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Abstract: As the primary industry in an economy, sustainable agricultural growth has attracted much attention from researchers and policy-makers worldwide. Digitalization reform and information technology greatly impact agriculture, rural areas, and farmers, improving high-quality development and green growth in the agricultural sector. Based on a measure of digitalization and a green productivity indicator, this paper investigates the impact of internet development on the economic and environmental performance of Chinese agriculture. Based on a measurement of digitalization and a green productivity indicator, this paper investigates the environmental performance and its relationship with internet development in the Chinese agricultural sector. The empirical results suggest that substantial green growth is observed in Chinese provincial agriculture, which is largely motived by technological progress. Internet popularization and digital technology indeed promote sustainable development in agriculture. Furthermore, the corresponding policy implications are provided to create a new path for steady growth in Chinese agriculture.

Keywords: Green growth; Internet development; Digitalization; Agricultural productivity.

JEL classification: O13, O47, P28.

1. Introduction

Agriculture is the foundation of a country's economic development. As a major indicator of evaluating agricultural development, total factor productivity (TFP) has always been a crucial measure for researchers (Wang et al., 2019; Sheng et al., 2020). Since the reform and the opening-up in 1978, Chinese agriculture has started to implement the household contract responsibility system (HCRS). Family farming stimulated the passion of farmers and liberated rural productivity. China's agriculture has achieved rapid development. Chinese total grain output reached 60 million tons in 2012, twice the amount in 1978. From 2015 to 2020, the grain yield exceeded 65 million tons for six years (CNBS). In the past 40 years, Chinese actual agricultural production value increased by about 5.3% per year, more than double that of the period 1952-1978 (Huang and Rozelle, 2018). 22% of the world's population is fed by Chinese agriculture which occupies only 10% of the world's cultivable land (Chen et al., 2021).

Different countries' agricultural structures and production patterns differ due to various economic development levels, natural conditions, systems, etc. Agriculture in developed countries such as America, French, and Japan is mainly characterized by industrialized management and mechanized production. In contrast, China's agricultural production mainly adopts the household contract responsibility system. Farms are mostly small and scattered. Land and family labor are still the primary inputs. In addition, China has a vast territory with a latitude of approximately 50 degrees from north to south. There are obvious differences in climate, soil, and even systems in different regions (Chen et al., 2009). Increasing agricultural production and income has always been a concern of the Chinese government.

For many years, Chinese agricultural growth relied on increased inputs (Su et al., 2020), ensuing waste of resources, and environmental pollution (Khanal et al., 2021). Chemical fertilizers, pesticides, and fossil fuels are widely used in agricultural production and cause carbon emissions (Chen et al., 2021) and agricultural nonpoint source pollution (ANSP) (Liu et al., 2021). According to the Communiqué of the Second National Pollution Source Survey, emissions of water pollutants from agriculture accounted for a large share of total pollution in 2017, with chemical oxygen demand (COD) accounting for 49.77%, total nitrogen 46.52% and total phosphorus 67.21% (CNBS). In terms of COD emissions, agriculture even surpasses the industrial sector, becoming the largest source of COD emissions. According to the China Committee for International Cooperation on Environment and Development, greenhouse gas emissions from the agricultural sector constitute nearly 17% of overall emissions. The rapid development of agriculture has become a reason for increasing carbon emissions

The Chinese economy is transforming from rapid growth to high-quality development. China is changing its development method and optimizing its economic structure. Agricultural development also needs to shift from quantity expansion to quality improvement, paying more attention to resource conservation and environmental protection to develop green agriculture. Green agriculture is central to implementing a sustainable agricultural development agenda (Fang et al., 2021). Chinese No.1 Central Document has focused on agricultural issues for 17 years, repeatedly emphasizing the importance of resource conservation, environmental protection, and high-quality development. However, due to the above-mentioned problems, green agricultural growth must address the twofold challenges of productivity and environmental performance. Improving green agricultural productivity (GAP) is the most effective way to promote green agricultural development under the current circumstances (Liu et al., 2020; Chen et al., 2021). The main contradiction in today's Chinese society has shifted from a growth in material and cultural needs of the population with retrograde societal production to a desire for a better life with unbalanced and inadequate development. The decline in Engel's coefficient also implies that consumers' demand for agricultural products is no longer just to obtain enough food, but more is the pursuit of high-quality products. Green organic agricultural products are more popular. Green agriculture, digital agriculture, and intelligent agriculture have been vigorously promoted in the current stage.

Farmers in remote mountainous areas have difficulty entering the market and obtaining income due to the obstruction of information and transportation. The problems also restrict them from learning and using modern agricultural production techniques or equipment. Fortunately, the development of the internet and communication technologies in rural areas improves the situation (Ogutu et al., 2014). In recent years, internet development and application in China have been unstoppable. Data from the "48th China internet Development Statistical Report" display that as of

June 2021, Chinese internet users are more than 1 billion, while the internet diffusion level has surpass 71.6% (CNNIC). The number of Chinese netizens ranks first in the world. Internet development has brought changes through combining internet information, communication technology, and internet platforms with other industries to create new industry ecology. In the past few years, China has continuously increased investment in agricultural research, using emerging technologies such as the internet, the Internet of Things (IoT), cloud computing, and blockchain to endorse the renewal of agricultural development (Zhu and Li, 2021). The use of the internet and digital technologies has positively contributed to agricultural growth. Some studies have found that the internet and communication technology improves green agricultural productivity (Benyam et al., 2021; Lioutas et al., 2021).

In summary, in the context of the urgent need to pay attention to both productivity and environmental performance in agricultural production, and the rapid development of the Internet. This paper used a modified by-production model to measure GAP. And on the basis of mechanism analysis, we explored the role of the level of Internet development on green growth in agriculture.

The originality of this paper is to examine green productivity growth and its relationship with internet development in the Chinese agricultural sector. The paper is structured as follows. The second section reviews the research on agricultural productivity and the internet development effect. The third section analyzes the influence mechanism of the internet on GAP. The fourth section is the model-building part. The data are described in Section 5 which also presents the empirical results, including the basic model, mediating effect, threshold regression results, and robustness test. The last section gives conclusions and policy recommendations.

2. Literature Review

2.1 Measurement of green agricultural productivity

The measurement of total factor productivity has been a crucial field of research in agricultural economics, as it estimates the extent of changes in the production process on farms (Balezentis et al, 2021). According to the different model settings and variable selection, the conclusions drawn are also different. Many earlier studies rarely considered environmental factors when calculating agricultural TFP (Li & Zhang, 2013; Chen et al., 2008). Until today, whether studying regional differences and convergence (Wang et al., 2019) or the historical level of TFP and its influencing factors (Sheng et al., 2020), environmental factors are still not considered in some agricultural productivity-related literatures. However, environmentally sustainable development has become a new path for high-quality economic growth in China today. In this process, sustainable agriculture is particularly important. Considering that long-term investment and pollution have seriously hindered the development of green agriculture in China (Fang et al., 2021). More and more studies have begun to consider environmental factors into the evaluation system when measuring agricultural productivity, and study how to improve agricultural productivity while reducing environmental impact.

Agricultural green productivity is considered an accurate indicator to measure the agricultural economy and environment. It reveals the part of sustainable growth under environmental pressure other than the input factors and has been applied in many studies. Liu et al. (2021) used the super SBM (slack-based model) to estimate Chinese GAP considering carbon emissions. Fang et al. (2021) applied the SBM-GML (Global Malmquist–Luenberger) index to estimate GAP using a panel data on provinces over the period 2002-2015. The results show that Chinese agriculture emits carbon dioxide following an inverted-U trend, and that overall growth is gradually decreasing. Chen et al (2021) used a three-step data envelopment analysis (DEA) framework and the SBM method to analyze the actual GAP of 30 Chinese provinces over the period 2000-2017. Further, many studies also decompose agricultural productivity into two parts: efficiency change (EC) and technological progress (TP), and explore the composition and growth sources of agricultural productivity (Deng et al., 2021; Rahman and Salim, 2013; Ma and Feng, 2013; Jin et al., 2010).

