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Creation or disruption? Doubts from the internet applications in China's rural sector

Feng Zhou[a], Hongtu Deng[b,*]

[a] Business School, Shandong University of Political Science and Law, Jinan, China
[b] School of Economics and Statistics, Guangzhou University, Guangzhou, China

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ABSTRACT

To address the current large gap in research on the Internet applications in the Chinese rural sector, this paper explores the effect of these applications on the labor productivity of Chinese farmers from a creative destruction perspective. First, we construct a model to analyze the direct and indirect paths of the Internet applications impact on the productivity of farm households at the theoretical level; second, we conduct an empirical study corresponding to the theory based on micro-survey data obtained from China's first nationwide large-scale social survey project. Specifically, we verified the Internet applications direct effect on farm household labor productivity through the mean treatment effect approach and explored the efficiency and mechanism of action of the Internet productivity effect in the rural sector using the mediating effect model, Probit model, and the counterfactual analysis framework. The study finds that the productivity effect of the rural Internet applications still has a certain gap compared with the urban sector, although it is not at the "Solow's paradox" stage. Further discussion reveals that the Internet adoption in rural areas is a process of "creative destruction", and its destructive effects are dominant at this stage, while the creative effects still need to be further explored. This paper emphasizes that, for developing countries, accurately identifying the development stage of the Internet applications and further exploring its creative role is an important way to improve labor productivity in rural areas, and it is also an important step to promote the construction of digital villages.

Introduction

Information and communication technology (ICT) refers to the software technologies needed to run information devices and perform information management (Kozma & Vota, 2014), which are integrated into industries or services or combined with new technologies in various fields such as robotics and nanotechnology, thereby connecting all products and services to the network (Kim, 2021). Since ICT technology applications are not yet fully popular in rural China, they are mostly embodied at the level of Internet technology (hereafter referred to as Internet applications). It is observed that modern technology with the Internet at its core has a dual effect of Schumpeterian creative destruction, which can both "destroy" the traditional smallholder production and management system and change the allocation of agricultural factors to create new agricultural production methods (Wan, 2015). This creative destruction mechanism formed by technological progress has successfully promoted the modernization of agriculture in rural areas and has become an important catalyst for small farmers to actively or passively transition from the traditional agricultural sector to the modern agricultural sector as new farmers or to completely leave agriculture for nonfarm occupations (Ma & Ning, 2017). This paper explores the "productivity effect" of Internet applications in the rural sector and the "transmission" mechanism from Internet applications to this effect.

In the early stage, Strassmann and Paul (1990) surveyed 292 companies and found that there was no direct correlation between companies' investment in the Internet and return on investment (ROI), a situation that was later called "Solow's paradox" by academics.[1] It was not until the mid-1990s that the literature confirmed the existence of the productivity effects of the Internet and the information industry (Amendola et al., 2005; Czernich et al., 2011; Jorgenson & Stiroh, 1999; Martínez et al., 2008; Oliner & Sichel, 2000). Solow admitted in 2000 that the "Solow paradox" had been solved. It is evident that even in developed countries, Internet development needs

* Corresponding author at: Guangzhou University City, 712, Wenqing Building, Teaching Area, Panyu District, Guangzhou City, Guangdong Province, China.
E-mail address: 654818739@qq.com (H. Deng).

[1] Also known as the "productivity paradox". Proposed in 1987 by Robert Solow, a Nobel Prize−winning economist, it means that although companies invest heavily in IT, they achieve little in terms of productivity.

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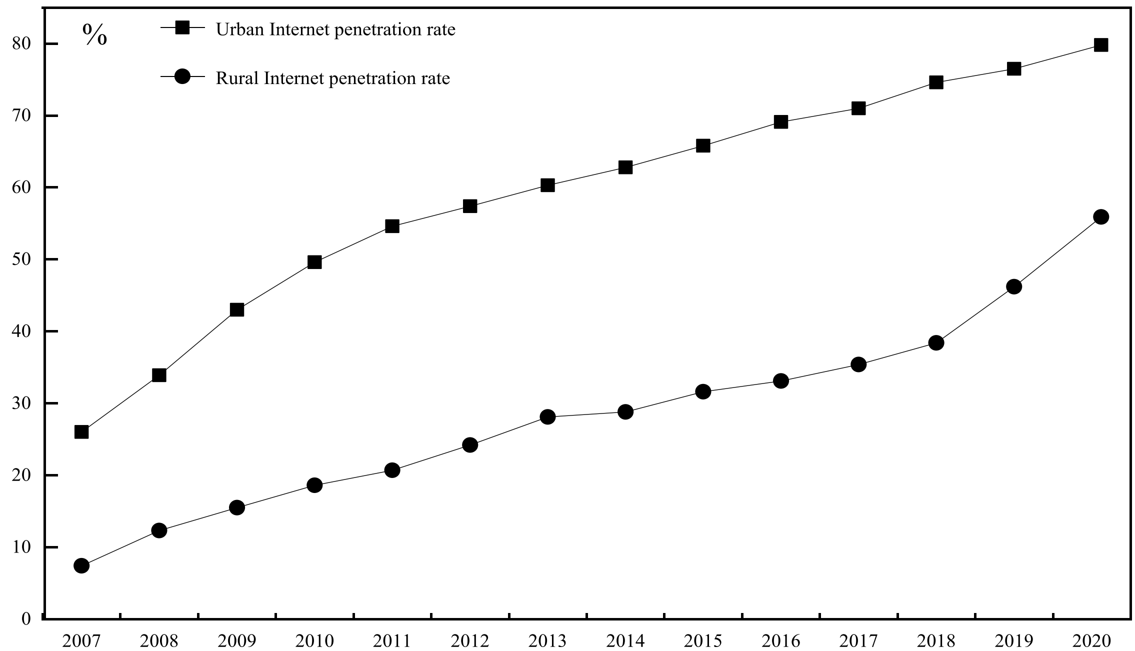

Fig. 1. China's Internet penetration profile, 2007–2020. Note: The information is obtained from the statistical survey on the development status of the Internet in China by the China Internet Network Information Center. Since the data for December 2019 were not published, they were replaced by the data published in March 2020.

to go through a very long period of "Solow's paradox" (Ping, 2001). In this stage, even if the Internet has been popularized, it does not mean that productivity has increased substantially.

As shown in Fig. 1, in the context of the urban-rural dual structure, the gap between Internet applications in the urban and rural sectors has only increased since 2007, and although there has been an inflection point of growth in rural Internet penetration since 2018, the gap between the two sectors has not changed substantially. Moreover, studies have shown that the consumption effects triggered by Internet applications differ significantly between urban and rural areas (Xiang, 2018). The income returns to rural households are much lower than those to urban residents (Tan et al., 2017). Both individual and urban-rural income disparities are increasing (Tan et al., 2017), and both individual and urban-rural income gaps are widening. Studies by Britz and Blignaut (2001) and Bonfadelli (2002) also suggest that ICT is beneficial only for the higher-income and higher social classes and that the introduction of ICT may not have a positive impact on farm households in developing countries. A synthesis of the literature reveals that the effects generated by the Internet are different in the urban and rural sectors. Due to the large gap between urban and rural areas in terms of infrastructure development, human capital reserves, industrial patterns, and economic development stages, the formation and transmission mechanisms of the Internet effect in urban and rural areas are also very different.

Based on the above points, and in order to further explore the digital transformation of the rural sector and the organizational skills of agricultural production, this paper makes a systematic and in-depth analysis of the "productivity effect" of the agriculture and rural sectors. The Fourth Plenary Session of the nineteenth Central Committee of the Communist Party of China proposed to improve the mechanism of labor, capital, land, knowledge, technology, management, data and other contributing production factors by market evaluation and remuneration based on contribution, raising data to the strategic level of production factors for the first time. However, as the foundation of the national economy and the "basic plate" for the comprehensive revitalization of rural areas in the new era, the combination of the digital economy and the revitalization of rural areas is still very low. In 2019, China's agricultural digital economy accounted for only 8.2 % of the industrial added value, which has not yet reached 25 % of the service industry and 50 % of the industry. It is urgent to carry out more theoretical research and practical exploration on the effective combination of modern agriculture and digital economy (Zhong & Liu, 2021). Therefore, there is a big gap in the current research in terms of exploring the relationship between the digital technology and modern agricultural development, especially with respect to the analysis of how the Internet applications lead to the transformation of agricultural digitalization. Thus, this research is necessary.

