Impacts of Smartphone Use on Agrochemical Use Among Wheat Farmers in China: A Heterogeneous Analysis

by Wanglin Ma and Hongyun Zheng

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Abstract

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 analyze a homogeneous relationship between the adoption of information technologies and farm input use, in this study, an instrumental variable quantile regression approach is utilized to capture the heterogeneous impacts of smartphone use on pesticide and fertilizer expenditures. Findings reveal that smartphone use affects pesticide and fertilizer expenditures heterogeneously, and its impacts on pesticide expenditure are larger than those on fertilizer expenditure. Specifically, at the lowest 20th quantile, smartphone use significantly increases pesticide expenditure by 33% and fertilizer expenditure by 18%. However, at the higher 60th and 80th quantiles, smartphone use significantly decreases pesticide expenditure by 36-39% and fertilizer expenditure by 14-19%. Our findings suggest that guiding farmers' agrochemical usage behaviors through smartphone-based information intervention can be a practical strategy to help reduce the excessive usage of chemical pesticides and fertilizers and preserve the environment and human health.

Keywords: Chemical pesticides; Chemical fertilizers; IVQR model; Smartphone use; Wheat production

JEL Codes: C21; Q18; L86

1. Introduction

Increased application of agrochemical inputs, such as pesticides and fertilizers, 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 a number of human diseases (e.g., respiratory disorders, cancer, reproductive disorders, neurological dysfunction, and diabetes) (Nicolopoulou-Stamati et al., 2016; Sabarwal et al., 2018; Zhao et al., 2021), a reduction of biodiversity (Beketov et al., 2013; Brühl and Zaller, 2019), and water and soil contamination (Rani et al., 2021; Thais et al., 2020). The overuse of chemical fertilizers 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 fertilizer 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 Fertilizers" by 2020 (hereafter "Action Plans") (Jin and 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 bio-pesticides as a composite strategy against hazardous pesticide use (Grovermann et al., 2017). This strategy could reduce the average use of hazardous pesticides by 34% but does not decrease the average farm income. Several agronomists have suggested that the substitution of chemical fertilizers with organic soil amendments (e.g., organic fertilizers and farm manure) can help mitigate the adverse effects of chemical fertilizer 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 fertilizer 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 and Tarp, 2019; Lio and Liu, 2006; Ma and Wang, 2020; Zheng et al., 2021; Zheng and Ma, 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 and 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 fertilizers 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 agricultural policies for countries like China, aiming to reduce the overuse of chemical pesticides and fertilizers.

The existing studies have provided some insights regarding the association of information technology intervention and the usage of pesticides and fertilizers. They capture information

[1] Information technologies are effective tools used for information exchange, including, for example, smartphones, tranditional mobile phones, computers, tablets, and radios. In some studies, people have used more generalzied 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).

technology intervention using mobile phone use (Cole and Fernando, 2012; Freeman and 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 fertilizer usage (e.g., Cole and Fernando, 2012; Issahaku et al., 2018; Kaila and Tarp, 2019; Ogutu et al., 2014). For example, Cole and Fernando (2012) showed that mobile phone use significantly increases pesticide and fertilizer use in India's cotton cultivation. By analyzing farm household data collected from Kenya, Ogutu et al. (2014) found that using ICT-based market information services increases purchased fertilizer application. On the other hand, two studies have shown that information technology affects pesticide and fertilizer 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 fertilizer expenditure. The study for Uganda by Freeman and Qin (2020) shows that access to mobile phones has a positive but insignificant impact on fertilizer use, but it significantly increases pesticide use.

Still, we are aware that three studies have illustrated the pesticide and fertilizer reduction effects of information technology adoption (Hou et al., 2019; Yuan et al., 2021; Zhao et al., 2021). By analyzing 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. (2020) examined the impact of Internet use on chemical fertilizer use based on a nationwide dataset of 7,766 rural households. They found that Internet use reduces chemical fertilizer use as it increases farmers' human capital. By estimating survey data of 670 vegetable growers in China, Zhao et al. (2020) 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 homogenous (mean-based) analytical methods they used, which can only provide a partial narrow picture regarding the impacts of information technology adoption on pesticide and fertilizer use. Information technology adoption may affect farmers who use a lower amount of chemical pesticides and fertilizers 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 fertilizer use may be affected differently by modern information technology. From a policy perspective, policymakers may have interests to get information about the influence of information technology adoption on pesticide and fertilizer use at different distributional points. However, the existing studies have failed to investigate whether information technology adoption affects pesticide and fertilizer use at the lower or upper end of their distributions heterogeneously.

