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Energy technology patents-CO_2 emissions nexus: an empirical analysis from China

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Abstract:

Energy technology innovation plays a crucial role in reducing carbon emissions. This paper investigates whether there is relationship between energy technology patents and CO_2 emissions of 30 provinces in mainland China during 1997 - 2008. Gross Domestic Product (GDP) is included in the study due to its impact on CO_2 emissions and energy technology innovation, thus avoiding the problem of omitted variable bias. Furthermore, we investigate three cross-regional groups, namely eastern, central and western China. The results show that domestic patents for fossil-fueled technologies have no significant effect on CO_2 emissions reduction; however, domestic patents for carbon-free energy technologies appear to play an important role in reducing CO_2 emissions, which is significant in eastern China, but is not significant in central, western, and national level of China. The results of this study enrich energy technology innovation theories and provide some implications for energy technology policy making.

Key words: energy technology patents, CO_2 emissions, dynamic panel data approach

1. Introduction

Under the stress of climate change and resource crises, cutting down greenhouse gas

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(GHG) emissions and slowing down the process of global warming have received increasing concern worldwide. Along with the growing energy consumption and CO_2 emissions, it is crucial for China to enhance energy security and reduce climate change. In 2008, China contributes 8.56 percent to the global GDP while accounts for 17.29 percent of the global energy consumption (CESY, 2009). At present China's economy grows rapidly, and is likely to keep its growth in the future. In this situation, China's CO_2 emissions will reach about 15.1 billion tons in 2020, and China will probably face 4.7 billion tons of CO_2 emissions gap in 2020 if none action is taken (Liu et al., 2008). Moreover, Chinese government has made a commitment in 2009 Copenhagen Climate Change Conference to reduce the intensity of CO_2 emissions per unit of GDP in 2020 by 40 to 45 percent compared with the level of 2005. Therefore, Chinese government is under great pressure to reduce CO_2 emissions.

Many factors determine CO_2 emissions, including economic scale, population, industrial structure, energy consumption structure, energy efficiency, energy intensity and the level of technology and management (Kaya, 1990; Wang and Huang, 2008; Xu et al., 2006). The increase of CO_2 emissions in China is driven by growing economy, coal-dominated energy structure, rising level of industrialization, and population growth (Xu et al., 2006; Wei and Yang, 2010). After scrutinizing the literature, we find that the role of energy technology in reducing emissions remains controversial. Some studies implied that energy technology innovation played a crucial role in reducing CO_2 emissions (Sagar and Holdren, 2002; Sun et al., 2008). Researchers also found that clean technology had a negative effect on CO_2 emissions in China (Wei and Yang, 2010; Wu et al., 2005). However, other scholars reported that the improvement of energy efficiency in China had no significant effect on reducing CO_2 emissions, and clean technology did not play its role of reducing CO_2 emissions (Hu and

Huang, 2008; Xu et al., 2006). These inconsistent results suggest that further research is needed to examine the impact of energy technology on CO_2 emissions. In this paper, we will address this issue from the perspective of energy technology patents.

Patent counts are commonly used to measure the output of innovation activities (Dechezlepretre et al., 2010; Popp, 2006; Popp et al., 2009). Energy technology patents directly reflect the performance of energy technology innovation activities and the development of energy technologies. The increase of patent counts in energy and environmental sectors implies the improvement of energy technology innovation ability (Liu and Sun, 2008). However, careful scrutiny of the literature on the main factors determining CO_2 emissions in China shows that almost no study has been executed to explore the impact of energy technology patents. Therefore, it is necessary to explore the relationship between energy technology patents and CO_2 emissions in China. On the one hand, this study could help get a better understanding of the relationship between energy technology innovation and CO_2 emissions; on the other hand, it could provide references for Chinese government to make energy technology policy.

The current study explores the relationship between energy technology patents and CO_2 emissions in China. Considering the potential different role of fossil-fueled and carbon-free technology innovations in reducing CO_2 emissions, we distinguish patents for fossil-fueled technologies from patents for carbon-free energy technologies. The former mainly refers to the patents relevant to fossil-fueled (coal, oil and natural gas etc.) technologies in energy sectors and energy user sectors, the latter mainly refers to patents relevant to nuclear and renewable energy technologies. Specifically, this research tries to answer the following research questions: (1) Is there a significant relationship between patents for fossil-fueled technologies and CO_2 emissions? (2) Is there a significant relationship between patents for carbon-free energy technologies and CO_2 emissions? (3) Are the relationships the same in eastern, central and western China? To avoid omitted variable bias, GDP is also included in the current study due to its important role in affecting CO_2 emissions and energy technology patents. To examine such relationships, dynamic panel data approach will be applied.

The rest parts of this paper are organized as follows: Part 2 introduces theoretical background; Part 3 explains energy uses and energy technologies in China's regions; Part 4 introduces data sources and data processing, elaborates model specification and methodology; Part 5 shows the empirical results and discussions of relationship between China's energy technology patents and CO_2 emissions, including the causality analyses between patents for fossil-fueled technologies and CO_2 emissions, and that between patents for carbon-free energy technologies and CO_2 emissions; The last part shows main conclusions and policy recommendations of the current research.

2. Theoretical background

The goal of this paper is to explore the relationship between domestic energy technology patents and CO_2 emissions in China. In this section, we first analyzed the role of energy technology patents in emissions reduction. The potential different impact of patents for carbon-free energy technologies and patents for fossil-fueled technologies on CO_2 emissions was also discussed. After that, we explained why only focusing on domestic energy technology patents.

2.1 The role of energy technology patents in carbon emission reduction

Many studies found that energy technology innovation and energy technology R&D could reduce carbon emissions (Garrone and Grilli, 2010). Technology innovation could help keep carbon emissions from increasing in the long run (IPCC, 2007; Popp et al., 2009). And it is promising for developing countries to reduce carbon emissions by applying new technologies (Bernstein et al., 2006). Previous studied also reported that increased R&D had negative influence on energy and emission intensities in developing countries (Fisher-Vanden and Wing, 2008). In China, indigenous R&D was negatively related to energy intensity and CO_2 emissions (Ang, 2009; Teng, 2009).

Energy technology R&D is used to measure input of innovation process, whereas energy technology patents directly reflect output of R&D investment and innovation performance (Grilliches, 1990). Energy technology patents provide a wealth of information on the nature of invention, and are usually used as indicators of advances in specific technological areas (Dechezlepretre et al., 2010; Jamasb and Pollitt 2011; Popp et al., 2011). Energy technology patents are highly related to energy technology R&D expenditure, and they are likely to increase as R&D activity increases (Margolis and Kammen, 1999). In addition, through defining intellectual property rights, the patents internalize spillover effect of energy R&D, and then improve knowledge creation and diffusion of energy technology, which in turn inspire innovation activities. Therefore, we may deduce that energy technology patents could help to reduce CO_2 emission.

Some studies show that carbon-free energy technologies (e.g. wind, nuclear etc.) have better CO_2 emission reduction effect than fossil-fueled technologies (e.g. gas-fired and coal-fired technologies). Chen et al. (2011) explored the contributions of various low-carbon technologies in CO_2 emission mitigation. They found that wind and nuclear were the best technologies with reduction rates of almost 100%. CCS (carbon capture and storage) was effective as well, with reduction rate ranging from 64% to 81%. Super-critical (SC), ultra-super-critical (UC) and integrated gasification combined cycle (IGCC) were the major promising high-efficiency generation technologies of coal. They could mitigate CO_2 emission intensity with moderate rates, and the rates were stabled at 15% for SC, slightly floating from 20% to 25% for UC, and ranges from 18% to 34% for IGCC (Chen et al., 2011). Gnansounou et al. (2004) studied the strategic technology options for mitigating CO_2 emissions in Shanghai electricity-generating system. They found that maximum potential effect of CO_2 emission mitigation of natural gas CCPP (combined cycle power plants) could reach 42.4 million tons, that of nuclear power plants could be 298.2 million tons, whereas that of combination of coal technologies with natural gas CCPP has very slight reduction emissions (0.4 million tons). Consistent with these previous studies, we expect impact of patents for carbon-free energy technologies on CO_2 emission reduction will be stronger than impact of patens for fossil-fueled technologies.

2.2 The barriers to international energy technology deployment and transfer

Usually, the deployment and diffusion of emerging energy technologies is slow and uncertain, and there are many obstacles to their wide-spread deployment, international transfer and diffusion (IPCC, 2000; Neuhoff, 2005; Stephens et al., 2008). In addition, previous works also reported that international transfer of energy and environmental technologies was limited in developing countries (Dechezlepretre et al., 2010; Popp, 2006; Popp et al., 2009). Therefore, in this study we focused on the impact of domestic energy technology patents on CO_2 emissions in China.

The “valley of death”- defined as the place “where good lab discoveries go to die because they lack the funding necessary to become a commercial product” (Heller and Peterson, 2005, p. 27) - is often cited as a key roadblock to the transformation of new discoveries to useful and innovative products and services (Ford et al., 2007). Generally, innovation processes involve three stages: basic research idea, technical/economic feasibility (transforming a discovery or idea generated by basic research into a potentially marketable product or service), and commercial production/diffusion. Often, the valley of death exists at Stage 1 and merely manifests at Stage 2 (George et al., 2007). Valley of death is often discussed as shortfall in research funding due to risk, appropriability, uncertainty, spillovers, increasing returns and coordination problems at intermediate stages (Auerswald and Branscomb, 2003). Therefore, these literatures show that the existence of “valley of death” has negative impact on emerging technology deployment and diffusion.

