Innovation and Green Total Factor Productivity in China: A Linear and Nonlinear Investigation

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Abstract: The empirical conclusions regarding the influence of innovation on green total factor productivity (GTFP) are relatively mixed. Based on China's provincial panel data from 1999 to 2015, this paper uses the number of patent applications to measure regional innovation capacity, and comprehensively examines the linear and nonlinear effects of innovation on GTFP. Our results show that innovation plays a leading role in promoting GTFP growth in China in general. However, two different types of patents, invention patents and non-invention patents, have heterogeneous impacts on China's green growth under the difference of innovation level. Additionally, the relationship between innovation and China's GTFP also differs significantly before and after 2009. A further nonlinear effect analysis based on a panel threshold model reveals that the impact of innovation on GTFP is higher with the rise of human capital, knowledge stock and financial development. However, only the appropriate environmental regulation stringency is conducive to promoting the influence of innovation on China’s green growth. Overall, our findings contribute to a better understanding regarding the impact of innovation on GTFP in China.

Keywords: innovation; green TFP; patent; heterogeneous effects; nonlinear effects; panel threshold model

1. Introduction

Over the past decades, there has been an increasing concern about the issue of green growth around the world, especially in developing countries (Lorek and Spangenberg 2014; Ackah and Kizys 2015; Kwakwa et al. 2018; Lv et al. 2018; Huang et al. 2020). As the world's largest developing country, China has achieved miraculous economic growth since 1978, with its real GDP increasing more than 30 times over the last four decades[1]. However, this growth is at the cost of huge energy consumption and environment pollution (Li and Wu 2017; Lin and Chen 2018; Wang and Feng 2018). According to British Petroleum (2018), China's primary energy consumption reached 3132.2 million tonnes oil equivalent in 2017, accounting for 23.2% of the world's total energy consumption. Whereas, referring to World Development Indicators (WDI) database from the World Bank[2], China's economy just accounted for 15.1 percent of the world economy in the same year. Additionally, China has become the biggest emitter of greenhouse gases in the world. The environmental degradation, particularly the severe haze pollution which frequently occurred since 2013, has constituted serious threat to China's socioeconomic development. It is widely recognized that improving green total factor productivity (GTFP), established by introducing energy consumption and pollution into traditional total factor productivity (TFP) to consider the impact of economic activity on both resources and environment, is an efficient way for the Chinese economy to transform the extensive growth mode to green development (Feng et al. 2018; Lin and Chen 2018; Song et al. 2018; Hou et al. 2020). In this context, it is of great importance to identify the key driving factors of China's GTFP improvement.

Innovation, which is not only regarded as the dominant source of productivity growth in the endogenous growth theories (Romer 1990; Grossman and Helpman 1991), but also saves energy and reduces pollutant emissions (Cheng and Li 2018; Jin et al. 2019), is supposed to play an important role in improving the GTFP. In recent years, a growing number of studies have used Research and Development (R&D) input as the proxy of innovation capacity to empirically analyze the influence of innovation on GTFP, but their conclusions are inconsistent. Most studies show that innovation has a significant role in promoting China's GTFP (Chen and Golley 2014; Wang and Shen 2016; Zhang and Tan 2016; Chen et al. 2018; Yuan and Xiang 2018; Shen et al. 2019), but there are also studies that have reached different conclusions (Liu and Xin 2019; Jin et al. 2019; Zhou et al. 2019).

[1] http://www.stats.gov.cn/
[2] https://data.worldbank.org/

This paper believes that the inconsistent research findings regarding the relationship between innovation and China's GTFP can be further understood from the following three aspect. First, there may be a nonlinear relationship between innovation and GTFP. The existing literature believed that the influence of innovation on TFP improvement and economic growth may be nonlinear, depending upon several relevant factors such as financial support, human capital, etc (Nicholas 2009; Dabla-Norris et al. 2012; Zanello et al. 2016; Brown et al. 2017; Park 2018). In this sense, special attention should be paid to explore the main factors affecting the innovation-GTFP link. However, to the best of our knowledge, just one paper in the literature has concerned about this issue from the perspective of environmental regulation (Jin et al. 2019).

Second, innovation may have heterogeneous effects on GTFP. As the research of Zhao and Liu (2011) shows, there are obvious differences in the effects of invention patents and non-invention patents on China's TFP under different innovation levels. Meanwhile, the research of Yuan and Xiang (2018) also shows that the effects of patent outputs of different technological levels on the GTFP of China's manufacturing industry are also different. In addition, in recent years, especially since the global financial crisis in 2009, the Chinese government has paid great attention to the enhancement of innovation capacity as well as the green economy transformation. The effect of innovation, especially the innovations of different technical levels, on China's GTFP may vary significantly in various periods.

Finally, compared with innovation input, the use of innovation output to reflect regional innovation capacity should be able to more directly and effectively identify the GTFP effect of innovation. Because the process of innovation is very complicated, the CDM model proposed by Crépon et al. (1998) can better analyze the "black box" problem regarding the innovation process by building an analytical framework of "innovation input-innovation output-productivity". Based on the above framework, innovation output is the result of R&D activities and the technology source of productivity growth, R&D input just has an indirect effect on productivity by the channel of affecting innovation output (Crépon et al. 1998; Pan et al. 2019). In many cases, huge R&D spending has been input into innovation activities but does not generate sufficient innovation output as we have expected (Fu, 2008). In this sense, investigating the impact of innovation output rather than innovation input on GTFP can more directly and effectively analyze the GTFP effect of innovation.

In order to have a deeper understanding of the relationship between innovation and China's GTFP, this paper employs the number of patent applications that are the most commonly used indicator of innovation output to measure regional innovation capacity (Acs et al. 2002), and examines the linear and nonlinear effects of innovation on GTFP, utilizing China's provincial panel data from 1999 to 2015. The main contributions of this paper are as follows: First, this paper assesses the nonlinear effect of innovation on GTFP. At present, many studies have analyzed the linear influence of innovation on GTFP, but few studies focus on the nonlinear relationship between the two, and the current paper expands this field by exploring the role of human capital, knowledge stock, financial development and environmental regulation in moderating the innovation-GTFP relationship. Second, this article comprehensively evaluates the heterogeneity of the impacts of innovation on of GTFP. In the study of linear relationship, we not only considered the heterogeneous effects of two different types of patents, inventions and non-invention patents, on GTFP under the difference of innovation level, but also compared the GTFP effects of various types of innovations before and after 2009. This provides more detailed evidence for understanding the linear relationship between the two. Third, this paper identifies the GTFP effect of innovation in a more effective way. Different from most papers in the literature, this study uses patent outputs rather than R&D input as the proxy of innovation capacity, this is supposed to better understand the role of innovation in driving China's green growth. Meanwhile, considering the huge adverse impact of severe haze pollution on China's sustainable economic development in recent years, the $PM_{2.5}$ concentration extracted from the global $PM_{2.5}$ grids is innovatively taken as one of the undesirable output variables to calculate China's provincial GTFP.

The estimation results of this paper indicate that innovation plays a leading role in promoting GTFP growth in China in general. Meanwhile, it is also found that only invention patents with higher novelty and technical quality have a significant impact on China's regional GTFP in general, which is similar to the finding of Yuan and Xiang (2018). Nevertheless, this study further discovers that the effect of patents, as well as the heterogeneous effects of different types of patents on GTFP in China differ in various periods. That is, the existence of significant and positive effects can only be verified during 2010-2015, and only invention patents exert a significant and positive influence on GTFP. Moreover, the nonlinear effect analysis based on a panel threshold model indicates that the effect of innovation on China's provincial GTFP is related to four selected factors, namely, human capital, knowledge stock, financial development and environmental regulation.

The remainder of the paper is organized as follows. The next section presents a brief review of the relevant literature. Section 3 provides the measurement methods and results of China's provincial GTFP. Relevant results regarding the linear influence of innovation on China's GTFP are reported and discussed in section 4. The results of the nonlinear effect of innovation on GTFP is provided in section 5. The final section provides a conclusion and policy implications on GTFP improvement in China.

2. Literature Review

Endogenous growth theory believes that innovation is the most important source of productivity growth, and a large volume of empirical research have proved that innovation has a significant and positive effect on productivity growth (Doraszelski and Jaumandreu 2013; Baumann and Kritikos 2016; Lopez-Rodriguez and Martinez-Lopez 2017). In recent years, there are a growing body of studies paying attention to the influence of innovation on GTFP. However, the extant research conclusions regarding the relationship between innovation and GTFP are relatively mixed.

Most empirical studies show that innovation is a critical driver of GTFP growth. Chen and Golley (2014) used the data of China's 38 industrial sectors from 1980 to 2010 to examine the determinants of GTFP. The results indicated that innovation, measured by R&D intensity, not only played an important role in industrial TFP improvement, but also had a significant and positive effect on industrial GTFP in China. Meanwhile, the results of several following pieces of literature further verified the existence of a positive correlation between R&D input and China's industrial GTFP (Wang and Shen 2016; Chen et al. 2018; Shen et al. 2019). Utilizing 285 prefecture-level cities' data in China over the period 2005-2012, Zhang and Tan (2016) investigated the influence of R&D expenditure on GTFP. The results based on three different estimators revealed that strengthening R&D input were beneficial for China's urban GTFP improvement.

However, a fraction of studies contended that there was no positive relationship between innovation and GTFP. Using a panel data of 30 provinces in China during 2006-2015, Zhou et al. (2019) pointed out that there was no evidence that R&D investment significantly promoted the enhancement of China's provincial GTFP. Using a dataset of 17 provinces along the Belt and Road Initiative route in China over the period 2003-2016, Liu and Xin (2019) obtained the similar conclusions based on the analysis of full sample as well as the subsamples of different regions. Jin et al. (2019) also confirmed that, overall, technology innovation had no significant influence on green total factor efficiency (GTFE) of industrial water resources in China.

Additionally, several studies proved that different types of innovations had distinct influences on GTFP. Cheng and Li (2018) used China's manufacturing panel data to test the effects of three different types of R&D investment (i.e., independent R&D, domestic technology introduction and foreign technology introduction) on GTFP and found that there was a significant industrial heterogeneity in the effects of various kinds of R&D investment on the green growth of China's manufacturing. To the best of our knowledge, Yuan and Xiang (2018) may be the first work using patent outputs as the proxy of innovation capacity to investigate the relationship between innovation and GTFP. They classified patent outputs into invention patents and non-invention patents and studied the influence of these two types of patents on the GTFP of Chinese manufacturing industry during 2003-2014. Their results showed that invention patents significantly promoted the improvement of GTFP, but non-invention patents were not significantly advantageous to GTFP of the manufacturing industry. Yet this effect may differ in various periods, since China has attached great importance to the improvement in innovation capacity and stressed the key role of innovation in promoting the economic transformation and upgrading after 2009 global financial crisis.

