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The Impact of Agglomeration of Scientific and Technological Talent on Urban Green Total Factor Productivity

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Abstract

The crucial role of scientific and technological talent agglomeration in promoting urban green development is widely recognized, yet its mechanisms and contextual conditions remain insufficiently explored. Using panel data for 284 prefecture-level cities in China over the period 2004–2019, this study examines the impact of scientific and technological talent agglomeration on green total factor productivity. The results show that such agglomeration significantly enhances urban green total factor productivity. Factor mobility plays a mediating role, through which scientific and technological talent agglomeration improves the efficiency of resource allocation, thereby enhancing green total factor productivity. Furthermore, the digital economy strengthens the impact of scientific and technological talent agglomeration on green total factor productivity, and this moderating effect is more pronounced in cities with higher levels of digital development. This study enriches the literature on talent agglomeration by integrating perspectives on green development and the digital economy and provides empirical evidence to support high-quality urban green growth.

Keywords: agglomeration of scientific and technological talent; green total factor productivity; factor mobility; digital economy

1. Introduction

Since China's reform and opening-up, the country has experienced rapid economic growth by relying on low-cost inputs and an extensive development model. However, the limitations of this model have become increasingly evident, particularly in the form of environmental degradation and inefficient resource utilization, which conflict with public aspirations for an improved quality of life. Hence, shifting to a more sustainable economic model and achieving a green, low-carbon transformation have emerged as central priorities for China's development [1]. In this context, green total factor productivity (GTFP), as a key indicator for assessing the quality of green economic development, has increasingly drawn attention from both policymakers and academia. GTFP integrates environmental and energy factors into the traditional total factor productivity framework, embodying the principles of green development, and allows for a more comprehensive assessment of economic performance, accounting for both quality and efficiency [2,3]. Enhancing GTFP has become a pivotal driver of China's green economic transition and sustainable development [4]. Despite widespread recognition of GTFP's significance, a

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key question remains unresolved: while China has shifted from a "demographic dividend" to a "talent dividend," the ecological implications of this shift are not well understood. Economic geography has long emphasized the advantages of agglomeration, such as knowledge spillovers and labor pooling, which are thought to enhance total factor productivity (TFP) [5,6]. However, it remains unclear whether the concentration of human capital results in a "green premium" or an "environmental burden" due to congestion effects. This issue has yet to be thoroughly explored, especially in light of China's dual objectives of fostering innovation and achieving decarbonization.

China's 14th Five-Year Plan explicitly emphasizes the need to advance talent-driven and innovation-led development strategies. As the cornerstone of innovation-driven growth, scientific and technological talent plays a crucial role in facilitating urban technological upgrading, enhancing technology absorption capacity, and improving the efficiency of technology commercialization. They serve as a sustained driving force for the growth of the TFP [5]. To capitalize on opportunities for innovative development, many cities have engaged in intense competition for talent, implementing a range of preferential policies and incentive measures to attract scientific and technological professionals, thereby strengthening urban innovation capacity. Although previous studies have paid attention to the impact of scientific and technological talent agglomeration (STTA) on economic growth and innovation, research on its effect on urban green total factor productivity (GTFP) remains relatively limited, particularly with regard to a systematic explanation of its underlying mechanisms. In fact, STTA can promote the efficient flow and optimal allocation of production factors such as labor, capital, and technology, thereby improving resource utilization efficiency and enhancing urban GTFP [7]. Meanwhile, cities are currently accelerating the development of the digital economy. The digital economy can effectively reduce information asymmetry and transaction costs and facilitate the efficient flow and precise matching of factors such as labor, capital, and technology, thereby improving resource allocation efficiency [8]. Therefore, the impact of STTA on urban GTFP is inevitably influenced by the level of digital economy development. Accordingly, this study focuses on the following three questions: First, can STTA significantly improve urban GTFP? Second, does STTA affect urban GTFP by promoting factor mobility and improving resource allocation efficiency? Third, does digital economy development strengthen the effect of STTA on urban GTFP?

Utilizing panel data from 284 prefecture-level cities in China from 2004 to 2019, this study empirically investigates the impact of STTA on GTFP. The marginal contributions of this study are as follows. First, the existing literature on STTA has primarily focused on its economic effects, such as economic growth and technological innovation, while comparatively limited attention has been paid to its effects on green development. By incorporating environmental and energy factors into the analytical framework of total factor productivity, this study systematically examines the impact of STTA on urban GTFP from a green-development perspective, thereby extending the literature on the relationship between STTA and green economic development [9]. Second, prior studies have mainly emphasized the direct effects of STTA. This study incorporates factor mobility into the analytical framework and reveals the underlying mechanisms through which STTA influences green development. Third, this study integrates digital economy development into the research framework and examines its moderating role in the relationship between STTA and urban GTFP, contributing to the literature on the synergistic relationship between the digital economy and green development.