Many researches exploring challenges of emerging energy technology deployment and diffusion have focused on technical, institutional, regulatory and legal, political, economic, social factors (Luthi and Prassler, 2011; Stephens et al., 2008). The barriers of information and financing constraints were particularly relevant in developing countries even after their technical feasibility had been demonstrated (Sagar and Zwaan, 2006). Specifically, Schroeder (2009) found that high project costs and the proof of additionality were general barriers to utilizing clean development mechanism (CDM) finance for renewable energy deployment in China.

Some barriers that impede international technology transfer in energy and environmental sectors include high tariffs, investment risk, high interest rates, inadequate understanding of local needs and demands, lack of confidence about ”unproven” technologies, and high transaction costs (IPCC, 2000). The often-cited barriers in climate change negotiations are intellectual property rights (IPR) and financial mechanism (Tawney andWeischer, 2011). In addition, China’s imperfect patent system and weak domestic technology absorptive capacity also impeded international technology importation (Wei and Yang, 2010; Teng, 2009).

Some scholars found that international transfer of energy and environmental technology is limited and occurs indirectly in developing countries. Dechezlepretre et al. (2010) analyzed patented inventions of 13 climate-related technology classes and found that innovation in climate change technologies was highly concentrated in Japan, Germany and USA. International transfers mostly occurred between developed countries (75% of exported inventions), and exports from developed countries to emerging economies were still limited (18%). Although China, Russia and South Korea were important innovators, there was nearly no flows between emerging economies. Popp (2006) studied international technology transfer of pollution control technologies and found that international transfer of these technologies occurred indirectly-via influencing domestic inventors-rather than directly. Direct adoption of new technologies might not be possible for the follower countries, and domestic R&D may be needed to modify foreign inventions to make them compatible with local markets (Lanjouw and Mody, 1996).

3. Energy consumption and energy technologies in China's different regions

The level of economic development and energy consumption in eastern, central and western China is different, which result in territorial differences in energy intensity and energy technologies.

3.1 The division of Eastern, Central and Western China

Along with the division of three major economic regions by China's National Bureau of Statistics, we divided 30 provinces and municipalities[2] of Chinese mainland into eastern,

[2] Chinese mainland includes 31 provinces and municipalities except for Hong Kong, Taiwan, Macao; besides, since the data of CO_2 emissions in Tibet is not available, Tibet is also not included. Therefore, this paper discussed 30 provinces and municipalities in mainland China.

central and western regions (Zeng and Chen, 2009). Eastern region includes 11 provincial administrative regions: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; central region includes eight provincial administrative regions: Heilongjiang, Jilin, Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan; Western region includes 11 provincial administrative regions: Sichuan, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi, and Inner Mongolia.

3.2 Energy consumption in China's different regions

At present, Chinese energy sources mainly include coal, oil, natural gas, hydropower, nuclear and wind, etc. Energy efficiency and pollution level of each kind of energy are different. Since 1985, coal is always the major energy consumption of China, and the consumption of new and renewable energy resources is very few (CESY, 2009). In 2008, coal consumption accounts for 70.3 percent of China's total energy consumption, and new energy formerly mentioned accounts for only 7.7 percent (CESY, 2009). In the future, new and renewable energy resources will remain subordinate to fossil energy resources. Along with the increasing population level as well as industrialization and urbanization, there will be soaring demand for fossil energy (e.g., coal). Such increasing demand for fossil energy will lead to increasing GHG emissions, which may sharpen the conflicts among resource constraint, environment protection and economic development.

Energy structure is quite different in China's different regions because of the difference in energy source and economic development, which has a significant impact on the regional energy intensity. There is a negative relationship between the level of regional economic development and energy intensity. Therefore, energy intensity in eastern China is lower than central and western China, which is also caused by advanced energy technology in eastern

China (Li and Wang, 2008). There is a negative relationship between the proportion of coal consumption in total energy consumption and energy intensity. The proportion of coal consumption is the highest in high energy - consuming region with the value of 74.3%, and the proportion of crude oil, natural gas and electricity is 25.7%. The proportion of crude oil, natural gas and electricity is the highest in low energy - consuming region with the value of 35.7%, and the proportion of coal consumption is 64.3% (Cui, 2007). Energy consumption structure in low energy-consuming region is more reasonable. High energy - consuming region is mainly located in western China, but low energy - consuming region is mainly located in eastern China (Cui, 2007).

3.3 Energy technology in China's different regions

In the past decades, China has realized the importance of energy technology innovation and made relevant policies to induce energy saving and reduce carbon emissions. As a result, substantial energy technology patents have been achieved. As shown in Table 1, China's energy technology patents have increased significantly since 1996. Specifically, energy technology patents in 2008 increased by five times during the past 13 years. Energy technology patents in eastern China have a higher growth rate than that in central and western China. The growth rate of energy technology patents in eastern China is higher than national average, and growth rates in central and western China are lower than national average.

Table 1

Growth rate of domestic energy technology patent applications in three regions of China

year	National (%)	Eastern (%)	Central (%)	Western (%)
1996	-	-	-	-
1997	4.27	07.24	10.22	0.33
1998	25.39	36.31	20.70	10.10

1999	30.96	41.06	29.84	24.43
2000	58.33	76.81	45.70	43.32
2001	66.63	93.10	47.04	29.64
2002	88.61	123.98	72.58	48.53
2003	105.70	155.32	75.54	38.11
2004	118.39	182.24	91.67	51.14
2005	167.06	247.51	122.31	95.77
2006	292.26	418.78	218.01	175.24
2007	354.37	530.88	250.27	166.45
2008	503.90	771.04	323.92	248.53

Source: Patent bibliographic database. State intellectual property office of the P.R.C, 2008. Available from http://www.sipo.gov.cn/sipo2008/.

We can divide energy technology patents into patents for fossil-fueled technologies and patents for carbon-free energy technologies (Dechezlepretre et al., 2010; Johnstone et al., 2010; Margolis and Kammen, 1999; Wang and Chen, 2010). As shown in Figure 1, the growth rate of patents for carbon-free energy technology is obviously higher than that of fossil-fueled technologies. Especially since 2000, the growth rate of patents for carbon-free energy technology has been higher. The growth rates of two kinds of patents in eastern China are both higher than that in Central and Western China. However it remains unknown whether domestic energy technology patents can help reduce CO_2 emissions. Analyzing the dynamic relationship between China's energy technology patents and CO_2 emissions is very important for China's future energy policies making.

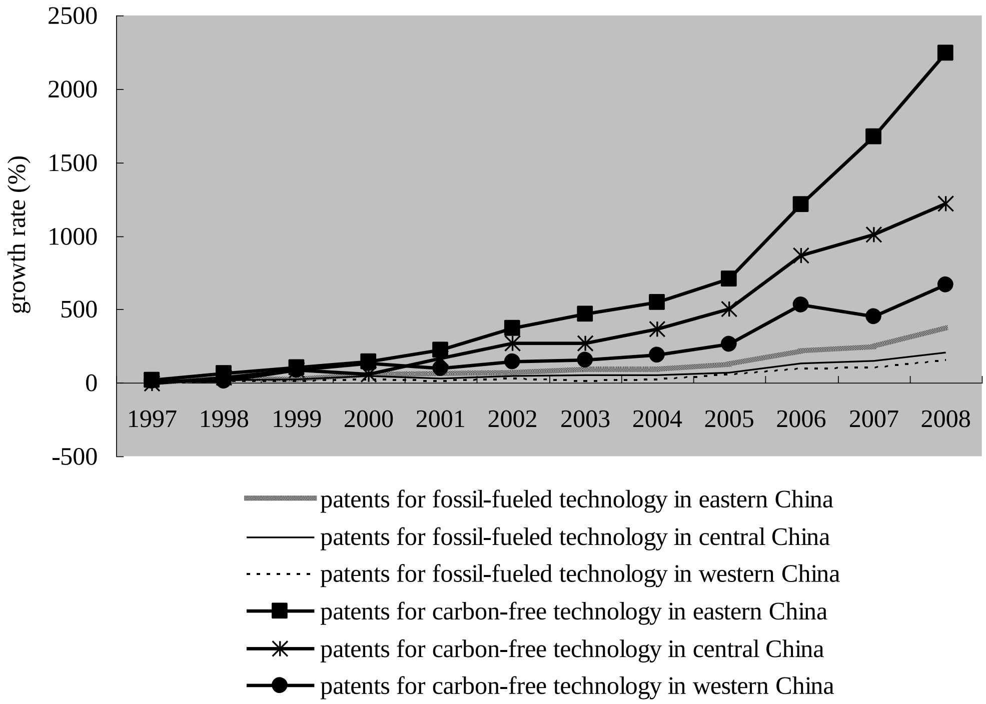

Fig. 1. Growth rate of domestic patent applications for fossil-fueled technologies and those for carbon-free energy technologies in three regions of China from 1997 to 2008

4. Data and methodology

The economic development levels are different in China's provinces and municipalities, and it has direct impact on the development of energy technology and amount of carbon emissions (Wei and Yang, 2010; Yu and Qi, 2007). So when analyzing the relationship between energy technology patents and CO_2 emissions in China (including its eastern, central and western regions), GDP was included as a control variable. We selected the following variables in this research: energy technology patents, CO_2 emissions and GDP.