2.2 Influencing factors of green agricultural productivity

Many studies also focus on influencing factors when measuring agricultural productivity. After the reform and opening-up, Chinese agricultural productivity experienced a period of fast growth (Lin, 1992; Gong 2018). Some studies believe that institutional reforms (Lin, 1992; Zhang and Carter, 1997) and high levels of input (Lin, 1992; Brown, 1995;) are the main reasons for productivity growth during this period. Several years later, the positive effects of family farming and HCRS gradually exhausted (Lin, 1992; Mead, 2003). The marginal output of inputs has also continuously reduced. The growth of agricultural productivity has begun to slow down.

From 1984 to 1987, Chinese agricultural yield increased at an average annual rate of only 4%, even lower than before 1984 (Ma and Feng, 2013).

By decomposing productivity into two parts: EC and TP. Some scholars have found that the key component for the increase in agricultural productivity in most provinces is technological progress, while production efficiency is deteriorating (Ma and Feng, 2013; Jin et al., 2010). Numerous studies on productivity growth in China confirm this finding. Their studies found that public research investment has a high rate of return, and increased investment promotes technological progress (Deng et al., 2021; Rahman and Salim, 2013). In addition to the above factors, some studies have also paid attention to the influence of other factors, such as crop insurance (Fang et al., 2021), rural financial inclusion (Hu et al., 2021), and human capital (Wang et al., 2021).

2.3 Internet development effect

The dynamic expansion of information and communication technologies (ICTs) in China has made people realize its significant impact on improving the economic condition in rural areas. However, due to the development gap between developed and developing countries, although some authors have explored the different returns of internet use (Ma et al., 2020; Li et al., 2021), few studies look at the consequences of internet usage on GAP (Li et al., 2020). Chang & Just (2009) surveyed farmers in Taiwan Province and concluded that the internet could increase farmers’ income. Ma et al. (2020) also established that the internet use meaningfully increased rural households' income and expenditure. Zheng et al. (2021) and Zhu et al. (2021) respectively set up that using the internet positively impacts the technical efficiency of banana and apple production.

Given the above content, the research of this paper has the following three essential contributions. (1) To the best of our knowledge, this is the first study on the influence of comprehensive internet development on GAP. (2) We analyzed the effect mechanism of internet diffusion on the GAP growth rate. Appropriate intermediary variables were selected, and this process was calculated. (3) The measurement of GAP growth is based on the modified by-production model, which is an empirical application of this improved model.

3. Mechanism analysis

3.1 The direct influence mechanism of internet development on green agricultural productivity

3.1.1 Internet development promotes the transmission of information

The development of ICT has promoted the transmission of information, so it is regarded as an important factor in increasing economic and productivity growth (Ma et al., 2020). Farmers in China and other developing countries need to obtain sufficient information and essential facilities to improve their practices. Therefore, it is critical to provide essential knowledge and services to farmers in remote areas in a timely and high-quality manner. In the past, restrictions on information asymmetry made it difficult for small-scale agricultural producers to enter the market and obtain income. This also restricted them from learning and using new technologies and equipment. Fortunately, ICT development can improve this situation. The internet can reduce information asymmetry because it is quick and inexpensive in transforming information. Many studies have confirmed that ICT can play a crucial role in delivering market information (Ogutu et al., 2014), pesticide use (Cole and Fernando, 2012), fertilizer use (Kaila and Tarp, 2019), usage of seeds (Kiiza and Pederson, 2012), and land management (Hou et al., 2019) to farmers.

Communication equipment such as radios and televisions allowed farmers to obtain information in the past. However, the one-way flow of information prevented them from asking agricultural departments and experts to find problem solutions (Aker, 2011). Today, smartphones with call and video capabilities can meet most needs and allow mutual communication between farmers and service providers. Smartphones are the most accessible communication equipment and main information exchange channel for farmers. The ratio of Chinese internet users through mobile phones to access the internet is as high as 99.6% (CNNIC). The increase in the utilization rate of smartphones helps farmers obtain more market information, improves the level of decision-making, and reduces transaction costs (Tadesse and Bahiigwa, 2015). In China, using smartphones has played an important role in sustainable agriculture. Smartphones help farmers obtain inputs (fertilizers, pesticides, and seeds), market information, improve production, and reduce poverty in rural areas (Ma et al., 2020).

With the diffusion of communication technology, agricultural producers can use an increasing number of devices, such as smartphones, tablets, laptops, and various applications ("apps"). The emergence of new equipment has made information acquisition channels more diversified. However, if farmers lack agricultural-related information sources, even with smartphones and other communication channels, their decision-making and management behaviors will not be significantly improved (Tadesse and Bahiigwa, 2015). Thus, the increase in information sources and data volume brought about by national internet development is also critical.

In summary, the development of ICT has given agricultural producers more opportunities. Farmers can learn and apply the latest technology and equipment more quickly, adjust the production structure according to market demand and price changes, improve production and sales by obtaining weather information, and obtain more insurance and subsidy policies to reduce costs or loss. Crop insurance is important to protect agricultural production and reduce economic losses. Related to moral hazard and adverse selection, insurance contracts enable to decrease the use of pesticides and fertilizers (Mishra et al., 2005). This is an efficient way to reduce chemical input waste and environmental pollution and thus to generate higher GAP levels (Fang et al., 2021).

3.1.2 Internet development promotes the digital agriculture

Organizations such as the OECD, FAO, and the World Bank believe that digital agriculture can achieve the Sustainable Development Goals by improving productivity and reducing pollutants. "Digital agriculture” uses new technologies such as artificial intelligence, robots, and sensors to farm production systems through the IoT (Lioutas et al., 2021). In other words, digital agriculture is realized by mixing the technologies of cloud computing and the IoT based on a large amount of farm data generated by modern agricultural operations (Rotz et al., 2019). After the industrial revolution, digital agriculture transformed from machine-led production to digital production. Digital agriculture encourages the application of existing or developing advanced technologies in agricultural production.

Studies have shown that farm management and efficiency can be improved by providing intelligent services and digital products for farmers (Lioutas et al., 2019). Artificial intelligence enhances farmers' decision-making ability by extracting critical information from big data and making predictions (Wolfert et al., 2017). Help farmers identify problems, determine cause and effect, and provide better solutions. For example, soil sensors can provide fertilization and irrigation schemes (Johnson et al., 2020); biosensors help crop disease and pest detection (Yang, 2020); drones and satellites provide more accurate weather fluctuation data (Goel et al., 2021); and mechanized machines can significantly increase productivity, reduce labor costs, and raise the quality of products (Sparrow and Howard, 2021). The application of digital systems saves more time and energy for farmers to manage their farms.

Furthermore, digital information tracking systems (such as blockchain) can improve consumers' awareness of the sustainability of the food purchased (Kamilaris et al., 2019). Handford et al. (2014) stated that nanotechnology improved the accuracy of agricultural management, allowing more effective use of chemical fertilizers and pesticides, thereby reducing agricultural waste. The information provided by digital devices can help farmers reduce the use of agricultural chemicals (Viani et al., 2016), increase their awareness of the impact of production activities on natural resources and the environment (Vilas et al., 2020), and improve agricultural activities' waste management (Rejeb et al., 2021). Therefore, digital agriculture may reduce agriculture's environmental footprint, which is also significant for improving GAP.

3.1.3 Internet development drives the E-Agriculture development

Small-scale agricultural producers face difficulties selling agricultural products in many developing countries due to geographical location and traffic conditions. The appearance and fast expansion of rural e-commerce in developing countries provide a new method for small farmers to overcome market entry barriers (Li et al., 2021). Internet communication technology and electronic devices (smartphones, laptops, etc.) are increasingly used in rural areas. Over the past few years, the penetration rate of e-commerce in the rural territories has increased. Rural e-commerce meets the requirements of the transformation and upgrading of rural industries, is a straightforward way to utilize the internet and ICT to obtain more profits, and provides a new impetus for the revitalization of the rural economy (Peng et al., 2021).

First, e-commerce allows farmers to sell products online, reducing intermediate links and lowering transaction costs. Almost all transaction costs of small-scale agricultural producers are very high (Poulton et al., 2010). Therefore, preventing intermediate sellers who trade products online can effectively reduce transaction costs. Second, e-commerce can help rural households improve information asymmetry. With more transparent market information, farmers can appropriately increase the selling prices of agricultural products, and market efficiency can be improved (Aker, 2010). Third, e-commerce can break geographical restrictions and enable farmers to retail food products to clients across the country (Tang and Zhu, 2020). Yu & Cui (2019) also found that the application of e-commerce allows families to reach many customers that they could not get before. The adoption of e-commerce has therefore encouraged farmers to produce and distribute more goods that are adapted to online retailing.

