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What Is the Relationship between Technological Innovation and Energy Consumption? Empirical Analysis Based on Provincial Panel Data from China

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Abstract: This paper investigates the relationship between energy consumption and technological innovation using a dynamic panel data model and regional-level data from China for the period 1995–2012. In contrast to previous studies, it examines the short and long-run bilateral relationship between technological innovation and energy consumption. The results show that in the short run, technological innovation leads to an increase in energy consumption, while energy consumption has no significant effect on technological innovation. In the long run, however, energy consumption is positively and bilaterally related to technological innovation. These findings suggest that although technological innovation does not directly lead to a reduction in energy consumption as mentioned in the extant literature, it could help achieve sustainability through improving energy efficiency and developing energy structure for developing countries.

Keywords: technological innovation; energy consumption; dynamic panel; sustainable development

1. Introduction

In recent years, energy consumption has come under intense scrutiny. China's total primary energy consumption was 3053 million tons of oil equivalent in 2016, which was seven times that of Africa's and accounted for 23% of the world's total primary energy consumption, the highest in the world assuredly. Meanwhile, China's coal and oil production continued to decline but its oil imports continued to increase. The overall standard environmental air quality among all cities was 78.8%. China's rapid economic growth has been accompanied by serious energy and environmental problems. Therefore, the Chinese government has been formulating policies to reduce energy consumption while expecting to achieve sustainable development.

Many scholars believe that technological innovation can improve energy efficiency and thereby lead to a reduction in energy consumption whether it is for total energy consumption or fossil fuels [1–6]. Over the past decade, Chinese companies have challenged the global technology leaders in the areas of solar, wind, electric, high-speed rail, nuclear, e-commerce, smartphones, private aircraft, and machine tools. Technology and innovation are seen as the primary drivers of the next stage of economic growth in China, but both the total and per capita energy consumption have been rising during the long run development of China. This cannot stop us from questioning whether technological innovation can actually reduce energy consumption. In 1992, Khazzoom and Brookes [7,8] presented a hypothesis: technological progress improves energy efficiency and saves energy, but it also contributes to economic growth, which in turn increases the demand for energy and finally promotes energy consumption in the long term. This phenomenon is defined as a rebound effect [9]. The development of technology may improve energy efficiency and reduce energy consumption in the short run, but the emergence of new technology is likely to promote energy consumption in the long run. Which effect is then stronger? Therefore, the role of technological innovation for sustainable development has also been questioned.

Based on the above analysis, we propose the first hypothesis (Hypothesis 1):

Hypothesis 1a (H1a). *In the short term, technological innovation can reduce energy consumption.*

Hypothesis 1b (H1b). *In the long run, technological innovation can make energy consumption increase.*

Meanwhile, some scholars believe that energy consumption will not be limited when the resources stock is rich, and people will not consider the issue of technological innovation [10,11]. Or when the energy supply is sufficient and its application is more and more mature, people will not consider using technological innovation to increase the supply of energy. When energy consumption grows, environment pollution, resource depletion, and other problems follow and ecological sustainability is difficult to achieve. People then begin to turn their attention to technological innovation and expect it to help them solve the above difficulties [12]. Therefore, energy consumption has, to some extent, also had a certain impact on technological innovation.

Therefore, we make the following hypothesis (Hypothesis 2):

Hypothesis 2a (H2a). *In the short term, energy consumption growth has no effect on technological innovation.*

Hypothesis 2b (H2b). *In the long run, energy consumption can also promote technological innovation.*

Most of the current research is focused on the general relationship between technological innovation and energy consumption and has not examined the differences between the long and short run in this relationship. Moreover, most research has had a unidirectional focus—the impact of technological innovation on energy consumption rather than the bilateral relationship between them. This in-depth study can help us understand how technological innovation and energy consumption affect each other. Accordingly, this paper will examine the abovementioned issues by investigating the short- and long-run bilateral relationships between technological innovation and energy consumption.