4.1 Energy technology patents in China's provinces

Energy technology patents in this study include innovation in energy sectors (e.g., power generation) and energy user sectors (e.g., car motors, heating plants and) (Van Vuuren et al., 2003). Advances in fossil-fueled technologies (e.g. gas-fired and coal-fired plant technologies) could have a limited effect on carbon emissions (Chen et al., 2011; Gnansounou et al., 2004). In contrast, nuclear and renewable energy technologies are typical low-carbon, even zero-carbon generation technologies. If hydropower and new renewable energy technologies are developed, and penetrate the power generation sector, investments in fossil-fuelled plants decrease and carbon emissions are expected to decrease as well (Luthi and Prassler, 2011). Therefore, we divided energy technology patents into patents for fossil-fueled technologies and patents for carbon-free energy technologies, and extracted energy technology patents relevant to energy saving and emissions reduction from 1997 to 2008 in China (Dechezlepretre et al., 2010; Popp, 2006; Popp et al., 2011). Fossil-fueled technologies[3] include technologies in energy sectors: coal, crude oil, gasoline, diesel and natural gas relevant to energy saving and emissions reduction (Margolis and Kammen, 1999); they also include technologies in energy user sectors: stoves relevant to energy saving and emissions reduction (including the sectors of metallurgy, building, cement, chemicals, heating plants, generating station and household), electricity-saving equipment or technology, electric vehicles, car motors, combustion engine, turbine, fuel injection, energy-efficient lighting and carbon capture & storage (CCS) (Dechezlepretre et al., 2010). The carbon-free energy technologies include[4]: solar, wind, ocean, geothermal, hydropower, nuclear, biomass and waste, synthesis Gas, hydrogen fuel, biomethane, biodiesel and ethanol (Johnstone et al., 2010; Popp et al., 2006; Popp et al., 2011; Wang and Chen, 2010). The technology fields covered by this study are reported in Table 2.

Table 2

Fossil-fueled and carbon-free energy technology fields covered

category	Technology field
Fossil-fueled	coal, crude oil, gasoline, diesel and natural gas relevant to energy

[3] http://www.51patent.net/patent/8/
[4] http://carbonfreeenergy.com/

	saving and emissions reduction; stoves relevant to energy saving and emissions reduction (including the fields of metallurgy, building, cement, chemical industry, heating plants, generating station and household); electricity-saving equipment or technology; electric vehicles; car motors, combustion, engine, turbine, fuel injection; energy-efficient lighting and carbon capture & storage (CCS)
Carbon-free	solar, wind, ocean, geothermal, hydropower, nuclear, biomass and waste, synthesis Gas, hydrogen fuel, biomethane, biodiesel and ethanol

According to China's patent law, patents have three types: invention, utility models and design applications (SIPO, 2008). Inventions refer to new technology solutions or improvement to products or methods; utility models refer to new technology solutions to the shape of products, structure or their combination; design applications only protect the appearance of products, so the patents of design applications were excluded from our search (Dechezlepretre et al., 2010; SIPO, 2008). Therefore, the counts of energy technology patents in this study include two types: invention and utility models. Based on an extensive literature of technology developments in the area of energy technology, we identified a set of keywords for this study (Dechezlepretre et al., 2010; Johnstone et al., 2010; Popp, 2006; Popp et al., 2011). These were used to determine appropriate International Patent Classification (IPC) codes which relate directly to energy technology patents for energy saving and emissions reduction in different subject areas. The IPC codes were identified in two ways based on the SIPO (State intellectual property office of the PRC) patent bibliographic database (SIPO, 2008). First, we searched the descriptions of the classes online to find which were appropriate; second, we searched patents titles and abstracts using relevant keywords (Dechezlepretre et al., 2010; Johnstone et al., 2010; Popp et al., 2011). Following the literatures (Dechezlepretre et al., 2010; Johnstone et al., 2010; Popp et al., 2011), when searching for relevant patents, two possible errors may arise: irrelevant patents are included and relevant patents are excluded. The first error happens if an IPC class includes some patents that bear no relation to energy saving and emissions reduction technologies. In order to avoid the first error, we carefully examined all patent titles in each IPC class considered for inclusion, and excluded those classes that include some patents not related to energy saving and emissions reduction technologies. This method lead to the second error and will be handled using the following method. In order to avoid missing relevant patents, we searched patent titles and abstracts using relevant keywords in those classes excluded when handling the first errors, e.g., electric vehicles, biodiesel, electricity-saving equipment or technology, car motors and heating plants.

Using the above approach, we got the data of patents for fossil-fueled technologies and data of patents for carbon-free energy technology. To organize the data, patents were sorted by their application year. Then, we got energy technology patents data of 30 mainland provinces and municipalities from 1996 to 2008. We also divided energy technology patent data into categories of eastern, central and western regions. Table 1 and Figure 1 shows the rising trend of national energy technology patents from 1997 to 2008, as well as the similar trend of eastern, central and western regions.

4.2 CO_2 emissions in China's provinces

As there is no direct data of CO_2 emissions in China, most previous studies got the data based on the estimates of energy consumption (Xu, 2010; Yi et al., 2011). Energy consumption data are obtained from energy balance sheets of all provinces in China Energy Statistical Yearbook (CESY, 2009), including 17 types of energy sources. Emission factors refer to the amount of GHG emissions per net calorific value that each energy generates by burning or using (IPCC, 2006). Emission factors of each type of energy are obtained from the Intergovernmental Panel on Climate Change (IPCC) Guidelines for National Greenhouse Gas Inventories (IPCC, 2006) (Table 3). As main energy consumption of electricity and heating is coal in China, the CO_2 emissions from electricity and heat are estimated based on energy input of thermal power and heating supply, and CO_2 emissions of electricity and heating from total final consumption is no longer calculated in this study following prior research (Zhao et al., 2009). CO_2 emissions per year of each province are calculated as follows (IPCC, 2006; Yi et al., 2011). We firstly calculated the heat of each energy based on energy consumption and average low calorific value of each energy; and then we calculated CO_2 emissions of each energy based on the heat and emission factor of each energy; finally, we summed up CO_2 emissions of each energy and obtained total CO_2 emissions of each province.

Table 3

Emission factor of each type of energy

Energy type	Kg CO_2/TJ	Energy type	Kg CO_2/TJ
Raw coal	95,700.00	kerosene	71,500.00
Cleaned coal	95,700.00	Diesel oil	74,100.00
Other washed coal	95,700.00	Fuel oil	77,400.00
briquettes	95,700.00	Liquefied petroleum gas	63,100.00
coke	107,000.00	Refinery gas	57,600.00
Coke oven gas	44,400.00	Natural gas	56,100.00

Other gas	44,000.00	Other petroleum products	73,300.00
Crude oil	73,300.00	Other coking products	80,700.00
gasoline	69,766.67		

Before 1996, energy consumption in Chongqing was contained in Sichuan Province. In order to accurately reflect CO_2 emissions of each province, we chose data during 1997-2008. We divided CO_2 emissions data of 30 provinces of mainland China during 1997-2008 into categories of eastern, central and western regions. As shown in Figure 2, CO_2 emissions of eastern, central and western regions were increasing gradually during 1997-2008. Especially during the period of 2002-2008, CO_2 emissions increased significantly at a high speed (see Figure 2). This was mainly due to China's rapid economic growth and continuous increase of energy consumption.

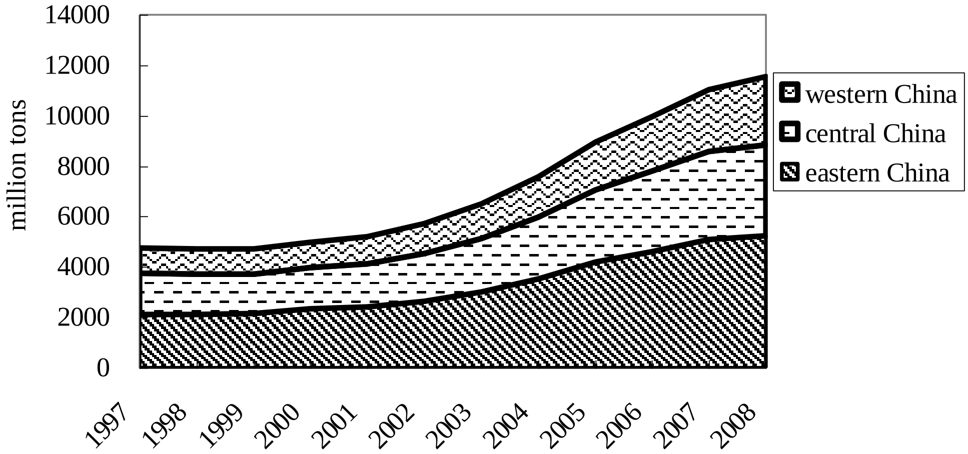

Fig.2. CO_2 emissions in eastern, central and western China

4.3 GDP of China's provinces

GDP reflects the value of all final products and services of economic activities in a nation or region in a certain period (a quarter or a year), and it is the symbol of economic development level of a nation or a region. All provincial GDP data comes from China Statistical Yearbooks. We summed up provincial GDP data according to the division of eastern, central and western China, and then obtained GDP data of three regions. Figure 3 shows GDP growth of eastern, central and western regions in China during 1997-2008. We find that GDP growth rates of three regions were obviously higher during 2002-2008. In this research, nominal GDP was used for analysis.

