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Research article

Unleashing the power of informatization: How does the "information benefiting people" policy affect green total factor productivity?

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ABSTRACT

Information development is a necessary means for China to achieve technology force and an effective path toward sustainable development. Regarding the "information benefiting people" policy led by the Chinese government as a quasi-experiment of information technology, this study builds an analysis framework for the impact of informatization on green total factor productivity (GTFP). Based on panel data at the Chinese city level from 2006 to 2019, this study further empirically evaluates the mechanism path, heterogeneity, and spatial spillover effects between informatization and GTFP by using a difference-in-difference (DID) model, a mediating model, and a spatial DID model. The results show that (1) the information benefiting people policy contributes considerably to greater GTFP levels in the pilot cities; (2) the policy also promotes the rapid growth of GTFP by fostering the advancement of education, the share of the number of ICT employees, and green technology innovation; (3) the information benefiting people policy raises GTFP in the eastern cities, small cities, and non-old industrial based cities; and (4) the policies lead to a large rise in local GTFP levels, but a decline in GTFP in surrounding cities. This paper offers valuable reference suggestions for the Chinese government to implement informatization-policies to support green development.

1. Introduction

China's economic development has soared and is now the second largest economy in the world due to the construction of new China and its reform and opening up (WB, 2022). However, in tandem with this development, China has become the world's largest emitter of carbon dioxide emissions and consumer of energy as a result of the severe toll rapid economic growth has taken on the country's resources and environment (Tian and Feng, 2022). China produced 30.7% of the world's carbon emissions in 2020, which has raised considerable concern among environmentalists and stakeholders seeking to mitigate the potential devastating effects of climate change (BP, 2022; Wang et al., 2023). The 14th Five-Year Plan of the Chinese government, which expressly specifies it will adhere to green and low-carbon growth, conserve resources, and apply sustainable development measures, acknowledges the aforementioned issues. The Chinese government proposed a target of carbon peaking by 2030 and carbon neutrality by 2060 during the 75th session of the United Nations General Assembly in 2020, establishing the foundation for China's green development path for the following 40 years. Therefore, the main challenge facing the Chinese government is how to achieve green and sustainable development.

In the aforementioned context, increasing green total factor productivity (GTFP) is a practical solution to the existing conundrum and a crucial overall indicator of the ability to achieve sustainable development, taking into account both environmental conservation and economic growth (Tian and Pang, 2022). Thus, another topic of interest for academia is the quest for factors influencing GTFP. Information and communication technology (ICT) has been proposed as a means of boosting economic productivity and successfully advancing GTFP in the modern era without adding needless social and environmental costs (Arushanyan et al., 2014; Zhang and Wei, 2022). As the cornerstone of ICT development, informatization has emerged as a crucial component of China's quick economic growth. A statistical report states that China's Internet penetration rate reached 73.0% in 2021, up 50.4 percentage points from 2008 (CNNIC, 2022). Informatization of government affairs has also advanced rapidly; by 2021, there were 921 million Chinese citizens – 89.2% of all Internet users - using government Internet services (CNNIC, 2022). With the rapid advancement of the digital era in

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[1] Web: https://www.researchgate.net/profile/Jianda-Wang; https://scholar.google.com.hk/citations?user=tObA28IAAAAJ&hl=zh-CN.

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China, informatization creates and makes use of essential information resources to encourage knowledge sharing and information exchange, which may successfully support high-quality economic growth (Ji and Li, 2021). As a result, informatization will be a key factor in China's future achievement of GTFP growth.

The Chinese government is also aware of the crucial role of informatization. In 2014, the National Development and Reform Commission issued the "Notice on Accelerating the Implementation of Information Benefiting People" project and set 80 cities as pilot cities for the information benefiting people policy.[2] The specific list of cities is shown in Fig. 1. The pilot cities will effectively use information resources under the policy's influence to achieve the optimal allocation of industry, raise the level of human resources and education level, increase the proportion of industries engaged in science and technology innovation, and strengthen the capacity of green innovation, which will effectively help the localities achieve healthy, green, and long-term development. Particularly, the information benefiting people policy efficiently encourages the spread of ICT goods in the industrial and service sectors, speeds up the efficiency of resource allocation, enhances the technical optimization of green and energy-saving products, and makes GTFP enhancement possible (Shi et al., 2022). On the other hand, the information benefiting people policy can also successfully convert carbon-intensive product activities and production into low-carbon product activities and production, producing a substitution impact that boosts economic activity while decreasing resource waste (Zhang and Liang, 2012). Given the environmental attributes of GTFP, it is important to consider its spatial spillover effects. Information technology has strong positive externalities and knowledge spillover effects, which can facilitate the exchange of information and resources, strengthen regional and industrial linkages, and promote the transition to a greener economy (Ruan and Zhang, 2021; Wang et al., 2021c). However, the significant influx of talent and technological resources to the region has led to a relative lack of supporting resources and policy support in the surrounding cities, which in turn has hindered their local sustainable development process (Gu et al., 2022; Wang et al., 2021c).

Related topics are not discussed much in available articles, and scholars focus more on the direct and indirect effects of digitalization affecting GTFP (Liu et al., 2022b; Zhao et al., 2022a; Zhu et al., 2022). For example, Internet development has enhanced China's GTFP by promoting technological innovation and industrial upgrading (Tian and Pang, 2022). Li and Liao (2022) confirm that energy efficiency and labor productivity are important mediators between digitalization and GTFP. However, the impact of informatization as an important part of digitalization and its green development has not been explored, and the impact mechanism is not yet clear. Meanwhile, few scholars have analyzed the relationship between informatization and GTFP through a policy perspective. In addition, due to the spillover effect of digitalization on green sustainability, a number of scholars have confirmed that digitalization has a significant impact on both local and neighboring cities (Gu et al., 2022; Lyu et al., 2023). However, the spillover impact is also questionable due to the uneven industrial mechanism and talent siphon effect (Chen et al., 2022). Scholars have paid scant attention to the impact of the spillover effect of informatization on GTFP.

Based on the background introduction provided above, it is important to note that while many scholars have examined the theoretical and empirical evidence for the green effects of informatization, relatively few have treated and analyzed informatization policies as quasi-natural experiments. Understanding the actual effects of China's informatization policies will help researchers and the government develop future green development strategies. We propose the following research questions to achieve this: (1) Has China's informatization policy effectively influenced the growth of GTFP? (2) How has China's informatization development influenced the growth of GTFP? (3) Does China's informatization policy affect GTFP with spatial spillover characteristics? Based on the above research topics, this work assesses the impact of informatization on GTFP using panel data from 282 Chinese prefecture-level cities and a difference-in-difference (DID) model in a quasi-natural experiment. The mechanism and spatial spillover effects of informatization and GTFP are also evaluated using a mediating effects model and a spatial DID model.

This paper makes the following research contributions. First, the "information benefiting people" pilot policy is used as a quasi-natural experiment in this paper's analysis of China's informatization strategy's effects on GTFP. This analysis helps the Chinese government determine the policy's potential for green development and its practical implications. Second, this paper explores the mechanisms through which informatization policies affect GTFP, assisting policymakers and scholars in deciding the best course for policy implications and offering useful recommendations for the nation's transition to a greener economy. Finally, this paper innovatively examines the spatial spillover characteristics of the impact of informatization policies on GTFP, which will provide effective recommendations to the government when choosing pilot cities and help local governments pool resources and develop synergistically to jointly promote green and sustainable development.

The next section presents the theoretical hypothesis of this research, and Section 3 introduce the methodology and data. The main results of this study are presented in Section 4, along with an analysis and discussion of the findings. Section 5 summarizes the full paper and makes policy recommendations.

2. Mechanism analysis and research hypotheses

2.1. *The direct effect of informatization on GTFP*

The digital economy is built on informatization, and the information network serves as its primary delivery system. As green efficiency and environmental pollution are gaining attention in various industries, the impact of informatization cannot be ignored (Dong et al., 2023; Mahdi et al., 2022; Mehdizadeh et al., 2023; Yousefi et al., 2021). First, the medium function of information substantially improves the effectiveness of resource allocation, stimulates market vitality and creativity, encourages the greening of traditional industries, and accelerates green economic growth (Deng et al., 2022). Second, the growth of information technology has sped up the flow of information and enhanced the effectiveness of matching supply and demand, leading to the rapid development and transformation of the Internet, cloud computing, and other information technology industries. It has also decreased the time and labor costs associated with information matching, which in turn has reduced resource waste and improved the area for green development. Third, the rapid growth of informatization can also encourage the creation of urban management models and concepts, boost city wisdom, improve the concept of green governance among officials and businesspeople, and accomplish local green development (Gu et al., 2022). A prominent example of a representative event for the transition of city informatization is the information benefiting people policy. The pilot cities will accelerate the development of information platforms, hasten resource integration, lessen duplication of investment, promote systems and institution innovation, and strengthen green governance capabilities. Therefore, we propose the following hypothesis.