In addition, some previous researchers believe that technological innovation reduces energy consumption that then leads to sustainable development [13,14]. Technological innovation is an important driving factor in reducing energy consumption. However, can technological innovation achieve sustainability in energy? Lund [15] holds that there are three ways to achieve sustainable development through technological innovation in energy: energy savings on the demand side, efficiency improvements in energy production, and replacement of fossil fuels by various sources of renewable energy. This paper is based on the above analysis. If technological innovation is beneficial for sustainable development, how does technological innovation affect sustainable development and what is the mechanism of its action?

The remainder of this paper is organized as follows: Section 2 presents the literature review, Section 3 describes the methods used in the paper, Section 4 describes the data, and Section 5 reports the empirical results and discussion. Finally, Section 6 concludes the paper.

2. Literature Review

2.1. Previous Research

Previous research in the past few decades has devoted considerable attention to the relationship between technological innovation and energy consumption. This research has studied whether technological innovation can achieve ecologically sustainable development from the perspective of different types of energy. As the proportion of fossil fuel consumption declines and the proportion of new energy consumption increases, research has focused on the change from the relationship between fossil fuel consumption and technological innovation to the relationship between renewable energy consumption and technological innovation. Since then, there has been a proliferation of such studies using various methods, time periods, and samples from different countries, as seen in Table 1.

Jin and Zhang [4] confirmed that technological innovation reduces fossil fuel consumption. Fei and Rasiah [16], focusing on the relationship between electricity consumption and technological innovation, suggested that technological innovation does not significantly influence the long-term variation in fossil fuel-powered electricity. Tang and Tan [3] found that technological innovation Granger-causes electricity consumption and has negatively affected electricity consumption in Malaysia. Compared with the direct combustion of fossil fuels, electricity use is able to support environmental improvement as renewable energy is more environmentally friendly. Irandoust [17] suggested that technological innovation Granger-causes renewable energy, and Aflaki et al. [18] argued that technological innovation positively affects renewable energy diffusion.

Each of the above studies is based on a specific type of energy. Sohag et al. [19], Yin and Yang [5], and Du and Yan [6] examined the relationship between total energy consumption and progress in a country, and all suggested that technological innovation reduces energy consumption which then realizes sustainability, although there was broad variation in the countries studied.

Table 1. Overview of the selected studies.

Study	Estimation Method	Period	Countries	Results
Du and Yan (2009) [6]	Regression analysis method	2007	China	Technological innovation reduces energy consumption.
Tang and Tan (2013) [3]	Granger causality test	1970–2009	Malaysia	Technological innovation Granger-causes electricity consumption, and technology innovation negatively affects electricity consumption.
Aflaki et al. (2014) [18]	CCE [1]	1990–2012	15 European Union countries [2]	Technological innovation has a positive impact on renewable energy diffusion.
Fei and Rasiah (2014) [16]	ARDL and VECM [3]	1974–2011	Canada, Ecuador, Norway, South Africa	Technological innovation does not significantly influence the long-term variation in fossil fuel-powered electricity.
Wei and Zhang (2014) [4]	Balanced Growth Path equilibrium		China	Technological innovation reduces fossil fuel consumption.
Yin and Yang (2014) [5]	Decoupling elasticity and Laspeyres index	1999–2010	China	Technological innovation reduces energy consumption.
Sohag et al. (2015) [19]	ARDL	1985–2012	Malaysia	Technological innovation reduces energy consumption.
Irandoust (2016) [17]	VAR [4] and Granger non-causality test	1975–2012	Nordic	Technological innovation Granger-causes renewable energy.

[1] Common Correlated Effects estimator; [2] The 15 countries include Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, The Netherlands, Portugal, Spain, Sweden, and the UK; [3] The autoregressive distributed lag and the vector error correction model; [4] The vector autoregression.

2.2. *How Is Technological Innovation Measured?*

To measure the relationship between technological innovation and energy consumption, it is necessary to address the question of how one should quantify technological innovation.

Griliches [20] described some of the main characteristics of patents and patent data and proposed the use of patents as an indicator of technological change. Acs [21] and Goto [22] used patents to measure innovations from regions and firms.

Some scholars [17–21,23] have argued that foreign direct investment (FDI), which accumulates human capital, plays a vital role in a country's level of technological innovation.