This study contributes to the literature by analyzing the heterogeneous impacts of modern information technology adoption on pesticide and fertilizer 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 fertilizer use in particular (Füsun Tatlidil et al., 2009; Hou et al., 2019; Min et al., 2020; Zanello, 2012; Zheng and 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 fertilizers at lower costs. The farm management skills acquired from smartphone use can also help farmers improve the efficiency of pesticide and fertilizer 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 and Hartje, 2016; Ma et al., 2020a; Min et al., 2020). Thus, as a further contribution, we utilize 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 and Hartje, 2016; Ma et al., 2020a, 2018b; Michels et al., 2020; Min et al., 2020; Nie et al., 2020; Zheng and 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 tons, accounting for 17.45% of the world's total wheat production (FAOSTAT). Pesticides and fertilizers are two key inputs in wheat production, and their costs account for the largest proportion (38%) of the total wheat production costs in 2018 (DPNDRC, 2019). As illustrated in Section 2 below, expenditures on pesticides and fertilizers 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

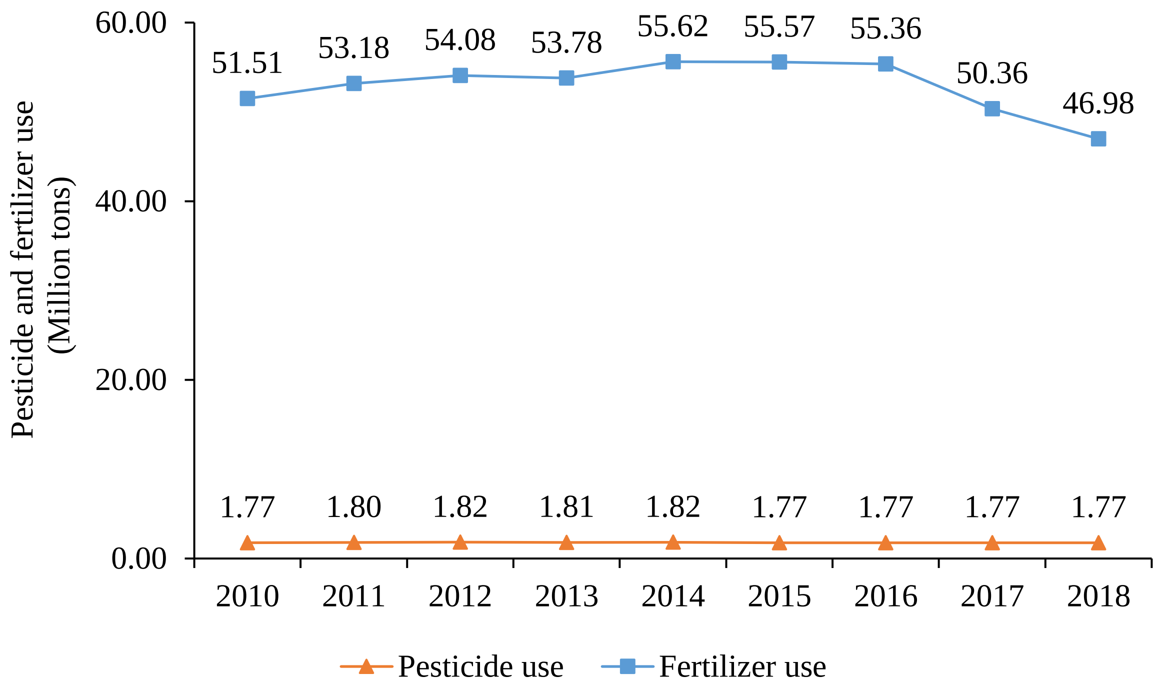
[2] As noted in Hübler and Hartje (2016), a traditional mobile phone can only be used for "voice" communication and message texting, while a smartphone is featured with a touch-screen and Internet access and it can provide diverse functions such as video communication, "apps" installation and webpage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

rate in China's rural area has increased from 32% in 2015 to 38% in 2018, and more than 95% of Internet users access the Internet via smartphones (CNNIC, 2019). Thus, it is significant to understand whether the adoption of information technologies such as smartphones can help reduce chemical pesticides and fertilizers in wheat production.

