The nonlinear effect of agricultural informatization on agricultural total factor productivity in China: a threshold test approach

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Abstract

This study focus on the nonlinear effect of agricultural informatization (AI) on agricultural total factor productivity (ATFP) in China, and resort to the panel threshold model to test the core questions: when rural human capital stock stays at different levels, the differential effect of AI on ATFP. The results show that there exist significantly double threshold effects of AI on ATFP when rural human capital is used as a threshold variable. Namely, when the level of rural human capital is lower than the first threshold value, no evidence showing any significant growth effect of AI on ATFP, while along with the accumulations of rural human capital, especially at the moment of crossing the threshold value, the significant growth effect starts to emerge, and intensifies later on. The threshold effects of the developmental level of AI and time are also shown in the agricultural sector. Policies should focus on raising the human capital stock of the rural labor and fostering their information awareness, information literacy and learning ability in the agricultural production.

keywords: Nonlinear effect. AI. ATFP.

1. Introduction

The driving forces of traditional Chinese agriculture are coming from the intensive inputs of production factors, but the more prominent features are high inputs of resources, high emission of pollution and ineffective utilization of energy. Accompanying with the acceleration of industrialization and urbanization, the environmental and resource endowment constraints of agricultural development are increasingly emerging, which “forces” the growth patterns to transform from traditional extensive style to modern intensive pattern as soon as possible (Song et al., 2016). To achieve this goal, the agricultural sector will have to mainly rely on the quality of factor inputs and the effective allocation efficiency of resources. An outstanding feature is reflected from the share of ATFP on agricultural growth (Chen et al., 2008). The ATFP reflects the change of non-factor input factors in agricultural economic growth, and this factors has a long-term growth effect on the agricultural sector. Therefore, studying the effects of total improvements of ATFP, will shows great significance on the sustainability of China’s agriculture.

The most important point to improve ATFP is searching for the driving mechanism. Among so many factors driving agricultural productivity, AI is the one that cannot be ignored. The main features of AI are that informational resource are applied to the stages of production and management, so that agriculture can be upgraded from extensive to intensive. On one hand, as an input factor, AI can coordinate the roles of factors (e.g., labor, land, et al.) in the production system efficiently, so that the allocation of resources is optimized. On the other hand, AI is sensitive to the changes of demand for technology in the process of industrial upgrading, so that the productivity can be enhanced. Some empirical studies confirm the growth effect of AI on productivity (Yin et al., 2010), but the results are mainly built on linear regression models assuming regional homogeneity, and the differences of resource endowment among different regions are ignored. In the process of AI diffusion, rural human capital is a key factor that needs to be considered. By influencing the efficiency of factor combinations, the application style and degree of diffusion of agricultural technology, then the ATFP is affected. If the stock of rural human capital in some regions is high, the labors there own stronger information learning ability, and they are better at using informational tools to search and distribute information, as well as applying information instruments efficiently, so the ATFP is enhanced, and vice verse. Therefore, due to the differences of rural human capital, the effect of AI on ATFP may be nonlinear. If the nonlinear relationship is ignored, the inner mechanism of AI on ATFP cannot be fully revealed as well. This is the key problem we try to solve.

In addition, the other point we try to elucidate is how to evaluate the true ATFP in the context of modern agricultural growth. In the process of modern agriculture production, the means of production, such as fertilizer, pesticide, agricultural machinery, are widely used. Though the production efficiency is enhanced, it also brings about serious environmental pollution (Xiong et al., 2016). If we do not consider the environmental costs when evaluating agricultural production efficiency, then the agricultural economic performance cannot be objectively evaluated, the consequences are that we may even propose misleading policy recommendations (Hailu & Veeman, 2000).

For that reason, this paper use a panel data set covering 30 provinces of China for the period 2005 to 2014, based on the ATFP measured under environmental constraints, and apply panel threshold model to test the effect of AI on ATFP. Our results show that, positive double threshold effects exist when the threshold variables are rural human capital. Only when the rural human capital stock accumulates to a certain level, the significant growth effect starts to emerge, and further intensifies. The threshold effects of AI and time are also shown in the agricultural sector in a way.

2. Theory and Literature Review

Theoretically, the potential channels of informatization on growth efficiencies are as follows: firstly, informational capital deepening can enhance output growth; secondly, the technology progress of the information production sector can improve TFP. Similarly, the impact mechanisms of AI on ATFP are also mainly driven by two channels, that is, factor inputs and technology progress. On one hand, AI optimizes the allocations of resources and improves the utilization efficiency of the factors. As a special resource factor, agricultural information almost penetrates into the whole processes of agricultural production and operation, and coordinates input factors, such as land, labor, and then the technology efficiency improves. From this point of view, the promotion of AI on the ATFP is mainly derived from the AI and other capital elements of the organic combination, which is the most important and universal impact channels. On the other hand, AI helps to accelerate technological progress. The combinations of modern information technology with the agricultural internal demand may cultivate a series of advanced affiliated new technologies. When new information techniques are distributed and applied to the agricultural production, the modern and intensive modes of production will inevitably enhance the agricultural efficiency (Wang, 2011).