Research and development (R&D) funding is one of the most frequently used inputs to study innovation occurrence [24–26]: Cohen and Klepper [27,28], Unger [29], Keller [30], and Qiang [31] have all argued that a greater investment in R&D reflects a greater promotion of technological innovation.

However, most scholars [32–37] have used total factor productivity (TFP) as a measure of technological innovation. TFP refers to the combined effect of institutional innovation, technological innovation, industrial structure adjustment, and resource allocation optimization, including labor and capital as resources. Thus, TFP is a more comprehensive measure of technological innovation than FDI or R&D. Of course, there are some deficiencies when we use TFP to measure the technological innovation. On the one hand, the growth of TFP contains other factors except innovation; on the other, the computational process of TFP is more complex and the parameter is not unique, which will influence results.

Duan and Yu [34] calculated the TFP growth of 35 sectors in China using stochastic frontier analysis and measured its impact on energy efficiency; they concluded that energy efficiency will be higher with a higher proportion of state-owned enterprises, a larger scale of enterprises, and a higher level of market openness. Zhang [35], Ladu and Meleddu [36], Shao et al. [37], Shu et al. [38], Liu and Liu [39], Li [40], and Zhang [33] used data from different regions for their studies; further, the first six of these authors considered both time and regional factors and used panel data for their analyses. Most of these authors argued that technological innovation is becoming a means of ensuring efficient energy use and energy savings. Zhang [33] suggested that environmental regulation intensity and industrial structure negatively affect TFP growth but that the energy consumption structure positively affects TFP growth.

In contrast to Ladu and Meleddu [36], we treat TFP, instead of GDP, as an indicator of technological innovation. We further use different methods to calculate TFP growth. Once the relationship between TFP growth and energy consumption in various regions of China is understood, it can be compared with the situation in other countries. Moreover, differences between developing and developed countries can be observed.

In this paper, a typical three-stage approach to panel data analysis is used to analyze the relationship between the TFP growth rate and energy consumption in China with respect to their long-run and short-run interrelationships. In contrast, previous scholars have used similar methods to examine the relationship between GDP and energy consumption [36].

3. Methodology

In line with prior research, the relationship between the TFP growth rate and energy consumption is tested in three stages in this research. First, panel unit root tests are used to avoid non-stationary problems [41]. If the data are not smooth when regressing, pseudo-regression will arise. If pseudo-regression occurs, the true trend and relationship between the variables cannot show and the subsequent calculation becomes meaningless; therefore, it is essential to ensure the stability of the data before the next cointegration test is conducted. Next, we use a panel cointegration test to measure the long-run relationship between the variables in question. We measure the existence of a long-term correlation relationship between energy consumption and the TFP growth rate; if it exists, we need to determine whether it is a positive or negative relationship. Finally, we employ static and dynamic panel causality tests to estimate the short-run cointegration and the direction of causality between the TFP growth rate and energy consumption. Following these steps, we obtain the relationship between energy consumption and TFP growth rate.

3.1. Panel Unit Root Tests

To guarantee robustness or the stability of the data, we reference the research of Ladu and Meleddu [36] and then apply five unit root tests. They are Phillips and Perron (PP) (1998), Breitung (2000), Levin et al. (LLC) (2002), Im et al. (IPS) (2003) and Fisher-ADF [42,43] (LLC, IPS and ADF are the abbreviations for the name of authors who invented the method). These methods have many similarities, so we just chose three key methods to introduce.

The ADF test is the basis of the above methods. The autoregressive model is as follows:

$$\Delta y_{it} = \rho y_{it-1} + \sum_{j=1}^{k_i} \gamma_{ij} \Delta y_{it-j} + Z'_{it} \varnothing + \varepsilon_{it} \quad (1)$$

where $i = 1, 2, \cdots, N$ regions observed over $t = 1, 2, \cdots, T$; Z_{it} denotes an exogenous variable column vector; and $\varnothing$ is a regression coefficient column vector. In our test, the null hypothesis is $\rho = 0$, which means that the unit root exists; the alternative hypothesis is $\rho < 0$, which means that the unit root does not exist.