The rest of this paper is outlined as follows: Section 2 presents the background regarding pesticide and fertilizer 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 fertilizer consumption in China

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

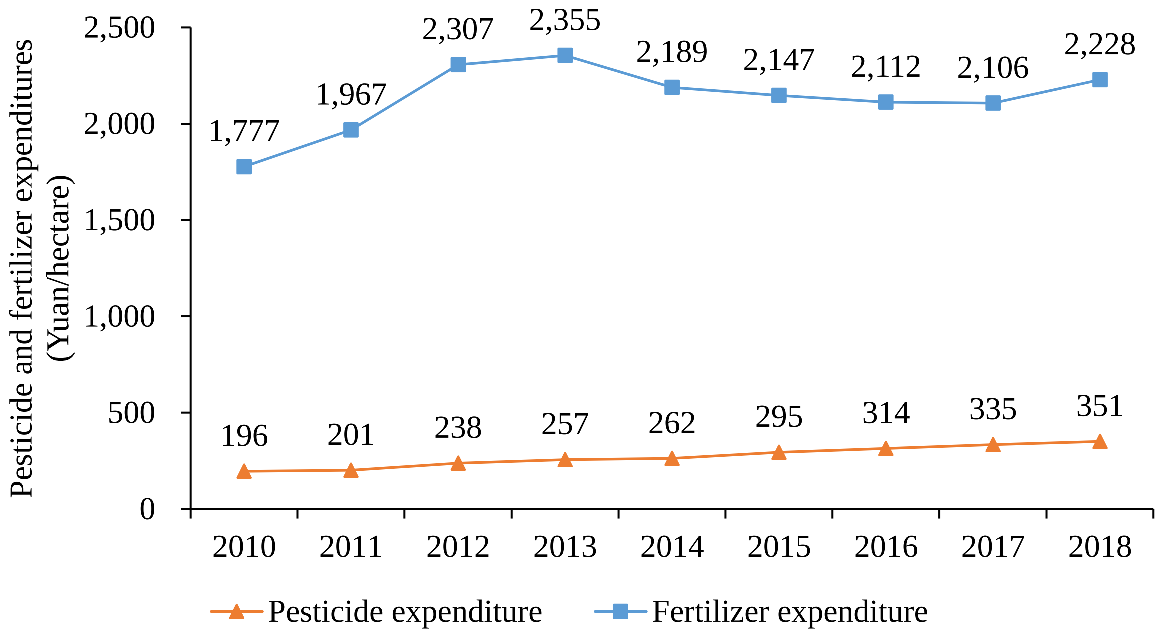


Data source: FAOSTAT

Figure 1 Pesticide and fertilizer use in agricultural production of China (2010-2018)

Recognizing the adverse effects associated with the overuse of pesticides and fertilizers, the Chinese government had started the "Action Plans" in 2015 to limit their applications (Jin and 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 fertilizers to substitute chemical pesticides and fertilizers, providing mechanization services to improve the inputs use efficiency, and accelerating technical training of advanced agronomic practices (Tang et al., 2019; Wang et al., 2019). Benefiting from these policy supports, pesticide use in China's agricultural production tends to decrease since 2015, while fertilizer use shows a non-increasing trend (see Figure 1).

Although pesticide use tends to reduce and fertilizer use maintains the same level in the whole agricultural sector of China since 2015, the amounts of pesticides and fertilizers consumed in the wheat industry show an increasing tendency. Figure 2 illustrates the pesticide and fertilizer 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 fertilizer 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 fertilizers was 2,228 yuan/hectare among wheat farmers in 2018 (DPNDRC, 2019). The corresponding amount of fertilizer input is 411.15 kg/hectare, accounting for three times more than the average world level (120 kg/hectare) (FAOSTAT).



