour, and since we do not know if hired labourers use the internet or not, our labour productivity indicators are for family labour only. The effects of internet use on agricultural productivity are estimated by the following model:

$$P_{it} = \lambda + \Omega I_{it} + \eta H_{it} + \theta V_{it} + \in_{it}, \tag{1}$$

where P represents agricultural productivity indicators. I is the main treatment variable showing whether the household uses the internet or not. H represents household characteristics and V is the vector of village characteristics, and $\in_i$ is the error term (see Appendix SA1 for the definition of the explanatory variables).

In Equation (1), I is likely endogenous as previous studies show that internet use is significantly determined by household characteristics (Briggeman & Whitacre, 2010; Mesch & Talmud, 2011; Sharma & Grote, 2019; Yang et al., 2021). The failure to control for unobservable variables which are significantly correlated with both internet use and productivity will lead to inconsistent and biased estimates (Greene, 2005). To address these concerns, we use the heteroscedasticity-based instrumental variable (IV) approach proposed by Lewbel (2012). Assuming that the household decision of using the internet is modelled as:

$$I_{it} = \partial + \pi Z_{it} + \xi_{it}, \tag{2}$$

where ξ is the residuals and Z are exogenous household demographic variables (age, gender, share of children, share of elder, household size) and village characteristics (geographical characteristics). With two main assumptions that (1) $Cov\left(Z'_{it}, \in_{it}\xi_{it}\right) = 0$ and (2) $\left(Cov\left(Z'_{it}, \xi^2_{it}\right) \neq 0\right)$, we can use $[Z'_{it} - E\left(Z'_{it}\right)]\xi\hat{}_{it}$ as instruments (IVs). In other words, when these two assumptions hold, the constructed instruments (IVs) are valid as with the first assumption $(Cov\left(Z'_{it}, \in_{it}\xi_{it}\right) = 0)$, IVs are uncorrelated with $\in_{it}$ in Equation (1); and with the second assumption $\left(Cov\left(Z'_{it}, \xi^2_{it}\right) \neq 0\right)$, IVs are correlated with I_{it} through ξ_{it}. We followed Baum and Lewbel (2019) to test these assumptions using the Pagan and Hall test and the Breusch–Pagan test, and results show that these two assumptions are satisfied (see Appendix SA3). Several post-estimation tests for underidentification, overidentification and weak identification following Staiger and Stock (1997) were undertaken and their results confirm the validity of our models (see Table 3). In addition, we also checked the VIF values for potential multicollinearity and the VIF values do not signal this problem (see Appendices SA4 and SA5). Furthermore, as robustness checks, we also used the propensity score matching method to examine the impact of internet use on agricultural productivity (see Appendix SA6).

Table 3 shows the estimations for the impact of internet use on agricultural productivity: Column 1 for production efficiency, Columns 2 and 3 for land productivity (crop revenue per ha, crop income per ha), Columns 4 and 5 for labour productivity (crop revenue per hour, crop income per hour), and Columns 6 and 7 for agricultural expenses (cost per ha and labour per ha). Model diagnostic tests are all satisfied and reported in the bottom rows of the table (an LM test based on Kleibergen and Paap (2006) for underidentification, the Hansen J test for overidentification, and the Cragg–Donald Wald F statistics for weak identification).

Findings show that internet use is significantly and positively correlated with production efficiency, land productivity, and labour productivity. This implies that internet use significantly increases the productivity of farmers. More specifically, using the internet increases crop revenue per ha by 14%, crop revenue per hour by nearly 20%, and efficiency score by 0.018 points. The significant impact of internet use makes sense since internet use could provide farmers with knowledge and information about production, technology, input and output prices, which would enable them to improve the efficiency of their production. Our results are also consistent with Kaila and Tarp (2019) showing a positive impact of internet use on total agricultural output value in rural Vietnam. Zheng et al. (2021) also note the positive effects of internet use on the production efficiency of banana farmers in China, arguing that lack of information is one of the main reasons why farmers cannot access productivity-enhancing inputs and cannot efficiently use available agricultural inputs.

