Green Finance

Green Finance, 1(2): 174–187.
DOI: 10.3934/GF.2019.2.174
Received: 15 April 2019
Accepted: 22 April 2019
Published: 30 April 2019

http://www.aimspress.com/journal/GF

Research article

An analysis of financial support, technological progress and energy efficiency: evidence from China

Gaoke Liao[1] and Benjamin M. Drakeford[2,*]

[1] College of Finance and Statistics, Hunan University, Changsha, China
[2] Economics and Finance Subject Group, Portsmouth Business School, University of Portsmouth, UK

* **Correspondence:** Email: ben.drakeford@port.ac.uk; Tel: +442392848513.

Abstract: In order to explore the nonlinear relationship between financial support, technological progress and energy efficiency, a panel smooth transition regression (PSTR) is developed to analyze the impact of financial support and technological progress on the energy efficiency. Based on panel data of 30 provinces in China from 2003 to 2016, the total-factor energy efficiency of 30 province-level divisions in China are evaluated using Data Envelopment analysis (DEA). The results show that financial support and technological progress are generally conducive to increasing energy efficiency. However, the increment effect of financial support and technological progress on energy efficiency transitions smoothly between high and low regimes with the changes of the transition variables, such as local government expenditure; foreign direct investment, energy structure and industrial structure. Therefore, the results emphasize the need for enhancing financial support and technological progress in increasing energy efficiency.

Keywords: financial support; technological progress; energy efficiency; PSTR model

JEL Codes: C33, O53, Q43, Q56

1. Introduction

In the course of economic development, humankind needs continuous exploitation of resources and energy consumption. However, while energy consumption has brought great convenience to human beings, it also faces problems, including environmental pollution and climate warming (Wei et al., 2014; Li and Wang, 2017; Hou et al., 2018). In the past 40 years of reform, China has maintained a rapid economic growth of about 10% per year for more than 30 years, and has achieved remarkable accomplishments (Wang et al., 2013; Wang and Wei, 2014; Shahbaz et al., 2018). However, this rapid economic development has been coupled with huge energy consumption and serious environmental problems (Chen and Jia, 2017). In 2017, China accounted for 23.2% of global energy consumption and 33.6% of global energy consumption growth. China has ranked first in global energy growth for 17 consecutive years. And China's environmental pollution situation is grim, the smog weather is frequent, the urban river water body is black and stink and soil pollution are prominent.

Environmental and resource issues have become important factors that have constrained the sustainable development of China's economy. Therefore, improving energy efficiency and achieving sustainable economic growth is one aspect that should not be ignored in the current phase of economic development. The main factors for improving energy efficiency are technological progress, energy prices, energy structure, industrial structure (and forms of ownership), among which the role of technological progress is particularly important, with technological progress requiring strong support from the financial system. At the same time, the coupled development of the financial industry and the energy industry plays an important role in optimizing and upgrading the energy industry structure and improving efficiency. Therefore, it is of great significance to explore the relationship between financial support, technological progress and energy efficiency.

Numerous studies have shown that financial support has a fundamentally important impact on technological progress (Benfratello et al., 2008; Kenney, 2011; Brown et al., 2013; Hsu et al., 2014). On the one hand, based on King and Levine's (1993) expansion of the new Schumpeter growth model, the continuous improvement of the financial system will enable financial intermediaries to obtain more effective project information, so as to better mobilize and use savings, and to invest more funds. Effective projects help firms to diversify risks and promote technological innovation. If the government takes carbon reduction as an important goal, under the guidance of government subsidies, firms will increase investment in technology research and development. Benfratello et al. (2008) shows that the development of the banking industry has influenced the possibility of process innovation, especially for companies in high-tech industries. Amore et al. (2013) shows that banking development plays a key role in technological progress and that bank deregulation has a significant positive impact on the quantity and quality of innovation activities. Kim and Park (2016) pointed out that financial development could reduce CO_2 emissions by addressing the role of financial markets in renewable energy. Normally, there is a positive correlation between the bank credit financing obtained by the company and the level of corporate innovation.

On the other hand, adjacent area increase in environmental protection constraints; high-pollution and high energy-consuming, enterprises migrate to their surrounding areas, causing negative external effects. Research and development of new energy technologies are often accompanied by high risks, and investors with low-risk preferences will evade the choice (Aguilera and Ortiz, 2013; Jabbour et al., 2015).

Technological progress is a key factor influencing energy efficiency. It has a rich connotation. Its impact on energy efficiency does not only refer to the promotion and application of energy-saving emission reduction technologies, but also manifests itself in many aspects of the entire economic operation. Endogenous growth theories attribute the important driving force of economic growth to innovation activities in various fields supported by the accumulation of knowledge in the whole society (Li et al., 2017; Liu, 2017). Jaffe et al. (2002) shows that technological advances may both increase and decrease CO_2 emissions. Mann and Richels (2004) believe that ignoring endogenous technological progress may exaggerate the impact of economic growth on the environment. Gerarden et al. (2017) demonstrate that energy-efficient technologies offer considerable promise for reducing the financial costs and environmental damages associated with energy use, but it has long been observed that these technologies may not be adopted by individuals and firms to the degree that might be justified, even on a purely financial basis. Costantini et al. (2017) show that the introduction and adoption of green technologies are considered the most cost effective way to reduce environmental pressure without compromising economic competitiveness.