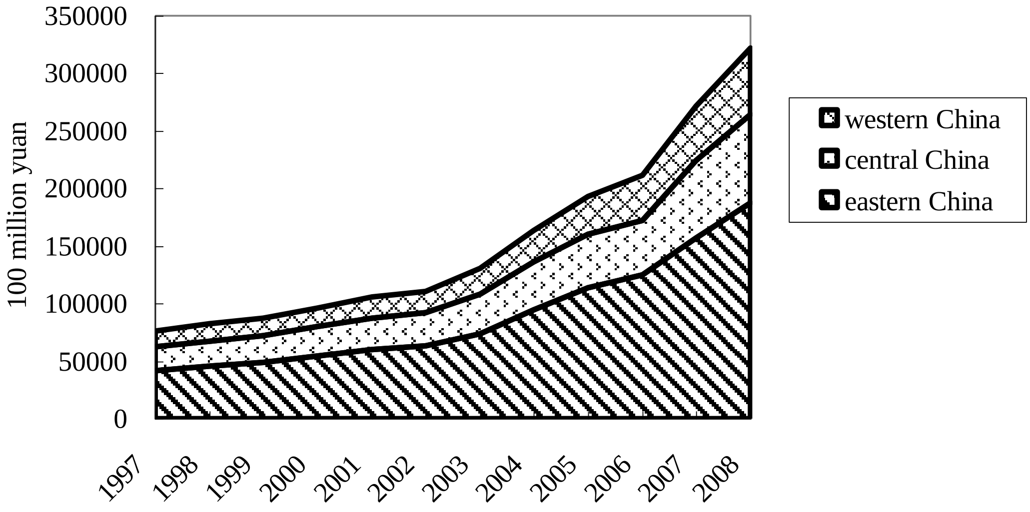

Fig.3. GDP in eastern, central and western China

In the following parts of this paper, we will use ETP to represent energy technology patents, EMS to represent CO_2 emissions, and GDP to represent gross domestic product. In order to reduce the volatility of data, we converted data to natural logarithm form, and named them as: LETP, LEMS, and LGDP. LETP stands for natural logarithm of energy technology patent, LEMS stands for that of CO_2 emissions and LGDP stands for that of gross domestic product.

4.4. Model specification and methodology

Panel data is also called as pool data, which involves two dimensions: a cross-sectional dimension and a time-series dimension. Panel data usually brings researchers a large number of data points, increasing degrees of freedom and reducing collinearity among explanatory variables, hence improving efficiency of econometric estimates (Hsiao, 2003). With repeated observations of enough cross-sections, panel data analysis permits researchers to study the dynamics of change with short time series (Yaffee, 2003). Panel data analysis endows regression analysis with both a spatial and temporal dimension. A general panel data regression model is written as:

$$y_{it} = \alpha + \beta^{'} x_{it} + u_{it} \qquad i = 1,2,..., N, t = 1,2,..., T \qquad (1)$$

Where i is the individual dimension and t is the time dimension.

Dynamic panel data was used in this paper to help verify the existence of causality between energy technology patents and CO_2 emissions. First, panel data unit root test was used to inspect stationarity of the series; second, panel cointegration test was conducted to verify whether there were long-run relationships among the series; at last, the method of dynamic panel estimation was used to determine the direction of causalities.

4.4.1 Panel unit root tests

Because of non-stationary nature of time series dada, it is essential to test their stationarity before panel data models are established. The regression of unstationary panel data will lead to problem of pseudo-regression. Therefore, stationarity of panel data has to be examined firstly using panel unit root test. Panel unit root test is based on the following autoregressive specification (Mahadevan and Asafu-Adjaye, 2007):

$$y_{it} = \rho_i y_{it-1} + \delta_i X_{it} + u_{it} \qquad i = 1,2,..., N, t = 1,2,..., T \qquad (2)$$

Where $i = 1,2,..., N$ represents provinces observed over periods $t = 1,2,..., T$, X_{it} are exogenous variables in the model including any fixed effects or individual trends, ρ_i are the autoregressive coefficients. If $|\rho_i| < 1$, y_i is said to be stationary and has no unit root. Conversely, If $|\rho_i| = 1$, then y_i contains a unit root and is not stationary. U_{it} are the disturbance terms.

The method of panel unit root tests is reported in Appendix A.

4.4.2 Panel cointegration tests

Panel cointegration tests can be done if panel data are unstationary and corresponding series are integrated with the same order. Cointegration test is used to determine long-run equilibrium relationship among series. According to the different characteristics of energy technology patents, CO_2 emission and GDP data, panel data model with variable coefficients was selected to conduct cointegrating regression:

$$LETP_{it} = \alpha_i + \beta_1 LEMS_{it} + \beta_2 LGDP_{it} + u_{it} \qquad (3)$$

Where α_i is the province-specific intercept, the slope coefficients β_{1i} and β_{2i} vary from one individual to another allowing the cointegration vectors to be heterogeneous across provinces. The method of panel cointegration tests is reported in Appendix B.

4.4.3 Panel causality tests

If there is cointegration among LEPT, LEMS and LGDP, VECM (Vector Error Correction Model) can be further established to test causalities. In order to verify the causality between energy technology patents and CO_2 emission, panel VAR model as equations 4a, 4b and 4c is established.

$$LETP_{it} = \alpha_1 + \sum_{j=1}^{m+1} \beta_{1j} LETP_{i,t-j} + \sum_{j=1}^{m+1} \gamma_{1j} LEMS_{i,t-j} + \sum_{j=1}^{m+1} \sigma_{1j} LGDP_{i,t-j} + \eta_{1i} + u_{1it} \quad (4a)$$

$$LEMS_{it} = \alpha_2 + \sum_{j=1}^{m+1} \beta_{2j} LETP_{i,t-j} + \sum_{j=1}^{m+1} \gamma_{2j} LEMS_{i,t-j} + \sum_{j=1}^{m+1} \sigma_{2j} LGDP_{i,t-j} + \eta_{2i} + u_{2it} \quad (4b)$$

$$LGDP_{it} = \alpha_3 + \sum_{j=1}^{m+1} \beta_{3j} LETP_{i,t-j} + \sum_{j=1}^{m+1} \gamma_{3j} LEMS_{i,t-j} + \sum_{j=1}^{m+1} \sigma_{3j} LGDP_{i,t-j} + \eta_{3i} + u_{3it} \quad (4c)$$

Where η_{1i} and η_{2i} are province-specific effects for the i^{th} individual in the panel, and η_{1i} and η_{2i} are the disturbance terms.

In equations 4a, 4b and 4c, the method of OLS will lead to biased estimation because of the correlation between the lagged dependent variables and province-specific effect. To avoid this bias, first differences are taken in the equations. However, any information about long-run adjustments of data may be omitted in the first differencing; therefore, VAR model should be adopted to express short-run relationships among the variables. According to Engle-Granger theory, as long as there is cointegration among variables, VECM can be deduced from VAR model. The promise of VECM is that unequilibrium which happens in a time point can be corrected in the next time point, and it is possible to identify different relationships between variables in a long-run and a short-run. Therefore, panel-based VECM as equations 5a, 5b and 5c is established:

$$LETP_{it} = \sum_{j=1}^{m} \beta_{1j} \Delta LETP_{i,t-j} + \sum_{j=1}^{m} \gamma_{1j} \Delta LEMS_{i,t-j} + \sum_{j=1}^{m} \sigma_{1j} \Delta LGDP_{i,t-j} + \lambda_1 ECT_{i,t-1} + \Delta u_{1it} \quad (5a)$$

$$LEMS_{it} = \sum_{j=1}^{m} \beta_{2j} \Delta LETP_{i,t-j} + \sum_{j=1}^{m} \gamma_{2j} \Delta LEMS_{i,t-j} + \sum_{j=1}^{m} \sigma_{2j} \Delta LGDP_{i,t-j} + \lambda_2 ECT_{i,t-1} + \Delta u_{2it} \quad (5b)$$

$$LGDP_{it} = \sum_{j=1}^{m} \beta_{3j} \Delta LETP_{i,t-j} + \sum_{j=1}^{m} \gamma_{3j} \Delta LEMS_{i,t-j} + \sum_{j=1}^{m} \sigma_{3j} \Delta LGDP_{i,t-j} + \lambda_3 ECT_{i,t-1} + \Delta u_{3it} \quad (5c)$$

ECT is error correction term attained from the residuals of estimated cointegration equation (1), reflecting long-run equilibrium among the variables. Coefficient of ECT denotes the adjusting velocity when equilibrium is deviated. Coefficients of the difference terms reflect influence of independent variables on dependent variables in short-run, and lagged difference terms that are not significant can be eliminated.

On the right side of equations 5a, 5b and 5c, lagged dependent variables have been included. As a result, regressors are inherently correlated with disturbance. In this case, OLS estimation will be biased and inconsistent. To solve the problem, Arellano and Bond (1991) proposed the estimator of first differenced GMM (DIF-GMM) in panel for the system 5a, 5b and 5c, using lagged dependent variables in levels as instrumental variables in first differences. Instrumental variables are affected only when disturbances are not correlated.

Blundell and Bond (1998) pointed out that DIF-GMM estimation may be easily affected by weak instrumental variables. As a result, biased estimation may be achieved. To resolve this problem, they proposed the method of System-GMM. We have tried to use System-GMM as estimating method, but it did not work. Therefore, Arellano and Bond (1991)'s first differenced GMM robust one-step estimator was adopted to solve the equations of 5a, 5b and 5c. The selection of lag order m_j for instrumental variables should meet the requirement that the problem of autocorrelation of residuals can be avoided. AR test is used to help inspect autocorrelation of residuals. AR (1) and AR (2) are usually used to conduct test, and the rule is that hypothesis of existence of AR (1) should be rejected and hypothesis of existence of AR (2) should not be rejected. Sargan test of over-identifying restrictions is processed to check validity of the instruments.

