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DIGITAL ECONOMY AND THE DRIVERS OF TOTAL FACTOR PRODUCTIVITY IN AGRICULTURE: AN EMPIRICAL EXAMINATION OF CHINA'S ECONOMY

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Abstract

The digital economy, represented by a new generation of digital technologies such as cloud computing, big data and artificial intelligence, is accelerating its penetration and integration into all areas of the economy and society, expanding the new space for economic development. The digital economy is playing an important role for countries all around the world in achieving inclusive growth and sustainable development, and has become an important driving force for high-quality economic development. Therefore, the current study considers the impact that the level of development in the digital economy calculated using the Entropy TOPSIS (technique of the order of preferences by similarity to the ideal solution) evaluation method, can have on total factor productivity in Chinese agriculture. In order to achieve this purpose, a panel data estimation method was used. For the sample, a representative sample of 19 major provinces of agricultural production in China were short listed, and time series data was collected for each of the province covering a time horizon of 2011-2019. Based on the unit root estimation, the current study adopted a fixed and random effects modelling approach. Besides, the Hausman test was used in order to check the appropriate analytical approach. In addition, this paper tries to incorporate the mediating role of education in this regard. The estimates derived from the fixed effects model analysis shows that the level of development of the digital economy contributes significantly to the total factor productivity of agriculture. Generalized method of movement (GMM) has confirmed the mediating contribution of education. In this research, urbanization, upgrading of industrial structure, inflation, seed technology, agricultural labor productivity, and disposable income are considered as control variables and they confirmed static affiliation with agricultural total factor productivity. Therefore, it is required to integrate the role of urbanization, industrial upgrading, labor productivity, modern technology and education in the formulation of policies related to digital economy development and agricultural total factor productivity.

1. Introduction

Long time ago, history recognized that agriculture growth is an imperative key for economic development (Johnston & Mellor, 1961). In both developed and the developing economies large portion of population are, either directly or indirectly associated with agriculture sector. However, as because of increased population, urbanization, diminishing marginal returns, decrease in the area of irrigated land, and the shortage of natural resources agricultural productivity tend to diminishes (Chen, 1997; and Warr, 2004). Hence, researchers and policy makers divert their attention towards the mean of uplifting agricultural productivity. It was disclosed that along with multiple socio-economic, and macro-economic factors digital economic growth also reckons a static place in the determination of agricultural productivity and growth (Nesterenko & Ritcher, 2020; and Liu, *et al*. 2022). With the passage of time, digital economy development not merely confirmed direct association with the total factor productivity, and economic growth. Besides, it also reckons a static place in advancement, upgrading, and promotion of industry structure (Kaike *et al*., 2020; and Yunhong & Heng, 2020). Digital economy development has transformed supply structure of the traditional factors and has improved factor allocation and efficiency (Lingjie & Liping, 2022). Ding Zhifan (2020) curtails that digital economy mechanism influence on economic development operates via three platforms that are enterprise development level, industrial innovation, and the elements. Digital economy development drives innovation supply and demand, promotes transform, and upgrade traditional industries that in the end results in the form of productivity growth and high economic development (Thompson & Garbac 2007; and Guoan, & Lin, 2019). Additionally, studies disclosed that digital economy development upsurge economic scale, promote R&D investment, improve coordination amid factors, and raise portion of high-end factors that in sum results in the form of improved production efficiency (Thompson & Garbac 2007; and Kaike *et al*., 2020). By considering all these assessment, this research explicate an in-depth analysis about digital economy development role in the promotion of total factors productivity growth via optimizing advance industrial structure, R&D (research & development) expenditures on industry, level of urbanization, and average schooling. The aim of this research is to integrate the impact of digital economy development on TFP (total factors productivity) in agriculture sector. Current study utilizes panel data estimation approach for the case selected regions of China. Time series data employed over the time frame 2011-2019, and fixed and random effect modeling is applied for checking long run affiliation between the examined factors of this study. The questions to be answered in the study are the following:

1. Does the development of the digital economy have an impact on agricultural TFP?
2. What is the impact of urbanization, R&D expenses, and education on the DEDI (digital

economy development index) and TFP relationships respectively?

2. Literature Review

Both the empirical and theoretical studies had documented the significance of total factor productivity for long-run economic growth (Solow, 1956; Kendrick, 1961; Otani & Viallanueva, 1990; Baier, Dwyer, & Tamura, 2002; and Jajri, 2007). Usually, researchers decomposed total factor productivity in disembodied and embodied technological change (Alston *et al*. 1998). Embodied technological change is stated as the change that apprehends factor inputs, for example improved breeds, seeds, or a new machinery (Kartz, 1969; and Bhaita, 1990). A large numbers of factors discovered by researchers that directly or indirectly determines TFP. For example, financial assistance of government had incurred positive association with TFP in China (Zhong, Hu, & Jiang, 2019). Fassio, Kalantaryan, & Venturini, (2020) demonstrated interrelationship between foreign human capital and total factors productivity which was proven statistically significant. Besides, contribution of agricultural total factors productivity in determining economic growth is highly remarkable. Agriculture sector plays a vital role in stimulation of TFP both in livestock and crop sectors (Johnston & Mellor, 1961; and Suphannachart & Warr, 2012). Agricultural growth also evolves living standards of rural inhabitants, uplift input factors efficiency, and assist in the maintenance of exports competitiveness (Chen, 1997; and Warr, 2004). Furthermore, Nelson *et al*. (2014); Zhong *et al*. (2015); and Bruke & Emerik (2016) initialized empirically significant involvement of global climate and biophysical shocks change with agriculture sector. While, some disclosed its role or association with industry sector (Krupina *et al*. 2020; and Li, *et al*. 2020). Also, there are some studies which reflects factors that determines agricultural total factor productivity. Likewise, Zhang and Hu, (2020) represented innovative human-capital as a primal determinant of agricultural total factor productivity. Environmental regulation was also provoked as a static determinant of agricultural total factor productivity (Li & Wu, 2017). Since from 20th Century, digital economy tends to capture the attention of researchers (Baryshnikova, Sukhorukova, & Naidenova, 2019). Rifkin (2011) labelled technological advancement as the third industrial revolution, for the first time. In this concern, Schwab (2016) introduced fourth industrial revolution, in this terminology he combined biological, physical, and digital world in one space. A vast number of literature studies had highlighted determinants of digital economy. Likewise, affiliation of digital economy with socio-economic development was also taken into consideration (Baryshnikova *et al*., 2019). It was also revealed that internet, information, and communication infrastructure promotes electronic commerce development that in turn provokes urbanization, industry sector development, and also economic growth (Lin, 2019). Antipina (2108); Liu, and Zhang (2018); Chen & Cai