With respect to control variables, we find that ethnic minority households have a lower level of agricultural productivity. In Vietnam ethnic minority households are generally poorer, less educated and live in remote areas with disadvantaged infrastructure conditions and far from markets. Their agricultural production activities also rely heavily on simple technologies and equipment. This is consistent with Nguyen et al. (2021) who find that the production efficiency of ethnic minority farmers is lower than that of ethnic majority households. Our results also show that male-headed households with a higher level of education appear to have higher land productivity. These results are consistent with Zheng et al. (2021) who find that male-headed households are more efficient in agricultural production than female-headed counterparts as they have a greater advantage in accessing inputs and information. The positive relationship between education level and agricultural productivity is because households with a higher education level have more knowledge and are better in managing and filtering information related to markets, production system, and technologies (Ebers et al., 2017; Nguyen et al., 2018). The number of owned tractors, an indicator of farm mechanisation, is shown to significantly and positively affecting both crop income per hour and crop income per ha. This is reasonable as farm mechanisation could significantly improve agricultural production by reducing the burden of labour shortages, reducing expenses for harvesting operations, land preparation, and harvesting losses. This result is consistent with Ebers et al. (2017), Nguyen et al. (2021), and Huan et al. (2022) showing positive effects of farm mechanisation on farm efficiency. Irrigated land area is positively correlated with labour productivity but weather shocks are negatively correlated with all productivity indicators. Mishra et al. (2015) also find that extreme weather events are major drivers of inefficiency in agricultural production. Weather shocks would

TABLE 3 Impact of internet use on agricultural productivity and cost.

	Heteroscedasticity-based instruments				
	(1) Production efficiency b/se	(2) Crop revenue per ha (ln) b/se	(3) Crop income per ha (ln) b/se	(4) Crop revenue per hour (ln) b/se	(5) Crop income per hour (ln) b/se
Internet use	0.018**	0.140**	0.220**	0.196*	0.193*
	(0.008)	(0.069)	(0.110)	(0.110)	(0.103)
Age head	0.000	0.002*	0.003	0.001	0.001
	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)
Ethnic minority	−0.012**	−0.172***	−0.033	−0.739***	−0.537***
	(0.006)	(0.057)	(0.093)	(0.076)	(0.071)
Male head	0.013***	0.085**	0.155***	0.135***	0.150***
	(0.004)	(0.036)	(0.053)	(0.042)	(0.038)
Year of education	−0.000	0.013**	0.017*	−0.006	−0.001
	(0.001)	(0.006)	(0.009)	(0.008)	(0.007)
Tractor	0.000	0.021	0.066*	0.041	0.072**
	(0.003)	(0.025)	(0.039)	(0.040)	(0.036)
Irrigated land area	−0.001	0.011	0.008	0.220***	0.168***
	(0.003)	(0.030)	(0.042)	(0.041)	(0.034)
Plot size	−0.005	−0.077	0.027	−0.069	0.021
	(0.007)	(0.066)	(0.078)	(0.115)	(0.106)
Distance to plots	−0.003	−0.039**	−0.064**	−0.023	−0.037**
	(0.002)	(0.017)	(0.026)	(0.019)	(0.018)
Weather shock	−0.012***	−0.065***	−0.149***	−0.063**	−0.109***
	(0.004)	(0.024)	(0.043)	(0.032)	(0.029)
Health shock	−0.008**	0.008	−0.041	−0.063	−0.081**
	(0.004)	(0.026)	(0.046)	(0.038)	(0.034)
Mountain	−0.009***	−0.059	0.008	−0.284***	−0.218***
	(0.003)	(0.037)	(0.065)	(0.047)	(0.042)
River	−0.001	−0.053	−0.074	0.120**	0.093**
	(0.003)	(0.035)	(0.054)	(0.055)	(0.045)
Other variables	Yes	Yes	Yes	Yes	Yes
No. of observations	2103	2103	2103	2103	2103
R^2	0.048	0.135	0.059	0.319	0.233
Underidentification	0.000	0.000	0.000	0.000	0.000
Overidentification	0.808	0.536	0.869	0.045	0.061
Weak identification	41.386	41.386	41.386	41.386	41.386
p Value	0.000	0.000	0.000	0.000	0.000

Note: Robust standard errors clustered at the village level in parentheses. The underidentification test is an LM test based on Kleibergen and Paap (2006) rk LM statistics with the null hypothesis that the model is underidentified. The overidentification test is based on the Hansen J test with the null hypothesis that all instruments are valid. For weak identification, Cragg–Donald Wald F statistics are reported. Full results are shown in Appendix SA7.