Although e-commerce breaks geographical restrictions and permits rural households to trade agricultural products to a larger area, it also means intensified market competition (Tang and Zhu, 2020). The demand of Chinese consumers has changed from simply getting enough food to pursuing high-quality products. An increasing number of consumers show a higher willingness to buy green, additive-free, and pollution-free products. Market demand promotes supply-side structural reforms, which are obviously of great significance for improving China's GAP.

3.2 The indirect influence mechanism of internet development on green agricultural productivity

3.2.1 Internet development, income increase, and green agricultural productivity

The positive contribution of rural e-commerce to the revenues of rural householders has been verified by numerous studies (Li et al., 2021; Peng et al., 2021). Li et al. (2021) found that the income of those who apply e-commerce is substantially higher than that of those who do not. The rise in income is mainly due to the boost in turnover. Luo & Niu (2019) surveyed household data in 80 Taobao villages, and their results also support the above conclusion that rural e-commerce impacts positively and significantly household revenu. China's experience clearly shows that rural e-commerce has a beneficial impact on the income of farm households. In 2020, the online retail sales observed in 832 poor counties reached 301.45 billion yuan, an increase of 26%

on average per year. The total number of online merchants reached 3.065 million, an increase of 13.7% year-on-year (CMC).

In the past few decades, stimulating rural economic growth has been a concern of the Chinese government. Increasing income is the foundation for improving the quality of life in rural areas, so it has become an important motive for agricultural producers to expand production scale, enhance product quality, and promote agricultural productivity. An increase in income will help increase farmers' consumption levels. Coupled with the growth of e-commerce, agricultural producers will have a more significant financial capacity and a broader consumption platform to purchase and use better materials or advanced equipment when carrying out agricultural production. An increased input level will further improve product quality, productivity, and income, forming a virtuous circle, which is important for enhancing GAP.

3.2.2 Internet development, human capital, and green agricultural productivity

Lio & Liu (2006) proved that rural human capital is critical in applying the internet and ICT. They found that the return on agricultural production of communications technology in wealthier countries is approximately twice that of poorer countries. The difference in human capital seems to be responsible for the low elasticity of ICT productivity in the poorest countries. As mentioned above, although we already know that the emergence of e-commerce has brought new opportunities for rural economic development, the adoption rate of e-commerce in many developing countries is still very low. Factors such as low education level, lack of awareness of the advantages of e-commerce, and backward rural ICT infrastructure limit the application of e-commerce in rural households. In particular, the lack of understanding of online businesses and their functions limits farmers to adopt and benefit from e-commerce (AliResearch, 2017).

Some recent studies have shown that with the popularization of e-commerce in rural China, the human capital of agricultural producers has also been improved (Fafchamps and Minten, 2012; Chan, 2015). Generally, farmers need to receive training before using e-commerce. Capable farmers can use e-commerce platforms to open online stores to sell products, and other farmers can also involve in associated work after exercise (Peng et al., 2021).

Agricultural extension services are an essential tool for governments to impart information, assistance, new technologies and practices to farmers and to promote agricultural development (Anderson and Feder, 2004). In the past, communication methods such as radio and telephone made agricultural extension services very limited and hindered the development of rural human capital. In the context of the information age, the increase of information sources and the diversification of communication equipment have enabled this plan to be better implemented. In addition, the difficulty for farmers to acquire knowledge is greatly reduced. The internet has a part to play in reducing the backwardness of rural education. Further, the improvement of knowledge level means that farmers can apply more advanced agricultural production concepts and digital agricultural equipment. This is conducive to increasing agricultural productivity.

3.2.3 Internet development, logistics development, and green agricultural productivity

We already know that the application of e-commerce can bring huge benefits. A variety of products are circulating in the world market thanks to the e-commerce. In rural China, the list of products sold online traditionally includes agricultural and food products such as herbs, fruits and tea. But beyond these products, we can also find processed non-agricultural goods such as clothes, furniture and books (Tang and Zhu, 2020; Zeng et al., 2019). However, it should be noted that the infrastructure related to e-commerce, including logistics, network infrastructure, road construction, etc., is the key support behind online business development (Li et al., 2021). The diversification of online products is inseparable from supporting multiple offline logistics and distribution methods. In developing countries such as India, Brazil, and Vietnam, the relatively underdeveloped facilities hinders e-commerce business development in rural areas (Jamaluddin, 2013).

As the scale of rural e-commerce continues to expand, the requirements for logistics are also increasing. A more efficient collection and distribution logistics network is needed. China's rural areas are vast and have a large population. Express delivery often needs to transport thousands of kilometers, but the cost is low. Therefore, the sharing economy is considered an excellent manner to better develop the logistics resource allocation, particularly for Chinese rural areas (Yang et al., 2020). For this reason, in the Rural Revitalization Plan, the Chinese government emphasizes the importance of establishing a shared logistics network and encourages cooperation between logistics companies to improve efficiency. Additionally, a number of other documents issued by the Chinese government, such as the Special Action for Efficient

Urban-Rural Distribution (2017-2020), consider the construction of shared logistics as the main element for the development of rural logistics.

In addition, a good logistics foundation is the construction of a more complete road system. In June 2020, China's last non-accessible organic village was opened to traffic. "If you want to get rich, build roads first." This slogan that every Chinese is familiar with is precisely the working idea of rural economic construction. In the five years from 2013 to 2017, the government invested 400 billion yuan in rural road construction and built more than 1.27 million kilometers of rural roads. More than 5,800 poverty-stricken areas are covered, and 24 provinces have all qualified townships and organized villages open to traffic (MTPRC).

3.2.4 Internet development, industrial integration, and green agricultural productivity

In recent years, some people from remote and impoverished villages have become internet icons by selling goods or exhibiting the culture of their hometown (Peng et al., 2021). They provided significant help in the online sales of hometown products and promoted the export of hometown culture and natural scenery, which also helped to encourage the development of tourism in their hometown. In the digital economy, with the continuous development of emergent technologies such as the internet, rural tourism has become increasingly intelligent and digital. The National Development and Reform Commission announced that it would vigorously promote the "Internet +" innovation model. Use the internet to develop service areas such as rural tourism with great potential for employment and are in urgent need of society.

"Internet + Rural Tourism" mainly relies on internet information platforms, integrates scattered rural tourism resources, strengthens online promotion and digital empowerment, and drives diversified innovation and entrepreneurship in the field of rural tourism. Closely combine leisure and entertainment, cultural creativity with rural tourism, folk culture, and modern agriculture. While actively developing a new model of rural tourism, it also promoted the development of modern agriculture. At present, most of China's rural tourism projects allow tourists to experience unique activities such as fruit and vegetable picking, tea picking, and horse riding. On the one hand, the experience narrows the distance between tourists and rural production. On another side, it also enable consumers to appreciate local, high-quality agricultural products. Tourism development also promotes agricultural development.