(2019) highlighted changes and effect on business activities as a result of transition to digitalization. Additionally, some researchers were also concerned about digital economy influence on economic growth (Castells, 1996; Madden & Savage, 2000; Dedrick, Gurbaxani, & Kraemer, 2003; Guo & Luo, 2016; and Nobre & Tavares, 2017). Despite this vast number of researches, there were only few studies that were considering impact of digital economy and technology on agricultural total factor productivity. Griffith *et al*. (2013) leveraged the impact of digital economy and broadband on smart farming in Australia. Significant possible benefits obtained from southern livestock industries as because of broadband, R&D investment, and digital economy (Griffith *et al*. 2013). Digitalization of agriculture in context of risk and strategic opportunities was also tested (Baryshnikova *et al*., 2019). Digital agriculture is one of the major driver of socio-economic efficiency and productivity level. Li, *et al*. (2020) determined the impact of internet development on green total factors productivity. A digital divide was found amid the different regions of China. As human capital exceeds threshold level, the impact of internet development on GTFP (green total factors productivity) tend to undergone a major structure change (Li, *et al*. 2020; and Zixun & Yahong, 2021). A complex nature of regional disparities, digital economy, and total factors productivity in context of Agriculture of China was taken into account (Jinghua & minmin, 2020; Subaeva, Nizamutdinov, & Mavieva, 2020; and Zixun & Yahong, 2021). A complex nature digital paradox in China's economy was also displayed (Yang, *et al*. 2020). Platform economy had an inverted U-shape association with high quality economic development. At the inflection point, right side platform economy had confirmed inhibitory affect while on the left side it confirmed affirmative and significant association with high quality economic development (Yang, *et al*. 2020). Institutional quality and regional disparities significantly influenced the U-shape association (Yang, *et al*. 2020). Additionally, changes incurred due to digitalization on potential of labor engaged with Agri. sector in the economy of Russia was covered by Subaeva, Nizamutdinov, & Mavieva, (2020). A one step ahead, digital economy efficiency with Agri-industrial complex was studied. SWOT (strength, weakness, opportunity, and threat) estimates shown that rational and intensive implementation of internet and digitalization in Agricultural sector will cause a high-tech turn in industry sector as of explosive productivity growth in Agriculture that in turn lower down the non-productive cost (Krupina, *et al*. 2020). Large database technology will play a static role in precision farming that in turn promotes a new wave of digital revolution (Nesterenko, and Ritcher, 2020). Hence it is proved that digital economy significantly promotes green total factors Productivity (Krupina, *et al*. 2020). Henceforth, Liu *et al*. (2022) incorporated influence of industrial structural development on digital economy and green total factors productivity affiliation. Digital economy influence on GTFP varies amid different regions and the development of industry structure significantly influences inter-correlation between GTFP and digital economy (Liu, *et al*. 2022). Pan in their study emphasized digital economy as an innovational driver of total factor productivity (Pan, *et al*. 2022). As because of regional diversities (that appears as because of cross-regional barriers in the way of launching new corporative programs, introducing technical innovation, and decentralization of infrastructure) digital integration accelerates high TFP in eastern China as compared to western and central regions (Pan, *et al*. 2022). Evolution and characterization of digital economy was also addressed. As it's already cleared that digital economy has had spatial spillover impact on regional green development. Plant-root network structure analysis revealed that self-organization do improve productivity and also influenced psychological behaviors (Zhou, Han, & Wang, 2022). Li and Xue (2022) integrated Interrelationship between regional total factor productivity and digital economy using fuzzy hierarchic VISC-algorithm. By using this methodology, information model capacity will be high, the digital economy utilization efficiency and TFP influence capacity might be improved. Hence why, researcher aimed to look at the inter-correlation between agri. total factor productivity and digital economy of selected regions of China. Aim of this research is to integrate role of digital economy in stimulation of total factor productivity in Agriculture sector of China's economy. In this section, researcher exhibited some crucial studies dominating in literature from past few years about digital economy and agriculture productivity. Along with digital economy and total factor productivity there is need to highlight factors that directly or indirectly may influence their association. However, in this regard, only a little work was done, few researches considered TFP and digital economy affiliation and do highlight the distressing variables between them. Such as infrastructure development (Yang *et al*. 2020); institutional quality (Nesterenko & Ritcher, 2020); lobar productivity, human capital (Li, *et al*. 2020); international trade Li & Xue, 2022); financial assistance from government (Zhong, Hu, and Jiang, 2019); Agri-industrial complex (Krupina *et al*. 2020); institutional quality and regional disparities (Yang *et al*. 2020); development of industry structure (Liu *et al*. 2022) and so on. Out of them, only one or two considered regional disparities prevailed in context of digitalization of agricultural TFP.

Based on the above analysis, this study proposes the following four hypotheses.

1. Hypothesis-1:

H01 = level of digital economy development significantly determines TFP in agriculture.

2. Hypothesis-2:

H02 = urbanization negatively associated with TFP.

3. Hypothesis-3:

H03 = Complex Agri-industrial association is a misconception.

4. Hypothesis-4:

H04 = Mediating role of education in effecting TFP and DEDI association. Henceforth, this paper tries to incorporate role of digital economy index in stimulation of agri. total factor productivity at provincial level. Researcher selected 19 big regions of China's economy that are largely dependent on agriculture sector. These regions were chosen because these 19 provinces account for more than 86% of China's total agricultural population, and they are China's major grain-producing regions, providing an important guarantee for China's food security. Research on 19 major agricultural provinces to determine the impact of China's digital economy on total factor productivity in agriculture, an important reference value for digitizing agriculture and improving the efficiency of the agricultural economy. Besides, with regard to the level of development of the digital economy, this research uses the Entropy-weighted TOPSIS method for estimation. Plus point of this method is that this approach successfully dodges subjective factors influence in the practice of allocating indicators.