***p < 0.01; **p < 0.05; *p < 0.1.

TABLE 4 Heterogeneous impact of internet use on agricultural productivity.

	Heteroscedasticity-based instruments				
	(1) Production efficiency b/se	(2) Crop revenue per ha (ln) b/se	(3) Crop income per ha (ln) b/se	(4) Crop revenue per hour (ln) b/se	(5) Crop income per hour (ln) b/se
Heterogeneous impact by age of head					
Internet × age head	−0.000	−0.001	−0.001	−0.007**	−0.005**
	(0.000)	(0.002)	(0.003)	(0.003)	(0.002)
Heterogeneous impact by gender of head					
Internet × male	−0.013*	0.055	−0.050	−0.049	−0.110*
	(0.007)	(0.057)	(0.105)	(0.065)	(0.067)
Heterogeneous impact by ethnicity					
Internet × minority	−0.005	−0.023	−0.121	0.274**	0.150
	(0.012)	(0.090)	(0.137)	(0.117)	(0.108)
Heterogeneous impact by average year of schooling					
Internet × education	−0.000	−0.026	−0.005	−0.058*	−0.042
	(0.002)	(0.019)	(0.029)	(0.031)	(0.027)

Note: Full results are in Appendices SA8–SA11.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

severely affect agricultural performance, as these events not only directly result in crop losses, but also increase households' spending on crops. Health shocks significantly reduce crop income per hour and production efficiency. Farming practice in Vietnam is generally labour intensive, therefore loss of labour supply due to health shocks could have a serious impact on farm performance. For village traits, living in mountainous regions is associated with a lower level of production efficiency, crop revenue per hour, and crop income per hour. In contrast, households living near rivers appear to have higher labour productivity, probably due to better soil fertility and irrigation.

4 | THE HETEROGENEOUS AND DISTRIBUTIONAL IMPACTS OF INTERNET USE ON AGRICULTURAL PRODUCTIVITY

In the second step of our empirical analysis, we examined which households benefit more from internet use. The interactions of internet connection with the gender, education, ethnicity, and age of household head were added to the estimation of and the new results are summarised in Table 4.

Our results in Table 4 show negative associations between crop revenue per hour and crop income per hour and the interaction of internet use with the age of household heads. This implies that the positive impacts of internet use on labour productivity are stronger for younger households. This makes sense as young households are better at searching the internet for information and may be more open to adopting information technology. This finding is in line with Kaila and Tarp (2019) who find that younger household heads benefit more from using the internet. For the gender aspect, the interaction between internet use and gender is negatively correlated with production efficiency and crop income per hour. However, the coefficients are only significant at the 10% level. This implies that internet use might benefit more female-headed households. It is argued that female farmers often have less access to input and market information due to gender inequality (Zheng et al., 2021); therefore, it is reasonable that internet use brings more benefits to female-headed households. A positive association between crop revenue per hour and the interaction of ethnicity with internet use suggests that internet use by ethnic minority households has a more positive impact on labour productivity compared to Kinh households. This is reasonable as ethnic minority farmers generally have lower levels of education and also tend to live in remote areas and therefore suffer greater barriers to accessing up-to-date information on markets, climate, and technologies (Nguyen, Nguyen, Do et al., 2022). This result is consistent with the finding that crop value per hour is negatively correlated with the interaction of education and internet use, implying that households with lower levels of education may benefit more from internet use. Low-educated farmers may lack information and knowledge about markets, climate, environment, production system or technologies. This leads to their lower productivity. Using the internet thus increases their productivity.