The impact of financial support on energy efficiency has two sides. Financial support to improve energy efficiency is mainly due to financial support to guide credit funds to low-carbon enterprises, forcing high-energy and high-pollution enterprises to transition to low-energy and low-pollution. Financial support can reduce the risk of low-carbon transformation of enterprises to improve total factor productivity. Further, support can drive technological innovation by screening and supporting research and development of low-carbon technologies. Financial support to reduce energy efficiency is mainly due to the use of financial resources to expand reproduction, enterprises will increase energy consumption in the initial stage of technology research and development, a large number of inputs cannot form effective output will lead to energy efficiency decline.

The above arguments refer to positive and negative effects between financial support, technological progress and energy efficiency. As the economy moves to higher levels of development, some effects outweigh others. Therefore, depending on the level of development there can be a nonlinear relation among variables. Based on these, taking China as an example, this paper will analyze the impact of the financial support and technological progress on energy efficiency. This paper will expand and supplement the existing literature from the following aspects. Firstly, this paper intends to reveal the promoting mechanism of the financial support and technological progress on energy efficiency, which can enrich the theoretical research of energy efficiency. Secondly, this paper measures energy efficiency in China using the DEA-Malmquist Model. Thirdly, the nonlinear relationship between financial support, technological progress and energy efficiency is tested by using the PSTR Model.

2. Variable definitions and model settings

2.1. Carbon dioxide emissions

Calculating energy efficiency first requires measuring CO_2 emissions. Given that the combustion of fossil fuels is the main source of carbon emissions in China, the estimation of carbon emissions is conducted under the framework proposed by the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (Zhang and Da, 2015; Zhang et al., 2017). Considering the circumstances of China, the calculation of carbon emissions is based on the consumption of coal, oil, and natural gas. This paper selects 30 provinces, excluding Tibet, Hong Kong, Macao and Taiwan from research sample, to preserve the integrity of the data. The sample interval used is annual data from 2003 to December 2016. The coal, oil and natural gas consumption data of all provinces comes from the Wind database, and is converted into standard coal according to the unified calculation of various energy consumption in the China Energy Statistical Yearbook, and the energy structure of coal, oil, and natural gas in each province is calculated. The estimation formula is:

$$CO_2 = \sum_{i=1} E_i \times T_i \times C_i \times R_i \times \frac{44}{12} \quad (1)$$

In formula (1), CO_2 is carbon dioxide emissions; E_i is the energy consumption, and I = 1, 2, 3 indicate coal, oil, and natural gas, respectively; T_i refers to the calorific value conversion coefficient of energy source i; C_i refers to the carbon emission coefficient of energy source i; R_i refers to the carbon oxidation coefficient of energy source i; and 44/12 is the chemical relative atomic mass ratio used to convert carbon to an equivalent amount of CO_2.

2.2. Energy efficiency

Parametric and non-parametric are commonly used methods for measuring efficiency. The parameter method needs to construct a specific optimal production preamble function to make the efficiency calculation of the decision-making unit. The non-parametric method does not need too many assumptions and directly uses the linear programming method to construct the optimal production frontier. Data envelopment analysis (DEA) is recognized in the literature as a powerful method, more suitable for performance measurement activities than traditional econometric methods, such as regression analysis and simple ratio analysis (Filippini and Zhang, 2016; Al-Refaie et al., 2016). Therefore, a calculation using DEA does not need to set various assumptions in advance, and does not need to look for the specific functional form of the production frontier.

Caves et al. (1982) define the Malmquist index as:

$$m_0(x_{t+1}, y_{t+1}, x_t, y_t) = \sqrt{\frac{d_0^t(x_{t+1}, y_{t+1})}{d_0^t(x_t, y_t)} * \frac{d_0^{t+1}(x_{t+1}, y_{t+1})}{d_0^{t+1}(x_t, y_t)}} \quad (2)$$

The index reflects the improvement of total factor productivity for each decision-making unit from period t to t + 1 under fixed-scale remuneration. If the index is greater than 1, it indicates that the efficiency has risen, and vice versa.

Fare et al. (1994) decompose the Malmquist index into the technical efficiency index (EFFCH) and technological progress index (TECHCH):

$$m_0(x_{t+1}, y_{t+1}, x_t, y_t) = \frac{d_0^{t+1}(x_{t+1}, y_{t+1})}{d_0^t(x_t, y_t)} \sqrt{\frac{d_0^t(x_{t+1}, y_{t+1})}{d_0^{t+1}(x_{t+1}, y_{t+1})} * \frac{d_0^t(x_t, y_t)}{d_0^{t+1}(x_t, y_t)}} \quad (3)$$
$$= EFFCH * TECHCH$$

According to the index construction and decomposition process, as long as the "input-output" indicators are selected, the energy efficiency can be measured and decomposed into TECHCH and EFFCH. EFFCH measures the distance from the decision-making unit to the production frontier from t to t + 1. In this paper, it refers to the technical efficiency in provinces. When EFFCH > 1, this indicates that the technical efficiency has improved, and vice versa. TECHCH measures the degree of excursion of the frontier of production in decision-making units. In this paper, it refers to the technological development. When TECHCH > 1, this indicates that there has been a technical advance, and vice versa.

