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Can Rural Industrial Convergence Improve the Total Factor Productivity of Agricultural Environments: Evidence from China

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Abstract: The convergence of rural industries has brought about significant changes in the traditional small-scale farmer management model, as well as new requirements for the quality and skills of agricultural practitioners in China. Meanwhile, it has inevitably affected the agricultural environmental total factor productivity (AETFP). This paper endeavors to assess the impact of industrial convergence on AETFP, striving to clarify their inherent connection and furnish insightful guidance for policymaking. Utilizing inter-provincial panel data from China spanning 2008 to 2021, this paper applies the SBM-GML model for measurement purposes and employs the entropy method to evaluate the extent of industrial convergence in rural areas. It delves into the mechanism through which industrial convergence influences AETFP, utilizing the intermediary effect model and incorporating two mediating variables: rural human capital and agricultural scale operations. The findings of this research reveal that industrial convergence exerts a direct positive influence on AETFP, while rural human capital and agricultural scale operations serve as partial mediators in this process. Additionally, the stability of the transmission mechanism receives further validation via the application of interaction terms. Consequently, it is possible to enhance AETFP via the expedited convergent development of industries, coupled with the strategic utilization of rural human capital and agricultural scale operations as catalysts for further improvements in AETFP.

Keywords: rural industrial convergence; TFP of agricultural environment; SBM-GML model; intermediary effect; rural human capital; agricultural scale operation

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1. Introduction

Agriculture serves as the foundation of the national economy and plays a crucial role in fostering stable social development. It is a knowledge-intensive industry that relies on advanced technology and knowledge to improve production efficiency, optimize resource allocation, reduce environmental impact, and achieve sustainable development [1,2]. In the field of agricultural economics, the emphasis has consistently been on evaluating economic growth in agriculture through productivity metrics [3]. Neoclassical economic growth theory posits that enhanced production efficiency leads to sustainable economic development. The existing studies have shown that enhancing total factor productivity (TFP), which refers to the accumulation and improvement of productivity factors, is an effective approach to optimizing economic development [4]. The neoclassical economic growth theory emphasizes that TFP is the source of sustained economic growth, and the continuous improvement of it is the sustained driving force for economic growth in countries and regions. As China's economy shifts from swift expansion to prioritizing high-quality development, the imperative to enhance TFP has become evident [5]. Traditional agricultural

TFP calculations neglect resource and environmental factors, vital components of agricultural transformation. This oversight can lead to underestimating the negative impacts of agricultural economic growth on social welfare, possibly resulting in an inflated perception of agricultural TFP's true level. This oversight can lead to misleading policy implications, particularly when ecological conflicts are prominent [6]. As China's agriculture enters a phase of green-driven high-quality development from 2021 to 2025, improving the AETFP is crucial for achieving high-quality development. Thus, it is essential to consider the agricultural TFP that incorporates resource and environmental factors, referred to as the AETFP, to accurately assess agricultural production performance [7].

At the same time, fostering synergy between agriculture and other industries has become a key policy strategy to bolster agriculture, rural development, and farmer welfare in China. This initiative contributes to the establishment and enhancement of a modern agricultural industry system, transforms agricultural development approaches, and broadens income opportunities for farmers. This proves to be an efficacious method for realizing comprehensive rural revitalization [8]. In 2015, the government explicitly advocated for progressive convergent transformation and the creation of a novel rural transformation model. The report of the 19th CPC National Congress introduced the strategy of rural revitalization, emphasizing the dynamic expansion of convergent rural sectors as a key component of its implementation. In 2022, the government underscored the need for "consistent facilitation of agriculture and allied industries' convergent advancement". The continued policy support demonstrates that the combined progression of rural sectors has become a notable focal point within the "agriculture, rural, and farmers" initiatives in China's new ordinary circumstances [9]. However, current theoretical research lacks analysis on the impact of industrial convergence on the AETFP. In practice, rural industrial convergent development also faces challenges such as insufficient depth of the industrial convergence, weak business entities, and inadequate reward mechanisms. This results in a lack of endogenous power to promote the enhancement of TFP in the agricultural environment [10].

This paper integrates two current hot issues in agricultural economic development: the AETFP and the convergence of agriculture and allied industries. It analyzes the impact and mechanism of the industrial convergence on the AETFP. The practice has shown that the convergence of rural industries not only changes China's traditional small-scale farmer management model but also sets new requirements for the quality and skills of agricultural practitioners in management, clean production, and other aspects. However, the existing research lacks theoretical exploration and empirical testing of the transmission mechanism between the two [11]. Therefore, it is crucial to construct an evaluation system for the level of industrial convergence and an AETFP measurement system during the critical period of deepening the development of industrial convergence in countryside. This empirical analysis will greatly contribute to promoting the quality and efficiency of agriculture and assisting the overall revitalization of rural areas, both theoretically and practically [12]. Using China's inter-provincial panel data from 2008 to 2021, this research conducts an empirical data test to examine the effect of the convergence of agricultural and non-agricultural sectors on the AETFP. The findings aim to clarify the intrinsic relationship between the two factors and provide valuable insights for the formulation of relevant policies.

The three main innovative aspects of this paper are as follows: (1) It constructs an AETFP framework in an innovative way. Currently, the academic community has not yet formed a unified system for measuring total factor productivity in agricultural environments. This paper defines AETFP as the efficiency relationship between agricultural input and output, considering the consumption of irrigation water resources, pollution from agricultural fertilizers, pollution from agricultural solid waste, and agricultural carbon emissions. This reshapes the AETFP measurement system. (2) The paper develops an evaluation system for the level of rural industrial convergence. Due to the relatively late start of convergent industrial development in China and the limited academic discourse on its assessment, this work, based on the practical development of China's rural industrial convergence, constructs an evaluation system. It considers aspects like the extension of agricultural industry chains, the expansion of agriculture's multifunctionality, and the deep penetration of information technology, providing a reference for quantitative research on rural industry integration in academia. (3) It attempts to explore the impact and mechanisms of convergent rural industrial development on the AETFP. In a critical phase of promoting convergent industrial development, establishing an evaluation system for this development level and an AETFP measurement framework, and empirically analyzing the impact of industrial convergence on the AETFP, are not only instrumental for China to achieve comprehensive rural revitalization but also hold significant referential value for the green transformation and sustainable development of agriculture in other developing countries and regions.

2. Literature Review and Theoretical Analysis

2.1. Literature Review

2.1.1. Research on Total Factor Productivity

China is currently experiencing a shift from rapid economic growth to the advancement of high-quality development. TFP serves as a comprehensive gauge that demonstrates the efficiency and quality of resource allocation within the economic framework, rendering it a pivotal metric for evaluating the caliber of economic expansion [13]. In macroeconomic research, the economic growth accounting framework provides the basis for the TFP theory. Traditionally, labor and capital have been considered as the primary drivers of economic growth. However, this perspective fails to fully explain the observed growth in output during production activities [14]. One crucial factor that is often overlooked in the economic growth accounting framework is TFP, also referred to as the "residual value". The concept of TFP was first introduced by economist Tinbergen, who incorporated the time variable into the C-D production function to analyze changes in efficiency [15]. TFP not only reflects technological progress but also represents the operational efficiency of production. The American economist Solow, who first proposed the concept of total factor productivity, pointed out that 87.5% of American economic growth comes from the improvement of TFP, which is an important force to promote sustainable economic growth [16]. Subsequently, George Stigler independently explored the concept of TFP and conducted research on TFP in the American manufacturing industry [17]. Hiam Davis provided a comprehensive definition of TFP in his book *Productivity Accounting*, stating that it specifically refers to the production efficiency of all input factors, including labor, capital, land, and others [18]. Edward F. Denison further developed the concept of the "Solow residual" and defined TFP as the residual efficiency after accounting for the growth rates of output and various input factors [19]. The Denison model is constructed based on the concept of "residual". Research on environmental TFP considers the impact of pollutants on agricultural productivity, offering a more precise portrayal of agricultural development. As a result, an increasing number of scholars are incorporating environmental factors into the TFP measurement system [20,21]. When measuring environmental TFP, environmental factors were initially considered as input factors. However, this approach may distort the relationship between input and output factors [22]. Following that, scholars have suggested utilizing the directional distance function to gauge effectiveness while taking into account undesired outcomes. The directional distance function allows decision-making units to improve in a specific direction, distinguishing between "positive output" and "negative output". As the theory of green development has deepened, scholars have also conducted extensive surveys in this area, referring to the agricultural TFP that considers undesired outputs as "the environmental TFP" or "the green TFP", among other terms [23,24].