Hypothesis 1. Informatization will effectively contribute to the improvement of the GTFP level.

2.2. *The indirect effects of informatization on GTFP*

Informatization will likely contribute to GTFP growth through three perspectives: education, the share of the number of ICT employees, and green technology innovation. First, we analyze the mechanism of

[2] http://www.gov.cn/xinwen/2014-06/23/content_2706766.htm.

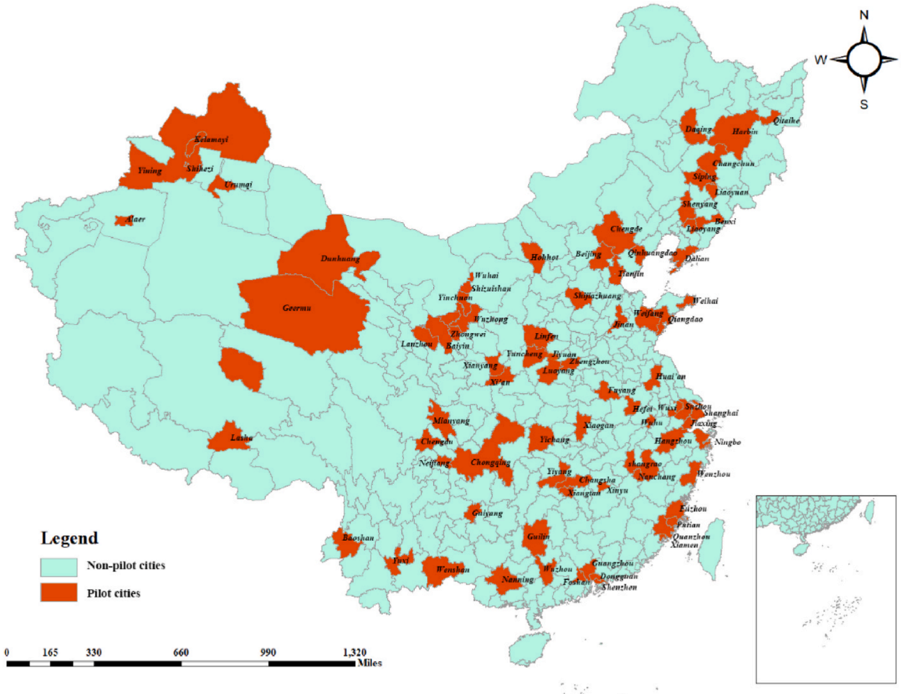

Fig. 1. Pilot cities of the "information benefiting people" policy.

education influence. The transformation of information development will facilitate significant changes in education. On the one hand, the growth of informatization has encouraged the government and enterprises to hire more top-tier talents and improve their team and talent structure, indirectly contributing to a positive educational match. On the other hand, informatization transformation offers additional employment opportunities and a wealth of online learning opportunities, which improves the quality of the labor force and job matching and raises the level of education (Wang et al., 2022a). High-quality education will contribute more significantly to green economic growth due to better capacity accumulation, richer knowledge, and more technical experience (Gu et al., 2022; Jiang et al., 2021). Therefore, we propose the following hypothesis.

Hypothesis 2. Informatization will indirectly promote GTFP by increasing the level of education.

Informatization will also promote the share of the number of ICT employees. The government's informatization policy will compel both the government and enterprises to adopt informatization equipment rather than the original equipment on a large scale, which will speed up the market's development and the manufacture of informatization products, thereby increasing the ICT industry's market size. As a result, the ICT industry will employ more workers for production. The ability of the ICT sector to dramatically improve product innovation and promote knowledge spillovers serves as evidence of this (Branstetter et al., 2018). Moreover, the increase in employment in the ICT industry has improved the quality of human capital, making high-end intelligent and high value-added production possible. This has significantly aided the transformation of traditional production, reduced resource and cost waste, and enhanced green efficiency (Tian and Pang, 2022). Therefore, we propose the following hypothesis.

Hypothesis 3. Informatization will indirectly promote GTFP by increasing the share of the number of ICT employees.

Finally, we propose the hypothesis of a green technology innovation path. Due to the capacity of digitalization and information penetration to stimulate innovation potential, enhance green innovation, and grow the exchange effect of information based on Schumpeterian Growth Theory of innovation and signaling, informatization can effectively promote green technology innovation (Sun, 2022). Moreover, information technology accelerates the pace of technological dissemination, fostering the development of green technologies through management, organization, and production methods (Haini, 2021; Higón, 2011). In addition, informatization itself represents an emerging technology. Through interactive platforms of information technology, such as the Internet, big data, and artificial intelligence, green technology is being developed and disseminated along with advances in the use of green technology. Scholars have also confirmed that green technology innovation can elevate the degree of GTFP. According to Wang et al. (2023), the expansion of green technological innovation will enhance the space for the use of clean energy, reduce regional pressure to decrease emissions and financing, and improve energy consumption efficiency, leading to the achievement of green growth. Zhao et al. (2022b) argue that green technology innovation minimizes resource consumption and the environmental costs of economic growth while generating economic value, thereby improving GTFP. Thus, we propose the following hypothesis.

Hypothesis 4. Informatization will indirectly promote GTFP by accelerating green technology innovation.

2.3. The spatial spillover effect of informatization on GTFP

Furthermore, informatization may generate spatial spillover effects on GTFP. On the one hand, the rapid development of informatization continuously reduces the cost of information transmission, significantly enhancing the sharing and mobility of knowledge and new technologies, and forming a larger industrial ecosystem, which is conducive to a significant improvement in GTFP within a certain spatial range (Chen et al., 2023a). On the other hand, informatization will have a tendency to reshape the local industrial structure, effectively promoting the development of the local information industry and squeezing the space of traditional industries (Cheng et al., 2023; Ren et al., 2023). This has led to the transfer of traditional energy-intensive industries to surrounding cities, causing industrial pollution. In addition, informatization has also caused the agglomeration of emerging technology industries, resulting in a siphonic effect on surrounding cities, causing the outflow of their technology and talent, which is detrimental to the improvement of GTFP in surrounding cities (Wang et al., 2022b). Therefore, we propose the following hypotheses.

Hypothesis 5. Informatization has a spatial spillover effect on GTFP.

3. Methodology and data

3.1. Estimation equation

This paper needs to explore the impact of the information benefiting people policy on GTFP. According to the fundamental principles of the Impact Population Affluence Technology (IPAT) model, it is believed that environmental impact (I) is generally influenced by population (P), affluence (A), and technology (T). The application of the IPAT theory can assist in gaining a better understanding of the impact of human activities on the environment (Koçak et al., 2021). For instance, by analyzing the trends in population, consumption, and technological levels, it is possible to forecast the future trends and degree of environmental impact, thereby formulating corresponding environmental protection policies and measures. York et al. (2003) linearized the aforementioned impacts and employed the concept of elasticity through an improved Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model to characterize their magnitude. In this study, we can regard informatization as a type of technological level variation and employ the framework of the STIRPAT model to investigate its impact on the GTFP. The information benefiting people policy is a policy variable, and we need to set it as a binary variable (*DID*) representing whether it is subject to policy shocks or not. First, we need to introduce a DID model to explore the differences in the changes between the treatment and control groups before and after the introduction of the policy. The specific model settings are as follows:

$$lnGTFP_{it} = \alpha_0 + \alpha_1 DID_{it} + \alpha_2 lnPGDP_{it} + \alpha_3 lnINV_{it} + \alpha_4 lnIND_{it} + \alpha_5 lnENT_{it} + \alpha_6 lnFIS_{it} + \theta_i + \eta_t + \varepsilon_{it} \tag{1}$$

Herein, α_0 is the constant term; $\alpha_1, \cdots, \alpha_6$ are the estimated coefficients; θ_i is the individual fixed effects; η_t is the year fixed effects; ε_{it} is the random error term; and i and t are the city and year. Regarding the variables, *GTFP* represents green total factor productivity (GTFP); *PGDP* represents economic growth; *INV* represents completed investment amount; *IND* represents industrial structure upgrading; *ENT* represents number of industries; and *FIS* represents fiscal expenditure.