2. Literature Review and Theoretical Background

2.1. Scientific and Technological Talent Agglomeration (STTA)

STTA refers to the phenomenon in which a significant number of scientific and technological professionals concentrate or cluster in physical or virtual spaces through structured mobility or migration [10]. The academic community has extensively examined the impact of STTA on industrial structure optimization and economic growth. It is widely acknowledged that a positive interactive relationship exists between STTA and the development of high-tech industries [11]. Some studies suggest that regions with a higher degree of STTA make a more significant contribution to economic growth [5]. Furthermore, some scholars have focused on the relationship between STTA and regional productivity, as well as innovation efficiency. Research indicates that both the scale and balance of STTA are significantly positively correlated with regional innovation efficiency [12]. However, some studies have also pointed out that the mismatch of innovation factors, such as human resources, across regions may result in efficiency losses, thereby hindering the growth of TFP [13]. Some studies suggest that excessive STTA may result in overcrowding, waste of innovative resources, and a decline in output efficiency, thereby negatively impacting production efficiency [13]. In addition, some scholars have argued that the relationship between STTA and regional knowledge innovation efficiency, patent innovation efficiency, and TFP follows an inverted U-shaped curve [5,14].

2.2. Green Total Factor Productivity (GTFP)

GTFP is an indicator of economic performance that builds upon the traditional total factor productivity framework, further incorporating dual resource and environmental constraints. It essentially reflects the efficiency of resource allocation in the context of sustainable development [15]. This indicator is used to assess whether a region can achieve long-term sustainable economic development, reflecting the core concept of green development. It is particularly aligned with the inevitable trend of Chinese-style modernization and the contemporary principles of green development [7]. As the importance of GTFP for sustainable economic growth has become increasingly evident [16], an increasing number of scholars have begun to focus on various factors influencing GTFP, such as the digital economy [15], green finance [17], and environmental regulation [18]. However, research on the relationship between STTA and GTFP remains limited. Talent is considered the primary driving force of development, and the level of STTA is directly linked to the advancement of regional GTFP. Therefore, exploring the mechanisms through which STTA influences GTFP has become a critical issue in promoting regional green economic growth and achieving sustainable development.

The nexus between STTA and regional green development has garnered significant academic attention, particularly regarding its role in bolstering GTFP and catalyzing low-carbon transitions. Yin et al. (2023) contend that the asymmetric distribution of STTA accelerates the cross-regional transfer and application of green technologies, thereby inducing carbon reduction benefits and a systematic improvement in GTFP [19]. Xu (2021) further elucidates that STTA promotes green R&D primarily through knowledge spillover effects, noting that this facilitative impact yields higher marginal dividends in regions with lower innovation capacity [20]. However, scholarly discourse also warns of the boundaries of STTA; excessive concentration may precipitate "congestion effects," leading to resource misallocation and diminished innovation efficiency. Consequently, the capacity of STTA in driving green development remains contingent upon the heterogeneity of regional innovation levels. Future research must further scrutinize these non-linear dynamics and the evolution of optimized policy frameworks.

2.3. Theoretical Background

Endogenous growth theory, developed by Romer and other scholars in the late 1980s and early 1990s, is also known as the new growth theory [21]. Endogenous growth theory primarily addresses the sources of long-term economic growth, highlighting the role of endogenous factors such as technological progress, human capital, and institutional change. Based on the assumptions of increasing returns to scale and imperfect competition, this theory posits that long-term economic growth arises from endogenous dynamic mechanisms, particularly increasing returns to inputs, where a rise in inputs leads to a more than proportional increase in output. Unlike the neoclassical view, which assumes diminishing returns to scale, endogenous growth theory suggests that the rate of return on capital can remain constant or even increase, enabling per capita output to grow continuously over the long term and potentially sustain unlimited growth [22]. Endogenous growth theory highlights the role of internal factors within the economic system, particularly human capital, in improving production efficiency. It emphasizes the positive impact of STTA on technological innovation. On the one hand, the concentration of scientific and technological talent enhances regional technological innovation capabilities, fostering the development and application of green technologies. On the other hand, a high concentration of such talent strengthens a region's technological absorption capacity, facilitating the assimilation and transformation of external green technologies. This improves the localized application efficiency of these technologies, ultimately contributing to the enhancement of GTFP.