In terms of measuring AETFP, there are two main categories: parametric estimation methods and non-parametric estimation methods. The former methods include the stochastic frontier production function method and the Solow residual method. The latter methods include the data envelopment analysis method, based on the non-angular non-radial SBM model, and the use of index calculations such as Malmquist and ML [16]. Over the years, there have been improvements in the measurement methods of AETFP. One example is the introduction of global measurement technology (Global) into the ML productivity index to create the GML index [25,26]. In selecting indicators for AETFP measurement, scholars generally converge on similar choices for input indicators, predominantly opting for an extension of the C-D production function. However, approaches to handling undesired outputs vary. Generally, there are two approaches: the input method, which considers resource and environmental factors as input indicators with shadow prices, and the output method, which treats pollutants as "negative outputs" in agricultural production processes. Current scholarly consensus indicates that the output method predominates in measuring environmental TFP, according to existing research. When using the output method to calculate undesirable outputs, scholars have different preferences for units of agricultural pollutants. These preferences are primarily determined by the characteristics of their research subjects [27,28]. In the case of the planting industry, pollution units typically encompass factors such as pesticides, fertilizers, and plastic films. On the other hand, the breeding industry commonly considers factors like livestock and poultry manure emissions. Regarding the functional factors of AETFP, there has been limited and fragmented research on the subject due to the relatively recent development of production efficiency measurement technology, including undesired output. Relevant scholars primarily utilize regional panel data to empirically analyze the effect of specific variables on the AETFP. These variables often include factors such as agricultural industrial structure, infrastructure investment, economic development level, trade openness, environmental regulation, and informatization level.

2.1.2. Research on Convergence of Rural Industries

The discussion of the industrial convergence in farming areas has been contributed to in previous studies by Marx and Marshall [29,30]. However, due to societal constraints, this topic did not garner widespread attention from social scientists. The current literature reveals that Western scholars generally analyze this phenomenon through the lens of technological cross convergence, while their Asian counterparts concentrate on the convergence between agriculture and related industries in rural regions [31,32]. Specifically, Japanese scholars have been pioneers in the theoretical exploration of industrial convergence. In 1994, agricultural economics expert Imamura Naraomi introduced a six-industry theory with agriculture as its core. This theory suggests that the addition of primary, secondary, and tertiary industries to agriculture yields six industrial correspondences (1 + 2 + 3 = 6). He also advocates for the reinvestment of added agricultural value from the subsequent industries back into agriculture and rural communities, fostering a multiplier effect across various industries in these regions [33]. Japan has effectively integrated agriculture-based production and operations with the secondary and tertiary sectors. This strategy has notably boosted farmers' enthusiasm for production and has effectively addressed social challenges, including surplus labor reallocation and advancing agricultural modernization in Japan. The six-industry theory and the multiplier effect of the three-industry promote the vertical and horizontal convergence of agricultural production, facilitating diversified business models such as agricultural production, processing, sales, leisure, and tourism. Since then, other Japanese scholars have also engaged in extensive studies on the six-industry theory [34,35]. In their study, the authors analyze both the present conditions and potential future developments of Japan's sixth industry, employing the previously discussed theory. Moreover, they have put forward recommendations for the integrated development of agriculture and related sectors in Japan. Other scholars have conducted theoretical research on industrial convergence from various perspectives [17]. It is believed that the development of industrial convergence in rural regions can significantly alleviate the multidimensional poverty of farmers [36]. A deeper comprehension of industrial convergence can enhance entrepreneurial education for migrant workers who are reintegrating into rural areas [37]. The harmonization of rural industries has a positive spatial spillover effect on urbanization construction and can effectively promote the urbanization rate [38,39].

Scholars have endeavored to gauge the development level of industrial convergence from various vantage points, engaging in empirical studies to uncover its driving factors. Key determinants include aspects such as rural e-commerce, farmers' awareness, governmental spending, rural financial services, human capital, consumer demand, and technological advancement [40].

Meanwhile, China has made significant progress in holistically advancing its rural industries. The Chinese government has provided a scientific definition of the industrial convergence in countryside, referring to it as the "convergent development of rural industries", which encompasses the agriculture and allied industries. Additionally, it has provided direction on development strategies, subject cultivation, and promotional mechanisms [41]. As a result, academics have conducted deeper research on industrial convergence in the countryside. Regarding the models of industrial convergence, they can be broadly classified into two categories. The first one pertains to industrial formats, which include the agricultural industry chain extension, agricultural multi-functional expansion, new technology penetration, and multi-business composite models [42]. The second one relies on the industry classification standards of the government, dividing industrial convergence into intra-industry pattern and inter-industry pattern [43]. Examples include models that integrate primary and secondary sectors, secondary and tertiary sectors, as well as all three sectors. To measure the extent of industrial convergence, scholars have employed various methods such as the gray correlation method, AHP method, Herfindahl index method, and entropy method. With the ongoing improvement of statistical data pertinent to industrial convergence, research has broadened from qualitative analysis to empirical studies [44,45].

2.2. Theoretical Analysis and Research Hypothesis

2.2.1. The Direct Impact of the Industrial Convergence on the AETFP

Agricultural pollution is a major concern that impedes the superior progression of agriculture. The overuse of chemical substances like pesticides and fertilizers can lead to detrimental effects on the ecological environment related to agriculture [46]. This goes against the concept of environmental agriculture, which advocates for incorporating resources and environmental factors into economic growth accounting [47]. Therefore, enhancing the AETFP and facilitating the transformation of developmental approaches is essential in attaining enduring sustainability in China's agricultural sector. Expanding the functionality of agriculture beyond production heavily depends on the pivotal role played by the convergence of industries in rural regions [48]. Through technological innovation, aggregation of production factors, and institutional innovation, it opens opportunities for agriculture in culture, tourism, scientific research, and more [49]. This convergence also fosters the emergence of new industries and formats. By supporting the adoption of new technologies, methods, and models in traditional agriculture, we can effectively address the high-risk and weak characteristics of traditional agriculture and strengthen the connection between households and enterprises [50]. Based on these considerations, this research proposes Hypothesis 1 (H1):

Hypothesis 1 (H1). *Overall, the convergence of agriculture and allied industries has a positive effect on improving the AETFP.*

2.2.2. The Indirect Impact of the Industrial Convergence on the AETFP

The convergence of industries in developing regions has led to an increased demand for high-quality compound talents [51]. In order to actively promote the convergence of the three major industries, relevant policies have been issued by the General Office of the State Council [52]. The importance of fostering convergent industry entities is highlighted by these policies. Currently, initiatives like the National New Professional Farmer Cultivation Project and Rural Practical Talent Training train over one million people each year, contributing to the improvement of rural human capital stock [53]. The benefit of rural labor on the AETFP can be observed in three main aspects: First, the substitution effect of rural labor. Farmers with higher quality levels possess stronger management capabilities, enabling them to better allocate agricultural production factors and reduce excessive reliance on chemical inputs [54]. Second, the bonding effect of human capital. The upgrading of agricultural industrialization is closely tied to the optimization of agricultural factor structure. High-quality rural labor can effectively align the direction of technological upgrading with the factor structure, thus promoting the transition of traditional agriculture to technology-intensive and capital-intensive industries [55]. Third, the spillover effect of human capital. Areas with a higher level of rural labor tend to foster technological innovation and dissemination, allowing neighboring regions to catch up with higher-technology areas through learning and emulation [34].

Hypothesis 2 (H2). *The convergence of agriculture and allied industries can improve the AETFP by improving the level of labor force.*

The convergence of rural industries promotes the agricultural operations towards compounding, scale, and intensification. This helps address the current challenges faced by small households, such as small business scale, low land intensity, and weak physical capital accumulation [56]. Agricultural scale operation has several positive effects on improving the AETFP. Firstly, the application of scale operations allows for the efficient allocation of factors, enhancing the utilization of indivisible production elements, and decreasing superfluous emissions of pollutants [57]. For instance, if agricultural machinery that can be used on 6666.7 m^2 of cultivated land is only used on 1333.4 m^2, it leads to 80% underutilization and reduces environmental efficiency. Secondly, scale operation facilitates unified standardized management and mechanized operation, resulting in cost savings per unit area, reduced manpower, and increased adoption of cleaner production technology. This, in turn, enhances the efficiency of socialized production services and contributes to improving the AETFP [58]. Thirdly, scale operation contributes to standardized agricultural production and significantly increases farmers' income. The implementation of a standardized agricultural production system is encouraged, facilitating routine inspections carried out by regulatory bodies to guarantee the quality and safety of agricultural products. Furthermore, apart from boosting farmers' income, large-scale operations can also enhance the overall agricultural ecosystem. When farmers' income from farming is too low, their efforts to implement cleaner production practices may not be effective. Therefore, by increasing the income level through large-scale operations, farmers can be motivated to focus on agricultural environmental production, which in turn enhances the TFP of the agricultural environment. This serves as a necessary condition for achieving this improvement [59]. Building upon this understanding, this paper puts forth Hypothesis 3 (H3).

Hypothesis 3 (H3). *The convergence of agriculture and allied industries can enhance the AETFP by expanding the operation scale.*

3. Data and Methods

3.1. Data Sources

Given the homogeneity and availability of data statistics, this research collects and organizes relevant data from 2008 to 2021 for 30 provinces in China (excluding Tibet, Hong Kong, Macao, and Taiwan). The data mainly comes from China Rural Statistics Yearbook, China Finance Statistics Yearbook, China Statistics Yearbook, China Civil Affairs Statistics Yearbook, China Water Resources Bulletin, National Bureau of Statistics (https://data.stats.gov.cn/, accessed on 1 November 2022), China Statistical Data Application System (http://vip.acmr.cn/, accessed on 1 January 2023), etc. In cases where there are missing values or outliers, methods such as linear interpolation are employed to address them.