More recently, some scholars realized that the relationship between innovation and GTFP may be non-linear. That is, the effect of innovation on GTFP would be contingent on other factors. Based on a panel data of 30 Chinese provinces from 2000 to 2016, Jin et al. (2019) evaluated the impact of interactions between technological innovation and environmental regulation on GTFE of industrial water resources in China. The results showed that the combined effect of these two factors was significantly positive, revealing that the influence of innovation on GTFE was in association with the condition of environmental regulation. However, the estimation strategy of constructing a linear interaction term between technological innovation and environmental regulation cannot effectively solve the problem of a structural break in the impact of innovation on GTFE (Huang et al. 2019a; Zhou et al. 2019).

In order to provide a greater understanding of the relationship between innovation and GTFP, this paper initially analyses the linear impact of patent outputs and different types of patents on China's GTFP in the full sample, and further selects the year 2009 as the break data to investigate whether the effect differs between different periods. Furthermore, in the nonlinear analysis, by employing a panel threshold regression model proposed by Hansen (1999), this paper explores four main factors affecting the innovation-GTFP relationship in China.

3. Measurement and Analysis of GTFP

3.1. Method

By incorporating energy consumption and pollutant byproducts into TFP framework, GTFP has been used as the measurement index for the green development of China's economy by an increasing number of studies (Feng et al. 2018; Yuan and Xiang 2018; Liu and Xin 2019; Shen et al. 2019). The GML index, constructed based on the global production technology set during the whole sample period, can not only avoid the unsolvable linear programming defect, but also be multiplicative in a cycle (Oh 2010; Lin and Chen 2018). Many scholars, thus, have used this index to construct GTFP (Tao et al. 2017; Chen et al. 2018; Lin and Chen 2018; Liu and Xin 2019). Additionally, the SBM directional distance function can diminish the measurement deviation caused by radial and angular problems (Tone 2001; Fukuyama and Weber 2009; Liu and Xin 2019). In order to measure the GTFP more effectively, we adopt a GML index based on a SBM directional distance function in this paper. The calculation method is briefly introduced as below:

In this study, each province in China is regarded as a decision-making unit (DMU). Under a penal of $k=1,\dots,K$ provinces and $t=1,\dots,T$ time periods, every province uses N inputs, $x=(x_1,x_2,\cdots,x_N)\in R_+^N$, and obtains M desirable outputs, $y=(y_1,y_2,\cdots,y_M)\in R_+^M$, and I undesirable outputs, $b=(b_1,b_2,\cdots,b_N)\in R_+^I$. Following the work by Oh (2010), this paper defines the global production technology set $P^G(x)$ as the union of all current production technology sets, making the production frontier comparable between each DMU as well as each time period. The set can be expressed as:

$$P^G(x)=\left\{(y^t,b^t):\sum_{t=1}^{T}\sum_{k=1}^{K}z_k^t y_{km}^t \ge y_{km}^t,\forall m;\quad \sum_{t=1}^{T}\sum_{k=1}^{K}z_k^t b_{ki}^t = b_{ki}^t,\forall i; \\ \sum_{t=1}^{T}\sum_{k=1}^{K}z_k^t x_{kn}^t \le x_{kn}^t,\forall n;\ z_k^t \ge 0,\forall k\right\} \tag{1}$$

where z_k^t denotes the weight of each cross-sectional observation, and constant returns to scale (CRS) is assumed for the setting.

Then, the global directional distance function with SBM is defined as:

$$\begin{aligned}
&\vec{S}^{G,k'}(x^{t,k'},y^{t,k'},b^{t,k'},g^x,g^y,g^b) \\
&\quad = \max_{s^x,s^y,s^b}\frac{\frac{1}{N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x}+\frac{1}{M+I}\left(\sum_{m=1}^{M}\frac{s_m^y}{g_m^y}+\sum_{i=1}^{I}\frac{s_i^b}{g_i^b}\right)}{2} \\
&s.t.\quad \sum_{t=1}^{T}\sum_{k=1}^{K}z_k^t x_{kn}^t + s_n^x = x_{k'n}^t,\forall n;\quad \sum_{t=1}^{T}\sum_{k=1}^{K}z_k^t y_{km}^t - s_m^y = y_{k'm}^t,\forall m; \\
&\qquad \sum_{t=1}^{T}\sum_{k=1}^{K}z_k^t b_{ki}^t + s_i^b = b_{k'i}^t,\forall i;\ z_k^t \ge 0,\forall k;\ s_m^y \ge 0,\forall m;\ s_i^b \ge 0,\forall i
\end{aligned} \tag{2}$$

Among them, $\vec{S}^{G,k'}$ is the distance of DMU, province *k*, to the global production frontier. When it is equal to 0, the DMU is located on the global production frontier, revealing that there is no technical inefficiency. (g^x,g^y,g^b) refer to the direction vectors, representing decreasing inputs, increasing desirable outputs and decreasing undesirable outputs, respectively. (s_n^x, s_m^y, s_i^b) denote the slack variables, representing redundant inputs, inadequate desirable outputs and redundant undesirable outputs, respectively.

Therefore, the GML index can be constructed as follows:

$$GML_t^{t+1} = \frac{1 + \vec{S}_c^G (x^{t,k'}, y^{t,k'}, b^{t,k'}, g^x, g^y, g^b)}{1 + \vec{S}_c^G (x^{t+1,k'}, y^{t+1,k'}, b^{t+1,k'}, g^x, g^y, g^b)} \tag{3}$$

The GML index reflects the change from period t+1 to period t. When this index is greater than 1, it means GTFP growth. If the index is less than 1, it represents GTFP decline.

3.2. Data and Variables

Given the uneven regional development in China, this paper attempts to calculate GTFP and investigate its determinants from the provincial level. Because of the relatively limited data in Tibet, Hong Kong, Macau, and Taiwan, this paper chooses 30 other provinces in China as our research focus. Due to data availability and the agreement of statistical caliber, the sample period for the measurement of GTFP runs from 1999 through to 2015. As described above, the indices of inputs and outputs are required to obtain for the GTFP's calculation.

3.2.1. Input Variables

Consistent with most studies in the literature (Tao et al. 2017; Lin and Chen 2018; Liu and Xin 2019), in this paper, labor, capital and energy are used as input variables. The measurement of such three inputs is specified as follows.

Labor input. The number of year-end employed people in each province is chosen as the proxy of labor input. The data of this indicator is collected from the Statistical yearbooks of various provinces.

Capital input. Capital stock, estimated by using the perpetual inventory method (PIM), is applied to measure capital input. Specifically, this study obtains the series of capital stock in each province except Sichuan and Chongqing before 2004 from Zhang (2008), who estimated China's provincial capital stock over the period 1952-2004. We update the data by adopting the same approach[3]. Since Chongqing was separated from Sichuan province in 1997, it should be noted that the capital stock of Chongqing was included in Sichuan province in the work of Zhang (2008). Considering the estimation results of capital stock based on PIM are sensitive to the selection of the base year, this paper chooses 1952 as the base period to diminish the measurement bias as far

[3] See Zhang (2008) for details.

as possible. However, the data of both fixed capital formation and its price index in Chongqing is not available before 1995. In terms of the estimation of capital stock in Chongqing during 1952-1995, this paper supposes that the fixed capital formation in Chongqing and Sichuan province accounts for the same proportion of gross capital formation before 1995, then Chongqing's fixed capital formation can be estimated from the gross capital formation of this area. As for capital price index in Chongqing, it is substituted by the fixed capital formation price index of Sichuan province before 1995. Additionally, to ensure the comparability of the data, the annual capital stock of each province is measured at the constant price of 1999. In the estimation of capital stock, the relevant data used in this paper comes from China Compendium of Statistics 1949-2008 and China Statistical Yearbook.

Energy input. The equivalent energy consumption after the standard coal method conversion of each province is used to measure the energy input. The data of this indicator is collected from the China Energy Statistical Yearbook.

3.2.2. Output Variables

Output indicators include desirable output and undesirable output, and their measurement is specified as follows.

Desirable output. The real GDP of every province at constant 1999 price is taken as the proxy for desirable output. The data of this indicator comes from the China Statistical Yearbook.

Undesirable output. The undesirable output is given by four indicators, namely CO_2 emissions, industrial SO_2 emissions, industrial COD emissions and the annual average of $PM_{2.5}$ concentration of each province. It is worth noting that there is no consensus on the chosen of undesirable output variables, the selection of the above four indicators in this paper is mainly based on the following considerations.

It is well known that CO_2 is the main contributor to the greenhouse effect, and China is the world's largest CO_2 emitter. The CO_2 emissions, thus, is taken as one proxy of undesirable output. The provincial CO_2 emissions cannot be obtained directly and are estimated following Wang and Zhao (2015). Given that emission reduction of both SO_2 and COD is taken as the main control objects in China's 11th, 12th and 13th five-year plan, the emissions of SO_2 and COD are also chosen as undesirable output in this study. Simultaneously, as the statistical caliber of both China's provincial gross SO_2 and COD emissions has changed in 2011, this paper ultimately uses industrial SO_2 emissions and industrial COD emissions to make the data comparable. Finally, given the fact that severe haze pollution frequently occurred in China in recent years, the annual average concentration of $PM_{2.5}$, widely used to reflect the haze intensity (Dong et al. 2019; Yang et al. 2019), is selected as a proxy of undesirable output in this paper. Since China's annual $PM_{2.5}$ concentration data is just officially published in the city level since 2013, this paper applies ArcGIS software to extract the provincial annual average concentration of $PM_{2.5}$ over the period 1999-2015 from the global $PM_{2.5}$ grids, which is provided by the Battelle Memorial Institute and the Center for International Earth Science Information Network (CIESIN) at Columbia University[4].

In terms of data source, except for $PM_{2.5}$ grids, the raw data of CO_2 emissions, industrial SO_2 emissions and industrial COD emissions are all collected from China Statistical Yearbook of Environment.

3.3. Measurement Results

The MaxDEA software is used to calculate the GML index of 30 Chinese provinces over the period 2000-2015 (see Table A1 in Appendix for details). Based on the estimation results, this paper calculates the geometric mean of GML index during the sample period in each province (presented in Figure 1), as well as the mean of 30 provinces' GML index in each year (depicted in Figure 2).