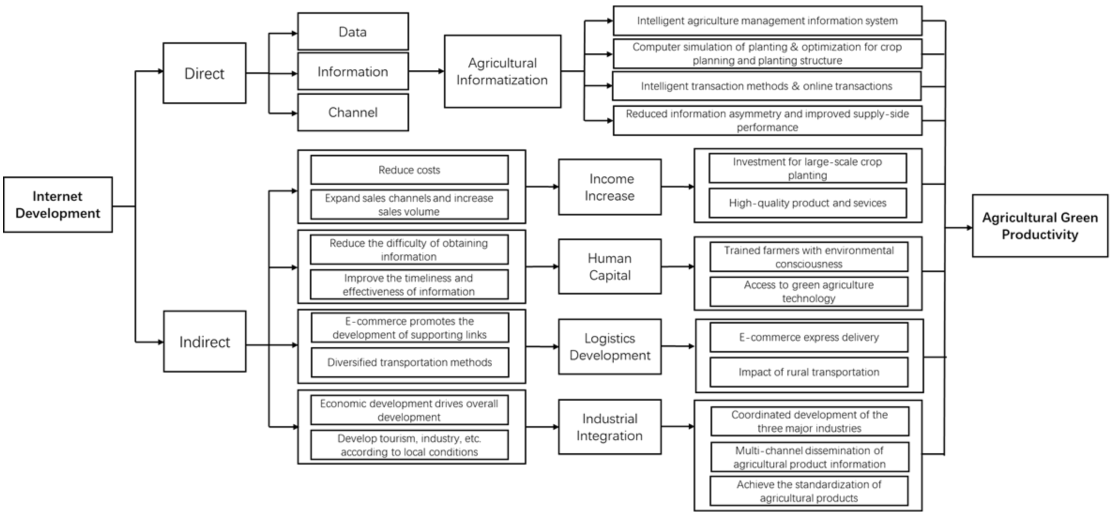

Figure 1 Mechanism analysis

4. Methodology

4.1. Green productivity indicator and its decomposition

Economic activities usually have negative externalities, generating pollution during the production process. Recently, much attention has been given to environmental protection and green sustainable development in related research. Parametric and nonparametric estimations can be used to gauge the distance functions that construct the environmental productivity indices for macro or micro performance analysis. This paper uses a nonparametric DEA model and directional distance function to evaluate China's GAP. This framework is widely employed to assess macro-level efficiency changes and productivity growth (Rath and Akram, 2017; Shen et al., 2021).

This paper incorporates undesirable outputs into the production process. Weak disposability axioms (Shephard, 1970; Shephard & Färe, 1974) and null jointness (Färe and Grosskopf, 2004) are popular to link good and bad outputs, allowing a proportional reduction of both types of output. However, this method is not applicable when undesirable emissions are easy to control. For example, SO_2 emissions can be completely dissolved in water. Subsequently, Murty et al. (2012) suggested a by-production model based on the assumptions of strong and costly disposabilities, isolating the pollution generation process and allows the pollution to be treated entirely. This method assumes two independent sub-technologies, one sub-technology (T1) is to model ideal outputs produced by all inputs, and another sub-technology (T2) is to analyze undesirable outputs and pollution-generating inputs.

Assuming K decision-making units (DMUs) are evaluated, the by-production production possibility set contains $Q+P$ outputs and $C+D$ inputs. Concerning outputs, Q types of desirable outputs, and P numbers of undesirable outputs (or by-production). Regarding inputs, C clean (nonpollution-generating) inputs only contribute to the desirable outputs, and D dirty (pollution-generating) inputs contribute to desirable and undesirable outputs. More specifically, let $\mathbf{x}^c \in R_+^C$ and $\mathbf{x}^d \in R_+^D$ be the vectors of clean and dirty inputs, respectively; let $\mathbf{y} \in R_+^Q$ and $\mathbf{z} \in R_+^P$ be the vectors of desirable and undesirable outputs, respectively. The by-production technology is then defined as (Murty et al., 2012):

$$\begin{aligned} T_{BP} &= T_1 \cap T_2 \\ &= \left\{(x^c, x^d, y, z) \in R_+^{C+D+Q+P} : (x^c, x^d) \text{ can produce } y \text{ ; } x^d \text{ can generate } z \right\}; \\ T_1 &= \left\{(x^c, x^d, y) \in R_+^{C+D+Q} \mid f(x^c, x^d, y) \le 0\right\}; \\ T_2 &= \left\{(x^d, z) \in R_+^{D+P} \mid g(z, x^d) \le 0 \right\}. \end{aligned}$$

(1)

where *f*(.) and *g*(.) are continuously differentiable functions satisfying strong disposability and costly disposability, respectively.

Chambers et al. (1996a) introduced the directional distance function (DDF) to estimate the efficiency of DMUs. More precisely, a DDF gauges the gap between an evaluated DMU and its benchmark or best performance (Production Frontier). A general DDF framework with inputs, good and bad outputs can be defined as:

$$D\left(x, y, z; g_x, g_y, g_z\right) = Max\left\{\delta \in \Re_+ : \left(x - \delta \otimes g_x, y + \delta \otimes g_y, z - \delta \otimes g_z\right) \in T\right\} \quad (2)$$

where δ is the inefficiency score measuring the potential input reductions, potential desirable output increases, or potential undesirable output decreasing. (g_x, g_y, g_z) is a nonnegative direction vector usually defined by the input/output quantity levels of the evaluated DMU (province).

In this paper, we adopt the output-oriented DDF, so the above basic formula can be modified accordingly as:

$$D\left(x, y, z; 0, g_y, g_z\right) = Max\left\{\delta \in \Re_+ : \left(x, y + \delta \otimes g_y, z - \delta \otimes g_z\right) \in T\right\} \quad (3)$$

A combination of distance functions can define procductivity indices. For instance, the Malmquist index is a ratio-based measure constructed by Shephard distance functions; the Luenberger indicator is a difference-based productivity measurement with DDF. In this paper, we adopt an output-oriented Luenberger productivity indicator (LPI) to obtain green growth over periods *t* and *t+1* (Chambers et al., 1996; Chambers, 2002) as:

$$LPI^{t,t+1} = \frac{1}{2}\left[D^{t}(x^{t}, y^{t}, z^{t}) - D^{t}\left(x^{t+1}, y^{t+1}, z^{t+1}\right) + D^{t+1}\left(x^{t}, y^{t}, z^{t}\right) - D^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}\right)\right] \tag{4}$$

According to Chambers et al. (1996b), the Luenberger indicator can be split into its two components : efficiency change (EC) and technological progress (TP). EC, commonly referred to as the catching-up effect (decreasing technical inefficiency), measures the changes in the gap between the evaluated DMU and the production frontier over time. This means the part can be improved if inputs can be used more efficiently. TP represents the frontier change due to technological innovation or organizational change from periods *t* to *t+1*. Its measurement becomes possible using various data combinations related to two time periods and reference techniques to estimate four different distance function values. The decomposition of productivity gain can be summarized as:

$$\begin{aligned} &LPI^{t,t+1} = EC^{t,t+1} + TP^{t,t+1}, \\ &EC^{t,t+1} = D^{t}\left(x^{t}, y^{t}, z^{t}\right) - D^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}\right), \\ &TP^{t,t+1} = \frac{1}{2}\left[\begin{aligned} &D^{t+1}\left(x^{t}, y^{t}, z^{t}\right) - D^{t}\left(x^{t}, y^{t}, z^{t}\right) \\ &+D^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}\right) - D^{t}\left(x^{t+1}, y^{t+1}, z^{t+1}\right) \end{aligned}\right]. \end{aligned} \tag{5}$$

All previous directional distance functions are defined in the output orientation and measured by a nonparametric approach. We adopt a model with a single dual price of polluting inputs introduced by Balezentis et al. (2021). A detailed linear programming model for measuring DDF is available in Appendix1.

4.2 Estimation strategy

4.2.1 Panel data model

To measure the internet development level, some papers collected different variables such as the number of internet users and internet penetration rate. Previous studies (Lum, 2009; Jiang, 2010;). However, some single-dimensional indicators, including the above indicators, cannot reflect the overall situation of China's internet development. It is necessary to construct a comprehensive multidimensional indicator to solve this problem. Based on the existing and available official statistical indicators and data, Wu et al. (2021) analyzed internet development in China’s provinces through from four items: internet facilities and equipment, internet industry development, internet business applications, internet development environment, and constructed a comprehensive indicator to represent the internet development. We take this comprehensive indicator as the core explanatory variable and chooses the provinces' agricultural financial input (Chen et al., 2021; Hu et al., 2021; Xu & Lin, 2017), agricultural disaster rate (Fang et al., 2021), and industrialization level (Fang et al., 2021; Hu et al., 2021) as the control variables.

According to the above variables, we set the basic model as Formula (6) below. In the selection of econometric methods, we first used pooled ordinary least squares (OLS) method to process the panel data without adding any other conditions. Then, considering the heterogeneity of different provinces and the time trend of the variable itself, a fixed-effects (FE) model was used. The province and time are fixed simultaneously. Furthermore, given that random error terms can lead to endogeneity issues and make empirical tests are biased and inconsistent. We address this problem by means of an instrumental variable model and two-stage least squares (2SLS). Finally, considering the hysteresis of agricultural production, we add the first-order lag term of LPI to the above model, and use the system generalized method of moments (GMM) to deal with the dynamic panel model.