In order to fill the research gap in the existing literature, this paper will expand and deeply analyze the existing studies in the following three aspects. First, Jiang (2017) and Cheng et al. (2020) did not pay attention to the special characteristics of the data elements and digital technologies generated behind the Internet application, and this paper focuses on the promotion effect while also focusing on the crowding out effect of the Internet application. Second, although Zhu et al. (2019), Li and Yin (2017)) have noted that the productivity effect of the Internet applications is limited by the allocation of labor resources, and the impact of agricultural informatization on total factor productivity in agriculture has a nonlinear effect with respect to the difference in the level of rural human capital. However, no study has yet given a general explanation for the biased technological changes in the direction of labor factors by the Internet applications in relation to consistency with their productivity effects. In this paper, we will compare the current status of Internet adoption in the rural and urban sectors in China, specifically verify the biased technological change in the direction of labor factors for Internet adoption, and respond positively to the key question of whether Internet adoption in rural China is still at the "Solow's paradox" stage. Third, Acemoglu (2014) re-examines the Solow paradox based on the U.S. manufacturing sector, and similarly based on doubts about the Solow paradox in the Chinese agricultural sector; this paper will investigate the "creative destruction effect" of the Internet in the agricultural and rural sectors at both the theoretical model and empirical evidence levels, and, on this basis, it provides a clear, economic analysis of the impact of the Internet applications on farmers' labor productivity theoretical logic and economical empirical framework as a way to provide scientific support for focusing on the cost effectiveness and impact of these technologies on small and large scale agriculture, as well as the socio-economic impact and security issues of applying the Internet applications such as artificial intelligence and Internet of Things (Patel, 2023).

Thus, to achieve this goal, we explore the effect of the Internet applications on the labor productivity of Chinese farmers from the perspective of creative destruction. This study followed the following steps and methods. First, we review the relevant literature based on ICT studies. Second, we draw on the theoretical framework of Han et al. (2011) and Mittal and Nault (2009) to explore the possible paths when Internet applications exert productivity effects in the rural sector, separating the direct path from the indirect path. Third, we apply ordinary least squares (OLS) and Probit model quantitative methods to empirically test the Chinese General Social Survey data. The database is currently a rare and nationally representative data on individual Internet use in China, and thus it can provide highly relevant data for this study. After processing, we finally obtain 3047 rural samples and 5467 urban samples, covering 28 provinces (autonomous regions and municipalities) in China. Finally, the empirical results are discussed and insights are provided.

Literature review

Most of the existing studies on ICT adoption focus on two levels, one is the firm level, for example, Kijek et al. (2019) studied the relationship between ICT investment and firm productivity through structural equation modeling, clarifying the Solow paradox and finding that process innovation is an important moderator between firm labor productivity and ICT technology adoption. Torrent et al. (2022) also found, through a study of Spanish firms, that when firm development focuses more on ICT investment, R&D activities, and product innovation, such firms develop a significant productivity advantage over other firms as a result; another is the agricultural level, where Yueh et al. (2013) found, based on a study of the geospatial attributes of farmers' associations, that the organizational digitization of farmers' associations effectively activates agricultural innovation and development, and Guo et al. (2018) found, through the analysis of micro data in suburban Beijing, that ICT technology changed the service model in the rural sector, and that rural distance education programs had a significant contribution to both farm household income and productivity levels. A number of scholars have also confirmed the beneficial effects of ICT technology applications in agriculture based on many case studies such as mushroom farm management (Kassim et al., 2019), modern pig farming (Mahfuz et al., 2022), aquaculture (Mustapha et al., 2021), and agricultural systems (Nayak et al., 2020).

However, there are also studies that confirm that the application of ICT technology is a great challenge for those farmers who cannot cope with the digital transformation and that it does not have only positive effects although the rural sector is undergoing a digital transformation process (Ferrari et al., 2022). This view coincides with the findings of Ogutu et al. (2014), who, in assessing the impact of ICT-based market information service programs on agricultural inputs in Kenya, found that while the interventions had significant boosts on seed, fertilizer, and labor productivity, they had negative effects on labor factor allocation. Among the existing studies on Internet applications in the rural sector in China, Zhu et al. (2019) also confirm that labor resource allocation is closely related to the productivity effect of Internet applications, and Han and Zhang (2015) similarly show that the effect of agricultural informatization on total factor productivity in agriculture has a nonlinear effect on differences in rural human capital levels through a study of panel data from 2002 to 2010.

Although some studies show that the Solow paradox in the urban sector has been resolved, the above studies suggest that there are still differences on whether the Internet application in the rural sector has a positive impact on agricultural labor productivity, and no study has yet given a general explanation for the biased technological change towards labor factors by Internet applications that is consistent with its productivity effect.

Previous studies on the productivity effects of the Internet in agriculture have mostly focused on the total factor productivity perspective (Han & Zhang, 2015; Yu & Zhu, 2011; Zhu et al., 2019). However, it is important to understand that the reason why developed countries reflect technological progress through TFP (Total Factor Productivity) is because their technological innovation relies on a large amount of R&D investment, which can then be measured through the residual term. As a developing country, China's latecomer advantage in technological innovation means that the new technologies it has introduced, including ICT, are generally solidified in infrastructure with public capital attributes, which is reflected more in labor and capital factors than in TFP. In particular, the data factors and digital technologies behind Internet applications have special characteristics that are different from traditional factors, and they are associated not only with the promotion effect but also with the crowding-out effect (Jiang & Sun, 2020; Zuo & Ai, 2021). This is especially true in rural areas. This paper argues that existing studies precisely ignore the indirect role played by the biased technological changes of the Internet on other factors in the Internet productivity effect (Kong et al., 2015). It is worth noting that the verified productivity effect of Internet applications from a labor factor allocation perspective based on provincial panel data, and the findings indicated that the structural shift in labor force employment plays a greater mediating role than that of rural population urbanization. Zhao (2015) proposed that Internet 2.0 has realized the decentralization of the industrial structure and has advanced from the "resource" nature of Internet 1.0 to the "capability" incarnation that can lead to the transmutation of the industrial competition pattern. The digital economy based on the Internet provides information support for high-quality agricultural development and promotes the process of the modernization of agriculture and rural areas (Wang et al., 2018).

However, as noted above, there are significant differences in the penetration of Internet applications between rural and urban areas. Whether or how the shift in labor employment plays the same mediating role in rural areas, and the specific impact of this mediating role on Internet adoption, remains to be explored. The development of the existing agricultural business model based on Internet technology means that new technology replaces the original agricultural model, and there is a demand for labor force with high human capital value and information technology. Some traditional smallholder agricultural operators have withdrawn, modern agricultural operators have entered. Additionally, agricultural information technology has pushed the modernization of agriculture while impacting traditional agricultural production methods, which is reflected in the decrease in traditional agricultural jobs and the increase in modern agricultural jobs. It should be noted that the jobs created by the creation effect not only accommodate the labor force transferred from traditional agriculture but are also an important alternative for the labor force eliminated by the destruction effect in the urban sector. If the productivity of the newly created jobs in the rural sector is not as high as that of the eliminated jobs in the urban sector, the inevitable result will be labor force inversion.

Therefore, attention to the creative disruptive effects of Internet applications in the rural sector has direct implications for preventing labor force inversion (Cai, 2021). Next, this paper will analyze the creative destructive effects of Internet applications in China's rural sector and their impact on the labor productivity of farm households at the theoretical and empirical levels, respectively.

Theoretical model

Before proceeding to the empirical study, we will theoretically explore the possible paths through which Internet applications exert their productivity effect in the rural sector and, more importantly,

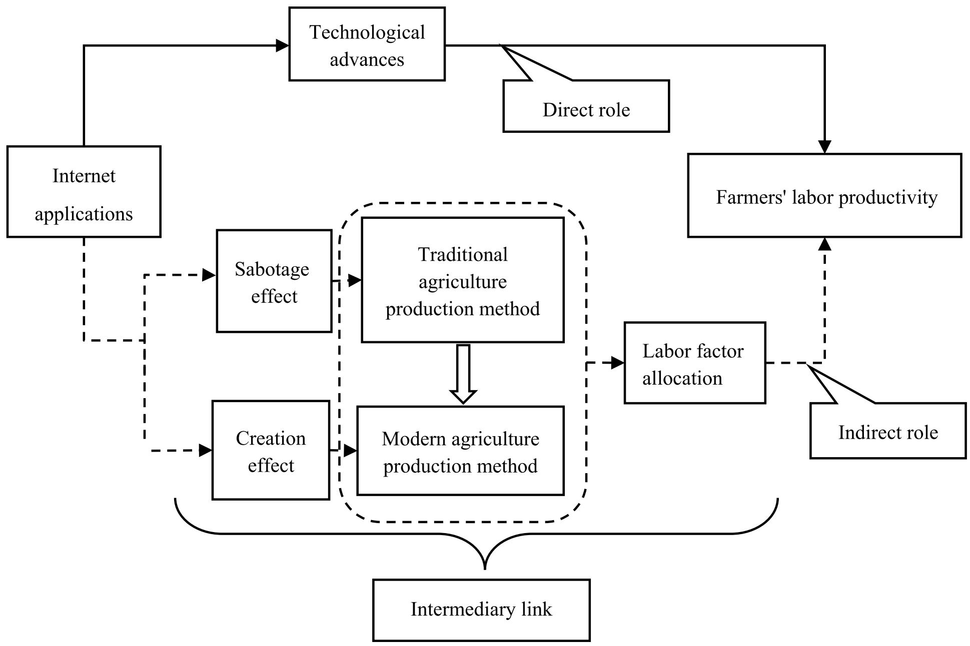

Fig. 2. The path of the effect of Internet applications on the labor productivity of farm households.

logically analyze the specific and practical aspects of the effect at both the direct and indirect levels. In Fig. 2, the solid line indicates the direct effect of Internet applications on the labor productivity of farmers, where the Internet itself acts as ICT capital input to promote enhanced technological progress, which directly affects agricultural production and operational processes and directly increases the labor productivity of farmers. The dotted line indicates the gradual change from traditional agricultural production methods to modern agricultural subsistence methods in the agricultural sector under the impact of the digital economy. The dashed line shows the indirect impact of the digital economy on the productivity of farm households, which is the result of the change from the traditional agricultural production method to the modern agricultural subsistence method. In this section, we explore whether Internet applications in rural China are in the "Solow paradox stage" and their paths of action.