Empirical evidence on the growth effect of informatization on productivity is ambiguous. Several literatures argue that IT investment has no significant effect on TFP and calls this phenomenon "the productivity paradox of information technology" (Brynjolfsson, 1993; Gordon, 1999). However, some empirical studies deny the existence of productivity paradox (Shao and Lin, 2001; Jorgenson et al., 2003). Some scholars realize that the relationship between IT investment and TFP may be nonlinear, and the productivity paradox does exist, but emerges only at different stages of development. That is, the IT investment has the so called threshold effect, only when the level of IT investment goes across some threshold or time, IT starts to show positive effect on TFP (Kraemer and Dedrick, 1994; Pohjola, 2000).

Agriculture is an important sector of the economic system, empirical inquiries of the relationship between informatization and productivity also attracts some author's attention, but compared with studies of firm performance at the micro level and studies on the whole economic system, the literature is not sufficient. Parts of the literature focuses on the effect of IT on the specific production process (Jensen, 2007; Aker, 2010; Shaukat & Shah, 2014). The representative view is that, the applications of agricultural expert system, the distribution of precision agriculture mode and the coverage of agricultural communication service, cast positive effects on the agricultural products, agricultural market analysis and forecasting, as well as the welfare of famers. Other parts of the literature focus on the aggregate level of AI, and study its effect on the overall agricultural sector's production performance (Kauffman and Kumar, 2008; Wang, 2011). In this strand of literature, most of them are based on finding alternative indicators of AI, and examine its effects on aggregate agricultural output or gross rural economic output, but only a few consider the studies of production efficiency. Further studies, though are very rare, find positive effects of AI on ATFP (Yin et al., 2010), but they only examine the linear mechanism, meanwhile, the informatization is measured by a single alternative index. To sum up, recent studies have generally confirmed the growth effect of AI on ATFP, but the linear regression framework may miss the periodical characteristics and regional heterogeneity. On one hand, just like the productivity paradox, which emerges at different stages of development in different countries. Here we want to ask: will the time threshold or the AI threshold also emerge in China's agricultural sector? On the other hand, more crucially, the good combination of AI and other capital elements is an important channel for the growth of ATFP. The working of the agricultural growth effect also depends on the corresponding aiding-factors, such as the matched organizational architecture, well-trained labor (Autor et al., 2003), to name a few. These aiding-factors are usually closely related to the levels of human capital (Liu, 2012). In the applications of the AI technology, rural human capital is the key to technology diffusion and adoption, which shows significant regional differences. The differential level of human capital will affect famer's ability to apply informational resource and technology directly, and further leads to the differences of the growth rate of regional ATFP. Hence, the relationship between AI and ATFP may be nonlinear under different levels of human capital. Formal test needs to be done.

Moreover, production efficiency evaluation is another focus. The growth of TFP is the best expression of the production efficiency and the prospects for longer term increases in output. It shows the relationship between growth of output and input, with productivity being raised when growth in output outpaces growth in input (Lipsey & Carlaw, 2000), the same is true of agricultural sector. Early literature is affected by the Solow residual method, the measurement of ATFP is mostly based on average production function (Lin, 1992; Wen, 1993). Along with the progress of methodology, the production frontier surface method, represented by stochastic frontier analysis (SFA) and data envelopment analysis (DEA), is very popular (Lambert and Parker, 1998; Li et al, 2011). However, in these measurements, the environmental constraints are ignored. To measure the true ATFP, the non-desirable output brought about by environmental pollution should be deducted. The Malmquist-Luenberger (ML) index, which incorporates desirable and non-desirable output into the measuring framework (Chung, 1997), shows good economic implications and is free of price information (Piot-Lepetit & Moing, 2007), so it can be used to measure TFP under environmental constraints. But when measuring mixed directional distance function, the linear programming may potential unsolvable, and the ML index represented in the form of geometric average is no longer transitive. The Global Malmquist-Luenberger (GML) index combines Global Malmquist (GM) index with directional distance function (Oh, 2010), so it not only avoids the deficiencies of ML index, but also solves the problem of multiple inputs and outputs, as well as the environmental pollution, which makes it possible to measure ATFP more precise.

This paper extends recent studies in two ways. First, we fully detect the sources of pollution across the production process, and incorporate the carbon emissions from the pollution sources (e.g., pesticide, agricultural film, diesel oil, tillage, irrigation) into the measuring framework, and introduce GML index to reevaluate the regional ATFP under carbon emissions through the provincial panel data in China form 2005 to 2014. Secondly, we build up the panel threshold model to analysis the periodic characteristics and regional heterogeneity of the effects of AI on ATFP. Thus, the nonlinear relationship between AI and ATFP can be systemically studied through the threshold variables, namely, the rural human capital, AI and time.

3. Materials and methods

3.1. The model

We consider the following panel threshold model:

$$ATFP_{it} = \beta_1 AI_{it} I(X_{it} \leq k_1) + \beta_2 AI_{it} I(k_1 < X_{it} < k_2) + \cdots + \beta_n AI_{it} I(k_{n-1} < X_{it} < k_n) + \beta_{n+1} AI_{it} I(X_{it} > k_n) + \lambda Control_{it} + \mu_i + \varepsilon_{it} \quad (1)$$

Where $ATFP_{it}$ is the ATFP for province i in period t, AI_{it} is the core variable of interest in this study, namely, the AI, $I(\cdot)$ is an indicator function, X_{it} is an threshold variable, here it is rural human capital, developmental level of informatization and time, variables $k_1, \ldots, k_n$ represent the threshold values, $Control_{it}$ is a vector of control variables, $\beta_1, \ldots, \beta_{n+1}$ and λ are parameters to be estimated. μ_i is the fixed effect which controls for the unobserved time-invariant province-specific characteristics, and ε_{it} is the random error term.

