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Estimating the effects of new smartphone-based agricultural extension services adoption on agricultural productivity in Zhejiang Province

Ni Zhuo (Presenter)

Institute of Rural Development, Zhejiang Academy of Agricultural Sciences, China

Email: zhuon@zaas.ac.cn

Chen Ji*

China Academy for Rural Development, Zhejiang University, China

Email: jichen@zju.edu.cn

Baozhi Li

Institute of Rural Development, Zhejiang Academy of Agricultural Sciences, China

Email: lbzjms@126.com

Qibiao Zhu

Institute of Rural Development, Zhejiang Academy of Agricultural Sciences, China

Email: zhuqibiao@zaas.ac.cn

Songqing Jin

Department of Agricultural, Food, and Resource Economics, Michigan State University

Email: jins@msu.edu

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Abstract: Smartphone use in rural China has grown rapidly, leading to the fast development of smartphone-based agricultural extension services. In this study, we analyze the causal effects of smartphone-based agricultural extension services (“Zhe’yang’shi” WeChat application as an example) on agricultural productivity in Zhejiang, China, using a staggered difference-in-differences method with panel data from 400 crop farmers. Our results show that adopting smartphone-based agricultural extension services increases agricultural productivity by 4.32%.

Key words: smartphone-based agricultural extension services; agricultural productivity; “Zhe’yang’shi”; staggered DID method

1. Introduction

Agricultural productivity growth is of great significance to food security and sustainable modern agricultural development. The Chinese government pays lots of attention to enhancing agricultural productivity, and its importance has been repeatedly addressed in the annual No. 1 document published by the central government. However, the growth rate of agricultural productivity in China is slowing down in recent years (Long and Zhang, 2021; Huang, 2021). How to keep a rapid growth of the agricultural productivity with restrained agricultural resources is a challenging issue for policy makers and researchers to resolve. Zhejiang province, which locates in southeast China, is endowed with very restrained natural resources. As technological innovation has been proved as an important means to increase agricultural productivity, especially through alleviating resource constraints and mitigating agricultural risks, Zhejiang provincial government issued a “5-year plan (2021-2025) to advance agricultural productivity through technological innovation and mechanization” in December, 2021.

ICTs are considered as new types of technology which promote information dissemination, market access, use inputs and resources environmentally and sustainably, and in turn it promotes agricultural productivity growth (Lio and Liu, 2006; the World Bank, 2011). There’s a large body of literature regarding the influence of mobile phone use/internet use on rural development (Zheng and Ma, 2021; Ongutu et al., 2014). While research related with ICTs and agricultural productivity from specific mobile phone services perspective emerge in recent years (Emeana et al., 2020; Gao et al., 2020), total number of studies in this strand remain very limited. Zhejiang province is a pioneer in agricultural digital transformation in China with a

high percentage of smartphone farmer owners, and farmers are skillful in using new mobile phone services to facilitate their production. For example, in Zhejiang province, crop farmers use a we-chat application named “Zhe’ yang’shi”¹ to adopt formula fertilizer in a more precise, efficient and sustainable way. It is reported that crop production productivity is greatly enhanced².

Regarding knowledge of ICT use and rural development, one strand of literature focuses on the role of digital agricultural extension services in economic development (Fabregas et al., 2019). Digital agricultural extension services tend to be more effective than conventional extension services because they facilitate the provision of site-specific extension recommendations to farmers (Ragasa & Mazunda, 2018; Oyinbo et al., 2020). Indeed, this is helpful in ensuring both food and environmental security (Fabregas et al., 2023; Mushtaq et al., 2017), and in improving the functioning of agricultural supply chains (Fabregas et al., 2019). Many studies have analyzed the factors influencing farmers’ choices of ICT-based extension tools (Oyinbo et al., 2020), and extension agents’ choices regarding the design of ICT-enabled digital agricultural extension tools (Oyinbo et al., 2020; Drewry et al., 2022). Arouna et al. (2021) found that personalized advice on nutrient management increased the profit from rice production in Nigeria, based on a randomized controlled trial (RCT) study. Further, Oyinbo et al. (2022) offered experimental evidence showing that maize farmers in Nigeria increased their gross and net revenue by obtaining site-specific nutrient management information and variability of expected returns.