Drawing on the theoretical framework of Han et al. (2011) and Mittal and Nault (2009), this paper sets the baseline production function in the form of a Cobb-Douglas function in the following form:

$$Y = AK^{\alpha}L^{\beta}T^{\gamma}Z^{\varphi} \tag{1}$$

where K represents non-ICT capital factor inputs other than ICT capital, Z is ICT capital factor input, L is labor factor input, T is land factor input, Y is total output of farm households, α, β, γ, and φ are the output elasticities of non-ICT capital, labor, land and ICT capital factor inputs, respectively. A is the Hicks neutrality function. It can be seen that A in this equation includes but does not effectively explain the biased technological change of ICT capital towards other factors, in particular, ICT capital input is not equivalent to the R&D input as directly reflected by total factor productivity. Therefore, the indirect spillover effect of Internet applications directly measured by total factor productivity is likely to cause bias.

The multiplicatively separable exponential form set by Mittal and Nault (2009), which can visualize the biased technical change of ICT capital on other factors, provides the possibility for this paper to portray the indirect effect of ICT capital on farm productivity. Specifically, the biased technical change of ICT capital on non-ICT capital, labor, and land is defined as a function of ICT capital, whereby $K\xi(Z), L\tau(Z), T\upsilon(Z)$, respectively, de$K_Z$noted by, L_Z, and T_Z.

Where $\xi'(Z) > 0, \tau'(Z) > 0, \upsilon'(Z) > 0$, assuming that $\xi(0) = \tau(0) = 1$, i.e., when there is no ICT capital input, there is no impact on factors such as non-ICT capital, labor, and land, which are therefore set to K_Z, L_Z and T_Z. This form, in fact, does not lose its generalizability. By substituting it into Eq. (1) and correcting it, we can finally obtain the expanded Cobb-Douglas function form as follows.

$$Y_c = SK_{Z\overline{\alpha}}L_{Z\overline{\beta}}T_{Z\overline{\gamma}}Z\overline{\varphi} \tag{2}$$

In Eq. (2), K, L, T, and Z meanings remain unchanged, as they were defined before. Y_c denotes the total output of farm households after the augmentation, and $\overline{\alpha}$, $\overline{\beta}, \overline{\gamma}$, and $\overline{\varphi}$ denote the parameters in the augmentation function that distinguish it from the baseline functional form; however, they all correspond to the baseline functional form, α, β, γ, and φ. In addition, the S in the extended form is compared with the A in Eq. (1), and it is clear that the former no longer contains the biased technological change of ICT capital of other elements.

To more precisely portray the indirect effects of ICT capital, we set the functional forms $K\xi(Z)$, $L\tau(Z)$, $T\upsilon(Z)$ of non-ICT capital, labor and land, respectively, to the exponential forms $Ke^{\eta z}, Le^{\mu z}, Te^{\rho z}$.

Substituting this into Eq. (2), the specific expression of the augmented functional form is obtained as follows.

$$Y_c = S[Ke^{\eta z}]\overline{\alpha}[Le^{\mu z}]\overline{\beta}[Te^{\rho z}]\overline{\gamma}Z\overline{\varphi} = SK\overline{\alpha}L\overline{\beta}T\overline{\gamma}Z\overline{\varphi}e^{GZ} \tag{3}$$

In Eq. (3), $G = \overline{\alpha}\eta + \overline{\beta}\mu + \overline{\gamma}\rho$ is the weighted average sum of the output elasticities of non-ICT capital, labor, and land in the incremental Eq, which means that when investment in ICT capital such as the Internet increases, non-ICT capital, labor, and land will each change in $\overline{\alpha}\eta$, $\overline{\beta}\mu$, and $\overline{\gamma}\rho$, which is the proportion of biased technological change.

To prove that the separation of the indirect effects by equation (3) is scientific, this paper finds the cross-partial derivatives of each factor on the ICT capital factor for Eqs. (1) and (3) and obtains.

$$\frac{\partial^2 Y}{\partial K \partial Z} = A\alpha K^{1-\alpha}L^{\beta}T^{\gamma}\varphi Z^{1-\varphi}$$

$$\frac{\partial^2 Y}{\partial L \partial Z} = A\beta L^{1-\beta}K^{\alpha}T^{\gamma}\varphi Z^{1-\varphi} \tag{4}$$

$$\frac{\partial^2 Y}{\partial T \partial Z} = A\gamma T^{1-\gamma} L^{\beta} K^{\alpha} \varphi Z^{1-\varphi}$$

$$\frac{\partial^2 Y_c}{\partial K \partial Z} = S\overline{\alpha} K^{1-\overline{\alpha}} L\overline{\beta} T\overline{\gamma}\left[\overline{\varphi} Z^{1-\overline{\varphi}} + GZ\overline{\varphi}\right] e^{GZ}$$

$$\frac{\partial^2 Y_c}{\partial L \partial Z} = SK\overline{\alpha}\overline{\beta} L^{1-\overline{\beta}} T\overline{\gamma}\left[\overline{\varphi} Z^{1-\overline{\varphi}} + GZ\overline{\varphi}\right] e^{GZ} \tag{5}$$

$$\frac{\partial^2 Y_c}{\partial T \partial Z} = SK\overline{\alpha} L\overline{\beta}\overline{\gamma} T^{1-\overline{\gamma}}\left[\overline{\varphi} Z^{1-\overline{\varphi}} + GZ\overline{\varphi}\right] e^{GZ}$$

A comparison of the above two equations indicates that the value of the proportional change in ICT capital's bias toward other factors is zero, i.e., $\eta = \mu = \rho = G = 0$, when Eq. (4) is equal to Eq. (5), which means that the incremental function obtained after the portrayal of the indirect effect of ICT capital does compensate for the possible bias in the original benchmark production function's measurement of the productivity effect of ICT capital. In addition, in keeping with the research theme of this paper, this paper assumes that $\eta = \rho = 0$; i.e., Internet adoption has not yet had a significant biased technological effect on land and non-ICT capital.[2]

To more intuitively show the separation of direct and indirect effects by the incremental function setting in this paper, we denote the logarithmic form of each variable in lowercase letters and take the logarithm of Eqs. (1) and (3), respectively, to obtain the resultant equations as follows.

$$y = a + \alpha k + \beta l + \gamma t + \varphi z + \varepsilon_1 \tag{6}$$

$$y = s + \overline{\alpha} k + \overline{\beta} l + \overline{\gamma} t + \overline{\varphi} z + GZ + \varepsilon_2 \tag{7}$$

In the above equation, a denotes the factor-neutral technological progress of the benchmark Cobb-Douglas model, l, t, and z denote the logarithms of L, T, and Z, respectively, the coefficients are the output elasticities of each factor, ε_1 and ε_2 are error terms that are consistent with independent identical distributions. GZ means the broadening effect of ICT capital on the labor factor and other factors separated from a. Therefore, the s in Eq. (7) is different from the a in Eq. (6). And since $G = \overline{\alpha}\eta + \overline{\beta}\mu + \overline{\gamma}\rho$, Eq. (7) can be further be written as the following equation.

$$y = s + \overline{\alpha}(k + \eta Z) + \overline{\beta}(l + \mu Z) + \overline{\gamma}(t + \rho Z) + \overline{\varphi} z + \varepsilon_2 \tag{8}$$

In Eq. (8), the direct effect of ICT capital on farmers' output is $\overline{\varphi}$z, and the indirect effects on the labor factor and other factors are $\overline{\alpha}\eta Z$, $\overline{\beta}\mu Z$ and $\overline{\gamma}\rho Z$.

Theoretical basis of the model

Intuitively, $L\tau(Z)$ denotes the biased technological change exhibited by Internet applications in the direction of labor factor allocation, which is an important manifestation of the creative destruction role of the Internet in the rural sector. Next, we will theoretically and logically analyze the specific manifestations of the creative destruction role of Internet applications in the rural sector and $L\tau(Z)$. What are the specific implications?