Two issues exist in estimating the panel threshold model: firstly, testing the significance of the threshold effect as well as its validity. Secondly, jointly estimating the threshold value k and slope β. The basic idea is, choosing an arbitrary k_0 first, initialize k, and then estimating the coefficients via OLS and compute the sum of squared errors $S_1(k)$. Repeat the upper steps, we can choose many k_0, and calculate many different $S_1(k)$. The threshold value $\hat{k}$ which makes the $S_1(k)$ minimal is the one that we want, namely, $\hat{k} = argminS_1(\hat{k})$. When the threshold value is determined, we get$\hat{\sigma}_1^2 = S_1(\hat{k})/[n(T-1)]$. To proceed, the slope can be estimated.

Then, we will test the significance of the threshold effect. Consider that testing for two or multiple threshold effects is similar to that of a single threshold, here we give the test procedure only on a single threshold, and the null hypothesis and test statistic are as follows:

$$H_0: \beta_1 = \beta_2 \qquad F_1 = \left(S_0 - S_1(\hat{k})\right)/\hat{\sigma}_1^2 \tag{2}$$

If we reject H_0, the threshold effect exists. Where S_0 and $S_1(\hat{k})$ are the sum of squared errors under null and alternative hypothesis, respectively, $S_0 \geq S_1(\hat{k})$, $\hat{\sigma}_1^2$ is the variance of the errors of the threshold estimation. Under H_0, the threshold is not identified, and the asymptotic distribution of F_1 is not standard, and strictly dominates the χ^2 distribution. Unfortunately, it appears to depend in general upon moments of the sample and thus critical values cannot be tabulated. To solve this problem, the bootstrap procedure attains the first-order asymptotic distribution, sop-values constructed from the bootstrap are asymptotically valid.

Next, we further test the validity of the threshold. The H_0 under the single threshold and the likelihood ratio statistic (LR) is:

$$H_0: \hat{k} = k_0 \qquad LR_1(k) = \left(S_1(k) - S_1(\hat{k})\right)/\hat{\sigma}_1^2 \tag{3}$$

Where $S_1(k)$ is the unrestricted sum of squared errors, although the distribution of $LR_1(k)$ is still non standard, its cumulative distribution function is $\left(1 - e^{-x/2}\right)^2$, the critical values can be calculated directly. Namely, when the significance level is α, and $LR_1(k) > -2ln\left(1 - \sqrt{1-\alpha}\right)$, the H_0 is rejected (Hansen, 1999).

3.2. Variables

Dependent Variable: ATFP. In non-desirable output, although the non-point source pollution of chemical fertilizers, pesticides and agricultural films is more intuitive, the decentralized characteristics of agricultural production make the positioning and quantification of pollution sources more difficult. Based on this we fully detect the sources of pollution across the production process, and incorporate the carbon emissions from the pollution sources into the non-desirable output measuring framework. Then, we construct a global production possibility set that contain both desirable output and non-desirable output (carbon emissions), and apply data envelopment analysis (DEA) based non-radial and non-oriented slacks-based measure (SBM) model (Tone, 2003), and combine Global Malmquist-Luenberger (GML) index (Oh, 2010) to measure provincial ATFP under environmental constraints. This approach not only takes into account the problem of nonconformity and relaxation in efficiency evaluation, but also circumvents the possible internal bias of the production frontier surface. In the actual estimation, the ATFP index needs to be converted into a cumulative form.

Agricultural input variables include land, labor, agricultural machinery, fertilizer, agricultural draught animal and irrigation. We use planting area to measure the land input. Employment is more suitable for reflecting the true utilizing of the agricultural labor, so we measure the labor input by the employment in the primary industry. We use the total power of agricultural machinery as a proxy for machinery input. Fertilizer input is the quantities of all kinds of fertilizer used in agricultural production, we use the quantities of fertilizer to measure it (delice of amount). Draught animal is mainly used for seeding, planting and transporting, and we use the quantities of agricultural draught animal from the large livestock to measure it. We calculate the irrigation input as the real efficient irrigation area per year.

Output includes desirable and non-desirable output. Consider that the labor, machinery and draught animal are inputs in a broad sense, so the desirable output is calculated from the aggregate output of farming, forestry, animal, husbandry and fishery in constant price of 2005. The non-desirable output is measured by the carbon emission in the production, the sources of carbon, coefficients and the references sources are given in Table 1. The method of commutating carbon emission is: assume that the aggregate quantities of carbon emission is C, the emission from each source is C_i, agricultural consumption from each carbon source is T_i, the emission coefficient of each source is δ_i, then the formula of calculating carbon emission is $C = \sum C_i = \sum T_i \times \delta_i$(Li et al., 2011). The unit and descriptive statistics of inputs and outputs variables are shown in Table 2.

Table1: Carbon sources, coefficient of carbon emissions and reference sources

Carbon source	Coefficient	Reference sources
Fertilizer	0.8956 kg▪kg-1	West and Marland (2002)
Pesticide	4.9341 kg▪kg-1	Oak Ridge National Laboratory (Zhi and Gao 2009)
Agricultural film	5.18 kg▪kg-1	Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University(Li et al.2011)
Diesel oil	0.5927 kg▪kg-1	IPCC(Li et al. 2011)
Tillage	312.6 kg▪km-2	Wu et al (2007)
Irrigation	25 kg▪Cha-1	Dubey and Lal (2009)

Note: The carbon emission coefficient of agricultural irrigation should be25kg/hm2, but consider that only the thermal power causes the demand for fossil fuel, which further causes the emission of carbon indirectly, hence, we multiply the 25kg by the thermal power coefficient (e. g, the ratio of thermal power to total power). According to the data from the China statistical yearbook across 2005 to 2014, the average thermal power coefficient is calculated as 0.7381, so the final agricultural irrigation coefficient is 18.4523/hm2.