Given the basic model and dynamic panel model as follows:

$$lpi_{it} = \beta_0 + \beta_1 inter + \sum_{k=1}^{3} \beta_k X_{it} + \varepsilon_{it} \tag{6}$$

$$lpi_{it} = \beta_0 + \beta_1 inter + \beta_2 L.lnlpi + \sum_{k=1}^{3} \beta_k X_{it} + \varepsilon_{it} \tag{7}$$

where i is the province, t is the year, lpi is LPI, $L.lpi$ is lpi lagged by one period, $inter$ is the internet development, and X is a series of control variables, ε_{it} represents the random error term.

4.2.2 Test of influence mechanism

In Section 3, we analyzed whether internet development influences LPI through four aspects: income increase, human capital, logistics development, and industrial integration. To test whether the internet can improve provincial LPI through farmers' income, human capital, logistics development, and industrial integration. According to Wu et al. (2021), construct an intermediary effect model:

$$lpi_{it} = \gamma_0 + \gamma_1 inter_{it} + \sum_{k=1}^{3} \gamma_k X_{it} + \varepsilon_{it} \qquad (8)$$

$$med_{it} = \varphi_0 + \varphi_1 inter_{it} + \sum_{k=1}^{3} \varphi_k X_{it} + \varepsilon_{it} \qquad (9)$$

$$lpi_{it} = \xi_0 + \xi_1 inter_{it} + \xi_2 med_{it} + \sum_{k=1}^{3} \xi_k X_{it} + \varepsilon_{it} \qquad (10)$$

where med_{it} is the mediator variable. Formula (8), Formula (9), and Formula (10) construct the intermediary effect model together.

4.2.3 Verification of non-linear relationship

In the above section, we analyzed to what extent the development of the Internet impacts the growth of LPI through income increases, human capital, logistics development, and industrial integration. However, internet development in China, especially in rural areas, has not grown overnight in the past ten years. The effect on LPI may have a non-linear effect. We select three indicators related to rural internet development to test the non-linear relationship, namely, rural postal delivery routes, express volume, and the number of internet ports, as threshold variables. Hansen (1999) introduced the threshold panel model to empirically test the non-linear relationship, which is defined as follows:

$$lpi_{it} = \sigma_0 + \sigma_1 inter * I(\delta_{it} \le \omega) + \sigma_2 inter * I(\delta_{it} > \omega) + \sum_{k=1}^{3} \sigma_k X_{it} + \varepsilon_{it} \qquad (11)$$

where δ_{it} is the threshold variable. ω is the threshold value to be estimated; $I(\cdot)$ is an instruction function.

5. Data and results

5.1 Data descriptive

The data consist of two parts, both of which are panel data from 30 provinces in China. The first part uses the data from 1997 to 2019 to calculate the LPI; the second part uses the data from 2007 to 2017 to examine the impact of internet development on the growth of LPI. Except for the comprehensive internet development data from Wu et al. (2021), other data are from the "China Statistical Yearbook" and the official website of CNBS. This article excludes Tibet, Hong Kong, Macao, and Taiwan data based on data availability. In the second part of the calculation, to avoid the influence of price fluctuations, the price-related data of each province are all deflated with 2007 as the base period. To eliminate the impact of heteroscedasticity, all data are processed in logarithm form. As a summary, the descriptive statistics of the variables are shown in Table 1:

Table 1 Descriptive statistics

Variable	Attributes	Definition	Obs	Mean	SD	Min	Max
lpi	Dependent variable	Agricultural green productivity	330	0.781	0.228	-0.421	1.092
inter	Core independent variable	Internet development	330	0.171	0.148	0.024	0.654
fep	Control variable	Agriculture accounts for total government expenditure	330	0.108	0.031	0.029	0.190
dr	Control variable	Disaster rate	330	0.208	0.149	0.000	0.696
ind	Control variable	Industrialization level	330	0.369	0.084	0.117	0.574
inc	Mediating variable	Farmers' income	330	8.845	0.465	7.753	9.994
idst	Mediating variable	Added value of the secondary and tertiary industries	330	9.229	1.090	5.676	11.39
edu	Mediating variable	Rural education level	330	105.0	103.2	2.200	758.9

lpl	Mediating variable; threshold variable	Rural postal delivery routes	330	11.39	0.921	8.515	12.55
lev	Threshold variable	Express volume	330	9.039	1.750	4.973	13.83
lpn	Threshold variable	Number of Internet ports	330	6.547	1.127	2.981	8.784

5.2 Empirical results and discussions

5.2.1 Green productivity analysis

The input and output of LPI are both divided into two categories. Labor is a clean input, but machinery, land, fossil fuels, pesticides, and fertilizers are all polluting inputs; outputs include total agricultural output value (desirable output) and carbon emissions (undesirable output). According to the revised by-production model and the DDF, construct the production frontier (best practice) and measure the performance of the evaluated DMU. On this basis, the LPI of each province was calculated from 1997 to 2019. Furthermore, decompose LPI into two parts, EC and TP. The results are shown in Figure 2 and Table 2 below:

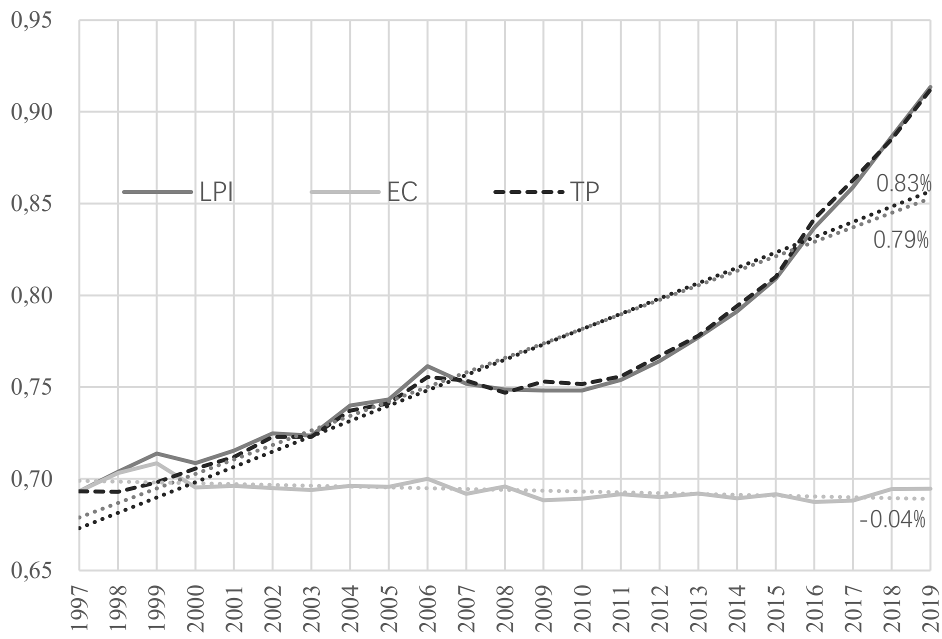

Figure 2 Cumulative green productivity growth and its decomposition

Table 2 Results for 30 provinces (%)

Province	LPI	EC	TP	Province	LPI	EC	TP
Beijing	-0.34	0.00	-0.34	Henan	1.69	0.07	1.65
Tianjin	0.50	-0.03	0.54	Hubei	0.79	-0.09	0.87
Hebei	1.84	-0.02	1.88	Hunan	0.93	-0.25	1.13
Shanxi	0.81	-0.06	0.85	Guangdong	1.45	0.00	1.44
Inner Mongolia	-0.06	-1.36	1.08	Guangxi	1.25	0.47	0.85
Liaoning	1.29	-0.09	1.37	Hainan	1.75	0.34	1.62
Jilin	0.55	-0.27	0.80	Chongqing	0.33	0.02	0.32
Heilongjiang	1.58	-0.14	1.65	Sichuan	0.60	0.00	0.60
Shanghai	0.06	0.00	0.06	Guizhou	-0.62	0.00	-0.62
Jiangsu	1.58	0.00	1.58	Yunnan	0.96	0.28	0.73
Zhejiang	1.78	0.00	1.78	Shaanxi	1.57	0.07	1.51
Anhui	0.80	-0.12	0.88	Gansu	1.50	0.15	1.40
Fujian	1.98	0.02	1.96	Qinghai	0.16	0.00	0.16
Jiangxi	1.18	-0.34	1.47	Ningxia	-4.79	0.00	-4.79
Shandong	1.60	0.00	1.60	Xinjiang	1.02	0.00	1.02

Figure 2 is the time change trend chart of the national average LPI obtained by averaging the LPI of 30 provinces from 1997 to 2019. Figure 2 illustrates that China's agricultural LPI has experienced a process of "fast-slowdown-fast" in the past two decades. The main driver for the LPI growth is TP while EC even shows negative contributions, which is in line with the results of preceding studies (Tian and Wan, 2000; Jin et al., 2010; Ma and Feng, 2013;). Table 2 shows each province's average LPI growth rate from 1997 to 2019. The results indicate that the average annual growth rate of LPI in most provinces is between 1% and 2%, while others are relatively low. Beijing, Inner Mongolia, Guizhou, and Ningxia even show negative growth. The decomposed results of each province are similar to the overall situation in China. Most provinces' EC has low or negative contributions, and the main contribution of LPI growth comes from TP.

