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Does green innovation induce green total factor productivity? Novel findings from Chinese city level data

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A B S T R A C T

Improving green total factor productivity (GTFP) is an important way to promote high-quality economic development. The "innovation dividend" based on green innovation is the key to enhancing green TFP. In this study, the effect of green innovation on GTFP in cities was empirically investigated. The results show that: (1) after including year and city-fixed effects and clustering over time and individuals, green innovation has a significant positive effect on GTFP. Financial development, population density, and environmental regulation correlate significantly negatively with GTFP, whereas urbanization promotes GTFP; (2) the effect of green innovation is more pronounced in the eastern region. The effect of green innovation on GTFP is more significant in non-resource-based cities or cities with higher levels of economic development or more government intervention; (3) the effect of green innovation on GTFP may be affected by the upgrading of industrial structure and innovation factor agglomeration. Cities where GTFP increases first have a first-mover advantage. After adding spatial factors to the model, a notable "positive spillover effect" of GTFP improvement can be observed in neighboring cities.

1. Introduction

The Chinese government is increasingly emphasizing high-quality economic development. The contribution of capital, labor, and other production factors to economic growth continues to decrease. If the growth of the Green Total Factor Productivity (GTFP) remains unchanged or even declines, the economic growth rate will surely slow down and continue to decline. If this situation continues for a long time, the economy will inevitably stagnate, and improving total factor productivity through technological innovation and efficiency improvement becomes the key to maintaining sustained economic growth (Romer, 1986; Mankiw et al., 1992).

In 2020, China's carbon dioxide emissions rank first worldwide, accounting for 9893.5 million tons. Faced with the urgent task of transforming production methods and improving the ecological environment, the 2021 Central Economic Work Conference has proposed that "*achieving peak carbon and carbon neutrality is an inherent requirement for promoting the high-quality development and should be strongly supported.*" The path to high-quality development with ecological priority and green and low-carbon development should be taken (Talwar et al., 2020; Cheng et al., 2021). In the stage of high-quality development, promoting technological innovation is the key to achieving harmony between economic development, resources, and the environment, thus enhancing GTFP. The main purpose of technological innovation in the traditional development model is simply to increase production and economic efficiency, which often results in the exchange of high pollution and high consumption for high economic efficiency, thus causing a series of ecological, environmental, and social problems. Green innovation reduces resource consumption and environmental costs of economic development while creating economic value, which could improve GTFP (Chen et al., 2019; Wurlod and Noailly, 2018; Zheng et al., 2021).

The term green innovation is used to describe technological innovations aimed at protecting the environment, with respect to new products or processes that contribute to sustainable development and environmental protection (Bernauer et al., 2007; Schiederig et al., 2012; Chaudhary et al., 2022). At present, the traditional development

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momentum of China's economy is constantly weakening, and the extensive growth mode is unsustainable. It must rely on green innovation to create a new development engine, so that China's economic growth will shift to a track that is more dependent on improving GTFP. Continuous innovation activities can enable innovation subjects to continuously understand and obtain innovative technological levels, thereby promoting the improvement of GTFP. Therefore, how to effectively allocate green innovation resources and optimize the green innovation structure to promote the improvement of GTFP is a major strategic issue that needs to be studied urgently to accelerate innovation-driven development (Begum et al., 2022; Khanra et al., 2022).

Numerous studies have explored the effect of green innovation on the GTFP (Wang et al., 2021a, 2021b; M. Wang et al., 2021; Saleem et al., 2019). However, despite excellent recent studies, the conclusions are inconsistent and diametrically opposed. In some of these studies, it has been concluded that green innovation notably affects TFP. For example, Wang et al. (2021a, 2021b) and M. Wang et al. (2021) argued that green innovation promotes the upgrading of industrial structures and improves the efficiency of energy use. They reported that green innovation has a significant positive effect on GTFP due to the spatial relationship among cities, but this positive effect is heterogeneous, and the influence of green innovation is more pronounced in eastern China. The results of another study showed that green innovation does not lead to the growth of TFP. For example, Rennings (2000) argued that the dual externality problem of green innovation causes the lack of incentives of firms to innovate. The lack of external incentives leads to green innovation, which is not effective. In addition, proponents of the “appropriateness” theory and the “Productivity Paradox” argue that it is difficult to match inappropriate green technological innovation with an economy's development stage and factor endowment structure, which will weaken the intrinsic motivation for technological innovation, and thus be detrimental to GTFP levels (Lin and Zhang, 2006).

Three methods can be used to measure the TFP index. The first is the Solow residual value method. In this method, after estimating the aggregate production function, the total factor productivity growth is measured using the residual value after deducting the growth rate of each input factor from the output growth rate (Solow, 1957). Due to the simplicity of the model and economic principles, this method has been used in numerous studies to measure the TFP (ten Raa and Shestalova, 2011; Awan et al., 2018; Madanaguli et al., 2021). The second method is the stochastic frontier analysis method. This method is used to estimate the TFP under technically inefficient conditions, which partially eliminates the effects of stochastic factors on the frontier production function component. However, both methods are parametric estimation methods and require a specific production function; therefore, it is difficult to guarantee results. The third method is a nonparametric method, represented by the DEA. Based on this method, first, a distance function is defined from the perspective of inputs or outputs, and then an index is constructed to measure the productivity based on the distance function (Liu et al., 2016; Wen et al., 2018). Existing studies on the treatment of environmental pollution in GTFP measurements within a Data Envelopment Analysis (DEA) framework broadly fall into two categories. One category introduces the effect of pollution emissions on the environment as an input factor in the production function (Chen et al., 2009; Ramanathan, 2005; Feng and Wang, 2019). The other category uses the proposed “directional distance function” by Chung et al. (1997) to include environmental pollution as a non-desired output in the DEA efficiency and productivity measurement model, which agrees with the actual production process. Currently, most studies use the directional distance function approach to include environmental pollution as a non-desired output to measure TFP (Chen et al., 2021; Zhu et al., 2018; Zhang and Vigne, 2021).

Existing studies have conducted preliminary discussions on the relationship between green innovation and GTFP. However, due to differences in indicator measurement, econometric models, and estimation methods, the impact of green innovation on GTFP is not clear and produces conflicting results. In addition, the mechanism of action at the micro and macro levels is not clear, which requires further discussion. The calculation of total factor productivity seldom considers resource and environmental constraints, and the non-radial and non-angular issues of the model. Given the limitations of existing studies, this study empirically examined the correlation between green innovation and GTFP growth based on data from 263 cities in China. The results provide new empirical evidence that reveals the factors that affect GTFP and a new analytical perspective to study the factors that affect GTFP in a broader sense. The main academic contributions of this study include the presentation of a more accurate measurement of green innovation. The green patent information for each city was collected and the overall patent quality of each city was measured by determining the knowledge width of each patent and the level of green innovation in each city was evaluated. The input–output data were then scientifically processed to fully consider environmental pollution. The unintended output SBM–DEA model was constructed. The Malmquist-Luenbergerproductivity index method was used to determine the GTFP of each sub-city more accurately in China. The direction and extent of the effect of green innovation on GTFP were measured by constructing an econometric panel model and heterogeneity analysis was performed based on different perspectives. In addition, the mechanisms underlying the effect of green innovation on GTFP were analyzed and the effects of the first-mover advantage and spatial factors on urban GTFP were discussed.

2. Theoretical analysis and research hypotheses

Currently, China faces multiple challenges, such as tightening energy supply, increasing energy demand, and increasingly stringent emission reduction requirements. In the high-quality development stage, improving the level of green innovation is the key to the growth of GTFP. The effect of the green innovation level on GTFP is reflected in the concentration of corporate innovation factors at the micro-level; in addition, it is reflected in the upgrade of the industrial structure at the macro-level.