Table2: Units and descriptive statistics of inputs and outputs variables

Variable	Unit	Mean	SD	Min	Max
Land	Thousand hectares	5316.4234	3571.9806	196.1000	14378.3000
labor	Ten thousand	1016.7573	796.0569	36.3450	5248.0572
Agricultural machinery	Ten thousand kilowatts	2962.0862	2808.5056	95.3216	13101.4000
Fertilizer	Ten thousand tons	181.2763	140.7164	6.9900	705.8000
Draught animal	Ten thousand head	406.2303	328.8566	5.4400	1558.5600
Irrigation	Thousand hectares	1986.5291	1474.0683	143.1000	5342.1000
Gross output value of farming	Billion Yuan	1630.8732	1182.1691	94.0416	5403.9181
Carbon emission	Million tons	272.6387	197.7537	11.3968	863.5333

Threshold-dependent Variables: AI. Chinese officials did not give an accurate definition of AI, but connectivity and content are considered to be two key elements of the AI model (Liu, 2012). This paper also builds the measurement index based on these two factors. Connectivity is closely related to the provider's information infrastructure and its quality, which can be measured by the aggregate coverage of agricultural broadcasting and agricultural TV programs, as well as the length of rural delivery route. Content can be reflected by the user's information appliance and their ability to pay, and the specific indicators include the ownership of telephones, mobile phones, televisions, color televisions and computers per 100 rural households. The entropy method is well known for choosing weights of the indicators based on their degrees of variation, so that the weight is not affected by artificial factors. Therefore, we choose the entropy method to assign the weight to the AI indicators, and then measure the AI through the weights. Assume that we have m regions and n AI indicators, H_{ij} indicates the j^{th} indicator in region i: (1) normalize the original data, $B_{ij} = (H_{ij} - H_{min(j)})/(H_{max(j)} - H_{min(j)})$, $(i = 1,2, \dots, m; j = 1,2, \dots n)$; (2) transform the weights, $C_{ij} = B_{ij}/\sum_{i=1}^{m} B_{ij}$; (3) calculate the entropy of each indicator, $D_j = -(lnm)^{-1}\sum_{i=1}^{m} C_{ij}lnC_{ij}, D_j \in [0,1]$; (4) calculate the information utility of the entropy, $E_j = 1 - D_j$; (5) calculate the weight, $W_j = E_j/\sum_{j=1}^{n} E_j$; (6) calculate the composite AI index of each region, $AI_i = \sum_{j=1}^{n} W_j B_{ij}$, the larger the value, the higher the AI.

Core threshold variable: Rural human capital (HUM). The main point in this paper is testing whether the effect of AI on ATFP shows threshold effect through the rural human capital, so the core threshold variable is HUM. The HUM is measured by the average years of schooling, which is calculated by multiplying the durations of different schooling levels by the fractions of different population groups that have attained different education levels. The durations (years) of education levels are: 0 for no formal education and in complete primary school, 6 for primary school, 9 for junior high school, 12 for senior high school and technical secondary school, 16 for junior college and higher ones.

Control variables. We consider the control variables from four aspects, namely, natural environment, regional character, policy support, and environmental regulation. Natural conditions are the determinants of agricultural economic efficiency (Adamišin et al., 2015). This paper measures the deterioration of the natural environment through the ratio of disaster area to total grain acreage (DIS %). Two indicators, urbanization and infrastructure investment are used to describe the regional characters. We measure the urbanization by the ratio of the quantities of permanent residents in cities and towns to the total population (URB %). Rural infrastructure is helpful to reduce the production cost and enhance efficiency (Mamatzakis, 2003), the measurement we choose is the rural traffic infrastructure. Including rural roads, provincial and national roads and highways, are also important exchange bridges of urban and rural products, so we use the log total mileage of road to measure the traffic infrastructure (INF). For the policy support, we use the ratio of fiscal expenditure of agriculture to the total fiscal expenditure, which reflects the strength of aiding (FIN %). Environmental constraint is a key factor that we have to consider in the modern agricultural production. However, the costs of environmental regulation are implicit and hard to measure, we use the ratio of the total emission fees to GDP as a proxy (REG %). Compared to other indicators, these values are very small. We multiply 100 to obtain comparable values.

3.3. Data source

Consider the continuity and intactness of the original data, our sample spans from 2005 through 2014, the cross sectional units include 30 provincial administrative units. All data are available through statistical data published by the National Bureau of Statistics of China. The datasets of input and output variables of the ATFP mainly come from China statistical yearbook, China rural statistical yearbook and China agricultural statistics during 2005 to 2014. The datasets of AI comes from China statistical yearbook and provincial statistical year book as well as survey statistical yearbook during 2005 to 2014. The datasets of HUM mainly come from China rural statistical yearbook. The datasets of control variables are basically the same as ATFP variable. All the nominal variables are deflated through GDP deflator, and the base year is set at 2005. The descriptive statistics of the estimated variables are reported in Table 3.