This article analyzes China's provinces' total factor energy efficiency from the perspective of factor input and output. Input indicators include energy input, labor input, and capital investment. Output indicators include expected economic output and unanticipated environmental pollution indicators. Among them, the input indicators are the total energy consumption of provinces converted to standard coal; the labor force is the number of employees at the end of the year in each province and capital investment is the fixed capital stock of each province. The output indicator is GDP (2002 constant RMB) and carbon dioxide emissions of each province.

Table 1 below summarise descriptive statistics for all variables used in our study. For each variable, we give average value, median, standard deviation, minimum and maximum values. Descriptive statistics are presented to describe the basic characteristics of data used in this study—concerning the 30 provinces of China over the period from 2003 to 2016.

Table 1. Descriptive statistics for input-output indexes of energy efficiency.

Index category	Index name	Mean	Std.Dev.	Minimum	Maximum
Input	Total number of employees (Ten thousand)	468.31	316.14	42.67	1973.28
	Total energy consumption (10,000 tons of standard coal)	11960.99	7883.32	683.74	38899.25
	Total investment in fixed assets of industry (Billion Yuan)	9245.97	9195.82	255.62	53322.94
Desirable output	Gross domestic product in the region (Billion Yuan)	14447.14	13919.62	390.20	80854.91
Undesirable output	carbon dioxide emissions (Tons)	7455.07	5234.63	390.41	25050.65

The MaxDEA software is used to measure energy efficiency, and the overall results of energy efficiency are shown in Table 2. Firstly, Guangdong, Jiangsu and Shandong performed well from 2003 to 2016. Their energy efficiency is all greater than 1. Secondly, Heilongjiang performs the worst, its average energy efficiency is 0.9281, which is the smallest among all the DMUs. Thirdly, more than half of the regions in China performed well from 2003 to 2016. 20 regions generate average energy efficiency that exceeds 1. Fourthly, the energy efficiency trend of regions is not promising since the energy efficiency of most the DMUs did not show any obvious increasing trend during the fourteen-year period. Also, taking Henan as an example, where energy efficiency had increased from 0.917 to 1.158 (2003–2009) and reduced from 1.158 to 0.993 (2009–2016). Finally, we find that the developed regions generally performed better than the less developed regions. Notably, all the efficient regions are developed regions. These results show us that the energy efficiency of the less developed regions in China is not optimistic and more action need to be taken, by both industry and government, in practice to handle with the undesirable outputs of the industrial enterprises.

Table 2. Energy efficiency different regions in China from 2003 to 2016.

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Beijing	1.047	1.058	1.013	1.024	1.057	1.006	1.108	1.007	0.985	1.001	1.029	0.987	0.998	0.965
Tianjin	1.077	0.971	0.944	1.031	1.059	1.18	1.277	1.268	1.064	1.017	1.153	1.068	1.08	1.032
Hebei	0.968	1.006	1.055	1.111	1.026	1.047	1.224	1.033	0.936	1.114	1.114	1.117	1.092	1.015
Shanxi	0.826	0.83	0.882	0.948	0.91	0.885	1.128	0.873	0.872	1.026	1.04	0.994	1.001	0.957
Inner Mongolia	0.97	1.087	1.099	1.032	1.015	0.932	1.151	1.013	0.947	1.04	1.147	1.18	0.771	1.081
Liaoning	0.981	1.094	1.084	1.122	1.079	1.099	1.116	1.083	0.952	1.123	1.095	0.946	0.812	1.066
Jilin	0.878	0.897	1.019	1.085	1.063	1.071	1.117	1.027	0.811	1.105	1.026	1.032	1.072	1.037
Heilongjiang	0.897	0.871	0.874	0.923	0.925	0.865	0.989	0.884	0.873	1.014	1.038	0.904	0.964	0.973
Shanghai	0.986	1.039	1.016	1.006	1.037	1.029	1.029	0.956	1.066	1.058	1.034	0.974	0.925	0.889
Jiangsu	1.294	1.001	0.987	1.09	1.102	1.163	1.196	1.205	1.165	1.117	1.18	1.079	1.047	1.006
Zhejiang	1.165	1.065	1.029	1.079	1.084	1.045	1.162	1.085	1.142	1.126	1.033	1.042	0.984	0.969
Anhui	0.978	1.003	1.067	1.139	1.148	1.109	1.202	1.128	0.955	1.131	1.147	1.128	1.063	1.047
Fujian	1.01	1.024	1.009	1.028	1.079	1.065	1.155	1.137	1.34	1.095	1.079	1.047	1.044	1.004
Jiangxi	1.099	1.02	1.024	1.026	1.044	1.148	1.184	1.098	0.94	1.101	1.117	1.068	1.06	1.051
Shandong	1.277	1.047	1.111	1.064	1.041	1.144	1.182	1.119	1.053	1.081	1.099	1.042	1.054	1.022
Henan	0.917	0.882	0.969	1.014	1.016	1.052	1.158	1.056	0.975	1.04	1.173	1.009	1.02	0.993
Hubei	0.931	0.929	0.921	0.968	0.855	0.951	1.053	1.028	1.024	1.064	1.104	1.019	1.027	1.009
Hunan	0.945	0.943	1.003	0.965	0.961	0.985	1.105	1.024	0.998	1.053	1.136	1.068	1.117	1.099
Guangdong	1.077	1.045	1.01	1.023	1.077	1.132	1.22	1.366	1.576	1.028	1.311	1.012	0.971	0.96
Guangxi	0.932	0.896	0.989	0.974	1.016	1.039	1.275	1.237	1.249	1.208	1.117	1.036	1.042	1.19
Hainan	0.946	0.921	0.925	0.911	0.9	0.923	1.031	0.95	0.937	1.071	1.114	1.085	1.056	0.987
Chongqing	1.098	1.056	1.047	1.084	1.099	1.08	1.22	1.127	1.058	1.027	1.091	1.02	0.987	0.961
Sichuan	1.01	0.955	1.044	0.986	1.03	1.055	1.392	1.064	0.914	1.064	1.163	0.96	0.931	0.96
Guizhou	0.935	0.908	0.914	0.913	0.889	0.844	0.995	0.905	0.904	0.981	0.973	0.981	1.027	1.083
Yunnan	0.973	0.929	1.107	1.018	1.015	0.95	1.074	0.961	0.943	1.016	1.034	0.944	0.955	1.011
Shanxi	0.94	0.901	0.911	0.949	0.973	0.936	1.034	0.945	0.944	1.064	1.15	1.052	1.03	1.052
Gansu	0.915	0.868	0.919	0.904	0.906	0.892	1.01	0.915	0.931	1.048	1.114	1.036	1.046	1.001
Qinghai	0.981	0.952	0.986	1.018	0.947	0.889	1.143	0.941	1.056	1.136	1.16	1.03	1.025	1.124
Ningxia	0.944	0.919	0.977	0.927	0.911	0.941	1.049	0.986	0.904	1.119	1.131	1.113	1.062	0.966
Xinjiang	0.934	0.901	0.925	0.925	0.93	0.889	1.021	0.841	0.915	0.96	0.983	1.004	1.112	1.049