3. Research data and sources

3.1 Measuring the level of development of the digital economy

At present, there are relatively few relevant studies involving the specific measurement of the digital economy: (Liu Jun *et al*., 2020) constructed a digital economy evaluation index system for China's sub-provinces from three dimensions: informatization development, Internet development and digital transaction development, and measured the data of 30 Chinese provinces from 2015 to 2018. Drawing on (Liu Jun *et al*., 2020) idea of constructing an indicator system that takes Internet development as the core of measuring the development level of the digital economy and adds digital transactions, this study measures the comprehensive development level of the digital economy in terms of both Internet development and digital financial inclusion, taking into account the availability of data related to China's 19 major agricultural production provinces. For this aspect of Internet development measurement, four indicators in terms of Internet penetration, related practitioners, related output and mobile phone penetration are used, drawing on the methodology of (Zhao Tao *et al*., 2020). The actual content of the above four indicators corresponds to: the number of Internet broadband access users per 100 people, the proportion of employees in the computer services and software industry to the number of employees in urban units, the total amount of telecommunication services per capita and the number of mobile phone users per 100 people. The raw data for the above indicators can all be collected from the China Urban Statistical Yearbook. For digital finance development, the China Digital Inclusive Finance Index was used, which was jointly compiled by the Digital Finance Research Centre of Peking University and Ant Financial Services Group (Guo Feng *et al*., 2020). The development level of the digital economy in this study was estimated using the Entropy TOPSIS method (Noted as DEDI). The Entropy TOPSIS method can effectively avoid the influence of subjective factors in the process of index assignment, and also has the advantages of a simple calculation process and reasonable measurement results of both the Entropy and TOPSIS methods, which can reasonably measure the development level of the digital economy.

Table 1: Indicator system for calculating the Digital Economy Development Index

variable	**Secondary indicators**	**Territory indicators**
Digital Economy Development Index	Internet penetration rate	Number of Internet users per 100 population
	Number of Internet-related workers	Percentage of people employed in computer services and software
	Internet-related output	Total telecommunication services per capita
	Number of mobile Internet users	Mobile phone subscribers per 100 population
	Digital Financial Inclusion Development	Digital Financial Inclusion Index

Source: Authors own calculation

In the above displayed table, estimation process of DEDI has been exhibited in a precise manner. Moreover, this table also replicates variables utilized in the calculation of DEDI for the selected regions of China. Internet perception rate, Number of Internet-related workers, Internet-related output, Number of mobile Internet users, and Digital Financial Inclusion Development are the factors that in sum integrates digital economy development index. This study uses the Super-SBM model to measure total factor productivity in agriculture. Data Envelopment Analysis (DEA) is a non-parametric efficiency analysis method that can be used to evaluate the relative efficiency of multiple decision making units (DMUs) with multiple inputs and outputs. To address the problem of slackness of variables and the measurement error caused by radiality, Tone (2001) proposed a non-radial, non-oriented SBM data envelopment analysis model based on slack variables. However, the traditional SBM model is unable to differentiate and sort multiple equally valid cells, and on this basis Tone proposed a super-efficient SBM model to solve this problem. The Super-SBM is utilized to measure regional total factor productivity in agriculture sector of China. Specifically, the total output value of agriculture, forestry, livestock and fisheries in each region was selected as the output indicator. Input indicators include labor, land, agricultural machinery, fertilizer and irrigation. Specifically, labor force is replaced by the number of people employed in the primary sector in each region, land area is replaced by the area of crops sown in each region, agricultural machinery is replaced by the total power of agricultural machinery, fertilizer input is replaced by the amount of fertilizer applied, and irrigation is replaced by the area of irrigated arable land.

Table 2: Total Factor Productivity Calculation

variable	Secondary indicators	Territory indicators
Total Factor Productivity in Agriculture	Inputs	Employees in the primary sector
		Crop sown area
		Total power of agricultural machinery
		Fertilizer application
	Outputs	Total agricultural output

Source: Authors own calculation

In the above displayed table, estimation process of TFP has been exhibited in a precise and clear manner. Besides, this table also represents indicators utilized in the calculation of TFP for the selected regions of China's economy. Employees in the primary sector, crop sown area, and total power of agricultural machinery, fertilizer application, and total agricultural output are the indicators that in sum integrates digital economy development index.

4. Materials and Methods

4.1. Models Description

This research occupies a panel data of the selected regions of China over the time frame 2011 to 2019. Selected regions under this research are Anhui, Fujian, Guangxi, Guizhou, Hebei, Heilongjiang, Henan, Hubei, Hunan, Inner Mongolia, Jiangsu, Jiangxi, Jilin, Liaoning, Shaanxi, Shandong, Sichuan, Yunnan, and Zhejiang. Data for examined series has been collected from well recognized and authentic platforms such as statistical yearbook of China's economy, China science and technology statistical yearbook, and so on. Overall, all the relevant data has been collected from China Urban Statistical Yearbook, China Rural Statistical Yearbook, selected provincial statistical yearbooks and from annual reports, statistical bulletins, and the Wind Information database. As we discussed, this research probes in the association of digital economy development and total factor productivity. However, for statistical estimation hybrid OLS, fixed & random effect modeling, generalized method of movement (GMM), and Tobit is employed. Mainly, this research has been grounded on the following econometric model:

$$TFP_{it} = \beta_{0it} + \beta_1 DEDI_{it} + \beta_2 URB_{it} + \beta 3LAISit + \beta 4LNCPIit + \beta_5 ST_{it} + \beta_6 ALP_{it} + \beta_7 EDU_{it} + \beta_8 LDI_{it} + u_{it}$$