Breitung eliminated the dynamic term Δy_{it-j} from Δy_{it} and y_{it} first, then implemented standardization and de-trending techniques, and finally used the ADF test to regress $\hat{\varepsilon}_{it} = \rho\hat{\varepsilon}_{it-1} + v_{it}$ to test the unit root. A characteristic of the panel unit root test of Breitung is that the AR(1) coefficient is identical for all individuals in the panel. This approach is similar to LLC. LLC used the proxy variables Δy_{it} and y_{it}, which eliminate autocorrelation based on Equation (1).

IPS overcomes the potential drawback of LLC by allowing different sequences to have different ρ_i in the panel. The test formula is as follows:

$$\Delta y_{it} = \rho_i y_{it-1} + \sum\nolimits_{j=1}^{k_i} \gamma_{ij} \Delta y_{it-j} + X'_{it} a + \varepsilon_{it} \quad (2)$$

where $i = 1, 2, \cdots, N$ regions observed over $t = 1, 2, \cdots, T$, ε_{it} ~IID(0,σ^2). The null hypothesis is $\rho = 0$, which means that the unit root exists, as in the LLC approach.

The Fisher-ADF test was devised under more general assumptions than the other four tests. It starts from the principle of Fisher. The main idea underlying the Fisher-ADF test is that it combines p-values from a unit root test applied to each group in the panel data [44]. In addition, the ADF test is used to calculate p_i. If the variables are uniformly integrated, we can proceed to the next step.

3.2. Panel Cointegration

The observed time series length is directly related to the effectiveness of the cointegration test. The longer the data series, the more effective the cointegration test will be. Econometricians generally try to integrate different economic entities to develop cointegration theories. According to the basic concept of the test method, panel cointegration testing is divided into two categories. The first category is based on a panel data cointegration regression to test the residual unit root, such as a generalization of the Engle and Granger [45] two-step method. The prominent features of this type of panel cointegration test are as follows: (1) it ignores the possible unobservable common factors, tries to utilize a de-trending method, or overcomes unobservable common effects through observable common effects; (2) it can be applied when one cointegration relationship exists between individual time series at most; and (3) it allows concurrent spatial correlation for panel data that do not have a general spatial correlation structure.

The other category is the Johansen and Juselius [46] trace test method. In contrast to the former method, this method cannot test only multiple cointegration relations but also allows the existence of a stationary or non-stationary common component of the panel data. Thus, we use a representative of this method—the Fisher-Johansen cointegration test—to perform our cointegration test [47].

Next, we need to consider the type of cointegration relationship that exists between the variables. Dynamic ordinary least squares (DOLS) is used in this paper. It is a single equation method proposed by Saikkonen (1991) and Stock and Watson (1993) that tests hypotheses regarding a co-integrating vector in panel data [48]. New technologies do not immediately save or waste energy, so it will be more scientific if there are lags in the equations and this also applies to the next short-term relationship test [16,17].

3.3. Testing for Causality

The cointegration test will determine the long-run relationship between the variables in question. Next, we use the VAR model to measure the short-run causal relationship between TFP and energy consumption. First, we use a dynamic panel data (DPD) analysis. The regression equation is as follows:

$$y_{it} = \sum_{k=1}^{K} \beta_k x_{kit-1} + \sum_{i=1}^{p} a_1 y_{i,t-l} + \xi_{yi} + \mu_{it} \quad (3)$$

$$x_{it} = \sum_{k=1}^{K} \delta_k x_{i,t-k} + \sum_{i=1}^{p} \gamma_1 y_{lit-k} + \xi_{xi} + v_{it} \quad (4)$$

where $i = 1, 2, \cdots, N$ regions observed over $t = 1, 2, \cdots, T$; $y_{i,t-l}$ and $x_{i,t-k}$ are the lags of the dependent variable in Equations (3) and (4); μ_{it} and v_{it} are error terms; and ξ_i represents the individual fixed effects for region i. There may be effects from determinants of energy consumption that change over time, such as income level and energy price [49], but in order to highlight the role of the heterogeneity among provinces and cities, we finally chose the fixed effect. Different generalized method of moments (GMM) [50] must be used for this purpose. A crucial assumption for the validity of GMM estimates is that the instruments are exogenous. If the estimation is exactly identified, invalid instruments cannot be detected. The Sargan-Hansen J test is used for the diagnostics of the GMM estimation for an over-identified model.

