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Heterogeneous impacts of information technology adoption on pesticide and fertiliser expenditures: Evidence from wheat farmers in China*

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This study examines the impacts of mobile information technology adoption on agrochemical expenditures, using data collected from 551 wheat farmers in China. Unlike previous studies that analyse a homogeneous relationship between the adoption of information technologies and farm input use, in this study, an instrumental variable quantile regression approach is utilised to capture the heterogeneous impacts of smartphone use on pesticide and fertiliser expenditures. Findings reveal that smartphone use affects pesticide and fertiliser expenditures heterogeneously, and its impacts on pesticide expenditure are larger than those on fertiliser expenditure. Specifically, at the lowest 20th quantile, smartphone use significantly increases pesticide expenditure by 33 per cent and fertiliser expenditure by 18 per cent. However, at the higher 60th and 80th quantiles, smartphone use significantly decreases pesticide expenditure by 36–39 per cent and fertiliser expenditure by 14–19 per cent. Our findings suggest that guiding farmers' agrochemical usage behaviours through smartphone-based information intervention can be a practical strategy to help reduce the excessive usage of chemical pesticides and fertilisers and preserve the environment and human health.

Key words: chemical fertilisers, chemical pesticides, IVQR model, smartphone use, wheat production.

JEL classifications: C21, Q18, L86

1. Introduction

Increased application of agrochemical inputs, such as pesticides and fertilisers, has significantly improved crop yields and food security in the past few decades. However, this has also caused a large number of adverse human health and environmental effects. For example, the excessive usage of chemical pesticides has been associated with many human diseases (e.g. respiratory disorders, cancer, reproductive disorders, neurological

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dysfunction and diabetes; Nicolopoulou-Stamati et al., 2016; Sabarwal et al., 2018; Zhao et al., 2021), a reduction in biodiversity (Beketov et al., 2013; Brühl & Zaller, 2019), and water and soil contamination (Rani et al., 2021; Thais et al., 2020). The overuse of chemical fertilisers has resulted in soil deterioration (Atafar et al., 2010; Gai et al., 2018; Yuan et al., 2021) and greenhouse gas emissions (Wu et al., 2021; Zhang et al., 2016).

Reducing pesticide and fertiliser usage is one of the critical drivers to preserve the environment and human health. It is also an essential action that helps achieve the Sustainable Development Goals of the United Nations. Different strategies, including policy instruments and new production technologies, have been implemented to achieve this agrochemical reduction goal. For example, in 2015, the Chinese government launched 'Action Plans to Achieve Zero Growth of Chemical Pesticides and Fertilisers' by 2020 (hereafter 'Action Plans'; Jin & Zhou, 2018). In northern Thailand, policymakers suggest combining integrated pest management, a progressive pesticide tax based on toxicity, with subsidies that lower the price of biopesticides as a composite strategy against hazardous pesticide use (Grovermann et al., 2017). This strategy could reduce the average use of hazardous pesticides by 34 per cent without decreasing the average farm income. Several agronomists have suggested that the substitution of chemical fertilisers with organic soil amendments (e.g. organic fertilisers and farm manure) can help mitigate the adverse effects of chemical fertiliser use (Gai et al., 2018; Luan et al., 2020; Tang et al., 2019; Wang et al., 2018; Xin et al., 2017; Ye et al., 2020).

This study explores whether or not information technology adoption can help reduce chemical pesticide and fertiliser use.[1] Prior evidence shows that access to sufficient information positively affects agricultural production and the sustainability of farming sectors (e.g. Hoang, 2020; Issahaku et al., 2018; Kaila & Tarp, 2019; Lio & Liu, 2006; Ma & Wang, 2020; Zheng & Ma, 2021; Zheng et al., 2021; Zhu et al., 2021). However, the situations of information asymmetry still prevail in many developing and transition countries. Information asymmetry constrains smallholder farmers' access to markets and limits their input use decisions and farm productivity (Hennessy & Wolf, 2018; Mitra et al., 2018; Ullah et al., 2020). For example, farmers may fail to make appropriate decisions for 'what and how much they should buy' when selecting and purchasing chemical pesticides and fertilisers due to information asymmetry in the imperfect competitive markets. Therefore, an in-depth analysis of the nexus between information technology adoption and agrochemical use would provide useful implications for designing appropriate

[1] Information technologies are effective tools used for information exchange, including smartphones, traditional mobile phones, computers, tablets and radios. In some studies, people have used more generalized terms, such as information and communication technology (ICT) adoption and Internet use, to measure information technology adoption (e.g. Al-Hassan et al., 2013; Ogutu et al., 2014; Yuan et al., 2020; Zhao et al., 2020).

agricultural policies for countries such as China, aiming to reduce the overuse of chemical pesticides and fertilisers.

The existing studies have provided some insights regarding the association between information technology intervention and the usage of pesticides and fertilisers. They capture information technology intervention using mobile phone use (Cole & Fernando, 2012; Freeman & Qin, 2020), ICT adoption (Al-Hassan et al., 2013; Ogutu et al., 2014) and Internet use (Yuan et al., 2021; Zhao et al., 2021). At least for now, the findings remain mixed. Some studies have found a positive relationship between information technology adoption and pesticide and fertiliser usage (e.g. Cole & Fernando, 2012; Issahaku et al., 2018; Kaila & Tarp, 2019; Ogutu et al., 2014). For example, Cole and Fernando (2012) showed that mobile phone use significantly increases pesticide and fertiliser use in India's cotton cultivation. By analysing farm household data collected from Kenya, Ogutu et al., (2014) found that using ICT-based market information services increases purchased fertiliser application. On the other hand, two studies have shown that information technology affects pesticide and fertiliser use differently. In particular, the analysis for Ghana by Al-Hassan et al., (2013) finds that ICT-based project participation significantly increases pesticide expenditure, but it has a negative and insignificant impact on fertiliser expenditure. The study for Uganda by Freeman and Qin (2020) shows that access to mobile phones has a positive but insignificant impact on fertiliser use, but it significantly increases pesticide use.