In the subsequent model-1, for examining inter correlation between total factor productivity and digital economy researcher utilized TFP (calculated by author using DEA-Malmquist index) as dependent variable. While, DEDI (calculated by author using Entropy weighted TOPSIS evaluation) as an independent variable. Here, control variables are urbanization, log of advance industry structure upgrading index (LAIS), log of CPI, seed technology (ST), agricultural labor productivity (ALP), education enrollment (EDU), and log of disposable income. In this model, spot light is thrown only on the affiliation between digital economy development and TFP. Then, TFP (dependent variable) is decomposed in two components named technical efficiency (EC) and technical progress (TC), and the following two models (model-2 and model-3) are constructed;

$EC_{it} = \beta_{0it} + \beta_1 DEDI_{it} + \beta_2 URB_{it} + \beta 3LAISit + \beta 4LNCPIit + \beta_5 ST_{it} + \beta_6 ALP_{it} + \beta_7 EDU_{it} + \beta_8 LDI_{it} + u_{it}$

And,

$TC_{it} = \beta_{0it} + \beta_1 DEDI_{it} + \beta_2 URB_{it} + \beta 3LAISit + \beta 4LNCPIit + \beta_5 ST_{it} + \beta_6 ALP_{it} + \beta_7 EDU_{it} + \beta_8 LDI_{it} + u_{it}$

However, in order to integrate the mediating effect of education, following models are constructed;

$TFP_{it} = \beta_{0it} + \beta_1 DEDI_{it} + \beta_2 URB_{it} + \beta 3LAISit + \beta 4LNCPIit + \beta_5 ST_{it} + \beta_6 ALP_{it} + \beta_7 LDI_{it} + u_{it}$

In the above model-4, TFP (dependent variable) affiliation with DEDI (explanatory variable) is checked with control variables. However, education (mediating factor) is not taken into consideration.

$DEDI_{it} = \beta_{0it} + \beta_1 URB_{it} + \beta 2LAISit + \beta 3LNCPIit + \beta_4 ST_{it} + \beta_5 ALP_{it} + \beta_6 EDU_{it} + \beta_7 LDI_{it} + u_{it}$

In the above displayed model-5, effect of education (mediating factor) on DEDI (explanatory variable) is examined. In the end of mediating mechanism testing, model-1 is tested, but this time DEDI is considered equal to zero.

In the subsequent section, abbreviated terms in models are presented:

TFP= Total factor Productivity

DEDI= Digital Economy Development Index

URB= Urbanization

LAIS= Log of Advance Industrial Structure upgrading index

LNCPI= Log of CPI inflation

ST= Seed Technology (log of annual seed industry innovation)

ALP= Agricultural Labor Productivity (total output value of agriculture, forestry, animal husbandry and fishery/employees in the primary sector)

EDU= Education (Average Year of schooling)

LDI= Log of Disposable Income

EC= Technical Efficiency

TC= Technical progress

ε = Error term

Besides, β0 reflects constant or intercept term. However, *β1 β2, β3, β4, β5, β6, β7, β8,* indicates coefficients that's need to be examined. The "t" reflects time period from 2011-2019 and the "i" represents provinces. Interrelationship or the variables utilized in the research are also exhibited in the following diagram.

4.2. Descriptive Statistics

For statistical estimation Eviews-9 software is used. It replicates large data set into a precise, arrange, and summarized manner. This estimation, highlights key features of the examined data series such as its average tendencies, range of data set (max. & min.), total number of observation, sum value, and standard deviation from actual mean. It also displays normality of distribution under consideration via skewness and kurtosis (Fisher, & Marshall, 2009). For better understanding see following results;

Table 4: Descriptive Statistics

Statistics	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Probability	Observations
TFP	1.0493	1.0855	1.9004	0.3897	0.2314	-0.9376	5.2873	0.0000	171
DEDI	0.2145	0.2191	0.4268	0.0226	0.0904	-0.1632	2.3855	0.1782	171
URB	0.551	0.557	0.7247	0.3503	0.0838	-0.1403	2.2834	0.1212	171
LAIS	3.7568	3.769	4.0448	3.3911	0.1433	-0.2214	2.2126	0.0546	171
LNCPI	4.6294	4.6267	4.6625	4.6138	0.0116	1.5006	4.5973	0.0000	171
ST	4.1836	4.304	6.4264	0.6931	1.0103	-0.4657	3.2855	0.0339	171
ALP	4.2329	3.9511	10.2171	0.8475	1.7551	0.8804	3.901	0.0000	171
EDU	8.9504	8.9823	10.1049	7.5886	0.5103	-0.5199	3.1536	0.0195	171
LDI	9.3042	9.3142	11.6347	8.3297	0.398	1.064	8.9518	0.0000	171
EC	1.0238	1	1.7904	0.665	0.148	2.1635	11.0162	0.0000	171
TC	1.0391	1.1014	1.3998	0.4	0.2288	-1.8752	5.5443	0.0000	171

Source: Authors calculations using Eviews

In the above exhibited table, descriptive statistics for selected variables is displayed. As we see that actual no. of observation in the data series for all listed variables is 171. However, each variable possesses different maximum and minimum values ranging from 11.63 (LDI) to 0.02 (DEDI). Besides, mean and median values shows average tendency for each variable. While considering overall standard deviation the highest deviation is confirmed by ALP (1.75). In order to check normality distribution and the tendency or shape of series skewness and kurtosis values are considered. Here, except LNCPI, ALP, LDI, and EC all other variables (TFP, DEDI, URB, LAIS, ST, EDU, and TC) are negatively skewed. Furthermore, DEDI, URB, and LAIS are platykurtic while TFP, CPI, ST ALP, EDU, LDI, EC, and TC are leptokurtic. In the end sum of all data in a series, along with total number of observation is displayed. The following will analyse the correlations between the variables examined in this study. By using correlation matrix not only the nature of association (positive correlation or negative correlation) between two variables can be measured but also one can check degree of correlation from this estimation. In order to avoid problem of multi-colinearity we need to check that correlation between any two variables of this research must be less than 90 percent. As in case of high correlation one can face Multi- colinearity. Besides, each variables shows perfect correlation with itself, which is reflected through diagonal digit in the matrix (Steiger, 1980). For better understanding see following results; for better understanding see following results;

