Do ICTs Boost Agricultural Productivity?

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Abstract: *Based on panel data from the Rural Fixed Point Survey of the Ministry of Agriculture over the period 2004-2016 and supplementary survey data on information and communications technology (ICT) applications in the countryside, this paper employs the difference in differences (DID) method to analyze the effects of ICT applications on rural households' agricultural total factor productivity (TFP) with mobile phone signal, internet and 3G mobile network connections as indicators, and decomposes and evaluates the constituent factors. Our findings reveal a positive effect of ICTs on rural households' TFP, which primarily stemmed from rising agricultural technical efficiency. However, ICTs exerted no significant effect on agricultural technical progress during this paper's data period due to limited rural human capital. These findings are consistent with robustness test results based on counterfactual and matching methods.*

Keywords: *ICT applications, agricultural total factor productivity (TFP), agricultural technical progress, agricultural technical efficiency*

JEL Classification Codes: D24, Q12, Q16

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1. Introduction

In the new era of Chinese socialism, China's economy has started to transition from rapid growth to high-quality development. As part of the modern economic system, China's agricultural sector has entered a critical stage of restructuring and shift towards higher quality and efficiency. China must increase agricultural productivity if it is to complete agricultural supply-side structural reforms and agriculture modernization. The *Report to the 19th CPC National Congress* called for raising total factor productivity (TFP), improving the quality of economic growth, implementing the "countryside rejuvenation strategy," and modernizing agricultural production and operation as key elements of the strategy. The *No.1 Central Document of 2018* further called for a shift of priority from agricultural yield to quality, innovation, and competitiveness. As China strives to modernize its agricultural sector, discussions on the key drivers of agricultural TFP growth are of great practical relevance.

The Chinese government has always attached great importance to information and communication technologies (ICTs) in agriculture, which play a unique role in optimizing resource allocation. Since

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the dawn of the 21st century, China's rapid industrialization, ICT transformation and urbanization have created tremendous opportunities for agricultural modernization. In recent years, the Chinese government has made great efforts to promote ICTs in agriculture and strengthened ICT infrastructure. By 2016, China's rural telephone, cable TV and broadband internet penetrations reached 99.5%, 82.8% and 89.9%, respectively, and 25.1% of villages were connected to e-commerce collection-and-delivery points.[1] The State Council, the Ministry of Commerce and the Ministry of Agriculture and Rural Affairs have launched a host of programs to promote ICT applications in agriculture and the countryside, including the "internet + agriculture," e-commerce for agriculture, and poverty reduction through e-commerce. To date, 28 provincial-level regions in China have introduced "internet+" action plans, 756 counties have been supported by rural e-commerce demonstration programs, and 18 provincial-level regions have carried out the "ICT to Rural Households" project.[2] ICT penetration and development have vastly transformed the ways Chinese farmers live and work.

According to the new economic growth theory, technical progress is the primary driver of economic growth. Hence, ICT applications in agriculture as a key aspect of agricultural technical progress should expedite agricultural transition and increase agricultural TFP. ICTs reduce the cost of access to agricultural information, facilitate information flow, and help bridge the digital divide between industry and agriculture. ICTs allow farmers to resist natural risks such as weather and pest infestations, employ the best available technologies, and optimize agricultural production. ICT-based agricultural resource allocation and organizational management are more efficient. Applying advanced information technologies in agricultural production (Han, Zhang, 2015) facilitates technology and knowledge diffusion in the countryside and is thus conducive to agricultural technical progress. Technology efficiency and progress are the two main sources of TFP growth. Theoretically, ICTs should contribute to agricultural TFP improvement.

After intense debates in the early times, academics have started to recognize the positive productivity effects of ICTs. At the end of the 1980s, many academics believed that ICTs did not promote economic growth and productivity as theoretically expected (Bailey, 1986; Roach, 1987, *et al.*). During the same period, Solow put forth the famous productivity paradox in 1987, arguing that "*Computers everywhere except in the productivity statistics*." Since the early 1990s, however, some academics have explained possible reasons behind the "productivity paradox" (Attewell, 1994; Brynjolfsson, 1993). After economists investigated this question with better theoretical and econometric methods, there emerged a large body of literatures that verified the positive effects of ICT applications on economic growth and productivity (Pilat, 2005; Luo *et al.*, 2008; Zheng *et al.*, 2014). Academics such as Solow who had held negative views began to change their attitudes and recognize the positive effects of ICTs on growth and productivity.

Yet in the agricultural sector, there has been a paucity of research on how ICTs influence agricultural productivity, and existing studies on this topic have reached inconsistent conclusions. Ogutu *et al.* (2014) employed the matching method to verify the positive effects of ICT-based market information services on labor and land productivity. Han and Zhang (2015) believed that ICT applications exerted non-linear effects on agricultural TFP, i.e. ICT applications would exert positive effects on TFP only when rural human capital reached a certain level. Yu and Zhu's (2011) study also demonstrated the positive effects of ICTs on agricultural TFP growth. However, evidence from Dutch dairy farms suggested that the deployment of sensors did not significantly increase TFP in the dairy business (Steeneveld *et al.*, 2015). In a study on the agricultural TFP effects of rural labor migration, Li and Yin (2017) included the level

[1] Source: *Communique on Key Data of the Third National Agricultural Survey,* http://www.stats.gov.cn/tjsj/tjgb/nypcgb/qgnypcgb/201712/t20171215_1563589.html.

[2] Source: The State Council Policy Briefing: Promoting Internet Applications in Agriculture for Integrated Primary, Secondary and Tertiary Industry Development, https://www.sohu.com/a/238938521_799855.

of ICT applications (number of telephones per hundred persons) as a control variable into their model, but the result showed that ICTs had a limited effect on agricultural TFP.