2.3. Financial support and transition variables

Financial support is mainly considered from the perspectives of banking, securities, and insurance. Financial support is measured by the ratio of total bank loans to GDP, the ratio of total market capitalization of listed companies to GDP, and the depth of insurance. In order to correctly identify the impact of financial support and technological progress on energy efficiency, this paper supplements the accuracy of empirical results by setting transition variables. Government intervention ability (GOV), is an effective remedy for market failure and plays an important role in the loss of industry energy efficiency. This indicator, expressed in terms of the proportion of the province's GDP results from the annual financial expenditures of various provinces in China. Foreign Direct Investment (FDI): The large inflow of FDI capital not only brings sufficient capital for the host's economic development, but also provides research and development funds for the improvement and upgrading of energy technologies, and promotes the improvement of energy resource utilization efficiency. This indicator is expressed in terms of the proportion of the total foreign investment actually utilized by Chinese provinces in the province's GDP. Energy consumption structure (ESC): The energy consumption structure has a major impact on the improvement of energy efficiency. In areas where consumption structures such as coal and petrochemical are the main components, the more that carbon emissions and other pollutants are emitted, which is detrimental to regional environmental quality and energy efficiency. Increased efficiency. This indicator uses coal consumption of all provinces in China as a percentage of the province's total energy consumption. Industrial Structure (IS): The energy consumption intensity of different industries varies greatly. The higher the proportion of high-energy-consuming industries in a region to the national economy of the entire region, the more difficult it is to increase energy efficiency. This indicator is expressed in terms of the ratio of the tertiary industry output value to the province's GDP. Table 3 below summarizes descriptive statistics for all variables used in our study.

Table 3. Descriptive statistic of the data.

Variables	Descriptive	Mean	Std. Dev	Minimum	Maximum
EE	Energy efficiency	1.0294	0.0974	0.7710	1.5760
TECH	Technical progress	1.0356	0.0962	0.6730	1.3410
LOAN	Total loans/ GDP	1.1517	0.3992	0.5372	2.5847
STOCK	Total market capitalization/ GDP	0.5875	1.4016	0.0578	18.6363
INSURE	Insurance penetration	2.7021	1.0134	0.4467	7.3900
GOV	Local government expenditure on science and technology	0.2043	0.0921	0.0792	0.6274
FDI	Foreign direct investment	0.3637	0.2823	0.0058	1.2999
ESC	Coal consumption/ energy consumption	0.6847	0.2618	0.0870	1.4495
IS	Share of service sector/ GDP	0.4160	0.0861	0.2860	0.8023

2.4. Model setting

Resulting from varying energy efficiency in different time periods, the influence factors on energy efficiency may have nonlinear characteristics. Therefore, it is necessary to construct a non-linear function model of the factors affecting the physical economic vulnerability. The panel smooth transition regression model (PSTR) can accurately describe the transition between the linear model and the asymmetric model in the process of energy efficiency by selecting different transition variables or transfer functions. Based on this, this paper adopts the panel smooth transition model analysis. The impact of financial support and technological advances energy efficiency. The basic expression equation form of the panel smooth transition model is:

$$y_{i,t} = \beta_0 x_{i,t} + \sum_{j=1}^{r} \beta_j x_{i,t} g_j\left(q_{i,t}^{(j)};\gamma_j;c_j\right) + \mu_i + \varepsilon_t \tag{4}$$