First, regarding the concentration of corporate innovation factors at the micro-level, the level of regional innovation represents the degree of attention and support from the local government for green innovation. A good policy that supports the environment will increase the green development of enterprises and reduce the investment risks and costs of green innovation. In turn, the region became a “cradle” for the development of “three high” enterprises with high added value, high technology content, and high-tech innovation, thus attracting spontaneous clustering and synergistic development of innovative enterprises (Brandt et al., 2012). When the level of green innovation in a certain region is significantly higher than other regions, more innovation factors, such as talent, capital, technology, and green innovation enterprises, will return and accumulate at the growth pole as the region becomes a growth pole of green innovation (Myrdal and Sitohang, 1957). Continuous gathering of innovative enterprises and factors in the region will promote the labor division and cooperation among the innovative enterprises through the agglomeration effect, thus improving the independent innovation ability and production efficiency of enterprises (Hong et al., 2014; Jang et al., 2017). In addition, regional agglomeration of innovative enterprises will lead to innovation networks between regions and enterprises. Simultaneously, access to high-quality financial investment and human capital will be provided and further reduce the emissions of undesirable pollutants (Zeng et al., 2019).

The improvement of GTFP due to the upgrades of the technology-driven industrial structure is reflected in the strengthening of the industrial structure based on technological innovation. Based on the structural effect theory, the economic structure of a region will first undergo a transformation from agriculture to energy-intensive heavy industries and then to low-pollution services and knowledge-intensive industries (Grossman and Krueger, 1995). The evolution of the industrial structure is accompanied by a change in the GTFP. This is because production factors can move between industries or sectors of different productivity levels, from low to high productivity. For example, based on the binary economic structure model, the traditional agricultural sector in developing countries has a surplus labor force with zero marginal productivity. The aggregate productivity level increases when surplus labor is invested from the traditional agricultural sector to the modern industrial sector with higher productivity growth (Lewis, 1954). Based on Porter's hypothesis (Porter, 1991; Porter and van der Linde, 1995), the production costs and residual values of traditional high-energy-consuming industries are declining, whereas innovative industries are accelerating to a golden stage of development. Therefore, as the level of regional green innovation continues to improve and the demand for green products continues to flourish, a spontaneous flow of production factors will be generated in the green innovation industry, which will have a catalytic effect on GTFP. Based on the findings mentioned above, Hypothesis 1 is put forward.

Hypothesis 1. Green innovation in cities will promote GTFP.

Currently, sustainability of economic growth in a city will be guaranteed and improving GTFP through technological innovation will become the key to maintaining sustainable economic growth (Mankiw et al., 1992). Therefore, if a city has a high GTFP, the positive effect of innovation is high, mainly because of the benefits of the improved innovation environment. From the output perspective of GTFP accounting, GTFP growth implies an increase in desired output and a decrease in undesired output. Cities with a higher GTFP are more developed or implement a "green development" model in their economic structure. In cities with relatively developed economies, more attention is paid to innovation investment, which leads to the flow and concentration of resources in the innovation field and promotes the economy from a crude growth mode of physical capital to an innovation-intensive growth mode, thus improving the innovation environment (Fan, 2011). Moreover, the model of "green development" implies the strict control of environmental pollution and the repair of damaged ecological environments. This requires further development of green technologies through science and technological innovation, low-carbon technologies, and clean energy technologies (Feng and Chen, 2018). With the widespread adoption of green innovation technologies, green and low-carbon production can be achieved, making the city's green innovation environment healthier and more harmonious.

The improved innovation environment leads to upgrades in the livability, research, production, software, and hardware, which will continue to attract the inflow of foreign enterprises and innovation factors, such as investment and technical talent, and reduce the emergence of opportunism, as well as the transaction costs of the city. One of the most important innovation factors is the inflow of innovative talent, especially for green high-end projects. A high level of human capital can contribute to the development of green innovation by increasing labor efficiency, improving professional equipment, and affecting the active level of R&D investments (Lee et al., 2010). Based on the new knowledge input, the positive effect of green innovation is more notable, and various material factors improve the innovation capacity (Acs and Varga, 2002). Based on the findings mentioned above, Hypothesis 2 is put forward.

Hypothesis 2. The effect of green innovation increases with increases in GTFP.

Based on the theory of spatial econometrics, geographic space is non-homogeneous and not in equilibrium. A certain economic, geographic phenomenon with respect to the spatial unit of one region correlates with the same economic phenomenon of the spatial units of other regions. In other words, the economic development of different regions is spatially interdependent (Elhorst, 2003). This means the growth of GTFP in a region results from its economic activities and in other regions. If cities interact positively with each other, the economic activities of neighboring regions will promote the GTFP of the region affected by the spatial interaction among cities. First, neighboring cities will improve GTFP in cities with a low level of GTFP development based on a positive "spillover effect." Based on the market mechanism, both the neoclassical economic growth theory and the new growth theory emphasize the free flow of labor, capital, and other factors between regions and the free trade of commodities, as well as knowledge spillover based on economic activities, which inevitably deepen the economic ties between regions (Brun et al., 2002; Ying, 2003). If the GTFP of a city is high, it will inevitably have a radiating effect on neighboring cities, thus generating a positive spillover effect and increasing the GTFP of neighboring cities. Second, neighboring cities will improve the GTFP of cities with a high level of GTFP development based on the "demonstration effect." If a city has a high GTFP, this means that it has a "greener" approach to development. Under pressure from performance evaluation, neighboring city governments will borrow the city's green development experience to reduce costs, such as initiatives related to environmental regulation and compensation policies, to encourage green innovation. In addition, neighboring cities will also introduce relevant upstream and downstream industries of the city to increase GTFP through industrial links (Li and Wu, 2017; Xie et al., 2021). Based on the findings mentioned above, Hypothesis 3 is presented.

Hypothesis 3. Based on spatial factors, the increase in the GTFP of a city will be affected by positive spillovers from neighboring cities.

3. Model and data

3.1. Model setting

To reveal the effect of green innovation on urban GTFP, the following benchmark model was constructed.

$$GTFP_{it} = \alpha + \beta_{11} Inn\_ql_{it} + \beta_{1n} control_{it} + \lambda_i + \lambda_t + \mu_{it} \tag{1}$$

where *GTFP* is the explanatory variable, that is, GTFP; Inn_ql_{it} is the core explanatory variable (green innovation); *control* is a series of control variables that include financial development, urbanization, environmental regulation, and population density; λ_i is the city-fixed effect; λ_t is the year fixed effect; and μ_{it} is the random error term. In this study, the coefficient of concern is β_{11}. If green innovation increases GTFP, the coefficient is significantly positive.

In this study, the following model was constructed based on the two-stage least squares (2SLS) approach to solve the potential endogeneity problem.

$$Inn\_ql_{it} = \psi + \theta_{11} IV_{it} + \theta_{1n} control_{it} + v_i + v_t + \varphi_{it} \tag{2}$$

$$GTFP_{it} = \psi' + \theta_{11}{}' Inn\_ql_{it}' + \theta_{1n}{}' control_{it} + v_i{}' + v_t{}' + \varphi_{it}{}' \tag{3}$$

Eqs. (2) and (3) indicate the first and second stages of the regression process, respectively, where IV_{it} is the instrumental variable of the city, which includes the first- and second-order lags of green innovation, the number time-honored brands of China, and environmental penalties; and *Inn_ql'* is the fitted regression result of green innovation from the first stage.