The following three reasons may explain the inconsistency of the above-mentioned research conclusions. First, some studies employed provincial-level aggregated data, which was vulnerable to the problem that ICTs were endogenous to economic growth. On the other hand, the use of aggregated data might have overshadowed the heterogeneous effects on micro-level farmer households. Second, most studies conducted by Chinese academics have employed obsolete indicators like the ownership of telephones or TV sets per hundred persons to measure the degree of ICT applications. With very high levels of mobile phone and TV penetrations in the countryside, limited indicator variance has led to a lack of stability in the empirical results. Third, the above-mentioned studies have employed data of early times when the effect of ICT applications was yet to fully materialize.

To address the problem of endogeneity between ICTs and agricultural TFP and precisely measure the agricultural TFP effects of ICTs, this paper makes the following improvements to the existing studies: First, it employs rural household data from the National Rural Fixed Point Survey. Since individual rural households cannot influence decisions to build ICT infrastructure in the local region, ICT applications are more exogenous to the microscopic data compared with macro data and to some extent avoid possible deviations in measuring agricultural TFP with macro data. Second, we have conducted a supplementary survey on when villages were connected to mobile phone signals, the internet and 3G mobile networks at the nationwide rural fixed observation points. This supplementary survey allows us to take diverse modern information tools into consideration and accurately evaluate the effects of ICT tools with the difference in differences (DID) method. Third, the long time span of data employed in this paper (2004-2016) fully captures the agricultural growth effects of changing ICTs. Aside from TFP, this paper also examines the effects of ICTs on the efficiency and progress of agricultural technology and the mechanism of such effects.

2. Analysis of Theoretical Mechanisms

ICTs can be regarded as an infrastructure with a public goods attribute, and the relationship between infrastructure and economic growth has always been a key topic of theoretical research in economics. From neoclassical growth theory to endogenous growth theory, the relationship between public investments, including infrastructure, and economic growth has always been a focus of attention for economists. Arrow and Kurz (1970) first introduced public capital into the production function. Based on the Arrow-Kurz model, Barro (1990) introduced productive public capital into the endogenous growth model, believing that infrastructure could promote economic growth through its investment effects directly and by raising TFP through its spillover effects indirectly. By introducing infrastructure's effects on technology level into the production function, Hulten *et al*. (2006) separated the direct and indirect effects of infrastructure on output and concluded that infrastructure could increase output by raising the marginal productivity of such factors as capital and labor and extending the production possibility frontier.

With respect to information infrastructure, Han *et al*. (2011) and Mittal and Nault (2009) employed Hulten *et al*.'s (2006) theoretical framework for the analysis of the indirect spillover effects of ICTs on output. This paper's theoretical model on the agricultural TFP effects of ICTs also references the ideas of Hulten *et al*. (2006) and Mittal and Nault (2009). This paper defines the benchmark production function in the following Cobb-Douglas function form:

$$Y=A(I)K^{\alpha}L^{\beta}I^{\gamma} \tag{1}$$

In equation (1), Y is total agricultural output; K is capital input; L is labor input; I is ICT input; α,

β and γ are the output elasticities of capital, labor and ICT inputs, respectively. As can be learned from equation (1), ICTs contribute output growth (i) directly as an input together with capital and labor, and (ii) indirectly through their spillover effect as reflected in the standard Hicks-neutral efficiency function $A(I)$, which includes the effect of ICTs on technical progress and allows the production function to move exogenously. Outward movement means increasing return to scale, and inward movement means increasing return to scale. $A(I)$ is also a direct manifestation of TFP, i.e.:

$$TFP=\frac{Y}{K^{\alpha}L^{\beta}I^{\gamma}}=A(I) \tag{2}$$

By disseminating information about agricultural supply and demand, ICTs influence the input of capital and labor in agriculture. To further separate the indirect effects of ICTs, this paper specifies the exponential effect of ICTs on capital and labor referencing Mittal and Nault's (2009) method[3] with the following expression:

$$K_I = K\zeta(I) = Ke^{\eta I} \tag{3}$$

$$L_I = L\tau(I) = Le^{\mu I} \tag{4}$$

In equations (3) and (4), the first-order derivatives of capital and labor with respect to ICTs are greater than 0, i.e. $\zeta^{'}(I)$>0, $\tau^{'}(I)$>0. When ICT input is 0, capital and labor inputs remain unchanged, i.e. $\zeta(0)=\tau(0)$=1.

Equations (3) and (4) are substituted into the Cobb-Douglas function to obtain an extended production function equation in the following form:

$$Y_{\alpha} = S(Ke^{\eta I})^{\bar{\alpha}}(Le^{\mu I})^{\bar{\beta}}I^{\bar{\gamma}} = Se^{kI}K^{\bar{\alpha}}L^{\bar{\beta}}I^{\bar{\gamma}} \tag{5}$$

In equation (5), $k=\bar{\alpha}\eta+\bar{\beta}\mu$, k is the weighted sum between capital and labor output elasticity, and it measures the indirect effects of ICTs on agricultural output; and $\bar{\gamma}$ measures the direct effects of ICTs as an input on agricultural output.

Based on the TFP equation, we further arrive at:

$$TFP=\frac{Y_{\alpha}}{K^{\bar{\alpha}}L^{\bar{\beta}}I^{\bar{\gamma}}}=Se^{kI} \tag{6}$$

By taking logarithms on both sides of equation (6), we obtain:

$$\ln TFP = \ln S + kI \tag{7}$$

Hence, we may test the relationship between ICTs and agricultural TFP in our model estimation according to equation (7), and k on the right side of equation (7) is the ICT influence parameter with which this paper is concerned.