3.2. Model

In this research, prior to establishing a linear relationship, we conducted necessary tests. It verified that the relationship between variables was more consistent with a linear pattern through observations of scatter plots and the use of statistical methods such as correlation coefficients. Thus, to analyze the influence of industrial convergence on the AETFP and its underlying mechanisms, this paper presents the following benchmark empirical model:

$$ETFP_{it} = \beta_0 + \beta_1 CON_{it} + \varphi X_{it} + \gamma_t + \alpha_i + \mu_{it} \quad (1)$$

As shown in Equation (1), i is the region, t is the year, *ETFP* is the AETFP, and *CON* is the core independent variable, which measures the convergence of rural industries. X is the control variable, γ and α are the year effect and the regional effect, respectively, μ is a random disturbance term, and β and φ are parameters to be estimated. To verify the transmission route of the mechanism "the convergence of agriculture and allied industries $\rightarrow$ rural human capital or agricultural scale operation $\rightarrow$ the AETFP", this paper uses the intermediary effect model to conduct an empirical test. The test steps are as follows: At the outset, determine if the rural industry's core components affect the AETFP by considering the overall level of convergent development. If the *CON* coefficient for the core explanatory factor is noteworthy in the empirical examination of Equation (2), it implies that the convergence of agriculture and allied industries influences the enhancement of AETFP. Equation (2) is presented below:

$$ETFP_{it} = \partial_0 + \partial_1 CON_{it} + \varphi X_{it} + \gamma_t + \alpha_i + \mu_{it} \quad (2)$$

To examine the impact of agriculture and allied industries' convergence on rural human capital (*H*) or agricultural scale operations (*S*), we conducted empirical tests using Equation (3). If the coefficient of the *CON* is found to be significant, it indicates that the rural industrial synergy affects the level of rural labor or the agricultural scale operation. Equation (3) is presented below:

$$H \ or \ S = \beta_0 + \beta_1 CON_{it} + \varphi X_{it} + \gamma_t + \alpha_i + \mu_{it} \quad (3)$$

Furthermore, we included the convergence of industries, rural labor, and agricultural scale operations simultaneously in Equation (4):

$$ETFP_{it} = \lambda_0 + \lambda_1 CON_{it} + \lambda_2 H_{it} \ or \ S_{it} + \varphi X_{it} + \gamma_t + \alpha_i + \mu_{it} \quad (4)$$

In the empirical test of Equation (4), if both coefficients λ_1 and λ_2 are significant, and β_1 in Equation (3) is also significant, while the absolute value of coefficient λ_1 in Equation (4) shows a downward trend compared to the value in Equation (2), it indicates a partial mediating effect. This means that the impact of the convergence of agriculture and allied industries on the AETFP partly comes from the transmission of rural labor or agricultural scale operations. On the other hand, if the coefficient in Equation (2) is significant, β_1 in Equation (3) is significant, while λ_1 in Equation (4) is insignificant and λ_2 is significant, it suggests a complete mediation effect. This implies that the impact comes entirely from the transmission of rural labor or agricultural scale operations. To further investigate the impact of the convergence of agriculture and allied industries on the AETFP through the improvement of rural labor or expansion of agricultural scale operations, this research introduces two interaction terms: the convergence of agriculture and allied industries and rural labor, and the convergence of rural industries and agricultural scale operations. These terms serve as the core independent variables to verify the transmission mechanism in Equation (5):

$$ETFP_{it} = \lambda_0 + \lambda_1 CON_{it} * H_{it} + \lambda_2 CON_{it} * S_{it} + \varphi X_{it} + \gamma_t + \alpha_i + \mu_{it} \quad (5)$$

3.3. Selection of Variables

3.3.1. Explained Variable

The concept of AETFP integrates environmental factors and resources into the framework to gauge the performance of agricultural production. This paper defines AETFP as the efficiency relationship between agricultural input and output factors, considering the consumption of irrigation water resources, pollution from agricultural fertilizers, pollution from agricultural solid waste, and agricultural carbon emissions. This approach offers a more precise depiction of the correlation between input and output in agricultural production. To establish a measurement system for AETFP, we have considered the practices of other scholars [60,61]. The research has selected several input indicators, including human capital, farmland, fertilizers, agricultural machines, effective irrigation area, and irrigation water resources. The agricultural total value represents the anticipated output. Undesirable outputs, such as farmland chemical fertilizer pollution, farmland solid waste pollution, and agricultural carbon emissions, have also been taken into account. Pollution from chemical fertilizers on farmland includes the discharge of TN and TP resulting from nitrogen fertilizers, phosphate fertilizers, and compound fertilizers. Farmland solid waste pollution includes emissions of COD, TN, and TP from straw waste of rice, wheat, corn, beans, and potatoes. Agricultural carbon emissions mainly comprise emissions from pesticides, fertilizers, plastic film, diesel, plowing, and farmland irrigation. The measurement system for AETFP, along with its variable description, is presented in Table 1.

Table 1. The AETFP measurement system and description of its indicators.

Primary Indicators	Secondary Indicators	Indicator Description
Input indicators	Labor force	Number of employees in agriculture (person)
	Land	Sown area of farm crops (hectare)
	Fertilizer	Converted amount of chemical fertilizers (t)
	Agricultural machinery Power	Total power of machinery in agriculture (kW)
	Effective irrigation area	Effective irrigation area (hectare)
	Irrigation water resources	Agricultural water consumption × 0.9 (m^3)
Expected output indicators	Total agricultural output value	Total agricultural output value (constant price in 2008, yuan)
Unexpected output indicators	Farmland fertilizer pollution	TN and TP emissions of chemical fertilizer (t)
	Farmland solid waste pollution	COD, TN, and TP emissions from straw waste from rice, wheat, corn, beans, and potatoes (t)
	Agriculture carbon emissions	Carbon emissions from agricultural production behavior (t)

This paper applies the Super-SBM model and utilizes the global reference Malmquist index (*GML*) to compute the AETFP of 30 provinces (excluding Tibet) in China from 2008 to 2021. The calculation method is as follows:

$$GML^{t,t+1}(x^t, y^t, b^t; x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + \vec{D}_0^G(x^t, y^t, b^t; y^t, -b^t)}{1 + \vec{D}_0^G(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \tag{6}$$

Equation (6) defines the directional distance function based on PG. The data for each period within the sample period is summarized by Global DEA, and the input and output components for each decision-making unit as a whole are optimized. Among them, $\vec{D}_0^G$ represents the optimal solution of the global production technology that satisfies variable returns to scale. Given that GML reflects the change rate of AETFP relative to the previous year, we refer to the adjustment method of existing research and assume that the AETFP of the base period is 1 at $t = 0$, and the AETFP of $t + 1$ year is $\mathrm{GML}^{t+1} = \mathrm{GML}^{t} \times \mathrm{GML}_{t}^{t+1}$. The GML index for other years can be calculated accordingly. Comparable to the decomposition of the ML index, the GML index can be broken down into a global index for technological progress and a global index for technical efficiency [62], as shown in Equation (7):

$$GML^{t,t+1} = \frac{1+\vec{D}_0^G(x^t, y^t, b^t; y^t, -b^t)}{1+\vec{D}_0^G(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \times \left[\frac{\dfrac{1+\vec{D}_0^G(x^t, y^t, b^t; y^t, -b^t)}{1+\vec{D}_0^t(x^t, y^t, b^t; y^t, -b^t)}}{\dfrac{1+\vec{D}_0^G(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})}{1+\vec{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})}} \right] \tag{7}$$

$$= GMLEC^{t,t+1} \times GMLTC^{t,t+1}$$

As shown above, the GML index can be decomposed into the GMLTC index and the GMLEC index, representing agricultural environmental technological progress and agricultural environmental technological efficiency, respectively. The product of the two is the GML index. Among them, the GMLTC index reflects the dynamic change in the production possibility frontier's external expansion, i.e., the speed of technological frontier progress in production practice, representing the contribution of agricultural scientific and technological innovation, green technology application, and other aspects to agricultural production efficiency. When the $GMLTC_{t,t+1}$ index is greater than 1, it means that the agricultural environmental frontier technology is higher than the previous period. The GMLEC index reflects the state of actual output approaching optimal output, representing the contribution of resource optimization allocation, scientific management, and operation to agricultural production efficiency. When the $GMLEC_{t,t+1}$ is greater than 1, it means that the technical efficiency is higher than the previous period, and vice versa.