According to Figure 1, it is found that most provinces in China have experienced GTFP growth during the sample period, but the growth rate is relatively slow, which is similar to the finding of Liu and Xin (2019). Clearly, except for Jiangxi, Hubei, Guangxi, Ningxia and Gansu provinces, the geometric means of GML index in other 25 areas of China are greater than 1, revealing that the economical production efficiency of most provinces has been enhanced after taking the environmental pollution factors into consideration. It can also be seen that, among China's 30 provinces, Beijing, Shanghai and Jiangsu province have the highest GTFP growth rate, in which the average annual growth rate (the geometric mean of GML index minus 1) all exceeds 2%. The annual growth rates of GTFP on average in 6 regions (Shandong, Tianjin, Sichuan, Chongqing, Guangdong and Zhejiang) range from 1% to 2%. Additionally, the average annual growth rates in seventy percent of the provinces of China (21 provinces) are all presented to be less than 1%. It is noteworthy that, China's provincial GTFP growth rate during the sample period is significantly slower when compared with its real GDP growth rate in the same phase, indicating that the rapid development of Chinese economy is mainly based on resource consumption input and pollutant emission and is at the cost of environmental quality (Lin and Chen 2018).

[4] http://www.ciesin.org/

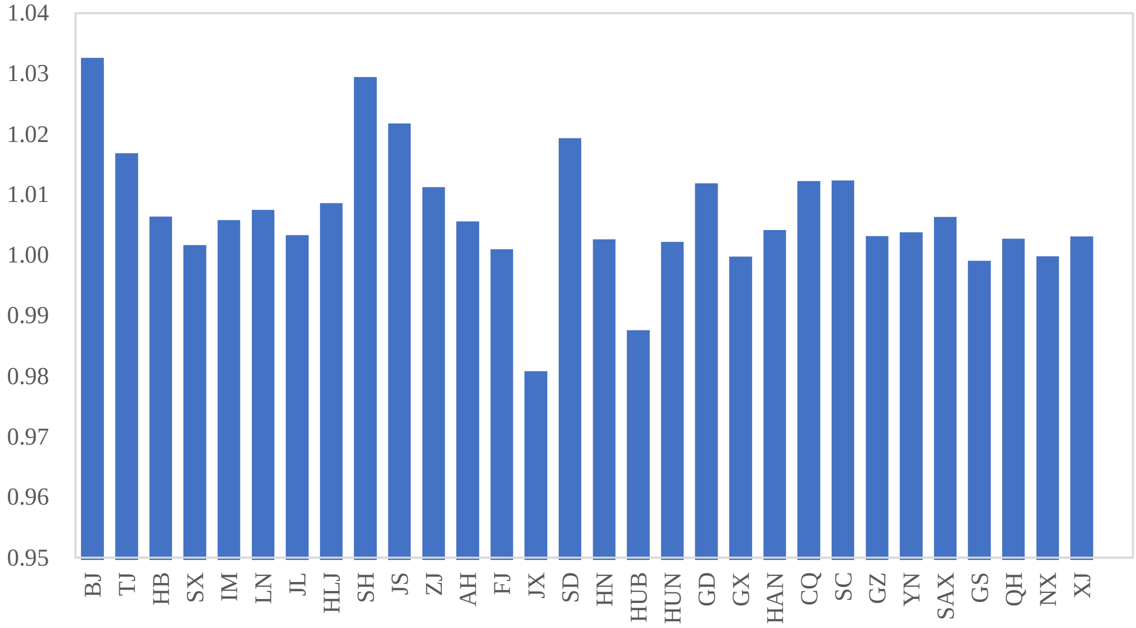

Fig. 1 Geometric mean of GML index in each province

Note: BJ=Beijing, TJ=Tianjin, HB=Hebei, SX=Shanxi, IM=Inner Mongolia, LN=Liaoning, JL=Jilin, HLJ=Heilongjiang, SH=Shanghai, JS=Jiangsu, ZJ=Zhejiang, AH=Anhui, FJ=Fujian, JX=Jiangxi, SD=Shandong, HN=Henan, HUB=Hubei, HUN=Hunan, GD=Guangdong, GX=Guangxi, HAN=Hainan, CQ=Chongqing, SC=Sichuan, GZ=Guizhou, YN=Yunnan, SAX=Shaanxi, GS=Gansu, QH=Qinghai, NX=Ningxia, XJ=Xinjiang

As shown in Figure 2, China's GTFP growth rate (mean of 30 provincial GTFP growth rates) in the sample period is less than 1% except in the year of 2012, 2014, 2015, further demonstrating that China has achieved extensive economic growth in general. In addition, the features of different phases of China's GTFP growth are clearly evident. In the first phase (from 2000 to 2009), the mean value of the GML index is 0.9997, suggesting that China's GTFP as a whole has changed very slightly. Simultaneously, the GTFP growth rate in 2001, 2003, 2004 and 2005 is all negative. The second phase, which begins in 2010, has recorded a relatively fast growth of GTFP in China. The GML index is still positive during this period, and the average of the index is 1.0159, which is much higher than that of the first phase. Meanwhile, the GTFP growth rate in 2012, 2014 and 2015 reaches 1.93%, 1.94% and 3.09%, respectively. Owing to the influence of global economic crisis as well as the tightening environmental constraints, the issues of economic transformation and upgrading, resource utilizing efficiency and environmental protection, have attracted increasing attention in China after 2009 global economic crisis. In this context, China's GTFP has experienced faster growth rates during the period 2010 to 2015. Moreover, in the following context, this study also attempts to investigate whether the impact of innovation on the GTFP in China differs between these two phases.

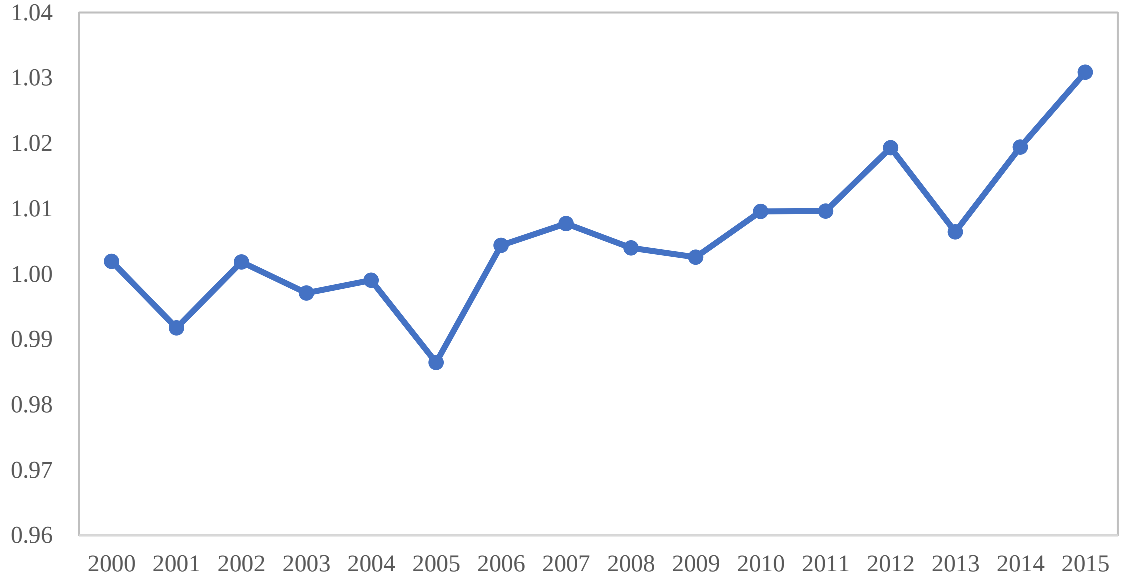

Fig. 2 Trends of China's GML index

4. Linear Impact of Innovation on GTFP

4.1. Model Specification

Theoretically, innovation has an impact on GTFP mainly through the following four paths. First, improving the use of production efficiency. By introducing new technologies into the production process, realizing the recombination and structural optimization of production factors, the efficiency of using capital, labor and other factors can be significantly improved, and economic growth can be achieved with relatively few factor inputs; Second, creating new economy growth points. By realizing the application and diffusion of new processes and new products in production and business, it will create new growth factors and promote the improvement of economic output; Third, promoting the upgrading of industrial structure. Through technological innovation, it will help drive the transfer and allocation of production factors from relatively low value-added sectors to higher value-added sectors, thereby promoting the optimization of industrial structure and the efficiency enhancement in economic growth; Fourth, reducing resource consumption and environmental pollution. The application of technologies, especially the green technologies such as clean energy and environment-friendly ones, can reduce resource energy consumption and environmental pollution levels in the production process (Huang et al. 2017; Cheng and Li 2018; Jin et al. 2019).

In order to evaluate the influence of innovation on China's GTFP, this paper runs the following regression following previous studies (Chen and Golley 2014; Chen et al. 2018; Song et al. 2018; Shen et al. 2019)[5]:

$$GTFP_{it} = \alpha + \beta_1 \ln Pat_{it} + \boldsymbol{\beta_2 X_{it}} + u_i + \varepsilon_{it} \tag{4}$$

Where $GTFP_{it}$ is green total factor productivity for province *i* and year *t*. *Pat* donates patent numbers, which is taken as a proxy of provincial innovation capacity in this study. The vector, **X**, includes the following set of control variables: human capital (*HC*), financial development (*FD*), environmental regulation (*ER*), openness degree (*Open*), industry structure (*IS*) and property right structure (*PR*). u_i is included in the model specification to control the provincial individual effects. ε is a disturbance term.

There are three types of patents in the Chinese system, i.e., invention, utility model and external design. According to the definition from the China Statistical Yearbook 2019[6], inventions patents refer to "new technical proposals to the products or methods or their modifications", utility model patents refer to "the practical and new technical proposals on the shape and structure of the product or the combination of both", external design patents refer to "the aesthetics and industrially applicable new designs for the shape, pattern and colour of the product, or their combinations". It can be seen from the above definition that, the invention patents embody the most significant technical improvement, the utility model patents have certain technical improvement, and external design patents embody the most incremental of improvements in aesthetic features rather than technical features (Fai, 2005). At the same time, the protection period of invention patents is 20 years, while the protection periods of both utility model and external design patents are only 10 years. Many scholars, thus, believe the novelty and importance of invention patents are remarkably higher than that of the other two types of patents (Fai, 2005; Zhao and Liu 2011).

It can be expected that the effects of different types of patents on GTFP should also be different. In terms of the invention patents, since their originality and technical level are significantly higher than that of the non-invention patents, they should also play a more significant role in improving the efficiency of factor use, creating new economic growth points, promoting industrial structure upgrading, and reducing resource consumption and environmental pollution. For example, from the perspective of the previous industrial revolutions, the diffusion and application of major original achievements in the production

[5] As all the variables in equation (4) and equation (5) except innovation related variables are in the form of proportion or index, this paper just performs the logarithmic transformation for innovation related variables (Ahi and Laidroo, 2019; Liu et al. 2020).

[6] http://www.stats.gov.cn/tjsj/ndsj/2019/indexeh.htm

process leads to the great improvement of productivity level. Therefore, the impact of invention patents on GTFP should be larger than that of the non-invention patents.