Still, we are aware that three studies have illustrated the pesticide and fertiliser reduction effects of information technology adoption (Hou et al., 2019; Yuan et al., 2021; Zhao et al., 2021). By analysing apple farmer data collected from China, Hou et al., (2019) revealed that Internet use via computers negatively affects the value of purchased pesticides. Yuan et al., (2021) examined the impact of Internet use on chemical fertiliser use based on a nationwide data set of 7,766 rural households. They found that Internet use reduces chemical fertiliser use as it increases farmers' human capital. By estimating survey data of 670 vegetable growers in China, Zhao et al., (2021) found that both the Internet use frequency and the number of Internet activities are associated with pesticide reduction among farmers.

The mixed findings of studies mentioned above can be partially attributed to the homogeneous (mean-based) analytical methods they used, which can only provide a partial narrow picture regarding the impacts of information technology adoption on pesticide and fertiliser use. Information technology adoption may affect farmers who use a lower amount of chemical pesticides and fertilisers and those who use a higher amount differently. This is entirely possible. Farmers are endowed with different personal characteristics (e.g. age, education and innate abilities) and resources (e.g. land fertility and income), so their decisions on pesticide and fertiliser use may be affected differently by modern information technology. From a policy perspective, policymakers may be interested in getting information about the influence of information technology adoption on pesticide and fertiliser use at different distributional points. However, the existing studies have failed to investigate whether information technology adoption affects pesticide and fertiliser use at the lower or upper end of their distributions heterogeneously.

This study contributes to the literature by analysing the heterogeneous impacts of modern information technology adoption on pesticide and fertiliser expenditures, focusing on smartphone use.[2] The role of smartphone use in influencing farm input use has been overlooked in the literature. Smartphone use may play a larger role than other information technologies such as radios or computers in supporting agricultural development in general and pesticide and fertiliser use in particular (Füsun Tatlidil et al., 2009; Hou et al., 2019; Min et al., 2020; Zanello, 2012; Zheng & Ma, 2021). For example, smartphone use allows farmers to acquire timely production information via mobile web browsing without spatial restrictions, and such a unique feature is not found in other information technologies. In practice, smartphones can provide farmers with information that enables them to identify reliable markets and purchase pesticides and fertilisers at lower costs. The farm management skills acquired from smartphone use can also help farmers improve the efficiency of pesticide and fertiliser use, reducing input use levels and costs. Because farmers self-select themselves to be smartphone users or non-users (self-selection), smartphone use variable is potentially endogenous in our case (Hübler & Hartje, 2016; Ma et al., 2020a; Min et al., 2020). Thus, as a further contribution, we utilise an instrumental variable quantile regression model to address the smartphone use variable's endogeneity issue. The findings of this study enrich the literature examining the effects of smartphone use on rural development (e.g. Hübler & Hartje, 2016; Ma et al., 2018b, 2020a; Michels et al., 2020; Min et al., 2020; Nie et al., 2020; Zheng & Ma, 2021).

We use data collected from wheat farmers in China. China is the largest wheat-producing country globally, and wheat production plays a crucial role in ensuring national food security. In 2019, China's total wheat production was 133.60 million tonnes, accounting for 17.45 per cent of the world's total wheat production (FAOSTAT). Pesticides and fertilisers are two key inputs in wheat production, and their costs account for the largest proportion (38 per cent) of the total wheat production costs in 2018 (DPNDRC, 2019). As illustrated in Section 2 below, expenditures on pesticides and fertilisers in wheat production do not show a stable decreasing trend after the Chinese government launched the 'Action Plans' in 2015. Besides, China provides an interesting case to explore smartphone use in rural areas. It is reported that the Internet adoption rate in China's rural area has increased from 32 per

[2] As noted in Hübler and Hartje (2016), a traditional mobile phone can only be used for 'voice' communication and message texting, while a smartphone is featured with a touchscreen and Internet access and it can provide diverse functions such as video communication, 'apps' installation and webpage browsing.

cent in 2015 to 38 per cent in 2018, and more than 95 per cent of Internet users access the Internet via smartphones (CNNIC, 2019). Thus, it is significant to understand whether adopting information technologies such as smartphones can help reduce chemical pesticides and fertilisers in wheat production.

The rest of this paper is outlined as follows: Section 2 presents the background regarding pesticide and fertiliser consumption in China. Section 3 introduces the estimation strategy. This is followed by a presentation of data and descriptive statistics in Section 4. Section 5 presents and discusses the empirical results, while the final section concludes with policy implications.

2. Pesticide and fertiliser consumption in China

China is the largest consumer of both pesticides and fertilisers for agricultural production around the world. In 2018, the amounts of pesticides and fertilisers consumed in China were 1.77 and 46.98 million tonnes, which account for 42.92 and 24.92 per cent of the world's total pesticide and fertiliser consumption, respectively (FAOSTAT). Although the excessive use of pesticides and fertilisers helps increase food production and ensure food security, this trend threatens environmental sustainability and human health (Huang & Jiang, 2019; Nie et al., 2018; Wang & Lu, 2020).