5.2.2 Panel regression result

By using Stata 16, we obtained the empirical results of the four methods corresponding to models (6) and (7), and performed weak instrumental variable tests on the employed instrumental variables. To make the regression results more intuitive, we present the results of pooled OLS regression, fixed-effects model, instrumental variable model, and dynamic panel model in one table. The all results mentioned above are shown in Table 3 and Table 4 below:

Table 3 Panel regression result

	(1)	(2)	(3)	(4)
	OLS	FE	2SLS	System-GMM
inter	0.321***	0.044	2.248***	0.033**
	(0.066)	(0.054)	(0.689)	(0.017)
fep	0.133	-0.241	5.986***	0.261***
	(0.686)	(0.418)	(1.982)	(0.043)
dr	-0.206**	-0.028	-0.139	-0.061***
	(0.086)	(0.030)	(0.137)	(0.007)
ind	0.412***	-0.093	1.638***	-0.045**
	(0.136)	(0.171)	(0.377)	(0.019)
L.lnlpi				1.014***
				(0.008)
_cons	0.603***	0.812***	-0.764*	-0.006
	(0.102)	(0.078)	(0.419)	(0.007)
Year Fe	NO	YES	YES	YES
Province Fe	NO	YES	NO	YES
N	330	330	308	280
R^2	0.085	0.442		

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4 Weak instrumental variable test results

Variable	R^2	Adjusted- R^2	Partial- R^2	Robust F(1,293)	Prob > F
inter	0.463	0.437	0.059	11.264	0.001

In the above results, although the results of the combined OLS method perform better, the reliability of the results is not high because no control conditions are added.

Second, the fixed effects model, after fixing time and province, reduces the possible impact of heteroscedasticity, but the result is not significant. Third, the instrumental variable model also obtained significant results after controlling for endogeneity. According to Table 4, the F-statistic of the first-stage regression in 2SLS is 11.264>10. It can be considered as strong instrumental variables. The results of this model suggest that Internet development promotes the growth of LPI. Finally, the results of the dynamic panel model processed by the system-GMM method also show that the Internet development has a promoting effect on LPI.

By comparing the results of methods (3) and (4), it can be found that after adding the lagging term of productivity, the promoting effect of Internet development on LPI is significantly weakened. This result is in line with the actual situation and our expectations. There is inertia in the growth of LPI. On the basis of using previous resources and technologies, agricultural production will further improve productivity based on experience and innovation. Therefore, the addition of the lag term makes the model more complete, and the impact level of Internet development on LPI is also more reliable. In addition, the regression results also show that the province's agricultural financial input and industrialization level also promote LPI; in contrast, the disaster rate shows a negative impact.

5.2.3 Empirical verification of transmission mechanism

Through the previous regression, we found that internet development can promote the growth of LPI. However, we are still curious about how internet development facilitates the growth of LPI. Section 3 analyzes the mechanism and believes that income increase, human capital, logistics development, and industrial integration have realized this process. In this section, we will verify this influence mechanism. Through the intermediary model in the previous section, we can obtain the following results:

Table 5 Empirical test of the transmission mechanism

Variable		*Med=inc*		*Med=edu*		*Med=idst*		*Med=lev*	
	(8)	(9)	(10)	(9)	(10)	(9)	(10)	(9)	(10)
inter	0.321***	1.332***	0.239***	201.746***	0.217***	3.176***	0.087	6.492***	-0.056
	(0.066)	(0.221)	(0.076)	(31.126)	(0.073)	(0.282)	(0.098)	(0.671)	(0.095)
inc			0.062**						
			(0.028)						
edu					0.001***				
					(0.000)				
idst							0.074***		
							(0.023)		
lev									0.058***
									(0.010)
fep	0.133	0.241	0.118	350.900*	-0.048	-0.444	0.165	3.610	-0.077
	(0.686)	(1.088)	(0.690)	(200.375)	(0.679)	(1.883)	(0.613)	(3.167)	(0.667)
dr	-0.206**	-1.412***	-0.119	22.201	-0.217**	-2.054***	-0.055	-4.819***	0.074
	(0.086)	(0.160)	(0.100)	(34.120)	(0.084)	(0.318)	(0.094)	(0.491)	(0.096)
ind	0.412***	-0.960***	0.471***	576.301***	0.115	2.788***	0.206	2.297**	0.278*
	(0.136)	(0.275)	(0.130)	(60.089)	(0.171)	(0.513)	(0.169)	(0.911)	(0.142)
_cons	0.603***	9.360***	0.024	-184.681***	0.698***	8.141***	0.003	7.710***	0.155*
	(0.102)	(0.218)	(0.270)	(34.450)	(0.111)	(0.316)	(0.156)	(0.638)	(0.093)
N	330	330	330	330	330	330	330	330	330
R^2	0.085	0.429	0.096	0.243	0.126	0.358	0.165	0.528	0.179

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Formula (8) shows the influence of internet development on LPI before adding the intermediary variable. In formula (8), the coefficient on the main dependent variable is significantly positive, implying that Internet expansion can dramatically promote LPI development. The results of formula (9) and formula (10) show that Internet development has contributed substantially to income gains, human capital improvements, logistics development, and secondary and tertiary industries. In Formula

(8), the core dependent variable coefficient is significantly positive, implying that internet development can dramatically promote the growth of LPI. The results of Formula (9) and Formula (10) suggest that the development of the internet has significantly promoted income growth, human capital improvement, logistics development, and secondary and tertiary industries. Then, the income increase, human capital, logistics development, and industrial integration have significantly increased LPI.

5.2.4 Verification results of a non-linear relationship

From the above research, we can find that the growth of LPI has phases. Combined with the reality of China, it is clear that the development of the internet it is not difficult to find that internet development in China is phased, especially in rural areas. As described in Section 4, we use a dynamic threshold panel model to test the threshold effect. The threshold variables are rural postal delivery routes, express volume, and the number of internet ports. To judge whether the model threshold exists, we use a bootstrapping approach to estimate the associated p-value and critical level, and the results are from 300 sampling simulations. Then, we conducted a hypothesis test on the existence of a single threshold and dual-threshold. Table 6 displays the results. The single threshold of the number of internet ports did not pass the significance test, while the dual thresholds are all significant. Consequently, we choose the dual-threshold panel model.

Table 6 Verification results of threshold model

Core independent variable	Threshold variable	Model	F-test	P-value	1%	5%	10%
inter	*lpl*	Single threshold	18.137**	0.030	21.126	16.855	13.650

	Double threshold	150.014***	0.000	5.802	-0.131	-2.224
lev	Single threshold	35.872*	0.090	77.462	45.966	33.440
	Double threshold	26.550***	0.000	12.398	1.708	0.418
lpn	Single threshold	32.395	0.233	157.913	134.593	82.016
	Double threshold	61.260***	0.000	27.977	18.707	12.313

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table 7 shows the double threshold panel model's threshold value and confidence interval. We take the limits of the critical value as the upper and lower bounds of the confidence interval if the likelihood ratio LR is below 5% and the critical value as the threshold if LR=0.