The key rubric for creative destruction is that the new structure creates a stronger incremental payoff effect than the old structure (Zhao, 2015). Specifically, in the rural sector, traditional agricultural production is strongly dispersed in space and time, and there is also a strong dependence on natural conditions, which makes it difficult to match agricultural output with labor inputs and to implement hourly or piecework wages, thus making it difficult to improve agricultural production efficiency. Digital agriculture based on the Internet, on the other hand, makes it possible to visualize and express the entire agricultural production process and allows farmers to become important nodes in modern agriculture, production fields, or distribution fields. In the context of upgraded consumer demands, the production model has successfully changed from a production orientation to a sales orientation, and production efficiency has greatly improved. Therefore, this change from traditional agricultural production methods to modern agricultural production methods driven by Internet applications is undoubtedly a creative destruction realization process. Currently, Internet applications are no longer simply a factor of agricultural production itself but have become a derivative of agricultural production efficiency. The platform characteristics have successfully broken the barriers between small farmers and large markets and helped the development of agricultural product e-commerce platforms while achieving the integration of logistics, capital flow and information flow in agricultural production (Wang et al., 2020). The theory of creative destruction emphasizes that the new production structure with new means of competition will overturn the traditional production structure, which means that the modern agricultural production method will directly impact traditional agriculture, and the traditional production structure will be replaced by modern agricultural business entities if they cannot quickly adapt and master the new means of competition.

As mentioned earlier, many elements are involved in this change, and the change in jobs is an important microcosm of this process. In terms of job creation effects, at the organizational level, the Internet provides natural connectivity for various agricultural organizations in the industrial chain. These organizations can be connected to new organizations on a larger scale based on various forms of cooperation in the production chain, providing a basis for the emergence of more leading enterprises. On the other hand, the relatively low-skilled labor force eliminated from the urban sector due to the development of the Internet may also become new farmers in this way. The destructive effect on jobs is manifested mainly in the passive withdrawal and independent withdrawal of traditional agricultural operators. Passive withdrawal is manifested in two aspects: the increase in production efficiency and organic composition of capital in traditional agriculture under Internet applications, which helps traditional agriculture achieve a reduced demand for labor, and the replacement of traditional agriculture by modern agriculture. The main operators can choose to withdraw only when they are unable to keep up with the pace of development. Independent withdrawal refers to the increase in the human capital of labor under Internet applications, and independent exit refers to the decision of the labor force to leave traditional agriculture and transfer to modern agriculture or nonagricultural work, driven by the effect of Internet applications on the improvement in the human capital level of labor (Ma & Ning, 2017), the expansion of information channels and the diversification of social networks (Wang & Zhou, 2013). Under the dual effect of the creation effect and the destruction effect of Internet applications, the quality of jobs in the rural labor market is improved, and the labor force shifts from traditional agriculture with lower productivity to modern agriculture or work in the nonagricultural sector with higher productivity, which is a process of achieving the optimization of labor factor allocation and "Pareto improvement".

The above studies are combined to derive the following hypotheses in this paper.

Hypothesis 1. : Internet applications have directly contributed to the increase in labor productivity of farmers in the form of enhanced technological progress based on the absolute marginal output of factors, and the rural sector is not currently in the "Solow paradox" stage.

[2] Although this hypothesis does not correspond to the actual situation, it does not undermine the basic logic of this study, specifically the indirect role played by land and capital, which the authors will examine further in subsequent studies.

Hypothesis 2. : Internet applications promote the change from traditional to modern agricultural production methods and, indirectly increase the productivity level of farmers under the dual effect of creation and destruction.

Materials and methods

Further empirical tests are needed to determine whether the economically logical conclusions obtained from the theoretical derivation strictly fit the empirical facts. Next, based on available data, we will further verify the biased technological change in labor factors under the effect of enhanced technological progress and creative destruction caused by Internet applications through an empirical analysis of the productivity effect of Internet applications in the rural sector.

Data sources

The data used in this paper come from the 2017 data released by the China General Social Survey (CGSS). The selection of these data is based mainly on the following considerations. First, the data are jointly executed by Renmin University of China and other academic institutions across China, making this the first national and comprehensive large-scale social survey project in China and giving it important reference value for exploring real social issues. Second, the CGSS collected a total of 12,582 valid samples from 28 provinces (autonomous regions and municipalities) in 2017, and the A and C modules of the year data both contain questions related to residents' use of the Internet. These are rare and nationally representative data on current individual Internet use in China that are highly relevant for this study. Third, the Internet tends to mature in all aspects of operation and use as the application time is extended; therefore, this paper does not pursue incremental sample sizes but selects the latest published 2017 data with a view to reflecting the most up-to-date situation of Internet applications in rural areas at the current stage.

Before the study, to ensure the quality of the sample, the data were processed as follows. (a)Residents of rural and urban areas were classified according to their places of residence, and the relevant variables were identified and processed separately. (b) The study population was controlled to the rural labor force population aged 18−65 and their corresponding households in order to restrict the data to those relevant to the study, and the individual information of each household member was summarized and analyzed. (c) The outliers of each variable were identified, and (d) the outliers were then identified and eliminated to ensure that all data used were valid samples. Ultimately, 3047 rural samples and 5467 urban samples were obtained, covering 28 provinces (districts and municipalities) in China.

Variable description

Based on the aforementioned logical derivation, this paper obtained various analytical variables with empirical and testable implications. This section will convert these analytical variables into core and control variables in the empirical analysis based on the available data. We draw on relevant studies (Cheng et al., 2020; Mao et al., 2019) to identify the variables as follows.

Labor productivity of farm households. The choice of the indicator of farm household labor productivity in this paper is based on two considerations; first, one of the purposes of this study is to analyze the creative destructive effect of interconnection applications on labor force employment in the rural sector, so for this paper, the choice of labor productivity rather than total factor productivity is more relevant to the main thrust of the analysis and more consistent with the needs of the preceding and following analysis. Second, the indicator is borrowed from the study of Mao et al. (2015), and is portrayed by the logarithm of the ratio of total income to the number of household labor, which includes income from agricultural operations and non-agricultural labor, reflecting both the level of agricultural productivity and non-agricultural production of farm households, so it also fits the theoretical mechanism part of this paper to some extent.

Internet applications. Focusing on the rural sector, this paper indicates the ICT capital investment of farm households through the current status of Internet applications. If members of the labor force had accessed the Internet through computers, cell phones or smart devices in the previous six months, the households to which they belong are considered to be connected to the Internet and to have invested in Internet applications.

Creation effect. Due to data availability, this paper considers the part of the labor force that used to work in nonagricultural jobs and has now returned home to farm owing to the attraction of new jobs created by modern agriculture, that is, the creation effect of Internet applications in the rural sector. Compared with the labor force that has not migrated, this part of the labor force has higher human capital value and social capital. This indicator reflects the creation effect of the Internet to a certain extent, but we admit that it does not fully reflect the creation effect of Internet applications in the rural sector. After all, the current attraction effect of modern agriculture on the labor force is not intuitively obvious, and the rise of modern agriculture is still emerging.

Destruction effect. This paper reflects the decline of traditional agriculture and the withdrawal of some small farmers by shifting the rural labor force in the employment structure; i.e., the value is 1 when a member of the rural labor force is currently engaged in non-agricultural work and 0 otherwise.

Other control variables. In addition to the core variables mentioned above, the control variables in this paper portray three main categories: individual characteristics of members of the labor force, the characteristics of the households to which they belong and the characteristics of the region. Individual characteristics include mainly the health status, education level, political outlook, gender and age, marital status and ethnicity of the labor force. Among them, health status is divided into five levels, from very unhealthy to very healthy, with values from 1 to 5. Education level is divided into uneducated, literacy class, elementary school, junior high school, vocational high school, general high school, secondary school, technical school, university specialist (adult formal education), undergraduate (adult formal education) and postgraduate, with values from 1 to 13. Political outlook is assigned a value of 1 if the individual is a member of the Chinese Communist Party and 0 otherwise. Age is calculated according to the actual survey year. Marital status is assigned a value of 0 if unmarried and 1 if married (including remarriage). Ethnicity is assigned a value of 0 for ethnic minorities and 1 for Han Chinese. Family characteristics are portrayed by the economic level of the family, assigned on a scale of 1 to 5 for far below average, below average, average, above average and far above average. Regional characteristics are set according to the region to which the individual belongs, with three dummy variables for the east, central and western regions. Table 1 reports the descriptive statistics of the variables examined in this paper.

Although the main object of this paper is rural residents, the urban sample is also analyzed because we want to form a control for the rural sample by examining the urban sample simultaneously to verify whether this paper has practical research significance and necessity and to test the of the findings. As shown in Table 1, not only is the overall labor productivity of the rural sample significantly lower than that of the urban sample but also the average value of the labor productivity of the group with Internet access is lower than that of the group without Internet access in urban areas. Therefore, it is necessary to analyze whether Internet adoption in the rural sector is at the "Solow paradox" stage. Focusing further on the rural sector,

Table 1
Descriptive statistics of regression variables.