Further, Farrell (1957) decomposed TFP into technical progress and change in technical efficiency, both of which may benefit from ICTs as a vehicle for spreading technology and information. Theoretically, ICTs may have helped spread advanced technologies in the countryside. On the other hand, agricultural ICTs also help bring about progress in agricultural technology. Aside from infrastructure, farmers' ICT skills also play a key role in determining the extent to which ICTs induce technical progress. Hence, until rural human capital reaches a certain level, it would be difficult to turn advanced agricultural technology into productivity even with ICT infrastructure. This problem is likely to occur given the poor human capital and brain drain in China's countryside.

[3] Refer to Mittal and Nault (2009) for the reasons of exponential specification.

Second, ICTs influence agricultural technical efficiency. Rural ICT applications have increased the flow of information in the countryside, substantially reduced the cost of information transmission and search, and can break through barriers of information asymmetry (Aker *et al*., 2016). On one hand, ICTs ensure prompt access to agricultural information, allowing farmers to arrange crop farming, raise technical efficiency, and seek clients. On the other hand, ICTs bring more job opportunities to farmers and facilitate labor migration to non-farming sectors (Lu *et al*., 2016; Zhou and Li, 2017). Despite the brain drain, mechanized farming and economies of scale will raise agricultural efficiency. Hence, ICTs may exert a positive effect on agricultural technical efficiency.

3. Methodology, Data and Variables Selection

3.1 Methodology

3.1.1 Estimation of agricultural TFP

To analyze the agricultural TFP effects of ICTs, this paper employs the panel fixed-effect stochastic frontier analysis (SFA) and the Malmquist productivity index to estimate and decompose agricultural TFP. Created by Caves and Diewert (1982) based on the Malmquist quantitative index and the Shepherd distance function, the Malmquist productivity index measures change in TFP. Existing studies have measured this index with parametric methods such as the SFA method and non-parametric method such as the data envelope analysis (DEA) method. While both methods have their respective pros and cons, SFA is more consistent with the intrinsic features of agricultural production by avoiding the impact of stochastic factors on the frontier (Fan and Li, 2012), and is less sensitive to outliers. Hence, this paper will employ the SFA-Malmquist productivity index method to estimate and decompose agricultural TFP. Based on Kumbhakar and Lovell's (2003) study, the SFA model takes the following panel data form:

$$\ln Y_{\mathrm{it}} = \ln f\left(X_{it}, t; \beta\right) + v_{it} - \mu_{it} \tag{8}$$

In equation (8), Y_{it} is the output of decision-making unit i (i=1,2,...,N) during period t (t=1,2,...,T); X_{it} is the input of decision-making unit i during period t; t is time trend; $f(.)$ is the specific form of function, and β is parameter to be estimated; v_{it} is stochastic error term, which conforms to normal distribution; μ_{it} is error arising from technical inefficiency and is assumed to conform to truncated normal distribution; v_{it} and μ_{it} are independent from each other, v_{it}~$N(0,\sigma_v^2)$ and μ_{it}~$N(\mu,\sigma_\mu^2)$. This model forms a constant or time-varying model depending on whether inefficiency term μ_{it} varies with time. In this paper, the time-varying model is adopted.

As for the form of $f(.)$, this paper selects a more flexible trans-log function, and adopts the panel fixed-effect SFA model developed by Greene (2005) to consider the unobservable individual effect of rural households, which takes the following form:

$$\begin{aligned} \ln Y_{it} = {} & \beta_0 + \sum_j \beta_j \ln X_{ijt} + \beta_t t + \sum_j \sum_l \beta_{jl} \ln X_{ijt} \times \ln X_{ilt} + \beta_{tt} t^2 + \sum_j \beta_{jt} t \times \ln X_{ijt} \\ & + \alpha_i + v_{it} - \mu_{it} \end{aligned} \tag{9}$$

In equation (9), i and t denote rural household and year, respectively; Y_{it} is the rural household's total output value from farming, forestry, livestock and fishery in the current year; X_{ijt} is factor input; j and l respectively denote factor inputs j and l; this paper selects land (S_{it}), material capital (K_{it}) and labor (L_{it}) as input indicators; α_i is the unobservable individual effect of rural households.

To satisfy the assumption of constant return to scale (CRS) and conform to the symmetry of trans-log function, the model's input and output variables are standardized in this paper with land input S_{it} referencing Liu and Meng's (2010) method, i.e. $y_{it}=Y_{it}/S_{it}$, $k_{it}=K_{it}/S_{it}$, $l_{it}=L_{it}/S_{it}$. Then, standardized input and output variables are substituted into equation (9) to arrive at the following regression model:

$$\begin{aligned}\ln y_{it} &= \beta_0 + \beta_1 \ln k_{it} + \beta_2 \ln l_{it} + \beta_3 (\ln k_{it})^2 + \beta_4 (\ln l_{it})^2 + \beta_5 \ln k_{it} \ln l_{it} + \\ &\quad \beta_6 t \ln k_{it} + \beta_7 t \ln l_{it} + \beta_8 t + \beta_9 t^2 + a_i + v_{it} - \mu_{it}\end{aligned} \tag{10}$$

After obtaining the model parameters, the following equation gives us the technical efficiency of decision-making unit i during period t:

$$EFF_i^t = \exp(-\mu_{it}), 0 \le \exp(-\mu_{it}) \le 1 \tag{11}$$

Change in the technical efficiency of decision-making unit i from period t to t+1 can be calculated with the following equation:

$$EFFCH_i^{t,t+1} = EFF_i^{t+1} / EFF_i^t \tag{12}$$

Technical change of decision-making unit i from period t to t+1 can be calculated by estimating the partial derivative of the parameter in period t with equation (10). Since technical change is non-neutral, the value of technical change varies with input vector. Hence, the values of technical change in adjacent periods t and t+1 should adopt geometric mean with the following expression:

$$TECH_i^{t,t+1} = \left[\left(1 + \partial f(x_{it}, t; \beta) / \partial t\right) \times \left(1 + \partial f(x_{i(t+1)}, t+1; \beta) / \partial (t+1)\right)\right]^{1/2} \tag{13}$$