Table3: Descriptive statistics of the estimated variables

Variable	Observations	Mean	SD	Min	Max
ATFP	300	1.2156	0.2703	0.9409	3.0915
AI	300	0.3330	0.1627	0.0538	0.8562
HUM	300	8.2920	0.8274	5.8855	10.7260
URB	300	0.5030	0.1388	0.2687	0.8960
FIN	300	0.0984	0.0307	0.0213	0.1709
DIS	300	0.2417	0.1488	0.0095	0.9357
REG (*100)	300	0.0543	0.0498	0.0017	0.4829
INF (logarithm)	300	11.4615	0.8663	9.0009	12.6435

4. Results and Discussion
4.1. Panel threshold regression

According to the above estimation model, this paper uses STATA12.0 software for threshold regression analysis. First of all, testing for the threshold effect is based on equation (1), and the results are shown in Table 4. We estimate three threshold models, and the threshold variable are separately rural human capital, AI and time. The null of single and double threshold are all rejected in these models, but we cannot reject the null of multiple threshold. Thence, there exist double threshold effects of AI on ATFP when the threshold variable is rural human capital, AI and time.

Table4: Test results of threshold effect

Threshold variable	Hypothesis	F value	P value	10%critical value	5%critical value	1%critical value
HUM	H0: Linear model H1: Single threshold	29.1251	0.0000	2.7192	4.0106	8.2223
	H0: Single threshold H1: Double threshold	5.5142	0.0280	2.6125	4.1143	8.4137
	H0: Double threshold H1: Multiple threshold	1.9209	0.1620	2.8190	3.9346	7.4111
AI	H0: Linear model H1: Single threshold	43.4184	0.0000	2.5975	4.1840	7.9579
	H0: Single threshold H1: Double threshold	28.0049	0.0000	-11.4263	-7.9350	0.4705
	H0: Double threshold H1:Multiple threshold	2.0833	0.1390	2.6412	4.1101	7.3028
TIME	H0: Linear model H1: Single threshold	35.8374	0.0000	2.7719	3.8504	8.3483
	H0: Single threshold H1: Double threshold	31.2793	0.0000	2.9753	4.1383	7.4390
	H0: Double threshold H1: Multiple threshold	2.0338	0.1460	2.7985	4.1511	7.6498

Note: Bootstrap critical values and p-values were calculated based on 1000 iterations.

When the null of no threshold effect is rejected, we need to further identify the threshold value and its validity sequentially. Table 5 reports the threshold values and their corresponding 95% confidence interval. We see that the 95% confidence intervals are all very narrow, showing that the identification of the threshold value is significant. Meanwhile, when the significance level is 5%, the LR ratios are all less than 7.35, showing that the threshold values are highly significant. The threshold values are equivalent to their true threshold values.

Table5: Threshold values and confidence intervals

Threshold variable	Threshold value		95% confidence interval
HUM	First threshold	8.4235	〔8.4235, 8.4851〕
	Second threshold	8.5773	〔6.6703, 9.7154〕
AI	First threshold	0.5866	〔0.5746, 0.5866〕
	Second threshold	0.6347	〔0.5385, 0.6347〕
TIME	First threshold	2012	〔2011, 2013〕
	Second threshold	2006	〔2006, 2007〕

According to the three threshold variables, each is identified with two threshold values and two threshold intervals. To proceed, we divide the provinces into three regimes by these intervals. Here we focus on the threshold interval of rural human capital. Table 6 depicts the regional distribution pattern of rural human capital in 2005, 2010 and 2014. In 2005, the number of provinces which did not cross the first threshold is 21, of which the number in the central and western regions are 17, but only 4 provinces in eastern regions appear in this interval, namely, Hainan, Jiangsu, Zhejiang, and Fujian. Except Shanxi, 8 provinces staying at the middle and high regimes all belong to the eastern region. In 2010, the number of provinces, whose rural human capital does not cross the first threshold, reduces to 12. The rural human capital of the central and western provinces, like Hunan, Heilongjiang, Shaanxi, Hubei, goes into the moderate regime, while the central provinces, Shanxi and Henan go into the high regime. Meanwhile, comparing to 2005, the provinces belonging to high rural human capital regime, the number increases from 6 to 13. In 2014, the number of provinces with high rural human capital further increases to 16, the number of provinces from central and western regions is also increased (e.g., Hunan, Hubei and Shanxi). On the whole, for the majority of the provinces, the level of rural human capital are all increased in a way. Figure 1 depicts the trends of the number of provinces belonging to different rural human capital regimes from 2005 to 2014, the number belonging to moderate regime was almost always stays stable, while the number belonging to low and high regimes appeared to decrease and increase, respectively.

Table6: Regional distribution patterns of rural human capital in 2005, 2010 and 2014

grouping	2005	2010	2014
Regions with low level of rural human capital (HUM $\leq$ 8.4235)	Heilongjiang,Henan,Hainan,Jiangsu,Hunan,Shaanxi,Hubei,Zhejiang,Jilin,InnerMongolia,Jiangxi,Fujian,Xinjiang,Sichuan,Chongqing,Anhui,Gansu,Guizhou,Yunnan,Ningxia,Qinghai	Jilin,InnerMongolia,Jiangxi,Anhui,Xinjiang,Sichuan,Chongqing,Gansu,Guizhou,Yunnan,Ningxia,Qinghai	Xinjiang,Jiangxi,Jilin,Chongqing,Anhui,Heilongjiang,Gansu,Sichuan,Ningxia,Yunnan,Guizhou,Qinghai
Regions with moderate level of rural human capital (8.4235<HUM$\leq$8.5773)	Guangxi, Shanxi , Guangdong	Hunan, Heilongjiang, Shaanxi, Fujian, Hubei	Zhejiang, Inner Mongolia
Regions with high level of rural human capital (HUM>8.5773)	Beijing, Shanghai, Tianjin, Hebei, Liaoning, Shandong	Beijing,Shanghai,Hebei, Liaoning,Shandong, Shanxi,Tianjin,Guangxi, Guangdong,Jiangsu, Hainan, Henan, Zhejiang	Beijing,Shanghai,Tianjin, Hebei,Guangdong,Shandong,Hainan,Shanxi,Henan,Jiangsu,Guangxi,Hunan,Liaoning,Hubei Shaanxi, Fujian