Data source: DPNDRC

Figure 2 Pesticide and fertilizer expenditures in wheat production of China (2010-2018)

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 fertilizer expenditures. We select the IVQR model rather than other approaches, such as the conditional quantile regression (CQR) model (e.g., Killewald and Bearak, 2014; Mishra and 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 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 and Hartje, 2016; 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 fertilizer 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:

$$ln(Y_i) = q(S, X', \mu) = \alpha_\tau S + \beta_\tau X' + \mu \quad (1)$$

where $q(\cdot)$ is a conditional $\tau-$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; 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 maximization 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 and Hartje, 2016; Min 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, i.e. $S^* = U^S - U^N > 0$. Although S^* is unobservable since it is subjective, it can be expressed as a latent variable function as follows:

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

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 one if a farmer's neighbor 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 A1 in the Appendix) show that the IV has significant effects on smartphone use but has no significant effects on pesticide expenditure and fertilizer expenditure. Second, we conducted a Pearson correlation analysis. The results (Table A2 in the Appendix) show that the IV is significantly correlated with smartphone use, but it is not correlated with the two outcome variables, even at the 10% significance level. The findings in Tables A1 and A2 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 and 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 minimization 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% 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 favorable climate 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. Third, 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 of 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 fertilizer expenditures in the wheat production, and smartphone use status of farmers and their neighbors. 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 fertilizer related information. They also use video and voice functions of Wechat (a Chinese multi-purpose messaging, social media, and mobile payment “APP” developed by Tencent) to communicate pesticide and fertilizer information with their peers, input dealers, and extension agents. The information they usually acquire includes, for example, “the stores of input dealers”, “the prices and functions of different pesticides and fertilizers”, and “the methods on how to use pesticides and fertilizers appropriately and efficiently”.

The treatment variable used in this study refers to smartphone use, which takes a value of one if a household head used a smartphone in 2018, and zero otherwise. The two outcome variables include chemical pesticide expenditure and chemical fertilizer 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 fertilizers. Our monetary measurement of pesticides and fertilizers is consistent with earlier studies (Jaraite and Kažukauskas, 2012; Ma et al., 2018a). It is worth noting that all wheat farmers have used different levels of chemical pesticides and fertilizers in wheat production. In contrast, only 0.91%

of farmers have used low-toxicity bio-pesticides, and 15.06% of them have adopted organic soil amendments (e.g., organic fertilizers 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 fertilizer 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 fertilizer expenditure (2,228 yuan/hectare) in wheat production (DPNDRC, 2019). Among sample farmers, 45% 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% in 2018 (CNNIC, 2019). The average age of household heads is 56.45 years, and 60% 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% of the sampled households have access to extension service in 2018.

Table 1 Variable definitions and summary statistics

Variables	Definition	Mean (S.D.)
Dependent variables		
Pesticide expenditure	Total chemical pesticide expenditure (100 yuan/hectare) [a]	7.10 (6.77)
Fertilizer expenditure	Total chemical fertilizer 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 recondita) 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 neighbors used smartphones, 0 otherwise	0.79 (0.40)

Note: [a] Yuan is Chinese currency (1USD = 6.90 yuan in 2019). S.D. refers to the standard deviation.

Table 2 presents the mean differences of the selected variables between smartphone users and non-users. The results show no statistical differences in pesticide expenditure and fertilizer expenditure between these two groups of farmers. However, one cannot use the findings to deduce the nexus between smartphone use and pesticide and fertilizer 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 fertilizer expenditures.

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
Fertilizer 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

Note: ** < 0.05, *** < 0.01.

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 A3 in the Appendix. The probit model is utilized to facilitate the estimations. The lower part of Table A3 reports a McFadden pseudo R^2 of 0.438. 82.16% of smartphone users and 78.70% 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 A3 to ease our understanding.

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%. Younger farmers usually have less farming experience, and 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% 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 and 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% more likely to use smartphones if their neighbors are also smartphone users. This is because farmers' behaviors of smartphone use tend to be spatially determined. In other words, farmers can realize the advantages of smartphones by observing their neighbors' adoption behaviors, 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 20^{th} quantile, smartphone use significantly increases pesticide expenditure by 33%. 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 60^{th} and 80^{th} quantiles, smartphone use significantly decreases pesticide expenditure by 36% and 39%, 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. (2020) for China.

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

	Selected quantiles (Dependent variable = Pesticide expenditure)			
Variables	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.

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 A4 in the Appendix. 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 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% 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%. This finding echoes with 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%. 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 service are less likely to overuse pesticides. Farmers who have experienced plant diseases appear to spend 18% 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% more on pesticides at the 20th quantile.