Recognising the adverse effects associated with the overuse of pesticides and fertilisers, the Chinese government had started the 'Action Plans' in 2015 to limit their applications (Jin & Zhou, 2018). Guided by this policy proposal, various programs have been implemented to help reduce agrochemical input use. For example, these include promoting biopesticides and organic fertilisers to substitute chemical pesticides and fertilisers, providing mechanisation services to improve the input use efficiency, and accelerating technical training of advanced agronomic practices (Tang et al., 2019; Wang et al., 2019). Benefiting from these policy supports, fertiliser use in China's agricultural production tended to decrease since 2015, while pesticide use shows a non-increasing trend (see Figure 1).

Although fertiliser use decreased and pesticide use maintained the same level in the whole agricultural sector of China since 2015, the amounts of pesticides and fertilisers used in the wheat industry show an increasing tendency. Figure 2 illustrates the pesticide and fertiliser expenditures in China's wheat production between 2010 and 2018. It shows that pesticide expenditure is growing monotonically, which has increased from 196 yuan/hectare in 2010 to 351 yuan/hectare in 2018 (DPNDRC, 2019). The fertiliser expenditure in wheat production increased from 2010 to 2013, then slightly decreased until 2017 and finally showed an upward tendency in 2017–2018. Notably, the average expenditure on fertilisers was 2,228 yuan/hectare among wheat farmers in 2018 (DPNDRC, 2019). The corresponding amount of fertiliser input is 411.15 kg/hectare, accounting for three times more than the average world level (120 kg/hectare) (FAOSTAT).

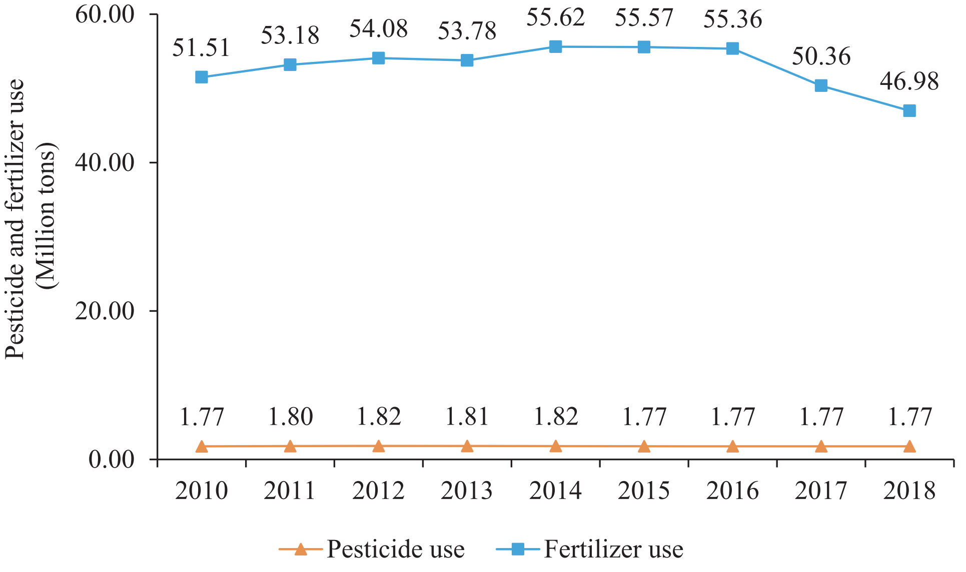

Figure 1 Pesticide and fertiliser use in agricultural production of China (2010–2018). Data source: FAOSTAT. [Colour figure can be viewed at wileyonlinelibrary.com]

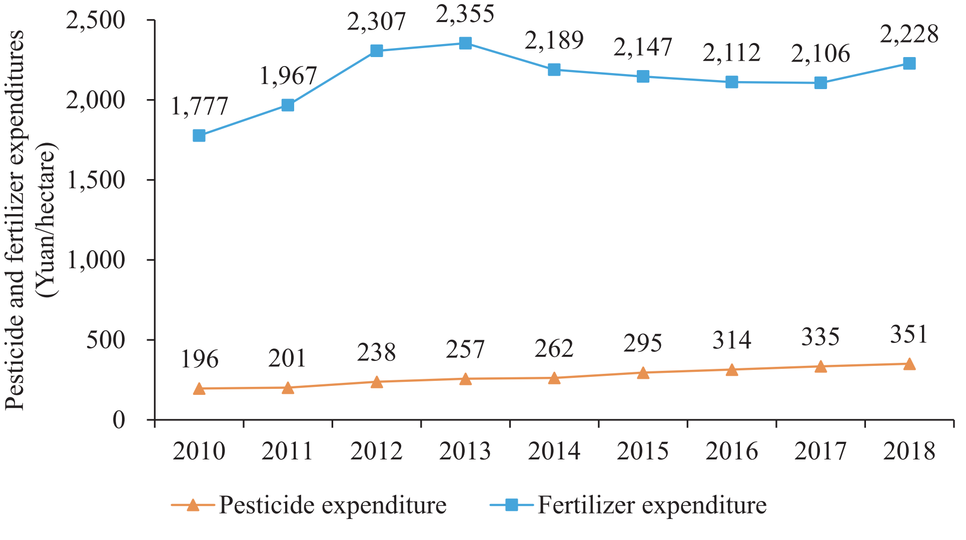

Figure 2 Pesticide and fertiliser expenditures in wheat production of China (2010–2018). Data source: DPNDRC. [Colour figure can be viewed at wileyonlinelibrary.com]