3. Hypothesis Development

3.1. Scientific and Technological Talent Agglomeration and Urban Green Total Factor Productivity

Endogenous growth theory posits that technological progress and innovation are the core drivers of economic growth, while human capital, particularly high-quality scientific and technological talent, is a key factor in driving technological innovation [21]. The positive effects of STTA on GTFP are primarily manifested in the following aspects. As carriers of knowledge, scientific and technological talent possess high human capital and labor productivity. This not only enables them to translate their knowledge and skills into innovation output but also generates substantial spillover effects through STTA [23]. Specifically, STTA contributes to increasing knowledge density and generating economies of scale, fostering collaboration among individuals. This facilitates the effective integration of their respective knowledge, thereby achieving a synergistic effect where $1 + 1 > 2$, which enhances regional innovation levels [14,24]. Furthermore, the cross-regional mobility of scientific and technological talent accelerates the dissemination of knowledge and fosters spillover effects, ensuring that innovative outcomes are not confined to the local region but extend to surrounding areas, thereby collectively enhancing regional innovation capabilities [25]. Based on the above analysis, we propose the following hypothesis:

H1. *Scientific and technological talent agglomeration has a positive impact on green total factor productivity.*

3.2. Mediating Role of Factor Mobility

Labor, capital, and technology constitute the three core factors of economic development. The labor factor generally refers to the physical and cognitive inputs of human beings in the production process, which is typically measured in terms of labor time input [26]. The capital factor mainly refers to the accumulation and investment of physical capital, including productive assets such as machinery, equipment, and buildings [27]. The technology factor reflects technological progress that improves production efficiency under

given levels of labor and capital inputs. Such progress is commonly manifested in patents and other innovation outcomes [21].

STTA has a positive influence on the three core production factors. First, in terms of labor, STTA enhances knowledge spillovers and expands production scale, thereby attracting a larger pool of labor. Meanwhile, workers can further improve their productivity through a learning-by-doing process during production [28]. Second, with respect to capital, the application of knowledge generated by STTA stimulates investment demand, while the reduction in information asymmetry improves returns on capital, thereby facilitating greater capital mobility and improving allocation efficiency [29]. Third, in terms of technology, STTA promotes knowledge spillovers and facilitates collaborative innovation among market participants, thereby accelerating the R&D process and enhancing innovation output [30]. Labor, capital, and technology also exert significant effects on GTFP. Specifically, labor enhances GTFP through the accumulation of skills and the optimization of the labor structure, which facilitates the diffusion of green skills and the adoption of cleaner production practices, thereby reducing resource consumption and pollution emissions [31]. Capital improves GTFP by promoting investment in green technologies and equipment, which enhances resource utilization efficiency [32]. Technology contributes to GTFP through innovation-driven processes and advances in clean technologies, thereby reducing energy consumption and emissions per unit of output and serving as a key driver of green transformation and GTFP growth [33]. Therefore, we propose:

H2. *Factor mobility mediates the relationship between scientific and technological talent agglomeration and green total factor productivity.*

3.3. Moderating Role of Digital Economy

The concept of the digital economy was first introduced by Don Tapscott and refers to a new form of economic development driven by the application of data, information, and knowledge based on the internet and information technologies [34]. The digital economy is characterized by the use of data as a factor of production, technology-driven development, and platform-based network structures. It is highly dependent on advanced technologies such as big data, cloud computing, and blockchain, through which data has increasingly become a key production factor in contemporary economic development [35].

The digital economy plays a crucial role in reducing information asymmetry, lowering transaction costs, and improving innovation efficiency [36]. When the level of digital economy development is high, the knowledge spillover effects generated by STTA are more pronounced, thereby enhancing green collaborative innovation and significantly improving urban green-development performance [37]. In contrast, when the level of digital economy development is low, market frictions and barriers are more severe, which constrains green collaborative innovation and limits improvements in urban green development. Based on the above discussion, the following hypothesis is proposed:

H3. *The digital economy positively moderates the relationship between scientific and technological talent agglomeration and green total factor productivity, such that the relationship is stronger when the level of digital economy development is higher, and weaker when it is lower.*

4. Model Construction

4.1. Methodological Summary and Rationale

This study adopts a panel data regression framework to examine the impact of scientific and technological talent agglomeration (STTA) on green total factor productivity (GTFP). This method is suitable because the sample covers 284 prefecture-level cities in mainland China from 2004 to 2019, allowing the study to control for both city-level het-

erogeneity and time-related shocks through fixed effects. To further strengthen the causal interpretation of the relationship between STTA and GTFP, instrumental variable estimation and placebo tests are also employed to alleviate potential endogeneity concerns and reduce the possibility of spurious correlations. In terms of variable measurement, GTFP is measured using the non-radial SBM directional distance function and the GML index because they can incorporate both desirable and undesirable outputs, while STTA is measured by the location entropy index to capture the relative concentration of scientific and technological talent across cities. The data are mainly obtained from the China City Statistical Yearbook, the China Statistical Yearbook, and relevant prefecture-level city statistical yearbooks, which provide a reliable basis for the empirical analysis.