5.3 Impacts on fertilizer expenditure

Table 4 reports the estimation results for the impact of smartphone use and control variables on fertilizer expenditure. The estimates show that the impacts of smartphone use on fertilizer expenditure are quite similar to their impacts on pesticide expenditure, but the impact magnitudes are small. Our estimates show that smartphone use increases fertilizer expenditure by 18% at the lowest 20th quantile. Smartphone use helps farmers with the lowest-level of fertilizer expenditure improve their application to improve farm productivity. At the higher 60th and 80th quantiles, smartphone use significantly decreases fertilizer expenditure by 14% and 19%, respectively. As its impact on pesticides, smartphone use helps farmers with higher levels of fertilizer expenditure reduce expenditures as it improves farmers' fertilizer market participation and utilization efficiency. The finding of the reduction effect of smartphone use on fertilizer expenditure is largely consistent with the finding of Yuan et al. (2020), who found Internet use reduces chemical fertilizer use in China.

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

	Selected quantiles (Dependent variable = Fertilizer expenditure)			
Variables	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 fertilizer 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.

For a comparison purpose, we also estimate the mean-based impact of smartphone use on fertilizer expenditure using the ETR model. Our results (see the last two columns of Table A4 in the Appendix) show that smartphone use has a positive but insignificant impact on fertilizer expenditure. This is another solid evidence that the IVQR model estimation can help better understand the nexus between smartphone use and fertilizer expenditure.

Among other factors that affect fertilizer 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 fertilizer expenditure by 0.5-0.6%. Age can be treated as a proxy of farming experience. With age increasing, farmers tend to accumulate more personal capital and farm management skills, which enable them to reduce fertilizer expenditure via improving the fertilizer 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 fertilizer 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% more on fertilizers 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 fertilizer 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 fertilizer expenditure by 1.9% 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 labor shortage issues in fertilizer application even during the busy farming season. Thus, they tend to use fertilizers more intensively to achieve higher farm productivity. Households with a college student member tend to spend 16% more on fertilizers 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 fertilizer to improve farm performance and finally increase farm income.

Ownership of assets such as agricultural machines is associated with reduced expenditure on fertilizers. Our estimates reveal that asset ownership decreases fertilizer expenditure by 13% at the 60th quantile, a finding that echoes with the result of Zhu et al. (2016), who also highlighted a negative relationship between machinery use and the amount of fertilizer use in China's wheat production. As an essential production input, machinery use can improve chemical fertilizers' utilization efficiency and lower costs. Access to extension service appears to affect fertilizer expenditure at all selected quantiles significantly and negatively. One more time visit of extension service would reduce fertilizer expenditure by 6-12%. Our findings emphasize the significant role of technical training in helping farmers reduce fertilizer use. Huang et al. (2012) found that providing training courses among farmers reduces nitrogen fertilizer use by 22% 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% more on fertilizers at the higher 60th and 80th quantiles, and those in Henan spend 13% more on fertilizers 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 fertilizer 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 fertilizer expenditures. The results (Table A5 in the Appendix) show that smartphone use intensity does not significantly affect pesticide expenditure at the selected quantiles, even at the 10% significance level. It has a positive and significant impact on fertilizer 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 fertilizer expenditures.

6. Conclusions and policy implications

The negative human health and environmental effects of chemical pesticides and fertilizers have been widely discussed. Reducing the overuse of chemical pesticides and fertilizers becomes a priority on the sustainable development agenda for countries like China. In this study, we contributed to the literature by exploring whether modern information technology adoption can help reduce pesticide and fertilizer expenditures, using smartphone use as an example. Unlike the existing studies that analyze the homogenous relationship between information technology adoption and farm input use, this study examined the heterogeneous impacts of smartphone use on pesticide and fertilizer expenditures. We employed the IVQR model to address the endogeneity issue of smartphone use and analyze 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 fertilizer expenditures. Specifically, at the 20th quantile, smartphone use significantly increases pesticide expenditure by 33% and fertilizer expenditure by 18%. Smartphone use has a negative but insignificant impact on both pesticide and fertilizer expenditures at the 40th quantile. However, at the higher 60th and 80th quantiles, smartphone use significantly decreases pesticide expenditure by 36-39% and fertilizer expenditure by 14-19%. Additional analysis showed that pesticide and fertilizer 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, existence of a college student in a household, asset ownership, and extension contact, were important factors driving wheat farmers' fertilizer 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 fertilizer 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 fertilizers and the functions and application methods of these two inputs.

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Appendix

Table A1 Falsification test for testing the validity of instrumental variable

Instrumental variable	Outcome variables	Statistics
Social network (IV)	Smartphone use	χ^2 =27.590***, *P*-value=0.000
Social network (IV)	Pesticide expenditure	*F*-value=0.060, *P*-value=0.800
Social network (IV)	Fertilizer expenditure	*F*-value=0.170, *P* -value=0.681

Note: *** < 0.01.