3. Estimation strategy

3.1 Model selection

This study employs an instrumental variable quantile regression (IVQR) model to estimate the heterogeneous impacts of smartphone use on pesticide and fertiliser expenditures. We select the IVQR model rather than other approaches, such as the conditional quantile regression (CQR) model (e.g. Killewald & Bearak, 2014; Lu & Kandilov, 2021; Mishra & Moss, 2013) and unconditional quantile regression (UQR) model (e.g. Khanal et al., 2018; Ma et al., 2020b; Zhou et al., 2020), for two major reasons. First, although both the CQR model and the UQR model have been applied to estimate the heterogeneous impacts of a treatment variable on outcome variables of interest, these two approaches assume that all covariates are exogenous, and they are not appropriate if the treatment variable is potentially endogenous. Second, in our case, the smartphone use variable is potentially endogenous as rural farmers self-select themselves to be smartphone users and non-users, depending on the individual, technological and socio-economic factors (Hübler & Hartje, 2016; Liu et al., 2021; Ma et al., 2020a; Min et al., 2020). Failing to address the endogeneity issue of the smartphone use variable would generate biased estimates. In general, the IVQR model has obvious advantages in estimating the heterogeneous distributional effects of the treatment variable on outcome variables and addressing the treatment variable's endogenous issue.

3.2 The IVQR model

The IVQR model estimates the τth quantile of the outcome variable (pesticide expenditure or fertiliser expenditure) as a linear function of the endogenous variable (S), a vector of an exogenous variable (X') and a nonseparable error term (μ) as follows:

$$\ln(Y_i) = q(S, X', \mu) = \alpha_\tau S + \beta_\tau X' + \mu. \tag{1}$$

Where $q(\cdot)$ is a conditional τ – quantile function, which is strictly increasing in τ; S is a binary variable indicating the smartphone use status of respondents (1 = smartphone users and 0=non-users); X' is a vector of the included exogenous variables (e.g. age, sex, education, household size and asset ownership); α_τ and β_τ are parameters to be estimated at the quantile τ; and μ is an error term, which is assumed to be distributed as uniform (0, 1).

To obtain the linear function for smartphone use, we follow the utility maximisation framework and assume that a farmer i compares the utility obtained from using the smartphone and that obtained from not using it. This assumption is consistent with the existing studies (Hübler & Hartje, 2016; Min et al., 2020; Nie et al., 2020). Let the utilities obtained from using the smartphone and not using be U^S and U^N, respectively, a risk-neutral farmer will choose to use the smartphone if the utility difference (S^*) is positive, that is $S^* = U^S - U^N > 0$. Although S^* is unobservable since it is subjective, it can be expressed as a latent variable function as follows:

$$S^* = \gamma_\tau X' + \delta_\tau Z + \varepsilon;\, S = \begin{cases} 1 & if S^* > 0 \\ 0 & if S^* \leq 0 \end{cases} \tag{2}$$

where S^* represents the probability that a farmer uses the smartphone, which is determined by the observed variable S ($S = 1$ for smartphone users and $S = 0$ for non-users). X' is defined earlier; Z is an excluded instrumental variable (IV); γ_τ and δ_τ are parameters to be estimated; and ε is an error term. In this study, a social network variable measuring farmers' neighbours' smartphone use status is employed as an excluded IV. The variable is given a value of 1 if a farmer's neighbour is a smartphone user and zero otherwise.

We have used two approaches to test the validity of the employed IV. First, following Di Falco and Chavas (2009), we run a falsification test. The results (Table S1) show that the IV has significant effects on smartphone use but has no significant effects on pesticide expenditure and fertiliser expenditure. Second, we conducted a Pearson correlation analysis. The results (Table S2) show that the IV is significantly correlated with smartphone use, but it is not correlated with the two outcome variables, even at the 10 per cent significance level. The findings in Tables S1 and S2 together confirm the validity and effectiveness of the IV.

Recall that the quantile regression model is identified by the moment conditions:

$$P[Y \leq \alpha_\tau S + \beta_\tau X' + \mu | X', Z] = \tau. \tag{3}$$

Under uncertain assumptions (Chernozhukov & Hansen, 2008; Mitra et al., 2015), this leads to the simplified objective function:

$$\min_{\alpha_\tau, \beta_\tau, \gamma_\tau, \delta_\tau} E(\rho_\tau[Y - \alpha_\tau S - \beta_\tau X' - \delta_\tau Z]). \tag{4}$$

The IVQR estimator is obtained as a solution to the minimisation program defined in Equation (4). Our implementation of the estimator follows the procedure developed by Kwak (2009).

4. Data and descriptive statistics

4.1 Data

The data used for the analysis were collected from a household survey in three major wheat-producing provinces in China. The survey was conducted between June and July 2019. The sample provinces, cities, towns, villages and rural households were selected using a stratified sampling technique. In the first stage, we purposely selected Shandong, Henan and Anhui provinces because these three provinces together cover 52.23 per cent of the total wheat-producing area in China in 2018 (CRSY, 2020). Shandong, Henan and Anhui provinces have sown areas of 4.06, 5.74, and 2.88 million hectares, respectively. These three provinces are endowed with favourable climates and natural resource endowments for high-quality wheat production. Improved wheat varieties, such as Yannong19, Jimai22 and Liangxing99, have been adopted by farmers. In the second stage, two cities in each selected province were selected. Specifically, we randomly selected Linyi and Zaozhuang in Shandong, Xinyang and Zhumadian in Henan, and Suzhou and Huaibei in Anhui. In the third stage, we randomly selected two to three towns in each city and then two to three villages in each town. Finally, around 10–30 households in each village were interviewed face-to-face by well-trained enumerators. The sampling procedure results in a total sample of 551 households, comprising 247 smartphone users and 304 non-users.