Under the CRS assumption[4], change in TFP can be expressed as the following based on the decomposition of Malmquist productivity index:

$$TFPCH_i^{t,t+1} = EFFCH_i^{t,t+1} \times TECH_i^{t,t+1} \tag{14}$$

3.1.2 Difference in differences (DID) method

The selection of indicators for ICT applications in the countryside is the groundwork of model estimation in this paper. Since the dawn of the 21st century, China has implemented a host of ICT construction projects to promote access to ICT services in the countryside, which led to notable improvements in access to mobile phone signals, the internet and mobile network in the countryside. With data availability considerations, this paper identifies access to mobile phone signals, the internet and 3G mobile networks in villages as the proxy variables of ICT applications. The three types of ICT infrastructure reflect a relatively full picture of ICT development in the countryside. Compared with mobile phones, access to the internet and 3G mobile network was achieved in the countryside more recently, so that the variance of these variables is more significant in sample years and can more clearly reflect the impact of ICT applications.

The most straightforward method to estimate the impact of ICTs on agricultural TFP is to compare the differences in agricultural TFP before and after rural households applied ICT tools. By exerting a certain influence over some regions without affecting others, the implementation of the above-mentioned ICT projects is analogous to a natural experiment. Hence, the DID method may examine the effects of ICTs on rural households in comparison with those outside the ICT project area. Since mobile phone signal, internet and 3G network connections were built at various time points across regions, we cannot specify a time point as the boundary for policy evaluation. Referencing existing studies, this paper realizes DID by controlling for the two-way fixed effects of individual farmer households and years in

[4] Many academics considered return to scale in agriculture to be constant (e.g. Xu *et al.*, 2011).

panel data (see Tan *et al*., 2015; Beck *et al*., 2010). In this manner, the regression equation specified in this paper is as follows:

$$\ln Y_{it} = \alpha + \beta D_{it} + \sigma X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{15}$$

In equation (15), Y_{it} is the agricultural TFP calculated with the SFA-Malmquist index method, as well as the technical progress and change in technical efficiency decomposed therefrom; D_{it} denotes whether the village of farmer household i was connected to mobile phone signal, the internet or 3G mobile network in year t, and the value is 1 if connected or 0 if not connected; X_{it} is other household- or village-level control variables that change with time and influence farmer households' agricultural TFP; μ_i and ν_t respectively denote the fixed effect of individual farmer households and the fixed effect of year; coefficient β is the core parameter with which this paper is concerned the most.

3.2 Data Source

This paper's main data is from the National Rural Fixed Point Survey of 2004-2016, and includes detailed information about the characteristics of farmer households and family members, household production and operation, household income and spending, and village characteristics, which provide solid data for our study.

The variables of ICTs in this paper are from a supplementary survey of the villages in the National Rural Fixed Point Survey. In order to precisely measure the impact of ICTs with the DID method, we have carried out a supplementary survey on the initial dates when some fixed-point villages were connected to mobile phone signals, the internet and 3G mobile network. This supplementary survey was carried out in February 2018 by students from China Agricultural University (CAU) when they returned to their hometowns during their winter vacation.[5] The students were told to ask village cadres and IT

Table 1: Number of Villages with Access to ICT Infrastructure, 2004-2016

Time of access	Mobile phone signal	Internet	3G mobile network	Time of access	Mobile phone signal	Internet	3G mobile network
Before 2004	27	13	0	2011	0	2	1
2004	1	1	0	2012	0	2	7
2005	1	2	0	2013	0	2	2
2006	2	2	0	2014	0	0	5
2007	2	5	0	2015	0	1	5
2008	1	0	0	2016	0	0	1
2009	0	3	3	After 2016	0	1	1
2010	1	2	6	Total	35	36	31

Source: Survey by authors.

[5] We chose to recruit students from the China Agricultural University (CAU) as surveyors for the following reasons: CAU is a key university under China's "211" and "985" programs, and the competence of CAU students ensures the quality of questionnaire survey. Most students from CAU are agriculture-related majors familiar with issues about China's agriculture, countryside and farmers.