4.2. Baseline Model

A panel regression model is constructed to examine the impact of STTA on GTFP. The model is as follows:

$$MI_{it} = \beta_0 + \beta_1 agg_{it} + \sum control + \mu_i + \omega_t + \varepsilon_{it} \quad (1)$$

MI represents GTFP; STTA represents the level of scientific and technological talent; $\sum control$ represents the set of control variables, including the following factors affecting GTFP: PGDP represents economic development level, measured by per capita GDP; HUM represents human capital, measured by the ratio of the number of higher education students to the total population at prefecture-level city; INDUS represents industrial structure, measured by the ratio of the output value of the secondary industry to GDP at the prefecture level; POST represents the informatization level, measured by the ratio of annual postal and telecommunications business volume to the year-end population at the prefecture level; FINS represents financial development, measured by the year-end loan balance of financial institutions at the prefecture level; INC represents the income level, measured by the average wage at the prefecture level. β_0 is the constant term; β_1 represents the coefficients of each variable, where i denotes different regions and t denotes the sample year; μ_i represents individual fixed effects; w_t represents time fixed effects; ε_{it} represents the random error term.

4.3. Sample

Considering data availability, this study uses panel data for 284 prefecture-level cities in mainland China over the period 2004–2019 to explore the impact of STTA on GTFP. The data are primarily sourced from the China City Statistical Yearbook (2005–2020), the China Statistical Yearbook (2005–2020), and selected statistical yearbooks of prefecture-level cities. For missing observations, linear interpolation based on the average values of the two preceding and two subsequent years is applied.

4.4. Measurement

The definition and measurement of green total factor productivity are based on the research of Lin and Meng [2]. GTFP is the core dependent variable. The study employs the non-radial SBM directional distance function and the GML index to measure the GTFP for 284 prefecture-level cities in mainland China from 2004 to 2019. Regarding the selection of input and output variables, this study uses capital input, labor input, and energy input as factor inputs, real regional GDP as the desirable output, and wastewater discharge, carbon dioxide (CO_2) emissions, and industrial dust emissions during production as undesirable outputs. The specific settings of these input and output indicators are shown in Table 1. Based on the selected indicators in the table, this study employs MaxDEA Pro 5.2 to calculate the GML index for the 284 selected prefecture-level cities.

Table 1. Input–output indicator system for green total factor productivity.

First-Order Indicator	Second-Order Indicator	Third-Order Indicator
Input	Capital Input	Capital input is represented by capital stock, which is calculated using the perpetual inventory method.
	Labor Input	Labor input is represented by the number of employed persons at year-end in each city (in ten thousand).
	Energy Input	Energy input is represented by the annual electricity consumption of the municipal districts (in 10,000 kW·h).
output	Desirable Output	The desirable output is represented by the real GDP of each prefecture-level city calculated at constant 2000 prices (in 10,000 yuan).
	Undesirable Output	The undesirable output is measured by the industrial wastewater discharge (in 10,000 tons), industrial carbon dioxide emissions (in 10,000 tons), and industrial dust emissions (in 10,000 tons) of each prefecture-level city. These indicators are integrated into a comprehensive environmental pollution index using the entropy method.

The National Medium- and Long-Term Plan for the Development of Scientific and Technological Talent (2010–2020) defines scientific and technological talent as workers who possess certain professional knowledge or specialized skills, engage in creative scientific and technological activities, and contribute to the development of science and technology as well as economic and social progress. The measurement of STTA is based on the study by Guo et al. [5]. This study uses the location entropy index to measure the STTA, which is calculated as the ratio of the share of employees in scientific research and technical services in each city to the total number of employees in that city, to the corresponding national share. The formula is as follows:

$$STTA_{it} = \frac{P_{it} / Q_{it}}{\sum_i P_{it} / \sum_i Q_{it}} \quad (2)$$

Here, $STTA_{it}$ represents the level of scientific and technological talent in city i in year t; P_{it} represents the number of employees in scientific research and technical services in city i in year t; and Q_{it} represents the total number of employees in city i in year t.