For, $i = 1,2,\cdots,N; t = 1,2,\cdots,T$. y_{it} is the dependent variable, x_{it} is the explanatory variables that changes over time. μ_i indicates the vector of the individual fixed effects and ε_t is a random disturbance. β_0 and β_j indicate respectively the parameter vector of the linear model and the non-linear model. $g_j\left(q_{i,t}^{(j)};\gamma_j;c_j\right)$ is the function of transition which depends on the transition variable of transition $q_{i,t}^{(j)}$, to the parameter of threshold c_j and to the smooth transition parameter γ_j .allows the system to transit gradually. The transition function is set in the form of a logistic function in the equation (5):

$$g_j\left(q_{i,t}^{(j)};\gamma_j;c_j\right) = \left[1 + \exp\left(-\gamma_j \prod_{k=1}^{m_j}\left(q_{i,t}^{(j)} - c_{j,k}\right)\right)\right]^{-1} \tag{5}$$

where $\gamma_j > 0, c_{j,1} \le c_{j,2} \le \cdots \le c_{j,m_j}$ and c_j is a vector of level parameter. γ_j represents the supposed positive smooth parameter.

To investigate the impact of financial support and technological progress on energy efficiency, we specify the following four models.

$$\begin{aligned} EE_{i,t} &= \mu_i + \beta_{00} TECH_{i,t} + \beta_{01} LOAN_{i,t} + \beta_{02} STOCK_{i,t} + \beta_{03} INSURE_{i,t} + \\ &\sum_{j=1}^{r} (\beta_{j0} TECH_{i,t} + \beta_{j1} LOAN_{i,t} + \beta_{j2} STOCK_{i,t} + \beta_{j3} INSURE_{i,t}) g_j\left(GOV_{i,t}^{(j)};\gamma_j;c_j\right) + \varepsilon_t \end{aligned} \tag{6}$$

$$\begin{aligned} EE_{i,t} &= \mu_i + \beta_{00} TECH_{i,t} + \beta_{01} LOAN_{i,t} + \beta_{02} STOCK_{i,t} + \beta_{03} INSURE_{i,t} + \\ &\sum_{j=1}^{r} (\beta_{j0} TECH_{i,t} + \beta_{j1} LOAN_{i,t} + \beta_{j2} STOCK_{i,t} + \beta_{j3} INSURE_{i,t}) g_j\left(FDI_{i,t}^{(j)};\gamma_j;c_j\right) + \varepsilon_t \end{aligned} \tag{7}$$

$$\begin{aligned} EE_{i,t} &= \mu_i + \beta_{00} TECH_{i,t} + \beta_{01} LOAN_{i,t} + \beta_{02} STOCK_{i,t} + \beta_{03} INSURE_{i,t} + \\ &\sum_{j=1}^{r} (\beta_{j0} TECH_{i,t} + \beta_{j1} LOAN_{i,t} + \beta_{j2} STOCK_{i,t} + \beta_{j3} INSURE_{i,t}) g_j\left(ESC_{i,t}^{(j)};\gamma_j;c_j\right) + \varepsilon_t \end{aligned} \tag{8}$$

$$\begin{aligned} EE_{i,t} &= \mu_i + \beta_{00} TECH_{i,t} + \beta_{01} LOAN_{i,t} + \beta_{02} STOCK_{i,t} + \beta_{03} INSURE_{i,t} + \\ &\sum_{j=1}^{r} (\beta_{j0} TECH_{i,t} + \beta_{j1} LOAN_{i,t} + \beta_{j2} STOCK_{i,t} + \beta_{j3} INSURE_{i,t}) g_j\left(IS_{i,t}^{(j)};\gamma_j;c_j\right) + \varepsilon_t \end{aligned} \tag{9}$$

3. Empirical results

Before testing the PSTR model, there are some pre-tests that should be performed. The first one tests for stationarity of all variable used in this study. The second tests the linearity or homogeneity and the third test is undertaken to identify the number of transition functions. Table 4 presents results of the panel unit root test. However, Table 5 below summarizes results of the test of linearity based on the statistics of LM Wald, LM Fisher and LR tests.

The procedures of PSTR specification rely on the assumption that all variables in Model (6) is I(1) process. To test for stationarity, we used the Levin, Lin, and Chu (2002) test and the Phillips and Perron (1988) test. Results displayed in table 4 indicate that the LLC and PP tests reject the null hypothesis at 1% and 5% significance level for all variables used in this study. From these results, we can conclude that all data are I(1) process.

Table4. Panel unit root test.

Variables	LLC	IPS	Variables	LLC	IPS
EE	−9.594(0.124)	−1.157(0.124)	D.EE	−18.815(0.000)	−8.294(0.000)
TECH	−9.031(0.0078)	−1.188(0.117)	D.TECH	−19.689(0.000)	−9.227(0.000)
LOAN	−6.933(0.7737)	1.173(0.88)	D.LOAN	−11.059(0.000)	−3.769(0.000)
STOCK	−12.307(0.000)	−2.682(0.004)	D.STOCK	−19.055(0.000)	−8.103(0.000)
INSURE	−9.388(0.0017)	−1.753(0.04)	D.INSURE	−10.831(0.000)	−2.528(0.006)
GOV	−8.342(0.000)	0.617(0.731)	D.GOV	−12.878(0.000)	−3.618(0.000)
FDI	−7.532(0.000)	−0.681(0.248)	D.FDI	−18.916(0.000)	−7.835(0.000)
ESC	−8.224(0.000)	−1.923(0.027)	D.ESC	−20.052(0.000)	−10.350(0.000)
IS	−7.519(0.0018)	−0.021(0.492)	D.IS	−14.643(0.000)	−4.781(0.000)

Note: p-statistics are shown in parentheses.