Variables	Rural				Cities and towns			
	No Internet connection		Access to the Internet		No Internet connection		Access to the Internet	
	Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
Labor productivity	8.75	1.12	9.36	0.99	9.62	0.99	10.38	1.02
Destructive effects	0.12	0.32	0.41	0.49	0.33	0.47	0.69	0.46
Creation effect	0.65	0.48	0.419	0.49	0.55	0.50	0.24	0.43
Health status	2.98	1.12	3.761	1.04	3.29	1.06	3.88	0.91
Education level	2.99	1.39	4.696	2.27	3.68	1.77	7.27	3.34
Political affiliation	0.03	0.18	0.069	0.26	0.06	0.24	0.14	0.35
Gender	0.46	0.50	0.507	0.50	0.44	0.50	0.49	0.50
Age	54.27	8.09	39.66	11.11	56.00	7.06	40.55	12.34
Marital status	0.89	0.33	0.840	0.37	0.85	0.35	0.76	0.43
Ethnicity	0.86	0.34	0.868	0.34	0.95	0.22	0.95	0.22
Family economic level	2.30	0.75	2.599	0.71	2.39	0.74	2.69	0.71
Eastern	0.15	0.36	0.214	0.41	0.47	0.50	0.61	0.49
Central	0.54	0.50	0.530	0.50	0.36	0.48	0.24	0.43
Western	0.31	0.46	0.257	0.44	0.17	0.38	0.15	0.36

we find that the average value of labor productivity of households connected to the Internet is 9.36, higher than that of households not connected to the Internet, which is 8.75. Additionally, the proportion of rural laborers in the group not connected to the Internet who have shifted their employment structure is 11.7 %, much lower than that of the group connected to the Internet, which is 41.1 %. This finding tentatively supports the hypothesis derived from the previous theoretical analysis that the productivity effect of the Internet applications in the rural sector is likely to be positive and to play a more significant role in creative destruction; i.e., $\mu \neq 0$. However, further empirical analysis is needed to determine whether there is an indirect effect on the labor productivity of farmers through the creative or destructive effect.

Model setting

Drawing on Baron and Kenny (1986), a test is proposed for the mediating effects and combined with the study reported in this paper, the benchmark model was set as follows.

$$LP = \alpha_0 + \beta_0 Inte + \gamma X + \varepsilon_0 \tag{9}$$

$$Labor_i = \alpha_1 + \beta_1 Inte + \delta X + \varepsilon_1 \tag{10}$$

$$LP = \alpha_2 + \beta_2 Inte + \beta_3 Labor + \theta X + \varepsilon_2 \tag{11}$$

In the above three equations, LP is the main dependent variable of this paper, indicating the labor productivity of the farm households in the sample. $Labor_i$ is the mediating variable, with $i = 1, 2$, denoting the creation and destruction effects of Internet applications in the rural sector, respectively. $Inte$ is the core explanatory variable, denoting Internet applications. X is the control variable that affects the labor productivity and creation-destruction effects of farm households. α is the intercept, andε denotes the random disturbance term. $\beta_0, \beta_1, \beta_2$ and β_3 are the coefficients to be estimated, and when the model β_0 is significant, it means that Internet applications have a significant aggregate effect on farmers' labor productivity. Furthermore, if β_1, β_2, and β_3 are significant and satisfy $\beta_0 > \beta_2$, then there is a partial mediating effect. When either β_1 or β_3 is not significant, then it is necessary to further test the product of coefficients; i.e., if the significance of the above conditions except β_2 is satisfied, then rural labor factor allocation has a full mediating effect on farm labor productivity. The Internet acts exclusively on farm labor productivity through its creation and destruction effects on agriculture.

Considering whether the farmer is connected to the Internet as a binary random variable $Inte_i$, we draw on Mao et al. (2015) empirical model, where $Inte_i = 1$ indicates that the farmer is connected to the Internet; otherwise $Inte_i = 0$ when the household is not connected to the Internet. Correspondingly, LP_{1i} denotes the actual observed labor productivity of the farmer with Internet access, and LP_{0i} denotes the labor productivity of the farmer without Internet access. It is easy to understand that $(LP_{1i} - LP_{0i})$ is the effect of the Internet on the labor productivity of farmers, which is the core subject of this paper. However, since it is not possible in reality to obtain both LP_{1i} and LP_{0i}, we define LP_i as follows.

$$LP_i = 1 - Inte_i \cdot LP_{0i} + Inte_i \cdot LP_{1i} = LP_{0i} + Inte_i \cdot (LP_{1i} - LP_{0i}) \tag{12}$$

$\alpha_1 = E(LP_{1i} - LP_{0i})$ shows the effect of Internet applications on the labor productivity of farmers, which is the average treatment effect of Internet applications. Therefore, this paper establishes the following empirical model I(Eq. (13)) on the basis of Eq. (9), which is used to estimate α_1.

$$LP_i = \alpha_0 + \alpha_1 \cdot Inte_i + \alpha_2 \cdot labor + \gamma X_i + \varepsilon_i \tag{13}$$

Considering the possible heterogeneity among different farmers, Model I is further extended, and Model II (Eq 14) is constructed as follows.

$$LP_i = \alpha_0 + \alpha_1 \cdot Inte_i + \alpha_2 \cdot labor + X_i - X_i^{-} /\delta \cdot Inte_i + \gamma X_i + \varepsilon_i \tag{14}$$

where X_i^{-} is the mean value of the X_i . As shown by the study of Han and Zhang (2015), there may be a nonlinear relationship between the explanatory variables and household labor productivity. Based on this possibility, we draw on Rosenbaum and Rubin (1983). The method of the logit model is used to obtain an estimate of the propensity score for each household. $\mathrm{P}(X_i)$ replaces the linear functions in Models (Ⅰ) and (Ⅱ), which in turn leads to Model (Ⅲ) (Eq. (15)) as follows.

$$LP_i = \alpha_0 + \alpha_1 \cdot Inte_i + \alpha_2 \cdot labor + \beta_i \cdot \mathrm{P}(X_i)$$

$$+P(X_i) - P(X_i^{-} /\delta \cdot Inte_i + \varepsilon_i \tag{15}$$

In addition, to analyze the creative destruction effect of Internet applications on the rural sector, this paper divides the employment status of the rural labor force (dependent variable y) into farming (=0) and nonfarm employment (=1). Considering that the discrete dependent variable is not suitable for regression by OLS, the Probit model of labor force employment is constructed based on Eq. (10).

$$Pr(labor = 1) = \Phi(\alpha_0 + \alpha_1 \cdot Inte_i + \gamma X_i + \varepsilon_i\ ) \tag{16}$$

In addition, since the aforementioned models are subject to the conditional independence assumption (CIA, also known as "selection by measurable variables"), potential unobservable variables that lead to higher labor productivity of the Internet-using farmers themselves may be unavoidable, specifically in the analysis of the creative destruction effect of Internet applications. This is due mainly to the higher education level of the group that may use the Internet and other unobservable variables that affect the employment decisions of the labor force, which requires the exclusion of possible "self-selection" problems from the empirical evidence to ensure that the CIA assumptions are satisfied and endogeneity is avoided. Therefore, this paper adopts a counterfactual causal framework for propensity score matching estimation based on the previous model estimation. The basic idea is to estimate the fitted values of the conditional probability of the sample using the Internet through the logit model; to match farmers using the Internet (treatment group) and those not using the Internet (control group) through different matching methods; and finally to obtain the average treatment effect (ATT) for the labor force using the Internet (participants), the average treatment effect for the labor force not using the Internet (nonparticipants) and the average treatment effect (ATU) for the total sample, which is also the average treatment effect (ATE) obtained from the aforementioned benchmark model. In comparison, the results of the ATT analysis are clearly more relevant to the effect of Internet applications on the labor productivity of farm households. The specific estimated model is as follows.

$$\mathrm{ATT} = E(LP_{1i}|Inte_i = 1) - E(LP_{0i}|Inte_i = 1) \tag{17}$$

$$\mathrm{ATE} = E(LP_{1i}|Inte_i = 1) - E(LP_{0i}|Inte_i = 0) \tag{18}$$

$$\mathrm{ATU} = E(LP_{1i}|Inte_i = 0) - E(LP_{0i}|Inte_i = 0) \tag{19}$$

$$\mathrm{ATE} = \mathrm{ATT} + E(LP_{0i}|Inte_i = 1) - E(LP_{0i}|Inte_i = 0) \tag{20}$$

Results and discussion

Results of empirical analysis

Table 2 shows the regression results of the effect of Internet applications on household labor productivity. The first four columns are obtained from the rural sample, and column (5) is obtained from the urban sample for comparison with the rural sample. Specifically, column (1) is the regression result for the core explanatory variables, while column (2) is the regression result for Model I with the average treatment effect obtained by ordinary least squares (OLS) after the control variables are added. The estimated coefficients decrease from 0.61 to 0.33, which fully indicates that the choice of control variables in this paper is scientifically valid. If these control variables are ignored, the regression results are more likely to be the "cumulative value" of the direct effect of Internet applications on labor productivity and the indirect effect of other variables on labor productivity mediated by Internet applications. The regression results are more likely to be "additive" between the direct effect of Internet applications on labor productivity and the indirect effect of other variables mediated by Internet applications. Column (3) of the table shows the regression results of Model II after different household heterogeneity extensions are considered based on Model I. Columns (4) and (5) are the estimated results of Model III after the nonlinear relationship between the control variables and labor productivity is avoided. Together, columns (3) and (4) show that the estimated coefficient of Internet applications remains significantly positive after further accounting for household heterogeneity and possible nonlinear relationships, and the intermediate value of the estimated coefficient obtained from Model I and Model II is obtained after accounting for nonlinear relationships. That is, for every 10 % increase in the penetration of Internet applications, the labor productivity of farm households will increase by 3.22 percentage points, which indicates that in the rural sector, Internet applications do have a more significant impact on improving household labor productivity. The platform economy based on Internet applications provides a new opportunity for rural agricultural development, which greatly improves the efficiency of rural economic operation by promoting the change from traditional agricultural production methods to modern agricultural production methods and to some extent verifies the hypothesis of this paper that the current development of ICT technology represented by Internet applications in rural China is not at the stage of "Solow's paradox" (Wang et al., 2022).