Drawing on existing studies, factor mobility generally encompasses three core dimensions: labor mobility, capital mobility, and technological mobility. Based on this framework, this study constructs an indicator system for factor mobility based on the study by Chen et al. [38]. Specifically, labor mobility is measured by the ratio of employment in the primary, secondary, and tertiary industries to the total regional population, reflecting the allocation and mobility of regional labor resources. Capital mobility is measured by the ratio of regional fixed asset investment to regional GDP, which captures the level of capital input and capital allocation. Technological mobility is measured by the ratio of the sum of regional patent applications and total expenditures on technology importation to the total regional population, thereby reflecting the level of regional technology diffusion, technol-

ogy introduction, and innovation resource mobility. By integrating these three dimensions, this study can more effectively capture the overall level of regional factor mobility.

The indicator system for measuring the level of digital economy development is constructed with reference to the study conducted by Zhao et al. [39]. The relevant data are obtained from the Peking University Digital Financial Inclusion Index. The digital economy is generally regarded as a dynamic new economic form that has developed on the basis of information and communication technologies (ICTs). Considering that technological progress and economic development continuously reshape the connotation of the digital economy, the concept of the digital economy has been closely associated with the "new economy." The emergence of the digital economy has also posed significant challenges to traditional agricultural and industrial economic models. Given that this study is conducted within the specific institutional and developmental context of China, certain foreign definitions may not be fully applicable. Therefore, drawing on the definition proposed by Zhao et al. (2020) [39], this study measures digital economy development as a comprehensive index encompassing both internet development and digital financial inclusion indicators. Specifically, the level of internet development includes the internet penetration rate, the proportion of internet-related employees, internet-related output, and the number of mobile internet users. Accordingly, the measurement system for digital economy development in this study consists of five dimensions. Internet penetration is measured by the number of internet users per 100 persons; internet-related employment is measured by the proportion of employees engaged in computer services and software industries; internet-related output is measured by per capita total telecommunications service volume; mobile internet development is measured by the number of mobile phone users per 100 persons; and digital financial inclusion is measured using the Peking University Digital Financial Inclusion Index.

Control Variables: Economic development level (PGDP) is measured by per capita GDP; human capital (HUM) is measured by the number of students enrolled in higher education institutions in each prefecture-level city; industrial structure (INDUS) is measured by the ratio of the value added of the secondary industry to GDP at the prefecture level; informatization level (POST) is measured by the ratio of annual postal and telecommunications business volume to the year-end population at the prefecture level; financial development (FINS) is measured by the year-end loan balance of financial institutions at the prefecture level; income level (INC) is measured by the average wage at the prefecture level.

5. Data Analysis and Hypothesis Testing

5.1. Descriptive Statistics

Table 2 reports the descriptive statistics of the main variables. The statistical results indicate that the maximum value of green total factor productivity (GTFP) is 2.95, whereas the minimum value is 0.09, revealing a substantial disparity. This finding suggests significant regional heterogeneity in GTFP levels across cities. Moreover, the sample mean of GTFP is 1.017, which is slightly above 1, suggesting that the overall level of urban GTFP was relatively stable around 1 during the sample period.

Table 2. Descriptive statistics.

Variable	N	Mean	SD	Min	Max
MI	4528	1.017483	0.1517821	0.09005	2.95175
EC	4528	1.019936	0.1615971	0.08993	3.51855
TC	4528	0.99964	0.0584253	0.37801	2.55142
STTA	4528	0.7137451	0.5453021	0	5.559841

Table 2. *Cont.*

Variable	N	Mean	SD	Min	Max
PGDP	4528	10.28148	0.7979437	4.59512	13.05569
HUM	4528	0.0164802	0.022361	0	0.1311
INDUS	4528	47.64053	11.07889	10.68	90.97
POST	4528	0.1078765	0.1843637	0	3.140994
FINS	4528	15.86841	1.322185	12.54772	20.41978
GOV	4528	0.1955492	0.0454547	0.0199	0.4974
PAT	4528	7.042776	18.57693	0	308.1363

5.2. Baseline Regression Results

As shown in columns (1) and (2) of Table 3, it can be seen that the coefficient of STTA is significantly positive at the 1% level, regardless of whether control variables are included, indicating that STTA contributes to the growth of GTFP.

Table 3. Regression results for the full sample.