In addition, in this study the effect of green innovation on the upgrading of the industrial structure and agglomeration of innovation factors was tested and the following model was constructed:

$$Ins_{it} = \omega + \gamma_{11} Inn\_ql_{it} + \gamma_{1n} control_{it} + \kappa_i + \kappa_t + \varsigma_{it} \tag{4}$$

$$Eag_{it} = \omega' + \gamma_{11}{}' Inn\_ql_{it} + \gamma_{1n}{}' control_{it} + \kappa_i{}' + \kappa_t{}' + \varsigma_{it}{}' \tag{5}$$

where Ins_{it} and Eag_{it} represent the upgrading of the industrial structure and the clustering of innovation factors, respectively. Based on the results of previous studies (Elhorst, 2010; LeSage and Pace, 2009), there are not only spatial interactions of GTFP among cities but also certain geospatial effects among other variables. In addition, the changes in GTFP depend on the time path and are affected by the economic activities of other cities in the previous period. In this study, the following spatial dynamic panel model was constructed:

$$\begin{aligned} GTFP_{it} = \chi + \rho_{11} GTFP_{i,t-1} + \rho_{12} WGTFP_{it} + \rho_{13} WGTFP_{i,t-1} + \eta_{11} X_{it} \\ + \eta_{12} WX_{it} + \delta_i + \delta_t + \xi_{it} \end{aligned} \tag{6}$$

where ρ_{11} responds to the effects of economic activities in a city in the previous period on the GTFP in the current period; ρ_{12} responds to the effects of economic activities in neighboring regions on the variable in the region in the current period; ρ_{13} responds to the effects of economic activities in neighboring regions in the previous period on the GTFP in the region; X_{it} represents green innovation and a series of control variables; and W is the spatial weight matrix of geographic distance. Geographic distance weights are based on the square of the inverse of the distance between cities i and j, that is, $w_{i,j} = 1/d^2$, which is the geographic spherical distance. The maximum likelihood estimation (MLE) method was chosen to estimate Eq. (6) in this study.

Considering the different degrees of effects of green innovation on urban GTFP in different development stages, the following quantile panel regression model was constructed:

$$GTFP_{it} = \partial\tau + \phi_{11}\tau Inn\_ql_{it} + \phi_{1n} control_{it} + o_i + o_t + \sigma_{it} \tag{7}$$

where τ is the quantile point. The effect of green innovation on the GTFP at each quantile point can be obtained after the multi-quantile fractionation of the GTFP.

3.2. Variable selection

1. Explanatory variable: GTFP-related research (Du and Lin, 2017; Ma et al., 2019). In this study, capital, labor, and energy were used as inputs. The real GDP was used as the desired output and industrial wastewater and $PM_{2.5}$ were used as non-desired outputs (Rodríguez Bolívar et al., 2016). Furthermore, DEA was used to measure the Malmquist–Luenberger productivity index as a proxy for GTFP. The capital stock was measured with the permanent inventory method, and the capital depreciation rate was set at 9.6 % to eliminate the effects of price fluctuations and consider the 2006 base period. The number of people employed in the three industries was used as a proxy for the labor input for the treatment of the urban labor input. Considering that electricity is the main form of energy consumption in China (Lin, 2003a, 2003b), the annual electricity consumption of the cities was selected in this study as an indicator of energy input. The nominal GDP and the conversion index were used to measure the real regional GDP of each city, with 2006 as the base period. Considering the realistic background of the increasing water and haze pollution, $PM_{2.5}$ concentrations of industrial wastewater and haze pollution were used as unintended output.

Based on the use of the SBM directional distance function, efficiency measurement errors caused by ignoring non-radial relaxation variables can be effectively avoided.

$$\begin{aligned} \vec{D}^G(x_k^t, y_k^t, b_k^t; g_x, g_y, g_b) = max \frac{\frac{1}{N}\sum_{n=1}^{N}\frac{S_n^x}{g_n^x} + \frac{1}{M+I}\left(\sum_{m=1}^{M}\frac{S_m^y}{g_m^y} + \sum_{i=1}^{I}\frac{S_i^b}{g_i^b}\right)}{2} \\ s.t. \sum_{t=1}^{T}\sum_{j=1}^{K}\lambda_j^t x_{jn}^t + s_n^x = x_{kn}^t, \forall n \\ \sum_{t=1}^{T}\sum_{j=1}^{K}\lambda_j^t y_{jm}^t - s_m^y = y_{km}^t, \forall m \\ \sum_{t=1}^{T}\sum_{j=1}^{K}\lambda_j^t b_{ji}^t + s_i^b = b_{ki}^t, \forall i \\ s_n^x \geq 0, \forall n; s_m^y \geq 0, \forall m; s_i^b \geq 0, \forall i \end{aligned} \tag{8}$$

In Eq. (8), (g^x, g^y, g^b) is a direction vector, where the elements represent the direction of input reduction, desired output increase, and non-desired output reduction, respectively; (s_n^x, s_m^y, s_i^b) is the slack variable, where the elements represent the amount of input redundancy, desired deficiency, and non-desired output excess, respectively. Based on the directional distance function of the SBM, GTFP growth can be further measured using the Malmquist-Luenberger productivity index:

$$GTFP_t^{t+1} = \frac{1 + \vec{D}^G(x^t, y^t, b^t; g_x, g_y, g_b)}{1 + \vec{D}^G(x^{t+1}, y^{t+1}, b^{t+1}; g_x, g_y, g_b)} \tag{9}$$

where $\vec{D}^G(x^t, y^t, b^t; g_x, g_y, g_b)$ represents the SBM directional distance function, which is constructed based on the global frontier surface. A GTFP index >1 indicates that GTFP has increased; a GTFP value <1 indicates that GTFP has decreased. A value of 1 implies that GTFP is in a stable state (Fig. 1).

3.3. Core explanatory variable: green innovation

First, this study refers to the "International Green Patent Classification List" launched by the World Intellectual Property Organization in 2010. This list was designed to facilitate the search for environmentally friendly technologies, which are scattered across various technological areas in the International Patent Classification and are divided into seven categories: alternative energy production, transportation, energy conservation, waste management, agriculture and forestry, administrative regulations and design, and nuclear power. The green patent information for each city was collected from the patent search and data analysis website of the State Intellectual Property Office of China and organized to measure the level of green innovation in each city (Calel and Dechezleprêtre, 2016; Zhu et al., 2019). Second, the patent quality of the cities was measured in this study by referring to Aghion et al. (2019), Akcigit et al. (2016), and other studies to determine the breadth of knowledge of each patent as a proxy variable for green innovation in cities. The breadth of patent knowledge is the complexity of the knowledge contained in each patent. This method reflects the quality of the patent from the perspective of the complexity and breadth of knowledge contained in a patent, which helps to overcome the shortcomings of measuring innovation activities by the number of patents only. It is an important proxy for measuring the quality of innovation activities.

The specific strategy is as follows: the IPC classification number information in enterprise patent documents of the State Intellectual Property Office of China is used. The format of the IPC patent classification number often takes the form "Department - major category - minor category - major group - minor group," such as "H02C01/00." The first letter of the classification number takes the range of value A–H to indicate eight categories. The second to third numbers indicate the major category, the fourth letter indicates the minor category, and the last number indicates the group, which can be divided into major and minor groups. The major and minor groups are separated by "/", such that the patent information of the technical field to which the product belongs can be easily retrieved based on the IPC classification number of a certain product. However, the quality of a patent cannot be accurately measured based solely on the number of patent IPC classifications. For example, although two patents contain the same number of IPC classification numbers, the more "major group" information is used, the greater the breadth of knowledge of the patent. Therefore, we searched the IPC classification number and the large group information for each patent. The Herfindahl–Hirschman index (HH) of each patent at the "major group" level was calculated and weighted drawing on the industrial concentration calculation method. The greater the difference between the patent classification numbers at the "large group" level is, the greater is the breadth of knowledge used in the creation process of that patent and the higher is the patent quality. After measuring the

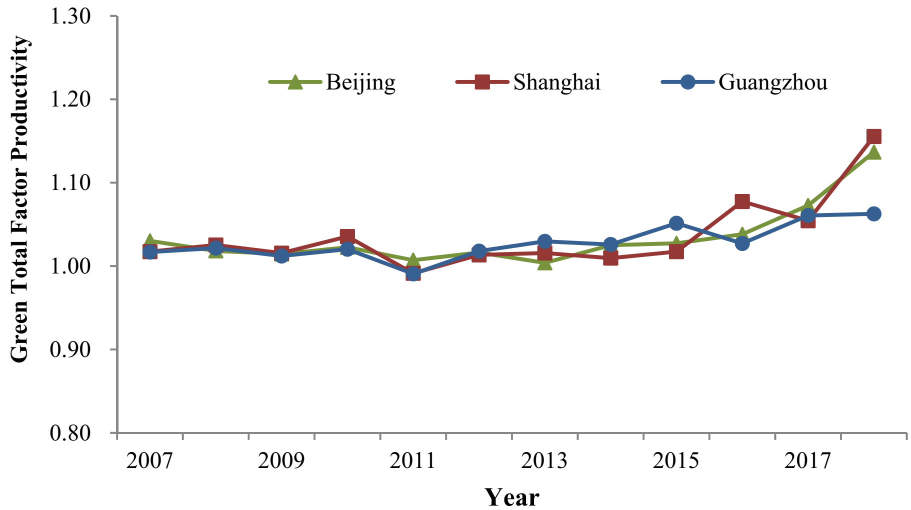

Fig. 1. Growth trend of GTFP in representative cities.

knowledge breadth information index based on the patent level, the knowledge breadth information about the patents was further summed to the city level using the summation method to measure the overall green innovation levels of cities (Fig. 2).