Table 5: Correlation Matrix

Variables	TFP	DEDI	URB	LAIS	LNCPI	ST	ALP	EDU	LDI	EC	TC
TFP	**1**										
DEDI	0.3292	**1**									
URB	0.0448	0.6094	**1**								
LAIS	0.1878	0.7775	0.4978	**1**							
LNCPI	-0.6227	-0.5448	-0.2314	-0.3819	**1**						
ST	0.0405	0.5284	0.3457	0.4932	-0.2039	**1**					
ALP	0.1442	0.6244	0.9016	0.5157	-0.2811	0.4257	**1**				
EDU	0.000612	0.3234	0.7924	0.1967	-0.1239	0.2005	0.6476	**1**			
LDI	0.09879	0.7998	0.6921	0.6330	-0.4052	0.5491	0.6991	0.4780	**1**		
EC	0.09544	-0.2987	-0.2710	-0.2131	0.3904	-0.2031	-0.2294	-0.2285	-0.3959	**1**	
TC	0.83811	0.4420	0.1670	0.2643	-0.7586	0.1550	0.2408	0.1319	0.2853	-0.4333	**1**

Source: Authors calculations using Eviews

Here, correlation or interrelationship among the examined variables of this research is exhibited. TFP confirmed perfect correlation with itself (shown by diagonal number, one). Besides, except LNCPI, TFP has confirmed positive correlation with all other variables DEDI, URB, LAIS, ST, ALP, EDU, LDI, EC, and TC. Furthermore, except LNCPI and EC, DEDI has confirmed positive correlation with all other variables TFP, URB, LAIS, ST, ALP, EDU, LDI, and TC. Similarly, URB has confirmed positive correlation with all variables TFP, DEDI, LAIS, ST, ALP, EDU, LDI, and TC while negative correlation with LNCPI and EC. Additionally, except EC, LAIS has confirmed positive correlation with all variables TFP, DEDI, URB, LAIS, ST, ALP, EDU, LDI, and TC. Although, LNCPI confirmed negative correlation with all variables, just EC confirmed positive association with LNCPI. And, ST, ALP, EDU, and LDI has confirmed affirmative association with all variables but LNCPI and EC are negative. Additionally, EC signified positive correlation with TFP and LNCPI but it shows negative correlation with other variables of the study. In the end, TC has confirmed positive correlation with all variables TFP, DEDI, URB, LAIS, ST, ALP, EDU, LDI, and TC while negative correlation with LNCPI and EC. All of the variables signified perfect correlation with themselves. Whenever, researcher employee time series data, the first step he needs to perform is unit root test. It shows either examined data series is stationary or not, or the problem of unit root confronts or not? Stationary check is a stochastic analytical procedure, in which unconditional joint distribution of probability may not change over the time frame. A series is referred as stationary, only if it fulfil following presented conditions;

1) E (Zt) invariant for the all "t"

2) Var (Zt) invariant for the all "t"
3) Cov (Zt, Zt+n) invariant for the all "t", also all the "n" are confirmed as non-zero. Mainly, a stationary series is a flat looking variable which is free from any kind of trend, invariant variance, and the invariant structure of auto-correlation. However, if any of the above condition violates it results in the form of unit root. For unit root estimation, LLC (Levin, Lin, and Chu) and IPS (Im-Pesaran-Shin) techniques has been utilized (Leybourne, & McCabe, 1994).

Table 6: Unit root test（Consider using the LLC test and IPS test)

Variable	**Differential pre-series**		**Stability**	**First order post-differential sequence**	**Stability**
	LLC test	**IPS test**		**LLC test**	
TFP	8.0667 (1.0000)	-3.2721* (0.0005)	**Stable**	-6.5635* (0.0000)	**Stable**
DEDI	-9.5127* (0.0000)	-0.3669 (0.3568)	**Stable**	-12.1714* (0.0000)	**Stable**
URB	-0.5663 (0.2856)	2.6308 (0.9957)	**Unstable**	-7.5328* (0.0000)	**Stable**
LAIS	-0.9551 (0.1698)	3.3900 (0.9997)	**Unstable**	-7.0661* (0.0000)	**Stable**
LNCPI	8.9135* (0.0000)	1.3751 (0.9155)	**Stable**	4.9727* (0.0000)	**Stable**
ST	7.5008* (0.0000)	5.9588* (1.0000)	**Stable**	-22.7526* (0.0000)	**Stable**
ALP	-4.5815* (0.0000)	1.2217* (0.8891)	**Stable**	-2.5279* (0.0057)	**Stable**
EDU	-10.6440* (0.0000)	-3.2746* (0.0005)	**Stable**	-18.2400* (0.0000)	**Stable**
LDI	-2.7797* (0.0027)	1.2102 (0.8869)	**Stable**	-6.4863* (0.0000)	**Stable**
EC	-5.0503* (0.0000)	-3.3312* (0.0000)	**Stable**	-4.1762* (0.0000)	**Stable**
TC	13.8315*	-2.3717*	**Stable**	5.9780*	**Stable**

	(0.0000)	(0.0089)		(0.0000)

Source: Authors calculations using Eviews **Note:** prob. Value is in (). And "*" shows significance at 1% level.

In above illustrated table, unit root estimation using 'common root test' and ''individual root test' presented by Levin, lin, & Chu and Im, Pesaran & Shin. Stationary for each variable has been checked on two grounds, at level (differential pre-series) and first difference (post differential series). All the examined variables of this results confirmed their statistical significance and has also rejected unit root possession. TFP, DEDI, URB, LAIS, LNCPI, ST, ALP, EDU, LDI, EC, and TC are statistically significant at 1% level of significance at the specified criteria of 1st difference. Although, at differential pre-series (level), except URB and LAIS all other variables such as TFP, DEDI, LNCPI, ST, ALP, EDU, LDI, EC, AND TC are statistically significant at 1% level of significance. In sum, as we see all examined variables of this research are co-integrated of I(0) but the two control variables (URB and LAIS) are insignificant here. Hence researcher decided to utilize OLS for analytical estimation. In Fixed effect modeling model parameters and group mean value of a population are non-random or they have fixed quantities. While in random effect modeling model parameters and mean value are random or they comprises non-fixed (random) quantities. For the case of panel data where longitudinal observations exist for the case of same subject fixed effect model symbolize the specific means of subject. Moreover, fixed effect modeling is persistent for individuals, while the random effect modeling tend to vary. Effects are non-random when sample (group) exhausts population. Also random for the case where sample size is a small fraction of whole population. A major difference between these two methodologies is that one (random effect modeling) considers constant term (or the impact of other variables, not included in our modeling). However, another one (fixed effect modeling) does not include intercept term and do consider it constant. Here, only the estimation approach changes, despite variables contained in all three models are similar to previous estimation. Almost all estimates obtained from random effect modeling confirmed same results as discovered in fixed effect modeling. Following table, contains both fixed and random effect modeling;