This study subdivides patent outputs into invention patents and non-invention patents (utility model and external design patents) to look at the heterogeneous effects of different types of innovation outputs on China's GTFP[7]. Function 5 shows a mathematical representation of the empirical model:

$$GTFP_{it} = \alpha + \beta_1 \ln Inv_{it} + \beta_2 \ln NInv_{it} + \boldsymbol{\beta_3 X_{it}} + u_i + \varepsilon_{it} \tag{5}$$

Where *Inv* and *NInv* refer to the numbers of invention patents and non-invention patents, respectively.

4.2. Variables and Data

First, the measurement of the dependent variable (GTFP) and core independent variables (innovation) in this study will be described. Then, according to the literature review, the selection of control variables in this study and their measurement will be introduced.

Green total factor productivity. Considering that the GML index represents the GTFP change of period *t*+1 relative to period *t*, which is not comparable, this paper transforms it into a cumulative index. Following the work of Song et al. (2018), Chen et al. (2019), Liu and Xin (2019), this paper supposes that the GTFP in the first period is 1. Then, the GTFP of the period *t*+1 can be calculated by the formula: $GTFP_{t+1} = GTFP_t \times GML_t^{t+1}$.

Innovation capacity. As discussed above, in order to investigate the impact of innovation on GTFP more effectively, this paper mainly uses patent output rather than R&D input to reflect the regional innovation capacity[8]. The patent index can be measured through patent applications and patent grants. As pointed out by Pan et al. (2019), the information of patent grants has been covered in patent applications. Simultaneously, pendency from patent applications to grant is necessary, patent grants cannot truly reflect the current level of

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[7] In theory, comparing the heterogeneity of the effects of the three different types of patents on GTFP should be able to obtain more detailed conclusions. However, three types of regional patent applications are highly correlated (In the sample period, the correlation coefficients between the number of invention and utility model patent applications, invention and external design patent applications, utility model and external design patent applications are 0.865, 0.565 and 0.669, respectively). Following Zhao and Liu (2011), Yuan and Xiang (2018), in order to avoid the possible multicollinear problem, this paper subdivides patent outputs into invention patents and non-invention patents to examine the heterogeneous effects of different types of patents on China's GTFP effectively.

[8] Although there are some shortcomings in using the number of patents to measure innovation ability (see Acs et al. (2002) for detail).

regional innovation capacity. Patent applications, thus, are regarded as a better proxy for innovation output (Wen et al. 2018b; Pan et al. 2019). In this paper, the number of patent applications per 100,000 population in each region is chosen as the index of provincial innovation capacity. Meanwhile, in the following empirical study, both R&D investment and patent grants are also taken as the proxies of regional innovation capacity for the robustness checks. In the analysis of heterogeneous effects under different innovation levels, regional invention patent outputs and non-invention outputs are measured by the number of invention patent applications per 100,000 population and the number of utility model and external design patent applications per 100,000 population in each province, respectively. The data to calculate this indicator is from the China Statistical Yearbook of Science and Technology and China Statistical Yearbook.

Human capital. Human capital is regarded as an important driving force of GTFP growth (Tao et al. 2017; Song et al. 2018; Jin et al. 2019). On one hand, the human capital level of residents reflects the knowledge and skills of the local labor force. The higher the human capital level, the more conducive is to produce and adopt new technologies, improving the resource utilization efficiency (Jin et al. 2019). On the other hand, the higher the human capital level, the greater the focus on pollution. In this sense, high population quality becomes a form of external supervision on environmental pollution (Song et al. 2018).

The average schooling years of residents in each province is used to reflect the regional human capital level. Consistent with the study of Jin et al. (2019), this paper sets the years of education for primary, junior high, senior high school, and college and above as 6 years, 9 years, 12 years, and 16 years, respectively. Then, the education level of residents in each province can be estimated as follows: HC = 6× percentage of population that has attained at most primary school education + 9× percentage of population that has attained at most junior high school education + 12× percentage of population that has attained at most senior high school education + 16× percentage of population that has attained at least tertiary education. The data of this indicator is collected from the China Statistical Yearbook.

Financial development. The important roles of financial development in raising productivity have been well documented and widely discussed in published reports (Jeanneney et al. 2006). A sound financial system can improve the allocation efficiency of funds, reduce the costs of enterprises, promote innovation, and thus contributes to the growth of GTFP (Jeanneney et al. 2006; Li and Wu 2017; Chen et al. 2019). It is noted that China's financial system is banking-led, and no uniform index of financial development exists (Jeanneney et al. 2006; Chileshe 2018; Chen et al. 2019).

To fully evaluate the status of regional financial development, three indicators, i.e., ratio of savings and loans of financial institutions to GDP, ratio of loans to savings and ratio of total market capitalization of listed companies to GDP in each province are chosen to reflect financial development scale, financial development efficiency and financial development structure, respectively. The financial development index of each region can be set up as follows.

First, the three indicators above are normalized by applying the Z-score formula: $x'_{ijt} = (x_{ijt} - \overline{x_j})/s_j$. Where x_{ijt} is the values of original series *j* for province *i* and year *t*. x'_{ijt} refers to the corresponding normalized values. $\overline{x_j}$, s_j refer to the mean and standard deviation of sample values of indicator *j*, respectively.

Then, the financial development index *FD* can be constructed as a weighted arithmetic average of three normalized indicators, using the following formula: $FD_{it} = \sum_{j=1}^{3} \frac{x'_{jit}}{3}$.

The data to calculate this indicator is from the Almanac of China's Finance and Banking and China Statistical Yearbook.

Environmental regulation. In recent times, the influence of environmental regulation on GTFP has received extensive academic attention. However, there has been little consensus concerning the relationship between environmental regulation and GTFP. On one hand, the traditional hypothesis supposed that increasing environmental regulation will lead to a higher production cost, crowding out the R&D investment of enterprise, and thus produce a restraining effect on the productivity and competitiveness of corporate (Siegel 1979; Christainsen and Haveman 1981). On the other hand, the “Porter Hypothesis” believed that more stringent but properly designed environmental regulation can trigger an “innovation compensation effect”, making the enterprise improve utilization efficiency of resources, strength technological innovation especially clean technological innovation, and ultimately promote environmental performance improvement and productivity growth (Porter 1991; Porter and Van der Linde 1995).

Following Zhao et al. (2018), this paper chooses ratio of industrial pollution abatement and control expenditure to their corresponding sales values and ratio of industrial pollution abatement and control expenditure to main industrial business costs in each region to measure the intensity of provincial environmental regulation. Meanwhile, these two indicators are also employed to build a composite index of environmental regulation by adopting the same method of constructing the financial development index introduced above.

Specifically, the two indicators are first normalized by employing the Z-score formula, then the environmental regulation index ER can be built as a weighted arithmetic average of these two normalized indicators.

The data to calculate this indicator comes from the China Environment Yearbook and China Statistical Yearbook.

Openness degree. Under the background of globalization, a growing number of researches have focused on the impact of economic openness on environmental performance and productivity growth of developing countries (Zhao and Liu 2011; Song et al. 2018; Liu and Xin 2019). However, there has continued to be great controversy regarding the relationship between economic openness and environmental quality as well as productivity. In terms of environmental quality, the “pollution halo” hypothesis believed that improving openness degree can help host countries learn management practices and introduce greener technologies, which will result in a clean environment (Zarsky 1999). However, according to the “pollution heaven” hypothesis, developing countries are always inclined to lower environmental standards to attract foreign direct investment, promote international trade, which may lead to worsening the environment (Copeland and Taylor 1994; Wen et al. 2018a). Regarding productivity, there is also no consensus on whether international technology spillover can promote productivity growth in developing countries (Crespo and Fontoura 2007). In this paper, the ratio of total imports and exports to GDP in each province is used to reflect the openness degree. The data of this indicator is from the China Statistical Yearbook.

Industry structure. Many scholars believe industry structure is one of the major influence factors of GTFP (Tao et al. 2017; Lin and Chen 2018; Song et al. 2018). In China, the secondary industry especially industry is the main source of resource consumption as well as environmental pollution. Hence, the higher the proportion of secondary industry in the total economy of one region, the lower the GTFP level in general. In this study, the share of value added of secondary industry to GDP in each province is chosen as the proxy of industry structure. The data of this indicator comes from the China Statistical Yearbook.

Property rights structure. In the context of Chinese economic transition (transforming from planned economy to market-oriented economy), the structure of property rights has been considered as a dominant factor affecting China’s TFP and GTFP (Zhao and Liu 2011; Chen and Golley 2014; Zhao et al. 2018; Shen et al. 2019). Specifically, accelerating privatization process is expected to be an important way to improve marketization degree and allocative efficiency. Accordingly, this paper uses the proportion of non-state-owned investment to fixed assets investment in each province to measure the property rights structure. The data of this indicator is collected from the China Statistical Yearbook.

The statistical information such as mean and standard deviation values of the dependent variable and independent variables are presented in Table 1.

Table 1 Descriptive statistics

Symbol	Definition	Unit	Mean	Std	Max	Min
GTFP	Green total factor productivity	—	1.01	0.12	1.60	0.68
lnPat	Log form of patent applications per 100,000 population	number	3.31	1.35	6.58	0.83
lnInv	Log form of invention patent applications per 100,000 population	number	1.98	1.51	6.02	-0.78
lnNInv	Log form of non-invention patent applications per 100,000 population	number	2.96	1.30	6.13	0.33
HC	Human capital	year	8.43	1.01	12.08	6.04
FD	Financial development index	—	0.00	0.60	5.48	-1.13
ER	Environmental regulation index	—	0.00	1.00	5.55	-1.11
Open	Openness degree	%	31.98	39.59	172.15	3.57
IS	Industry structure	%	39.25	8.00	53.04	13.12
PR	Property rights structure	%	35.81	12.41	70.26	11.45

4.3. Full Sample Results

In this subsection, the impact of total patent applications on China's provincial GTFP is initially empirically analyzed. Then, the heterogeneous effects of different types of patents on GTFP are investigated. By employing the panel data model, this paper gets the corresponding empirical results shown in Table 2 and Table 3, respectively.

According to Table 2, a significant and positive effect of innovation (measured by total patent applications per 100,000 population) on China's GTFP can be observed. As shown in column 2 to column 4 in Table 2, the estimated coefficients of *lnPat* are all positive and statistically significant at 1% significance level, based on the results of Ordinary Least Squares (OLS), Fixed effects (FE) and Random effects (RE) estimations. When taking into account of control variables in the model, it is seen that innovation still exert a significant and positive effect on GTFP in column 5 and column 7 of Table 2. These findings suggest that innovation is an unneglectable driving force of China's GTFP growth, which is in accordance with the studies of Chen and Golley (2014), Zhang and Tan (2016), Chen et al. (2018). This is mainly because innovation is not only a key channel to enhance traditional TFP, but also one of the fundamental methods for solving low resource efficiency to achieve energy conservation and emission reduction (Jin et al. 2019).