The objective of this empirical study is to confirm that there is a non-linear relationship. To this end, we conduct a test of linearity against the PSTR model. The null hypothesis is H_0: $\beta_1 = 0$ and the alternative is H_1: $\beta_1 \neq 0$. However, the test will be nonstandard since, under H_0 the PSTR model contains unidentified nuisance parameters. The transition function will be replaced by its first order Taylor expansion round $\gamma = 0$. The null hypothesis of this test becomes, H_0: $\gamma = 0$ .This null hypothesis may be conveniently tested by a Wald and Likelihood ratio test, the test can be written in the equation (10) as:

$$LM = \frac{TN(SSR_0 - SSR_1)}{SSR_0}, LM_F = \frac{(SSR_0 - SSR_1)/mk}{SSR_1/(TN - N - mk)}, LRT = -2\log\frac{SSR_1}{SSR_0} \tag{10}$$

Where, SSR_0 is the panel sum of squared residuals under H_0 and SSR_1 is the panel sum of squared residuals under H_1. LM_F is assumed to follow Fisher distribution with mk and $TN - N - mk$ degrees of freedom $(F(mk, TN - N - mk))$. Under the null hypothesis, all linearity tests follow a chi-2 distribution with k degrees of freedom $(\chi^2(k))$.

If the "non-linearity test" rejects the original hypothesis, further "surplus non-linearity test (H0: r = 1; H1: r = 2)" is required, which means the test has one or two transition functions. At this point, the smoothing parameter for the second transition function is expanded into a first-order Taylor linear expression at 0, and an auxiliary regression equation is constructed. Using a method similar to "linearity test", the LM, LM_F, and LRT statistics are calculated. If you still reject H_0, you need to continue the "remaining non-linearity test" until you cannot reject H_0. Finally, the number of optimal transition functions r for the model can be obtained.

Models non-linearity test and residual nonlinear test results are shown in Table 5.

Table 5. Linearity test.

Model	Transition Variable	H_0: r = 0; H_1: r = 1			H_0: r = 1; H_1: r = 2		
		LM	LM_F	LRT	LM	LM_F	LRT
(6)	GOV	22.323(0.000)	5.417(0.000)	22.938(0.000)	5.410(0.248)	1.233(0.296)	5.445(0.245)
(7)	FDI	18.569(0.000)	4.733(0.000)	18.731(0.000)	3.952(0.413)	0.898(0.465)	3.971(0.410)
(8)	ESC	15.667(0.000)	4.320(0.000)	15.706(0.000)	3.993(0.407)	0.907(0.460)	4.013(0.404)
(9)	IS	13.500(0.000)	4.211(0.000)	13.514(0.000)	3.669(0.453)	0.833(0.505)	3.685(0.450)

From Table 5, we can see that in the four control variables, as the transition variable model, the three statistics of the nonlinear test LM, LMF and LRT are significant at the 1% level, strongly rejected the number of transition functions as The null hypothesis of 0, that is, the number of transfer functions should be at least 1, there is a nonlinear transition mechanism, and the PSTR model should be used for estimation. In the remaining non-linear tests, the LM, LMF and LRT statistics in all models are not significant, which means the number of transfer functions should be considered to be 1. Therefore, the number of the transfer functions r of models (6) to (9) is all determined to be 1.

Table 6 presents the estimation of PSTR model for the whole sample of 30 provinces of China during the period 2003–2016.

The results of model (6) show that the positional parameter of the model is 0.266, which means that the value of its government intervention variable is 0.266, which indicates that the energy efficiency is impacted by the different effects of technological progress and financial support. When the government intervention variable value is lower than 0.266, the PSTR model tends to low regime, the maximum value of the technical progress on energy efficiency promotion is 0.7574, and when the government intervention variable value is greater than 0.266, the PSTR model tends to high regime, and technological progress on energy efficiency. The impact weakened to 0.4839 through the smooth transfer function, which means that the increase in government intervention will reduce the impact of technological progress on energy efficiency. For financial support variables, the PSTR model tends to low regime, the maximum value of bank loans for energy efficiency promotion is −0.0014, the PSTR model tends to high regime, and the effect of bank loans on energy efficiency eventually increases to 0.1149 through smooth transfer function. The increase in government intervention will increase the impact of bank support on energy efficiency. When the PSTR model tends to low regime, the maximum value of the listed company's total market value for energy efficiency promotion is 0.001. When the PSTR model tends to high regime, the impact of the listed company's total market value on energy efficiency eventually weakens to 0.0479 through the smooth transfer function. The increase in government intervention will reduce the impact of capital markets on energy efficiency. The impact of the insurance industry on energy efficiency is not significant.

Table 6. Coefficient estimation of the PSTR model.