Causalities between variables are identified by verifying significance of coefficient of the dependent variables in panel VECM. First, short-run causalities are identified by testing hypothesis as follows:

(1) $H_0: \ \gamma_{1j} = 0, \forall j = 1,...,m$ and $H_0: \ \sigma_{1j} = 0, \forall j = 1,...,m$ in Eqs. $(5a)$;

(2) $H_0: \ \gamma_{2j} = 0, \forall j = 1,...,m$ and $H_0: \ \sigma_{2j} = 0, \forall j = 1,...,m$ in Eqs. $(5b)$;

(3) $H_0: \ \gamma_{3j} = 0, \forall j = 1,...,m$ and $H_0: \ \sigma_{3j} = 0, \forall j = 1,...,m$ in Eqs. $(5c)$;

And then, the significance of the ECT coefficients determines the existence of a long-run causality. At last, a simple Wald test can be applied to examine the direction of causal relationship between the variables.

5. Results and discussion

5.1. Results of panel unit root tests

All statistics in LLC, IPS, Fisher-ADF and Fisher-PP and some statistics in Breintung test indicate that null hypotheses of LETP (LETP is analyzed based on patents for fossil-fueled technologies and patents for carbon-free energy technologies), LEMS and LGDP having a unit root are not rejected at 5% or 10% level, so the series are not stationary. However, null hypothesis that first difference of each variable has a unit root is rejected at 10% level, indicating that most of tests provide supporting evidence that the series are integrated of first order. The results of panel unit root tests in the national, eastern, central and western China are reported in Appendix A (Tabel A1, Tabel A2, Tabel A3 and Tabel A4).

5.2 Results of panel cointegration tests

The series of LETP, LEMS and LGDP are all integrated of order one in the national, eastern, central and western China, thus we can proceed to conduct cointegration tests. On the one hand, for fossil-fueled technologies, all statistics in Panel PP, Panel ADF, Group PP and Fisher tests and some statistics in other tests reject null hypothesis of no cointegration at 10% level; on the other hand, for carbon-free energy technologies, all the resulting statistics, except for Panel v-Statistic, Panel rho-Statistic and Group rho-Statistic in pedroni test, reject null hypothesis of no cointegration at 1% level. Above results indicate that LETP, LEMS and LGDP are cointegrated series. Therefore, there is a long-run relationship between the series for provinces in the panel for fossil-fueled technologies and carbon-free energy technologies, which means that the series move together in the long-run. The results of panel cointegration tests are reported in Appendix B (Tabel B1 and Tabel B2).

5.3 Results and discussion of panel causality tests on fossil-fueled technologies

Table 4

The results of DIF-GMM estimation on fossil-fueled technologies

		National	Eastern	Central	Western
The number of lags	Eqs. (5a)	2	2	1	2
	Eqs. (5b)	2	2	2	2
	Eqs. (5c)	1	1	2	2
Validity (Yes or No)	Sargan test	Yes	Yes	Yes	Yes
significance (Yes or No)	m_1	Yes	Yes	Yes	Yes
	m_2	No	No	No	No

In order to determine the direction of causal relationship between the series, VECM (Eqs. (5a), (5b) and (5c)) is estimated using DIF-GMM estimator (Arellano and Bond, 1991). Table 4 shows the estimates, the sargan test results and m_1 and m_2 statistics on fossil-fueled technologies. Complete estimates are reported in Appendix C (Table C1, Table C2, Table C3 and Table C4). The estimates show that 2 lags or l lag is selected to make the disturbance have no serial correlation in the national and other regions. The results of m_1 and m_2 show that significant first order serial correlation is found in the first differenced residuals, while there is no evidence of second order serial correlation. The sargan statistics do not reject the validity of the instruments.

To distinguish the possible different sources of causation, Table 5 shows the statistic values of wald test of no causality on fossil-fueled technologies. Firstly, we analyzed short-run causality between LEMS and LETP. On the one hand, there is a positive causal relationship running from LEMS to LETP in eastern and national level of China at the 1% significant level, indicating that increase in CO_2 emissions pushes up increase in patents for fossil-fueled technologies. The reasons are as follows. Economy and technology in eastern

China has developed relatively rapidly, and there is a substantial increase in CO_2 emissions because of fossil-fueled dominated energy structure. To achieve higher energy efficiency and reduce CO_2 emissions, the development of fossil-fueled technologies for energy saving and emissions reduction is promoted.

On the other hand, there is a positive causal relationship running from LETP to LEMS in eastern and national level of China at the 10% significant level, indicating that increase in patents for fossil-fueled technologies causes increase in CO_2 emissions. Our result is in line with the findings of Hu and Huang (2008) who found that the current technology did not help reduce CO_2 emissions in China. This may be due to several reasons. Most advances in gas-fired and coal-fired plant technologies could have a limited effect on CO_2 emissions (Chen et al., 2011; Gnansounou et al., 2004). The cost and risk is higher while firms are going to employ advanced fossil-fueled technologies which tend to have positive externality. Private firms are reluctant to invest in these technologies if no payoff is guaranteed (Popp, 2009). Therefore, some of the present patents for fossil-fueled technologies could not be adopted widely to reduce emissions. In addition, use of energy-efficient fossil-fueled technologies may have produced relevant rebound effects (Sorrell et al., 2009), which may lead to CO_2 emissions increase to some extent.

Table 5

Statistic values for panel causality tests on fossil-fueled technologies

	Dependent	Source of causation (Independent)			
		Short-run			Long-run
		ΔLETP	ΔLEMS	ΔLGDP	ECT
National	ΔLETP		0.4666 [a]	0.0636	0.8913 [a]
	ΔLEMS	0.0181 [b]		0.1868 [a]	0.5998 [a]
	ΔLGDP	0.0143	0.5726 [a]		0.8442 [a]

Eastern	ΔLETP		1.3421 [a]	-0.1104	1.0150 [a]
	ΔLEMS	0.0239 [b]		0.1785 [a]	0.5329 [a]
	ΔLGDP	-0.0237	0.5626 [a]		0.9077 [a]
Central	ΔLETP		0.0277	0.0727	0.6418 [a]
	ΔLEMS	0.0172		0.0987 [b]	0.5308 [a]
	ΔLGDP	0.0226	0.8178 [a]		1.0247 [a]
Western	ΔLETP		0.1293	0.8144 [a]	0.9080 [a]
	ΔLEMS	0.0061		0.4187 [a]	0.7209 [a]
	ΔLGDP	0.0471 [b]	0.4177 [a]		0.5127 [a]

[a] The null hypothesis of no causation is rejected at the 1% level.

[b] The null hypothesis of no causation is rejected at the 10% level.

The short-run and positively bidirectional causality between LEMS and LETP is not significant in central and western China. On the one hand, increase in CO_2 emissions does not significantly push up increase in patents for fossil-fueled technologies. This may be due to poor technology infrastructure and insufficient investment in energy technology R&D in central and western China, which also impedes the absorption of energy-efficient fossil-fueled technologies (Wei and Yang, 2010). On the other hand, patents for fossil-fueled technologies could not curb CO_2 emission. The result is closely related to low energy efficiency and lower transformation rate of patents in central and western China.

Secondly, we analyzed short-run causality between LEMS and LGDP, and short-run causality between LETP and LGDP. There is a positive causal relationship running from LEMS to LGDP in eastern, central, western, and national level of China at the 1% significant level. The main cause of CO_2 emissions is energy consumption, while economic growth needs energy consumption. There is a positive causal relationship running from LGDP to LEMS in eastern, central, western, and national level of China at the 1% or 10% significant level, which shows that the higher GDP, the greater CO_2 emissions are. This result is affected by coal dominated energy consumption structure. There is also evidence of positively bidirectional causality between LETP and LGDP in western China, which implies that increase in patents for fossil-fueled technologies improves GDP output and increase in GDP promotes increase in patents for fossil-fueled technologies. However, the linkage between LETP and LGDP is not significant in, eastern, central, and national level of China.

Thirdly, we analyzed long-run causality among three variables. If the coefficent of ECT is not equal to zero significantly, a long-run causality among the variables will exist and positive coefficient indicates that the variables deviate from long-run equilibrium. The Coefficients of ECT in eastern, central, western, and national level of China are positive and significant in Eqs. (5a), (5b) and (5c) at the 1% level. These results suggest that patents for fossil-fueled technology, CO_2 emissions and GDP are heavily reliant on each other in the long run, and they all respond to a deviation from the long-run equilibrium in the previous period.

5.4 Results and discussion of panel causality tests on carbon-free energy technologies

Table 6

The results of DIF-GMM estimation on carbon-free energy technologies

		National	Eastern	Central	Western
The number of lags	Eqs. (5a)	2	2	2	2
	Eqs. (5b)	1	2	1	1
	Eqs. (5c)	2	2	2	2
Validity (Yes or No)	Sargan Test	Yes	Yes	Yes	Yes
significance (Yes or No)	m_1	Yes	Yes	Yes	Yes
	m_2	No	No	No	No

Table 6 shows the estimates, the sargan test and m_1 and m_2 statistics on carbon-free energy technologies. Complete estimates are reported in Appendix D (Table D1, Table D2, Table D3 and Table D4). The estimates show that 2 lags or l lag is selected to make the disturbance have no serial correlation in the national and other regions. The results of m_1 and m_2 show that significant first order serial correlation is found in first differenced residuals, while there is no evidence of second order serial correlation. The sargan statistics do not reject the validity of the instruments.