Table 2 Results of the effect of innovation on GTFP

Variables	Dependent variable: GTFP					
	OLS	FE	RE	OLS	FE	RE
lnPat	0.0409***	0.0258***	0.0268***	0.0326***	0.0098	0.0137**
	(11.78)	(8.66)	(9.13)	(5.05)	(1.45)	(2.12)
HC				0.0220***	0.0544***	0.0505***
				(3.19)	(4.68)	(4.76)
FD				0.0084	0.0025	0.0042
				(0.85)	(0.31)	(0.51)
ER				0.0027	0.0031	0.0026
				(0.50)	(0.79)	(0.68)
Open				0.0006***	-0.0005**	-0.0002
				(4.20)	(-2.10)	(-1.16)
IS				-0.0017**	-0.0055***	-0.0052***
				(-2.45)	(-7.68)	(-7.48)
PR				0.0021***	0.0006	0.0008*
				(3.94)	(1.23)	(1.71)
Cons	0.878***	0.928***	0.925***	0.692***	0.735***	0.727***
	(70.88)	(90.66)	(50.75)	(10.57)	(7.68)	(8.13)
N	480	480	480	480	480	480

Note: ***, **and * represent significance levels of 1%, 5% and 10%, respectively. *t* statistics are shown in parentheses.

Table 3 reports the effects of different types of patents on China's regional GTFP. Various types of patens have distinct impacts on GTFP in China. It is seen that the estimated coefficients of *lnInv* are all significant positive in column 2 to column 7 of Table 3, revealing that invention patents have a robust positive influence on China's provincial GTFP. Whereas, the impact of non-invention patents on GTFP in China is found to be insignificant, which is similar to the finding of Yuan and Xiang (2018). As discussed above, compared with non-invention patents, the novelty, as well as the importance of invention patents, is much higher. Thus, applying these advanced technologies, new products and processes can remarkably improve economic performance, enhance resource utilization efficiency, reduce pollutant discharge intensity, and achieve a win-win for economic development and environmental protection. By contrast, utility model and external design patents also play a positive role in economic growth to a certain extent, but cannot significantly promote the improvement of utilization efficiency of resources owing to the relatively low technical quality. As a result, the relationship between non-invention patents and China's GTFP is not significant.

In terms of control variables, both human capital and property right structure appear to exert significant and positive effects on GTFP in China, and the rise of the ratio of the secondary industry is found to have inhibited the GTFP, which is in line with what we would expect based on the economic theory. It is also found that the environmental regulation has an insignificant influence on GTFP, and the effect of openness degree turns out to be not robust, which may be related to the very complex influence mechanism of both environmental regulation and economic openness on GTFP discussed above (e.g., positive and negative influence mechanism). It is noted that the impact of financial development on China's provincial GTFP is positive, but not statistically significant. This may be primarily attributed to the fact China's financial system is not yet perfect or sound, which leads to the relatively low-efficient capital allocation. On the other hand, though financial development exerts an insignificant influence on GTFP in general, it may have an indirect effect on GTFP through the channel of stimulating innovation.

Table 3 Results of the heterogeneous effects of different types of patents on GTFP

Variables	Dependent variable: GTFP					
	OLS	FE	RE	OLS	FE	RE
lnInv	0.0467***	0.0218***	0.0226***	0.0314***	0.0184**	0.0166**
	(5.67)	(2.75)	(2.94)	(3.39)	(2.35)	(2.16)
lnNInv	-0.0103	-0.0009	-0.0005	-0.0001	-0.0119	-0.0056
	(-1.08)	(-0.09)	(-0.05)	(-0.01)	(-1.25)	(-0.60)
HC				0.0150**	0.0539***	0.0499***
				(2.00)	(4.61)	(4.66)
FD				0.0067	0.0018	0.0038
				(0.67)	(0.22)	(0.46)
ER				0.0029	0.0034	0.0029
				(0.54)	(0.89)	(0.74)
Open				0.0007***	-0.0005**	-0.0002
				(4.81)	(-2.19)	(-1.12)
IS				-0.0014*	-0.0055***	-0.0052***
				(-1.93)	(-7.68)	(-7.44)
PR				0.0020***	0.0007	0.0009*
				(3.81)	(1.52)	(1.92)
Cons	0.951***	0.973***	0.970***	0.784***	0.765***	0.756***
	(63.16)	(57.11)	(44.99)	(10.94)	(7.69)	(8.11)
N	480	480	480	480	480	480

Note: ***, **and * represent significance levels of 1%, 5% and 10%, respectively. *t* statistics are shown in parentheses.

To check the robustness of the results, several alternative estimations are carried out in this study. In terms of the results of the impact of regional innovation capacity on GTFP, this paper first re-estimates equation 4, using R&D input intensity (ratio of R&D expenditure to GDP) and the number of patent grants per 100,000 population in each province as the alternative measure of regional innovation capacity, respectively. The results reported in column 2 and column 3 in Table 4 suggest that both R&D investment and patent grants exert positive effects on GTFP, which is in line with those shown in the baseline (Table 2).

Second, this paper checks whether the effect of innovation on GTFP could be biased because of endogeneity, which may be caused by the reverse causality or the fact that unobserved factors not included in the estimation framework may jointly affect the changes in regional innovation capacity and GTFP. To address this issue, the fixed effects instrumental variables (FE-IV) estimators are employed to re-estimate equation 4[9], which use a one-year lagged value of the log of the number of patent applications per 100,000 population as the first instrument variable[10]. Meanwhile, as proposed by Lewbel (1997), the third-order centered moments of the log of the number of patent applications per 100,000 population was employed as the second instrument variable. The results in column 4 and column 5 in Table 4 indicate that the estimates obtained using these two alternative specifications are similar to those obtained in the baseline, further demonstrating that strengthening technological innovation is an efficient way for China to promote the GTFP improvement.

Finally, considering that technological innovation may have a time lagged effect on GTFP, and relevant empirical research shows the commercial value of patent applications can be realized over 3 years (Ernst, 2001; Christodoulou et al. 2018). Therefore, one-year, two-years and three-years lagged value of the number of patent applications are introduced to examine their impacts on China's GTFP, respectively. The results in column 6 of Table 4 show that the effects of three-years lagged value of the number of patent applications on China's GTFP are still significant and positive[11], further confirming the robustness of the results.

By adopting the similar method, it can also be observed that the robustness test results of the influence of different types of patents on GTFP (column 7 to column 10 in Table 4) are not statistically significantly different from those presented in the baseline (Table 3), confirming the validity of the baseline results.

Table 4 Results of robustness checks

[9] The F test and Hausman test results shown at the bottom of Table 4 indicate a preference for the FE specification.

[10] The lagged value of the endogenous variable is widely used as the instrument variable (e.g., Zhao et al. 2018).

[11] For the sake of simplicity of expression, we have not presented the estimation results using one-year and two-years lagged value of the number of patent applications as the independent variable. The results are available on request.

Variables	Dependent variable: GTFP								
	R&D Input	Patent Grants	FE-IV1	FE-IV2	Three-years lagged	Patent Grants	FE-IV1	FE-IV2	Three-years lagged
R&D	0.0808*** (7.86)								
lnPat		0.0168** (2.45)	0.0204*** (2.62)	0.236*** (5.42)					
L3.Pat					0.0265*** (3.49)				
lnInv						0.0205*** (3.05)	0.0296*** (2.77)	0.269*** (6.09)	
lnNInv						-0.0038 (-0.45)	-0.0149 (-1.10)	-0.0858** (-2.12)	
L3.lnInv									0.0218** (2.23)
L3.lnNInv									0.00163 (0.15)
HC	0.0392*** (4.96)	0.0447*** (3.76)	0.0399*** (3.12)	-0.241*** (-4.11)	0.0305** (2.48)	0.0401*** (3.34)	0.0394*** (3.08)	-0.237*** (-3.87)	0.0292** (2.31)
FD	-0.0002 (-0.03)	0.0015 (0.18)	-0.0014 (-0.16)	-0.0078 (-0.49)	-0.00570 (-0.62)	0.0018 (0.22)	-0.002 (-0.23)	-0.0153 (-0.89)	-0.0066 (-0.71)
ER	0.0029 (0.81)	0.0031 (0.80)	0.0024 (0.56)	-0.0012 (-0.17)	0.00648 (1.37)	0.0027 (0.72)	0.0026 (0.59)	0.0038 (0.47)	0.00626 (1.32)
Open	-0.0003 (-1.07)	-0.0005* (-1.90)	-0.0007*** (-2.61)	-0.0006 (-1.40)	-0.0014*** (-4.93)	-0.0005** (-2.19)	-0.0007*** (-2.81)	-0.0009* (-1.73)	-0.0013*** (-4.85)
IS	-0.004*** (-6.30)	-0.006*** (-7.74)	-0.005*** (-7.05)	-0.007*** (-5.06)	-0.004*** (-4.77)	-0.005*** (-7.56)	-0.005*** (-6.98)	-0.007*** (-4.44)	-0.004*** (-4.97)
PR	0.0012*** (2.66)	0.0007 (1.40)	0.0008 (1.50)	0.0054*** (4.26)	0.00079 (1.30)	0.001** (1.99)	0.001* (1.87)	0.0071*** (4.76)	0.0009 (1.48)
Cons	0.719*** (9.29)	0.800*** (8.08)	0.807*** (7.93)	2.363*** (6.77)	0.847*** (8.32)	0.869*** (8.41)	0.857*** (8.08)	2.772*** (6.59)	0.900*** (8.23)
F test	44.24***	34.32***	34.96***		40.13 ***	34.28***	34.70***		39.30***
Hausman test	23.55***	12.12*	13.90*		16.83**	13.84*	13.44*		17.93**
N	480	480	450	480	390	480	450	480	390

Note: ***, **and * represent significance levels of 1%, 5% and 10%, respectively. *t* statistics are shown in parentheses.

4.4. Results in Different Periods

As described in Section 2, the GTFP growth rate in China over the period 2010-2015 turns out to be much higher than that during the period 2000-2009[12]. In this context, it is interesting to investigate whether the influence of innovation on China's regional GTFP differs between these two periods.

[12] The Chow test also reveals that the coefficient of slopes in both equation 4 and equation 5 in period 2010-2015 are statistically significant different from that in period 2000-2009, at 1% significance level.