Figure 1 presents the changes in China's TFP of agricultural environment GML index and its decomposition index from 2009 to 2021. Throughout the sample period, China's AETFP remained consistently above 1, with an average growth rate of 3.69%. When analyzing the decomposition index of the GML index, it is observed that the GMLTC index has consistently exceeded 1 for many years, significantly contributing to the growth of the AETFP. On the other hand, the GMLEC index remains below 1, indicating a clear decline. Based on the sample period, we can infer that technological advance serves as the primary catalyst for TFP growth, while technical efficiency imposes a constraining impact.

3.3.2. Core Explanatory Variable

The core variable that stands alone is the development level of the rural industrial synergy (CON). The convergence of industries covers various aspects and is a broad and abstract concept. The existing research has not established a standardized measure for assessing the level of the convergence of rural industries, and most research uses an assessment system to create a comprehensive indicator [63]. In this paper, we use data from 30 provinces (excluding Tibet) spanning from 2008 to 2021 to compute the level of convergent development of agriculture and allied industries by employing the entropy value approach. It establishes an assessment system for the level of the convergence of industries by taking into account aspects such as the elongation and amalgamation of the industry chain, the enlargement and unification of agricultural multi-functions, and the profound infiltration of information technology [64]. The evaluation system for the convergence of agriculture and allied industries is depicted in Table 2.

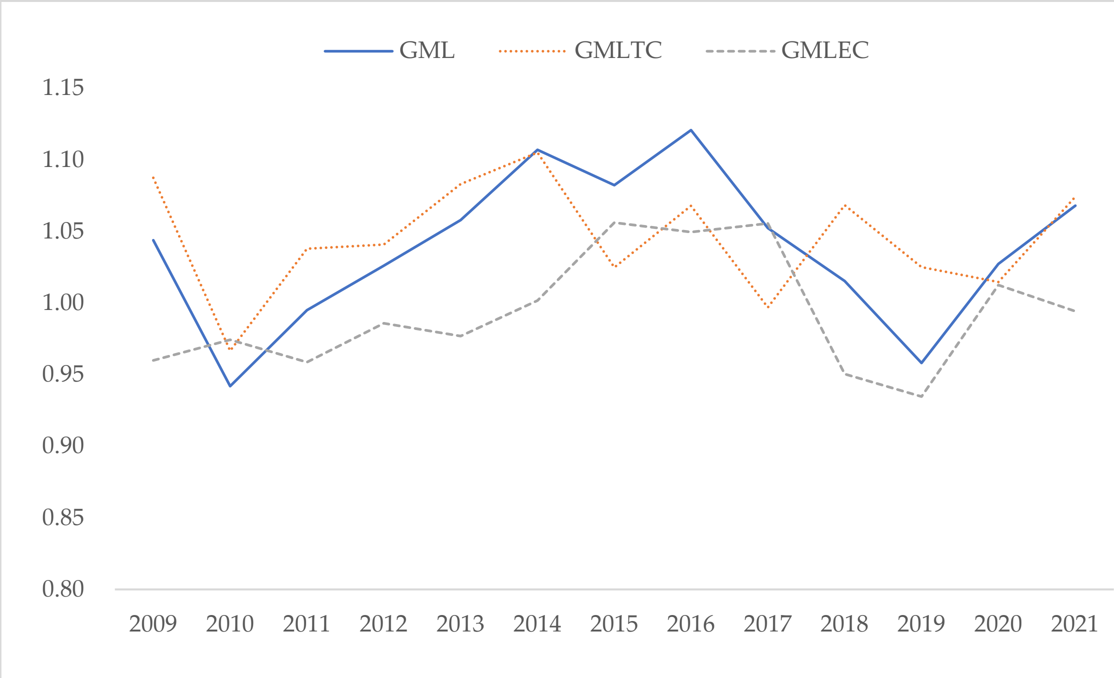

Figure 1. The average change in China's TFP of agricultural environment and its decomposition index from 2009 to 2021.

Table 2. Evaluation system for the convergence of agriculture and allied industries.

Primary Indicators	Secondary Indicators	Third-Level Indicators	Unit
Extension of agricultural industry chain	Agricultural product processing industry	Agricultural product processing main business income/added value of the primary industry (C1)	%
	Farmer interest connection	Social groups per 10,000 people (C2)	person
	Agricultural mechanization	Total power of agricultural primary processing industry machinery/total power of agricultural machinery (C3)	%
Convergence of agricultural multi-function	New agricultural formats	Facility agriculture area/farmland area (C4)	%
	Rural Employment	Rural secondary and tertiary industry employees/rural employees (C5)	%
	Rural service industry	Added value of agriculture, forestry, animal husbandry and fishery service industry/added value of primary industry (C6)	%
	Leisure agriculture and rural tourism	leisure agriculture and beautiful countryside counties/all counties (C7)	%
Deep penetration of information technology	Rural e-commerce	Taobao villages/number of all villages (C8)	%

Among them, the extension of the agricultural industry chain selects the development level of the agricultural product processing industry (the ratio of the agricultural product processing main business income to the added value of the primary industry), the level of farmer interest connection (the number of social groups per 10,000 people in rural areas), and the level of agricultural mechanization (the ratio of the total power of agricultural primary processing industry machinery to the total power of agricultural machinery). The convergence of agricultural multi-function selects the level of cultivating new agricultural formats (the ratio of the area of facility agriculture to the area of farmland), the level of rural employment personnel (the ratio of employees in agricultural allied industries to rural employees), the level of rural service industry (the ratio of added value of agricultural allied industries to the primary industry), and the level of leisure agriculture and rural tourism (the proportion of leisure agriculture and beautiful countryside counties to all counties); the depth of information technology penetration is measured by the level of rural e-commerce development (the proportion of Taobao villages to all villages).

The measurement of industrial synergy employs the entropy value method. This approach, as an unbiased assignment technique, determines the weight of indicators by assessing the informational content they carry. It effectively avoids subjectivity in assignment. The first step is indicator selection. Suppose there is year h, province m, and evaluation indicators n. $X_{\lambda ij}$ is the indicator value of λ in province i in year j. Secondly, the range standard method is used to perform dimensionless processing on each indicator, and the indicators are normalized. For positive indicators, $Z_{\lambda ij} = (x_{\max} - x_{\lambda ij})/(x_{\max} - x_{\min})$; for negative indicators, $Z_{\lambda ij} = (x_{\lambda ij} - x_{\min})/(x_{\max} - x_{\min})$. Among them, i is the province, j is the evaluation index, X_{max} is the maximum value j of different evaluation indicators among all evaluation objects, X_{min} is the minimum value j of different evaluation indicators among all evaluation objects, $X_{\lambda ij}$ is the original index value, and $Z_{\lambda ij}$ is the dimensionless value. Subsequently, the indicator value is normalized, $P = Z_{\lambda ij}/\sum\limits_{\lambda=1}^{h}\sum\limits_{i=1}^{m} Z_{\lambda ij}$, $0 < P_{\lambda ij} < 1$. Again, calculate the entropy value of each indicator and its redundancy value, $E_i = -k\sum\limits_{\lambda=1}^{h}\sum\limits_{i=1}^{m} P_{\lambda ij} ln P_{\lambda ij}$, where $k = 1/ln(h \times m)$. In the calculation of the entropy value, if $P_{\lambda ij}$ is 0 and logarithmic calculation cannot be performed, add 1 to it and then perform the calculation. When calculating the redundancy of the entropy value of each indicator, $D_j = 1 - E_i$. Finally, the weight of each indicator is calculated, and based on the weight value and indicator value, the level of the convergence in each province is calculated $C_{\lambda i} = P_{\lambda ij} \times W_j$.

From 2008 to 2021, Figure 2 depicts the interdependence between rural and industrial sectors in China and its subregions. Overall, the level of industrial convergence in China is on the rise, increasing from 1.0452 in 2008 to 2.423 in 2021. The analysis of subregions reveals that the level of the convergence of agriculture and allied industries has been consistently increasing in the different regions. Notably, the eastern region has experienced the highest growth rate and has achieved a significantly higher level of development compared to the other three regions. Over the sample period, the convergence in the eastern region increased from 1.414 to 3.145. The central region follows the eastern region in terms of the level. Although its growth rate has been relatively slow, it has risen from 1.202 to 1.834 during this period. On the other hand, the western region has a poor foundation for convergent development, with a relatively slow growth rate from 0.723 to 1.284. Similarly, the northeastern region also faces challenges in terms of the foundation for convergent development, but it has exhibited strong growth momentum, increasing from 0.772 to 1.352. Moreover, the regional differences were minimal in 2009, but they gradually became significant over time, leading to an increasing gap between regions. This can be attributed to the policy advantages enjoyed by the eastern region, coupled with years of rapid economic development that have fostered a favorable market atmosphere and facilitated the rapid growth of e-commerce. This has provided robust external support for the convergence of agriculture and allied industries.

3.3.3. Mediating Variables

Mediating variable 1: Rural labor comprehensive index (H). The comprehensive index of rural labor is constructed using the entropy method, which incorporates rural educational human capital, rural health human capital, and innovation environment support. Following the previous approaches [65,66], rural educational labor is further divided into primary, secondary, and higher education human capital, with heterogeneous human capital calculated using the cumulative years of education method. The situation of rural health human capital is reflected through the annual rural per capita health care expenditure. The innovation environment support is assessed based on two aspects: the intensity of scientific research investment and the level of financial support for agriculture. It is determined by the proportion of scientific research funding investment in the regional GDP. The calculation method for the level of fiscal support for agriculture is based on relevant research [67]. The indicators and accounting methods at all levels are presented in Table 3.