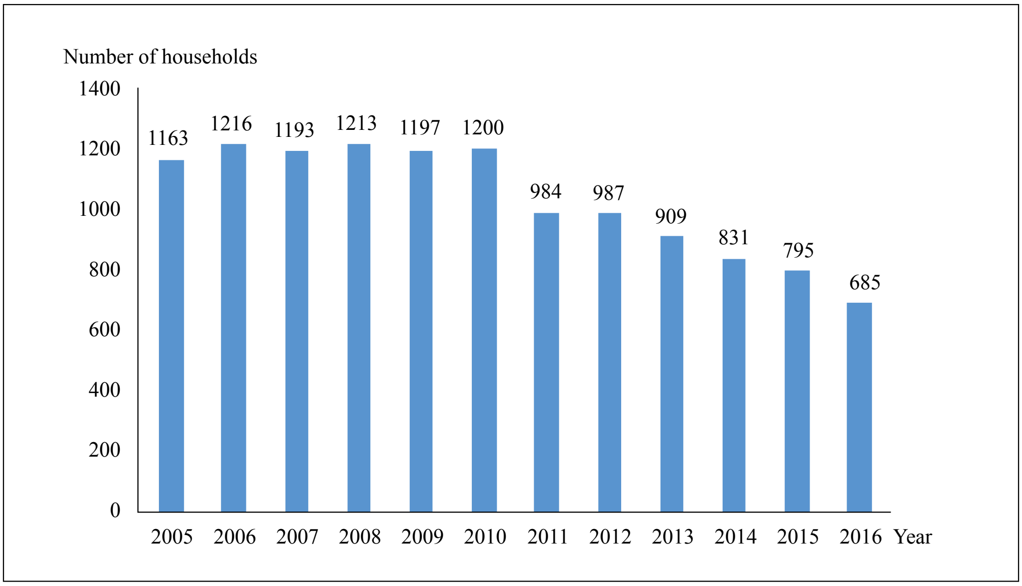

Figure 1: Distribution of Sample Years

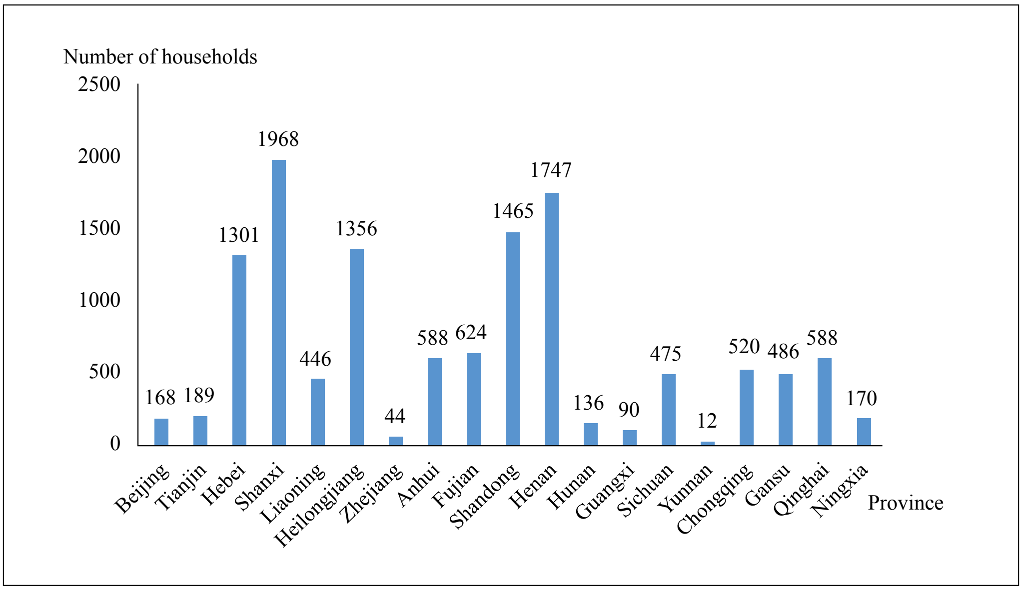

Figure 2: Distribution of Sample Provincial-Level Regions

managers about when their villages were connected to ICT infrastructure. In total, we recruited 50 student surveyors who completed 45 questionnaires and retained 36 valid ones after a quality check. The samples cover 36 fixed-point villages in 19 provinces, autonomous regions, and municipalities in China.[6]

[6] Beijing, Tianjin, Hebei, Shanxi, Liaoning, Heilongjiang, Zhejiang, Anhui, Fujian, Shandong, Henan, Hunan, Guangxi, Sichuan, Yunnan, Chongqing, Gansu, Qinghai and Ningxia.

Table 1 shows the time when the villages were connected to the three types of ICT infrastructure.

After consolidating the supplementary survey data with fixed-point farmer household data, we have obtained data of 14,943 farmer households for the period 2004-2016. Since the TFP estimate is a dynamic efficiency assessment, after excluding the data of 2004, we have ended up with 12,373 samples, and such data is non-equilibrium panel data. Figure 1 shows the distribution of sample years, and Figure 2 shows the distribution of provincial-level regions.

3.3 Variables Specification and Descriptive Statistics

3.2.1 Explained variables

The explained variables in the model are rural households' agricultural TFP and decomposed technical progress and change in technical efficiency. Based on the Cobb-Douglas production function and the input-output relationship of agricultural production, this paper selects the following indicators for measuring agricultural TFP: the aggregation of rural households' incomes from farming, forestry, livestock and fishery (in yuan) as the production indicator,[7] the sum of farmland area, garden area, forest area, pasture area, and water surface area (in *mu*) as the indicator for land input, the aggregated costs of innovation, fertilizer, agricultural film, pesticide, utilities and irrigation, animal power, mechanical operation, fixed asset depreciation and maintenance, small farm implements, cubs, feedstock, disease prevention and treatment and other costs (in yuan) as the indicator for capital input,[8] and the sum of household labor inputs and hired labor input for farming, forestry, livestock and fishery production (in days) as the indicator for labor input. Based on equations (11)-(14), we have estimated rural households' agricultural technical efficiency, technical progress, and TFP.

3.2.2 Explanatory variables and control variables

Explanatory variables include whether the village of rural households were connected to mobile phone signals, the internet, and 3D mobile network. Referencing existing studies, this paper has introduced three groups of control variables, including household head's individual characteristics, household characteristics and village economic conditions, into the model. Specifically, control variables include the gender, age and education level of household head, the proportion of agricultural workforce in the household, household per capita arable land area, the logarithm of household per capita income, distance between the village and trunk road, and the logarithm of village per capita income. Table 2 reports the descriptive statistics of variables in the model.

4. Impact of ICTs on Agricultural TFP

4.1 Estimation of Farmer Households' Agricultural TFP

Table 3 reports the estimated results of the SFA model. Based on the parametric estimation results and equations (11)-(14), we may obtain a change in sample rural households' agriculture technical efficiency, technical progress, and TFP. Since the conclusions of the SFA model are considered to be highly dependent on the form of the model's function specification, this paper performs a likelihood ratio (LR) test on the model's specification in the following three aspects to ensure the robustness of estimation results: (i) Null hypothesis is that the frontier production function should adopt the C-D function form; (ii) null hypothesis is that technical progress does not exist; (iii) null hypothesis is that

[7] Since it is unreasonable to aggregate the quantities of different types of agricultural produce, this paper aggregates monetary incomes from agricultural produce as the output indicator, which have been adjusted for the agricultural production price index.