Variable	(1) MI	(2) MI
STTA	0.013 ***	0.030 ***
	(0.004)	(0.009)
cons	1.008 ***	1.131 ***
	(0.0037)	(0.2186)
PGDP		−0.025
		(0.019)
HUM		0.220
		(0.267)
INDUS		−0.001
		(0.001)
POST		0.005
		(0.015)
FINS		0.012
		(0.015)
GOV		−0.045
		(0.076)
PAT		0.000
		(0.000)
Time-fixed	YES	YES
Individual-fixed	YES	YES
N	4528	4528

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, unless otherwise noted.

5.3. Robustness Test

This study employs the average STTA level of other cities within the same province as an instrumental variable for the focal city's STTA level. Regarding relevance, cities within the same province exhibit a high degree of homogeneity in policy orientation, industrial structure, talent attraction and cultivation policies, and overall economic development environment. As a result, there are strong spatial linkages and demonstration or imitation effects in STTA across prefecture-level cities within the same province. Accordingly, the average STTA level of other cities within the same province is inherently highly correlated with that of the focal city, thereby satisfying the relevance requirement of a valid instrumental variable. Regarding exogeneity, STTA in other cities within the same province is primarily determined by those cities' own resource endowments and local development strategies. It is unlikely to exert a direct impact on the green total factor productivity of a

specific city, nor is it expected to be systematically correlated with omitted variables or the stochastic error term in the empirical model. Therefore, it satisfies the exogeneity condition required for a valid instrumental variable. In sum, the average STTA level in other cities within the same province constitutes an appropriate and valid instrumental variable for the core explanatory variable in this study.

As shown in Table 4, the instrumental variable passes the weak-identification test, indicating that it satisfies the relevance requirement. Meanwhile, in the regression model incorporating the instrumental variable, the effect of STTA on GTFP remains statistically significant.

Table 4. Instrumental variable test.

Variable	(1) MI
STTA	0.043 *
	(0.024)
_cons	1.109 ***
	(0.202)
PGDP	−0.024
	(0.015)
HUM	0.235
	(0.407)
INDUS	−0.001
	(0.001)
POST	0.003
	(0.026)
FINS	0.013
	(0.013)
GOV	−0.043
	(0.086)
PAT	0.000
	(0.000)
Time-fixed	YES
Individual-fixed	YES
N	4528
F-statistic for the weak-instrument test	17.51

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, unless otherwise noted.

Provincial capital cities and municipalities were excluded from the robustness check. Compared with ordinary prefecture-level cities, provincial capital cities and municipalities directly under the central government typically possess superior resource endowments, stronger policy support, and more substantial fiscal guarantees. They also tend to outperform other cities in terms of policy implementation efficiency and factor allocation capacity. In addition, their strong comprehensive economic strength and a higher level of urban development may exert heterogeneous effects on GTFP, thereby potentially biasing the baseline regression results.

To mitigate the potential interference of sample heterogeneity associated with core cities and to further verify the robustness of the baseline findings, this study re-estimates the model after excluding municipalities directly under the central government and 27 provincial capital cities. The empirical results in Table 5 show that the sign of the coefficient of the core explanatory variable is unchanged and statistically significant at the 1% level. This indicates that the baseline regression results are not driven by the inclusion of core cities and confirms the robustness and reliability of the findings.

Table 5. Robustness check by excluding provincial capital cities and municipalities.

Variable	(1) MI
STTA	0.024 ***
	(0.009)
_cons	1.149 ***
	(0.233)
PGDP	−0.030
	(0.022)
HUM	0.395
	(0.428)
INDUS	−0.001
	(0.001)
POST	0.006
	(0.017)
FINS	0.015
	(0.015)
GOV	−0.039
	(0.085)
PAT	0.000
	(0.000)
Time-fixed	YES
Individual-fixed	YES
N	4528

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, unless otherwise noted.

To further alleviate potential concerns arising from omitted variables and unobserved heterogeneity that may bias the baseline regression results, this study conducts a placebo test as an additional robustness check. Specifically, the core explanatory variable, STTA, is randomly shuffled to construct a pseudo-treatment variable. With all control variables held constant, the regression is repeated 500 times to generate the distribution of estimated coefficients under the null hypothesis of no true treatment effect. The results in Figure 1 show that the placebo estimates are predominantly concentrated around zero and approximately follow a normal distribution. In contrast, the estimated coefficient from the baseline regression is substantially larger than the placebo estimates and lies clearly outside the distribution of randomly generated coefficients. These findings indicate that the positive effect of STTA on GTFP is unlikely to be driven by omitted variables or unobserved factors, thereby further supporting the robustness and reliability of the baseline regression results.