To further examine the distributional effects of internet use on agricultural productivity, we employed both conventional quantile regression and unconditional quantile regression (see Borgen, 2016). The results of unconditional quantile estimation (Panel A, Table 5) and conventional quantile estimation (Panel B, Table 5) are fairly consistent, showing that the benefits of internet use are skewed in favour of farmers at the lower end of the distribution. Both estimation methods show significant and positive effects in the four percentile groups (10th, 25th, 50th, and 75th). In particular with regard to the crop revenue per ha, the highest effect is observed in the lowest percentile group (10th). Similarly, the impact of internet use on crop revenue per hour is positive and significant in the bottom three percentile groups (10th, 25th, and 50th). The impact of internet use on production efficiency is positive and significant in the two lowest quantile groups (10th, 25th) (see Panel A) and in the second lowest group (25th) (see Panel B). This significant impact of internet use on the group of farmers at the bottom of the distribution could be explained by the fact that these households often face greater barriers to access markets and information. Thus, they have lower agricultural productivity. Using the internet could help them overcome these barriers and significantly boost their productivity. These results are consistent with Table 4 which shows that internet use benefits more disadvantaged farmers such as ethnic minorities, female-headed farmers, and those with low levels of education. Kaila and Tarp (2019) also find that farmers living in less developed regions have benefited the most from the arrival of the internet. They argue that marginal productivity is lower in areas where agricultural productivity is initially higher. This results is consistent with Zheng et al. (2021) who show that the impact of internet use on agricultural production efficiency is greatest for households in the lower bottom part of the distribution.

The findings reported above on the effects of internet use suggest that it is important to promote internet use in rural areas of Vietnam. Obviously, smallholder farmers use the internet only when it is available. Thus, the government of Vietnam should support investments in information and communication technology (ICT) infrastructure. Figures in Table 2 show that the majority of farmers use smart phones or tables to connect to the internet. It is therefore also needed to support them to be able to purchase these devices and to pay for internet subscription fees. In the short-run, improving access to credit would be useful. In the medium- and long-run, previous studies (Briggeman & Whitacre, 2010; Galperin & Fernanda Viecens, 2017) find

TABLE 5 Distributional impact of internet use on agricultural productivity.

	10th (1)	25th (2)	50th (3)	75th (4)	90th (5)
Panel A: Unconditional quantile regression					
Impact on production efficiency					
	0.015*	0.014***	−0.000	0.001	−0.000
	(0.009)	(0.005)	(0.003)	(0.002)	(0.002)
Impact on crop value per ha					
	0.095*	0.047*	0.066***	0.048*	0.025
	(0.049)	(0.027)	(0.023)	(0.025)	(0.047)
Impact on crop income per ha					
	0.149	0.059	0.049	0.042	0.032
	(0.095)	(0.054)	(0.039)	(0.040)	(0.064)
Impact on crop value per hour					
	0.196***	0.120***	0.076*	0.048	−0.008
	(0.048)	(0.041)	(0.043)	(0.049)	(0.071)
Impact on crop income per hour					
	0.173***	0.179**	0.218**	0.373*	−0.220
	(0.064)	(0.074)	(0.107)	(0.209)	(0.532)
Panel B: Conventional Quantile Regression					
Impact on production efficiency					
	0.015	0.014***	0.002	−0.000	0.001
	(0.009)	(0.004)	(0.003)	(0.002)	(0.003)
Impact on crop value per ha					
	0.086*	0.061**	0.056***	0.056**	0.082
	(0.046)	(0.029)	(0.021)	(0.028)	(0.059)
Impact on crop income per ha					
	0.215**	0.076	0.017	0.033	0.075
	(0.101)	(0.056)	(0.040)	(0.040)	(0.077)
Impact on crop value per hour					
	0.129***	0.104**	0.081*	0.041	0.069
	(0.041)	(0.050)	(0.042)	(0.047)	(0.069)
Impact on crop income per hour					
	0.167***	0.191**	0.138	0.057	−0.155
	(0.054)	(0.086)	(0.137)	(0.258)	(0.718)

Note: Full results are in Appendices S12–S21.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

that promoting education and off-farm employment in rural areas would enhance internet use of rural population. Evidence from Vietnam's neighbouring countries such as China (Ma et al., 2023) and Thailand (Nguyen, Nguyen, & Grote, 2022) also support these measures.