We used a structured questionnaire to collect information on the individual-, household- and farm-level characteristics (e.g. age, sex, education, household size and asset ownership), pesticide and fertiliser expenditures in the wheat production, and smartphone use status of farmers and their neighbours. The final survey questionnaire was modified based on the feedback we gathered during our preliminary survey test. This ensures the reliability and validity of the questionnaire.

In our survey questionnaire, we have designed a series of open questions to collect the information searched by the wheat farmers. We found that sample farmers have used the web browser (e.g. Baidu) and smartphone-based agriculture-related ‘Apps’ (e.g. Nongxintong) to search the pesticide- and fertiliser-related information. They also use video and voice functions of WeChat (a Chinese multipurpose messaging, social media and mobile payment ‘App’ developed by Tencent) to communicate pesticide and fertiliser information with their peers, input dealers and extension agents. The information they usually acquire includes ‘the stores of input dealers’, ‘the prices and functions of different pesticides and fertilisers’, and ‘the methods on how to use pesticides and fertilisers appropriately and efficiently’.

The treatment variable used in this study refers to smartphone use, which takes a value of 1 if a household head used a smartphone in 2018, and zero otherwise. The two outcome variables include chemical pesticide expenditure and chemical fertiliser expenditure, which are measured at yuan/hectare. Expenditures rather than quantities are used in this study because farmers have used significant diverse units to measure pesticides and fertilisers. Our monetary measurement of pesticides and fertilisers is consistent with earlier studies (Jaraite & Kažukauskas, 2012; Ma et al., 2018a). It is worth noting that all wheat farmers have used different levels of chemical pesticides and fertilisers in wheat production. In contrast, only 0.91 per cent of farmers have used low-toxicity biopesticides, and 15.06 per cent of them have adopted organic soil amendments (e.g. organic fertilisers and farmyard manure) in wheat production.

4.2 Descriptive statistics

The definitions and descriptive statistics of the selected variables are presented in Table 1. It shows that the average pesticide expenditure and fertiliser expenditures are 710 yuan/hectare and 2,736 yuan/hectare, respectively. These values are both higher than the national-level pesticide expenditure (351 yuan/hectare) and fertiliser expenditure (2,228 yuan/hectare) in wheat production (DPNDRC, 2019). Among sample farmers, 45 per cent of them used smartphones in 2018. This is a considerable adoption rate of smartphones as the Internet penetration rate in China's rural area reached 38 per cent in 2018 (CNNIC, 2019). The average age of household heads is 56.45 years, and 60 per cent of them are male. Farmers in our sample receive 4.77 years of education on average. Sample households have around 4–5 members on average. Only 18 per cent of the sampled households have access to extension services in 2018.

Table 2 presents the mean differences of the selected variables between smartphone users and non-users. The results show no statistical differences in

Table 1 Variable definitions and summary statistics

Variables	Definition	Mean (*SD*)
Dependent variables		
Pesticide expenditure	Total chemical pesticide expenditure (100 yuan/hectare)[a]	7.10 (6.77)
Fertiliser expenditure	Total chemical fertiliser expenditure (100 yuan/hectare)	27.36 (12.08)
Treatment variable		
Smartphone use	1 if household head used a smartphone in 2018, 0 otherwise	0.45 (0.50)
Independent variables		
Age	Age of household head (years)	56.45 (11.23)
Sex	1 if household head is male, 0 otherwise	0.60 (0.49)
Education	Educational level of household head (years)	4.77 (3.83)
Household size	Number of household members (persons)	4.71 (2.44)
College student	1 if household has a college student, 0 otherwise	0.11 (0.31)
Asset ownership	1 if household owns agricultural machines, 0 otherwise	0.81 (0.39)
Extension contact	Frequency of contacting extension agents in 2018 (times)	0.18 (0.74)
Disease experience	1 if household experienced plant diseases (e.g. Fusarium head blight, Erysiphe graminis or Puccinia econdite) in wheat production, 0 otherwise	0.34 (0.47)
Shandong	1 if household resides in Shandong province, 0 otherwise	0.48 (0.50)
Henan	1 if household resides in Henan province, 0 otherwise	0.26 (0.44)
Anhui	1 if household resides in Anhui province, 0 otherwise	0.27 (0.44)
Instrumental variable		
Social network	1 if household's neighbours used smartphones, 0 otherwise	0.79 (0.40)
Sample size		551

[a]Yuan is Chinese currency (1USD = 6.90 yuan in 2019). *SD* refers to the standard deviation.

pesticide expenditure and fertiliser expenditure between these two groups of farmers. However, one cannot use the findings to deduce the nexus between smartphone use and pesticide and fertiliser expenditures. This is because the mean comparisons in Table 2 did not control confounding factors (e.g. age, education and household size) that may affect farmers' smartphone use decisions and agrochemical expenditures. Notably, smartphone users and non-users are systemically different in terms of some observed characteristics. Compared with non-users, smartphone users tend to be younger, better educated and interact with extension agencies more frequently. Thus, addressing smartphone use's endogeneity issue is essential to obtain rigorous heterogeneous effects of smartphone use on pesticide and fertiliser expenditures.

5. Empirical results

5.1 Determinants of smartphone use

The results that demonstrate the factors affecting farmers' decisions to use smartphones are presented in Table S3. The probit model is utilised to facilitate the estimations. The lower part of Table S3 reports a McFadden pseudo-R^2 of 0.438. 82.16 per cent of smartphone users and 78.70 per cent of non-users are correctly predicted. The findings suggest that our probit model estimation is a good fit. Given that the coefficient estimations are not straightforward in interpretation, we calculate and present the explanatory variables' marginal effects in the last column of Table S3 to ease our understanding.