Table 5 depicts the empirical results of the impact of innovation on China's regional GTFP. It shows that the relationship between innovation and GTFP in China differs notably in various phases. As presented in column 2 to column 4 of Table 5, the results of OLS, FE and RE estimators all suggest that innovation exerts an insignificant effect on GTFP in China over the period 2000-2009. On the contrary, there exists a significant and positive association between patent applications and China's GTFP between 2010 and 2015 (column 5 to column 7 in Table 5). These findings suggest that innovation has become the primary impetus for the relatively rapid GTFP growth in China since 2010. In recent years, Chinese government has attached great importance to the improvement in innovation capacity and stressed the key role of innovation in boosting the socio-economic development, introduced a series of major policies to stimulate technological innovation (e.g., the government brought forward the indigenous innovation strategy in 2006 and set the task to become an "innovation-oriented country" in 2020, proposed the strategy of innovation-driven development in 2012 to place the innovation at the heart of the country's development). Under this background, innovation plays a more important role in promoting the GTFP growth in China.

Table 5 Results of the effect of innovation on GTFP in different periods.

Variables	Dependent variable: GTFP					
	2000-2009			2010-2015		
	OLS	FE	RE	OLS	FE	RE
lnPat	-0.0074	0.0104	0.0102	0.0446***	0.0302**	0.0258**
	(-0.77)	(1.50)	(1.52)	(4.12)	(2.48)	(2.19)
HC	0.0118	0.0265***	0.0228**	0.0465***	0.0376*	0.0827***
	(1.64)	(2.63)	(2.47)	(3.51)	(1.72)	(4.23)
FD	0.0125	0.0080	0.0092	-0.0075	-0.0957***	-0.0421*
	(1.27)	(1.34)	(1.55)	(-0.38)	(-3.92)	(-1.73)
ER	-0.0010	-0.0039	-0.0040	0.0059	-0.0008	-0.0074
	(-0.20)	(-1.32)	(-1.38)	(0.39)	(-0.11)	(-0.85)
Open	0.0009***	0.0006***	0.0006***	0.0012***	-0.0038***	-0.0014***
	(5.23)	(2.63)	(2.94)	(3.15)	(-7.73)	(-3.48)
IS	0.0012	-0.0031***	-0.0024***	-0.0027**	-0.0069***	-0.0052***
	(1.56)	(-3.36)	(-2.87)	(-2.18)	(-4.33)	(-3.30)
PR	0.0015***	0.0012***	0.0012***	0.0030***	0.0012	0.0015
	(2.59)	(2.65)	(2.97)	(3.23)	(1.10)	(1.34)
Cons	0.782***	0.805***	0.808***	0.426***	0.941***	0.401**
	(11.76)	(9.05)	(9.82)	(3.21)	(4.61)	(2.15)
N	300	300	300	180	180	180

Note: ***, **and * represent significance levels of 1%, 5% and 10%, respectively. *t* statistics are shown in parentheses.

Table 6 reports the results of the impact of various types of patents on China’s GTFP in different phases. It is seen that the influence of different types of patents on GTFP also differs in various periods. According to column 2 to column 4 in Table 6, neither invention patents nor non-invention patens have a significant effect on the GTFP in China during the period 2000-2009. Over the period 2010-2015, the invention patents are found to exert a significant and positive effect on GTFP, while the effect of non-invention patents is insignificant, which is in line with the empirical results in the full sample. Simultaneously, these findings also suggest that invention patents rather than utility model and external design patents are the major driving force of China’s GTFP growth since 2010.

Concerning the control variables, it is observed that both human capital and property right structure have significant and positive effects on China’s GTFP, environmental regulation exert an insignificant impact, and the estimated coefficients of *IS* are significant and negative during two different periods in general, which is similar to the findings in the full sample. It is worth mentioning that financial development appears to exert a positive and insignificant impact on GTFP between 2000 and 2009 but harms GTFP to some extent (not robust) since 2010. Although China’s finance sector has experienced fast growth in recent years, the relationship between China's real economy and its financial sector has weakened (Pan and Mishra 2018). Consequently, the financial sector growth will crowd out the real economic growth to a certain extent and not be conducive to the improvement in China’s GTFP. Additionally, the impact of openness degree on China’s GTFP is significant and positive over the period 2000-2009, whereas such an effect has changed to be un-robust negative during the period 2010-2015. With the rapid improvement in China’s innovation capacity, the technology gap between China and developed countries has become much narrower, and the enterprises in the advanced nations will have an incentive to prevent technology leakage and spillovers to the local competitors (Malik 2015). In this context, the domestic corporates in China will gain less technological benefits through productivity spillovers. On the other hand, according to the “pollution heaven” hypothesis, the relatively low environmental standards and regulations in China may lead to worsening the environment. This may be the main reason why the effect of economic openness on China’s GTFP differs in various periods.

Table 6 Results of the heterogeneous effects of different types of patents on GTFP in different periods

Variables	Dependent variable: GTFP					
	2000-2009			2010-2015		
	OLS	FE	RE	OLS	FE	RE
lnInv	0.0138	0.0084	0.0077	0.0733***	0.0333***	0.0285**
	(1.38)	(1.06)	(1.01)	(4.06)	(3.10)	(2.38)

lnNInv	-0.0223*	-0.0019	-0.0009	-0.0214	-0.0041	-0.0022
	(-1.82)	(-0.19)	(-0.10)	(-1.23)	(-0.31)	(-0.16)
HC	0.0075	0.0280***	0.0241***	0.0307**	0.0287	0.0759***
	(0.98)	(2.77)	(2.60)	(2.24)	(1.29)	(3.82)
FD	0.0111	0.0078	0.0090	-0.0152	-0.0903***	-0.0377
	(1.13)	(1.29)	(1.52)	(-0.78)	(-3.74)	(-1.56)
ER	-0.0009	-0.0038	-0.0040	0.0013	-0.0021	-0.0089
	(-0.18)	(-1.28)	(-1.37)	(0.09)	(-0.27)	(-1.02)
Open	0.0010***	0.0006**	0.0006***	0.0013***	-0.0038***	-0.0014***
	(5.50)	(2.57)	(2.97)	(3.65)	(-7.89)	(-3.33)
IS	0.0014*	-0.0031***	-0.0024***	-0.0018	-0.0063***	-0.0047***
	(1.84)	(-3.33)	(-2.83)	(-1.44)	(-3.98)	(-2.93)
PR	0.0014**	0.0012**	0.0012***	0.0032***	0.0012	0.0014
	(2.38)	(2.59)	(2.90)	(3.47)	(1.11)	(1.34)
Cons	0.827***	0.816***	0.818***	0.563***	1.039***	0.467**
	(11.22)	(8.87)	(9.60)	(4.25)	(5.02)	(2.47)
N	300	300	300	180	180	180

Note: ***, **and * represent significance levels of 1%, 5% and 10%, respectively. *t* statistics are shown in parentheses.

5. Nonlinear Effect of Innovation on GTFP

5.1. Panel Threshold Model Setting

As noted already, the effect of innovation on GTFP may be nonlinear. That is, the relationship between the two should depends on other factors. In order to explore the main factors moderating innovation-GTFP link in China, the panel threshold model proposed by Hansen (1999) is adopted in this study. Following the previous studies, this paper believes that the innovation-GTFP relationship in China may mainly depend on the following four factors.

First, human capital. We first discuss the moderating role of human capital in the innovation-GTFP relationship. On the one hand, human capital accumulation can promote the diffusion and application of new technologies. Compared with areas with low levels of human capital, managers in areas with high levels of human capital generally have higher levels of education, and they are more likely to introduce new technologies into production process (Nelson and Phelp, 1966), which will be beneficial to the application of new products and new processes. In addition, high-skilled human capital can also help solve the problems in the application of new technological achievements, and thus accelerate the absorption, diffusion and application of new technologies (Nicholas, 2009; Che and Zhang, 2018). This will eventually lead to the increasement of economic output, reduction of resources consumption and improvement of the productivity effect of innovation. Based on the empirical research of Chinese listed companies, Song et al. (2019) also found that in companies with a high proportion of highly skilled labor in the total labor, basic research investment has a greater role in promoting the corporate TFP level. This also shows from the micro level that human capital has a positive moderating role in the innovation-productivity relationship. On the other hand, residents in areas with higher levels of education generally have stronger environmental awareness, and their demand for environment-friendly products is also higher. This will help promote the commercial application of innovations, especially green innovations, and reduce energy consumption and discharge of pollutants. Finally, research by Huang and Chen (2020) also shows that human capital has a positive moderating role in the impact of R&D input on China's energy efficiency. In summary, this article expects that compared with areas with low levels of human capital, the impact of innovation on GTFP will be more prominent in areas with high levels of human capital.

Second, knowledge stock. This paper believes that the innovation-GTFP relationship is also related to the level of knowledge stock in a region. Since innovation is incremental and path dependent, compared with regions with a low level of knowledge stock, enterprises and other innovation entities in regions with a high level of knowledge stock can better discover the linkage between new technologies and existing technologies due to their deeper and extensive experience accumulation (Wadhwa and Kotha, 2006; Kuo et al. 2018). Clearly, enterprises in areas with high levels of knowledge stock can better absorb and apply new technologies by relying on the rich knowledge accumulation in the past. Meanwhile, the areas with high levels of knowledge stock have better supporting resources (e.g., interfirm linkages, social networks, an available workforce with the relevant technological skills) in general (Matusik et al. 2019), this will also help promote the spread of new technologies in the region, accelerating the translation of innovation outputs (including green innovation outputs) into practice. Thus, it is expected that the impact of innovation on GTFP will be greater for those regions with higher knowledge stock than those with lower knowledge stock.

Third, financial development. The invention, as well as adoption and commercialization of technology, are costly and risky activities, which requires outside financing. It can be expected that the impact of innovation on a region's GTFP will be related to its financial development level. For regions with higher levels of financial development, the financial system will be more complete, and the financial sector will be more inclined and more capable of allocating funds to those good innovation projects rather than bad ones. Thus, the commercialization of these high-quality innovative projects can be efficiently promoted by sharing innovation risks and reducing costs. Specifically, in the context of China's emphasis on improving GTFP under resource and environmental constraints, financial sectors in regions with high levels of financial development will be more likely to support environmental-friendly innovative projects or innovative companies with highest underlying productivity, this can more effectively improve the size of the return to innovation (that is, the impact of innovation on GTFP) (Dabla-Norris and Kersting 2012; Chileshe 2018). Therefore, this paper believes that the higher the level of financial development in regions, the greater the impact of innovation on GTFP.