To distinguish the possible different sources of causation, Table 7 shows the statistic values of wald test on carbon-free energy technologies. Firstly, we analyzed short-run causality between LEMS and LETP. There is a negative causal relationship from LEMS to LETP on carbon-free energy technologies in eastern, central, western, and national level of China at the 1% or 10% significant level, indicating that increase in CO_2 emissions do not promote carbon-free energy technologies. This result may be due to several reasons. Coal accounts for 70.4% of China's energy use and coal in electricity generation accounts for 83% of China's all power generated in 2007 (Wang and Chen, 2010). This unreasonable energy structure has a serious threat to China's energy security. Therefore, the main reason that Chinese government has tried to reduce dependence on fossil-fueled energy and promote the development of carbon-free energy technologies (e.g. solar, hydropower, wind and nuclear etc.) lies in energy security and not emissions reduction. In addition, renewable energy production and fossil-fueled production could be assumed to be perfect substitutes from the perspectives of consumer demand (Fisher and Newell, 2008). There is a positive relationship from CO_2 emissions to fossil-fueled technologies, so a negative relationship may exist from CO_2 emissions to carbon-free energy technologies.

There is a negative short-run causality from LETP to LEMS on carbon-free energy technologies, which is significant in eastern China at the 10% level, indicating that patents for carbon-free energy technologies could reduce emissions in eastern China. The results are consistent with the previous study (Wei and Yang, 2010). Eastern China has strong economic basis and pays more attention to develop carbon-free energy technologies (e.g. hydropower and new renewable technologies) which have strong effect for reducing carbon emissions. If they penetrate the power sector and other sectors, carbon emissions are expected to decrease. However, patents for carbon-free energy technologies have limited impact on emissions reduction in eastern China; when patents for carbon-free energy technologies increase by 1%, then CO_2 emissions will decrease by 0.02%. Possible reason is that private firms face higher cost and risk, so they are not actively adopting efficiency-energy technologies. For example, China has strong R&D ability and market competitiveness in the field of solar photovoltaic which have dominated about 70% market share in the world, but only 3% to 4% capacity is digested in China and the rest of 96% capacity is sold to the abroad (Gonsense, 2011). However, as a matter of fact, China's R&D investment and ability in many fields of carbon-free energy technologies has larger gap compared with developed countries (Ma et al., 2003). In addition, the actual time for a patent application to be granted lasting 5 to 6 years also hinders them from reducing CO_2 emissions (Liu and Zheng, 2008). The negative short-run causality from LETP to LEMS in central and western China is not significant, indicating that the role of patents for carbon-free energy technologies reducing emissions is not obvious. Possible reason is that R&D investment is not sufficient and energy infrastructures are so imperfect that efficiency-energy technologies can't get large-scale application in central and western China.

Table 7

Statistic values for panel causality tests on carbon-free energy technologies

	Dependent	Source of causation(Independent)			
		Short-run			Long-run
		ΔLETP	ΔLEMS	ΔLGDP	ECT
National	ΔLETP		-0.5344 [a]	0.0996 [b]	0.9671 [a]
	ΔLEMS	-0.0039		0.1423 [a]	0.6039 [a]
	ΔLGDP	0.0138 [b]	0.5907 [a]		0.8178 [a]
Eastern	ΔLETP		-0.7070 [b]	-0.1901 [b]	0.8666 [a]
	ΔLEMS	-0.0202 [b]		0.0887 [b]	0.6640 [a]
	ΔLGDP	-0.0096 [b]	0.5616 [a]		0.9036 [a]
Central	ΔLETP		-0.5394 [b]	0.1572 [b]	0.9389 [a]
	ΔLEMS	-0.0018		0.0914 [b]	0.4432 [a]
	ΔLGDP	0.0492 [b]	0.8540 [a]		1.0850 [a]
Western	ΔLETP		-0.5684 [b]	0.5237 [b]	1.0376 [a]
	ΔLEMS	-0.0052		0.3633[a]	0.5298[a]
	ΔLGDP	0.0096 [b]	0.4125 [a]		0.4406 [a]

[a] The null hypothesis of no causation is rejected at the 1% level.

[b] The null hypothesis of no causation is rejected at the 10% level.

Secondly, we analyzed short-run causality between LEMS and LGDP, LETP and LGDP. There is evidence of short-run and positively bidirectional causality between LEMS and LGDP in, eastern, central, western, and national level of China at the 1% or 10% significant level, indicating that increase in CO_2 emissions pushes up GDP, and increase in GDP leads to increase in CO_2 emissions. There is a positive short-run causality from LETP to LGDP in eastern, central, western, and national level of China at the 10% significant level, which implies that increase in patents for carbon-free energy technologies contributes to GDP growth. The short-run LGDP has a positive and statistically significant impact on LETP in central, western, and national level of China at 10% level, indicating that increase in GDP promotes increase in patents for carbon-free energy technologies.

Thirdly, we analyzed long-run causality among three variables on carbon-free energy technologies. The coefficients of ECT in eastern, central, western, and national level of China are positive and statistically significant in Eqs. (5a), (5b) and (5c) at the 1% level. These results add extra evidence for a long-run relationship among carbon-free energy technologies, CO_2 emissions and GDP, and they all respond to a deviation from the long-run equilibrium in the previous period.

6. Conclusions and policy recommendations

6.1 Conclusions

This paper empirically studied whether there was a causal relationship between energy technology patents and CO_2 emissions from the perspective of energy technology innovation output. Our findings fill the literature gap of ignoring this important relationship and enrich energy technology innovation theory and CO_2 emissions reduction literature. The 1997-2008 panel data of 30 provinces and municipalities in mainland China were collected, and used to examine causal relationship between patents for fossil-fueled technologies and CO_2 emissions, between patents for carbon-free energy technologies and CO_2 emissions in eastern, central, western, and national level of China. Using the dynamic panel data approach, unit root test and cointegration test on patents for fossil-fueled technologies, patents for carbon-free energy technologies, CO_2 emissions and GDP were conducted to determine stationarity of the series and whether there are long-run relationships between the series. Then, the dynamic relationships between the series were examined using DIF-GMM.

We find that there is a long-run causality among patents for fossil-fueled technologies, CO_2 emissions and GDP, and there is also a long-run causality among patents for carbon-free energy technologies, CO_2 emissions and GDP. In the short-run: (1) From the perspective of patents for fossil-fueled technologies, there is positively bidirectional causality between LEMS and LETP, and it is significant in eastern and national level of China, while not significant in central and western China. (2) From the perspective of patents for carbon-free energy technologies, there is a significantly negative causality from LEMS to LETP in eastern, central, western, and national level of China; There is a negative causality from LETP to LEMS, and it is significant in eastern China, while not significant in central, western, and national level of China. According to our findings, patents for fossil-fueled technologies have no effect on emissions reduction. However, patents for carbon-free energy technologies are found to help reduce CO_2 emissions, which is significant in eastern China, while not significant in central and western China. It is consistent with findings that the effect of domestic innovation on emissions reduction is clearly different in eastern, central and western China (Wei and Yang, 2010).

6.2 **Policy recommendations**

Our findings have some implications for Chinese government to design energy technology policy. On the whole, China’s investment in energy R&D is insufficient. Although energy technology patents have increased greatly, many energy-efficient technologies have not been widely adopted. China’s government needs to promote energy structure adjustment and develop carbon-free energy technologies. And a portfolio of instruments involving technology-push, market creation and interface improvement policies are essential to reduce CO_2 emissions.

Firstly, Chinese government could make technology-push policies to produce innovation through reducing the private cost (Nemet, 2009). Public energy R&D investment has unique long-term mitigation effects and should focus on technologies that are riskier and more immature. Chinese government should place emphasis on increasing R&D investment in carbon-free energy technologies, especially in central and western China. In addition, because of fossil-fueled energy dominated energy structure, it is difficult for carbon-free energy technologies to play a leading role in the short-term; Chinese government should also increase R&D investment in fossil-fueled technologies. Some measures targeted to support the domestic energy innovation systems are warranted, such as: government sponsored R&D, tax credits for companies to invest in R&D and funding demonstration projects (Nemet, 2009).

Secondly, the government could make market creation policies to attain successful innovation through increasing the private payoff (Nemet, 2009). Market creation measures that support the development of carbon-free or low-carbon technologies and their deployment and diffusion across the energy users and utilities are essential to reduce CO_2 emissions. The role of China's carbon-free energy technologies in reducing emissions is limited: when patents for carbon-free energy technologies increase by 1%, then CO_2 emissions will decrease by 0.02%. Some measures targeted to support market creation policies are warranted especially in central and western China, such as: intellectual property protection; government procurement of carbon-free energy technologies; create customers for carbon-free energy technologies, either through subsidies or through mandates/standards; production subsidy for carbon-free energy (Nemet, 2009; Taylor, 2008). In addition, some measures (e.g. emissions price, emissions performance standard, and tax on fossil-fueled energy) could affect the fossil-fueled sector directly and create the demand for energy-efficient technologies. They could simultaneously give incentives for fossil energy producers to reduce emission intensity and for carbon-free energy producers to expand production (Fischer and Newell, 2008).

Thirdly, interface improvement policies are needed. These policies focus on improving the interface between technology suppliers and users, can bring new technologies to the market, and curb transactions costs of carbon-free and low-carbon technologies. Chinese government could perform the role of installer between technology inventors/manufactures and end-users. The government could ensure quality installers through decentralized policies like training and certification programs, and ensure quality installations through decentralized policies like inspection programs and warranty requirements (Taylor, 2008).