[8] Capital input is adjusted for the price index of the means of agricultural production.

Table 2: Descriptive Statistics of Variables

Variable	Variable specification	Mean	Standard deviation	Min.	Max.
Mobile phone signal	Connected=1; not connected=0	0.979	0.145	0	1
Internet	Connected=1; not connected=0	0.724	0.447	0	1
3G mobile network	Connected=1; not connected=0	0.301	0.459	0	1
Gender of household head	Male=1; Female=0	0.961	0.194	0	1
Age of household head	Years	54.761	11.063	18	91
Education of household head	Years	6.549	2.454	0	15
Agricultural technical education or training	Yes=1; No=0	0.095	0.293	0	1
Proportion of household agricultural workforce	%	50.030	31.386	0	100
Household per capita arable land area	*mu*	2.515	3.497	0	30
Household per capita income	yuan	7,693.269	5,801.189	1,166.620	39,905.950
Distance between village and trunk road	km	3.029	3.994	0	20
Village per capita income	yuan	3,854.648	1,787.224	565.337	14,861.820

Note: Price adjustments have been made for household per capita income and village per capita income.
Source: Data from the National Rural Fixed Point Survey.

Table 3: Estimated Results of Panel Fixed Effect with the SFA-Malmquist Model

	Estimated coefficient	Standard error
$\ln k$	0.108^{***}	0.024
$\ln l$	0.077^{***}	0.017
$(\ln k)^2$	0.044^{***}	0.002
$(\ln l)^2$	0.048^{***}	0.002
$\ln k \ln l$	-0.044^{***}	0.003
$t\ln k$	-0.001	0.001
$t\ln l$	0.004^{***}	0.001
t	0.014^{***}	0.005
t^2	-0.001^{***}	0.000
Sigma_u	0.229^{***}	0.004
Sigma_v	0.241^{***}	0.003
Lambda	0.953^{***}	0.006
Likelihood	-4439.191	
Observations	14,943	

Notes: (i) Both input and output variables are standardized with land input; (ii) *, ** and *** respectively denote significance at 10%, 5% and 1%.

Table 4: Comparison of Agricultural TFP, Technical progress and Technical Efficiency of Rural Households Connected and Not Connected to ICTs

	Not connected			Connected		
	Observations	Mean	Standard deviation	Observations	Mean	Standard deviation
Mobile phone signal						
TFPCH	265	0.946	0.201	12,108	0.998	0.136
TECH	265	1.014	0.005	12,108	1.001	0.011
EFFCH	265	0.933	0.198	12,108	0.997	0.135
Internet						
TFPCH	3,413	0.991	0.167	8,960	0.999	0.124
TECH	3,413	1.008	0.009	8,960	0.999	0.011
EFFCH	3,413	0.982	0.166	8,960	1.000	0.124
3G mobile network						
TFPCH	8,187	0.999	0.142	3,524	0.988	0.121
TECH	8,187	1.006	0.009	3,524	0.990	0.007
EFFCH	8,187	0.993	0.140	3,524	0.998	0.122

Source: Survey by authors and data from the National Rural Fixed Point Survey.

technical progress is Hicks-neutral. With LR statistic, it can be found that all the three null hypotheses are rejected, and that most variables in the model's estimate results are highly significant. The implication is that the SFA model chosen in this paper has a good fit, which paved the way for further estimation with the DID model.

Table 4 presents the initial statistical results of agricultural productivity, technical progress and technical efficiency of rural households connected and not connected to ICTs.

4.2 Test of Assumptions with the DID Method

This study is based on the assumption that the time of a village's access to ICTs was not subject to pre-existing agricultural TFP. Yet ICTs are not strictly exogenous. The government or telecom operators would decide when to build ICT infrastructure in a locality according to its economic development level, population and market potentials. These factors may be related to the level of agricultural development in the locality. For instance, high agricultural productivity is associated with economic prosperity that increases a village's chance to be connected to ICT infrastructure, and vice versa. To exclude the impact of such endogeneity, this paper performs the Cox regression for duration analysis to test the above assumption referencing Beck *et al*. (2010).

Duration analysis, also known as "conversion analysis" or "survival analysis," investigates the time it takes for an individual to shift from one state to another. In empirical research, the explained variable of duration analysis is the duration of a certain activity. As a common method for duration analysis, the Cox regression model is widely applied to estimate the impact of various factors on the survival times. In this paper, the Cox regression model is employed to test whether agricultural productivity would influence the duration of a village's lack of access to ICTs, i.e. whether agricultural TFP would influence

Table 5: Impact of Agricultural TFP, Technical progress and Change in Technical Efficiency on the Time of Access to ICT Infrastructure

	Mobile phone signal	internet	3G mobile network
Logarithm of agricultural TFP	0.346(1.296)	0.614(1.802)	0.051(1.875)
Control variable	Yes	Yes	Yes
Likelihood	-97.47	-83.29	-77.25
Observations	40	135	269
Logarithm of agricultural technical progress	-1.222(13.915)	-23.081(55.666)	-6.579(45.996)
Control variable	Yes	Yes	Yes
Likelihood	-97.48	-83.27	-77.24
Observations	40	135	269
Logarithm of change in agricultural technical efficiency	0.365(1.344)	0.641(1.811)	0.069(1.876)
Control variable	Yes	Yes	Yes
Likelihood	-97.47	-83.29	-77.25
Observations	40	135	269