5 | CONCLUSION

The internet is spreading rapidly and recognised as a key factor in promoting economic development, alleviating poverty, educating people, and achieving sustainable development goals. However, little is known about the impact of internet use on agricultural productivity in developing countries. Therefore, this study aims to investigate the effects of internet use on agricultural productivity by using a dataset of more than 2000 households collected in 2016 and 2017 in three rural provinces of Vietnam. Methodologically, we employ heteroscedasticity-based instrumental models to examine the effects of internet use on various agricultural productivity indicators, and then apply quantile regression models to examine the heterogeneity and distribution of the effects.

Our results show that internet use has positive effects on agricultural productivity. However, these impacts are heterogeneous across different groups of rural households. Internet use has been shown to benefit more disadvantaged groups (female-headed and ethnic minority households). The positive impact of internet use is also more pronounced in households with a lower level of education. Meanwhile, younger households appear to be using the internet more. Results from quantile regression also show heterogeneous effects of internet use on the productivity distribution, with benefits of using internet being skewed towards a group of farmers at the bottom of the productivity distribution.

The positive association between internet use and agricultural productivity and the relatively higher benefits from using the internet for disadvantaged groups demonstrate that facilitating internet use in rural areas leads to more efficient and inclusive rural development. Therefore, internet use in rural areas should be enhanced. This could be done by promoting investments in ICT infrastructure, by enhancing the access to credit sources for farmers so that they are able to pay for devices needed to connect to the internet and internet fees. In addition, promoting education and off-farm employment opportunities in rural areas would also be useful.

Regarding other control factors, it is shown that the educational level of households and tractors is positively associated with agricultural productivity. In addition, agricultural productivity could be significantly increased with more irrigated areas. Weather shocks and health shocks are now recognised as the main causes of inefficiency in agricultural production. Our results also show that ethnic minority and female-headed households are generally much less productive than Kinh and male-headed households, respectively. Thus, facilitating farm mechanisation, promoting education, and improving irrigation systems are also recommended. In addition, supporting farmers to cope with climate disasters is needed. The support should be prioritised for female and ethnic minority farmers.

Even though our study provides insight on the linkages between internet use and agricultural productivity, it has some limitations. First, our data are from only three provinces and 2 years. Collecting more data from more provinces and years would allow for generalization of research findings. Second, our data do not include information on prices of each input and output of farm production. This does not allow us to evaluate profit efficiency of agricultural production. Third, we are not able to establish valid external instruments and this prevents us from using other methods such as the stochastic metafrontier corrected selection bias model or the stochastic frontier approach with matching methods. Future studies should account for these limitations.

ACKNOWLEDGEMENTS

The authors thank the farmers in our study sites in Vietnam for their support and cooperation. The authors appreciate the financial support from the German Research Foundation (DFG) through the long-term Thailand-Vietnam Socioeconomic Panel Project (DFG - FOR 756/2) (www.tvsep.de). The constructive comments from from Editor Wanglin Ma and three reviewers, and from the discussant and participants at the virtual Asian Development Bank Institute (ABDI) Conference '*Rural and Agricultural Development in the Digital Age*' in 8–12 August 2022 are acknowledged. Open Access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data for this study are provided for free from the long-term Thailand-Vietnam Socioeconomic Panel Project (www.tvsep.de) or upon request from the corresponding author.

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REFERENCES

Aker, J. C., & Ksoll, C. (2016). Can mobile phones improve agricultural outcomes? Evidence from a randomized experiment in Niger. *Food Policy*, *60*, 44–51.

Alheneidi, H. (2019). *The influence of information overload and problematic Internet use on adults' wellbeing* [Doctoral dissertation]. Cardiff University.

Amare, M., Jensen, N. D., Shiferaw, B., & Cissé, J. D. (2018). Rainfall shocks and agricultural productivity: Implication for rural household consumption. *Agricultural Systems*, *166*, 79–89.