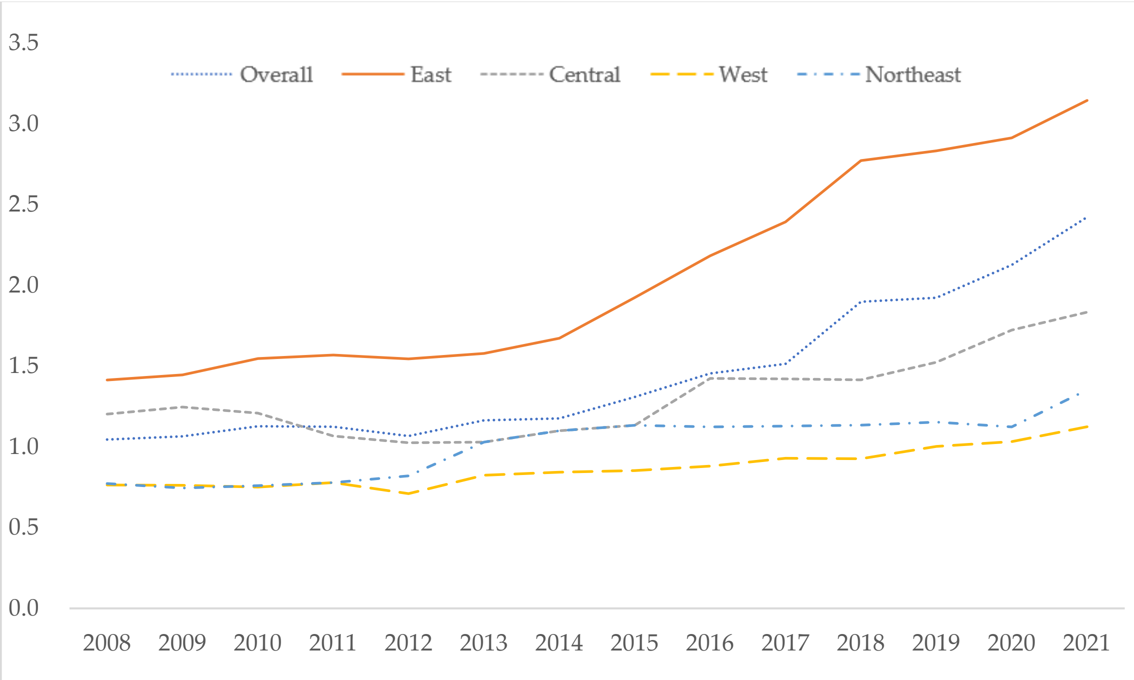

Figure 2. The trend of the rural industrial convergence in China and subregions from 2008 to 2021.

Table 3. Human capital comprehensive index evaluation system and index calculation method.

Primary Indicators	Secondary Indicators	Calculation Method
Educational human capital (core elements)	Primary education human capital Secondary education human capital Higher education human capital	The cumulative years of education method is used to calculate heterogeneous rural labor: $H=\sum_{i=1}^{K} p_i n_i (i=1,2,3,4,5,6)$ $PRI=\sum_{i=1}^{2} p_i n_i, SEC=\sum_{i=3}^{5} p_i n_i, HIG=p_6 n_6$ Among them, n_i represents the years of education of the rural labor force at different stages, which are divided into six types: no schooling, primary school, junior high school, high school, technical secondary school, junior college, and above, with corresponding weights. They are 0, 6, 9, 12, 12, and 16, respectively. P_i represents the proportion of the rural labor force with each level of education. H represents the stock of rural educational human capital. PRI, SEC, and HIG represent the rural primary, secondary, and advanced education human capital, respectively.
Health human capital (basic elements)	Health and medical investment	Annual rural per capita health care expenditures.
Innovation environment support (supporting elements)	Scientific research investment intensity	The proportion of scientific research investment in regional GDP.
	Level of fiscal support for agriculture	The scope of fiscal support for agriculture is determined based on the total expenditure dedicated to agriculture, forestry, and water-related affairs.

Mediating variable 2: Agricultural scale operation comprehensive index (S). The comprehensive index of agricultural scale operations is constructed using the entropy method to measure the land scale, degree of intensification, and physical capital accumulation. The per capita cultivated land area in countryside is chosen to evaluate the land scale, while the total crop sown area to the agricultural population is selected. The degree of intensification is represented by the agricultural machinery input density and the agricultural film input density, which are measured by the total power of agricultural machinery to the total crop sown area and the amount of agricultural film used to the total sown area of crops, respectively. To measure the accumulation of physical capital, the original value of productive fixed capital per capita of rural households is selected [68]. The indicators and accounting methods at all levels are presented in Table 4.

Table 4. Rural scale operation comprehensive index evaluation system and indicator calculation method.

Primary Indicators	Secondary Indicators	Calculation Method
Land size (core factor)	Per capita farmland area in rural areas	Total crop sown area to agricultural population.
Degree of intensification (basic factor)	Agricultural machinery input density	The total power of agricultural machinery to the total sown area of crops.
	Agricultural film input density	The amount of agricultural film used to the total sown area of crops.
Physical capital accumulation (supporting factor)	Original value of productive fixed capital per capita in rural households	The original value of productive fixed assets per capita of rural households.

3.3.4. Control Variables

Referring to the previous research, the control variables areas follows: Natural Environment (ENVI): the ratio of disaster-stricken area to crop sown area; Agricultural Structure Adjustment Coefficient (STRU): the ratio of grain sown area to total crop sown area; and Urbanization Rate (URB): the ratio of non-agricultural population to total population [69]. Table 5 presents the descriptive statistics for each variable.

Table 5. Descriptive statistics of variables.

Variable Categories	Variable Name	Variable Abbr.	Mean	Max	Min
Explained Variable	AETFP	ETFP	1.252	2.110	0.705
Core Explanatory Variable	The convergence of rural industries	CON	1.458	5.779	0.422
Mediating Variables	Rural labor comprehensive index	H	0.398	0.812	0.116
	Agricultural scale operation comprehensive index	S	0.413	0.825	0.143
Control Variables	Natural environment	ENVI	0.749	106.525	0.000
	Agricultural structural adjustment coefficient	STRU	0.540	0.794	0.343
	Urbanization rate	URB	0.416	0.933	0.162

4. Results and Analysis

4.1. Benchmark Regression Results

Based on the Hausman test results, all three decimal places of the p value are 0, indicating a significant rejection of the null hypothesis that the individual effect is unrelated to the explanatory variables. To address potential issues of autocorrelation and heteroscedasticity in panel data, as well as variations in the basic conditions and development levels among provinces, this paper employs the FGLS method within the fixed-effects model for estimation.

Table 6 presents the baseline regression results of the influence of industrial convergence on the AETFP. To ensure robust estimation, this section employs a stepwise regression approach to investigate the impact of industrial convergence on the AETFP. Initially, model (1) analyzes the effect of the convergence (CON) on the AETFP, followed by the inclusion of control variables such as natural environment (ENVI), agricultural structural adjustment coefficient (STRU), and urbanization rate (URB) in models (2), (3), and (4), respectively. It enables the assessment of the collective influence of numerous factors on the effect of the industrial convergence on the AETFP. The results demonstrate a high level of consistency with the benchmark regression findings.

Table 6. Benchmark regression results.

	(1)AETFP	(2)AETFP	(3)AETFP	(4)AETFP
	Coeff (Std.err) *p*-Value	**Coeff (Std.err) *p*-Value**	**Coeff (Std.err) *p*-Value**	**Coeff (Std.err) *p*-Value**
CON	0.0870 *** (0.0273) 0.0034	0.1316 *** (0.0258) 0.0000	0.2034 *** (0.0472) 0.0002	0.2835 *** (0.0568) 0.0000
ENVI		−0.0018 ** (0.0008) 0.0322	−0.0021 *** (0.0007) 0.0055	−0.0034 *** (0.0010) 0.0020
STRU			1.6436 *** (0.3746) 0.0001	1.3715 *** (0.4295) 0.0034
URB				−0.0729 (0.1769) 0.6833
Control variable	No	Yes	Yes	Yes
Constant	1.1683 *** (0.0698) 0.0000	1.1462 *** (0.0892) 0.0000	0.2530 (0.2528) 0.3252	0.3574 (0.2519) 0.1666
Sample size	420	420	420	420

Note: ** means it at the 5% level, *** means it at the 1% level, and the values in parentheses are standard errors.

According to the findings in Table 6, the coefficient of industrial convergence in countryside is both significant and positive. This suggests that the industrial convergence has a significant impact on improving AETFP. The results of the stepwise regression analysis also support this finding, indicating the robustness of the relationship and providing evidence for Hypothesis 1.