Notes: (i) Numbers in parentheses are standard errors; (ii) *, ** and *** denote significance at 10%, 5% and 1%, respectively; (iii) control variables include whether the village is located in mountainous area, the village's year-end permanent population, the village's distance to trunk road, and the logarithm of the village's per capita income. Estimated results are omitted in the interest of length.

the time of villages' access to mobile phone signal, the internet and 3G mobile network. In this paper, the beginning year of samples is 2005, and the survival time is the duration from 2005 to access to ICT infrastructure. The independent variable is the mean of rural households' agricultural TFP in various villages, and control variables include the permanent year-end population of the village, the logarithm of per capita income, whether the village is located in mountainous areas, and the distance between the village and a trunk road. Aside from agricultural TFP, this paper has also tested the relationship between agricultural technical progress/change in technical efficiency and the time of access to ICTs.

Table 5 shows the model's estimated results. The Cox regression results reveal that agricultural TFP, technical progress and technical efficiency would not change the time of the village's access to ICT infrastructure of whichever type, i.e. reverse causality did not exist. This result provides confidence for this paper's use of the DID method to identify the impact of ICTs.

4.3 Analysis of Results Estimated with the DID Model

With the DID model, this paper compares the average difference in the agricultural TFP between villages connected to the three types of ICT infrastructure and those not connected. Table 6 through Table 8 present the estimated results.

The estimated results suggest that mobile phone signal, internet and 3G mobile network connections have exerted significantly positive effects on agricultural productivity, and that such effects primarily stemmed from increased agricultural technical efficiency. This implies that ICT applications in the countryside have indeed contributed to agricultural productivity and efficiency. While inducing a rural labor migration, ICT applications did not impede growth in agricultural technical efficiency and TFP by causing a brain drain. Instead, ICT applications led to an improving structure of agricultural production

Table 6: Impact of Mobile Phone Signal Connection on Rural Households' Agricultural TFP, Technical progress and Change in Technical Efficiency

	Logarithm of agricultural TFP	Logarithm of agricultural technical progress	Logarithm of change in agricultural technical efficiency
Mobile phone signal	0.057***(0.018)	0.000(0.000)	0.056***(0.018)
Gender of household head	0.008(0.010)	-0.001**(0.000)	0.009(0.010)
Age of household head	0.000(0.000)	0.000(0.000)	0.000(0.000)
Educational level of household head	-0.005**(0.002)	0.000(0.000)	-0.005**(0.002)
Agricultural technical education or training	0.009(0.008)	0.001***(0.000)	0.009(0.008)
Proportion of agricultural workforce in household	0.000(0.000)	0.000***(0.000)	0.000(0.000)
Household per capita arable land area	-0.006***(0.001)	-0.000***(0.000)	-0.005***(0.001)
Logarithm of household per capita income	0.035***(0.004)	0.000***(0.000)	0.035***(0.004)
Distance between the village and trunk road	0.004***(0.001)	-0.000**(0.000)	0.004***(0.001)
Logarithm of village per capita income	0.024***(0.004)	0.000***(0.000)	0.023***(0.004)
Intercept	-0.543***(0.058)	0.012***(0.001)	-0.555***(0.058)
R^2	0.040	0.957	0.035
Observations	12,285	12,285	12,285

Notes: (i) All the models have controlled for the fixed effect of farmer households and the fixed effect of year; (ii) numbers in parentheses are standard errors; (iii) *, ** and *** denote significance at 10%, 5% and 1%, respectively, and the same below; (iv) all the fixed-effect models have adopted the Robust square structure to correct the cross-sectional heteroscedasticity, and the same below.

Table 7: Impact of Internet Access on Agricultural TFP, Technical progress and Change in Technical Efficiency

	Logarithm of agricultural TFP	Logarithm of agricultural technical progress	Logarithm of change in agricultural technical efficiency
Internet	0.013***(0.005)	0.000(0.000)	0.013***(0.005)
R^2	0.038	0.957	0.033
Observations	12,285	12,285	12,285

Notes: All the models have controlled for control variables, the fixed effect of farmer household, and the fixed effect of year. Control variables are the same with Table 6 with similar coefficients. In the interest of length, control variables are not shown in this paper, but available upon request. The same as in the following table.

Table 8: Impact of 3G Mobile Network Connection on Agricultural TFP, Technical progress and Change in Technical Efficiency

	Logarithm of agricultural TFP	Logarithm of agricultural technical progress	Logarithm of change in agricultural technical efficiency
Internet	$0.010^{**}(0.005)$	0.000(0.000)	$0.010^{**}(0.005)$
R^2	0.039	0.957	0.034
Observations	11,623	11,623	11,623

factors and raised agricultural efficiency by enabling economies of scale. According to our survey, an agricultural household invested 4,502.96 yuan on average in agricultural machinery in 2016, up 30% over 2005. Obviously, part of the labor force is effectively replaced by agricultural mechanization, which has raised agricultural technical efficiency and TFP.

Many international academics have found a positive impact of ICTs on the adoption of advanced agricultural technology by rural households (Adegbola and Gardebroek, 2011; Larochelle *et al*., 2019, *et al*.). However, their conclusion is not supported by this paper's estimated results. A possible reason is that China's agriculture remains in a transition stage from traditional to modern agriculture (Li, *et al*., 2009). In this stage, ICTs are yet to be fully integrated into agricultural technology, not to mention the lack of competence of Chinese farmers, in general, to apply ICT-based technologies. It should be noted that this result is not contradictory with the mass applications of new agricultural technologies in China. The only implication is that observable technical progress may not be caused by ICT development.