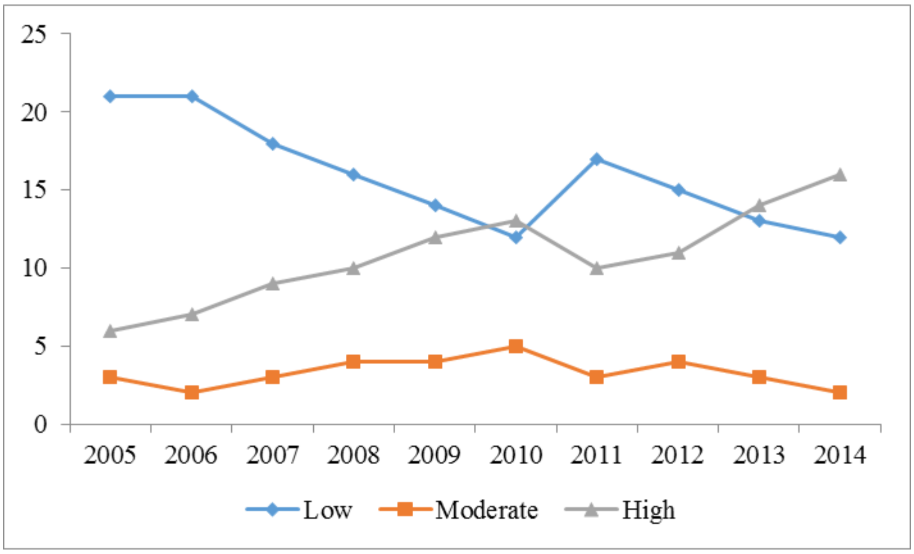

Figure 1: Trends of the number of provinces in different rural human capital regimes

After determining the threshold values, the nonlinear double threshold model (1) can be estimated. For comparison, we also estimate the linear fixed effect model. The results are reported in Table 7. No matter it is the fixed effects or the double threshold model, the significance and the signs of the coefficients of the explanatory variables are by and large the same, showing that the results are robust. In this section, we will focus on the estimation based on the double threshold model. The signs of the natural environment in the three panel threshold models are negative, this suggests that the aggravation of environment hiders the sustainable growth of ATFP. The coefficients for urbanization are positive and statistically significant at the 1% level for all three regressions, the reason may be that the efficient utilization of rural labor and land caused by urbanization, promoting the production patterns transformed to modern ways so that the production efficiency increased (Nin-Pratt, 2010). The coefficients for fiscal support are significantly positive for all regressions, suggesting that the fiscal support sponsored by the government contributes to the growth of ATFP. The coefficients for environmental regulation are significantly negative, showing that environment regulation is not yet the main motivate mechanism to promote agricultural technology progress, instead, the unsoundness of the implementation causes the regulation to have a negative impact on the production technology and efficiency. The coefficient for infrastructure is significantly positive in the panel threshold regression where the threshold variable is AI, but it is not significant in the other two regressions.

Now we turn to the estimation results of the threshold effect. We focus on the case when the threshold variable is rural human capital. From Table 7, we can see that, as the increases of rural human capital, the effect of AI on ATFP shows significant double threshold effect. Specifically, when the level of rural human capital is lower than the first threshold value (HUM ≤ 8.4235), the coefficient for AI is positive, but not significant, illustrating that the growth effect does not exist in this low regime. When the level of rural human capital crosses the first threshold value but is still lower than the second threshold value (8.4235 < HUM ≤ 8.5773), the coefficient for AI is positive and significant at the level of 1%, and its value is 0.6860, this suggests that AI promotes the sustainable growth of ATFP in the moderate regime. When the level of rural human capital is larger than the second threshold value (HUM > 8.5773), the coefficient of AI is 0.8683 and significant at the 1% level. The positive effect is more prominent. The above results further show that the effect of AI on ATFP is not linear but changes with the different levels of rural human capital. Whether AI can effectively promote the growth of ATFP is constrained by the levels of rural human capital. To be specific, only if the levels of rural human capital reaches to and crosses the first threshold value, the growth effect will emerge. Therefore, in the process of implementing AI, the users and beneficiaries are rural labors, and if and only if the labors possessing the high levels of human capital, the informational resources can be effectively integrated, learned and absorbed, so that the productivity is constantly promoted. But if the rural human capital stays at a low level, the applications of informational resource and technology are limited, and then even if the AI grows gradually, it is insufficient to drive the growth of ATFP persistently.