Amare, M., Pryanka, P., & Nguyen, T. T. (2023). Micro insights on the pathways to agricultural transformation: Comparative evidence from Southeast Asia and sub-Saharan Africa. *Canadian Journal of Agricultural Economics*. https://doi.org/10.1111/cjag.12326

Anderson, J., & Rainie, L. (2017). The future of truth and misinformation online. Pew Research Center. https://www.pewresearch.org/internet/2017/10/19/the-future-of-truth-and-misinformation-online/

Aragón, F. M., Restuccia, D., & Rud, J. P. (2022). Are small farms really more productive than large farms? *Food Policy*, *106*, 102168.

Barbier, E. B. (2023). Overcoming digital poverty traps in rural Asia. *Review of Development Economics*, *27*(3), 1403–1420. https://doi.org/10.1111/rode.12962

Baum, C. F., & Lewbel, A. (2019). Advice on using heteroskedasticity-based identification. *The Stata Journal*, *19*(4), 757–767.

Borgen, N. T. (2016). Fixed effects in unconditional quantile regression. *The Stata Journal*, *16*(2), 403–415.

Briggeman, B. C., & Whitacre, B. E. (2010). Farming and the internet: Reasons for non-use. *Agricultural and Resource Economics Review*, *39*(3), 571–584.

Cash, H., Rae, D. C., Steel, H. A., & Winkler, A. (2012). Internet addiction: A brief summary of research and practice. *Current Psychiatry Reviews*, *8*(4), 292–298.

Chen, H., Chen, C., Li, Y., Qin, L., & Qin, M. (2022). How internet usage contributes to livelihood resilience of migrant peasant workers? Evidence from China. *Journal of Rural Studies*, *96*, 112–120.

Djido, A. I., & Shiferaw, B. A. (2018). Patterns of labor productivity and income diversification–empirical evidence from Uganda and Nigeria. *World Development*, *105*, 416–427.

Dubbert, C. (2019). Participation in contract farming and farm performance: Insights from cashew farmers in Ghana. *Agricultural Economics*, *50*(6), 749–763.

Duwayri, M., Tran, D. V., & Nguyen, V. N. (2000). *Reflections on yield gaps in rice production*. RAP Publication (FAO) http://www.fao.org/3/a-x6905e.pdf

Dzanku, F. M., Osei, R., & Osei-Akoto, I. (2021). The impact of mobile phone voice message reminders on agricultural outcomes in Mali. *Agricultural Economics*, *52*(5), 789–806.

Ebers, A., Nguyen, T. T., & Grote, U. (2017). Production efficiency of rice farms in Thailand and Cambodia: A comparative analysis of Ubon Ratchathani and Stung Treng provinces. *Paddy and Water Environment*, *15*(1), 79–92.

Fafchamps, M., & Minten, B. (2012). Impact of SMS-based agricultural information on Indian farmers. *The World Bank Economic Review*, *26*(3), 383–414.

FAO. (2014). *A regional rice strategy for sustainable food security in Asia and the Pacific*. FAO.

FAO. (2018). Tackling poverty and hunger through digital innovation. https://www.fao.org/3/ca1040en/CA1040EN.pdf

Galperin, H., & Fernanda Viecens, M. (2017). Connected for development? Theory and evidence about the impact of internet technologies on poverty alleviation. *Development Policy Review*, *35*, 315–336.

Gautam, M., & Ahmed, M. (2018). Too small to be beautiful? The farm size and productivity relationship in Bangladesh. *Food Policy*, *84*, 165–175.

Ghimire, S., & Kapri, K. P. (2020). Does the source of remittance matter? Differentiated effects of earned and unearned remittances on agricultural productivity. *Economies*, *8*(1), 8.

Goyal, A. (2010). Information, direct access to farmers, and rural market performance in Central India. *American Economic Journal: Applied Economics*, *2*(3), 22–45.

Greene, W. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics*, *126*, 269–303.

Grote, U., Fasse, A., Nguyen, T. T., & Erenstein, O. (2021). Food security and the dynamics of wheat and maize value chains in Africa and Asia. *Frontiers in Sustainable Food System*, *4*, 617009. https://doi.org/10.3389/fsufs.2020.617009

Gupta, H. (2017). Pattern of online technology and its impact on productivity at workplace. *European Psychiatry*, *41*(S1), S460.