Table 7 Estimation of threshold value and confidence interval

Core independent variable	Threshold variable	Model	Threshold value	95% confidence interval
inter	*lpl*	Double threshold	11.308	[11.173,11.308]
			12.271	[12.145,12.275]
	lev	Double threshold	7.338	[7.121,7.986]
			9.022	[8.388,9.152]
	lpn	Double threshold	7.506	[7.366,7.876]
			5.344	[5.150,5.710]

The threshold effect is confirmed by the above process. Figure 3 shows the figure of the likelihood ratio function related to the dual-threshold model of the threshold variables (*lpl*, *lev*, and *lpn*). Figure 3 clearly shows the construction process of the threshold estimate. On this basis, we further check whether the threshold estimate is equal to its actual value. The horizontal axis characterizes the threshold parameter, the vertical axis denotes the LR value, and the red dotted line indicates the critical value of the non-standard chi-square distribution at the 5% significance level. From the diagram, it can be accepted that the estimated threshold level is close to its actual level.

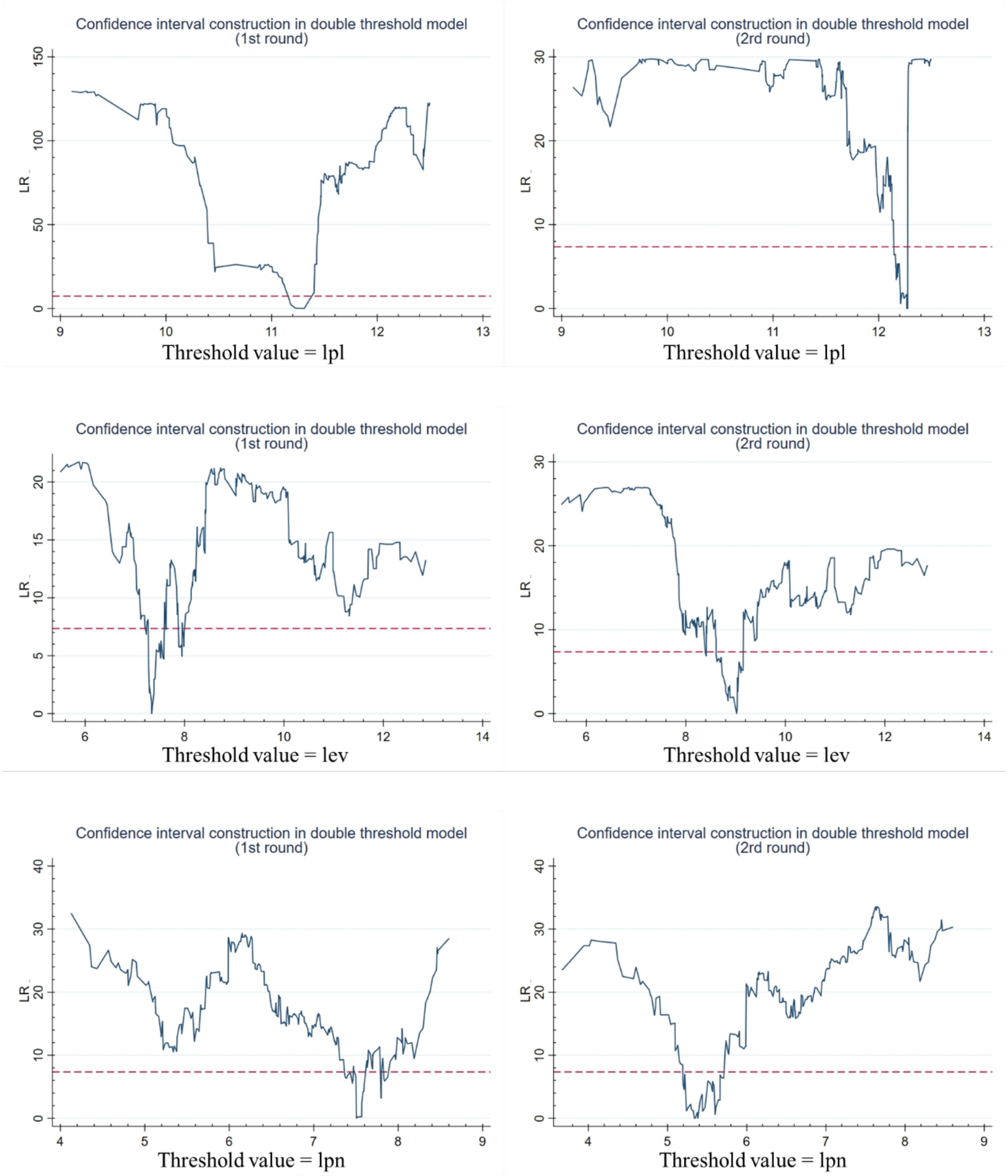

Figure 3 Threshold values of threshold variables

Table 8 shows the regression results of the panel threshold model. In the first stage, the coefficient of the core variable is significantly negative. We think this is related to the information asymmetry problem mentioned earlier. The internet development process must be that urban areas precede rural areas, which has led to the aggravation of information asymmetry in the early stages of internet development. This is unfavorable for remote rural areas, so the regression coefficients are negative in the first stage. With the further improvement of the internet, in the second and third stages, the regression coefficients are significantly positive, which supports internet development to promote the growth of LPI. In addition, it is also found that the coefficients of the core variables have apparent changes within the value range of the threshold variables (*lpl*, *lev*, and *lpn*), which suggests that the threshold effect is significant.

From the result of Model (1), with the gradual increase in rural postal delivery routes (*lpl*), the influence of internet development on LPI presents a "weak-strong-weak" inverted U-shaped trend. Internet development has not yet penetrated the countryside in the first stage, and the regression coefficient is negative. Internet development has the most vital role in promoting LPI in the second stage. During this period, the internet developed in rural areas, and with the development of rural roads, its role in promoting roads was continuously demonstrated. When the second threshold is exceeded, the promotion of LPI by internet development weakens. At this stage, the increase in demand may prompt agricultural producers to expand their production scale and increase pollution input. In addition, the marginal utility of road construction is diminishing. After the essential function of connecting urban and rural areas is realized, the effect of building more roads will gradually weaken. Therefore, the reduction in LPI promotion is in line with reality.

The results of Model (2) and Model (3) are basically the same. The influence of internet development on LPI growth has been increasing from negative to positive. Express volume (*lev*) reflects the rural sales and consumption level, and the number of internet ports (*lpn*) is a prerequisite for using the internet. This result proves once again that the expansion of the Internet is having a continuing impact on LPI and will become one of the principal contributors to its growth.

Table 8 Threshold panel model regression results

Variables	Model (1) *Thvar=lpl*	Model (2) *Thvar=lev*	Model (3) *Thvar=lpn*
*inter*I(Thvar<C₁)*	-0.478***	-1.061***	-0.795***
	(-4.77)	(-5.09)	(-4.11)
*inter*I(C1≤Thvar<C2)*	0.809***	-0.235**	0.148***
	(10.41)	(-2.03)	(2.72)
*inter*I(Thvar≥C2)*	0.369***	0.248***	0.428***
	(4.75)	(4.84)	(7.42)
_cons	0.958***	0.478***	0.532***
	(16.62)	(9.01)	(10.12)
Control variables	YES	YES	YES
N	330	330	330
R^2	0.429	0.314	0.329

Notes: *Thvar*=threshold variable; Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

5.3 Robustness test

The above analysis leads to the main conclusion that internet development can endorse the growth of LPI. To verify the reliability of the conclusion, we use two methods to perform the robustness test: (1) Replace the core independent variables. We use another method to gauge the internet development and introduce it as a core independent variable into the four regression methods of the panel model. (2) Replace the regression method. Instead of using a GMM method, we adopt the feasible generalized least squares approach (FGLS) to re-estimate the effects of the internet on LPI.