Otherwise, we also test the threshold effects of AI and time, the results are reported in Table 7. When AI is the threshold variable, its effect on ATFP is also nonlinear. When the AI is lower than the first threshold value, the coefficient for AI is not significant, a signal of productivity paradox. However, when the AI crosses the first and the second threshold value, the effect becomes significantly positive, the productivity paradox disappears. We further find that when AI stays at moderate and high levels, as the AI increases, its coefficients are prone to decrease, showing that the effect follows the law of decreasing return to scale. When the time is treated as the threshold variable, the regression results show that, two time thresholds are identified, that is, 2006 and 2012. The effect of AI on ATFP in these two periods are all significantly positive, and as time goes by, the positive effect becomes more and more strong.

Table7: Estimation Results of the Fixed Effect Model and Threshold Effect Model

Variable	Fixed effect model	Double threshold model		
		HUM	AI	TIME
AI*I (HUM≤8.4235)	--	0.3818 (1.59)	--	--
AI*I (8.4235<HUM≤8.5773)	--	0.6860*** (2.60)	--	--
AI*I (HUM>8.5773)	--	0.8683*** (3.20)	--	--
AI*I (AI≤0.5866)	--	--	0.0427 (1.62)	--
AI*I (0.5866<AI≤0.6347)	--	--	1.0220** (2.47)	--
AI*I (AI>0.6347)	--	--	0.3735* (1.80)	--
AI*I (TIME≤2006)	--	--	--	0.6931*** (2.99)
AI*I (2006<TIME≤2012)	--	--	--	1.0512*** (4.16)
AI*I (TIME>2012)	--	--	--	1.4079*** (4.73)
AI	0.5330** (2.44)	--	--	--
URB	1.4684*** (6.26)	1.2322*** (6.06)	1.5027*** (7.03)	0.5530*** (2.73)
FIN	1.7893*** (3.70)	1.5247*** (3.69)	1.9360*** (4.07)	0.6589* (1.76)
DIS	-0.0864**(-2.08)	-0.0801**(-2.12)	-0.0708 (-1.62)	-0.0705**(-2.24)
REG	-0.4199**(-2.31)	-0.4520***(-2.74)	-0.4490***(-2.82)	-0.4082***(-3.20)
INF	0.0650 (1.55)	0.0591 (1.53)	0.0889** (2.31)	-0.0086 (-0.21)

Note: The result of a Hausman test shows that the fixed effect model is statistically preferred to the random effect model. *, **, *** denote significance at the 10%, 5% and 1% respectively. T-values are reported in parentheses.

4.2. Additional analysis

In this paper, we find that there exist double threshold effects of AI on ATFP through rural human capital (HUM), showing that the growth effect of AI on ATFP depends on human capital deepens. Hence, AI and HUM interact with each other, so the interactive coupling relationship between them may exist. We resort to the coupling coordination model to further verify the threshold effect. The coordination degree model between AI and HUM is:

$$C = 2\sqrt{(U_1 \times U_2)}/(U_1 + U_2) \tag{4}$$

Where C is the coordination degree, U_1 is the synthetic evaluation value of AI, U_2 is the synthetic evaluation value of HUM. Then, we construct the coupling coordination degree model:

$$\begin{cases} D = \sqrt{C \times T} \\ T = aU_1 + bU_2 \end{cases} \tag{5}$$

Where D is coupling coordination degree, T is the aggregate coordination index of AI and rural human capital, reflecting the overall synergy effect. Both a and b are parameters, $a + b = 1$, and we set $a = b = 0.5$. The coupling coordination degree is divided into four stages: $D \in (0, 0.3)$ is the low coordination, $D \in [0.3,0.5)$ is the moderate coordination, $D \in [0.5, 0.8)$ is the high coordination, and $D \in [0.8,1)$ is the super coordination.

Furthermore, we calculate the geometric averages of the provincial AI and HUM during 2005-2014, and normalize them based on the range. Then, we calculate the coupling coordination degrees of AI and HUM, and based on the coupling coordination degree, we divide the sample into four states. Applying the quartiles, we divide the sample into low, moderate, high and super coordination states. To make analysis clear, we visualize the provincial AI and HUM, and is given in Figure 2. In our sample, the coupling coordination degree between provincial AI and HUM are generally high, especially in Jiangsu, Zhejiang, and so on. Combining with the stylized facts of ATFP, the ten provinces with the highest average level of ATFP from 2005 to 2014 were Jiangsu (1.1336), Zhejiang (1.0778), Shaanxi (1.0522), Tianjin (1.0480), Fujian (1.0476), Jiangxi (1.0459), Shandong (1.0446), Hebei (1.0439), Henan (1.0411) and Shanxi (1.0397). As a whole, provinces with high degrees of coupling coordination tend to have high ATFP. The exception is that Beijing, Shanghai and Guangdong have higher coupling coordination degree, but the ATFP does not show a significant advantage. The reason may be that, the scales of agricultural industrialization in these provinces are relatively small and stable, and the development of the agriculture are already at high levels, making the growth potential of production efficiency tend to small. Overall this result also verifies that the effect of AI on ATFP is nonlinear. When AI and HUM couples with each other, the AI is better at improving the growth of ATFP.