Variable	Model (6)	Model (7)	Model (8)	Model (9)
β_{01}	0.7574*** (15.6541)	−3.1345*** (−9.4459)	−3.1179*** (−3.6278)	−3.0014*** (3.9274)
β_{02}	−0.0014** (−2.1167)	2.1646** (2.4676)	2.6310*** (4.225)	−2.9918*** (−4.1621)
β_{03}	0.0010** (2.5422)	0.2016** (2.3569)	−0.2930** (−2.1214)	0.3786*** (3.7288)
β_{04}	0.0016 (0.2866)	0.0639 (0.4853)	−0.1223 (−0.4905)	0.5501 (0.4511)
β_{11}	−0.2735*** (−5.9175)	3.3511*** (5.0318)	3.5621*** (3.4879)	3.4836*** (3.6923)
β_{12}	0.1463*** (4.8233)	−1.645** (−1.7847)	−2.0032*** (−3.3348)	3.0017** (2.0250)
β_{13}	−0.0489** (−2.0322)	−0.2816*** (3.6902)	−0.3016* (1.7863)	−0.3016** (−2.3383)
β_{14}	0.0147* (1.7499)	−0.0659 (−1.1747)	0.0053 (1.3536)	0.0021 (1.4747)
Location parameters c	0.2666	0.5294	0.7141	0.5800
Slopes parameters γ	6.1718	5.9440	17.0194	10.5413
AIC criterion	−5.673	−5.617	−5.615	−5.591
Schwarz Criterion	−5.577	−5.521	−5.519	−5.495

Note: t-statistics are shown in parentheses below the estimated coefficients. "***", "**" and "*" Denote statistical significance at the 10%, 5%, and 1% levels.

The results of Model (7) show that the positional parameter of the model is 0.5294, that is, when the value of the foreign direct investment value is 0.5294, the energy efficiency is affected by the intermediate effects of the technical effects and financial support. When the government intervention variable value is lower than 0.5294, the PSTR model tends to low regime, the maximum value of technical progress on energy efficiency promotion is −3.1345, and when the value of foreign direct investment variable is greater than 0.5294, PSTR model tends to high regime, and technological progress on energy. The effect of efficiency is finally enhanced to 0.2166 through the smooth transfer function, which means that the increase of foreign direct investment will increase the impact of technological progress on energy efficiency. For financial support variables, when the PSTR model tended to low regime, the maximum value of bank loans for energy efficiency promotion was 2.1646. The PSTR model tended to high regime, and the effect of bank loans on energy efficiency eventually weakened to 0.5196 through the smooth transfer function. The increase of foreign direct investment will reduce the impact of bank support on energy efficiency. When the PSTR model tended to low regime, the maximum value of the listed company's total market value for energy efficiency promotion was 0.2016. When the PSTR model tended to high regime, the impact of the listed company's total market value on energy efficiency eventually weakened to −0.08 through the smooth transfer function. This means that the increase of foreign direct investment will reduce the impact of capital markets on energy efficiency. The impact of the insurance industry on energy efficiency is not significant.

The results of model (8) show that the positional parameter of the model is 0.7141, that is, when the energy consumption structure variable value is 0.7141, the energy efficiency is affected by the intermediate point of different effects produced by technological progress and financial support. When the government intervention variable value is lower than 0.7141, the PSTR model tends to low regime, and the maximum value of technological advancement for energy efficiency promotion is −3.1179, while when the energy consumption structure variable value is greater than 0.7141, PSTR model tends to high regime, and technological progress to energy. The effect of efficiency is eventually enhanced to 0.4442 through the smooth transfer function, implying that the increase in energy consumption structure will increase the impact of technological advances on energy efficiency. For the financial support variables, the PSTR model tends to low regime, the maximum value of bank loans for energy efficiency promotion is 2.631, the PSTR model tends to high regime, and the effect of bank loans on energy efficiency eventually weakens to 0.6728 through the smooth transfer function, implying that the increase in energy consumption structure will reduce the impact of bank support on energy efficiency. When the PSTR model tended to low regime, the maximum value of the listed company's total market value for energy efficiency promotion was −0.2930. The PSTR model tended to be high regime, the impact of the listed company's total market value on energy efficiency eventually weakened to −0.5946 through the smooth transfer function. This means that the increase in energy consumption structure will reduce the impact of capital markets on energy efficiency. The impact of the insurance industry on energy efficiency is not significant.

The results of model (9) show that the positional parameter of the model is 0.58, that is, the industrial structure variable value is 0.58, and the energy efficiency is affected by the technical development and financial support. When the government intervention variable value is lower than 0.58, the PSTR model tends to low regime, the maximum value of technological progress on energy efficiency promotion is −3.1179, and when the industrial structure variable value is greater than −3.0014, the PSTR model tends to high regime, and technological progress on energy. The effect of efficiency is eventually enhanced to 0.4482 through the smooth transfer function, implying that the increase in industrial structure will increase the impact of technological advances on energy efficiency. For the financial support variable, the PSTR model tends to low regime, the maximum value of bank loans for energy efficiency promotion is −2.9918, thePSTR model tends to high regime, and the effect of bank loans on energy efficiency ultimately increases to 0.0099 through smooth transfer function. The increase in industrial structure will increase the impact of bank support on energy efficiency. When the PSTR model tends to low regime, the maximum value of the listed company's total market value to promote energy efficiency is 0.3786, the PSTR model tends to high regime, and the impact of the listed company's total market value on energy efficiency eventually weakens to 0.077 through the smooth transfer function. The improvement of industrial structure will reduce the impact of capital markets on energy efficiency. The impact of the insurance industry on energy efficiency is not significant.