Table A2 Pearson correlation analysis for testing the validity of instrumental variable

Instrumental variable	Outcome variables	Correlation	*P*-value
Social network (IV)	Smartphone use	0.386***	0.000
Social network (IV)	Pesticide expenditure	0.023	0.595
Social network (IV)	Fertilizer expenditure	-0.014	0.742

Note: *** < 0.01.

Table A3 Determinants of smartphone use: Probit model estimation

Variables	Coefficients	Marginal effects
Age	-0.086 (0.009)***	-0.019***
Sex	-0.082 (0.160)	-0.018
Education	0.146 (0.022)***	0.032***
Household size	-0.010 (0.030)	-0.002
College student	0.223 (0.226)	0.048
Asset ownership	0.018 (0.179)	0.004
Extension contact	0.096 (0.097)	0.021
Disease experience	0.139 (0.152)	0.030
Shandong	0.085 (0.177)	0.018
Henan	-0.086 (0.199)	-0.019
Social network	1.309 (0.249)***	0.284***
Constant	2.817 (0.576)***	
Summary statistics		
McFadden's pseudo R^2	0.438	
Model χ^2	332.040 (0.000)***	
Log-likelihood	-212.950	
Users correctly predicted	82.16%	
Non-users correctly predicted	78.70%	
Sample size	551	551

Note: The reference province is Anhui; Standard errors are presented in parentheses; *** < 0.01.

Table A4 Impact of smartphone use on pesticide and fertilizer expenditures

Variables	ETR model		ETR model	
	Selection	Pesticide expenditure	Selection	Fertilizer expenditure
Smartphone use		-0.520 (0.320)		0.021 (0.113)
Age	-0.083 (0.009)***	-0.012 (0.008)*	-0.086 (0.009)***	-0.002 (0.003)
Sex	-0.010 (0.157)	-0.147 (0.073)**	-0.084 (0.160)	0.026 (0.041)
Education	0.135 (0.022)***	0.021 (0.016)	0.146 (0.022)***	-0.004 (0.007)
Household size	0.003 (0.029)	0.010 (0.013)	-0.010 (0.030)	0.006 (0.008)
College student	0.271 (0.219)	-0.009 (0.106)	0.220 (0.226)	0.067 (0.059)
Asset ownership	0.079 (0.176)	-0.050 (0.082)	0.018 (0.179)	-0.133 (0.047)***
Extension contact	0.102 (0.088)	-0.106 (0.046)**	0.098 (0.098)	-0.146 (0.025)***
Disease experience	0.183 (0.149)	0.177 (0.072)**	0.141 (0.153)	0.100 (0.041)**
Shandong	0.167 (0.176)	0.101 (0.077)	0.088 (0.178)	0.123 (0.044)***
Henan	-0.042 (0.192)	0.151 (0.090)*	-0.084 (0.199)	0.119 (0.052)**
Social network (IV)	1.216 (0.267)***		1.305 (0.250)***	
Constant	2.515 (0.566)***	7.095 (0.511)***	2.825 (0.578)***	7.932 (0.205)***
Observations	551		551	

Note: ETR model refers to endogenous treatment regression model; The log-transformed forms of the pesticide expenditure and fertilizer expenditure variables are used as the dependent variables; The reference province is Anhui; Standard errors are presented in parentheses; * < 0.10, ** < 0.05, and *** < 0.01.

Table A5 Impact of smartphone use intensity on pesticide expenditure: Quantile regression results

	Selected quantiles (Dependent variable = Pesticide expenditure)			
Variables	20th	40th	60th	80th
Smartphone use intensity	0.055 (0.045)	0.028 (0.032)	-0.020 (0.026)	-0.014 (0.031)
Control variables	Yes	Yes	Yes	Yes
	Selected quantiles (Dependent variable = Fertilizer expenditure)			
	20th	40th	60th	80th
Smartphone use intensity	-0.018 (0.016)	-0.010 (0.013)	0.011 (0.018)	0.024 (0.013)*
Control variables	Yes	Yes	Yes	Yes
Sample size	551	551	551	551

Note: The log-transformed forms of the pesticide expenditure and fertilizer expenditure are used as the dependent variables; The reference province is Anhui; Standard errors are presented in parentheses; * < 0.10.