Significant negative impacts on the AETFP are observed from the control variables, highlighting a robust association between natural conditions and agricultural production activities. The coefficient for adjusting the agricultural structure has a noticeable and favorable effect on the AETFP, indicating that the enhancement of agricultural structure facilitates the efficient utilization of agricultural resources and fosters the advancement of AETFP. The urbanization rate has a negligible negative effect on the AETFP, primarily due to the selective migration of young and middle-aged farmers, resulting from urbanization.

4.2. Mechanism Analysis

The analysis of the impact mechanism demonstrates that the benchmark regression outcomes reveal a substantial enhancing impact on the AETFP due to the industrial convergence. Following this, the intermediary effect model mentioned above was utilized to examine the two mechanisms by which the industrial convergence affects the AETFP. Mechanism 1 revolves around the industrial convergence → rural human capital → the AETFP pathway, whereas Mechanism 2 revolves around the industrial convergence → agricultural scale operation → the AETFP pathway.

The results of the empirical test for the intermediary effect are presented in Table 7. In model (4), the coefficient of CON is 0.2491, which is smaller than the coefficient of 0.3235 in model (1). This comparison shows a downward trend in the coefficient. It indicates that rural labor plays a role as a partial intermediary between the industrial convergence and the AETFP. In simpler terms, the convergence can boost the growth of AETFP by improving the rural human capital, thus confirming Hypothesis 2. Likewise, in model (5), the coefficient for rural industrial convergent development is 0.1984, compared to 0.3235 in model (1). This demonstrates a downward trend in the coefficient as well. It suggests that agricultural scale operations also act as a partial intermediary between the industrial convergence and the AETFP. Thus, the convergence can enhance the AETFP through the expansion of scale operations, providing support for Hypothesis 3.

Table 7. Mediating effect estimation results.

	Step1	Step2		Step3	
	AETFP(1)	**H(2)**	**S(3)**	**AETFP(4)**	**AETFP(5)**
	Coeff (Std.err) *p*-Value	**Coeff (Std.err) *p*-Value**	**Coeff (Std.err) *p*-Value**	**Coeff (Std.err) *p*-Value**	**Coeff (Std.err) *p*-Value**
CON	0.3235 *** (0.0367) 0.0000	0.0568 *** (0.0066) 0.0000	0.0148 *** (0.0028) 0.0000	0.2491 *** (0.0402) 0.0000	0.1984 *** (0.0375) 0.0000
H	-	-	-	-	2.4660 *** (0.3148) 0.0000
S	-	-	-	0.7259 * (0.3933) 0.0752	-
ENVI	−0.0047 *** (0.0007) 0.0000	0.0010 * (0.0006) 0.1000	0.0003 *** (0.0001) 0.0055	−0.0027 *** (0.0009) 0.0055	−0.0059 *** (0.0007) 0.0000
STRU	1.2573 *** (0.3548) 0.0014	0.1775 ** (0.0724) 0.0205	0.1821 *** (0.0460) 0.0004	0.5669 (0.4722) 0.2396	1.2546 *** (0.3634) 0.0017
URB	−0.0643 (0.1934) 0.7419	0.2868 *** (0.0241) 0.0000	0.3026 *** (0.0386) 0.0000	−0.5327 * (0.3120) 0.0984	−0.6728 * (0.3904) 0.0955
Constant	0.3376 (0.2544) 0.1948	0.0714 ** (0.0319) 0.0330	0.1436 *** (0.0237) 0.0000	0.7320 *** (0.2531) 0.0072	0.1424 (0.2868) 0.6233
Sample size	420	420	420	420	420

Note: * means significant at the 10% level, ** means it at the 5% level, *** means it at the 1% level, and the values in parentheses are standard errors.

4.3. Robustness Tests

The mediation model is used to investigate the effect of convergence on the AETFP. To ensure the credibility of the results, the study incorporates interaction terms between the main variables and the mediating variables in order to conduct a comprehensive examination of their impact mechanism.

Table 8 presents the results of the interaction term test. In Model (1), the impact of the interaction term between the rural sectoral convergence and the human capital on the AETFP is examined. The interaction term is found to be significantly positive at the 1% level. This suggests that in provinces (autonomous regions, municipalities) with a higher level of development, improving rural labor has a more noticeable effect on agricultural TFP, thereby providing further support for Hypothesis 2. Moving on to Model (2), the interaction term between the convergence of rural industries and agricultural scale operations is explored. It is observed that the interaction term has a greater impact on the AETFP. Specifically, for the impact of AETFP, the interaction term is significantly positive at the 1% level. This indicates that in areas with a higher level of rural sectoral convergence development, the effect of agricultural scale operations on the AETFP is more pronounced, thereby further confirming Hypothesis 3.

Table 8. Robustness test results.

	Impact Mechanism Test (1) (Rural Human Capital)	Impact Mechanism Test (2) (Agricultural Scale Operation)
	Coeff (Std.err) *p*-Value	Coeff (Std.err) *p*-Value
CON * H	0.7839 *** (0.0756) 0.0000	-
CON * S	-	0.6635 *** (0.0645) 0.0000
ENVI	−0.0042 ** (0.0017) 0.0196	−0.0030 *** (0.0006) 0.0000
STRU	1.2313 *** (0.4211) 0.0066	0.9057 ** (0.3932) 0.0286
URB	−0.4745 * (0.2676) 0.0867	−0.4244 * (0.2428) 0.0911
Constant	0.7438 ** (0.3614) 0.0487	0.8636 *** (0.2697) 0.0033
Sample size	420	420

Note: * means significant at the 10% level, ** means it at the 5% level, *** means it at the 1% level, and the values in parentheses are standard errors.

5. Conclusions and Recommendations

To analyze the impact and mechanism of rural industrial convergence on AETFP, the article integrates these two hot topics in current agricultural economic development. It analyzes the level of the convergence of agriculture and allied industries and the changes in the AETFP in 30 provinces (excluding Tibet) in China from 2008 to 2021. It utilizes the fixed effect FGLS estimation method and analyzes the impact of the industrial convergence on the AETFP from two perspectives: human capital and agricultural scale operation. The findings are as follows: (1) Overall, the convergence of rural industries has a significant effect on the AETFP. Accelerating the process of industrial convergence can effectively promote the improvement of environmental TFP and facilitate the shift from factor-driven to technologically innovative agricultural production. (2) The intermediary effect model's empirical results indicate that the rural labor and the agricultural scale operations act as intermediary variables between the convergence and the AETFP. In other words, there are two mechanisms at play: Mechanism 1: The convergence of agriculture and allied industries → Human capital → The AETFP; Mechanism 2: The convergence of agriculture and allied industries → Agricultural scale operation → The AETFP. (3) The transmission mechanism is further tested using interaction terms. The results demonstrate an interaction between the convergence of agriculture and allied industries and the AETFP. The harmonization of rural industries strengthens the positive impact of rural labor and scale operations on the AETFP. The findings of this paper further validate the positive impact of industrial convergence on TFP growth. For instance, in the field of digital economy, which has a long history of research on industrial convergence, scholars argue that the inter-industry development resulting from digital technology innovation has created a conducive environment for technological innovation and diffusion. This, in turn, has significantly improved the production efficiency of enterprises in related fields and even the entire industry. Moreover, the convergence of modern service and advanced manufacturing, through innovations in business and management models, has greatly contributed to regional TFP growth, thereby demonstrating the positive effect of industrial convergence. This paper expands the scope of research on industrial convergence to include China's agricultural and rural areas, exploring this new paradigm of rural economic development. Through empirical testing, it not only confirms the promotion effect of industrial convergence on TFP, but also sheds light on the mechanism of interaction between industrial convergence and agricultural and rural TFP. Furthermore, the conclusions of this article further validate the effectiveness of China's recent policies promoting industrial convergence. Developing countries can draw lessons from this experience in agricultural and rural development to expedite the process of rural industrial convergence and achieve comprehensive growth in AETFP.

Based on the previous findings of the paper, the following policy recommendations can be inferred:

(1) In order to enhance the AETFP, it is essential to focus on expediting the convergent level of rural industries and reducing the obstacles that hinder this development. For instance, adopting the "land composite utilization + planning" method for rural farmland use to support the projects of industrial convergence, introducing special subsidies or special bonds for the convergence of agriculture and allied industries, and further enhancing the mechanisms that guarantee the industrial convergence. Additionally, implementing a phased evaluation and reward system, along with providing subsidies and tax incentives to regions that demonstrate exceptional results in the evaluation process.
(2) By promoting the accumulation of rural labor, it creates a suitable policy environment for the improvement of AETFP. This objective can be accomplished by augmenting the allocation of resources towards rural education and vocational skill training, optimizing the proficiency and expertise of the rural labor force, nurturing a heterogeneous reservoir of talents via novel training initiatives for aspiring farmers, and attending to the talent prerequisites of convergent rural sectors.
(3) It highlights the role of scale operations in improving the TFP of the agricultural sector and promoting the transition from decentralized smallholder operations to moderate-scale operations. One way to achieve this is by establishing regional land transfer platforms, which would include multi-level platforms at the village, county, and township levels. These platforms would help standardize farmland management rights transfer contracts and facilitate the transfer and trading of these rights. To ensure a smooth process, farmland management rights transfer and trading centers would be set up at the county and township levels, while village-level units would have land management rights transfer service stations to streamline the contract process. Additionally, efforts would be made to develop intermediary service organizations that specialize in the land rights transfer, thus reducing the risk of default in these transactions.