Table 2
Impact of Internet applications on household labor productivity.

Variables	Labor productivity				
	Rural				Cities and towns
	(1)	(2)	(3)	(4)	(5)
Internet applications	0.61***	0.33***	0.31***	0.32***	0.37***
	(15.69)	(7.19)	(6.53)	(6.13)	(7.18)
Health status		0.12***	0.15***		
		(7.06)	(6.11)		
Education level		0.09***	0.08***		
		(8.46)	(4.32)		
Political appearance		0.07	0.06		
		(0.85)	(0.66)		
Gender		−0.07*	−0.06*		
		(−1.78)	(−1.70)		
Age		0.01***	−0.00		
		(3.35)	(−1.00)		
Marital Status		−0.09	−0.13**		
		(−1.54)	(−2.18)		
Ethnicity		0.17***	0.18***		
		(3.01)	(3.24)		
Family level		0.38***	0.37***		
		(14.33)	(9.67)		
West		−0.42***	−0.43***	−0.569***	−0.68***
		(−7.61)	(−7.90)	(−9.97)	(−17.59)
Middle		−0.17***	−0.17***	−0.22***	−0.63***
		(−3.48)	(−3.55)	(−4.27)	(−21.15)
_pscore				0.85***	0.66***
				(6.85)	(5.33)
Interaction items	N	N	Y	Y	Y
Constant	8.75***	7.04***	7.62***	8.83***	9.64***
	(312.62)	(43.23)	(30.78)	(146.24)	(139.80)
Observations	2955	2955	2955	2955	5399
R-squared	0.07	0.24	0.24	0.13	0.23

Note: ***, **, and * represent significance at the 1 %, 5 %, and 10 % levels, respectively, with robust standard errors in parentheses. Other tables are the same as this one, so they are omitted.

However, whether the gap between the productivity effects of Internet applications in the rural and urban sectors exists, and if so to what extent, requires further analysis. For this reason, this paper analyzes the urban sample on this basis. Considering that the estimation results of Model III for the rural sample are more robust, we compare the regression results obtained based on Model III (column (5)) with the rural sample. The comparison reveals that the regression coefficient of Internet applications on labor productivity in the urban sector is 0.368, which is larger than the regression coefficient of Internet applications in the rural sector of 0.32. Additionally, the productivity effect of Internet applications is 14.3 percentage points in the urban sector than in the rural sector, a result that also confirms the inference contained in the statistical description of this paper. In the context of the urban-rural dichotomy, there is not only a large gap between urban and rural areas in terms of the Internet penetration rate but also a difference of nearly 15 % in the productivity effect based on it. Therefore, an in-depth discussion of the mechanism of the effect of Internet applications on the labor productivity of rural households in the rural sector will be important for the transformation and long-term economic growth of China's rural economy.

Meanwhile, the regression results for the control variables are largely in line with expectations as well. Among individual and household characteristics, the coefficients of health status and education level are both significantly positive, indicating that both better physical health and higher education significantly contribute to household labor productivity. In contrast, the effects of marital status and gender on labor productivity are negative, and it can be argued that when other variables remain constant, marital status makes a relatively low contribution to household labor productivity. The reason may be that the dependent variable in this paper is labor productivity per unit of household, and there is a more common phenomenon of "marriage without family separation" in the survey sample, especially in rural areas. In terms of regional characteristics, the productivity effect of Internet applications is significantly lower in the western and central regions than in the eastern region, indicating that not only do Internet applications show a gap between urban and rural areas, but the productivity effect also differs between different regions where there is a gap in the level of economic development. Using data from 13 prefecture-level cities in Jiangsu Province from 1996 to 2014, Chen (2014) investigated the differences in ICT and total factor productivity in different regions by dividing Jiangsu into three regions: southern, central and northern Jiangsu. It was found that the higher the level of economic development, the smaller the negative effect of factor productivity, which eventually transformed into a positive promotion effect. The findings coincide with those obtained in this paper, suggesting that infrastructure construction in regions with lower levels of economic development may still be inadequate in terms of the Internet applications, and efforts should be made to increase infrastructure investment.

This section further investigates whether the creative destruction effect of Internet applications in the rural sector exists and what role it actually plays in the Internet productivity effect. To this end, this paper tests the possible mechanisms of the effect of Internet applications on the labor productivity of farm households based on the aforementioned model setup.

As shown in Tables 3 and 4, the paper estimates the creation and destruction effects on Internet applications in the rural sector through Probit, and the results are tested for robustness through a multinomial Probit model (The results are listed in columns 2, 3 and 4). As seen from the Probit model, the results of the creation effect exhibited by Internet applications are negative and significant at the 1 % statistical level, although, as mentioned earlier, the indicators selected in this paper cannot fully reflect the creation effect of the Internet due to data availability. Therefore, the negative result does not mean that current Internet applications in the rural sector have failed to promote the rise of modern agriculture or inhibit its rise. However, this result also suggests that current modern agriculture in rural areas has not yet been able to significantly attract returning labor, which reminds us that there is indeed a need to strengthen the applications of the Internet in the rural sector. In terms of control variables, the regression coefficients of health status and education level are also significantly negative. This result is more consistent with the reality that the better the health status and the higher the education level of the labor force that has left the country, the lower the probability that they will return to the rural sector to farm. To further test the robustness of this result, this paper differentiates the returning labor force according to whether they have jobs and finds that Internet applications have an inhibitory effect on the returning labor force in the rural sector after regression with a multinomial Probit model, which indicates that the current status of Internet applications in the rural sector does not have an attractive effect on the returning labor force to the rural sector compared to increasing the probability of the rural labor force moving to the urban sector. This suggests that the current state of Internet adoption in the rural sector does not have an attractive effect on the return of labor to the rural sector compared to increasing the probability of rural labor moving to the urban sector. This result further corroborates the results of the Probit model. However, it is reasonable to infer from the promotion effect of Internet adoption on rural labor migration that although the creation effect is negative, the destruction effect is likely to be positive.

Therefore, we further analyze the disruptive effect of Internet applications, and the results in Table 4 show that when other variables are controlled, the Internet exhibits a significant disruptive effect in the rural sector, implying that Internet applications in the rural

Table 3
Creative effects of Internet applications in the rural sector.

Variables	Creation effect	Working Outside	Returning to unemployment	Return to farming
	Probit	Mprobit		
	(1)	(2)	(3)	(4)
Internet Applications	−0.11***	0.09***	−0.02	−0.08**
	(0.04)	(0.03)	(0.03)	(0.03)
Health Status	−0.05***	0.05***	−0.03***	−0.02*
	(0.01)	(0.01)	(0.012)	(0.01)
Education level	−0.03***	0.03***	0.01*	−0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
Political affiliation	−0.01	0.00	0.05	−0.06
	(0.05)	(0.06)	(0.05)	(0.04)
Gender	−0.13***	0.13***	−0.21***	0.08***
	(0.03)	(0.03)	(0.02)	(0.02)
Age	0.00**	−0.00***	0.001	0.00**
	(0.002)	(0.001)	(0.001)	(0.001)
Marital status	0.01	−0.01	−0.03	0.04
	(0.04)	(0.04)	(0.037)	(0.03)
Ethnicity	−0.06	0.06	−0.02	−0.04
	(0.04)	(0.04)	(0.04)	(0.04)
Family economic level	−0.07***	0.07***	−0.05***	−0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Western	0.30***	−0.31***	0.01	0.29***
	(0.04)	(0.04)	(0.04)	(0.04)
Central	0.21***	−0.22***	0.07**	0.16***
	(0.03)	(0.03)	(0.03)	(0.03)
Sample size	1541	1541	1541	1541

Note: Marginal effects are reported in the table, with robust standard errors in parentheses.

Table 4
Disruptive effects of Internet applications in the rural sector.