4. Data

Annual data covering the period 1995–2012 is used for this study. Energy consumption data can be obtained from the China Energy Statistical Yearbook, and per capita values can be calculated based on the resident population from the statistical yearbook. Based on reality, economic research does not focus on the concept of level but focuses on the incremental, so this paper uses the growth rate of TFP and not TFP on behalf of technological innovation. At present, the accounting methods to determine the TFP growth rate include the Solow residual method, the invisible variable method, the stochastic frontier production function method, and the Malmquist index method. The first two methods have more limitations, such as perfect competition in the market, constant returns to scale, and Hicks neutral technological innovation; however, these conditions are difficult to satisfy in the real economy and the results consider only technological innovation and ignore the impact of technical efficiency. For the stochastic frontier production function method, small changes in the model or data will have a substantial impact on the results. The Malmquist index method is widely used in specific econometric analysis because the production function structure does not need to be assumed in advance to estimate the parameters; moreover, it allows for the existence of inefficient behavior and can decompose changes in TFP [51]. The Malmquist index method was proposed in 1953 by the Swedish statistician Sten Malmquist. Fare et al. (1997) combined data envelopment analysis (DEA) with the Malmquist index to establish a new method to analyze the TFP growth rate. The TFP growth rate can be decomposed into technical innovation and technical efficiency, and the source of the TFP growth rate can be further analyzed [52]. In this paper, the Malmquist index method is used to calculate the TFP growth rate in 28 Chinese provinces. According to the Malmquist index calculation method of TFP growth rate, the output data of this paper is based on the constant price GDP of 1995 to 2012 based on 1995. Labor and capital investment are input variables. Labor data is the number of employed individuals of a population for each region at the end of each year; capital investment is represented by fixed capital stock which is calculated using the whole society fixed asset investment, capital stock, and the depreciation rate of each region in every year by the perpetual deposit method [53]. The above data are derived from the China Statistical Yearbook and the regional statistical yearbook. Table 2 reports the descriptive statistics of the computed TFP for each region and they are shown in the form of the average of the entire time span under investigation.

Table 2. TFP growth descriptive statistics.

Region	Average	SD	Min	Max
Anhui	0.9803333	0.0224866	0.927	1.011
Beijing	1.0780556	0.0473802	0.939	1.155
Fujian	0.9628333	0.0263779	0.895	1.004
Gansu	0.9798333	0.0278235	0.921	1.041
Guangdong	1.0841111	0.0250526	1.024	1.137
Guangxi	0.9461111	0.0385256	0.866	0.997
Guizhou	0.9748333	0.0222268	0.942	1.019
Heibei	1.0475556	0.052416	0.952	1.114
Henan	0.9605	0.0404188	0.895	1.043
Heilongjiang	0.9891667	0.0290522	0.921	1.023
Hubei	0.9638889	0.0329418	0.868	1
Hunan	0.9716667	0.0234721	0.949	1.025
Jilin	1.059	0.0479141	0.987	1.137
Jiangsu	1.1190556	0.0156524	1.097	1.149
Jiangxi	0.9933333	0.0493773	0.913	1.13
Liaoning	1.0948889	0.0238325	1.059	1.134
Neimenggu	1.1176667	0.0608363	0.986	1.261
Ningxia	1.0257778	0.0224147	0.971	1.074
Qinghai	1.0757778	0.0359388	0.998	1.123
Shandong	1.034	0.0436065	0.975	1.087
Shanxi	0.9675556	0.0484164	0.872	1.045
Shanxian [1]	0.9747778	0.0244962	0.945	1.025
Shanghai	1.0908889	0.0389145	0.998	1.156
Sichuan	0.9626111	0.0361519	0.885	1.029
Tianjin	1.1118889	0.0237335	1.056	1.156
Xinjiang	1.0618333	0.0381734	0.969	1.128
Yunnan	0.9626667	0.0342379	0.906	1.022
Zhejiang	1.0531667	0.0816277	0.829	1.123

[1] Its provincial capital is Xi'an and its name is Shanxi. However, in order to distinguish it from another Shanxi, here it is named Shanxian.