Second, we need to measure the mechanism paths by which policy affects GTFP. According to Baron and Kenny (1986), we will evaluate the mechanism paths by using two-step estimation:

$$lnMediating_{it} = \beta_0 + \beta_1 DID_{it} + \beta_2 lnPGDP_{it} + \beta_3 lnINV_{it} + \beta_4 lnIND_{it} + \beta_5 lnENT_{it} + \beta_6 lnFIS_{it} + \theta_i + \eta_t + \varepsilon_{it} \tag{2}$$

$$lnGTFP_{it} = \lambda_0 + \lambda_1 DID_{it} + \lambda_2 lnMediating_{it} + \lambda_3 lnPGDP_{it} + \lambda_4 lnINV_{it} + \lambda_5 lnIND_{it} + \lambda_6 lnENT_{it} + \lambda_7 lnFIS_{it} + \theta_i + \eta_t + \varepsilon_{it} \tag{3}$$

where β_0 and λ_0 are the constant terms; $\beta_1, \cdots, \beta_6$ and $\lambda_1, \cdots, \lambda_7$ are the estimated coefficients; *Mediating* denotes the mediating variables, which is proxied by education (*EDU*), the share of the number of ICT employees (*ICT*), and green technology innovation (*GTI*). If the coefficients of β_1 and λ_2 are significant, the mechanism path is established.

Third, we further assess whether the policy impact of GTFP has spatial spillover properties, and therefore we consider applying a spatial econometric model. In general, the spatial econometric model contains a spatial lag model (SLM), a spatial error model (SEM), and a spatial Durbin model (SDM). SDM is the most general form of the spatial model, i.e., it contains the spatial lag term of the dependent variable and the spatial term of the independent variable. In most cases, spatial lag and spatial error often coexist (LeSage and Pace, 2009). The basic equation of SDM is as follows:

$$lnGTFP_{it} = \rho \sum_{j=1}^{N} w_{ij} lnGTFP_{it} + X_{it}\Phi + \sum_{j=1}^{N} w_{ij} X_{it} \Psi + \theta_i + \eta_t + \varepsilon_{it} \tag{4}$$

Herein, ρ is a spatial correlation coefficient; Φ and Ψ are the coefficient matrix; X is the vector of independent variables, including the policy dummy variable (*DID*); w is $n \times n$ order spatial weight matrix. Here, we consider two types of weight matrices, which are the adjacency (01) weight matrix:

$$w1_{ij} = \begin{cases} 0, i \text{ is not adjacent to } j \\ 1, i \text{ is adjacent to } j \\ 0, i = j \end{cases} \tag{5}$$

and the geographic weight matrix:

$$w2_{ij} = \begin{cases} \frac{1}{|d_{ij}|}, i \neq j \\ 0, i = j \end{cases} \tag{6}$$

Herein, d_{ij} denotes the great-circle distance calculation based on the longitude and latitude between city i and city j, and w_{ij} is standardized after every element value being divided by the sum of its row to ensure the sum of every row is 1.

3.2. Measurement of variables

3.2.1. Dependent variable

We use the cumulative multiplicative Global Malmquist-Luenberger (GML) index as a proxy variable for GTFP.[3] Among the input variables, we select the number of employees, the stock of fixed assets at the end of the year, and energy consumption. The stock of fixed assets is calculated by the perpetual inventory method, with the based year being 2003. Energy consumption is treated with reference to Zhong et al. (2007). The desired output is GDP, which is treated at constant 2003 prices. Industrial wastewater emissions and industrial sulfur dioxide emissions are the main pollutants controlled by China's environmental regulations (Liu and Zhu, 2022), and carbon dioxide emissions are the primary target of green sustainable development governance (Balsalobre-Lorente et al., 2018; Shahbaz et al., 2018). Thus, considering the completeness and accessibility of the data, the undesired outputs include carbon dioxide emissions, industrial wastewater emissions, and industrial sulfur dioxide emissions.

3.2.2. Independent variable

The independent variable is a binary dummy variable (*DID*) obtained by multiplying a time dummy variable (*Time*) and an individual dummy variable (*Treat*), i.e., $DID = Time \times Treat$. Specifically, the time dummy variables are assigned a value of 1 after the implementation of the policy in 2014, and 0 before 2014. The individual dummy variables are set to 1 for cities subject to policy shocks, and 0 for other cities.

3.2.3. Control variables

This paper selects a total of five control variables affecting GTFP. (1) Referring to Yu et al. (2023b), economic growth (*lnPGDP*) is selected as a control variable, which is proxied by the level of GDP per capita. (2) According to Deng et al. (2022) and Tian and Pang (2022), investment (*lnINV*) is a critical variable that affects GTFP. We use the amount of completed investment in residential development as a proxy variable for investment. (3) Industrial structure upgrading (*lnIND*) can be quantitatively measured by a weighted sum of the contribution of each sector,

[3] See the supplementary materials for a detailed introduction.

where the weight coefficients are determined by the relative proportion of value added generated by the primary, secondary, and tertiary sectors. Specifically, the upgrading index can be expressed as follows: the percentage contribution of the tertiary sector to the total value added multiplied by three, plus the percentage contribution of the secondary sector to the total value added multiplied by two, plus the percentage contribution of the primary sector to the total value added multiplied by one (Xie et al., 2021). (4) Industry is a major source of pollutants, so the number of industrial enterprises above the scale (*lnENT*) will also have an impact on the governance of GTFP (Li et al., 2020), which we include as a necessary control variable. (5) Referring to Gu et al. (2022), local finance general budget expenditure (*lnFIS*) is selected as one of the control variables affecting GTFP.

3.2.4. Mediating variables

A total of three mediating variables are included in this paper, namely education (*lnEDU*), share of the number of ICT employees (*lnICT*), and green technology innovation (*lnGTI*). In this case, education is measured by the average number of years of education, specifically by calculating the average number of years of schooling for all educated people (Wang et al., 2022a). Following Xu et al. (2023), Yang and Wang (2022), Chen et al. (2023b), and Yu et al. (2023a), green technology innovation is proxied by the number of green patent applications. This is due mainly to the fact that green patents can most intuitively reflect the output of enterprises' green technology innovation activities and have a clear technology classification, revealing the different value connotations and contributions of innovation activities (Feng et al., 2022).

3.3. Data sources

This paper explores the impact of the information benefiting people policy on GTFP using panel data from 2006 to 2019 for 282 prefecture-level cities in China. The undesired output of carbon dioxide emissions for calculating the dependent variable is obtained from manual collation by the authors according to IPCC calculation. The data of green patent applications come from the CNOpenData database.[4] Data for all the other variables are obtained from the China City Statistical Book (NBS, 2020). The basic descriptive statistics of the main variables are listed in Table 1.

4. Empirical results and discussion

4.1. Benchmark results

To assess the impact of the information benefiting people policy on GTFP, we estimated it through an econometric model, and present the results in Table 2. Column (1) shows the results of fixed-effects estimation without control variables; column (2) shows the results of random-effects estimation; columns (3) and (4) show the results fixed for the time and individuals, respectively; and column (5) shows the results of double fixed for time and individuals. We observe that the coefficient of the interaction term *DID* is highly positive, indicating that the information benefiting people policy significantly increases GTFP in the pilot cities. The coefficient of *DID* in column (5) is 0.057, which is significant at the 1% level of significance, meaning that the level of GTFP in the pilot cities increases by 5.7% relative to the non-pilot cities. From the policy documents of the national pilot cities of information benefiting people, we can see that the pilot cities will focus on resource integration, realize the centralized collection of basic information, and accelerate resource sharing, which will reduce waste and promote the efficient use of resources. The implementation of information benefiting people policy can enhance the convenience and efficiency for citizens to access information, making it easier for the public to comprehend and utilize information related to green production technologies and products. Furthermore, it promotes the production efficiency of green enterprises. Additionally, the government can strengthen the supervision and management of green production by conducting online monitoring and disclosing information, to prevent environmental pollution and other related issues, and improve the efficiency of green production (Chang et al., 2022; Eisner, 2004). In addition, the information benefiting people policy has accelerated the innovative use of space and the level of information-based offices. Computers, ICT products, and big data services are rapidly applied to city government departments and enterprises, promoting paperless offices and improving green efficiency. Therefore, informatization policies are confirmed by theory and empirical evidence to be conducive to green development. Many scholars have supported this view (Debbarma et al., 2022; Tian and Pang, 2022; Wang et al., 2021a), but exploring it through a policy perspective is still an innovative initiative.