Variables	Destructive effects Probit	Unemployment Mprobit	Farming	Nonfarm Payrolls
	(1)	(2)	(3)	(4)
Internet applications	0.15***	−0.05**	−0.10***	0.15***
	(0.02)	(0.023)	(0.02)	(0.02)
Health status	0.04***	−0.05***	0.01	0.04***
	(0.01)	(0.01)	(0.011)	(0.01)
Education level	0.03***	0.02***	−0.05***	0.03***
	(0.004)	(0.01)	(0.01)	(0.01)
Political affiliation	0.02	0.06	−0.07	0.01
	(0.04)	(0.05)	(0.05)	(0.04)
Gender	0.13***	−0.22***	0.09***	0.13***
	(0.02)	(0.02)	(0.02)	(0.02)
Age	−0.00***	−0.00**	0.01***	−0.00***
	(0.001)	(0.001)	(0.001)	(0.001)
Marital status	0.07***	−0.14***	0.07**	0.07***
	(0.02)	(0.03)	(0.03)	(0.02)
Ethnicity	0.04**	−0.01	−0.03	0.04*
	(0.02)	(0.03)	(0.03)	(0.02)
Family economic level	0.05***	−0.05***	−0.01	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Western	−0.17***	−0.08***	0.26***	−0.18***
	(0.02)	(0.03)	(0.03)	(0.02)
Central	−0.16***	−0.01	0.18***	−0.17***
	(0.02)	(0.03)	(0.03)	(0.02)
Sample size	3047	3047	3047	3047

Note: Marginal effects are reported in the table, with robust standard errors in parentheses.

sector do lead to the decline of traditional agriculture and that traditional farmers who fail to respond favorably to this change are being marginalized as a result. Specifically, Internet applications can increase the probability of shifting rural labor jobs from agriculture to nonfarm work by 15.3 %. To test the robustness of this result, this paper further subdivides the dependent variables into unemployment, farming, and nonfarm employment to distinguish the labor force that fails to be employed. The study finds that compared with unemployment, Internet applications can still increase the probability of the nonfarm employment of rural laborers by 15.1 %, which is only 0.2 percentage points different from the former result, indicating that the regression results of this paper's Probit model are somewhat biased upward but are generally robust. Columns (2) and (3) show that Internet applications reduce the probability of labor force unemployment and farming by 4.8 and 10.3 %, respectively. This result coincides with the previous finding that Internet applications have caused the destruction of traditional agricultural jobs and reduced the probability of rural laborers working in agriculture. This finding is consistent with existing research (Wang et al., 2022); by examining broadband development projects in China, which is consistent with this paper, it is concluded that the deployment of high utility broadband promotes regional employment in the technology services sector. Moreover, this effect is greater in regions with a higher number of educated residents.

Regarding the other control variables, both the health status and education level of the labor force can robustly and significantly increase the probability of nonfarm employment, but the coefficients are only 0.04 and 0.03, which means that when other factors are controlled, a one-level increase in the health status and education level of the labor force can increase the probability of nonfarm employment but the marginal effect of the coefficient Internet application is relatively small. The probable reason is that while Internet applications cause the decline of traditional agriculture, they also complement the increase in the human and social capital of the labor force itself, which in turn confers the same opportunities for labor with low human capital levels to move to higher productivity sectors as highly qualified labor.

Tables 3 and 4 verify the creative destruction effect of Internet applications, but this indicates only the presence or absence of the effect and is not yet sufficient to prove that the effect plays a role in the Internet productivity effect, especially the difference between the creation effect and the destruction effect, which both need further discussion. For this reason, this paper incorporates the creation effect and the destruction effect into the Eq and estimates Eq. (11) according to Models I–III. Owing to space limitations, the creation effect regression results are listed only for the more robust Model III, as shown in Table 5. In general, the coefficient signs and significance of the regression results obtained from each model in Table 5 are consistent, which indicates that the model setting and the selection of variables in this paper are reasonable. Specifically, the regression results in columns (1)–(5) of Table 5 indicate that the regression coefficients of Internet applications on labor productivity are still significantly positive after the job creation effect and the job destruction effect of Internet applications are added. Specifically, when the coefficients of the creation effect and the destruction effect are observed, the results indicate that both are significant at the 1 % statistical level. However, the former is positively promoted, while the latter is not, which implies that the current labor force return does not contribute to the increased labor productivity of farm households. However, a further comparison of the regression results in Tables 5 and 2 reveals that the regression coefficients of Internet applications in the rural sector decreased from 0.32 to 0.27 and 0.17, respectively, which means that they have decreased, indicating that both the creation and destruction effects of Internet applications indirectly affect the productivity effect of Internet applications. Thus far, the biased technical change in labor factors by Internet applications is significantly nonzero, and it indirectly increases the productivity level of farmers by optimizing the allocation of labor factors. Thus, Hypothesis 2 is

Table 5
Mechanisms of the impact of Internet applications on labor productivity.

Variables	Labor productivity				
	(1)	(2)	(3)	(4)	(5)
Internet applications	0.45***	0.28***	0.27***	0.27***	0.17**
	(11.20)	(6.12)	(5.56)	(5.24)	(2.46)
Destructive effects	0.55***	0.33***	0.32***	0.43***	
	(12.53)	(7.76)	(7.58)	(9.66)	
Creation effects					−0.37***
					(−6.77)
Health status		0.11***	0.14***		
		(6.53)	(5.90)		
Education level		0.08***	0.08***		
		(7.62)	(4.09)		
Political affiliation		0.06	0.05		
		(0.78)	(0.63)		
Gender		−0.11***	−0.10***		
		(−2.84)	(−2.74)		
Age		0.01***	−0.00		
		(3.89)	(−0.45)		
Marital status		−0.11*	−0.15**		
		(−1.80)	(−2.42)		
Ethnicity		0.16***	0.17***		
		(2.80)	(3.02)		
Family economic level		0.36***	0.35***		
		(13.87)	(9.46)		
Western		−0.35***	−0.36***	−0.47***	−0.52***
		(−6.32)	(−6.60)	(−8.30)	(−7.05)
Central		−0.11**	−0.11**	−0.14***	−0.22***
		(−2.30)	(−2.40)	(−2.81)	(−3.62)
_pscore				0.71***	0.73***
				(5.83)	(3.86)
Interaction items	N	N	Y	Y	Y
Constant term	8.68***	7.03***	7.52***	8.74***	9.27***
	(308.28)	(43.71)	(30.67)	(145.53)	(95.21)
Sample size	2955	2955	2955	2955	1515
R-squared	0.118	0.251	0.256	0.154	0.132

Table 6
Balance test results.

Matching variables	Before matching After matching	Average value		Standard deviation (%)		T-test
		Processing group	Control group	Deviation	Reduction	*P*> |t|
Gender	U	0.51	0.47	7.4		0.05
	M	0.51	0.51	0.3	95.7	0.94
Age	U	39.58	54.26	−151.7		0.00
	M	40.27	40.75	−5.0	96.7	0.26
Marriage	U	0.84	0.88	−12.4		0.00
	M	0.87	0.88	−3.4	72.8	0.38
Ethnicity	U	0.87	0.86	1.7		0.64
	M	0.87	0.88	−3.9	−126.7	0.30
Health	U	3.78	3.00	71.7		0.00
	M	3.74	3.54	18.4	74.4	0.00
Education	U	4.70	2.99	90.5		0.00
	M	4.40	4.45	−2.9	96.8	0.52
Political affiliation	U	0.71	0.04	16.2		0.00
	M	0.07	0.71	−1.1	93.0	0.80
Family economic level	U	2.60	2.31	40.1		0.00
	M	2.60	2.63	−5.5	86.3	0.13
Area of affiliation	U	1.96	1.85	15.9		0.00
	M	1.95	1.98	−3.1	80.5	0.43

confirmed. This finding further confirms existing research findings that training services for farmers, including wheat growers, on Internet applications should be expanded, as it could help improve growers' ability to increase agricultural productivity and household income (Khan et al., 2022). It also responds to the concerns in existing studies about the increase in income inequality among rural populations as a result of Internet development from a creative destruction perspective (Nguyen et al., 2022).

Endogeneity test

While Internet adoption affects the labor productivity of rural households, the prevalence of Internet adoption may be implied by households with higher labor productivity, and there may be other unobserved variables in the group connected to Internet adoption that lead to the higher labor productivity of rural households. To avoid the endogeneity problem caused by the possible "self-selection bias" of such samples, this paper constructs a counterfactual analysis framework to further analyze the relationship between Internet adoption and labor productivity in rural samples by using the propensity score matching method (PSM) to verify the robustness of the previous analysis.

The premise of using propensity score matching to obtain robust estimates is that there is no systematic difference between the treatment and control groups after the covariates are matched. In this paper,[3] three matching methods, K-order nearest neighbor matching, radius matching and kernel matching, are used to test the results of the equilibrium test in Table 6. Most of the *t*-tests results after matching were not significant, indicating that the original hypothesis that there were no systematic differences between the treatment and control groups was accepted; i.e., this matching result balanced the data better. Further examination of the common range of values for the propensity scores also visually reflected that most observations were within the common range of values, so this matching only lost a small number of samples.[4]

Table 7 shows the estimation results obtained in this paper after K-order nearest neighbor matching, radius matching and kernel matching. The estimates obtained by the three matching methods

Table 7
Estimation results in the counterfactual analysis framework.

	Farmers' labor productivity		
	Nearest neighbor matching	Radius matching	Nuclear matching
	(1)	(2)	(3)
ATT	0.32***	0.31***	0.32***
	(3.05)	(3.96)	(3.86)
ATU	0.34***	0.31***	0.30***
	(3.95)	(4.18)	(3.73)
ATE	0.33***	0.31***	0.31***
	(4.47)	(5.36)	(4.93)

are all significant at the 1 % statistical level, and the estimates obtained by different matching methods have the same sign and comparable magnitude. These results are basically consistent with the previous baseline regression results, which indicates that the previous results are still robust even after the endogeneity problem is considered and even if the estimation is performed by different matching methods.