Therefore, our research adopts a staggered Difference-in-Differences (DID) method to evaluate the influence of new mobile phone service on agricultural productivity by using “Zhe’ yang’shi” we-chat application as an example. The contributions of our study are as follows: (1) The research provides a new perspective to understand ICT use and agricultural productivity in China’s context. Different from existing literature which apply general mobile phone/internet use as the ICT indicator, our study uses specific smartphone agricultural service (we-chat application) adoption as the ICT application. (2) Current studies mainly adopt cross sectional

¹ “Zhe’ yang’shi” is an intelligent “soil testing formula fertilizer” we-chat application designed by ministry of agriculture in Zhejiang Province in 2016. Farmers are able to precisely adopt formula fertilizer according to the advice offered by the application at village and industrial level just through inserting his/her location and crop type in the application. The advice are generated from testing, calculating and computing of all lands soil in Zhejiang. The application also provides fertilizer information and consulting services to farmer users. Experimental counties started to use “Zhe’ yang’shi” since 2017, and it was promoted at provincial level in 2020. Till now, there are 12,600 households in 59 counties in Zhejiang Province are “Zhe’ yang’shi” we-chat application users.

² https://www.sohu.com/a/488623292_121117477

data to estimate the effects of ICTs on agricultural productivity, which means the endogeneity problem caused by farmer's selection bias exist. The DID method applied by our study contribute the estimate the causal effects more accurately.

The remainder of our paper is structured as follows. Section 2 provides the background of the research. Section 3 discusses the empirical strategy, following which Section 4 describes the data source and presents summary statistics of the variables. Section 5 shows the results, and Section 6 discusses the conclusions, limitations, and policy implications of the study.

2. Background of the research

“Zhe’yang’shi” is an intelligent agricultural extension WeChat application that provides soil testing formula fertilizer advice to farmers. Farmers can precisely adopt formula fertilizers according to advice, both at the village and product levels, simply by inputting their crop types and farm location into the application. The advice offered is obtained from the testing, calculation, and computation of all the soil qualities in Zhejiang. The application also provides fertilizer information and consulting services to farmers. Certain pilot counties started to use “Zhe’yang’shi” in 2017, and it was promoted at the provincial level in 2020. So far, 12,600 households in 59 counties have used “Zhe’yang’shi” in Zhejiang Province (Li et al., 2022b). Figure A1 shows four screenshots from the “Zhe’yang’shi” WeChat application.

(Insert Figure 1 here)

3. Empirical strategy

In this paper, agricultural productivity is the main dependent variable. Here, agricultural productivity is measured in terms of the monetary value of the output produced per mu of land divided by the monetary value of the input produced per mu of land.

The main objective of this study is to estimate the causal effect of the adoption of smartphone-based agricultural extension services on agricultural productivity. In an ideal research setting, we would like the implementation time of smartphone-based agricultural extension services for any given farmer to be randomly assigned, creating a variation in the implementation time that is uncorrelated with the observed and unobserved characteristics across individual farmers. However, it is not possible for us to conduct a randomized controlled trial (RCT), as the “Zhe’yang’shi” is out of the testing/trial phase and is available to any farmer in Zhejiang Province. In this study, we employ the DID approach to identify the causal effect of the adoption of smartphone-based agricultural extension services on agricultural productivity

while controlling for the many confounding factors. The basic DID specifications are as follows:

$$Y_{it} = \beta_0 + \beta_1 Treat_{it} + D_t + \varphi_i + \varepsilon_{it} \quad (1)$$

where Y_{it} is the logarithm of agricultural productivity of farmer i in year t ; $Treat_{it}$ represents farmer i 's treatment indicator, which is equal to one if farmer i adopted the smartphone-based agricultural extension services in year t and after, and zero otherwise; φ_i refers to farmer-level fixed effects controlling time-constant unobserved factors that may be simultaneously correlated with farmers' adoption of the smartphone-based agricultural extension services and agricultural productivity; D_t is the time fixed effects controlling for the time trends that are common across all farmers. The key coefficient of interest in this study is β_1 .

4. Data source

The dataset employed in this study is a household-level panel dataset from an annual longitudinal survey of 400 farmers in Zhejiang Province from 2017 to 2021. It contains detailed information on household basic demographic and economic characteristics, input, output volume and value of crops, as well as the smartphone-based agricultural extension services adoption timeline of farmers. Four cities (Jiaxing, Shaoxing, Jinhua, and Taizhou) were selected randomly for the survey. A map of Zhejiang Province and the sample cities is shown in Figure 2.