Table 1
Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
lnGTFP	3948	0.2376	0.2666	−0.8376	2.2809
DID	3948	0.1094	0.3122	0.0000	1.0000
lnPGDP	3948	10.1353	0.7868	7.8198	12.7174
lnINV	3920	13.4716	1.3840	4.3567	17.2958
lnIND	3948	5.4195	0.0629	5.2100	5.6462
lnENT	3945	6.5463	1.1227	2.9444	9.8412
lnFIS	3948	14.4537	0.9464	10.9619	18.2405
lnEDU	3948	5.9489	0.7826	2.8587	8.2012
lnICT	3948	0.0641	0.5246	−3.0808	2.3848
lnGTI	3889	3.6902	0.9325	2.9957	8.8743

4.2. Test on policy effectiveness

To further explore the effective impact of the policy, this paper uses the event study method to explore the differences between the treatment and control groups before and after the impact of the policy. The specific test equation is as follows:

$$lnGTFP_{it} = \delta_0 + \sum_{k=-8}^{5} \gamma_k D_{i,m+k} + \sum_{h=1}^{5} \delta_h X_{it,h} + \theta_i + \eta_t + \varepsilon_{it} \tag{7}$$

Herein, δ_0 is a constant term, $\delta_1, \cdots, \delta_5$ are the estimated coefficients of the control variables. $D_{i,m+k}$ is a dummy variable, m denotes the year in which the information benefiting people policy was implemented, k denotes the year after the reform was implemented. $D_{i,m+k}$ is equal to 1 when the treatment group's city implemented the policy after k year, and 0 otherwise. Therefore, γ_k represents the difference in GTFP between the treatment group and the control group in k year after the implementation of the information benefiting people policy. The research time span is from 2006 to 2019, and the time of the reforms is 2014, so the value range of k is [−8,5]. Here, to eliminate the effect of multicollinearity, we remove one period before the start of the policy in the model.

Fig. 2 presents the results of the parallel trend test, and shows that the test coefficients are not significant before the policy started, indicating that there is no significant difference between the treatment and control groups. In the third year after the policy started, the estimated coefficient significantly rejects the null hypothesis, indicating a significant difference between the treatment and control groups. In other words, in the third year after the implementation of the information benefiting people policy, the effect of the policy on the promotion of GTFP began to appear. The promotion of information technology, resource integration, and inclusive services by the policy only highlights its benefits on their green impact effects after two years, which explains

[4] See https://www.cnopendata.com/.

Table 2
The main results of information benefiting people on GTFP.

Dependent variable: *lnGTFP*					
Variable	(1)	(2)	(3)	(4)	(5)
DID	0.076*** (0.0115)	0.045*** (0.0110)	0.039*** (0.0112)	0.071*** (0.0130)	0.057*** (0.0114)
lnPGDP		0.202*** (0.0149)	0.299*** (0.0268)	0.122*** (0.0071)	0.244*** (0.0344)
lnINV		−0.026*** (0.0063)	−0.031*** (0.0066)	0.002 (0.0059)	−0.034*** (0.0066)
lnIND		0.088 (0.1120)	−0.030 (0.1264)	0.292*** (0.0858)	−0.432*** (0.1555)
lnENT		−0.086*** (0.0078)	−0.089*** (0.0111)	−0.040*** (0.0057)	−0.087*** (0.0124)
lnFIS		0.081*** (0.0100)	0.039** (0.0158)	−0.017* (0.0093)	−0.039* (0.0207)
_cons	0.229*** (0.0028)	−2.551*** (0.5497)	−2.188*** (0.6186)	−2.120*** (0.4115)	1.695* (0.9487)
Year fixed effect	Yes		No	Yes	Yes
City fixed effect	Yes		Yes	No	Yes
R^2	0.6560		0.6423	0.3038	0.6672
Log *likelihood*		1281.813			
Obs	3948	3917	3917	3917	3917

Notes: Robust standard errors in parentheses; *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

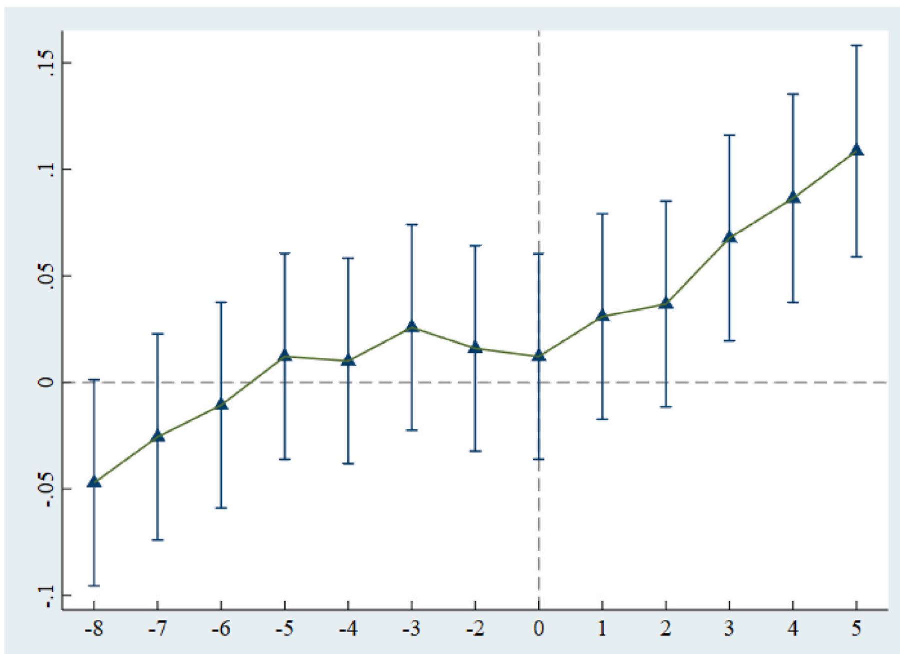

Fig. 2. Results of the parallel trend test.

why the policy's green impact has a slight lag.

4.3. Robustness check

4.3.1. Placebo tests

First, we perform a placebo test. The placebo test is used to ensure that the DID regression results are not influenced by factors such as other unobservable urban characteristics (Lee et al., 2022). It is tested as follows: we randomly select 500 samples from 282 cities, and in each sample, 80 cities are randomly selected as the dummy treatment group, and the remaining cities are used as the control group for DID estimation. We note that the kernel density distribution of the coefficients and the p-values (in Fig. 3) are concentrated around 0 and the principle original estimated coefficients, which confirms the robustness of the results.

4.3.2. Replacing the dependent variable

Next, we will introduce three robustness tests in Table 3. First, we replace carbon dioxide emissions with $PM_{2.5}$ emissions in calculating the undesired output of GTFP and recalculate the data of GTFP using the GML method as a new dependent variable. The estimated results are presented in column (1) of Table 3, where the coefficient of the dummy variables (*DID*) shows significant positivity, indicating that cities under policy shocks significantly increase the level of GTFP. This is consistent with the results of the benchmark regression.

4.3.3. Other policy disruptions

In 2013, China's State Council released the implementation plan for the "Broadband China" strategy, which aims to enhance the country's information infrastructure and support the development of the Internet of Things, cloud computing, and other advanced technologies. From 2014 to 2016, China released three batches of "Broadband China" pilot cities in succession, so we create broadband dummy variables (*Broadband*), set the pilot cities to 1 after the pilot year, and add them to the original DID model for estimation. The results are listed in column (2) of Table 3. The coefficient of the dummy variable of the information benefiting people policy remains significantly positive, which indicates that the interference of the "Broadband China" pilot policy did not affect the information benefiting people policy in promoting GTFP.