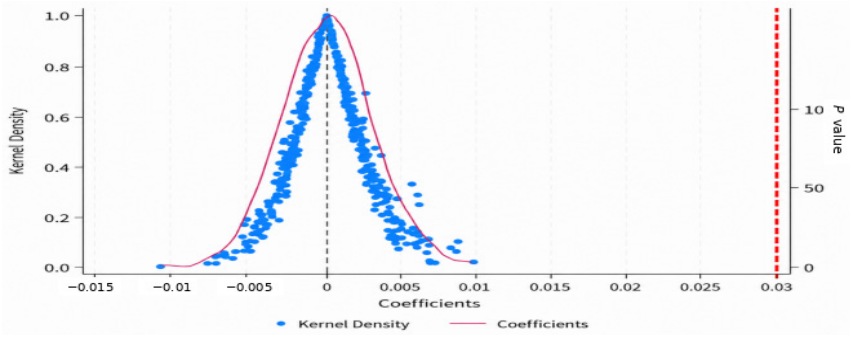

Figure 1. Placebo test.

5.4. Mediation Effect Analysis

This study uses factor mobility as the mediating variable and examines the effect of scientific and technological talent agglomeration on factor mobility. As shown in Table 6,

the coefficient of STTA is significantly positive at the 1% level. This suggests that STTA can promote more efficient regional factor allocation and accelerate the cross-regional and cross-sectoral mobility of production factors such as labor, capital, and technology.

Table 6. Mediation analysis.

Variable	(1) Factor Mobility
STTA	0.019 ***
	(0.006)
_cons	0.028
	(0.120)
PGDP	0.014 **
	(0.007)
HUM	−0.681 ***
	(0.267)
INDUS	0.001 ***
	(0.000)
POST	0.008
	(0.016)
FINS	−0.002
	(0.007)
GOV	−0.121 *
	(0.065)
PAT	0.002 ***
	(0.000)
Time-fixed	YES
Individual-fixed	YES
N	1981

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, unless otherwise noted.

5.5. Moderation Effect Analysis

The above table reports the results of the moderating effect of digital economy development. The interaction term between STTA and digital economy development is introduced. The estimated coefficient is statistically significant in Table 7 and in Figure 2, indicating that digital economy development positively strengthens the marginal effect of scientific and technological talent agglomeration on GTFP.

Table 7. Moderation analysis.

Variable	Moderation Effect MI
Interaction	0.174 *
	(0.095)
_cons	1.451 ***
	(0.347)
PGDP	−0.010
	(0.025)
HUM	0.747 *
	(0.411)
INDUS	−0.001
	(0.001)
POST	0.006
	(0.018)
FINS	−0.016
	(0.021)

Table 7. *Cont.*

Variable	Moderation Effect MI
GOV	−0.111
	(0.115)
PAT	0.000
	(0.000)
Time-fixed	YES
Individual-fixed	YES
N	3113

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, unless otherwise noted.

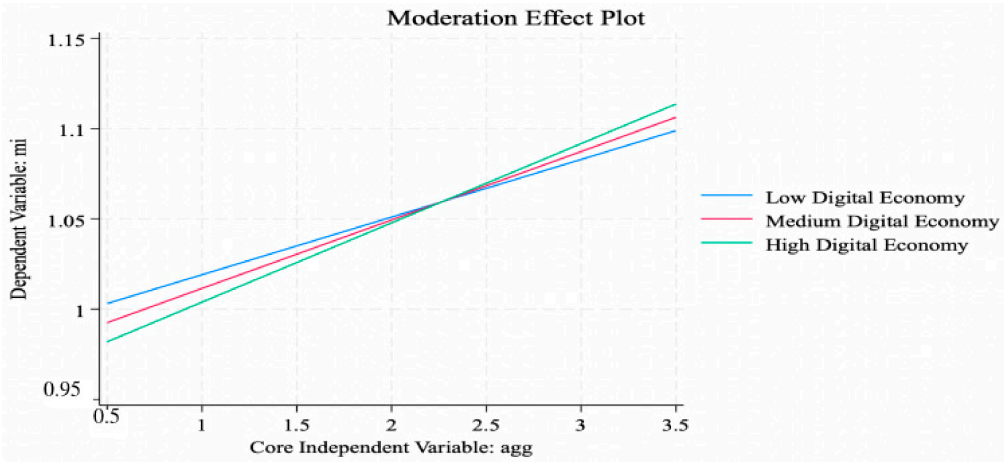

Figure 2. Moderation effect.

5.6. Heterogeneity Test

Regional heterogeneity analysis: Cites are classified into eastern, central, and western regions.