6. Limitations of the Study

However, this paper has certain limitations. It explores the impact of the convergence of agriculture and allied industries on the AETFP. Further research can be conducted regarding various aspects:

(1) The intermediary variables can be further expanded to provide a more comprehensive meaning. The Solow residual defines TFP as the growth in output resulting from comprehensive factor productivity, excluding the contributions of traditional production factors such as labor and capital. It is important to note that changes in TFP are influenced by various factors, including technological progress, diffusion, optimal

allocation of factors, business decision optimization, policy and system changes, and many others. Therefore, it is necessary to further expand the intermediary variables based on these factors.

(2) It is recommended to conduct regional comparative studies by further categorizing the types of convergent development of rural industries. For instance, the numerous provinces and regions across the country can be classified into different types based on the degree of convergence: high, medium, and low. By considering regions with different degrees of convergence, it would be valuable to analyze the impact of their convergence on the AETFP through regional comparative research. Furthermore, regional division can be based on various criteria such as grain production areas or agricultural development areas.

(3) One detailed approach is to select provinces and regions that have experienced rapid convergence of rural industries and conduct micro-case studies. By focusing on regions with a high level of convergence of rural industries, we can provide further evidence of the positive impact of its development on the AETFP. These micro-level case studies will help demonstrate the benefits of industrial convergence in the countryside.

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References

1. Manioudis, M.; Meramveliotakis, G. Broad strokes towards a grand theory in the analysis of sustainable development: A return to the classical political economy. *New Political Econ.* **2022**, *27*, 866–878. [CrossRef]
2. Tomislav, K. The concept of sustainable development: From its beginning to the contemporary issues. *Zagreb Int. Rev. Econ. Bus.* **2018**, *21*, 67–94.
3. Ma, L.; Long, H.; Tang, L.; Tu, S.; Zhang, Y.; Qu, Y. Analysis of the Spatial Variations of Determinants of Agricultural Pro-duction Efficiency in China. *Comput. Electron. Agric.* **2021**, *180*, 105890. [CrossRef]
4. van der Ploeg, J.D.; Renting, H.; Brunori, G.; Knickel, K.; Mannion, J.; Marsden, T.; de Roest, K.; Sevilla-Guzman, E.; Ventura, F. Rural Development: From Practices and Policies towards Theory. *Sociol. Rural.* **2000**, *40*, 391–408. [CrossRef]
5. Xu, J.; Wang, Y.; Zhao, X.; Etuah, S.; Liu, Z.; Zhu, H. Can agricultural trade improve total factor productivity? Empirical evidence from G20 countries. *Front. Sustain. Food Syst.* **2023**, *7*, 1100038. [CrossRef]
6. Ding, C.; Zhang, R. The Measurement and Influencing Factors of Total Factor Productivity in the Chinese Rural Distribution Industry. *Sustainability* **2021**, *13*, 8581. [CrossRef]
7. Han, H.; Zhong, Z.; Wen, C.; Sun, H. Agricultural environmental total factor productivity in China under technological heterogeneity: Characteristics and determinants. *Environ. Sci. Pollut. Res.* **2018**, *25*, 32096–32111. [CrossRef]
8. Zhou, J.; Chen, H.; Bai, Q.; Liu, L.; Li, G.; Shen, Q. Can the Integration of Rural Industries Help Strengthen China's Agricultural Economic Resilience? *Agriculture* **2023**, *13*, 1813. [CrossRef]
9. Ye, F.; Qin, S.; Nisar, N.; Zhang, Q.; Tong, T.; Wang, L. Does rural industrial integration improve agricultural productivity? Implications for sustainable food production. *Front. Sustain. Food Syst.* **2023**, *7*, 1191024. [CrossRef]

10. Tsoraeva, E.; Bekmurzov, A.; Kozyrev, S.; Khoziev, A.; Kozyrev, A. Environmental issues of agriculture as a consequence of the intensification of the development of agricultural industry. In *E3S Web of Conferences 2020*; EDP Sciences: Les Ulis, France, 2020; Volume 215. [CrossRef]
11. Sun, Y. Environmental Regulation, Agricultural Green Technology Innovation, and Agricultural Green Total Factor Productivity. *Front. Environ. Sci.* **2022**, *10*, 955954. [CrossRef]
12. Ma, G.; Lv, D.; Luo, Y.; Jiang, T. Environmental Regulation, Urban-Rural Income Gap and Agricultural Green Total Factor Productivity. *Sustainability* **2022**, *14*, 8995. [CrossRef]
13. Geng, Z.; Song, G.; Han, Y.; Chu, C. Static and dynamic energy structure analysis in the world for resource optimization using total factor productivity method based on slacks-based measure integrating data envelopment analysis. *Energy Convers. Manag.* **2020**, *228*, 113713. [CrossRef]
14. Rovigatti, G.; Mollisi, V. Theory and Practice of Total-Factor Productivity Estimation: The Control Function Approach using Stata. *Stata J. Promot. Commun. Stat. Stata* **2018**, *18*, 618–662. [CrossRef]
15. Tinbergen, J. Professor Douglas' Production Function. *Rev. Linstitut Int. Stat.* **1942**, *10*, 37–48. [CrossRef]
16. Solow, R.M. Technical Change and the Aggregate Production Function. *Rev. Econ. Stat.* **1957**, *39*, 312. [CrossRef]
17. Stigler, G.J. Trends in Output and Employment. *J. Political Econ.* **1967**, *75*, 287–318. [CrossRef]
18. Davis, H.S. *Productivity Accounting*; University of Pennsylvania Press: Philadephia, PA, USA, 1954.
19. Denison, E.F. *The Measurement of Productivity*; National Bureau of Economic Research: Philadelphia, PA, USA, 1962.
20. Berg, S.A.; Førsund, F.R.; Jansen, E.S.; Berg, S.A.; Forsund, F.R. Malmquist Indices of Productivity Growth during the Deregulation of Norwegian Banking, 1980–1989. *Scand. J. Econ.* **1992**, *94*, S211. [CrossRef]
21. Nanere, M.; Fraser, I.; Quazi, A.; D'souza, C. Environmentally adjusted productivity measurement: An Australian case study. *J. Environ. Manag.* **2007**, *85*, 350–362. [CrossRef]
22. Byerlee, D.; de Janvry, A.; Sadoulet, E. Agriculture for Development: Toward a New Paradigm. *Annu. Rev. Resour. Econ.* **2009**, *1*, 15–31. [CrossRef]
23. Chung, Y.H.; Färe, R.; Grosskopf, S. Productivity and Undesirable Outputs: A Directional Distance Function Approach. *J. Environ. Manag.* **1997**, *51*, 229–240. [CrossRef]
24. Coomes, O.T.; Barham, B.L.; MacDonald, G.K.; Ramankutty, N.; Chavas, J.-P. Leveraging total factor productivity growth for sustainable and resilient farming. *Nat. Sustain.* **2019**, *2*, 22–28. [CrossRef]
25. Hu, Y.; Liu, C.; Peng, J. Financial inclusion and agricultural total factor productivity growth in China. *Econ. Model.* **2020**, *96*, 68–82. [CrossRef]
26. Oh, D.-H. A global Malmquist-Luenberger productivity index. *J. Prod. Anal.* **2010**, *34*, 183–197. [CrossRef]
27. Deng, X.; Wang, G.; Song, W.; Chen, M.; Liu, Y.; Sun, Z.; Dong, J.; Yue, T.; Shi, W. An Analytical Framework on Utilizing Natural Resources and Promoting Urban–Rural Development for Increasing Farmers' Income Through Industrial Development in Rural China. *Front. Environ. Sci.* **2022**, *10*, 865883. [CrossRef]
28. Li, Y.; Liu, B.; Zhao, P.; Peng, L.; Luo, Z. Can China's ecological civilization strike a balance between economic benefits and green efficiency? A preliminary province-based quasi-natural experiment. *Front. Psychol.* **2022**, *13*, 1027725. [CrossRef]
29. Marx, K. *Capital*; Fowkes, B., Translator; Penguin Books: London, UK, 1990; Volume 2.
30. Marshall, A. *Principles of Economics*; Macmillan: New York, NY, USA, 1890.
31. Tian, X.; Wu, M.; Ma, L.; Wang, N. Rural finance, scale management and rural industrial integration. *China Agric. Econ. Rev.* **2020**, *12*, 349–365. [CrossRef]
32. Li, Z.; Rui, C.; Liu, Y.; Wang, Y. Research on problems and countermeasures of rural industry integration development. *Highlights Bus. Econ. Manag.* **2023**, *14*, 184–188. [CrossRef]
33. He, Y.; Zhou, G.; Tang, C.; Fan, S.; Guo, X. The Spatial Organization Pattern of Urban-Rural Integration in Urban Agglomerations in China: An Agglomeration-Diffusion Analysis of the Population and Firms. *Habitat Int.* **2019**, *87*, 54–65. [CrossRef]
34. Yang, Y.; Bao, W.; Wang, Y.; Liu, Y. Measurement of urban-rural integration level and its spatial differentiation in China in the new century. *Habitat Int.* **2021**, *117*, 102420. [CrossRef]
35. Chen, M.; Zhou, Y.; Huang, X.; Ye, C. The Integration of New-Type Urbanization and Rural Revitalization Strategies in China: Origin, Reality and Future Trends. *Land* **2021**, *10*, 207. [CrossRef]
36. Yang, G.; Zhou, C.; Zhang, J. Does industry convergence between agriculture and related sectors alleviate rural poverty: Evidence from China. *Environ. Dev. Sustain.* **2022**, *25*, 12887–12914. [CrossRef]
37. Shen, W.; Liu-Lastres, B.; Pennington-Gray, L.; Hu, X.; Liu, J. Industry Convergence in Rural Tourism Development: A China-Featured Term or a New Initiative? *Curr. Issues Tour.* **2019**, *22*, 2453–2457. [CrossRef]
38. Cao, L.; Li, L.; Wu, Y.; Zeng, W. Does industrial convergence promote regional metabolism? Evidence from China. *J. Clean. Prod.* **2020**, *273*, 123010. [CrossRef]
39. Tang, D.; Li, B.; Qiu, Y.; Zhao, L. Research on Urban and Rural Coordination Development and Its Driving Force Based on the Space-time Evolvement Taking Guangdong Province as an Example. *Land* **2020**, *9*, 253. [CrossRef]
40. Barkley, D.L.; Henry, M.S. Rural Industrial Development: To Cluster or Not to Cluster? *Rev. Agric. Econ.* **1997**, *19*, 308. [CrossRef]
41. Song, M.; Tao, W. Coupling and Coordination Analysis of China's Regional Urban-rural Integration and Land-use Efficiency. *Growth Change* **2022**, *53*, 1384–1413. [CrossRef]