Table 7: Estimated Results of Digital Economy on Total Factor Productivity in Agriculture

Variable	**Hybrid OLS**	**Fixed Effect**	**Random Effect**	**Tobit**
Explanatory Variable:	0.1153*	0.6837*	0.3153*	1.0708*
DEDI	(0.3279)	(0.6996)	(0.3317)	(0.3192)
Control variables:	-1.4212*	-2.6552**	-1.4212*	-1.3735*
URB	(0.5087)	(1.1696)	(0.5152)	(0.4957)
LAIS	-0.1078**	-0.5776***	-0.1078*	-0.1374***

	(0.1505)	(0.2490)	(0.1519)	(0.1465)
	-11.4050*	-10.9729*	-11.4050*	-6.7880*
LNCPI	(1.3804)	(1.5465)	(1.3896)	(1.3405)
	0.0225***	0.0136	0.0197**	0.0297*
ST	(0.0160)	(0.0372)	(0.0165)	(0.0153)
	0.0592*	0.0054	0.0592*	0.0358*
ALP	(0.0179)	(0.0176)	(0.0178)	(0.0176)
	0.0608**	0.0821*	0.0608*	0.0349**
EDU	(0.0458)	(0.1077)	(0.0445)	(0.0447)
	0.2406*	0.2383*	0.2406*	0.1811*
LDI	(0.0620)	(0.0825)	(0.0615)	(0.0604)
	56.3233*	56.4216*	56.3233*	28.6757*
C	(6.4514)	(7.3517)	(6.5262)	(6.2794)
F/J-Statistics	8.3291*	6.2820*	19.0618*	7.1788*
R^2	0.3455	0.5314	0.4848	0.5103

Source: Authors calculations using Eviews ***Note:*** *Standard Dev. Value is in (). And "*, **, ***" shows significance at 1%, 5%, and 10% level*

In the above table, empirical estimates of rural China has been displayed using statistical techniques such as Hybrid OLS, fixed and random effect models, and Tobit. With the help of this table, researcher tries to explore the long run affiliation between digital economy development level and total factors productivity of rural China. This table occupies model-1, where central focus has been spotted on the interrelationship between TFP and level of development of digital economy. As we see, statistical estimates revealed statistically significant association (at 1%) between TFP in agriculture and DEDI, for the case of all four techniques examined above. DEDI will incur 0.11, 0.68, 0.31, and 1.07 variation in TFP, and this change is affirmative in nature. Higher the level of digital economy development the higher the TFP. Hence, for the case of selected regions of China, level of development of digital economy significantly contributes TFP in agriculture (Linly, 2021). Overall estimates of this model are statistically significant as F-Statistics value is significant. Besides, R-square value signifies that model is around 34% to 53% best fitted. And on the basis of durbin Watson we can reject presence of auto-correlation in this model. On the basis of model-1 estimation, we accept alternative hypothesis-1 (Ha1). And can reject the null hypothesis-1. Alternative hypothesis-1 states that level of digital economy development significantly determines TFP in agriculture. However, urbanization has disclosed negative association with TFP of rural China, in accordance to all four method detailed above. As the people tend to migrate in urban areas and leave rural areas this will cause a static decline in agricultural TFP level. On the basis of model-1 estimation, we accept null hypothesis-2 (H02) and cannot accept the alternative hypothesis-2. Alternative hypothesis-2 states that level of urbanization significantly determines TFP in agriculture. While, the null hypothesis conclude that there is negative correlation between urbanization and TFP. Besides, advancement in industry structure upgrading has confirmed negative interrelationship with TFP, as there will be 10%, 57%, 10%, and 13% decline in TFP by one unit increase in LAIS. As expected LAIS revealed affirmative affiliation with TFP of agriculture sector. Because, growth or advancement of one sector is linked with other sectors. Industrial development results in the form of high economic growth that in turn generate overall productivity growth (Thompson & Garbac 2007; and Guoan, & Lin, 2019). Hence, we can reject null hypothesis-3 (H03) which states that agri-industry growth possesses complex association. It is now confirmed that LAIS asserts negative effect on TFP level of agriculture. Advancement in industry sector is a key for amplified economic growth, efficient resources utilization, and the development of all sectors of the society including agriculture. Literature proved that agriculture and industrial growth both are linked either directly or indirectly. Hence, an advancement or increase in productivity of one sector will assert static impact on the productivity level of another (Krupina *et al*. 2020; and Liu *et al*. 2022). Nonetheless, as like URB and LAIS, inflation (LNCPI) also asserts negative relationship with total factors productivity. An increase in general price level, when there's slight or no increase in productivity incurs negative effect on growth level of TFP. Additionally, backward sector of the economy suffers the most in case of high inflation, as they got low prices for their product (Zhong *et al*. 2015). Although, improvement in seed technology will raises TFP level around 1% & 2%.Usage of modern technology in agriculture such as introduction of modern seed technology will raise TFP in agriculture (Baryshnikova, Sukhorukova, & Naidenova, 2019). However, an increase in agricultural labor productivity raises TFP level up to 5%. Here, statistical estimates fails to confirm their significance in fixed effect modeling but hybrid OLS, random effect, and Tobit model statically proved their significance at 1% level. Education has confirmed positive interrelationship with TFP, as there will be 6%, 8%, 6%, and 3% increase in TFP by one unit increase in EDU. EDU has also revealed statistically significant results, as because of an increase in average schooling year (education) TFP will increase. A qualified or educated person can utilize available resources efficiently and can easily adjust according to technological advancement (Subaeva, Nizamutdinov, Mavieva 2020; and Yang *et al*. (2020). Based on this approximation, we can reject null hypothesis-4 (H04), and accept the alternative hypothesis-4 which states that education causes affirmative influence of TFP. Conversely, an increase in disposable income level will asserts positive impact on TFP level, as there will be 24%, 23%, 24%, and 18% increase in TFP by one unit increase in LDI. C term for all four methods is statistically significant. According to hybrid OLS, model-1 explains TFP around 34%. But according to fixed effect, it explains 53% variation in TFP. Besides, random effect model revealed 48% variation in dependent is explained by model-1 variables, but Tobit modeling disclosed that 51% change in TFP will be explained by variables of model one.