Table 2 Mean differences of the selected variables between smartphone users and non-users

Variables	Smartphone users	Non-users	Mean differences
Dependent variables			
Pesticide expenditure	7.31 (8.01)	6.93 (5.58)	0.37
Fertiliser expenditure	27.96 (12.88)	26.88 (11.38)	1.08
Independent variables			
Age	49.32 (9.73)	62.24 (8.76)	−12.92***
Sex	0.60 (0.49)	0.61 (0.49)	−0.01
Education	6.56 (3.44)	3.31 (3.51)	3.25***
Household size	4.82 (1.93)	4.61 (2.79)	0.21
College student	0.13 (0.34)	0.09 (0.29)	0.04
Asset ownership	0.83 (0.38)	0.79 (0.41)	0.04
Extension contact	0.27 (0.97)	0.11 (0.46)	0.16**
Disease experience	0.34 (0.48)	0.33 (0.47)	0.02
Shandong	0.49 (0.50)	0.46 (0.50)	0.03
Henan	0.25 (0.43)	0.26 (0.44)	−0.01
Anhui	0.26 (0.44)	0.28 (0.45)	−0.02
Social network	0.97 (0.18)	0.65 (0.48)	0.31***
Sample size	247	304	551

** <0.05.
*** <0.01.

The results show that the marginal effect of the age variable is negative and statistically significant, suggesting that one more year increase in farmers' age decreases the probability of smartphone use by 1.9 per cent. Younger farmers usually have less farming experience. Thus, they may be more likely to rely on smartphones to acquire agriculture-related information and facilitate their decision-making in production and marketing. Our finding that younger farmers have more interest in using modern information technologies is well in line with the results of Kongaut and Bohlin (2016) for Sweden, Michels et al., (2020) for Germany, and Hoang (2020) for Vietnam. The education variable has a positive and significant marginal effect, and the finding indicates that better-educated farmers are 3.2 per cent more likely to use smartphones. Education enables farmers to collect and process information regarding new information technologies more easily. The finding is consistent with the results of previous studies (Kongaut & Bohlin, 2016; Ma et al., 2020a; Michels et al., 2020). Finally, the marginal effect of the social network variable is positive and statistically significant, suggesting that farmers are 28.4 per cent more likely to use smartphones if their neighbours are also smartphone users. This is because farmers' behaviours of smartphone use tend to be spatially determined. In other words, farmers can realise the advantages of smartphones by observing their neighbours' adoption behaviours, which induce them to make the adoption decision.

5.2 Impacts on pesticide expenditure

The results for the impacts of smartphone use and other control variables on pesticide expenditure are presented in Table 3. At the lowest 20th quantile, smartphone use significantly increases pesticide expenditure by 33 per cent. Farmers with the lowest level of pesticide expenditure are usually those who apply pesticides inadequately. Thus, they may use smartphones to search, collect and process information related to pesticides and then increase their usage as a yield-increasing input. At the higher 60th and 80th quantiles, smartphone use significantly decreases pesticide expenditure by 36 and 39 per cent, respectively. For farmers with a high level of pesticide expenditure, smartphone use can provide them with sufficient information to purchase pesticides at lower costs and improve usage efficiency, finally contributing to a reduced pesticide expenditure. The finding of the negative relationship between smartphone use and pesticide expenditure is largely consistent with Zhao et al., (2021) for China.

For comparison, we also estimate the mean-based impact of smartphone use on pesticide expenditure using the endogenous treatment regression (ETR) model. We present the results in the second and third columns of Table S4. The ETR model can address the selection bias issues arising from observed and unobserved factors (Ma et al., 2020b). Our estimates show that smartphone use has a negative and insignificant impact on pesticide expenditure. The findings suggest that using a mean-based approach, such

Table 3 Impact of smartphone use on pesticide expenditure: IVQR model estimation

Variables	Selected quantiles (dependent variable = pesticide expenditure)			
	20th	40th	60th	80th
Smartphone use	0.326 (0.119)***	−0.149 (0.105)	−0.357 (0.106)***	−0.390 (0.121)***
Age	0.003 (0.004)	−0.005 (0.004)	−0.006 (0.004)	−0.005 (0.004)
Sex	−0.179 (0.100)*	−0.129 (0.089)	−0.133 (0.090)	−0.174 (0.102)*
Education	−0.012 (0.013)	0.004 (0.012)	0.021 (0.012)*	0.020 (0.014)
Household size	−0.006 (0.019)	−0.005 (0.017)	0.001 (0.017)	0.010 (0.019)
College student	−0.002 (0.142)	0.102 (0.126)	0.049 (0.127)	0.006 (0.144)
Asset ownership	0.071 (0.114)	−0.089 (0.101)	−0.036 (0.102)	−0.119 (0.116)
Extension contact	−0.163 (0.061)***	−0.100 (0.054)*	−0.115 (0.055)**	−0.089 (0.062)
Disease experience	−0.006 (0.099)	0.029 (0.088)	0.051 (0.088)	0.183 (0.101)*
Shandong	0.048 (0.108)	−0.140 (0.096)	0.005 (0.097)	0.110 (0.110)
Henan	0.279 (0.127)**	0.078 (0.112)	0.075 (0.113)	−0.060 (0.129)
Constant	5.571 (0.330)***	6.767 (0.292)***	6.957 (0.295)***	7.253 (0.335)***
Sample size	551	551	551	551

Note: The log-transformed form of the pesticide expenditure variable is used as the dependent variable; The reference province is Anhui; standard errors are presented in parentheses: *<0.10, **<0.05 and ***<0.01.

as the ETR model, would only provide a narrow picture regarding the association between smartphone use and pesticide expenditure. In comparison, the IVQR model estimation provides more significant insights.