3.4. Control variables

Based on existing studies, four indicators that could affect urban GTFP were selected as control variables in this study (Zhou and Ma, 2003; Ayadi et al., 2015). First, financial development (Fd) was measured as the ratio of total bank deposits and loans to the GDP. Second, the population density (Pd) was measured as the ratio of the urban population to the area of the administrative area. Third, with respect to environmental regulations (Er), in this study three single indicators were selected and standardized, that is, the comprehensive rate of use of general industrial solid waste, the harmless rate of domestic waste treatment, and the centralized rate of treatment of wastewater treatment plants. The entropy value method was used to determine the indicator weights and the environmental regulation index was calculated based on the weights and standardized values. Fourth, urbanization (Urb) was measured as the ratio of the non-agricultural resident population to the resident population.

3.5. Data specification

Based on data availability, GTFP was measured in this study using data from 2006 to 2018 for 263 cities in China. The other data sample period was 2007–2018. Data were obtained from the China City Statistical Yearbook, EPS database, statistical yearbooks of each city, statistical bulletins of national economic and social development of each city, and the official website of the National Bureau of Statistics of China. $PM_{2.5}$ concentration was obtained from the Atmospheric Composition Analysis Group at Dalhousie University (Han et al., 2015; H. Chen et al., 2018; J. Chen et al., 2018). Table 1 indicates the data statistics.

4. Empirical tests and analysis of the results

4.1. Benchmark regression analysis

Table 2 lists the benchmark regression results. Columns (1)–(2) indicate the regression results without city and year effects, clustering to time, and individuals. Model (1) indicates the results of the regression solely based on the explanatory variables. The estimated coefficient is 0.1398 and passes the significance test at the 1 % level, indicating that green innovation effectively contributes to GTFP. Model (2) indicates the regression results after adding the control variables. The estimated

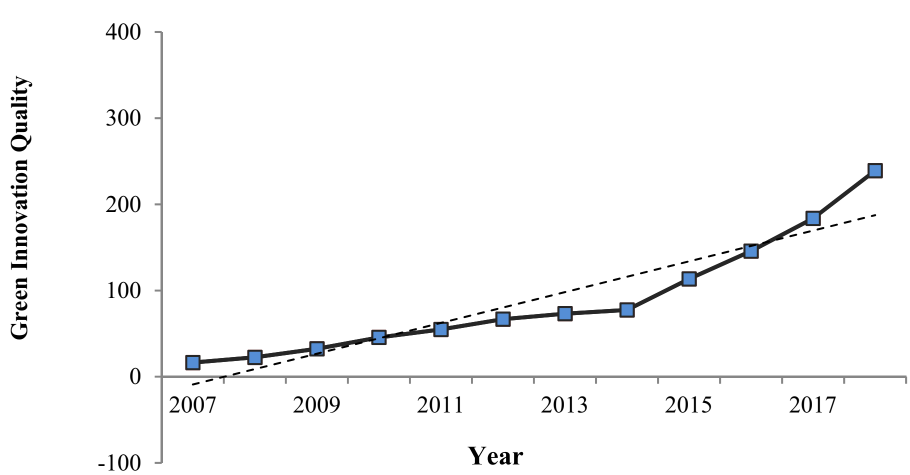

Fig. 2. Average value of green innovation quality in all cities.

Table 1
Descriptive statistics.

Variables	Symbol	Obs	Mean	Std. dev	Min	Max
Green Total factor productivity (Depreciation rate 9.6 %)	*GTFP*	3156	1.0052	0.0439	0.6263	1.5504
Total factor energy productivity (Depreciation rate 10.96 %)	*GTFP_Z*	3156	1.0052	0.0440	0.6259	1.5461
Total factor energy productivity (SBM Model)	*GTFP_S*	3156	1.0175	0.1539	0.2808	3.5156
Green innovation quality	*Inn_ql*	3156	0.0089	0.0282	0.0000	0.5076
Green innovation quantity	*Inn_qn*	3156	0.0213	0.0655	0.0000	1.0697
Financial development	*Fd*	3156	0.0224	0.0125	0.0056	0.1672
Population density	*Pd*	3156	4.4752	3.3726	0.0482	26.4826
Environmental regulation	*Er*	3156	0.0178	0.0015	0.0115	0.0200
Urbanization	*Urb*	3156	0.5141	0.1620	0.0306	1.0000

coefficient of green innovation is 0.1930 and passes the significance test at the 1 % level. The regression coefficient has improved compared to that of model (1). Model (3) is based on the inclusion of control variables, year fixed-effects, and clustering over time and individuals. The estimated coefficient for the core explanatory variables is significant and above zero but is smaller than model (2). The regression results in columns (4)–(6) include the year and city-fixed effects, but the clustering differs. Model (4) represents the regression results based on clustering over individuals, model (5) indicates the regression results based on clustering over time, and model (6) represents the regression results based on clustering over individuals and time. The magnitude of the regression coefficients of models (4) to (6) is 0.1684, and the coefficient passes the significance test, which partially verifies Hypothesis 1, which is consistent with existing research (Wang et al., 2021a, 2021b; M. Wang et al., 2021; Song et al., 2022). The coefficients estimated for the three model control variables have a consistent size and sign, and all of them pass the significance level test. Financial development, population density, and environmental regulations negatively affect GTFP. Financial development and population density pass the significance test at the 1 % level, and environmental regulation passes the significance test at the 5 % level. In comparison, the level of urbanization positively affects GTFP.

4.2. Regression analysis of instrumental variables

Due to mutual causality, endogeneity may exist between green innovation and TFP. Furthermore, although baseline regressions include fixed effects for the year and city and several key control variables that affect the energy TFP, several unobservable variables may be missed. Therefore, four instrumental variables were selected, that is, the number of Chinese pension firms in each city, explanatory variables with one lag, explanatory variables with two lags, and environmental penalties, to consider endogeneity using the 2SLS approach. Note that all instrumental variable regressions include control variables and the year- and city-fixed effects.