Table 8: Hausman Test

Variable	**Fixed**	**Random**	**(Diff.)**	**Prob.**
Explanatory Variable:				
DEDI	0.6837	0.1153	0.3795	0.0109
Control Variables:				
URB	-2.6552	-1.4212	1.1025	0.0399
LAIS	-0.5776	-0.1078	0.0388	0.0171
LNCPI	-10.9729	-11.4050	0.4496	0.0193
ST	-0.0136	-0.0197	0.0011	0.8554
ALP	0.0054	0.0592	0.0004	0.0076
EDU	0.0821	0.0608	0.0095	0.0276
LDI	-0.2383	-0.2406	0.0029	0.0664
Test Value	**Chi^2= 18.5254**		**Prob>Chi^2 =0.0295**	

Source: Authors calculations using Eviews

Hasuman test estimates demonstrates either fixed model estimation is better for examining current data series or the random effect. Null assumption of this test states that random effect are independent from explanatory variables (or random effect modeling is appropriate) while alternative hypothesis says that the null hypothesis is not true. In our estimation, we find out that for examined model in table 4, random effect is the appropriate as probability value is less than 5%. Hence, here for above model we can reject the null hypothesis and can accept the alternative one.

Table 9: Decomposition of Total Factor Productivity in Agriculture: EC And TC

Variable	**EC**	**TC**
Explained Variable lag:	-2.3102**	----
EC(-1)	(1.1936)	
		-0.0549***
TC(-1)	----	(0.0330)
Explanatory Variable:	0.2255*	0.7236*
DEDI	(0.0973)	(0.2916)
Control Variables:	-0.1763	-1.1426*

URB	(0.1512)	(0.4529)
	0.0780***	-0.1390**
LAIS	(0.0447)	(0.1338)
	-1.1087*	-14.2767*
LNCPI	(0.4099)	(1.2277)
	0.0313*	0.0008
ST	(0.0048)	(0.0145)
	0.0147	0.0338**
ALP	(0.0055)	(0.0165)
	0.0271**	0.0910**
EDU	(0.0139)	(0.0417)
	0.1077*	0.0936*
LDI	(0.0187)	(0.0561)
	-3.2145***	68.0394*
C	(1.9154)	(5.7371)
F	7.1367*	31.4405*
R^2	0.5439	0.6373

Source: Authors calculations using Eviews **Note:** Standard Dev. Value is in (). And "*, **, ***" shows significance at 1%, 5%, and 10% level

In the above displayed table, empirical estimation for the case of rural China has been exhibited by using statistical technique generalized method of movement. With the help of this table, researcher tries to explore the long run affiliation between digital economy development level and total factors productivity of rural China. But this time, total factors productivity of agriculture is decomposed in two major components that are technical efficiency and technical progress. This table occupies model-2 and model-3, where central focus has been spotted on the interrelationship of EC and TC with the level of digital economy development. Besides, R-square value signifies that model-2 is around 54% while model-3 is around 63% best fitted. Overall estimates of this model are statistically significant as F-Statistics value is significant. On the basis of model-2 and model-3 estimation, robustness of model-1 also validates as both components of TFP are statistically significant. Lagged value of EC and TC is statistically significant at 5% and 10% level of significance respectively. As we see, statistical results exposed affirmative association between EC in agriculture and DEDI. Here, DEDI will incur 22% variation in EC at 1% significance level and this variation is affirmative in nature. Conversely, TC affiliation with DEDI is also exhibited here. DEDI will incur 72% variation in TC at 1% significance level and this variation is affirmative in nature. Higher the level of digital economy development the higher the technical efficiency and technical progress in agriculture sector. Hence, for the case of selected regions of

China, level of development of digital economy significantly contributes EC in agriculture (Linly, 2021). On the basis of this estimation we can say that technical progress is highly sensitive to change in DEDI as compared to EC. Cooperatively, we accept alternative hypothesis-1 (Ha1) and reject the null hypothesis-1. However, urbanization has disclosed negative association with both EC and TC of rural China, in accordance to model-2 and model-3. But for the case of model-2, URB is insignificant while for the case of model-3, URB is significant. Based on this, we accept null hypothesis-2 (H02). Although, advancement in industry structure upgrading has confirmed affirmative interrelationship with EC, as there will be 7% increase in EC by one unit increase in LAIS. However, LAIS has confirmed negative relationship with TC, as there will be 13% decrease in TC as by one unit increase in LAIS. Hence, we can't reject null hypothesis-3 (H03) which states that agri-industry growth possesses complex association. It is now confirmed that LAIS asserts both positive and negative effect, as one component of TFP level (EC) confirmed negative while another one (TC) confirmed negative effect. Advancement in industry sector is a key for amplified economic growth, efficient resources utilization, and the development of all sectors of the society including agriculture. Nonetheless, as like URB and LAIS, inflation (LNCPI) also asserts negative relationship with both EC and TC of agriculture. Although, improvement in seed technology will raises EC level around 3%. But for the case of ST affiliation with TC, results shows insignificant association. Usage of modern technology in agriculture such as introduction of modern seed technology will raise technical efficiency in agriculture. Nonetheless, an increase in agricultural labor productivity raises technical progress up to 3%, but EC is insignificant when it affiliates with ALP. Additionally, education has confirmed positive interrelationship with both EC and TC, as there will be 2% and 9% in EC and TC respectively by an addition in EDU. Based on this calculation, we can reject null hypothesis-4 (H04), and accept the alternative hypothesis-4 which states that education causes positive effect. Conversely, an increase in disposable income level will asserts positive impact on EC and TC level, as there will be 10% and 9% increase in EC and TC respectively by an addition in LDI. Here, constant term for both models is statistically significant. Model-2 is 54 percent best fitted while model-3 is 63% best fitted.