5. Empirical Results

5.1. Unit Root Test and Cointegration Test

The unit root tests were conducted for the variables under investigation. Tests were performed both with a constant and with a constant and trend. In this paper, TFP growth rate represents technological innovation; the corresponding energy consumption is expressed in differences, which is an incremental representation. The results are shown in Table 3. If the *p*-value is less than 0.05, the null hypothesis is rejected, indicating that the data are stable. Fisher-PP, Breitung, IPS, and Fisher-ADF certificate $\triangle$EC (energy consumption) are stable at the 1% significance level. Fisher-PP, LLS, IPS, and Fisher-ADF certificate TFPG (TFP growth rate) are stable at the 1% significance level. We can see that the test results are very satisfactory.

Table 3. Panel unit root test.

Variables	Fisher-PP		Breitung	LLC [1]		IPS [1]		Fisher-ADF	
	Constant	Constant + Trend	Constant + Trend	Constant	Constant + Trend	Constant	Constant + Trend	Constant	Constant + Trend
ΔEC	148.29 ***,[2]	171.60 ***	−2.98 ***	−1.97 **	−1.79 *	−6.04 ***	−7.01 ***	143.64 ***	144.10 ***
TFPG	198.49 ***	180.61 ***	−1.34	−9.16 ***	−8.13 ***	−7.97 ***	−6.83 ***	171.23 ***	144.80 ***

[1] LLC and IPS tests are distributed as N(0, 1) under the null hypothesis of non-stationarity. The Fisher test is the Chi-square distributed with 2N degrees of freedom; [2] *, **, and *** are the significance levels at the 10%, 5%, and 1% levels, respectively.

Next, we tested whether a long-run relationship exists between the variables. Here, we report only the results of the Johansen test. From Table 4, the probability (Prob.) value in the third row tells us the cointegration test rejected the statement that there is no cointegration relationship between the TFP growth rate and △EC. Hence, there is a long-run relationship between these two variables. We then used DOLS to achieve consistency in the covariance vector estimation; the results are shown in Table 5. We see that △EC and the TFP growth rate are positively correlated in the long run from the two coefficient values, at the same time, from the results of two *T* tests; independent variables have significant explanatory effects on dependent variables so an increase in △EC will lead to an increase in TFP growth rate and vice versa. This conclusion proves the existence of the rebound effect. The H1b (hypothesis one b) and H2b (hypothesis two b) that we made are also confirmed.

Table 4. Unrestricted cointegration rank test 1 (Trace and maximum eigenvalue).

Hypothesized	**Fisher Stat. ***		**Fisher Stat. ***	
No. of CE [1] (s)	(from Trace Test)	Prob. [3]	(from Max Eigen Test)	Prob.
None	195.2	0.0000	155.6	0.0000
At most [2]	155.3	0.0000	155.3	0.0000

[1] CE is the abbreviation of cointegration. [2] Lag intervals (in differences):1 1; [3],* Probabilities (Prob.) are computed using an asymptotic Chi-square distribution.

Table 5. Dynamic ordinary least squares (DOLS) result [1].

Dependent Variable TFPG		**R-Squared 0.863520**	
Variable	Coefficient	t-Statistic	Prob.
ΔEC	0.097790	0.018937	0.0000
Dependent Variable ΔEC		R-squared 0.601049	
Variable	Coefficient	t-Statistic	Prob.
TFPG	1.480264	0.435531	0.0008

[1] lead = 1, lag = 1.

The rapid growth in energy consumption may be caused by lower energy efficiency, but previous research [54,55] has improved energy efficiency and has increased in recent years in China. Therefore, technological innovation improves energy efficiency, increases consumer demand for energy, and then increases energy consumption in the long run.