First, because the effect of green innovation on GTFP is not instantaneous, it takes time for the level of innovation to increase, innovative technologies to emerge and innovative activities to influence GTFP. Therefore, following Xu et al. (2021), the first and second lag periods of green innovation were used in this study as instrumental variables. Second, the number of China's time-honored brands in each city is an instrumental variable. China's time-honored brands are national brands with distinctive Chinese traditional culture and profound cultural heritage in industries such as healthcare and food processing. The number of China's time-honored brands was chosen as an instrumental variable for urban green innovation because the urban economy has inheritance and continuity. The more time-honored brands a city has, the higher the green innovation of the city. Furthermore, the number of China time-honored brands has no direct impact on a city's GTFP, which satisfies the exogeneity requirement of the instrumental variable. Note that the number of China's time-honored brands is cross-sectional data and cannot be used directly for the regression of instrumental variables. Therefore, we referred to Nunn and Qian (2014) and Gibbons et al. (2019). The number of China's time-honored brands in each city was selected to construct an interaction term with the national R&D expenditures in the previous year, which was converted into panel data from the first and second batches of "China's time-honored brand" lists released by the Chinese Ministry of Commerce. Second, environmental penalties were selected as instrumental variables of green innovation. Strict environmental penalties prompt enterprises to reduce pollutant emissions and force them to engage in green patent R&D, thus enhancing the increase in green innovation (H. Chen et al., 2018; J. Chen et al., 2018; Du et al., 2019). Furthermore, environmental penalties are independent of the socioeconomic system and have no direct impact on GTFP, which satisfies the exogeneity requirement of instrumental variables. Data were obtained from information on the environmental violations of listed Chinese companies published by the Public Environment Research Center. Table 3 lists the 2SLS regression results for the instrumental variables. (See Table 4.)

Table 2
Benchmark regression results.

Variables	Explained variable: green total factor productivity					
	Model(1)	Model(2)	Model(3)	Model(4)	Model(5)	Model(6)
Inn_ql	0.1398***	0.1930***	0.1751***	0.1684***	0.1684**	0.1684***
	(5.6000)	(6.3100)	(5.5400)	(3.5300)	(2.7500)	(3.7200)
Fd		−0.6209***	−0.4582***	−0.9493***	−0.9493***	−0.9493***
		(−5.1300)	(−4.2800)	(−4.2800)	(−4.8200)	(−4.3700)
Pd		−0.0003	−0.0001	−0.0051***	−0.0051***	−0.0051***
		(−1.1800)	(−0.5500)	(−3.4600)	(−5.9400)	(−3.3400)
Er		−0.054	−0.5554	−1.6695**	−1.6695*	−1.6695**
		(−0.1000)	(−1.0000)	(−2.0400)	(−1.9000)	(−2.2100)
Urb		0.0264***	0.0223***	0.0342**	0.0342	0.0342**
		(4.5200)	(3.8600)	(2.2800)	(1.5500)	(3.3200)
Constant	1.0040***	1.0059***	1.0129***	1.0597***	1.0597***	1.0597***
	(1228.7700)	(107.2300)	(105.1500)	(59.5500)	(47.7000)	(56.35000)
Year	NO	NO	YES	YES	YES	YES
city	NO	NO	NO	YES	YES	YES
Obs	3156	3156	3156	3156	3156	3156

Note: The t-statistics are in brackets; ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Based on Table 3, all coefficients estimated for the instrumental variables mentioned above on green innovation based on first-stage regressions are positive and pass the significance test, indicating that these instrumental variables contribute significantly to green innovation. The effect of green innovation on urban GTFP can be determined using the second stage of regression. First, the instrumental variables were identified for the under testing. Based on the underidentification tests of models (1)–(4), the original hypothesis of underidentification is significantly rejected at the 1 % level. All Cragg–Donald Wald F-statistics are greater than the critical value at the 10 % level of the Stock–Yogo weak identification test. This indicates that there is no weak instrumental variable problem and that the 2SLS regression results obtained for the instrumental variables are reasonable. The results of the second stage regressions show that the estimated coefficients for the effects of instrumental variables on urban GTFP are above zero in all models and higher than those of the baseline regressions. This indicates that the effect of green innovation on GTFP will be underestimated if endogeneity is not considered and that the issue of endogeneity can be addressed with the instrumental variables selected in this study. In summary, after considering endogeneity, the regression results support the results of the benchmark regression.

4.3. Robustness tests

To ensure the accuracy of the regression results, robustness tests were conducted by replacing explanatory variables, removing outliers of the explanatory variables, and replacing the core explanatory variables. All models included fixed effects for the year and the city.

First, the core explanatory variables were replaced. The capital stock is recorded at a depreciation rate of 10.96 % and the urban GTFP is remeasured based on the SBM–DDF model. Then urban TFP is measured using the SBM model based on the original input–output data. The results of models (1)–(4) indicate that green innovation still contributes significantly to GTFP after replacing the core explanatory variables. Financial development, population density, and environmental regulations still weaken the GTFP. In contrast, the level of urbanization contributes to the increase in GTFP, which is consistent with the results of the benchmark regression. Second, an outlier removal test was performed. To reduce the possible effects of outliers of explanatory variables on empirical results, the explanatory variables in models (5) and (6) were trimmed by the 1 % and 99 % quartiles and data below the 1 % and above the 99 % quartiles were replaced with the 1 % and 99 % quartiles, respectively. Green innovation still contributes to GTFP, and the coefficients estimated based on the inclusion of the control variables are significantly larger than those without the control variables. Finally, the explanatory variables were replaced with the number of green patents per city. The results show that with every unit increase in the number of green innovations, GTFP increases by 5.84 units after including the control variables. Green innovation still contributes significantly to the increase in TFP. In summary, the results of the robustness tests verify the accuracy of the benchmark regressions and support the conclusion that an increase in green innovation contributes to GTFP in cities.

5. Heterogeneity analysis

5.1. Regional heterogeneity analysis

There is heterogeneity between cities regarding R&D investment, technology spillover, and innovation agglomeration among green innovation agents, such as firms, universities, and research institutions. This leads to significant heterogeneous differences in the spatial distribution of the impact of green innovation on the TFP. Based on the regional division of the three major subdivisions, regression analysis was conducted in the sample cities to evaluate whether there was regional heterogeneity in the impact of urban green innovation on the improvement of the GTFP. The regression results of the heterogeneity test are shown in Table 5. Regression results for the three major regions with and without control variables are provided and all regressions include time and individual fixed effects. The regression results provided in the first two columns of Table 5 show that the increase in green innovation has a positive contribution to the increase in GTFP in the eastern region. The positive contribution becomes more notable after the addition of control variables. The coefficient reaches 0.2002, which is higher than the coefficient of the benchmark regression results and is significant at the 1 % level. In contrast, the regression results in columns (3)–(6) show that the increase in green innovation has a smaller effect on GTFP in the central region and a non-significant negative effect on GTFP in the western region. Although the regression coefficients in the central and western regions are not mathematically significant, the impact effect decreases from positive to negative from east to west and a significant regional heterogeneity can be observed. The main reason for this is that the eastern region has a higher level of economic development and a more optimized industrial structure, which has attracted many science- and innovation-oriented enterprises and green innovation resources. The application effect of green innovation patents is further brought into play and thus has a significant contribution to the improvement of GTFP. In the future, narrowing the gap between regions will be the key to optimizing China's GTFP.

Table 3
Regression results for instrumental variables.

Variables	The first stage regression: the explained variable *Inn_ql*			
	Model(1)	Model(2)	Model(3)	Model(4)
IV	1.1344***	1.3026***	0.0025***	0.0049***
	(173.69)	(106.5100)	(60.9800)	(12.7000)
Constant	−0.0108***	−0.096***	−0.0432***	−0.0489***
	(−4.7700)	(−5.5700)	(−8.9400)	(−6.3400)
Variables	The second stage regression: explained variable *GTFP*			
	Model(1)	Model(2)	Model(3)	Model(4)
Inn_ql	0.1942***	0.2406***	0.2332***	0.4145*
	(3.4900)	(3.6500)	(3.4900)	(1.8600)
Constant	1.0497***	1.0302***	1.0638***	1.0600***
	(47.9700)	(42.5400)	(53.3300)	()43.8600
Underidentification test	2662.2450***	2178.2200***	1779.4280***	168.0900***
Weak identification test	30,169.5600	11,344.9100	378.9590	161.3100
Stock-Yogo bias critical value	16.38 (10 %)	16.38 (10 %)	16.38 (10 %)	16.38 (10 %)
Control variable	YES	YES	YES	YES
Year	YES	YES	YES	YES
city	YES	YES	YES	YES
Obs	2893	2630	3156	2893

Note: The t-statistics are in brackets; ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 4
Robustness regression results.