Lastly, environmental regulation. At present, there have been many studies investigating the impact of environmental regulation on innovation or GTFP, but there are relatively few studies discussing the moderating role of environmental regulation in the innovation-GTFP relationship. This paper believes that the impact of innovation on GTFP is also related to the environmental regulation stringency in a region. This is because the increase in the intensity of environmental regulations usually encourages residents adopt environment-friendly products or products produced by green production processes. At the same time, companies engaged in green innovation-related activities often receive more policy support such as low-cost loans (Rennings and Rammer, 2011; Yao et al. 2019), which will help promote the application of green technologies in production process. As a result, strengthening environmental regulation will make innovation play a greater role in saving energy consumption and reducing pollutant emissions. Meanwhile, Yao et al. (2019) and Hu et al. (2020) used Chinese listed companies as the sample and found that environmental regulations play a positive moderating role in the relationship between innovation and corporate value. However, the economic development of China is currently in the process of transforming from a factor-driven to innovation-driven mode (Zhao et al. 2019). If the excessively strong environmental regulations are implemented, it may lead to a substantial increase in the production costs. This will not only crowd out the R&D investment of the enterprise, but also result in the issue of funds insufficiency in the process of the commercialization of new technologies. As a result, it will reduce the productivity promotion effect of technological innovation. In summary, this article believes that the impact of innovation on China's GTFP will increase as the level of environmental regulation increases, but when the intensity of environmental regulation reaches a certain level, its effect will decline. In other words, a moderate level of environmental regulation is conducive to improving the GTFP effect of China's innovation.

If human capital, knowledge stock, financial development and environmental regulation mentioned above affect the innovation-GTFP relationship, the coefficients on innovation will vary with such four factors. In other words, there can be threshold effects (nonlinear relationship) between regional innovation capacity and GTFP. Obviously, the traditional linear panel data model is not suitable for this study. In order to capture the threshold effects as well as avoid the bias from an artificially set of thresholds (cut-off values), the panel threshold model developed by Hansen (1999) is employed and the endogenous threshold effects are determined based on the characteristics of the data themselves, following the studies of Huang et al. (2019a), Wang and Shao (2019), Zhou et al. (2019). The panel threshold regression model with a single threshold is described in equation 6:

$$GTFP_{it} = \alpha + \beta_{11} \ln Pat_{it} I(q_{it} \leq \gamma) + \beta_{12} \ln Pat_{it} I(\gamma < q_{it}) + \mathbf{\beta_2 X_{it}} + u_i + \varepsilon_{it} \tag{6}$$

Where $I(\cdot)$ denotes the indicator function. q_{it} is a group of threshold variables, i.e., human capital (HC), knowledge stock (KS), financial development (FD) and environmental regulation (ER). In this study, patent stock per 100,000 population in each province is taken as the proxy of the regional knowledge stock level. Following Xu and Chiang (2005), the patent stock is calculated from patent applications based on the perpetual inventory model. γ represents threshold value. For any given threshold value γ, the slope coefficients can be estimated and the corresponding sum of squared residuals $S_1(\gamma)$ will be obtained. The threshold value can then be estimated via minimizing $S_1(\gamma)$, that is: $\hat{\gamma} = \arg\min_{\gamma} S_1(\gamma)$.

Panel threshold regression model with multiple thresholds can be extended accordingly. For details, please see Hansen (1999).

5.2. Threshold Examination and Analysis

This study first tests the existence of threshold effects between regional innovation capacity and GTFP by selecting human capital, knowledge stock, financial development and environmental regulation as the threshold variables. As panel threshold regression model is sample-data-driven, the number of threshold values is determined according to the significance level of each threshold value. If the *n*th threshold value of a threshold variable is not statistically significant while its *n-1*st threshold value is significant at 90% or above confidence level, the threshold variable has *n-1* threshold values (Hansen 1999; Zhou et al. 2019). The results for the threshold effect test are reported in Table 7.

As demonstrated in Table 7, there exist significant threshold effects between regional innovation capacity and China's GTFP. According to the P-values for these four threshold variables, it is observed that both provincial financial development level and environmental regulation intensity have a single threshold effect with the threshold values of 0.602 and -0.314, respectively. Simultaneously, the two threshold values of both regional human capital quality (9.63 and 10.69) and capital stock level (52.02 and 191.01) are identified. These findings suggest that the impact of innovation on GTFP in China is sensitive to the changes in human capital, knowledge stock, financial development and environmental regulation. That is to say, the innovation-GTFP relationship has experienced structural breaks when human capital, knowledge stock, financial development and environmental regulation are at different regimes, respectively.

Table 7 Tests for threshold effects between innovation and GTFP in China

Threshold variable	No. of thresholds	F-value	P-value	Threshold estimates	Critical value		
					10%	5%	1%
Human Capital	Single	178.06***	0.000	10.69 [10.65, 10.95]	30.35	37.04	49.93
	Double	34.17*	0.092	9.63 [9.48, 9.64]	30.27	127.05	200.91
	Triple	11.34	0.538	8.43 [8.32, 8.43]	118.92	176.62	256.30
Knowledge Stock	Single	191.01***	0.000	140.82 [123.96, 140.86]	28.11	33.79	47.15
	Double	52.02**	0.014	62.89 [62.03, 66.22]	26.59	32.08	61.52
	Triple	16.38	0.530	35.28 [32.86, 36.07]	41.38	59.43	108.73
Financial Development	Single	26.84*	0.077	0.602 [0.579, 0.615]	24.46	31.64	47.01
	Double	12.75	0.276	-0.050 [-0.072, -0.048]	19.73	24.25	33.08
Environmental Regulation	Single	30.91**	0.029	-0.314 [-0.412, -0.307]	21.52	25.71	39.04
	Double	10.18	0.315	-0.746 [-0.792, -0.743]	15.58	18.93	28.25

Note: ***, **and * represent significance levels of 1%, 5% and 10%, respectively; *P*-value and critical values are the results of the bootstrap simulation for 1000 times. 95% confidence intervals of thresholds are shown in parentheses.

Table 8 provides the estimated parameters for panel threshold regression. The impact of innovation on GTFP differs when the threshold variables are at different levels. As shown in column 2 of Table 8, when human capital is selected as the threshold variable, the size of the coefficient on innovation (*lnPat*) increases with the rise of human capital, which is in accordance with the theoretical expectation. Specifically, when human capital is below the first threshold (9.63 years), the estimated coefficient of *lnPat* is 0.0281. When the human capital increases but still lies between the first threshold and the second threshold (10.69 years), the coefficient then increases to 0.0461 accordingly. Once human capital exceeds the second threshold, the coefficient is found to reach 0.0913.

When knowledge stock is less than or equal to 62.89 patents per 100,000 population in the first regime, the results reveal that there is an insignificant relationship between innovation and GTFP in China. Once knowledge stock is more than 62.89 patents per 100,000 population, there exists a significant and positive relationship between regional innovation capacity and GTFP in both the second regime (62.89 to 140.82 patents per 100,000 population) and the third regime (greater than 140.82 patents per 100,000 population). Meanwhile, it is observed that the coefficient of *lnPat* in the third regime (0.0436) is remarkably higher than that in the second regime (0.0191). These results suggest that the higher the knowledge stock level in one region, the greater the influence of innovation on GTFP, which is in line with the theoretical analysis discussed above.

According to column 4 in Table 8, the positive but different significances of the coefficients on innovation reveals that the effects of innovation on GTFP in China are contingent on regional financial development level. By contrast, innovation appears to exert an insignificant impact on GTFP in the provinces in the lower end of the financial development level (i.e., financial development index ≤ 0.602). Only when financial development index in each region is greater than 0.602, can regional innovation capacity promote the improvement in local GTFP. This is consistent with the previous theoretical analysis.

It is worth noting that when environmental regulation is chosen as the threshold variable, the coefficient on innovation (*lnPat*) changes from being significantly positive to insignificant once environmental regulation index exceeds the first threshold (-0.314). These findings indicate that the appropriate (neither too strict nor too loose) environmental regulation stringency is conducive to promoting the positive influence of innovation on GTFP in China. Similarly, the empirical results support the previous theoretical analysis.

Table 8 Threshold regression estimation results

Coefficients	Threshold variable			
	Human capital	Knowledge stock	Financial development	Environmental regulation
lnPat $I(HD_{it} \leq 9.63)$	0.0281^{***}			
	(4.86)			
lnPat $I(9.63 < HD_{it} \leq 10.69)$	0.0461^{***}			
	(6.80)			
lnPat $I(10.69 < HD_{it})$	0.0913^{***}			
	(11.33)			
lnPat $I(KS_{it} \leq 62.89)$		0.005		
		(0.91)		
lnPat $I(62.89 < KS_{it} \leq 140.82)$		0.0191^{***}		
		(3.38)		
lnPat $I(140.82 < KS_{it})$		0.0436^{***}		
		(7.40)		
lnPat $I(FD_{it} \leq 0.602)$			0.007	
			(1.06)	
lnPat $I(0.602 < FD_{it})$			0.0211^{***}	
			(3.02)	

lnPat $I(EV_{it} \leq -0.314)$				0.0123^{*}
				(1.87)
lnPat $I(-0.314 < EV_{it})$				0.0013
				(0.19)
HC	0.0237^{**}	0.0275^{***}	0.0528^{***}	0.0522^{***}
	(2.37)	(2.89)	(4.66)	(4.63)
FD	-0.0295^{***}	-0.0032	-0.0072	-0.0048
	(-4.06)	(-0.47)	(-0.88)	(-0.59)
ER	0.0024	-0.0028	0.0012	0.0097^{**}
	(0.76)	(-0.89)	(0.33)	(2.46)
Open	-0.0006^{***}	0.0003	-0.0004^{*}	-0.0005^{**}
	(-3.16)	(1.55)	(-1.69)	(-2.08)
IS	-0.0041^{***}	-0.0026^{***}	-0.0048^{***}	-0.0059^{***}
	(-6.67)	(-4.22)	(-6.69)	(-8.43)
PR	0.002^{***}	0.0009^{**}	0.0008^{*}	0.0006
	(4.78)	(2.24)	(1.66)	(1.37)
Cons	0.814^{***}	0.812^{***}	0.712^{***}	0.773^{***}
	(10.15)	(10.54)	(7.64)	(8.31)
N	480	480	480	480

Note: ***, **and * represent significance levels of 1%, 5% and 10%, respectively. *t* statistics are shown in parentheses.

Table 9 further gives the proportion of provinces that fall into a particular regime of the four threshold variables. In terms of human capital, knowledge stock and financial development, it is apparent that overwhelming majority of provinces in China lie in the regimes in which these three threshold variables are lower than the respective cut-off value. Meanwhile, the ratio of provinces with human capital, knowledge stock and financial development above the threshold value in the coastal region is remarkably higher than that in the inland region. It is noted that there are only three provinces (i.e., Beijing, Shanghai and Tianjin) where human capital, knowledge stock and financial development are all above the first or the second threshold value in 2015. These findings reveal that improving related supporting conditions may be an efficient way for China to promote the effect of innovation on GTFP. Regarding environmental regulation, it is observed that nearly half (47.5%) of the observations are below the threshold level. It is, therefore, necessary for such corresponding regions to enhance environmental regulation intensity appropriately to make innovation playing a more important role in promoting local GTFP growth. Additionally, it is found that the proportion of regions with knowledge stock and financial development above the threshold value during the period 2010-2015 is much higher than that before 2010, which can explain why innovation just exerts a significant and positive influence on China's GTFP since 2010 to a certain extent.