In 2011, 2014, and 2017, the country released three batches of national e-commerce demonstration cities in succession. According to the policy instructions, the pilot cities will play a prominent role in opti-

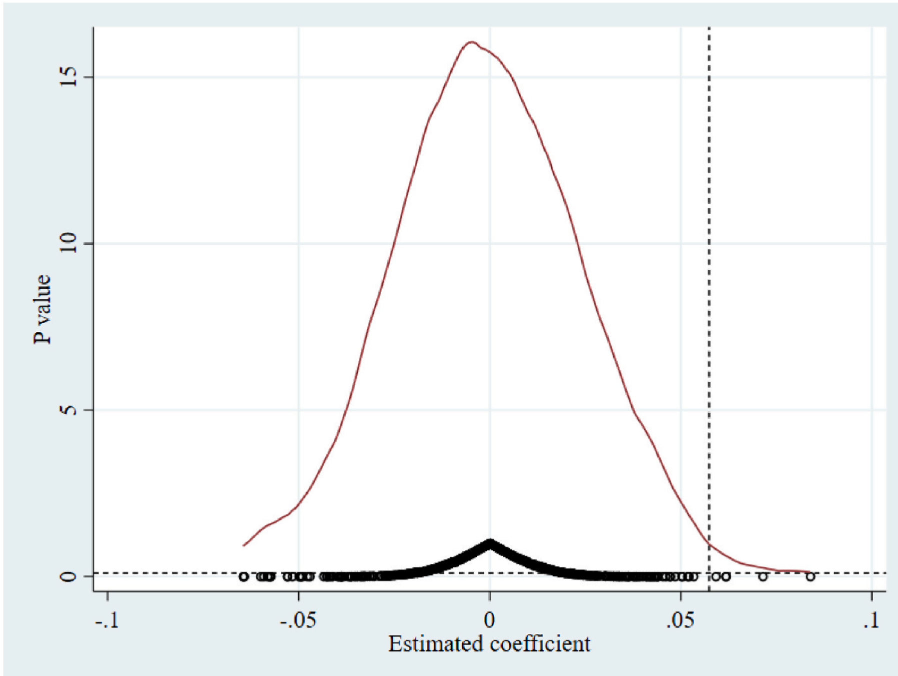

Fig. 3. Placebo test for lnGTFP.

Table 3
Results of robustness checks.

Dependent variable: *lnGTFP*							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DID	0.078*** (0.0114)	0.049*** (0.0120)	0.050*** (0.0124)	0.056*** (0.0115)	0.055** (0.0225)	0.047*** (0.0170)	0.026** (0.0130)
Broadband		0.025** (0.0107)					
Ecommerce			0.019 (0.0127)				
Lowcarbon				0.018* (0.0101)			
$DID_{i,\ t\text{-}1}$					0.003 (0.0222)		
$DID_{i,\ t\text{-}2}$						0.013 (0.0170)	
lnPGDP	0.302*** (0.0342)	0.245*** (0.0344)	0.247*** (0.0345)	0.240*** (0.0345)	0.244*** (0.0344)	0.245*** (0.0344)	0.186*** (0.0572)
lnINV	−0.036*** (0.0065)	−0.034*** (0.0066)	−0.034*** (0.0066)	−0.034*** (0.0066)	−0.034*** (0.0066)	−0.034*** (0.0066)	−0.028*** (0.0094)
lnIND	−0.387** (0.1544)	−0.422*** (0.1555)	−0.418*** (0.1558)	−0.409*** (0.1560)	−0.432*** (0.1555)	−0.432*** (0.1555)	−0.152 (0.2969)
lnENT	−0.098*** (0.0124)	−0.087*** (0.0124)	−0.086*** (0.0125)	−0.085*** (0.0125)	−0.087*** (0.0125)	−0.087*** (0.0125)	−0.057*** (0.0200)
lnFIS	−0.026 (0.0205)	−0.037* (0.0207)	−0.040* (0.0207)	−0.041** (0.0207)	−0.039* (0.0207)	−0.039* (0.0207)	0.059* (0.0332)
_cons	0.782 (0.9417)	1.605* (0.9490)	1.596* (0.9509)	1.623* (0.9493)	1.694* (0.9490)	1.678* (0.9490)	−0.932 (1.8134)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.6968	0.6676	0.6673	0.6674	0.6641	0.6672	0.7876
Obs.	3917	3917	3917	3917	3917	3917	1974

Notes: Robust standard errors in parentheses; *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

mizing resource allocation, enhancing industrial structure, and driving employment, thus achieving the purpose of reducing energy consumption and developing a green economy. Cao et al. (2021) have pointed to the significant effect of national e-commerce demonstration cities in reducing GTFP. Therefore, we construct a new dummy variable (*Ecommerce*), setting the pilot city to 1 for the pilot time horizon, and 0 for the others, to be added to the original model. We present the estimation results in column (3) of Table 3. We note that the coefficient of *DID* is still significantly positive at the 1% level, which indicates that the disturbance of the new policy did not affect the green efficiency improvement of the original policy.

Another pilot policy that aims to build a green-friendly society is the low-carbon pilot city policy. In 2010 and 2012, the country released two batches of pilot cities. These cities will be favored by the low-carbon policy to build a low-carbon-led industrial system and consumption pattern to promote green urban development. Qiu et al. (2021) and Liu et al. (2020) confirm that the low-carbon pilot policy helps raise GTFP levels by using a DID model. Therefore, we add the dummy variable of low-carbon pilot cities to the original model (*Lowcarbon*), and again this variable is set to 1 for pilot cities and pilot times, and 0 for others. The estimation results are presented in column (4) of Table 3 and show that the coefficient of *DID* remains positive, which indicates that the low-carbon pilot cities do not interfere with the benchmark regression results of this paper.

4.3.4. Expectation effect test

We are trying to exclude the case that the pilot cities take early deployment in anticipation of the implementation of the policy, leading to the formation of the expected effect. Columns (5) and (6) of Table 3 include first-order and second-order lags of the dummy variable *DID* ($DID_{i,t-1}$ and $DID_{i,t-2}$), respectively, to re-estimate the policy effects (Yang and Wang, 2022). The results show that the coefficients of the *DID* are all significantly positive and the coefficients of the lagged terms are all insignificant, which indicates that the cities do not produce the expectation effect of the information benefiting people policy.

4.3.5. Shortening the observation period

In the context of event study methodology, a prolonged observation period may lead to imprecise results. To address this issue, we reduced the observation window to only include data from the three periods prior to and after the policy implementation, and performed a re-estimation. The estimated results are presented in column (7) of Table 3, with the coefficient of *DID* remaining positive and significant. Furthermore, we conducted a parallel trends test, as shown in Fig. 4. We observed a significant divergence between the treatment and control groups in the third period after the policy implementation. Thus, after narrowing the observation window, the pilot policy was found to effectively promote the improvement of GTFP.

4.3.6. Additional unobserved confounding variables

We must acknowledge the fact that the section of pilot cities is not completely exogeneous; when selecting pilot cities, the state takes into account a city's economic development, urban population, and political status, which leads to some selective bias in the estimation results of the DID model. Heckman et al. (1997) and Heckman et al. (1998) point out that the pilot cities can be matched using certain confounding variables to find similar state treatment and control groups for estimation, which is the basic principle of the propensity score matching (PSM)-DID model. In this paper, we select five confounding variables based on policy requirements and national pilot planning policies, namely, the level of economic growth (*PGDP*), the number of international Internet users (*INTER*), local fiscal general budget expenditures (*FIS*), the number of year-end cell phone subscribers (*PHONE*), and scientific expenditures (*SCI*). The bias of the confounding variables was significantly lower in both the matched treatment and control groups, as shown in Fig. 5. Here we choose mainly kernel matching (the estimated results are shown in column (1) of Table 4), 1:2 nearest neighbor matching (the estimated results are shown in column (2) of Table 4), and 1:3 nearest neighbor matching methods (the estimated results are shown in column (3) of Table 4). Their results show that the coefficients of $PSM - DID$ are all significantly positive, which indicates that the results of the benchmark regression in this paper are robust.

4.4. Mechanism tests

To further assess the mechanism of the impact of the information benefiting people policy on GTFP, this paper uses a mediating effect model to evaluate three paths, namely education (*lnEDU*), the share of the number of ICT employees (*lnICT*), and green technology innovation (*lnGTI*). Table 5 shows the results of the mediating effects. Columns (1) and (2) show the results of the two-step estimation of education as a mediating variable. Columns (3) and (4) show the results of the two-step estimation of the share of the number of ICT employees as a mediating variable. Columns (5) and (6) show the results of the two-step estimation of green technology innovation.