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Appendix A. Panel unit roots tests and results

Panel unit roots tests

The method of panel unit root test can be classified into two groups. One is based the assumption that the unit roots of all individuals are identical. The method in this group mainly includes LLC (Levin-Lin-Chu) (2002) test, Breitung (2000) test, and Hadri (2000) test. The alternative is based on the assumption that different individuals have different unit roots. The method in this group mainly includes IPS (Im-Pesaran-Skin) (2003) test, Fisher-ADF test, and Fisher-PP test (Maddala and Wu, 1999). As each method has certain shortages, to overcome the bias of only using single method, five methods of LLC, Breitung, IPS, Fisher-ADF and

Fisher-PP were used simultaneously in panel unit root test for the series of LETP, LEMS and LGDP.

Results of panel unit root tests

We selected the LLC, Breintung, IPS, Fisher-ADF and Fisher-PP panel unit root tests to examine stability of LETP, LEMS and LGDP respectively. As the series includes time trend, individual intercept and individual trend are selected to carry out above tests. The results of LLC, Breintung, IPS, Fisher-ADF and Fisher-PP panel unit root tests in the national, eastern, central and western China are presented in TableA1, TableA2, TableA3 and Table A4.

Table A1

Results of panel unit root tests in the national level of China

Variable		LLC	Breintung	IPS	Fisher—ADF	Fisher—PP
LETP	Fossil-fueled	3.86	3.90	4.27	43.99	51.36
	Carbon-free	-1.38	-1.92 [b]	2.67	47.87	50.69
LEMS		3.04	4.59	7.98	9.50	1.83
LGDP		17.10	8.44	18.59	2.88	1.68
ΔLETP	Fossil-fueled	-18.23 [a]	-7.21 [a]	-13.09 [a]	251.79 [a]	326.07 [a]
	Carbon-free	-25.04 [a]	-17.70 [a]	327.94 [a]	448.78 [a]	448.78 [a]
ΔLEMS		-7.14 [a]	0.96	-3.96 [a]	103.06 [a]	127.43 [a]
ΔLGDP		-6.71 [a]	-6.24 [a]	-3.71 [a]	106.61 [a]	126.95 [a]

[a] Rejection of the null hypothesis at the 1% significance level.

[b] Rejection of the null hypothesis at the 5% significance level.

[c] Rejection of the null hypothesis at the 10% significance level.

Table A2

Results of panel unit root tests in eastern China

Variable		LLC	Breintung	IPS	Fisher—ADF	Fisher—PP
LETP	Fossil-fueled	4.92	4.18	4.75	11.00	10.39
	Carbon-free	0.51	0.67	3.51	15.35	14.47
LEMS		-0.51	2.27	3.47	4.58	0.77

LGDP		9.38	3.85	10.31	1.25	0.71
ΔLETP	Fossil-fueled	-9.84 [a]	-4.63 [a]	-6.84 [a]	86.37 [a]	110.04 [a]
	Carbon-free	-16.57 [a]	-5.00 [a]	-10.74 [a]	113.88 [a]	155.71 [a]
ΔLEMS		-5.19 [a]	1.13	-3.82 [a]	50.63 [a]	55.59 [a]
ΔLGDP		-6.09 [a]	-4.79 [a]	-3.36 [a]	46.92 [a]	54.82 [a]

[a] Rejection of the null hypothesis at the 1% significance level.

[b] Rejection of the null hypothesis at the 5% significance level.

[c] Rejection of the null hypothesis at the 10% significance level.

Table A3

Results of panel unit root tests in central China

Variable		LLC	Breintung	IPS	Fisher—ADF	Fisher—PP
LETP	Fossil-fueled	0.20	1.10	1.92	12.34	19.67
	Carbon-free	-1.17	-3.15 [a]	1.67	7.43	10.68
LEMS		3.28	2.51	4.76	2.72	0.36
LGDP		7.28	4.15	7.89	1.52	0.91
ΔLETP	Fossil-fueled	-9.89 [a]	-3.97 [a]	-6.31 [a]	63.72 [a]	80.78 [a]
	Carbon-free	-12.81 [a]	-3.75 [a]	-10.05 [a]	100.12 [a]	138.48 [a]
ΔLEMS		-3.11 [a]	1.29	-1.29 [c]	20.57	23.30 [c]
ΔLGDP		-2.97 [a]	0.69	-2.48 [a]	33.10 [a]	45.66 [a]

[a] Rejection of the null hypothesis at the 1% significance level.

[b] Rejection of the null hypothesis at the 5% significance level.

[c] Rejection of the null hypothesis at the 10% significance level.

Table A4

Results of panel unit root tests in western China

Variable		LLC	Breintung	IPS	Fisher—ADF	Fisher—PP
LETP	Fossil-fueled	-0.74	-1.01	0.66	20.53	21.03
	Carbon-free	-3.90 [a]	-4.04 [a]	-0.60	25.10	25.53
LEMS		3.16	2.34	5.65	2.20	0.70
LGDP		13.05	5.76	13.64	0.11	0.05

ΔLETP	Fossil-fueled	-11.69 [a]	-3.94 [a]	-9.34 [a]	100.75 [a]	134.31 [a]
	Carbon-free	-13.87 [a]	-4.31 [a]	-9.88 [a]	113.97 [a]	154.59 [a]
ΔLEMS		-4.06 [a]	-1.09	-1.63 [c]	31.86 [c]	48.55 [a]
ΔLGDP		-10.49 [a]	-6.19 [a]	-4.74 [a]	68.08 [a]	99.4 [a]

[a] Rejection of the null hypothesis at the 1% significance level.

[b] Rejection of the null hypothesis at the 5% significance level.

[c] Rejection of the null hypothesis at the 10% significance level.

Appendix B. Panel cointegration tests and results

Panel cointegration tests

At present, the method of panel cointegration test can be divided into two types. One type is the progress of EG (Engle-Granger) two steps, which is based on constructing statistics with residuals in the panel model (e.g., Pedroni (1999) and Kao (1999)). The alternative is the progress of trace statistics forwarded by Johansen (1995), which is based on regression coefficient (e.g. Fisher). Two different types of testing method have been proposed by Pedroni (1999) in dealing with panel cointegrating test. One is based on the scale of panel, including panel v-statistic, panel ρ-statistic, panel PP-statistic, and panel ADF-statistic. The alternative is based on the scale of group, including group-statistic, Group PP-statistic, and group ADF-statistic. There are two types of test statistics in Johansen cointegrating test: trace statistic and maximum eigenvalue statistic, which can be obtained by solving Π matrix. When testing long-run relationships among the series, in order to avoid the bias of using only one test method, Pedroni, Kao and Johansen were used simultaneously during panel cointegration test for the series of LETP, LEMS and LGDP.

Results of panel cointegration tests

We selected Pedroni, Kao and Fisher panel cointegration tests to examine the long-run equilibrium relationships between LETP, LEMS and LGDP. The results of Pedroni, Kao and Fisher panel cointegration tests in the national, eastern, central and western China are presented in Table B1 and Table B2.

Table B1

Results of panel cointegration tests on fossil-fueled technologies

statistics	National	Eastern	Central	Western
Panel v	0.6299	0.3853	-0.4738	0.5742
Panel rho	-1.0557 [c]	-1.0880	0.3617	-0.5707
Panel PP	-6.1528 [a]	-4.3640 [a]	-1.8271 [a]	-3.6417 [a]
Panel ADF	2.1974 [a]	-1.4923 [c]	-1.6915 [a]	-1.2792 [a]
Group rho	1.3144	0.6327	1.2063	0.5331
Group PP	-10.2449 [a]	-6.3489 [a]	-5.0038 [a]	-6.2639 [a]
Group ADF	-2.9308 [a]	-0.5559	-2.8188 [a]	-1.900 [b]
Kao-ADF	-0.7917	-1.5296 [c]	-0.6447	-0.3341
Fisher (trace test)	116.1 [a]	48.0100 [a]	51.1500 [a]	49.9900 [a]
Fisher (max-eigen test)	116.1 [a]	40.7300 [a]	44.6700 [a]	49.9900 [a]

[a] Rejection of the null hypothesis of no cointegration at the 1% significance level.

[b] Rejection of the null hypothesis at the 5% significance level.

[c] Rejection of the null hypothesis at the 10% significance level.

Table B2

Results of panel cointegration tests on carbon-free energy technologies

statistics	National	Eastern	Central	Western
Panel v	-0.8176	-0.7056	0.2525	-0.8234
Panel rho	-0.6036	-0.2320	-0.7173	-0.1722
Panel PP	-9.7876 [a]	-6.5271 [a]	-5.5328 [a]	-5.2950 [a]
Panel ADF	-7.6739 [a]	-3.6746 [a]	-4.4070 [a]	-5.0616 [a]
Group rho	1.8570	1.3777	0.3456	1.3942
Group PP	-15.1029 [a]	-8.6719 [a]	-9.8280 [a]	-7.8884 [a]

Group ADF	-10.2777 [a]	-3.2448 [a]	-6.8555 [a]	-7.8818 [a]
Kao-ADF	-4.7471 [a]	-3.6447 [a]	-4.3630 [a]	-2.7460 [a]
Fisher (trace test)	132.5000 [a]	73.0700 [a]	82.7400 [a]	73.1000 [a]
Fisher (max-eigen test)	132.5000 [a]	65.3700 [a]	81.2400 [a]	73.1000 [a]

[a] Rejection of the null hypothesis of no cointegration at the 1% significance level.

[b] Rejection of the null hypothesis at the 5% significance level.

[c] Rejection of the null hypothesis at the 10% significance level.