Turning to other control variables, we show that male household heads spend around 17 per cent less on pesticides at the 20th and 60th quantiles than female household heads. Women usually spend more time on household activities such as cooking and looking after children and elders. In comparison, men devote more time to farm works, including learning how to manage the farm better and use pesticides more efficiently (Yang et al., 2019). Therefore, men spend less on pesticides than their women counterparts. The positive and statistically significant coefficient of the education variable at the 60th quantile suggests that one more year increase in education increases pesticide expenditure by 2.1 per cent. This finding echoes the finding of Salazar and Rand (2020) for Vietnam but contrasts with the results of Jallow et al., (2017) for Kuwait.

Access to extension service significantly reduces pesticide expenditure by 10–16 per cent. The importance of extension service intervention in reducing pesticides has been reported in previous studies (Asfaw et al., 2009; Jallow et al., 2017; Ying et al., 2017). In their studies for Kuwait, Jallow et al., (2017) showed that farmers who received advice from extension services are less likely to overuse pesticides. Farmers who have experienced plant diseases appear to spend 18 per cent more on pesticides at the 80th quantile. The pesticide application can help farmers combat disease infestation to sustain agricultural productivity, and thus, disease experience is associated with high expenditure on pesticides. The IVQR results show that relative to farmers producing wheat in Anhui (reference region), those in Henan spend 28 per cent more on pesticides at the 20th quantile.

5.3 Impacts on fertiliser expenditure

Table 4 reports the estimation results for the impact of smartphone use and control variables on fertiliser expenditure. The estimates show that the impacts of smartphone use on fertiliser expenditure are quite similar to their impacts on pesticide expenditure, but the impact magnitudes are small. Our estimates show that smartphone use increases fertiliser expenditure by 18 per cent at the lowest 20th quantile. Smartphone use helps farmers with the lowest level of fertiliser expenditure improve their application to improve farm productivity. At the higher 60th and 80th quantiles, smartphone use significantly decreases fertiliser expenditure by 14 and 19 per cent, respectively. As its impact on pesticides, smartphone use helps farmers with higher levels of fertiliser expenditure reduce expenditures as it improves farmers' fertiliser market participation and utilisation efficiency. The finding of the reduction effect of smartphone use on fertiliser expenditure is largely consistent with the finding of Yuan et al., (2021), who found Internet use reduces chemical fertiliser use in China.

For a comparison purpose, we also estimate the mean-based impact of smartphone use on fertiliser expenditure using the ETR model. Our results (see the last two columns of Table S4) show that smartphone use has a positive but insignificant impact on fertiliser expenditure. This is another solid evidence that the IVQR model estimation can help better understand the nexus between smartphone use and fertiliser expenditure.

Among other factors that affect fertiliser expenditure, the age variable's coefficients are negative and statistically significant at the 40th, 60th and 80th quantiles. The results indicate that one year increase in age decreases fertiliser expenditure by 0.5–0.6 per cent. Age can be treated as a proxy of farming experience. With age increasing, farmers tend to accumulate more personal

Table 4 Impact of smartphone use on fertiliser expenditure: IVQR model estimation

Variables	Selected quantiles (dependent variable = fertiliser expenditure)			
	20th	40th	60th	80th
Smartphone use	0.178 (0.071)**	−0.094 (0.062)	−0.142 (0.063)**	−0.185 (0.072)**
Age	0.002 (0.003)	−0.005 (0.002)**	−0.006 (0.002)**	−0.006 (0.003)**
Sex	0.049 (0.060)	0.026 (0.053)	0.049 (0.053)	0.101 (0.061)*
Education	−0.012 (0.008)	0.001 (0.007)	−0.001 (0.007)	−0.012 (0.008)
Household size	0.009 (0.011)	0.012 (0.010)	0.003 (0.010)	0.019 (0.011)*
College student	0.015 (0.084)	−0.005 (0.074)	0.055 (0.075)	0.157 (0.086)*
Asset ownership	−0.064 (0.068)	−0.098 (0.060)	−0.134 (0.060)**	−0.106 (0.069)
Extension contact	−0.121 (0.036)***	−0.086 (0.032)***	−0.058 (0.032)*	−0.073 (0.037)**
Disease experience	0.030 (0.059)	0.062 (0.052)	0.073 (0.052)	0.092 (0.060)
Shandong	0.074 (0.064)	0.094 (0.057)*	0.109 (0.057)*	0.192 (0.065)***
Henan	0.111 (0.075)	0.085 (0.066)	0.134 (0.067)**	0.113 (0.077)
Constant	7.415 (0.196)***	7.971 (0.173)***	8.232 (0.174)***	8.371 (0.200)***
Sample size	551	551	551	551

Note: The log-transformed form of the fertiliser expenditure variable is used as the dependent variable; the reference province is Anhui; standard errors are presented in parentheses: *<0.10, **<0.05 and ***< 0.01.