Variables	Replace the explained variable: (*GTFP_Z*)		Replace the explained variable: (*GTFP_S*)		Interpreted variable ending (1 % points and 99 % points)		Replace core explanatory variables (*Inn_qn*)	
	Model(1)	Model(2)	Model(3)	Model(4)	Model(5)	Model(6)	Model(7)	Model(8)
Inn_ql	0.1290***	0.1657***	0.2890**	0.3855***	0.1332***	0.1709***		
	(2.8200)	(3.6800)	(2.1300)	(2.8400)	(3.1900)	(4.1800)		
Inn_qn							0.0375***	0.0584***
							(1.9000)	(2.9300)
Fd		−0.9559***		−2.3244***		−0.6978***		−0.9578***
		(−4.3800)		(−4.3000)		(−5.2900)		(−4.4000)
Pd		−0.0050***		−0.0141***		−0.0049***		−0.0047***
		(−3.3300)		(−2.6200)		(−3.5100)		(−3.0100)
Er		−1.6737**		−7.4680**		−1.5739***		−1.6910**
		(−2.1300)		(−2.5700)		(−2.6300)		(−2.1500)
Urb		0.0347**		0.0911*		0.0302**		0.0335**
		(2.3300)		(1.7700)		(2.3900)		(2.2700)
Constant	1.0041***	1.0594***	1.0149***	1.2153***	1.0038***	1.0536***	1.0044***	1.0595***
	(1172.0500)	(56.4500)	(348.0600)	(16.8400)	(1459.23)	(74.57)	(1178.23)	(56.0600)
Year	YES	YES	YES	YES	YES	YES	YES	YES
city	YES	YES	YES	YES	YES	YES	YES	YES
Obs	3156	3156	3156	3156	3156	3156	3156	3156

Note: The t-statistics are in brackets; ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 5
Regression results of the heterogeneity test based on the regional heterogeneity.

Variables	East		Central		West	
	Model(1)	Model(2)	Model(3)	Model(4)	Model(5)	Model(6)
Inn_ql	0.1247**	0.2002***	0.0969	0.0334	−0.0032	−0.0794
	(2.4200)	(4.3900)	(0.8100)	(0.2900)	(−0.0300)	(−0.5100)
Fd		−1.1866**		−0.8818***		−0.4575
		(−2.4500)		(−3.4300)		(−1.2300)
Pd		−0.0073***		−0.0020		0.0071
		(−3.7700)		(−0.8200)		(0.4600)
Er		−3.8951**		0.7930		−1.4953
		(−2.2700)		(−0.7100)		(−1.0900)
Urb		0.0572**		0.0261		−0.0269
		(2.2200)		(1.1400)		(−1.0200)
Constant	1.0053***	1.1142***	1.0037***	1.0303***	1.0036***	1.0305***
	(721.1300)	(24.6500)	(148.0700)	(45.5200)	(629.6900)	(−1.0200)
Year	YES	YES	YES	YES	YES	YES
city	YES	YES	YES	YES	YES	YES
Obs	1176	1176	1452	1452	528	528

Note: The t-statistics are in brackets; ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 6
Regression results of the heterogeneity test for resource-based and non-resource-based cities.

Variables	Resource-based city				Non-resource-based city
	Model(1)	Model(2)	Model(3)	Model(4)	Model(5)
Inn_ql	−3.4221	−0.6743	0.1683	0.8734	0.1863***
	(−0.2800)	(−1.5700)	(0.1500)	(1.3000)	(3.8600)
Fd	−2.3931***	−0.2134	0.1154	0.4539	−1.1833***
	(−3.3600)	(−1.2000)	(0.2300)	(1.2400)	(−4.0500)
Pd	−0.0493	−0.0051	−0.0115	0.0025	−0.0046***
	(−0.6000)	(−1.2400)	(−1.9400)	(0.5600)	(−2.6100)
Er	−5.9321	−1.3746	−0.5077*	−4.3175	−1.7972
	(−1.0800)	(−0.9800)	(−0.7000)	(−1.4300)	(−1.6100)
Urb	0.0506	0.0203	0.0272	0.0045	0.0426*
	(0.6400)	(0.9100)	(1.7900)	(0.1100)	(1.7800)
Constant	1.2358***	1.0395***	1.0396***	1.0609***	1.0657***
	(6.6700)	(32.7100)	(37.7300)	(16.1100)	(36.7500)
Year	YES	YES	YES	YES	YES
city	YES	YES	YES	YES	YES
Obs	108	720	252	156	1920

Note: The t-statistics are in brackets; ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

5.2. Classification of resource-based cities

As an important strategic guaranteed base for energy resources, resource-based cities are an important form of support for national economic development and play a significant role in improving the GTFPs of cities. In this study, the 263 sample cities were divided into 126 resource-based cities and 137 non-resource-based cities according to the National Sustainable Development Plan for Resource-Based Cities (2013−2020). Furthermore, resource-based cities were divided into four categories according to their developmental stages: growth, decline, maturity, and regeneration. The mature cities accounted for the highest proportion, including 66 cities. Regenerative cities accounted for the lowest proportion, including only 16 cities. Subsample regressions were performed for the types of cities to determine if the effect of urban green innovation on the improvement of GTFP by resource type is heterogeneous. The regression results are provided in Table 6. All regressions control for time and individual fixed effects. The regression results obtained for resource-based cities show that the effect of green innovation on TFP is negative for growing and mature cities. In contrast, the impact effect of declining and regenerating cities is positive, but the regression results are not significant. The coefficient of the effect of green innovation on the GTFP for non-resource-based cities is 0.1863, indicating that green innovation makes a significant contribution to GTFP. This is due to the greater dependence of resource-based cities on energy inputs and the overall lower technical efficiency of green innovation production factors, which leads to a reduction in GTFP. The regression coefficients of the control variables for resource-based cities are mostly insignificant; only the level of financial development in growth cities has a significant inhibitory effect on GTFP, which is significant at the 1 % level. In contrast, the control variables of non-resource-based cities are more significant. All variables except the environmental regulation variable are significant, which is similar to the results of the benchmark regression.

5.3. Level of economic development

The improvement in GTFP depends on the green innovation and technological resources of the cities for high-quality economic development. The ability to apply green innovation and technological resources varies depending on the stage of economic development of the city. In this study, GDP per capita was used as a proxy for the level of economic development. Cities with a higher or lower than average GDP per capita in 2018 were classified as having a high or low level of economic development, respectively. Table 7 presents the regression results for the levels of economic development, controlling for time and individual fixed effects. The regression results show that green innovation in cities with high levels of economic development has a significant positive contribution to GTFP. The effect is significantly enhanced by adding control variables to the regression. The estimated regression coefficient improves to 0.1658 and the significance level is higher. Consistent with the baseline regression estimates, financial development and population density have negative effects on GTFP, whereas the level of urbanization positively contributes to GTFP, and the environmental regulation control variable is insignificant; this is consistent with the existing research (Pingali, 2012). In contrast, although green innovation in cities with low levels of economic development positively contributes to GTFP, the regression results are statistically insignificant and only the control variables for financial development and population density pass the significance test. The regression results indicate that the GTFP of cities with high levels of economic development increases significantly with increases in urban green innovation, whereas this positive contribution effect does not exist in cities with low levels of economic development. A reason for this correlation is that cities with high levels of economic development continuously improve energy efficiency through the aggregation of green innovations, leading to a positive cumulative cycle. In contrast, the starting point for green innovation in low economic development-level cities is low and is difficult to improve the energy production efficiency in the cumulative cycle.