To examine regional heterogeneity, this study divides the full sample into eastern, central, and western regions for subsample regressions. The results show that the effect of scientific and technological talent agglomeration on GTFP is insignificant in the eastern region, significantly positive at the 5% level in the central region, and significantly positive at the 10% level in the western region. In the eastern region, where economic development is advanced and the green-development system is relatively mature, GTFP improvements mainly depend on technological frontiers, institutional innovation, and industrial upgrading. The marginal contribution of additional talent agglomeration is therefore limited, leading to an insignificant effect.

In the central region, which is at a stage of industrial upgrading and green transformation, talent agglomeration effectively supports industrial restructuring and technological application, resulting in a significant positive effect at the 5% level. In the western region, constrained by weaker economic foundations and limited talent absorption capacity, the effect of talent agglomeration is relatively weak and only significant at the 10% level. See Table 8.

To examine heterogeneity across economic development levels, this study divides cities into high- and low-income groups based on per capita GDP and conducts subsample regressions. The results in Table 9 show that the positive effect of scientific and technological talent agglomeration on GTFP is significant at the 1% level in high-income cities and at the 5% level in low-income cities, indicating that talent agglomeration improves green productivity in both groups, though with different intensities. In high-income cities, better infrastructure, stronger innovation capacity, and more developed industrial systems enable

talent agglomeration to fully realize knowledge spillovers and technological synergy, resulting in a stronger positive effect on GTFP. In low-income cities, constrained by weaker economic foundations and limited innovation resources, the effect remains positive but relatively weaker.

Table 8. Regional heterogeneity analysis.

Variable	Eastern Region MI	Central Region MI	Western Region MI
STTA	0.011	0.030 **	0.040 *
	(0.013)	(0.013)	(0.021)
_cons	0.598 *	0.952 ***	1.610 ***
	(0.324)	(0.351)	(0.376)
Time-fixed	YES	YES	YES
Individual-fixed	YES	YES	YES
N	1600	1600	1328

Note: ***, **, * represent significance at the 1%, 5%, and 10% levels, respectively, unless otherwise noted.

Table 9. Economic heterogeneity analysis.

Variable	High-Economic-Level Group MI	Low-Economic-Level Group MI
STTA	0.032 ***	0.034 **
	(0.012)	(0.014)
_cons	1.063 ***	1.138 ***
	(0.264)	(0.355)
Time-fixed	YES	YES
Individual-fixed	YES	YES
N	2272	2256

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, unless otherwise noted.

6. Conclusions and Discussion

6.1. Major Conclusions

This study empirically examines the impact of STTA on GTFP using panel data from 284 prefecture-level cities in mainland China from 2004 to 2019. The findings are as follows: First, STTA significantly promotes urban GTFP, green technical efficiency, and green technological progress. Second, factor mobility serves as a mediating variable in the relationship between STTA and GTFP. Specifically, STTA promotes the cross-regional flow and optimal allocation of production factors, thereby enhancing resource allocation efficiency and ultimately contributing to improvements in GTFP. Third, the level of digital economy development positively moderates the relationship between STTA and GTFP. In regions with a higher level of digital economy development, the positive effects of STTA on GTFP are more pronounced.

6.2. Implications

First, actively foster an innovation ecosystem conducive to the development and agglomeration of scientific and technological talent. Local governments should explore the establishment of special funds and entrepreneurial support funds to promote the development of scientific and technological talent. Addressing support needs such as housing, research funding, and education for their children will provide scientific and technological talent with a favorable living and working environment, thereby maximizing the potential of STTA.

Second, cities should further optimize the efficiency of factor allocation by breaking regional barriers and institutional constraints that hinder the free flow of production factors. Governments should promote cross-regional mobility and the efficient allocation of capital, technology, labor, and information resources, thereby enhancing resource allocation efficiency and providing sustained momentum for improvements in GTFP.

Third, governments should accelerate the development of the digital economy and strengthen digital infrastructure construction, including broadband networks, data platforms, and intelligent information systems. By enhancing digital connectivity and improving the level of digital technology application, cities can amplify the positive effects of STTA and factor mobility on GTFP, thereby promoting high-quality and green urban development.

6.3. Limitations and Future Research

First, the robustness check remains relatively limited, and we plan to further validate the findings using the propensity score-matching method in future research. Second, in terms of measurement, electricity consumption as an indicator of energy use may not fully reflect overall energy consumption, especially in some industrial cities where reliance on coal or other forms of energy may be more significant, and electricity consumption accounts for only part of total energy consumption. Additionally, the measurement of STTA has not fully accounted for engineers, which may also affect the comprehensiveness of the study.

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