Mediating effect test

Although the paper has previously conducted a basic analysis and mechanism exploration of the relationship between Internet adoption, creative destruction effects and labor productivity under different model settings, it has also solved the possible endogeneity problem through the PSM approach and thus obtained a more accurate treatment of the effects. However, the shortcoming is that the above analysis has not yet examined the mediating role of the result of the creative destruction effect, i.e., labor factor allocation, in the relationship between Internet adoption and labor productivity. Therefore, this section will test the mediating effect of the mediating variables through the Sobel test method and bootstrap method (bootstrap).

To compare the relationships among the coefficients more clearly, this paper first concentrates the key coefficients of the regression results from Table 2 to Table 5 in the previous section in columns (1) to (5) of Table 8. A comprehensive comparison reveals that after the disruption effect is added, the productivity effect of Internet applications decreases from 0.32 to 0.27 and is significant at the 1 % level. The labor factor allocation also shows a significant contribution to labor productivity, indicating that Internet applications do provide a certain impetus to the decline of traditional agriculture and have an

[3] K = 3 in K-order nearest neighbor matching and caliper in radius matching $\varepsilon \leq 0.25$ $\sigma_{pscore} = 0.06$. Robustness tests were conducted with different parameters.

[4] Due to space limitations, only the balance test results of the matching results after K-order nearest neighbor matching are reported here; others are available upon request.

Table 8
Results of the intermediate effect test.

Variables	Labor productivity	Destructive effects	Labor productivity	Creation effect	Labor productivity
	(1)	(2)	(3)	(4)	(5)
Internet applications	0.32***	0.15***	0.27***	−0.11***	0.17**
	(6.13)	(0.02)	(5.24)	(0.04)	(2.46)
Destructive effects			0.43***		
			(9.66)		
Creation effect					−0.37***
					(−6.77)
Interaction items	Y	N	Y	N	Y
Control variables	Y	Y	Y	Y	Y
Constant	8.83***		8.74***		9.274***
	(146.24)		(145.53)		(95.21)
R-squared	0.13		0.15		0.13
Observations	2955	3047	2955	1541	1515
P-value of the Sobel test	1.369e-07			0.01	
Bootstrap Confidence interval	[0.03∼0.07]			[0.01∼0.05].	
Bootstrap	0.05***			0.03 **	
	0.29 ***			0.20***	

Note: The bootstrap confidence intervals shown in the table are the confidence intervals for the indirect effects; the bootstrap test results above are the coefficient values for the indirect effects, and the results below are the coefficient values for the direct effects.

indirect effect on labor productivity through this path. In the results of the Sobel test, the p-value is less than 0.05, and the indirect disruptive effect of Internet applications accounts for 14.5 % of the total effect. It should be noted that although the test power of the Sobel method is higher than that of the stepwise regression coefficient test, the derivation of the statistic for the coefficient product of the Sobel test requires the assumption that the coefficient product $(\beta_1\beta_3)$ obeys a normal distribution, which is difficult to guarantee. Therefore, to avoid the possible bias caused by this limitation, this paper further uses the bootstrap test for robustness testing of mediating effects. Bootstrap samples are obtained by repeated sampling with put-back; the estimates of the product of the coefficients are then obtained, and they are sorted from the smallest to the largest values. When the confidence interval consisting of the 2.5th percentile and the 97.5th percentile does not contain 0, it indicates that the mediation effect holds. As Table 8 shows, the confidence interval of the indirect effect obtained by bootstrapping do not contain 0, indicating that the mediating effect holds, further proving the robustness of the previous analysis. As mentioned previously, after the creation effect of Internet applications is added, the promotion effect of Internet applications on farmers' labor productivity also decreases significantly. Furthermore, the coefficient of creation effect is significantly negative is as the coefficient of Internet applications on the creation effect. In this paper, the mediating effect is also tested by the Sobel and bootstrap methods. The results of the Sobel test indicate that the p-value is less than 0.05, and the indirect effect from the destruction effect of Internet applications accounts for 11.6 % of the total effect, which is lower than the indirect effect of the destruction effect. The bootstrap test results also verify this conclusion; the confidence interval of the indirect effect is [0.01∼0.05], and the coefficients of the indirect effect and direct effect are significant at the 5 and 1 % levels, respectively.

Implications to theory and practice

Our research findings drive us to develop several implications for theory. First, compared with existing studies (Cheng et al., 2020), this paper makes a comparative analysis of the current situation of Internet applications in rural and urban sectors in China, and specifically analyzes the rural sectors whose Internet penetration rate is lower than that in cities, providing a more complete perspective for an integrated examination of the current situation of Internet applications and labor market development in the urban and rural sectors. Research shows that Internet applications in the rural sector have cracked the Solow paradox, but there is still a large gap with the urban sector.

Second, through theoretical models and empirical tests, this paper identifies and deeply analyzes the creative destructive effects of Internet applications in the rural sector. Therefore, the direct and indirect impact paths of Internet applications on agricultural labor productivity have been confirmed, especially through the indirect impact paths of labor factors, which need to be further excavated, confirming the conclusion of existing studies that the potential structural differences between information technology applications in ICT capital intensive and non ICT capital intensive sectors, that is, the indirect impact of information technology on production efficiency is dominant in ICT capital intensive sectors, while it is only secondary in non ICT capital intensive sectors (Dumagan et al., 2003).

Thirdly, the specific examination of the creative destruction effect of the Internet on the allocation of labor factors in this paper differs from previous direct analyses of rural labor transfer, and the perspective of this paper further extends the Chinese application of Lewis' analysis paradigm. Preventing labor force involution in the era of the digital economy and promoting the healthy and benign development of the labor market are of great significance.

Based on the conclusions of this paper, the following insights or suggestions are drawn. First, in promoting Internet applications and developing the digital economy, special attention should be paid to the impact on labor force employment. The current mismatch in quantity and quality between new jobs created by Internet applications and old jobs destroyed by them is a key issue that needs to be addressed in the current labor market. This paper provides an important perspective to solve this problem. That is, paying attention to the development of Internet applications in backward regions, promoting their creation effect in those regions, and providing jobs with productivity equivalent to the original jobs for the labor force eliminated by the destruction effect in urban sectors is an important breakthrough for adapting to the wave of new technology and promoting the healthy development of the digital economy and the steady progress of digital village construction. Second, Internet applications and the optimal allocation of production factors such as labor and land between urban and rural areas are two important aspects that cannot be neglected in terms of improving farmers' labor productivity. Therefore, narrowing the multidimensional "digital divide" between urban and rural areas is not only a strategic direction for rural revitalization but also an important part of building a digital China. Third, the current education level in rural areas is still a key factor limiting the widespread use of Internet applications. Although current

Internet applications have effectively improved the labor productivity of households, there are still many dividends in rural areas that have not been exploited under the Internet sharing economy. To make full scientific and efficient use of the Internet dividends, developing countries should increase public education investment and media information dissemination in rural areas, carry out Internet training, and steadily promote the construction of digital villages to achieve sustained growth in the labor productivity of farm households. Fourth, local governments should actively develop corresponding labor training programs and introduction policies to give full play to the human capital of returning laborers and promote the long-term development of the rural economy by promoting the further optimal allocation of labor factors (Santoro & Usai, 2018).

Conclusion, limitations and suggestion for future work

This paper focuses on the rural sector and uses a mediating effects model and a counterfactual analysis framework to theoretically explore the mechanism of the productivity effect of Internet applications and it empirically analyzes the impact of Internet applications on the labor productivity of farm households and its mechanism of action based on CGSS data. The main conclusions of this paper are as follows. First, Internet applications are not at the stage of "Solow's paradox" in China's rural sector; in contrast, Internet applications have played a significant role in improving the labor productivity of farmers in terms of both direct and indirect effects. Second, Internet applications have promoted changes in traditional agricultural production methods to modern agricultural production methods and optimized the allocation of labor factors under the coupling effect of the creation effect and destruction effect, indirectly improving the productivity level of farmers. Third, compared with the disruptive effect, the creation effect of the Internet is currently not obvious in the rural sector. This also indicates that there is still much room for the development of modern agriculture in rural China, and that the space for returning labor is still limited.

The results of this work should be considered in light of its limitations. First, the methodology used in the paper is scientific, but the data sample is small and the data collected is not thoroughly studied. Therefore, this paper has not yet tested the lag of Internet applications, and can only reflect the policy effect of current Internet applications on agricultural production efficiency. Second, our data source is survey data from China's rural sector, which fails to empirically test the Internet applications in other developing countries, and can not directly reflect the current situation of Internet applications in developing countries. Therefore, in future research, it is necessary to collect Internet application data from different developing countries, and then compare the process and influencing factors of the current digital transformation of agricultural production in developing countries. At the same time, we should also conduct in-depth research on the indirect impact path of Internet applications in the rural sector, so as to provide practical policy suggestions for the digital transformation of the rural sector.

Declaration of Competing Interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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