Table 9 Proportion of provinces in each threshold variable regime

Threshold variables	Regime	Ratio of provinces in each regime
Human capital	$HC \leq 9.63$	90.83%
	$9.63 < HC \leq 10.69$	6.67%
	$10.69 < HC$	2.50%
Knowledge stock	$KS \leq 62.89$	91.04%
	$62.89 < KS \leq 140.82$	5.63%
	$140.82 < KS$	3.33%
Financial development	$FD \leq 0.602$	89.58%
	$0.602 < FD$	10.42%
Environmental regulation	$ER \leq -0.314$	47.29%
	$-0.314 < ER$	52.71%

6. Conclusions and Policy Implications

This paper contributes to the literature by systematically and comprehensively investigating the linear and nonlinear relationship between innovation and green development using China's provincial panel data covering 30 regions over the period 1999-2015. More specifically, this paper firstly calculates the provincial GTFP to measure the green development of China's economy by GML index based on a SBM directional distance function, then employs penal data model to look at the linear influence of innovation on GTFP in the full sample as well as in various periods, lastly explores the nonlinear relationship between the two by investigating the role of human capital, knowledge stock, financial development and environmental regulation in moderating the innovation-GTFP link based on a panel threshold model. The main findings can be summarized as follows.

(1) China has achieved extensive economic development in general. Although most provinces in China have experienced GTFP growth during the sample period, only eight regions' average annual growth rate exceeds 1%, suggesting that the growth rate of GTFP in China is relatively slow in general. Meanwhile, the features of different phases of China's GTFP growth are clearly evident. That is, the GTFP growth rate during the period 2010 to 2015 is higher than that in the period 2000-2009.

(2) Overall, innovation measured by patent applications plays a significant role in promoting the GTFP growth in China. Simultaneously, the relationship between innovation and GTFP in China differs notably in various periods. To be more specific, the existence of a significant and positive correlation between innovation and China's GTFP just can be verified during the period of 2010-2015.

(3) Different types of patents have heterogeneous effects on China's green growth. More specifically, invention patents have a significant and positive impact on GTFP, but the effect of non-invention patents is insignificant. Moreover, the influence of different types of patents on GTFP differs in various periods. It is found that neither invention nor non-invention patens have a significant effect on the GTFP in China during the period 2000-2009. Over the period of 2010-2015, the invention patents are found to exert a significant and positive effect on GTFP, while the effect of non-invention patents is insignificant.

(4) The effect of innovation on China's provincial GTFP is related to the level of human capital, knowledge stock, financial development and environmental regulation. Specifically, the influence of innovation on regional GTFP will increase with the rise of human capital, knowledge stock and financial development. However, only the appropriate (neither too strict nor too loose) environmental regulation stringency is conducive to promoting the positive impact of innovation on GTFP in China.

Some key policy implications can be drawn from this study.

First, this paper demonstrates that innovation activity is a primary source of GTFP growth in China. Accordingly, in order to transform the extensive growth mode to green development, policymakers should strive to encourage enterprises to increase R&D investment, strength innovation capacity, accelerate the transformation and application of innovation outputs by improving capital support as well as creating a favorable external environment (Cheng and Li 2018; Li et al. 2018; Huang et al. 2019b).

Second, the empirical results of this paper confirm that invention patents rather than non-invention patents are the major driving force of China's green growth especially since 2010, therefore, the importance of innovation outputs of high novelty and technical quality should be highlighted. However, between 1999 and 2015, invention patents always command less than 30 percent of China's domestic total patent applications except for the case after 2013. By contrast, the share of invention patents in foreign patent applications still fluctuates around 85% in the same phase. This phenomenon reveals that domestic companies and individuals in China are more concerned with "marginal" innovations than with those "core" technologies to a large extent (Sun 2003; Zhao and Liu 2011). Hence, China must pay more attention to the pursuit of original innovation by supporting basic research, promoting high-tech industry development, etc.

Third, considering that the positive impact of innovation on China's regional GTFP will increase with the rise of the level of human capital, knowledge stock and financial development, the local government need take measures to enhance human capital quality, accelerate knowledge accumulation as well as build a sound finance system accordingly (Nicholas 2009; Qamruzzaman and Wei 2019).

Finally, because the results of this paper indicate that only the appropriate environmental regulation stringency is beneficial for promoting the influence of innovation on China's green growth, the local authorities should properly set environment control rules in light of their own situation.

As part of future research, it would also be interesting to analyze whether the conclusions in this study are applicable to other developing countries such as India, Brazil and Russia. What's more, a further step for the research using industrial-level data may also be of great importance and significance. Finally, under the background of increasing attention to green innovation, examining the heterogeneity of the effects of green patents and non-green patents on GTFP is also the area of our future research.

Appendix

Table A1 GML index of each province in China from 2000 to 2015

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
BJ	1.011	1.008	1.015	1.012	1.004	1.017	1.021	1.048	1.061	1.027	1.036	0.993	1.039	1.035	1.050	1.101
TJ	1.003	1.008	1.011	1.008	1.011	1.006	1.011	1.012	1.018	1.018	1.007	1.015	1.023	1.022	1.027	1.038
HB	0.992	1.003	1.005	0.998	1.003	0.999	0.998	1.000	0.999	1.002	1.016	1.006	1.014	1.001	1.025	1.021
SX	1.002	0.996	1.004	1.000	1.009	0.987	0.990	1.001	1.004	0.992	1.005	1.005	1.008	0.997	1.010	1.001
IM	1.017	1.014	0.985	0.977	1.000	0.996	0.992	1.008	1.008	1.012	1.015	1.013	1.013	1.005	1.009	1.010
LN	1.015	1.022	1.048	1.014	0.975	0.956	0.998	0.996	0.956	1.013	1.025	1.034	1.034	1.015	1.018	0.984
JL	1.005	1.009	0.999	0.991	1.006	0.978	0.978	0.999	1.000	1.004	1.010	1.018	1.024	1.005	1.013	0.996
HLJ	1.014	1.029	1.035	1.007	1.075	1.015	1.022	0.979	0.982	0.984	1.008	1.022	0.993	0.962	1.011	0.983
SH	1.019	1.007	1.009	1.013	1.020	1.012	1.021	1.048	1.029	1.001	1.050	1.023	1.186	0.912	1.096	1.000
JS	1.006	1.005	1.014	0.997	1.005	0.976	1.014	1.030	1.018	0.999	1.007	1.013	1.042	1.027	1.065	1.098
ZJ	0.972	1.008	0.982	0.985	0.992	0.976	1.016	1.011	1.018	1.017	1.020	1.025	1.028	1.028	1.036	1.041
AH	1.018	1.012	1.016	1.002	1.013	0.987	1.002	1.008	1.004	1.002	1.012	1.007	0.994	0.970	1.012	1.012
FJ	1.000	1.000	1.000	1.000	0.920	0.917	1.015	1.017	0.992	0.980	1.019	0.994	1.012	1.037	1.024	1.083
JX	0.812	0.963	0.978	0.942	0.969	0.985	0.991	0.998	1.010	0.989	1.007	1.012	1.016	1.012	1.013	1.021
SD	0.966	0.990	0.969	0.993	1.010	0.986	1.002	1.012	1.017	0.995	0.996	1.046	1.026	1.030	1.045	1.212
HN	0.987	1.003	0.997	0.993	0.995	0.986	0.993	0.986	0.997	0.999	1.002	1.015	1.017	1.007	1.028	1.020
HUB	1.000	0.889	0.948	0.960	0.982	0.969	0.989	1.001	1.020	1.011	1.001	0.991	0.995	0.994	1.024	1.037
HUN	1.014	0.975	0.997	0.995	0.989	0.963	0.993	1.007	1.006	1.000	0.995	0.982	1.016	1.034	1.017	1.036
GD	1.176	0.866	1.059	1.091	1.000	0.930	1.075	1.000	1.000	0.997	1.003	1.000	1.000	1.000	0.967	1.034
GX	0.982	1.001	1.007	0.989	0.981	0.991	0.994	0.991	0.989	0.992	0.994	1.003	1.005	1.021	1.009	1.035
HAN	1.005	0.991	0.996	1.000	1.018	1.020	1.007	1.029	0.967	0.990	1.013	0.990	1.006	1.003	1.004	1.011
CQ	1.027	0.990	1.003	0.992	0.991	0.985	0.999	1.009	1.010	1.011	1.012	1.023	1.022	1.037	1.021	1.040
SC	1.002	0.977	0.990	0.985	1.009	1.006	1.006	1.017	0.990	1.015	1.016	1.060	1.028	1.024	1.005	1.044
GZ	0.998	0.997	0.998	0.994	0.999	1.003	1.004	1.005	1.005	1.003	1.003	0.994	1.003	1.009	1.002	1.014
YN	1.010	0.999	1.001	0.995	0.990	0.987	1.001	1.005	1.009	1.006	0.999	0.990	1.008	1.012	1.008	1.022
SAX	1.004	0.996	1.003	0.998	1.004	0.994	0.998	1.004	1.013	1.005	1.005	1.009	1.013	1.005	1.022	1.009

GS	0.992	1.006	0.986	0.988	0.998	0.983	0.998	0.999	0.985	1.005	1.004	0.999	1.009	1.003	1.006	1.010
QH	1.006	0.988	1.003	1.000	1.000	0.986	1.002	1.003	1.006	1.005	1.003	1.006	1.004	0.994	1.009	1.012
NX	0.996	0.996	0.998	0.994	0.999	0.997	0.999	1.001	1.001	0.998	1.000	1.000	1.002	0.999	1.001	1.002
XJ	1.005	1.002	1.001	1.000	1.001	0.998	1.002	1.008	1.006	1.004	1.003	1.003	1.000	0.994	1.005	1.000

Note: BJ=Beijing, TJ=Tianjin, HB=Hebei, SX=Shanxi, IM=Inner Mongolia, LN=Liaoning, JL=Jilin, HLJ=Heilongjiang, SH=Shanghai, JS=Jiangsu, ZJ=Zhejiang, AH=Anhui, FJ=Fujian, JX=Jiangxi, SD=Shandong, HN=Henan, HUB=Hubei, HUN=Hunan, GD=Guangdong, GX=Guangxi, HAN=Hainan, CQ=Chongqing, SC=Sichuan, GZ=Guizhou, YN=Yunnan, SAX=Shaanxi, GS=Gansu, QH=Qinghai, NX=Ningxia, XJ=Xinjiang

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

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

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

SL contributed to the idea of the paper, designed the econometric models, and drafted the article. PH provided core advice on the idea, gathered the data, discussed the results and revised the manuscript. YG collected and analyzed the data. YT revised the manuscript and discussed the results. All authors read and approved the final manuscript.

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