Table 10: Mechanism Test (Mediating Effect)

Variable	**DEDI to TFP**	**DEDI to EDU**	**DEDI, EDU to TFP**
Explained Variable lag:	8.3914*		6.2123*
TFP(-1)	(0.7206)	----	(2.4735)
Explanatory Variable:	0.2461*		0.3154*
DEDI	(0.3242)	----	(0.3279)

Mediating Variable:		0.0523***	0.0608**
EDU	----	(0.0277)	(0.0469)
Control Variables:	-0.2816*	0.1693*	-0.2212*
URB	(0.3806)	(0.3536)	(0.5093)
	-0.1499	0.2207*	-0.1078
LAIS	(0.1473)	(0.0315)	(0.1505)
	-11.5890*	-5.5991*	-11.4042*
LNCPI	(1.3761)	(1.7523)	(1.3805)
	0.0180*	0.0238**	0.0197**
ST	(0.0163)	(0.0105)	(0.0164)
	0.0537*	0.0352*	0.0592*
ALP	(0.0182)	(0.0127)	(0.0186)
	0.2330*	0.0865*	-0.2406*
LDI	(0.0630)	(0.0134)	(0.0631)
	57.5965*	-26.9671*	56.3194*
C	(6.3894)	(8.1050)	(6.4512)
J-Statistics	163.00*	163.00*	162.00*
R^2	0.4795	0.8064	0.4848

Source: Authors calculations using Eviews **Note:** Standard Dev. Value is in (). And "*, **, ***" shows significance at 1%, 5%, and 10% level.

In this subsequent table, mediating mechanism between total factors productivity (TFP) of agriculture, digital economy development index (DEDI), and education (EDU) has been displayed. Generalized method of movement is selected for statistical examination. With the help of this table, researcher tries to explore the mediating effect of education that in turn disturbs DEDI and TFP association. In this regard, in column one of this table, model-4 is considered which highlights impact of digital economy on TFP of agriculture. This model is differentiated from model-1, as here role of education was not added, only the impact of DEDI on TFP is tested. After that in model-5 (detailed in column 2) DEDI impact on education is tested. With the help of model-5, effect of explanatory variable (DEDI) on mediating factor (EDU) is tested. In the last column again model-1 is utilized, however, here DEDI is held constant in order to integrate mediating role of education. In all three models, the R-square value for first case is 47%, 80% for the second one, while it is 48% for third case. Overall estimates of this model are statistically significant as J-Statistics value is significant. Lagged value of TFP is statistically significant at 1% level of significance. As we see, statistical results of model-4 shows affirmative association between TFP in agriculture and DEDI. If we ignore the mediating role of education there's around 24%. While when we add mediating effect the contribution of DEDI to TFP is 31%. Except, LAIS all other control variables of model four are statistically significant. Constant term is also significant for model-4. Furthermore, according to model-5 estimation, an increase in DEDI will raise education up to 5%. All other control variables of model-5 are also statistically significant. Additionally, statistical estimates in column three, reveals that EDU contributes 6% in TFP of agriculture. And DEDI will contributes 31% here, which is 7% higher than model-4. Hence, mediating role of EDU is statistically confirmed here. Besides, as because of EDU mediating effect control variables effect also got disturbed. Coefficient terms of URB, LAIS and LNCPI decreases, while ST, ALP, and LDI increases slightly.

5. Conclusion and Policy Implications

This research aimed to integrate role of digital economy development level on total factor productivity of China. Besides, researcher also considers mediating role of education. Education plays a vital role in determining digital economy development level that in turn affects total factors productivity. Furthermore, impact of urbanization, industrial development (in the sense of structure development), inflation, modern technology, average labor productivity, and disposable income has also been taken into consideration. In order to empirically examine this phenomenon, research selected China's economy for empirical examination. Panel data estimation was finalized and time series data has been collected for the selected 19 regions of China, over the time period 2011-2019. These regions are mainly dependent on agriculture and do produce a large share of total grain production in case of China. After examining unit root analysis, it was decided that the hybrid least square will be applied. However, as for safety concern in order to avoid problem of endogenity, this research occupied fixed & random effect regression along with GMM and tobit modeling. In this regard, for checking appropriate method for analytical examination Hausman test was performed which revealed that there is need to apply random effect modeling, particularly for model-1. Thus, random effect modeling was utilized. Statistical results revealed that all five empirical models examined in this research are statistically significant, well determined, and do possesses long run cointegration. Besides, mediating effect of education has also proved its statistical significance. Likewise, all variables such as advance industrial structure (AIS), modern technology, average labor productivity, and disposable income do confirmed positive correlation with TFP, except urbanization (URB) and inflation. Here, level of urbanization and inflation has revealed negative affiliation with TFP of agriculture in China. After obtaining statistical estimates, now we can confirm that digital economy development level significantly determines TFP of agriculture in China, The development of the digital economy can contribute to sustainable growth in total factor productivity in agriculture. Based on the empirical estimates obtained from fixed and random effect modeling this research presents some effective policy implications. While forming polices regarding TFP and digital economy development policy makers needs to consider the followings:

1. As urbanization has confirmed negative correlation with TFP, Hence there's need to integrate rural development polices (providing market and other better facilities) in order to overcome the decline in TFP as because of increased urbanization trend.
2. For uplifting TFP growth in agriculture, there is need to promote education. As increase schooling year causes a static rise in TFP.
3. An improvement in the usage of modern technology expenses in agriculture sector will cause an increase in TFP. Thus, there's need to introduce advancement in modern methods and technologies.
4. Advance industrial structure either directly or indirectly raise TFP. Hence, while forming polices needs to consider both agriculture and industrial sector. As the development or growth of both sectors will cause a static increase in overall economic growth.

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