5.3.1 Robustness test (1)

Wu et al. (2021) also introduced a graph index method of full polygon arrangement to reflect internet development. This is another method to comprehensively analyze the Internet diffusion from multiple dimensions. We take the comprehensive expansion of the Internet obtained by this method as the main independent variable to exchange the original central explanatory variable. Without changing the estimation method, we recalculate and obtain the results shown in Table 9 below:

Table 9 Threshold regression results

	(1)	(2)	(3)	(4)
	OLS	FE	2SLS	GMM
inter	-0.367	0.029	17.113	0.028***
	(0.238)	(0.025)	(19.965)	(0.005)
fep	-0.693	-0.226	-5.731	0.291***
	(0.613)	(0.415)	(5.407)	(0.098)
dr	-0.224**	-0.029	-0.634	-0.057***
	(0.088)	(0.030)	(0.723)	(0.011)
ind	0.334***	-0.089	-0.162	-0.023
	(0.125)	(0.172)	(1.411)	(0.020)
L.lnlpi				1.027***
				(0.009)
_cons	0.927***	0.804***	-5.519	-0.034**
	(0.118)	(0.078)	(7.085)	(0.015)
Year Fe	NO	YES	YES	YES
Province Fe	NO	YES	NO	YES
N	330	330	308	280
R^2	0.066	0.441		

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Comparing the results of Table (1) and Table (9), we can find that except the results of the system-GMM method, the results of other methods are not consistent. As we described in the methodology section, the four econometric methods we use are progressive. We are confident that the results derived from the system-GMM approach for dynamic panel models should be the best. The results in Table (1) confirm our idea. Since the first three models have certain flaws, their results are not the best. The results of robustness test (1) further confirmed this conjecture. The results obtained by the defective model are not stable, while the better dynamic panel model guarantees the stability of the results. In Table (9), method (4) obtains significant results, and the coefficient related to Internet development level appears very close to the results in Table (1). Once again confirmed that the Internet expansion has a role in promoting LPI.

5.3.2 Robustness test (2)

Since the results of the fixed-effects model in Table (1) are not significant, simply fixing time and individuals is unreliable. The FGLS method can handle models where the form of the heteroskedastic function is unknown. Therefore, we choose the FGLS method to deal with the problem of individual heterogeneity in the model. Without changing the variables, the FGLS results are listed in Table 10:

Table 10 Threshold regression results

	(1)	(2)	(3)	(4)
	OLS	FE	2SLS	FGLS
inter	0.321***	0.044	2.248***	0.296***
	(0.066)	(0.054)	(0.689)	(0.102)
fep	0.133	-0.241	5.986***	-0.299
	(0.686)	(0.418)	(1.982)	(0.550)
dr	-0.206**	-0.028	-0.139	-0.092
	(0.086)	(0.030)	(0.137)	(0.094)
ind	0.412***	-0.093	1.638***	0.575***
	(0.136)	(0.171)	(0.377)	(0.154)
_cons	0.603***	0.812***	-0.764*	0.531***
	(0.102)	(0.078)	(0.419)	(0.102)
Year Fe	NO	YES	YES	YES
Province Fe	NO	YES	NO	NO
N	330	330	308	330
R^2	0.085	0.442		

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

According to the above table, the results of the FGLS method also prove that the diffusion of the Internet stimulates LPI. The comparison of results from the FGLS and system-GMM methods, we can find that the overall performance of the FGLS method is not good enough due to the unresolved endogeneity problem. In addition, the coefficient of the Internet development variable is larger than the above results because the lagging term of LPI is not added into the model. Within the acceptable range, the FGLS method also demonstrated the robustness of the results.

6. Conclusions and policy implications

Using green productivity growth as the dependent variable, based on panel data from 30 provinces from 2007 to 2017, we investigate the impact of internet development on Chinese green agricultural growth. The empirical analysis is carried out from two aspects: the intermediary effect and the threshold effect. This paper proves that ICT has become a major driving force for green growth in Chinese rural areas. From our results, we can conclude as follows: The main conclusions are as follows:

First, in the past two decades, China's LPI has experienced a "fast-slowdown-fast" growth process. Overall, there is a greater level of improvement compared with the past. Furthermore, the results after decomposition show that TP is the primary source of LPI growth, and EC even contributes negatively. Second, the development of ICT in China impacts the growth of LPI positively. and this result appears to be robust to the various tests we have carried out. Furthermore, the development of the internet can indirectly affect LPI by promoting income increases, human capital, non-agricultural industries, and logistics foundations. Finally, the threshold regression results prove that internet development's influence on LPI is non-linear.

To better appreciate the role of Internet development in promoting LPI growth and rural economic development, some policy recommendations can be suggested:

Firstly, increase the attention and importance of promoting agriculture's green development. GAP is an accurate indicator of agricultural and environmental performance. The current performance of LPI is poor, and it is necessary to start from multiple angles to increase the attention of various departments to the green development of agriculture. Improve agricultural producers' awareness of green production, build a green production concept at the institutional level, and accelerate innovation and application of green production technologies.

Secondly, heighten resource utilization efficiency and optimize resource allocation. From the calculation results, the contribution of EC to the growth of LPI is low or even negative, which indicates that the level of resource utilization is poor. On the one hand, improving resource utilization efficiency across the country is necessary. On the premise of ensuring food production, the input level should be lowered as much as possible. On the other hand, China is a wide country, and its regions contrast in their factor endowments. The unbalanced and uncoordinated allocation of resources between regions needs to be improved.

Thirdly, enhance the quality of rural labor to meet the needs of new economic models. Given the problem that the quality of the agricultural labor force needs to be improved, on the one hand, the quality of training should be improved by improving training methods and intensity and long-term monitoring and evaluation. On the other hand, given that the situation cannot be improved overnight, with the phenomenon of part-time jobs and aging agriculture, the agricultural socialized service system still plays an important role. While the upgrading of workers' skills seems essential, it is also necessary to further improve the agricultural socialized service system to cope with the current situation.

Fourthly, promote the integrated development of industries based on the characteristics and development of rural industries in various regions. Integrate agricultural resources with secondary and tertiary industries and develop distinctive new industrial models in agricultural production, product processing, leisure tourism, etc. Make rational use of various resources in rural areas, innovate industrial models to meet the new social and economic development requirements, and achieve complementary advantages and win-win cooperation between different industries. Creating more income promotes the growth of rural LPI.

Finally, based on all these suggestions above, the government needs to further improve the policy support system. Since the requirements for green production are different from the behavior and goals of traditional agriculture in the past, it is even more necessary for the government to actively guide and support this transformation process. It is necessary to provide various green production subsidies for agricultural producers and encourage farmers to actively conserve resources and reduce pollution. Strengthen supervision and gradually improve the quality requirements of agricultural products. Also be aware of the difficulties in mountainous areas and improve infrastructure such as roads and communications. By promoting industrial integration, the main focus is on agricultural development and rural economic revitalization.

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Appendix1 A refined model with a single shadow price of pollution-generating inputs

According to Balezentis et al. (2021), due to the lack of connection between the two sub-technologies of the by-production model, the pollution prices in the two directions are different. With the help of the directional distance function, Balezentis et al. (2021) suggest the envelope form of the modified original model, which clearly depicts the connection between the two sub-technologies:

$$
\begin{aligned}
& D^b(\mathbf{x}^a, \mathbf{y}^a, \mathbf{z}^a; \mathbf{0}, \mathbf{g}_y^a, \mathbf{g}_z^a) = \max_{\delta,\theta,\lambda,\sigma} \delta \\
s.t.\ & \sum_{k=1}^{K} \lambda_k y_k^{m,b} \geq y_{k'}^{m,a} + \delta g_y^{m,a},\ \forall \\
& \sum_{k=1}^{K} \lambda_k x_k^{n,b} \leq x_{k'}^{n,a},\ \forall n \\
& \sum_{k=1}^{K} \lambda_k x_k^{p,b} \leq x_{k'}^{p,a}\ ,\forall p \\
& \sum_{k=1}^{K} \sigma_k x_k^{p,b} = \sum_{k=1}^{K} \lambda_k x_k^{p,b}, \forall p \\
& \sum_{k=1}^{K} \sigma_k z_k^{j,b} \leq z_{k'}^{j,a} - \delta g_z^{j,a},\ \forall j \\
& \sum_{k=1}^{K} \lambda_k = 1, \\
& \sum_{k=1}^{K} \sigma_k = 1, \\
& \lambda_k \geq 0,\ \forall k \qquad\qquad \text{(LP1)} \\
& \sigma_k \geq 0,\ \forall k.
\end{aligned}
$$

where, compared with the original model, the modified model adds a new constraint—the fourth constraint. The fourth constraint ensures that the benchmarks of the two sub-technologies are consistent. This new restriction requires that the pollution inputs used in the two sub-technologies are essentially equivalent.