5. Robustness Test

5.1 Counterfactual Test

Through the DID model test in the preceding section, this paper found that the three types of ICT infrastructure all exerted significant effects on the agricultural technical efficiency and TFP of rural households. However, we did not know for sure whether these effects were attributable to access to ICTs. If ICT infrastructure was built in a year when another event also occurred that significantly influenced agricultural production, the estimated result would contain the impact of other factors or policies. To verify the existence of such a possibility, we have specified three dummy times of access to the three types of ICT infrastructure for each village for a counterfactual test. We selected the periods from the starting year (2005) of samples to the midpoint years before connection to ICT infrastructure. For instance, if a village was connected to the internet in 2009, its virtual time is specified to be 2007. If the test result remains significant, the implication is that significant change had already occurred in the dependent variable with which this paper is concerned before access to the ICT tools, and that the estimated result of the above DID method is likely to contain other unobserved factors.

Judging by the estimated results of Table 9, after the dummy year is defined as the time truncation point, none of mobile phone signal, the internet and 3G mobile network had any significant impact on agricultural TFP and change in technical efficiency, which excludes the possibility that exogenous factors and ICT applications influenced agricultural TFP at the same time. That is to say, this paper's estimated results are relatively robust and reflect the role of ICTs. As far as the test result of agricultural technical progress is concerned, the effect of access to the internet is significantly positive, but the coefficient of

Table 9: Counterfactual Test

	Logarithm of agricultural TFP	Logarithm of agricultural technical progress	Logarithm of change in agricultural technical efficiency
Mobile phone signal	0.055(0.055)	0.001(0.001)	0.054(0.054)
R^2	0.027	0.944	0.024
Observations	7,341	7,341	7,341
Internet	0.012(0.010)	0.001***(0.000)	0.011(0.010)
R^2	0.032	0.930	0.031
Observations	4,788	4,788	4,788
3G mobile network	-0.000(0.006)	0.000(0.000)	-0.000(0.006)
R^2	0.033	0.931	0.032
Observations	4,668	4,668	4,668

Notes: (i) All models have controlled for control variable, the fixed effect of farmer households, and the fixed effect of year; (ii) numbers in parentheses are standard errors.

effect is rather small (0.001) and shows no significant impact in the benchmark model. Therefore, the robustness of this paper's results is not affected.

5.2 Test of Propensity Score Matching Method (PSM)

To exclude the long-term trend interference that may exist, this paper again employs the DID method for a test with the propensity score matching (PSM) method, i.e. samples are matched before regression. Specifically, we select various indicators of rural households one year before they were connected to ICT infrastructure for propensity score matching with the indicators of rural households who were not connected to ICT infrastructure in the same year.[9] For rural households connected to the internet in 2008, as an example, we matched their various indicators of 2007 with the 2007 data of rural households who were not connected to the internet in 2008. After matching the data of various years, we excluded samples outside the common support area and finally used matched samples to re-perform the DID analysis. Since only a small proportion of rural households were not connected to mobile phone signal, so that data volume cannot be properly matched, this paper only tests the effects of access to the internet and 3G mobile network.

As can be seen from the estimated results in Table 10, the matched results are consistent with the benchmark model's results, and after excluding the long-term trend interference, the impact of ICT applications becomes larger. Hence, ICT applications are further proven to have generated growth effects

[9] Matched covariates include 16 variables about village, household and household head characteristics: Whether the village is located in mountainous area; year-end village prominent population; distance between village and trunk road; village per capita income; type of farmer household; chief source of household income; main business operated by the household; whether any family member is a national government cadre; whether any family member is a countryside government cadre; family size; per capita arable land area; per capita income; gender, age and education level of household head; whether household head has received any agricultural technical education or training. This paper has selected the radius matching method with the radius specified to be 0.001. In the interest of length, the matching results are not displayed.

Table 10: Propensity Score Matching (PSM) Test

	Logarithm of agricultural TFP	Logarithm of agricultural technical progress	Logarithm of change in agricultural technical efficiency
Internet	0.019**(0.009)	0.000(0.000)	0.019**(0.009)
R^2	0.043	0.950	0.035
Observations	5,847	5,847	5,847
3G mobile network	0.016**(0.007)	0.000(0.000)	0.016**(0.007)
R^2	0.038	0.942	0.031
Observations	8,264	8,264	8,264

Notes: (i) All models have controlled for control variable, the fixed effect of farmer households, and the fixed effect of year; (ii) numbers in parentheses are standard errors.

on agricultural TFP and technical efficiency.

6. Conclusions and Policy Implications

Based on rural households' data from the National Rural Fixed Point Survey of 2004-2016 and supplementary survey on access to ICTs in some villages, this paper employs the DID method to estimate the effects of mobile phone signal, the internet and 3G mobile network on agricultural TFP, including technical progress and technical efficiency. Our study finds that ICTs have contributed to agricultural TFP improvement mainly by raising agricultural technical efficiency. However, the impact of ICTs on agricultural technical progress is insignificant during this paper's research period probably due to rural human capital constraints. In the robustness test, counterfactual and matching methods have led to similar results.

This paper's conclusions are of great policy significance. As a large agricultural producer, China is yet to enhance the quality, competitiveness and productivity of its agricultural sector. In this historic process, the integration between ICTs and agriculture offers great potentials. As can be learned from the estimated results in this paper, ICTs have indeed significantly raised agricultural TFP and technical efficiency. However, the lack of human capital in the countryside presents a hindrance to ICT integration in agriculture that would otherwise have brought about more agricultural technical progress. While expediting rural ICT applications, China should attach great importance to encouraging and training rural households to apply ICTs, fostering rural ICT experts and professional farmers, and raising rural workforce's technical competence as an essential human capital condition for further ICT applications in agriculture. Efforts should also be made to increase agricultural economies of scale and mechanization to compensate for the rural brain drain and raise efficiency.

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