Appendix C Results of DIF-GMM estimation on fossil-fueled technologies

Table C1

DIF-GMM estimation[a] in the national level of China on fossil-fueled technologies

	dependent		
Independent	$\Delta LETP_{it}$	$\Delta LEMS_{it}$	$\Delta LGDP_{it}$
$\Delta LETP_{i,t-1}$	2.44 [c]	-1.80 [c]	-0.83
$\Delta LETP_{i,t-2}$	1.84 [c]	-2.85 [c]	-0.52
$\Delta LEMS_{i,t-1}$	-1.78 [c]	-1.18	-2.06 [c]
$\Delta LEMS_{i,t-2}$	-0.56	-1.22	-0.63
$\Delta LGDP_{i,t-1}$	-0.70	-1.87 [c]	1.25
$\Delta LGDP_{i,t-2}$	0.06	-0.54	-1.14
$ECT_{i,t-1}$	-12.23 [b]	-3.33 [b]	-4.49 [b]
Sargan test	134.43	114.64	158.47
m_1	-2.15 [b]	-2.11 [c]	-2.82 [b]
m_2	-1.19	-1.07	1.23

[a] All tests are based on one-step robust GMM estimations, except Sargan test which is based on one-step GMM estimates.

[b] Significant at the 1% level.

[c] Significant at the 10% level.

Table C2

DIF-GMM estimation[a] in eastern China on fossil-fueled technologies

Independent	dependent		
	$\Delta LETP_{it}$	$\Delta LEMS_{it}$	$\Delta LGDP_{it}$
$\Delta LETP_{i,t-1}$	1.14	-1.93 [c]	-0.08
$\Delta LETP_{i,t-2}$	1.30	-2.26 [c]	0.38
$\Delta LEMS_{i,t-1}$	0.31	0.55	-3.43 [b]

$\Delta LEMS_{i,t-2}$	-4.48 [b]	1.52	-0.32
$\Delta LGDP_{i,t-1}$	-0.50	-1.97 [c]	1.36
$\Delta LGDP_{i,t-2}$	-0.65	0.495	-1.01
$ECT_{i,t-1}$	-17.80 [b]	-1.66 [c]	-16.32 [b]
Sargan test	87.48	96.07	70.00
m_1	-1.83 [b]	-1.89 [c]	-1.44 [c]
m_2	-1.47	-1.53	1.26

[a] All tests are based on one-step robust GMM estimations, except Sargan test which is based on one-step GMM estimates.

[b] Significant at the 1% level.

[c] Significant at the 10% level.

Table C3

DIF-GMM estimation[a] in central China on fossil-fueled technologies

	dependent		
Independent	$\Delta LETP_{it}$	$\Delta LEMS_{it}$	$\Delta LGDP_{it}$
$\Delta LETP_{i,t-1}$	2.54 [c]	-1.55	0.62
$\Delta LETP_{i,t-2}$	0.48	-0.40	-1.08
$\Delta LEMS_{i,t-1}$	-0.32	2.60 [b]	-0.41
$\Delta LEMS_{i,t-2}$	-0.25	1.80 [c]	-1.90 [c]
$\Delta LGDP_{i,t-1}$	0.22	-1.65 [c]	1.59
$\Delta LGDP_{i,t-2}$	-0.04	-0.28	-0.47
$ECT_{i,t-1}$	-6.98 [b]	-2.33 [c]	-4.40 [b]
Sargan test	56.52	45.32	49.33
m_1	-2.27 [c]	-2.06 [c]	-1.82 [c]
m_2	-1.28	1.03	0.45

[a] All tests are based on one-step robust GMM estimations, except Sargan test which is based on one-step GMM estimates.

[b] Significant at the 1% level.

[c] Significant at the 10% level.

Table C4

DIF-GMM estimation[a] in western China on fossil-fueled technologies

	dependent		
Independent	$\Delta LETP_{it}$	$\Delta LEMS_{it}$	$\Delta LGDP_{it}$
$\Delta LETP_{i,t-1}$	4.00 [b]	-0.69	-1.93 [c]
$\Delta LETP_{i,t-2}$	2.34 [c]	-0.89	-1.42
$\Delta LEMS_{i,t-1}$	-1.76	0.69	-0.46
$\Delta LEMS_{i,t-2}$	0.78	0.63	1.89 [c]

$\Delta LGDP_{i,t-1}$	-1.99 [c]	-2.15 [c]	-0.95
$\Delta LGDP_{i,t-2}$	0.37	-2.44 [c]	1.10
$ECT_{i,t-1}$	-9.55 [b]	-2.90 [b]	-1.85 [c]
Sargan test	52.17	84.56	60.90
m_1	-1.70 [c]	-1.77 [c]	-1.81 [c]
m_2	-0.73	-1.63	1.55

[a] All tests are based on one-step robust GMM estimations, except Sargan test which is based on one-step GMM estimates.

[b] Significant at the 1% level.

[c] Significant at the 10% level.

Appendix D Results of DIF-GMM estimation on carbon-free energy technologies

Table D1

DIF-GMM estimation[a] in the national level of China on carbon-free energy technologies

	dependent		
Independent	$\Delta LETP_{it}$	$\Delta LEMS_{it}$	$\Delta LGDP_{it}$
$\Delta LETP_{i,t-1}$	0.66	-0.50	-2.03 [c]
$\Delta LETP_{i,t-2}$	-1.99 [c]	-0.23	-1.06
$\Delta LEMS_{i,t-1}$	-0.88	-0.89	-2.25 [c]
$\Delta LEMS_{i,t-2}$	-2.83 [b]	-1.01	-1.06
$\Delta LGDP_{i,t-1}$	-1.57	-2.17 [c]	1.25
$\Delta LGDP_{i,t-2}$	-2.20 [c]	-0.58	-0.68
$ECT_{i,t-1}$	-8.91 [b]	-2.59 [b]	-4.71 [b]
Sargan test	106.99	113.64	149.03
m_1	-3.98 [b]	-2.47 [c]	-2.41 [c]
m_2	-1.65	-1.66	1.40

[a] All tests are based on one-step robust GMM estimations, except Sargan test which is based on one-step GMM estimates.

[b] Significant at the 1% level.

[c] Significant at the 10% level.

Table D2

DIF-GMM estimation[a] in eastern China on carbon-free energy technologies

Independent	dependent		
	$\Delta LETP_{it}$	$\Delta LEMS_{it}$	$\Delta LGDP_{it}$
$\Delta LETP_{i,t-1}$	0.09	0.89	0.44
$\Delta LETP_{i,t-2}$	-0.39	1.76 [c]	-0.55 [c]
$\Delta LEMS_{i,t-1}$	1.89 [c]	1.47	-2.13 [c]
$\Delta LEMS_{i,t-2}$	0.07	-0.97	-0.81
$\Delta LGDP_{i,t-1}$	-1.31	0.02	-0.73

$\Delta LGDP_{i,t-2}$	-1.82 [c]	2.2 [c]	-0.97
$ECT_{i,t-1}$	-7.40 [b]	-2.32 [c]	-6.12 [b]
Sargan test	71.21	65.36	70.22
m_1	-2.23 [c]	-1.74 [c]	-1.73 [c]
m_2	-1.83	0.54	-0.75

[a] All tests are based on one-step robust GMM estimations, except Sargan test which is based on one-step GMM estimates.

[b] Significant at the 1% level.

[c] Significant at the 10% level.

Table D3

DIF-GMM estimation[a] in central China on carbon-free energy technologies

	dependent		
Independent	$\Delta LETP_{it}$	$\Delta LEMS_{it}$	$\Delta LGDP_{it}$
$\Delta LETP_{i,t-1}$	-1.10	-0.70	-2.61 [b]
$\Delta LETP_{i,t-2}$	-5.56 [b]	1.18	-0.71
$\Delta LEMS_{i,t-1}$	-0.21	3.81 [b]	-0.49
$\Delta LEMS_{i,t-2}$	-1.40 [c]	1.14	-2.44 [c]
$\Delta LGDP_{i,t-1}$	-1.69 [c]	-1.30 [c]	1.96 [c]
$\Delta LGDP_{i,t-2}$	-1.02	0.16	0.18
$ECT_{i,t-1}$	-4.80 [b]	-2.07 [c]	-5.04 [b]
Sargan test	44.83	48.07	23.94
m_1	-2.21 [c]	-2.02 [c]	-2.19 [c]
m_2	-1.26	0.01	1.40

[a] All tests are based on one-step robust GMM estimations, except Sargan test which is based on one-step GMM estimates.

[b] Significant at the 1% level.

[c] Significant at the 10% level.

Table D4

DIF-GMM estimation[a] in western China on carbon-free energy technologies

	dependent		
Independent	$\Delta LETP_{it}$	$\Delta LEMS_{it}$	$\Delta LGDP_{it}$
$\Delta LETP_{i,t-1}$	2.25 [c]	-0.46	-1.78 [c]
$\Delta LETP_{i,t-2}$	1.06	-0.50	-1.15
$\Delta LEMS_{i,t-1}$	-0.73	0.87	-0.82 [c]
$\Delta LEMS_{i,t-2}$	-1.13 [c]	1.21	-0.07
$\Delta LGDP_{i,t-1}$	-0.36	-4.10 [b]	0.53
$\Delta LGDP_{i,t-2}$	-1.43 [c]	-0.82	4.15 [b]
$ECT_{i,t-1}$	-6.52 [b]	-2.41 [c]	-1.42 [c]

Sargan test	51.50	62.96	73.05
m_1	-2.60 [b]	-1.87 [c]	-1.81 [c]
m_2	-0.90	-1.77	0.75

[a] All tests are based on one-step robust GMM estimations, except Sargan test which is based on one-step GMM estimates.

[b] Significant at the 1% level.

[c] Significant at the 10% level.