5.4. Government intervention level

The urban green innovation system relies on market players, such as enterprises and research institutions, and requires the government to effectively lead the green innovation system to play an active role through macro-regulation. Thus, government intervention can improve GTFP performance, but too much government intervention can also reduce the efficiency of green innovation market resource allocation. To assess whether government intervention can effectively enhance the positive effect of green innovation on GTFP, we referred to Shao and Yang (2014). We used the ratio of government expenditure (excluding education, science, and technology expenditures) to regional GDP to construct government intervention indicators. Furthermore, we used the average value of the government intervention lever in 2018 as the boundary to divide all sample cities into 109 and 154 cities with high and low levels of government intervention, respectively. Table 7 indicates the regression results, all of which include fixed effects of time and individuals. The results of categorical regressions for models (5) and (6) indicate a significant positive effect of urban green innovation on GTFP at high levels of government intervention. The regression coefficients are significant at the 1 % level with or without the inclusion of

Table 7
Regression results of the heterogeneity test based on the level of economic development and government intervention.

Variables	Level of Economic Development				Level of Government Intervention			
	High		Low		High		Low	
	Model(1)	Model(2)	Model(3)	Model(4)	Model(5)	Model(6)	Model(7)	Model(8)
Inn_ql	0.1132**	0.1658***	0.2119	0.1316	0.2411***	0.2513***	0.0370	0.0935**
	(1.9800)	(2.9100)	(0.9100)	(0.5900)	(3.2700)	(3.5000)	(0.8000)	(2.0200)
Fd		−1.7693***		−0.7748***		−0.7488***		−1.4359***
		(−2.8900)		(−3.4200)		(−2.9300)		(−3.4100)
Pd		−0.0038**		−0.0058*		−0.0052		−0.0030**
		(−2.2000)		(−1.7700)		(−0.8600)		(−2.0600)
Er		−2.5684		−1.3206		1.5518		−1.9259**
		(−1.1000)		(−1.6500)		(−1.2000)		(−2.1000)
Urb		0.0576*		0.0222		0.0073		0.0526***
		(1.9200)		(1.5100)		(0.2900)		(2.9100)
Constant	1.0063***	1.0859***	1.0030***	1.0545***	1.0030***	1.0594***	1.0054***	1.0583***
	(521.4800)	(19.3100)	(916.9900)	(50.0900)	(720.8000)	(31.1600)	(1021.0900)	(48.4900)
Year	YES	YES	YES	YES	YES	YES	YES	YES
city	YES	YES	YES	YES	YES	YES	YES	YES
Obs	972	972	2184	2184	1308	1308	1848	1848

Note: The t-statistics are in brackets; ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

control variables. The effect coefficient increases to 0.2513 with the addition of control variables, which is slightly higher than the baseline regression significance coefficient. This suggests that, in cities with high levels of government intervention, GTFP increases significantly with increasing green innovation. The results of categorical regressions in columns (7) and (8) of the model show that green innovation in cities with low levels of government intervention leads to an increase in GTFP without the addition of control variables, but the regression coefficients are insignificant. After adding control variables, the coefficients of the green innovation variable in cities are significantly positive. However, in cities with low government intervention, the coefficient is only 0.0935, that is, less than half the value of the coefficient in cities with high government intervention. The regression results further indicate that the government positively affects the green technology innovation system by using economic, legal, and administrative instruments to strengthen the guidance, which in turn enhances the positive contribution of green innovation to GTFP.

6. Further analysis

6.1. Examination of the influence mechanism

In this section, the influence mechanisms are examined in terms of upgrading the industrial structure upgrading and clustering of innovation factors to provide evidence for Hypothesis 1.

The practice showed that upgrading the industrial structure is closely related to improving GTFP. During industrialization, priority is often given to the development of industries with high pollution; that is, higher energy consumption is exchanged for faster economic growth. During stable industrialization, several industries with low resource consumption and good economic efficiency gradually occupy a dominant position in economic development. They promote the continuous upgrading of industrial structures and thus support the improvement of GTFP. Based on existing studies, we adopted the shares of the tertiary and secondary industries as proxies for the improvements of the industrial structure. The regression results show that green innovation has a significant positive effect on the optimization and upgrading of industrial structures. Improvements in green innovation capability motivate industries to achieve leapfrog development by creating new industries and launching new products. In addition, green innovation capacity improvements upgrade industrial structures and transform traditional industries based on the introduction of innovative technologies and equipment.

Innovation factors are clustered within the same geographical space. This is conducive to making full use of the scale effect due to the clustering of innovation factors to reduce the production and transaction costs of enterprises, prompting them to make more use of energy-saving and emission reduction technologies in their production activities and improve energy utilization efficiency. However, the clustering of innovation elements generates knowledge spillover effects and strengthens the communication and collaboration among enterprises in the energy industry. Advanced production technologies and management concepts improve the production R&D and management levels of enterprises, thus increasing their productivity. The productive service industry is knowledge-intensive, with low pollution, low consumption, and high output. In this study, the diversity agglomeration index of the productive service industry was used as a proxy for the agglomeration of innovation factors (Combes, 2000). The larger the index, the higher the agglomeration of innovation factors. Based on the study by Ke et al. (2014) and statistics for employment by industry in Chinese cities, the productive service diversity agglomeration measurement model was constructed:

$$DV_i = \sum_s \frac{E_{is}}{E_i} \left[\frac{1 \Big/ \sum_{s'=1, s' \neq s}^{n} \left[E_{is'} / (E_i - E_{is}) \right]^2}{1 \Big/ \sum_{s'=1, s' \neq s}^{n} \left[E_{s'} / (E - E_s) \right]^2} \right] \tag{10}$$

where E_{is} represents the employment in the productive service industry s in city i, E_i represents the total employment in city i, E_s represents the employment in the productive service industry s nationwide, E is the total employment nationwide, $E_{s'}$ represents the employment in productive service industry s other than the productive service industry s nationwide, and $E_{is'}$ represents employment in productive service industries other than the productive service industry s in city i. Based on the regression results shown in Table 8, the coefficients of green innovation estimated with the models mentioned above are significantly positive and pass the significance test. This indicates that green innovation promotes innovation factor agglomeration. The higher the degree of innovation factor agglomeration, economies of scale, and knowledge spillover from innovation factor agglomeration led to the increase in GTFP.

6.2. Quantile regression: first-mover advantage or backward disadvantage?

Based on the previous analysis, green innovation significantly contributes to cities' GTFP, but the effect of green innovation on the cities' GTFP may significantly vary depending on the cities' own GTFP. It remains unclear whether cities with different levels of GTFP development have a backward disadvantage or backward advantage. In this section, quantile regressions were used to examine the effects of green innovation on the GTFP of cities at quantiles of 0.1, 0.3, 0.5, 0.7, and 0.9. The results of the quantile regressions are listed in Table 10. The effect of green innovation on urban GTFP at each quantile of GTFP is significantly positive. Starting from the 0.3 quantile, the estimated coefficient for the effect of green innovation on urban GTFP increases with increasing quantile. At the 0.3 quantile of the GTFP distribution, the coefficient is 0.1161 and passes the 1 % significance level test. At the 0.9 quantile of the GTFP distribution, the coefficient is 0.3469 and passes the 1 % significance level test. The extent of the effect of green innovation on TFP is increasing, which may be because cities with a high GTFP tend to have a high level of economic development, a high level of science and technology, a better industrial base, and can adapt to the promotion and application of several emerging green patents. Therefore, the effect of green innovation on cities with a high GTFP may be stronger, which verifies Hypothesis 2.

6.3. Spatial factors: spillover or siphon effect?

GTFPs may be spatially correlated, that is, the level of GTFP in one city may be affected by that of surrounding cities. Ignoring this spatial correlation will lead to biased estimates. In addition, spatial effects can be positive and negative. Whether the increase in GTFP in a neighboring city has a "positive spillover effect" or "negative siphon effect" on that city must be further evaluated.