42. Lu, Q.; Yao, S. From Urban–Rural Division to Urban–Rural Integration: A Systematic Cost Explanation and Chengdu's Experience. *China World Econ.* **2018**, *26*, 86–105. [CrossRef]
43. Liu, H.; Li, G.; Wang, K. Homestead reduction, economic agglomeration and rural economic development: Evidence from Shanghai, China. *China Agric. Econ. Rev.* **2021**, *14*, 274–293. [CrossRef]
44. Ma, W.; Jiang, G.; Chen, Y.; Qu, Y.; Zhou, T.; Li, W. How feasible is regional integration for reconciling land use conflicts across the urban–rural interface? Evidence from Beijing–Tianjin–Hebei metropolitan region in China. *Land Use Policy* **2019**, *92*, 104433. [CrossRef]
45. Shan, B.; Zhang, Q.; Ren, Q.; Yu, X.; Chen, Y. Spatial heterogeneity of urban–rural integration and its influencing factors in Shandong province of China. *Sci. Rep.* **2022**, *12*, 14317. [CrossRef]
46. Fu, W.; Zhang, R. Can Digitalization Levels Affect Agricultural Total Factor Productivity? Evidence From China. *Front. Sustain. Food Syst.* **2022**, *6*, 860780. [CrossRef]
47. Jiang, G. How Does Agro-Tourism Integration Influence the Rebound Effect of China's Agricultural Eco-Efficiency? An Eco-nomic Development Perspective. *Front. Environ. Sci.* **2022**, *10*, 921103. [CrossRef]
48. Song, M.; Du, J.; Tan, K.H. Impact of fiscal decentralization on green total factor productivity. *Int. J. Prod. Econ.* **2018**, *205*, 359–367. [CrossRef]
49. Dong, F.; Li, Y.; Qin, C.; Sun, J. How Industrial Convergence Affects Regional Green Development Efficiency: A Spatial Conditional Process Analysis. *J. Environ. Manag.* **2021**, *300*, 113738. [CrossRef]
50. Yao, Y. Rural industry and labor market integration in eastern China. *J. Dev. Econ.* **1999**, *59*, 463–496. [CrossRef]
51. Xiao, H.; You, J. The Heterogeneous Impacts of Human Capital on Green Total Factor Productivity: Regional Diversity Perspective. *Front. Environ. Sci.* **2021**, *9*, 713562. [CrossRef]
52. Gu, J.; Zheng, J.; Zhang, J. Research on the coupling coordination and prediction of industrial convergence and ecological environment in rural of China. *Front. Environ. Sci.* **2022**, *10*, 1014848. [CrossRef]
53. Pan, W.; Wang, J.; Li, Y.; Chen, S.; Lu, Z. Spatial pattern of urban-rural integration in China and the impact of geography. *Geogr. Sustain.* **2023**, *4*, 404–413. [CrossRef]
54. Li, Y.; Liu, Y.; Long, H.; Cui, W. Community-based rural residential land consolidation and allocation can help to revitalize hollowed villages in traditional agricultural areas of China: Evidence from Dancheng County, Henan Province. *Land Use Policy* **2014**, *39*, 188–198. [CrossRef]
55. Long, H. Land consolidation: An indispensable way of spatial restructuring in rural China. *J. Geogr. Sci.* **2014**, *24*, 211–225. [CrossRef]
56. Liu, Y.; Wang, Y. Rural land engineering and poverty alleviation: Lessons from typical regions in China. *J. Geogr. Sci.* **2019**, *29*, 643–657. [CrossRef]
57. Hou, S.; Song, L. Market Integration and Regional Green Total Factor Productivity: Evidence from China's Province-Level Data. *Sustainability* **2021**, *13*, 472. [CrossRef]
58. Hou, D.; Wang, X. Measurement of Agricultural Green Development Level in the Three Provinces of Northeast China Under the Background of Rural Vitalization Strategy. *Front. Public Health* **2022**, *10*, 824202. [CrossRef] [PubMed]
59. Sheng, Y.; Tian, X.; Qiao, W.; Peng, C. Measuring agricultural total factor productivity in China: Pattern and drivers over the period of 1978–2016. *Aust. J. Agric. Resour. Econ.* **2019**, *64*, 82–103. [CrossRef]
60. Guan, Y.; Wang, H.; Guan, R.; Ding, L. Measuring inclusive green total factor productivity from urban level in China. *Front. Environ. Sci.* **2022**, *10*, 966246. [CrossRef]
61. Zhao, P.; Wu, H.; Lu, Z.; Kou, J.; Du, J. Spatial differences, distributional dynamics, and driving factors of green total factor productivity in China. *Front. Environ. Sci.* **2022**, *10*, 1058612. [CrossRef]
62. Ye, W.; Li, Z. The Impact of Food Production Comparative Advantage on Green Total Factor Productivity: The Moderating Role of Environmental Regulation. *Agriculture* **2023**, *13*, 2058. [CrossRef]
63. Cao, W.; Zhou, S.; Zhou, M. Operational Pattern of Urban-Rural Integration Regulated by Land Use in Metropolitan Fringe of China. *Land* **2021**, *10*, 515. [CrossRef]
64. Li, Z.; Liu, C.; Chen, X. Power of Digital Economy to Drive Urban-Rural Integration: Intrinsic Mechanism and Spatial Effect, from Perspective of Multidimensional Integration. *Int. J. Environ. Res. Public Health* **2022**, *19*, 15459. [CrossRef]
65. Du, B.; Wang, Y.; He, J.; Li, W.; Chen, X. Spatio-Temporal Characteristics and Obstacle Factors of the Urban-Rural Integration of China's Shrinking Cities in the Context of Sustainable Development. *Sustainability* **2021**, *13*, 4203. [CrossRef]
66. Xu, C.; Qian, C.; Yang, W.; Li, B.; Kong, L.; Kong, F. Spatiotemporal Pattern of Urban-Rural Integration Development and Its Driving Mechanism Analysis in Hangzhou Bay Urban Agglomeration. *Int. J. Environ. Res. Public Health* **2022**, *19*, 8390. [CrossRef] [PubMed]
67. Sun, Y.; Yang, Q. Study on Spatial–Temporal Evolution Characteristics and Restrictive Factors of Urban–Rural Integration in Northeast China from 2000 to 2019. *Land* **2022**, *11*, 1195. [CrossRef]
68. Li, J.; Chen, J.; Liu, H. Sustainable Agricultural Total Factor Productivity and Its Spatial Relationship with Urbanization in China. *Sustainability* **2021**, *13*, 6773. [CrossRef]
69. Li, Q.; Wu, X.; Zhang, Y.; Wang, Y. The Effect of Agricultural Environmental Total Factor Productivity on Urban-Rural Income Gap: Integrated View from China. *Sustainability* **2020**, *12*, 3327. [CrossRef]