(Insert Figure 2 here)

Surveys were conducted from January 2018 to March 2022. Moreover, face-to-face interviews were carried out in 2018 and 2019 by well-trained enumerators who spoke Mandarin and the local languages. The enumerators were professional assistant researchers. Online surveys were conducted by the same enumerators in 2020, 2021, and 2022 because of the COVID-19 pandemic. The enumerators and farmers were able to communicate through WeChat groups when they encountered problems with filling out the questionnaires.

5. Main Results

Table 1 reports the DID estimates of the effects of the adoption of the smartphone-based agricultural extension services on agricultural productivity. The results for the base model with control variables are reported in columns 1. The results without control variables are reported in columns 2. The base model results show that the effects of the adoption of the smartphone-based agricultural extension services on agricultural productivity are positive and significant.

More specifically, the adoption of the smartphone-based agricultural extension services causes a significant increase in agricultural productivity by 4.32%.

6. Conclusions and implications

We aim to fill the existing research gap by examining the effect of the adoption of smartphone-based agricultural extension services on agricultural productivity, drawing on five-year panel data from 400 farmers in Zhejiang Province, China. The spatial and temporal variation in the time of adopting the smartphone-based agricultural extension services allows us to utilize the time-varying staggered DID method to identify the causal effect of the adoption of smartphone-based agricultural extension services on agricultural productivity.

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Figures and Tables.

Top Left Screenshot (4:08): Home screen of the 'Zhe Yang Shi' WeChat application. It displays a banner for the '2022 Zhejiang Province Fertilizer Policy' and a list of principal locations.

Top Right Screenshot (4:08): Home screen of the 'Zhe Yang Shi' WeChat application. It displays a banner for the '2022 Zhejiang Province Fertilizer Policy' and a list of principal locations.

Bottom Left Screenshot (5:54): Soil Quality Information screen. It shows a table of soil test results for Field Point A, including pH, nutrient levels, and exchangeable cations.

Field Point Name	Field Point A
Name of township	Qiaoying
Name of village	Tianhang Village
Field area	70
Crop Type	Asparagus, green beans
Year of sampling	2020
Sampling depth	15
Water soluble salt (g/kg)	0.78
PH	5.48
Organic matter (g/kg)	43.95
Total nitrogen (g/kg)	2.75
Available phosphorus (mg/kg)	664
Available potassium (mg/kg)	176.3
Exchangeable calcium (cmol/kg)	5.30
Exchangeable magnesium (cmol/kg)	0.70
Available sulfur (mg/kg)	35.8
Available silicon (mg/kg)	197
Available copper (mg/kg)	3.15
Available zinc (mg/kg)	25.87

Bottom Right Screenshot (4:10): Recommendation on Soil Testing Formula Fertilizer Use screen. It shows a table of fertilizer application recommendations for wheat.

Programme	Plow	500 kg / acre
1 base fertilizer	Commercial organic fertilizer	28 kg / mu
Direct spread	Amonium bicarbonate	50 kg / mu
Direct spread	Calcium magnesium phosphate	
2 tiller fertilizer	5-7 days after sowing	
Direct spread	urea	6.5 kg / mu
3 flower promoting fertilizer	Before flowering	
Direct spread	urea	6.5 kg / mu
Direct spread	potassium chloride	6.5 kg / mu
4 panicle fertilizer	Groening period	
Direct spread	urea	2.5 kg / mu
Direct spread	potassium chloride	6.5 kg / mu
Quota control fertilizer purity	Recommended dosage	Quota standard
Nitrogen dosage	11.89-11.96	17
Phosphorus dosage	6.00-6.00	/
Potassium dosage	7.80-7.90	/
Total Purity	25.69-25.86	26

Figure 1. Four screenshots of “Zhe’yang’shi” WeChat application

Source: The original language of “Zhe’yang’shi” WeChat application is Chinese, and they are translated into English by the authors.



Figure 2. The map of Zhejiang Province and sample cities of our study

Table 1. DID basic results

<i>Dependent Variables</i>	Log (agricultural productivity)	Log (agricultural productivity)
	(1)	(2)
Treat (i, t)	0.0423*** (0.0107)	0.0415*** (0.0102)
Observations	2000	2000
Adjusted R -squared	0.1530	0.1526
Control variables	Yes	No
Household FE	Yes	Yes
Year FE	Yes	Yes

Notes: Standard errors are listed in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.