Table 9 lists the spatial regression results for models (1) and (2) without control variables. Model (3) includes control variables but does not examine the spatiotemporal effects of explanatory variables. Model (4) includes the temporal, spatial, and temporal effects of the explanatory variables and has the maximum log likelihood. Model (4) yields a better fit than the other models and thus is the focus of this section. Regarding the time dimension, the coefficient of the time-lagged term of the GTFP is −0.1132. This implies that the GTFP in the previous period inhibits the increase in the GTFP in the current period. Regarding spatial dimension, the spatial lag coefficient of the GTFP is 0.5282 and passes the 1 % significance test. This indicates a spatial spillover effect of GTFP and that improving GTFP in neighboring cities will lead to improving local GTFP. This also verifies Hypothesis 3. New energy technologies that are developed and used by local enterprises will spread to neighboring cities, and the application of innovative technologies by enterprises in neighboring cities will lead to productivity improvements. However, the competitive effect due to newly developed technologies of

Table 8
Regression results of the mechanism test.

Variables	Explained variable: upgrading of industrial structure			Explained variable: agglomeration of innovative elements		
	Model(1)	Model(2)	Model(3)	Model(4)	Model(5)	Model(6)
Inn_ql	2.0130***	−2.6958***	1.8324***	0.2917***	0.8845***	0.3412***
	(7.95000)	(−4.5800)	(7.0100)	(8.7100)	(12.4200)	(8.9700)
Constant	1.3558***	2.0914***	0.8779***	0.1276***	0.1347***	0.1788***
	(197.3500)	(15.0200)	(4.5300)	(220.1500)	(11.1200)	(13.5700)
Control variable	NO	YES	YES	NO	YES	YES
Year	YES	NO	YES	YES	NO	YES
city	YES	NO	YES	YES	NO	YES
Obs	3156	3156	3156	3156	3156	3156

Note: The t-statistics are in brackets; ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 9
Quantile regression results.

	Explained variable: green total factor productivity				
	Quantile = 0.1	Quantile = 0.3	Quantile = 0.5	Quantile = 0.7	Quantile = 0.9
Inn_ql	0.1998***	0.1161***	0.1323***	0.1617***	0.3469***
	(3.4300)	(6.2600)	(10.1600)	(9.6600)	(5.9400)
Constant	0.9949***	0.9930***	1.0003***	1.0061***	1.0402***
	(59.1000)	(185.2900)	(265.8400)	(207.9700)	(61.6500)
Control variable	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
city	YES	YES	YES	YES	YES
Obs	3156	3156	3156	3156	3156

Note: The t-statistics are in brackets; ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

local enterprises will prompt enterprises in neighboring cities to accelerate the development of innovative technologies and new products, thus increasing GTFP. In terms of the spatiotemporal dimension, the coefficient of the spatiotemporal lag term of GTFP is 0.0433. This indicates that GTFP has a positive spatiotemporal effect, that is, a higher GTFP in a city in the previous period positively affects the increase in GTFP in neighboring cities in the current period. This phenomenon may be due to the technology spillover and competition effects of local enterprises, which have a certain time lag in neighboring cities and do not have an immediate impact. In addition, after adding the spatial factor, green innovation still has a positive effect on GTFP.

7. Conclusions and implications

In this study, we provide new evidence on the factors that influence the GTFP from green innovation, using green patent data that cover 263 prefecture-level cities in China from 2007 to 2018. To address the potential endogeneity problem and spatial correlation in the baseline model, we propose the instrumental variable model and spatial econometric models, respectively. Finally, we verify the impact mechanism of green innovation on GTFP.

Table 10
Regression results for the spatial effects.

Variables	Explained variable: Green total factor productivity			
	Model(1)	Model(2)	Model(3)	Model(4)
$GTFP_{t-1}(\theta)$	−0.1164***	−0.1197***	−1.0717***	−0.1132***
	(6.8500)	(−6.5800)	(−6.3600)	(−6.3300)
$W^*GTFP(\rho)$	0.5379***	0.5429***	0.5198***	0.5282***
	(18.7900)	(18.4300)	(41.0100)	(17.6500)
$W^*GTFP_{t-1}(\alpha)$		0.0214		0.0433***
		(0.5000)		(1.00000)
Inn_ql	0.1267**	0.1273**	0.1769***	0.1774***
	(2.4700)	(2.4800)	(3.2000)	(3.2100)
Control variable	NO	NO	YES	YES
W(Control variable)*	NO	NO	YES	YES
Year	YES	YES	YES	YES
city	YES	YES	YES	YES
Log likelihood	5208.1765	5208.8060	5266.0559	5267.3525
AIC	−10,430.71	−10,430.69	−10,530.45	−10,531.59
Obs	3156	3156	3156	3156

Note: The t-statistics are in brackets; ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

After adding year and city-fixed effects, clustering to time and individuals, green innovation has a significant positive impact on GTFP. The instrumental variable regression and robustness test support the above conclusion, consistent with existing research (Awan and Sroufe, 2020; Begum et al., 2021; Chu et al., 2021). Furthermore, this study attempts to add spatial factors to the model, and finds that the improvement of GTFP in neighboring cities has a significant "positive spillover effect" on the city.

These conclusions have some policy implications for the growth of GTFP. First, Green innovation is not limited to improvements in economic efficiency. It emphasizes the greening of the economic production process, which helps to reduce the damage to the ecological environment. Promoting sustainable economic and social development is the theme of the present era and the only way China can achieve high-quality development. Policy makers should improve financial support, increase the greenness of taxation, and encourage the willingness of enterprises to innovate green technologies by imposing environmental resource and compensation taxes. They should accelerate the cultivation of topics of green innovation, support the free flow of green high-tech enterprises, promote the implementation of inclusive policies to stimulate R&D, guide enterprises to become the main body of investment in green technology innovation, and support enterprises in building application-oriented basic R&D institutions. In addition, cross-regional market-based synergistic cooperation between innovation and industry chains should be strengthened, green technology small to medium enterprises (SMEs) should be supported to become stronger and larger, and the cultivation and growth of innovation clusters represented by high-growth green technology innovation enterprises should be accelerated.

Differentiated GTFP enhancement paths should be developed for the types of cities. Eastern regions should take full advantage of spatial spillover channels and extended industrial chains with strong capital, advanced technology, and innovation infrastructure to lead the development of green innovation. Central and western regions should improve their contribution to green innovation to GTFP and build major R&D platforms with developed regions. Due to the single industrial structure of resource-based cities, urban development is heavily dependent on available resources, and it is difficult to achieve GTFP without overcoming the "resource dependency syndrome." Resource-based cities should use existing resource advantages to expand, strengthen, and refine resource industries. New and high-tech industries should be actively cultivated to become pioneer industries for regional economic development.

Last, intercity exchanges and cooperation should be strengthened to stimulate the synergistic potential of green innovation and achieve positive synergistic growth of GTFP. First, cities should break through the original administrative division restrictions, break local protection barriers, and increase the transmission channels of urban GTFP. The limitations of scattered development in small- and medium-sized cities should be eliminated. The optimal state of resource integration should be realized so that the market, government, and private forces become the main forces for the synergistic development of the urban GTFP. Second, the difference in urban GTFP development should be reduced, and the benign development model of developed cities driving backward cities should be realized based on the spillover and leading role of cities with better GTFP.

This study has limitations. In addition to the industrial effect, there are other influencing mechanisms of green innovation that effect GTFP, which need to be further explored. The selection of instrumental variables in this paper still has room for expansion to better solve the endogeneity problem. Therefore, for data limitations, this research can only be conducted until 2018. With the release of additional relevant data, the sample period of this paper should be expanded.

Ethics approval and consent to participate

Not applicable.

Consent to publish

Not applicable.

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CRediT authorship contribution statement

Xin Zhao: Conceptualization, Methodology, Writing - Original draft preparation.

Joanna Nakonieczny: Data curation, Investigation, editing, Literature review.

Fauzia Jabeen: Draft, Revision, Literature review, Policies.

Umer Shahzad: Writing - Reviewing and Editing, Visualization.

Wenxing Jia: Supervision, Concept, Software, Validation, Preparing draft.

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

The datasets used during the current study are available from the corresponding or first author on reasonable request.

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