Hartwig, T., & Nguyen, T. T. (2023). Local infrastructure, rural households' resilience capacity and poverty: Evidence from panel data for Southeast Asia. *Journal of Economics and Development*, *25*(1), 2–21. https://doi.org/10.1108/JED-10-2022-0199

Hills, T. T. (2019). The dark side of information proliferation. *Perspectives on Psychological Science*, *14*(3), 323–330.

Huan, M., Dong, F., & Chi, L. (2022). Mechanization services, factor allocation, and farm efficiency: Evidence from China. *Review of Development Economics*, *26*(3), 1618–1639.

Kaila, H., & Tarp, F. (2019). Can the internet improve agricultural production? Evidence from Viet Nam. *Agricultural Economics*, *50*(6), 675–691.

Kleibergen, F., & Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics*, *133*, 97–126.

Le, Q. H., Quach, M. H., & Tran, H. L. (2022). Credit composition and income inequality in Vietnam: An empirical analysis. *Journal of Economics and Development*, *24*(4), 365–377. https://doi.org/10.1108/JED-08-2020-0110

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business and Economic Statistics*, *30*, 67–80.

Li, X., & Huo, X. (2022). Agricultural labor markets and the inverse plot size–productivity relationship: Evidence from China's apple growers. *Review of Development Economics*, *26*(4), 2163–2183.

Ma, W., Qiu, H., & Rahut, D. B. (2023). Rural development in the digital age: Does information and communication technology adoption contribute to credit access and income growth in rural China? *Review of Development Economics*, *27*(3), 1421–1444. https://doi.org/10.1111/rode.12943

Ma, W., & Wang, X. (2020). Internet use, sustainable agricultural practices and rural incomes: Evidence from China. *Australian Journal of Agricultural and Resource Economics*, *64*(4), 1087–1112.

Ma, X. (2023). Internet usage and the income gap between self-employed individuals and employees: Evidence from China. *Review of Development Economics*, *27*(3), 1509–1536. https://doi.org/10.1111/rode.12969

Mesch, G. S., & Talmud, I. (2011). Ethnic differences in internet access: The role of occupation and exposure. *Information, Communication and Society*, *14*(4), 445–471.

Mishra, A. K., Mottaleb, K. A., Khanal, A. R., & Mohanty, S. (2015). Abiotic stress and its impact on production efficiency: The case of rice farming in Bangladesh. *Agriculture, Ecosystems Environment*, *199*, 146–153.

Misra, S., Roberts, P., & Rhodes, M. (2020). Information overload, stress, and emergency managerial thinking. *International Journal of Disaster Risk Reduction*, *51*, 101762.

Močnik, D., & Širec, K. (2010). The determinants of internet use controlling for income level: Cross-country empirical evidence. *Information Economics and Policy*, *22*(3), 243–256.

Mora-Rivera, J., & García-Mora, F. (2021). Internet access and poverty reduction: Evidence from rural and urban Mexico. *Telecommunications Policy*, *45*(2), 102076.

Muyanga, M., & Jayne, T. S. (2019). Revisiting the farm size-productivity relationship based on a relatively wide range of farm sizes: Evidence from Kenya. *American Journal of Agricultural Economics*, *101*(4), 1140–1163.

Nguyen, T. T., & Do, M. H. (2022). Female rural-urban migrants and online marketplaces in emerging economies: Comparative evidence from Thailand and Vietnam. *Asia and the Pacific Policy Studies*, *9*(3), 317–342.

Nguyen, T. T., Do, T. L., Parvathi, P., Wossink, A., & Grote, U. (2018). Farm production efficiency and natural forest extraction: Evidence from Cambodia. *Land Use Policy*, *71*, 480–493.

Nguyen, T. T., Nguyen, T., & Grote, U. (2022). Internet use, natural resource extraction and poverty reduction in rural Thailand. *Ecological Economics*, *196*, 107417.