capital and farm management skills, which enable them to reduce fertiliser expenditure via improving the fertiliser use efficiency and managing the farm more appropriately and professionally. The finding is consistent with the results of Hassen (2018), who noted that older farmers tend to use less mineral fertiliser in Ethiopia. The sex variable has a statistically significant coefficient in the last column of Table 4. The finding suggests that male household heads spend 10 per cent more on fertilisers at the highest 80th quantile than their female household heads. Emmanuel et al., (2016) also reported that relative to women, male farmers have a higher probability of adopting chemical fertiliser in Ghana's rice production. The positive and statistically significant coefficient of household size in the last column of Table 4 suggests that an additional household member increases fertiliser expenditure by 1.9 per cent at the highest 80th quantile. The finding is consistent with the finding of Croppenstedt et al., (2003) for Ethiopia. Households with a larger member size are less likely to encounter labour shortage issues in fertiliser application even during the busy farming season. Thus, they tend to use fertilisers more intensively to achieve higher farm productivity. Households with a college student member tend to spend 16 per cent more on fertilisers than those who do not have a student member. This may be explained by the fact that households with student members usually face greater financial pressure, so they may rely on productivity-enhancing inputs such as fertiliser to improve farm performance and finally increase farm income.

Ownership of assets such as agricultural machines is associated with reduced expenditure on fertilisers. Our estimates reveal that asset ownership decreases fertiliser expenditure by 13 per cent at the 60th quantile, a finding that echoes the result of Zhu et al., (2016), who also highlighted a negative relationship between machinery use and the amount of fertiliser use in China's wheat production. As an essential production input, machinery use can improve chemical fertilisers' utilisation efficiency and lower costs. Access to extension service appears to affect fertiliser expenditure at all selected quantiles significantly and negatively. One more time visit of extension service would reduce fertiliser expenditure by 6–12 per cent. Our findings emphasise the significant role of technical training in helping farmers reduce fertiliser use. Huang et al., (2012) found that providing training courses among farmers reduces nitrogen fertiliser use by 22 per cent in maize production in China without lowering the maize yields.

Regarding regional variables, the results indicate that relative to wheat farmers in Anhui (reference province), those in Shandong significantly spend 11–19 per cent more on fertilisers at the higher 60th and 80th quantiles, and those in Henan spend 13 per cent more on fertilisers at the 60th quantile. The findings suggest the geographic-related characteristics (e.g. institutional arrangements and social–economic conditions) also matter with farmers' input use decisions in agricultural production.

5.4 Impacts of smartphone use intensity on pesticide and fertiliser expenditures

To enrich our understanding, we estimated the impact of smartphone use intensity (i.e. the average time spent on smartphones per day) on pesticide and fertiliser expenditures. The results (Table S5) show that smartphone use intensity does not significantly affect pesticide expenditure at the selected quantiles, even at the 10 per cent significance level. It has a positive and significant impact on fertiliser expenditure exclusively at the 80th quantile. The findings suggest that the length of time wheat farmers spend on smartphones does not really matter with their pesticide and fertiliser expenditures.

6. Conclusions and policy implications

The negative human health and environmental effects of chemical pesticides and fertilisers have been widely discussed. Reducing the overuse of chemical pesticides and fertilisers becomes a priority on the sustainable development agenda for countries such as China. In this study, we contributed to the literature by exploring whether modern information technology adoption can help reduce pesticide and fertiliser expenditures, using smartphone use as an example. Unlike the existing studies that analyse the homogeneous relationship between information technology adoption and farm input use, this study examined the heterogeneous impacts of smartphone use on pesticide and fertiliser expenditures. We employed the IVQR model to address the endogeneity issue of smartphone use and analyse the farm household survey data collected from three major wheat-producing provinces (Shandong, Henan and Anhui) in China.

The empirical findings revealed that smartphone use has heterogeneous impacts on pesticide and fertiliser expenditures. Specifically, at the 20th quantile, smartphone use significantly increases pesticide expenditure by 33 per cent and fertiliser expenditure by 18 per cent. Smartphone use has a negative but insignificant impact on both pesticide and fertiliser expenditures at the 40th quantile. However, at the higher 60th and 80th quantiles, smartphone use significantly decreases pesticide expenditure by 36–39 per cent and fertiliser expenditure by 14–19 per cent. Additional analysis showed that pesticide and fertiliser expenditures are not necessarily determined by the length of time wheat farmers spend on smartphones.

We found that farmers' decisions to use smartphones are affected by their age, education level and social network. In addition to smartphone use, pesticide expenditure was also affected by sex, education, extension contact and disease experience. Household heads' age and sex, household size, the existence of a college student in a household, asset ownership and extension contact were important factors driving wheat farmers' fertiliser expenditure.

Our findings suggest that, to a large extent, smartphone use can help reduce agrochemical expenditures (except for the 20th quantile). Thus, smartphone technology should be further diffused and disseminated in rural areas. As younger people usually lead the way in smartphone ownership and usage, rural development programs should consider providing smartphone use training among mid-aged and older farmers. This can help more farmers better understand the benefits of modern mobile technology and improve agricultural production. Extension access largely reduces pesticide and fertiliser expenditures. Thus, the government can collaborate with agricultural cooperatives to enhance extension service programs in rural areas, with the aim of improving farmers' understanding of the negative effects of chemical pesticides and fertilisers and the functions and application methods of these two inputs.

Conflict of interest

There is no conflict of interest.

Data availability statement

The data that support the findings of this study are available from the second author, Hongyun Zheng, upon reasonable request.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table S1. Falsification test for testing the validity of instrumental variable.

Table S2. Pearson's correlation analysis for testing the validity of instrumental variable.

Table S3. Determinants of smartphone use: probit model estimation.

Table S4. Impact of smartphone use on pesticide and fertiliser expenditures.

Table S5. Impact of smartphone use intensity on pesticide expenditure: quantile regression results.