First, column (1) of Table 5 demonstrates the impact of the pilot policy shock on education level; the coefficient of *DID* is significantly positive, indicating that government informatization effectively promotes the positive development of education level. This might be as a result of the increased bar for hiring by businesses and increased alignment between the educational system and society brought about by the amount of informatization in society (Donahue et al., 2000). The coefficient of education in column (2) is significantly positive, indicating that education contributes significantly to the growth of the GTFP level. This study shows that improving education will contribute to the upgrading of China's industrial structure, the growth of the technological level, and improved environmental awareness, which in turn will contribute to China's green development (Liu et al., 2022a). Therefore, we can conclude that the information benefiting people policy will accelerate the GTFP level by promoting education enhancement.

Second, we investigated the function of mechanisms in determining the share of the number of ICT employees. The coefficient of *DID* in column (3) of Table 5 is significantly positive, indicating that the information benefiting people policy effectively promoted the share of the number of ICT employees. This is not difficult to understand because the policy requires accelerating the degree of informatization of the

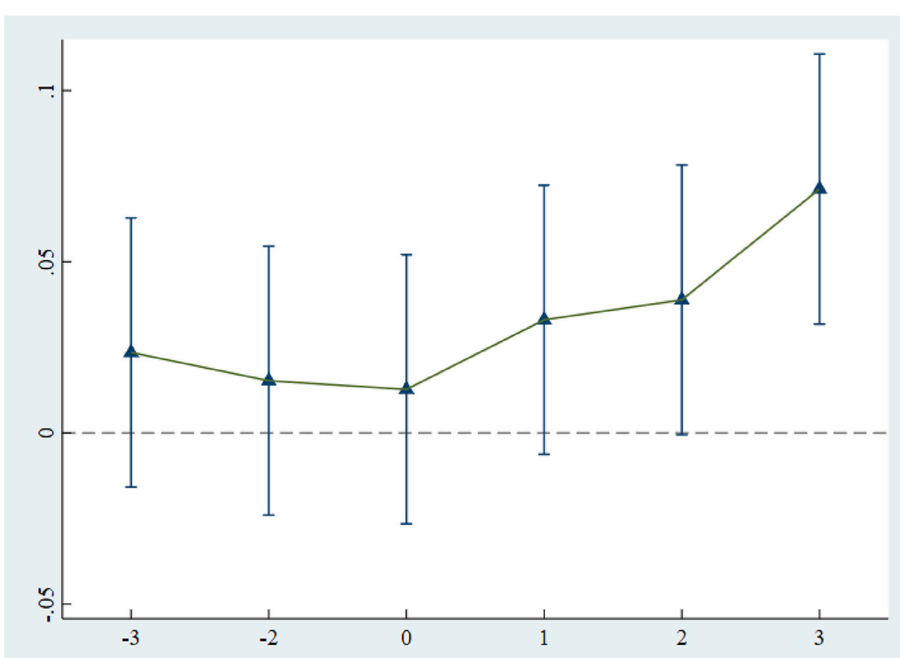

Fig. 4. Results of the parallel trend test for shortening the observation period.

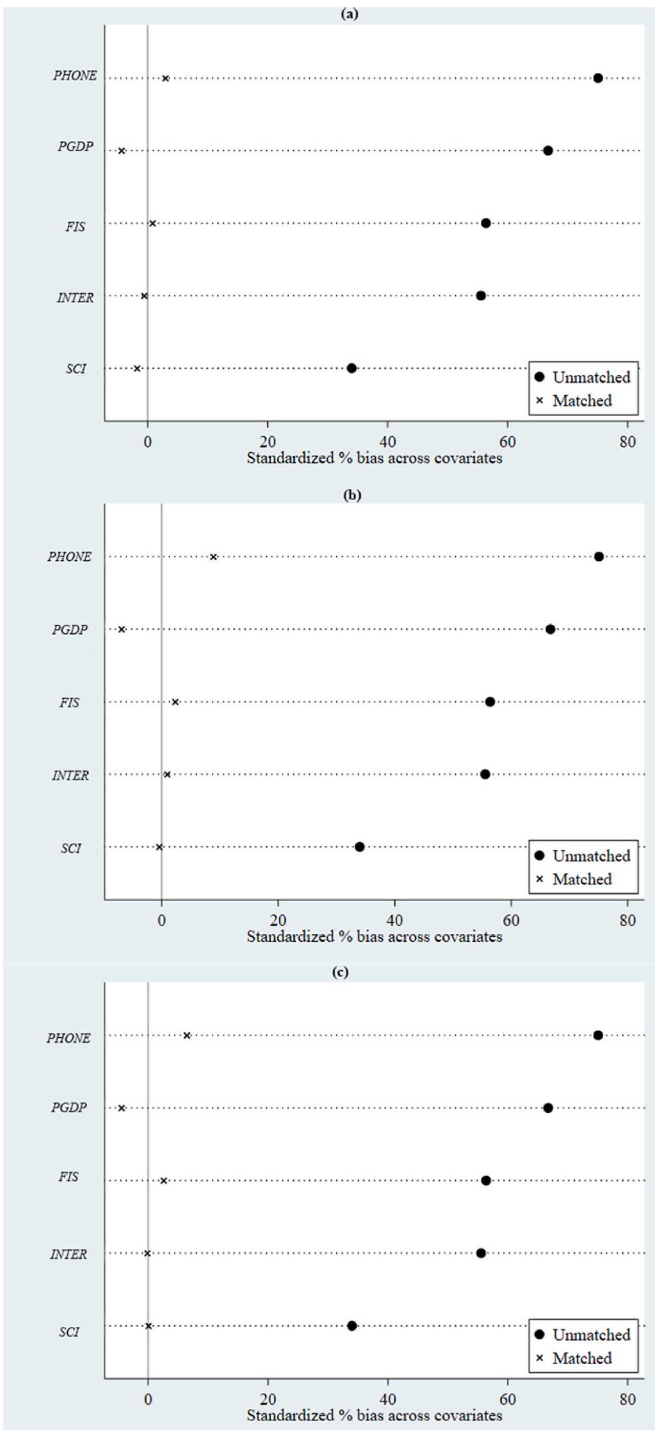

Fig. 5. Bias before and after matching.

government and enterprises to avoid the formation of information silos, which will certainly introduce a large number of ICT products, including electronic equipment, cloud computing equipment, and Internet of Things devices, etc., thereby increasing the number of employees in the ICT industry. The *lnICT* coefficient in column (4) is significantly positive, further confirming that the share of the number of ICT employees is conducive to a rapid increase in GTFP levels. The growth of ICT employment reflects, to a certain extent, the level of development of the ICT industry and the increase in the scale of the industry. Hao et al. (2022) state that ICT industry development will promote economic development, green energy utilization technology, and industrial

Table 4
Results of PSM-DID model.

Dependent variable: *lnGTFP*			
Variable	(1)	(2)	(3)
PSM-DID	0.028* (0.0168)	0.030** (0.0143)	0.037*** (0.0126)
lnPGDP	0.360*** (0.0679)	0.355*** (0.0569)	0.305*** (0.0486)
lnINV	−0.046*** (0.0128)	−0.050*** (0.0103)	−0.049*** (0.0089)
lnIND	−0.904** (0.3486)	−0.371 (0.3532)	−0.395 (0.2968)
lnENT	−0.080*** (0.0200)	−0.103*** (0.0192)	−0.085*** (0.0169)
lnFIS	−0.033 (0.0283)	−0.015 (0.0288)	−0.026 (0.0234)
_cons	3.092* (1.8714)	0.186 (2.0815)	0.869 (1.7165)
Year fixed effect	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes
R^2	0.7153	0.7020	0.7056
Obs.	1433	1885	2247

Notes: Robust standard errors in parentheses; *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

structure optimization to achieve a GTFP enhancement effect. Therefore, we believe that the information benefiting people policy will promote the level of GTFP by boosting the share of the number of ICT employees.