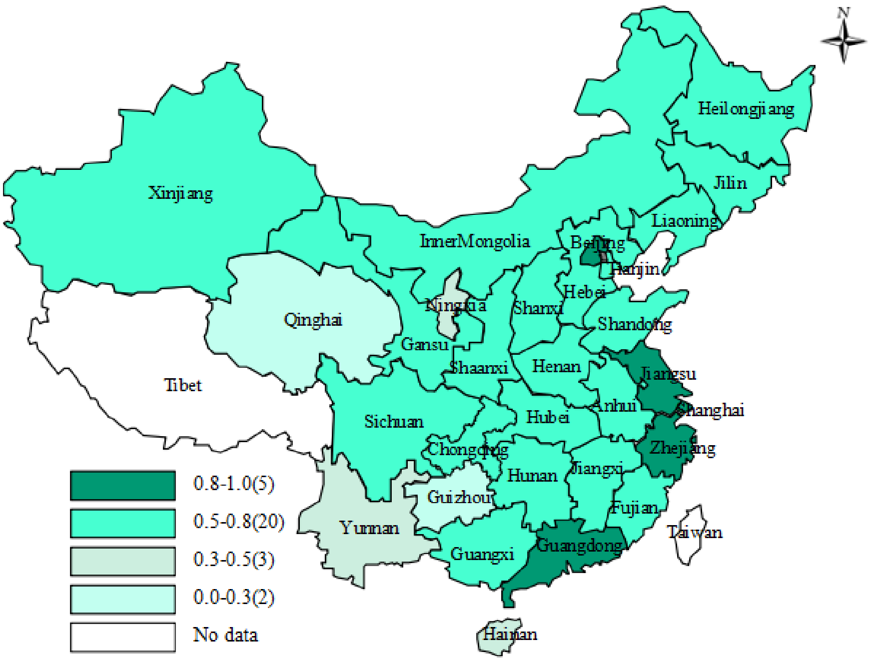

Figure 2 The spatial distribution of coupling coordination degree between AI and HUM

4.3. Robust checks

To enhance the credibility of results, we conduct a series of robustness checks, but the focal points here center on the model with double threshold effects, in which the threshold variable is rural human capital. A first test is concerned with adapting the indicators of AI, and we replace the composite index of AI with the ownership of telephones per 100 households (Model I). The second test concerns adding new control variables, namely, we add a new variable (*IND*) reflecting the production structure of different crops in the planting industry. We measure this variable by the ratio of the grain acreage to total acreage (Model II). The third test is concerned with replacing the indicators of the control variable, the environment regulation variable is replaced by the ratio of the investment funding in pollution abatement to GDP (Model III). The results are reported in Table 8. The estimation shows that, under different model specifications, the double threshold effects of rural human capital still exist, which suggests that our results are robust.

Table8: Robustness checks

Variable	Model I	Model II	Model III
AI*I (HUM≤X1)	0.0056 (0.36)	0.3932 (1.60)	0.4555 (1.63)
AI*I (X1<HUM≤X2)	0.0265** (1.83)	0.6965** (2.57)	0.7483*** (2.63)
AI*I (HUM> X2)	0.0433** (2.21)	0.8785*** (3.15)	0.9246*** (3.19)
URB	1.5006*** (7.40)	1.2351*** (6.14)	1.2936*** (5.93)
FIN	1.7377*** (4.09)	1.4906*** (3.67)	1.8226*** (4.52)
DIS	-0.1062** (-2.51)	-0.0831** (-2.17)	-0.0972** (-2.55)
REG	-0.4941*** (-3.04)	-0.4617*** (-2.76)	-3.0142 (-1.64)
INF	0.0687 (1.55)	0.0590 (1.52)	0.0648 (1.63)
IND	--	0.2700 (0.78)	--
F	4.4979	5.4968	5.1597
P value	0.0400	0.0250	0.0300

Note: *, **, *** denote significance at the 10%, 5% and 1% respectively. T-values are reported in parentheses.

5. Conclusions

The central contribution of this paper is that we study the nonlinear effect of AI on ATFP through panel threshold model. We test the differential effects of AI on ATFP under the condition that the threshold variable of rural human capital stays at different levels. We also consider the threshold effects of AI and time. The main conclusions include:

There exist double threshold effects of AI on ATFP when the threshold variable is rural human capital. Specifically, when the level of rural human capital is lower than the first threshold value, the positive impact of AI on ATFP is not significant. But when the rural human capital reaches to a specific level, especially when it crosses the first threshold value, the growth effect starts to emerge and becomes stronger along with the accumulation of rural human capital. Therefore, whether AI enhances the growth of ATFP or not, the mechanism depends on the level of rural human capital.

Based on the two threshold values of the rural human capital, we divide the 30 provinces into three regimes, namely, high, moderate and low regimes. In our sample period, the number of provinces belonging to the low regime decreases gradually, while the number of provinces belonging to high regime increases gradually. On the whole, the levels of rural human capital in the majority of the provinces are increasing in a way.

The threshold effects of AI and time are also emerged in the agricultural sector. When AI is lower than the first threshold value, the productivity paradox appears, but when it crosses the first and the second threshold values, the effects are significantly positive. Moreover, two time thresholds are identified when time is the threshold value, namely, the years of 2006 and 2012. The panel threshold regression results show that as time goes by, the positive effects of AI on ATFP gets stronger.

In the sample period, the degrees of the coupling coordination between AI and rural human capital are generally high, and at the same time, provinces with higher degrees tend to also have higher ATFP. This result suggests that only when AI and rural human capital couples with each other, then AI promotes the growth of ATFP more efficiently.

Our empirical findings suggest important policy implications. To enhance the growth of ATFP, not only will we increase the inputs of informational infrastructure and communication appliances, but also will we put more weight on increasing the stock of rural human capital, cultivating labors' learning capacity, information perception and awareness, and then the supporting environment of diffusing, digesting and absorbing agricultural informational technology can be formed.

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