4. Conclusion

In this paper, we use the DEA-Malmquist model to measure the energy efficiency of China's provinces, and use the PSTR to empirically test the nonlinear relationship between financial support, technological progress and energy efficiency. The results show that financial support and technological progress generally is conducive to increasing energy efficiency. However, the increment effect of financial support and technological progress on energy efficiency transitions smoothly between high and low regimes with the changes of the transition variables, such as local government expenditure; foreign direct investment, energy structure and industrial structure. Specifically, government intervention will reduce the effect of technological advancement on energy efficiency, and increase the effect of bank loans and the total market value of listed companies on energy efficiency. Foreign direct investment, energy consumption structure and industrial structure, will improve the effect of technological progress on energy efficiency. Foreign direct investment and energy consumption structure will reduce the effect of bank loans on energy efficiency, where as industrial structure will increase the effect of bank loans on energy efficiency. Foreign direct investment, energy consumption structure and industrial structure will reduce the efficiency of listed companies in promoting energy efficiency. The effect of insurance depth on energy efficiency is not significant.

Acknowledgements

We are grateful to the anonymous reviewers and editors of Green Finance.

Conflict of interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

References

Aguilera-Caracuel J, Ortiz-de-Mandojana N (2013) Green innovation and financial performance: An institutional approach. *Organ Environ* 26: 365–385.

Al-Refaie A, Hammad M, Li MH (2016) DEA window analysis and Malmquist index to assess energy efficiency and productivity in Jordanian industrial sector. *Energy Effic* 9: 1299–1313.

Amore MD, Schneider C, Zaldokas A (2013) Credit Supply and Corporate Innovation. *J Financ Econ* 109: 835–855.

Benfratello L, Schiantarelli F, Sembenelli A (2008) Banks and Innovation: Microeconometric Evidence on Italian Firms. *J Financ Econ* 90: 197–217.

Brown JR, Martinsson G, Petersen BC (2013) Law, Stock Markets, and Innovation. *J Financ* 68: 1517–1549.

Chen L, Jia G (2017) Environmental efficiency analysis of China's regional industry: a data envelopment analysis (DEA) based approach. *J Clean Prod* 142: 846–853.

Costantini V, Crespi F, Marin G, et al. (2017) Eco-innovation, sustainable supply chains and environmental performance in European industries. *J Clean prod* 55: 141–154.

Filippini M, Zhang L (2016) Estimation of the energy efficiency in Chinese provinces. *Energy Effic* 9: 1315–1328.

Gerarden TD, Newell RG, Stavins RN (2017) Assessing the energy-efficiency gap. *J Econ Lit* 55: 1486–1525.

Hou J, Teo TS, Zhou F, et al. (2018) Does industrial green transformation successfully facilitate a decrease in carbon intensity in China? An environmental regulation perspective. *J Clean Prod* 184: 1060–1071.

Hsu PH, Tian X, Xu Y (2014) Financial Development and Innovation: Cross-Country Evidence. *J Financ Econ* 112: 116–135.

Jabbour CJC, Jugend D, de Sousa Jabbour ABL, et al. (2015) Green product development and performance of Brazilian firms: measuring the role of human and technical aspects. *J Clean Prod* 87: 442–451.

Jaffe AB, Newell RG, Stavins RN (2002) Environmental policy and technological change. *Environ Resour Econ* 22: 41–70.

Kenney M (2011) How Venture Capital Became a Component of the US National System of Innovation. *Ind Corp Change* 20: 1677–1723.

Kim J, Park K (2016) Financial development and deployment of renewable energy technologies. *Energy Econ* 59: 238–250.

King RG, Levine R (1993) Finance and growth: Schumpeter might be right. *Q J Econ* 108: 717–737.

Li Z, Wang Z, Huang Z (2017) Modeling Business Cycle with Financial Shocks Basing on Kaldor-Kalecki Model. *Quant Financ Econ* 1: 44–66.

Manne A, Richels R (2004) The impact of learning-by-doing on the timing and costs of CO_2 abatement. *Energy Econ* 26: 603–619.

Shahbaz M, Bhattacharya M, Mahalik MK (2018) Financial development, industrialization, the role of institutions and government: a comparative analysis between India and China. *Appl Econ* 50: 1952–1977.

Wang K, Wei YM (2014) China's regional industrial energy efficiency and carbon emissions abatement costs. *Appl Energy* 130: 617–631.

Wang K, Wei YM, Zhang X (2013) Energy and emissions efficiency patterns of Chinese regions: a multi-directional efficiency analysis. *Appl Energy* 104: 105–116.

Wei J, Guo X, Marinova D, et al. (2014) Industrial SO_2 pollution and agricultural losses in China: evidence from heavy air polluters. *J Clean Prod* 64: 404–413.

Zhang YJ, Da YB (2015) The decomposition of energy-related carbon emission and its decoupling with economic growth in China. *Renew Sust Energy Rev* 41: 1255–1266.

Zhang YJ, Peng YL, Ma CQ, et al. (2017) Can environmental innovation facilitate carbon emissions reduction? Evidence from China. *Energy Policy* 100: 18–28.