In turn, energy consumption growth also promotes technological innovation. The rapid growth of energy consumption brings serious environmental pollution so carrying out R&D on alternative energies, developing energy-saving and emission reduction technologies become inevitable options; this is an important driving force of technological innovation.

5.2. Causality Results

Having established that a cointegration relationship does exist between the variables under investigation, this subsection presents the results with respect to the causality hypothesis. The results for the short-run relationship, which are estimated by GMM, are reported in Table 6. The first column includes the estimated coefficients, the numbers in parentheses behind ΔEC and TFP growth rate are lag orders. N is the number of total panel observations. From the J-statistic and Prob (J) of the Sargan–Hansen J test, we know that whether the estimation is exactly identified and the instrument variables are appropriate, the larger the Prob (J) is, the greater the effect will be. The second column shows the estimated results for the relationship from TFP growth rate to ΔEC and the third column shows the converse result.

Table 6. Generalized method of moments (GMM) result.

Estimated Coefficients	Dependent Variable	
	ΔEC	TFPG
△EC (−1)	0.141471 ***,[1]	0.004314 *
△EC (−2)	0.064288 ***	0.000650
TFPG (−1)	0.539022 ***	0.337396 ***
TFPG (−2)	0.264603 ***	0.079271 ***
N	392	392
J-statistic	26.91545	27.20033
Prob (J-statistic)	0.308410	0.295202

[1] * and *** are significant at the 10% and 1% levels, respectively.

It is evident that in the short run, there is unidirectional causality from the TFP growth rate to ΔEC. However, the coefficient for the relationship from ΔEC to TFP growth rate is not significant. That is, an increase in ΔEC has no significant effect on the TFP growth rate, but an increase in the TFP growth rate has a catalytic effect on ΔEC. The former result proves that our H2a is reasonable. It stems from obvious path-dependent characteristics of energy consumption. When some energy is widely used, along with the maturity of the technology application and a reduction in the energy costs of mining, energy extraction increases unless energy is exhausted. The path dependence of energy use will lead to technology lock-in in the field of energy development and use; in other words, related enterprises and institutions are more concerned about energy efficiency improvement than about the development of new energy sources and the introduction of new technologies. The latter result is contrary to our H1a. This may be related to the application of new technology, which requires a transitional period. The use of new technology does not mean the complete elimination of an old technology. At the same time, the immaturity of new technology applications makes energy consumption rise. Consequently, feedback cannot be acquired from the market in the short run.

5.3. Discussion

It should be noted that technological innovation leads to an increase in energy consumption whether in the long or short run. In the long run, energy efficiency, which is improved with technological innovation, is expected to reduce the amount of energy consumption; however, increased energy efficiency will increase the demand for energy consumption. When an increased amount of energy consumption offsets the partly or completely reduced energy consumption, which is caused by energy efficiency promotion, the final energy consumption will increase and the rebound effect of energy efficiency will occur. For example, due to the use of energy-saving technology, the fuel consumption of cars is reduced and the owners are more willing to drive frequently. The impact of the rebound effect makes the resulting effort, which was intended to reduce energy consumption, less than ideal, especially in developing countries such as China. Previous research [56] has proven that the energy rebound effect amounted averagely to 53.2% over the period 1981–2009 in China. Therefore, when taking measures to improve energy efficiency, we cannot ignore the problem brought about by the rebound effect.

However, from the current causality results, the time interval between the improvement in energy efficiency and the increase in final energy consumption is not so long, meaning that energy policy promulgation or the use of new technology will also lead to the rebound effect in the short term; this time span is not as long as expected. Therefore, the negative effects brought about by the rebound effect should be considered in policy formulations and energy prices and other related factors should be considered in order to minimize the rebound effect of energy.