Finally, we test the effectiveness of the mechanism of green technology innovation. In column (5) of Table 5, the coefficient of *DID* is significantly positive, indicating that the information benefiting people policy has effectively promoted the level of green technology innovation in local cities. This is due to the policy-led cities that will facilitate the integration of innovative resources to enhance the development of green buildings, investments, and services, such as the rise of green service platforms. In addition, column (6) shows the significant contribution of green technology innovation to GTFP. Wang et al. (2021b), Jiakui et al. (2023), and Zhao et al. (2022b) also confirm the accuracy of this paper's results. This is because the significant improvement in technology innovation has greatly reduced the costs of green production, increased production profits, and accelerated the transformation and upgrading of the green economy. Therefore, we can determine that the information benefiting people policy will improve GTFP by promoting the level of green technology innovation in society.

Fig. 6 is also drawn to facilitate readers' understanding of the mechanism path of this paper.

4.5. *Heterogeneity tests*

4.5.1. *Tests of regional heterogeneity*

We divided the cities in the corresponding provinces into three groups, namely, eastern cities, central cities, and western cities. Specifically, column (1) in Table 6 presents the estimated results for the eastern region; column (2) shows the estimated results for the central region, and column (3) presents the estimated results for the western region. We note that the coefficient of *DID* is significantly positive for the eastern and western cities, but the coefficient of the dummy variable is not significant for the central cities. This suggests there is significant heterogeneity in the impact of the information benefiting people policy on GTFP across regions in China, with policy shocks having a more significant positive effect on increasing GTFP levels in the eastern and western regions. The explanation that exists is that the abundant information resources in the eastern region have facilitated faster local implementation of policy measures, industrial layout, and green development. The central region, on the other hand, may have received a large transfer of energy-intensive industries from the eastern region, with a lower role for information benefiting people policy. Finally, although the western region has also played a role in promoting GTFP, the role is lesser than the eastern region, and the long-term development of information technology policy will benefit the green development of

Table 5
Results of mediating effects.

Dependent variable	*lnEDU*	*lnGTFP*	*lnICT*	*lnGTFP*	*lnGTI*	*lnGTFP*
Variable	(1)	(2)	(3)	(4)	(5)	(6)
DID	0.115*** (0.0085)	0.043*** (0.0117)	0.182*** (0.0236)	0.046*** (0.0114)	0.365*** (0.0234)	0.048*** (0.0117)
lnEDU		0.122*** (0.0222)				
lnICT				0.064*** (0.0080)		
lnGTI						0.020** (0.0081)
lnPGDP	−0.431*** (0.0257)	0.297*** (0.0356)	−0.235*** (0.0710)	0.259*** (0.0342)	−0.538*** (0.0706)	0.266*** (0.0345)
lnINV	0.025*** (0.0049)	−0.037*** (0.0066)	−0.015 (0.0136)	−0.033*** (0.0065)	0.056*** (0.0137)	−0.034*** (0.0066)
lnIND	0.405*** (0.1160)	−0.482*** (0.1552)	−0.600* (0.3207)	−0.394** (0.1543)	−0.592* (0.3257)	−0.478*** (0.1580)
lnENT	0.018* (0.0093)	−0.089*** (0.0124)	−0.074*** (0.0257)	−0.082*** (0.0124)	−0.099*** (0.0256)	−0.085*** (0.0125)
lnFIS	0.049*** (0.0154)	−0.045** (0.0206)	−0.061 (0.0426)	−0.036* (0.0205)	0.044 (0.0428)	−0.043** (0.0208)
_cons	6.956*** (0.7079)	0.848 (0.9575)	7.252*** (1.9565)	1.233 (0.9424)	11.568*** (1.9839)	1.690* (0.9666)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.9790	0.6698	0.6410	0.6728	0.8890	0.6772
Obs.	3917	3917	3917	3917	3858	3858

Notes: Robust standard errors in parentheses; *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

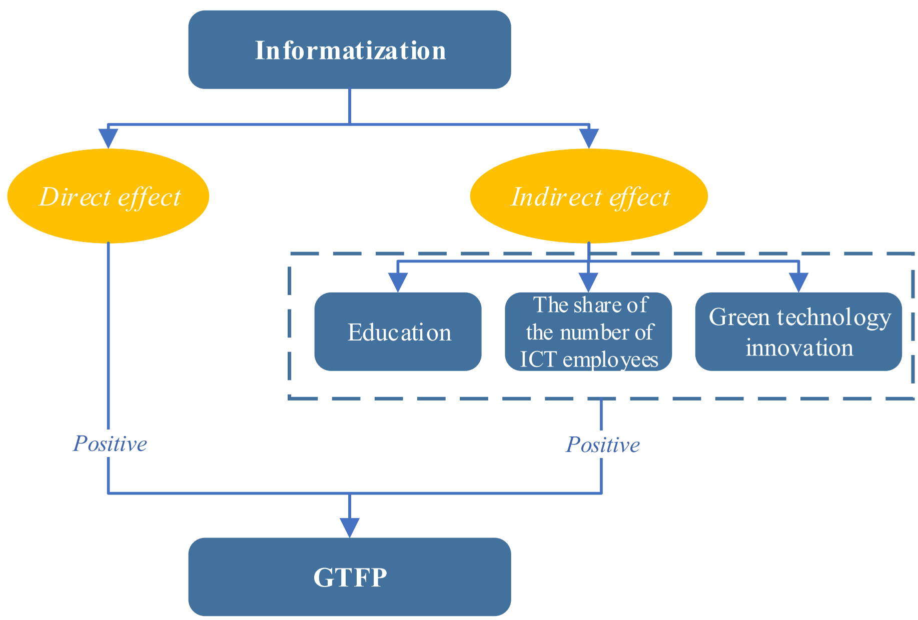

Fig. 6. Impact mechanism between informatization and GTFP.

Table 6
Results of regional heterogeneity test.

Dependent variable: *lnGTFP*			
Variable	Eastern cities	Central cities	Western cities
	(1)	(2)	(3)
DID	0.098*** (0.0201)	0.018 (0.0184)	0.041* (0.0214)
lnPGDP	0.017 (0.0805)	0.302*** (0.0477)	0.319*** (0.0700)
lnINV	0.014 (0.0162)	−0.046*** (0.0098)	−0.046*** (0.0105)
lnIND	−0.280 (0.3376)	−0.183 (0.2251)	−0.995*** (0.3030)
lnENT	−0.044* (0.0246)	−0.103*** (0.0213)	−0.152*** (0.0243)
lnFIS	−0.018 (0.0393)	−0.037 (0.0378)	−0.091** (0.0356)
_cons	1.986 (2.0634)	0.015 (1.3780)	5.207*** (1.9254)
Year fixed effect	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes
R^2	0.6136	0.6928	0.7057
Obs.	1397	1380	1140

Notes: Robust standard errors in parentheses; *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

the western region.

4.5.2. *Tests for heterogeneity of city scale*

Columns (1) and (2) of Table 7 show the estimation results for the large cities group and the small cities group. For the classification criteria of city scale, we refer to *Notice on Adjusting the Criteria for Urban Planning*.[5] Among them, municipality- or prefecture-level cities with a population greater than one million are defined as large cities. The results show that although the coefficients of the dummy variables are significantly positive for both the large and small cities groups, the coefficients of the dummy variables are higher for the small cities group. This may be because information and resources are more easily integrated in smaller cities, which is more conducive to comprehensive governmental information transformation and more effective policies.

4.5.3. *Tests for heterogeneity of city characteristics*

In 2013, the State Council released the *National Old Industrial Base Adjustment and Transformation Plan (2013–2022)*, which selected 120

[5] http://www.gov.cn/zhengce/content/2014-11/20/content_9225.htm.

Table 7
Results of heterogeneity of city characteristics.