Nguyen, T. T., Nguyen, T. T., Do, M. H., Nguyen, D. L., & Grote, U. (2022). Shocks, agricultural productivity, and natural resource extraction in rural Southeast Asia. *World Development*, *159*, 106043.

Nguyen, T. T., Tran, V. T., Nguyen, T. T., & Grote, U. (2021). Farming efficiency, cropland rental market and income effect: Evidence from panel data for rural Central Vietnam. *European Review of Agricultural Economics*, *48*(1), 207–248.

Penard, T., Poussing, N., Mukoko, B., & Piaptie, G. T. (2015). Internet adoption and usage patterns in Africa: Evidence from Cameroon. *Technology in Society*, *42*, 71–80.

Pennycook, G., & Rand, D. G. (2021). The psychology of fake news. *Trends in Cognitive Sciences*, *25*, 388–402.

Phan, Q. A. (2019). The introduction of Internet to Vietnam as the technological foundation for online gaming: An analysis. *Asia-Pacific Social Science Review*, *19*(3), 1–15.

Quandt, A., Salerno, J. D., Neff, J. C., Baird, T. D., Herrick, J. E., McCabe, J. T., Xu, E., & Hartter, J. (2020). Mobile phone use is associated with higher smallholder agricultural productivity in Tanzania, East Africa. *PloS One*, *15*(8), e0237337.

Sarbu, M. (2017). Does social media increase labour productivity? *Jahrbücher für Nationalökonomie Und Statistik*, *237*(2), 81–113.

Sharma, R., & Grote, U. (2019). *MRS No. 58. Determinants of internet use among migrants in South-East Asia: A case study of internal migrants in Thailand and Viet Nam*. International Organisation for Migration (IOM).

Shrivastava, A., Sharma, M. K., & Marimuthu, P. (2016). Internet use at workplaces and its effects on working style in Indian context: An exploration. *Indian Journal of Occupational and Environmental Medicine*, *20*(2), 88–94.

Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, *65*, 557–586.

United Nations. (2010). Internet can help reach anti-poverty goals, UN official tells governance forum. https://news.un.org/en/story/2010/09/350702-internet-can-help-reach-anti-poverty-goals-un-official-tells-governance-forum

United Nations. (2018). Achieving universal and affordable internet in the least developed countries. https://www.un.org/ohrlls/sites/www.un.org.ohrlls/files/ict-ldcs-and-sdgs.pdf

Vatsa, P., Li, J., Luu, P. Q., & Botero-R, J. C. (2023). Internet use and consumption diversity: Evidence from rural China. *Review of Development Economics*, *27*(3), 1287–1308. https://doi.org/10.1111/rode.12935

WBGU. (2019). *Towards our common digital future. Flagship report*. WBGU.

World Bank. (2021a). Connecting for broadband: Access for all. https://www.worldbank.org/en/topic/digitaldevelopment/brief/connecting-for-inclusion-broadband-access-for-all

World Bank. (2021b). GDP per capita, PPP (constant 2017 international $) – Vietnam. https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD?locations=VN

World Bank. (2022). Individuals using the internet (% of population). https://data.worldbank.org/indicator/IT.NET.USER.ZS

Yang, J., Wang, H., Jin, S., Chen, K., Riedinger, J., & Peng, C. (2016). Migration, local off-farm employment, and agricultural production efficiency: Evidence from China. *Journal of Productivity Analysis*, *45*(3), 247–259.

Yang, L., Lu, H., Wang, S., & Li, M. (2021). Mobile internet use and multidimensional poverty: Evidence from a household survey in rural China. *Social Indicators Research*, *158*, 1065–1086. https://doi.org/10.1007/s11205-021-02736-1

Zhang, J., Mishra, A. K., & Zhu, P. (2021). Land rental markets and labor productivity: Evidence from rural China. *Canadian Journal of Agricultural Economics*, *69*(1), 93–115.

Zheng, H., & Ma, W. (2023). Economic benefits of internet use for smallholder wheat farmers. *Applied Economics*. https://doi.org/10.1080/00036846.2023.2167928

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.

SUPPORTING INFORMATION

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

How to cite this article: Nguyen, T.-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