The traditional theory of sustainable development suggests that technological innovation will contribute to savings in the total amount of resources—such as the reduction in energy consumption—while promoting regional economic growth. However, our research shows that technological innovation brings about rapid economic growth while the energy consumption is also increased for developing countries such as China. Does this signify that Chinese development is not sustainable? Further analysis shows that although Chinese total energy consumption is increasing, the energy efficiency and energy consumption structure are significantly improved. Chinese unit GDP energy consumption decreased by 28.6% in 2015 compared to 2010. Chinese coal consumption decreased to its lowest level in 2016 while the renewable energy consumption growth rate increased to 33.4% [57]. It is undeniable that this is a kind of sustainable development performance. Due to the rebound effect, the improvement in energy efficiency failed to achieve a reduction in energy consumption. Therefore, we should formulate relevant policies to achieve a more reasonable system to improve energy efficiency. We believe that China has a large population and a weak economic base as a developing country; in order to achieve sustainable development, its energy consumption will inevitably undergo a rapid growth process. In the early stages of economic development in developing countries, energy and other resource inputs cannot be as efficient as in developed countries. As the total energy consumption grows, the energy structure and efficiency improvements are accumulating strength for reducing the future energy consumption, a process that developed countries have also experienced.

As a developing country, China can achieve sustainable development through technological innovation in energy via two ways: efficiency improvements in energy production, and the replacement of fossil fuels by various sources of renewable energy. This situation is consistent with the early-stage development in developed countries. In the United States, for example, its energy consumption increased at a high rate before 1972. The growth rate of energy consumption then gradually slowed after 1972 after which the total energy consumption tended to be stable. Its decline trend arose in 2016. This is largely due to the improvement in energy efficiency and changes in energy structures that were brought about by technological innovation [58]. Therefore, in the process of achieving sustainable development, an improvement in efficiency and structure leads to a reduction in energy consumption, but the current level of Chinese energy efficiency is still low compared with developed countries. The energy structure needs to be improved. Therefore, the power of both has not yet reached the level where energy consumption can be significantly reduced. To improve energy efficiency and energy structure, in addition to technological innovation, energy price regulation, energy tax, and other energy policies are also needed.

6. Conclusions

In this paper, we systematically analyzed the relationship between technological innovation and energy consumption at the regional level rather than the national level. In our view, data at the national level tend to obscure the intrinsic heterogeneity among regions; for example, the level of economic development, climate and resource conditions in different regions will affect the relationship between technological innovation and energy consumption. To avoid the impact of this intrinsic heterogeneity, this study analyzed regional-level data that came from 28 provinces in China for the period 1995–2012.

Our empirical study provides several new insights on the relationship. In the short run, technological innovation positively affects energy consumption growth, while energy consumption growth has no significant effect on technological innovation. In the long run, energy consumption growth is positively and bilaterally related to technological innovation. The results show that technological innovation is unlikely to reduce energy consumption growth, as some academics and government agencies have recognized. In contrast, it has a catalytic effect on energy consumption growth, which means that technological innovation will further increase energy consumption. Therefore, increased energy efficiency does not mean a reduction in energy consumption. Governments should be soberly aware that energy consumption growth is an inevitable trend along with technological innovation and social development at the present development stage of China. At the same time, under the constraint of finite resources and environmental pollution, energy consumption growth will also promote technological innovation rather than lead to path dependence and technology lock-in in the long run.

Based on the above analysis, it is obvious that saving resources are important but it does not mean that our vision should be confined to it. If we want to achieve sustainable development, when developing energy-saving technologies for efficient use of existing resources, we should actively focus on detection and exploitation of new energy and energy price reforms at the same time, so that we could address the resource depletion and environmental pollution caused by energy consumption growth. We cannot simply rely on a reduction in energy consumption; rather, we should rely on technological innovation to improve energy efficiency and prevent the occurrence of a rebound effect. In addition, we should formulate policies about energy price reform and carbon tax. At the same time, we should develop new energy sources in order to change the energy consumption structure and reduce pollutant emissions. The Chinese government is already working on this; at the G20 Summit in 2016, China pledged to the world that its coal production capacity would be reduced by 500 million tons in three to five years for green development.

This paper studied only 28 provinces in China; hence, whether the conclusions are applicable to other developing countries requires further investigation. In addition, the TFP growth rate selected in this study can be further broken down into technical innovation indicators and technical efficiency indicators. A follow-up study could examine the impact of each of the two variables on energy consumption growth.

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