Dependent variable: *lnGTFP*				
Variable	Big cities	Small cities	Old industrial base	Non-old industrial base
	(1)	(2)	(3)	(4)
DID	0.026** (0.0128)	0.070*** (0.0215)	0.012 (0.0183)	0.085*** (0.0142)
lnPGDP	0.181*** (0.0431)	0.308*** (0.0549)	0.384*** (0.0490)	0.117*** (0.0450)
lnINV	−0.051*** (0.0100)	−0.035*** (0.0092)	−0.033*** (0.0105)	−0.032*** (0.0082)
lnIND	−1.324*** (0.2024)	0.352 (0.2377)	−0.355 (0.2250)	−0.033 (0.2042)
lnENT	−0.134*** (0.0155)	−0.039** (0.0198)	−0.013 (0.0178)	−0.143*** (0.0163)
lnFIS	−0.042* (0.2569)	−0.022 (0.0329)	−0.067** (0.0299)	0.023 (0.0272)
_cons	7.868*** (1.2024)	−3.755** (1.4676)	−0.201 (1.3830)	0.245 (1.2378)
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
R^2	0.7012	0.6506	0.7456	0.6322
Obs.	2124	1793	1317	2600

Notes: Robust standard errors in parentheses; *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

prefecture-level cities as the focus of the transformation of old industrial bases.[6] According to the planning instructions, these cities have obvious characteristics of declining or stagnant leading industries, and thus their industrial transformation and renovation face certain difficulties. In this paper, 282 cities are classified into old industrial-based cities and non-old industrial-based cities according to the classification criteria in the above document, and they are estimated separately. Columns (3) and (4) of Table 7 show that the coefficient of the dummy variable for the non-old industrial-based cities is significantly positive, while the coefficient of the dummy variable for the old industrial-based group is not significant. This indicates that the effect of the information benefiting people policy is limited to regions with more solid energy-intensive industries, and stronger policy measures are needed to promote the optimization of their resource allocation.

4.6. Spatial spillover tests

We further consider whether the pilot policy is likely to have a spatial spillover effect on GTFP. Table S1 and Fig. S1 show the results of the global and local Moran's I test, and confirm that spatial autocorrelation exists in China's GTFP (see Supplementary Material). Further, we determine the choice of spatial model for this research through a series of tests, and the results are shown in Table 8. The Lagrange Multiplier (LM) and robust LM tests show significant spatial lag effects for GTFP, and thus, the spatial model is further considered. The LR and Wald tests show significant statistics, thus rejecting the null hypothesis that the SDM could be transformed into an SEM and SLM. The Hausman test statistic is at the 1% significance level, so the fixed-effects SDM is chosen.

Columns (1) and (2) of Table 9 show the results of SDM estimation using 01 weight matrix and geographical weight matrix, respectively. The estimated results show that the coefficient of *DID* is significantly positive, which is consistent with the results of the benchmark regression. The coefficient of the spatial lag term ρ is significantly positive, which represents a positive association of GTFP among neighboring cities. From the decomposition terms, the coefficient of the direct effect is significantly positive, and the coefficient of the indirect effect is significantly negative. This suggests the impact of the information benefiting people policy has contributed to the growth of the local GTFP and reduced the level of GTFP in neighboring cities. There may be two reasons for this. One is that the pilot cities were influenced by the policy and began to actively deploy a large number of information technology industries, and moved a large number of heavy industries and energy-intensive industries out to the surrounding cities, causing a decline in GTFP in the surrounding cities. On the other hand, the pilot cities will cause an agglomeration of ICT industries, attracting a large number of skills and talents and promoting high-quality economic development (Wang et al., 2022b), but this will result in the loss of a large number of skills and talents from the surrounding cities. Furthermore, information benefiting people policy aimed at promoting social welfare have led to an increase in competitiveness among local businesses, which has created a certain amount of competitive pressure on enterprises in surrounding cities. Given that China's information benefiting people policy has tended to focus on cities with more developed local resources within the province, the lack of equivalent policy support for enterprises in surrounding cities can result in a decline in their green benefits.

Table 8
Test results of spatial econometric model selection.

	01 weight matrix		Geographic weight matrix	
	Statistics	P-value	Statistics	P-value
LM_lag	224.864	0.000	224.86	0.000
LM_err	377.336	0.000	377.336	0.000
Robust_LM_lag	19.785	0.000	19.785	0.000
Robust_LM_err	172.257	0.000	172.257	0.000
LR_lag	5.39	0.0203	7.35	0.0067
LR_err	4.43	0.0353	3.65	0.0562
Wald_lag	17.04	0.0091	16.45	0.0115
Wald_err	20.14	0.0026	19.15	0.0039
Hausman	23.60	0.0006	145.78	0.0000

Table 9
Results of SDID model regression.

Dependent variable: *lnGTFP*		
	01 weight matrix	Geographic weight matrix
	(1)	(2)
DID	0.042*** (0.0112)	0.049*** (0.0113)
lnPGDP	0.258*** (0.0288)	0.202*** (0.0296)
lnINV	−0.044*** (0.0068)	−0.041*** (0.0067)
lnIND	0.555 (0.1411)	0.018 (0.1541)
lnENT	−0.050*** (0.0086)	−0.040***(0.0084)
lnFIS	0.008 (0.0170)	−0.016 (0.0169)
*W*DID*	−0.049** (0.0213)	−0.105*** (0.0386)
ρ	0.118*** (0.0235)	0.674*** (0.0512)
Direct effect	0.041*** (0.0114)	0.049*** (0.0116)
Indirect effect	−0.048** (0.0236)	−0.219* (0.1157)
Total effect	−0.007 (0.0265)	−0.170 (0.1162)
Year fixed effect	Yes	Yes
City fixed effect	Yes	Yes
R^2	0.2600	0.2666
Obs.	3384	3384

Notes: Robust standard errors in parentheses; *, **, and *** represent the significance at 10%, 5%, and 1% levels, respectively.

5. Conclusions and policy implications

In this study, we use panel data from 282 Chinese cities and a DID model to assess the effect of the information benefiting people policy on GTFP. Additionally, we evaluate their mechanism, heterogeneity, and spatial spillover effects. We came to the following research conclusions.

First, in the framework of IPAT theory, the information benefiting

[6] https://www.ndrc.gov.cn/xxgk/zcfb/ghwb/201304/t20130402_962134.html?code=&state=123.

people policy considerably contributes to greater GTFP levels in the pilot cities, and the results of the parallel trend test indicate that there is a two-year lag in the influence of the policy. Second, by encouraging the advancement of education, promoting the share of the number of ICT employees, and green technology innovation, the information benefiting people policy achieves rapid growth of GTFP. Third, the results from the heterogeneous analysis indicate that policies have the most impact on increasing GTFP in the eastern cities; small cities and non-old industrial-based cities are more vulnerable to the environmental effects of policies. Finally, there is a significant spatial spillover effect on the impact of the information benefiting people policy on GTFP; specifically, the policy drives a significant increase in local GTFP levels but causes a decrease in GTFP levels in neighboring cities.

The information benefiting people policy advocates the construction of technology-oriented information and reform by local governments, thus achieving the purpose of promoting high-quality economic and environmental development. The results of this paper confirm this argument, which suggests that the Chinese government's implementation of the information benefiting people policy is beneficial to the development of the local green economy. The Chinese government needs to do the following three things in the future to ensure sustainable development with the policy support of information technology. First, it is crucial for the government to implement the information benefiting people policy consistently throughout the country. This will have several benefits, including increased productivity for both government and businesses, and a reduction in information asymmetry and resource waste. To achieve this, the government should prioritize investment in the construction of information technology infrastructure, including high-speed interconnected networks, network security, and policies aimed at disseminating information for public benefit. Furthermore, the government should focus on strengthening the construction of information technology systems for government affairs. This means promoting the transition of government services towards digitization, networking, and intelligence. By doing so, the government can enhance the efficiency and quality of public service delivery, while improving ecological conditions. This will not only benefit the public but also help the government in achieving its goals in a more effective and efficient manner.

Second, to ensure the successful implementation of information policies and achieve their intended benefits, the government should prioritize education, science, and technology, as well as green supporting policies. It is crucial to invest in cultivating technical professionals in the information-related fields and improving the quality of talent. The government can attract high-quality talent to the information sector by providing attractive incentives and career development opportunities. Furthermore, the government must increase its funding for information technology patents and projects, encourage corporate initiative, and promote investment in research and innovation. This will accelerate the dissemination of government information technology and promote coordinated development of a green economy between the government and enterprises.

Third, the government must be mindful of the potential impact of the information policy that benefits people on the outflow of talent from neighboring technology cities, which could lead to the formation of a technological island. To avoid this, inter-regional governments should work together to deploy resources, complement each other's strengths, and synchronize policies to promote green and sustainable development. For instance, provinces with robust information technology capabilities can establish cooperative industrial parks with neighboring cities, enhance interregional industrial connectivity, and leverage each other's strengths to expand the scope of green industrial services. This approach will promote comparative advantages among industries and foster a collaborative environment for innovation and growth.

Credit author statement

Xi Chen: Data curation, Methodology, Writing - Original Draft, and Supervision; **Jianda Wang:** Conceptualization, Methodology, Validation, Writing - Original Draft, and Writing - Review & Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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