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How does green technology influence CO_2 emission in China? - An empirical research based on provincial data of China

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Abstract

This paper investigates the role of green innovations aimed at reducing carbon dioxide emissions as a factor that compensates for growth and population effects. It has been shown from tests that the positive effect of green innovations on carbon emissions exists within a STIRPAT framework from a local perspective. The panel data is derived from China Statistical Yearbook and China Intellectual Property Office covered from 1999 to 2013. In addition,the static panel model was run to estimate the diversity among three typical regions of China. The main result shows that the green technology change has not played a dominant role yet in promoting environmental protection, while a scale effect (Affluence and Population)still prevails, although green patents show positive influences on the CO_2 emission reduction inthe whole country as well as the East and West regions, except the Central region. Moreover, it turns out that the classical EKC hypothesis does stand in China, referring to the three regions with the inverted "U" shape. The analysis gives suggestions to the policy makers, which would support enlarging the investment scale on green patents and encourage international corporation with environmental related innovations..

Key words

CO_2 Emissions, Green patent, STIRPAT Model, Regional effect

Introduction

China has set their sights more on the environment and carbon dioxide issues in recent years due to deteriorating air, water, energy and other climatic factors, especially given the occurence of hazy weather in north of China. It is generally considered that development of science and technology is a key to solve these climatic change problems and economic crises (Sarnoff, 2011; Abbott, 2009; Thomas, 2008). According to the context which has been pointed out explicitly in the report of 18th Party Congress of China, the policies focus on promoting natural restoration, and striving for green economic, sustainable and low-carbon development. Economists have increasingly paid attention to the relationship between technology change and environmental performance. This research traditionally draws conclusions in one of two ways. Firstly, some demonstrate that the technological change play a positive role in reduction of CO_2 emissions. Zhu *et al.* (2010) suggested that China should increase its investment in CO_2 capture, sequestration and raise the level of energy-efficient technologies. Li *et al.* (2012), Kuang (2008), Jiang and Wang (2003) and Zhao (2003) gave similar conclusions. Secondly, some researcher suggest that technology plays a less significant role to other factors. Ping *et al.* (2013) drew conclusion that population was the most important impact factor in CO_2 emissions, but other factors such as technology level and the level of foreign trade were less important.

Several factors affect CO_2 emissions according to variety of research variables, such as population, affluence and public policy. Shi (2003), York *et al.* (2003a), Cole and Neumayer (2004) and Martínez-Zarzoso *et al.* (2007) estimated variable impact of population growth on emissions by a variety of data samples, which conclude that the influence was more than proportional for the new EU members. Knight and Eugene (2012) tested the effects of household size and number on wood consumption as fuel using data for 87 developing countries. Wei (2011) build an alternative model which argues specifications in STIRPAT can be one reason for why estimated environmental impact of population and affluence differ among studies. Zhang and Lin (2012) analyzed the impact of urbanization on energy consumption and CO_2 emission by STIRPAT model.

Various methods have been adopted to measure the technology. In previous studies, environmental innovation has been commonly measured through questionnaire surveys (e.g., Anton, Deltas, and Khanna, 2004; Christmann, 2000). Some scholars have examined environment related patents which are an effective tool to use in an aggregate country or on industry level (Brunnermeier and Cohen, 2003; Jaffe and Palmer, 1997). Fischer and Varga (2003) and Popp (2001, 2006) both used patent data as a proxy variable to determine an estimation. Lanjouw and Mody (1996), Kemp and Oltra (2009) discovered that the patent date was suitable for the research of environmental technology.

Despite that, the literature specifically on the effects of green innovation on the environment performance of local sights is still scarce. So this paper will focus on the influence of green technologies influence on the change of CO_2 emissions by using green patents data as proxy variable to technology from the provincial perspective. Regional analyses of environmental topics are useful for allowing focusing the investigation on structural and idiosyncratic features compared to national averages, and providing political and economical implications which can be differentiated across various regions and territories. This is especially relevant to a country like China which is characterized by high levels of disparity, such as the East-Central-West divide.

Preliminary evidence shown in Fig.1, Fig.2 and Fig.3 confirms previous expectations of heterogeneity in the East-Central-West disparities. Fig.1 illustrates the status of total carbon emissions and green patents of China. Total green patents have increased at an average rate of 30.7%, a faster pace than the total carbon emission at 9.7%. High economic growth rate of the East has made it of the largest contributor of absolute carbon emissions. The achievements of green patent also demonstrate that there is a large gap between the East and the other two regions in green patents. The amount of green patents in the East surged to 4559, which was over three times more than the sum of the Central and West regions (911, 487 respectively). Thus, it can reasonably inferred that economic prosperity provide a solid research foundation for the development of technology and green innovation. Consequently, the present study investigates the role of green technological advances aimed at reducing carbon dioxide as a factor within a STIRPAT framework.

Materials and Methods

The IPAT model originally arose about environmental driving factors, considering the P-population size, A-Affluence, T-Technology indicators and forming the formula by integrating mutual effect of these three factors working on environmental pollution factor I (Impact) Ehrich and Holdren (1971). To overcome the defects of IPAT model, various improved models were proposed by some scholars, such as IPBAT (Impacts by Regression on Population, Behavior, Affluence and Technology) models by Schulze (2002). Dietz and Rosa (1994) transformed the IPAT model into a stochastic one; the STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model, which greatly expands the factors which impact the environment including carbon dioxide emissions.

Methodology : This paper used STIRPAT model, which can do non-proportional impact analysis of all factors.

$$I_{it} = aP_{it}^{b} \cdot A_{it}^{c} \cdot T_{it}^{d} \qquad (1)$$

Chang into Logarithmic form,

$$\ln I_{it} = \ln a + b \ln P_{it} + c \ln A_{it} + d \ln T_{it} + \ln e_{it} \qquad (2)$$

Where, *t* indicates the year, b, c, d represent the impact elasticity of number of population, per capita real GDP, and technology indicator effect on carbon dioxide emissions respectively. This paper adopts the green patent data as the technology indicator. Given the close relationship between the carbon dioxide emissions and economic growth, the analysis cannot be ignored in this research about green patents' influence on emissions by using EKC curve to prove the inverted U shape relationship. The variable of $(\ln A_{it})^2$ was introduced, which changes the equation into:

$$\ln I_{it} = \ln a + b \ln P_{it} + c_1 \ln A_{it} + c_2 (\ln A_{it})^2 + d_1 \ln T_{it} + d_2 \ln E_{it} + \ln e_{it} \qquad (3)$$

Judging by the indicators of c_1 and c_2, relationship between several types of typical carbon dioxide emissions and economic growth could be determined. Meanwhile, according to coefficients from the results of regression, the turning points (TP) of U shaped or inverted U-shaped curve could be calculated as.

Data Description and Calculation : A data-set was chosen related to population, GDP and energy consumption of all the provinces of China. In addition, the region of Tibet was not included in our consideration due to lack of data. It also treated the province of Sichuan and Chongqing as one region. All the data were gathered from *China Statistical Yearbook* and *China Energy Statistical Yearbook*. According to the selected data, the related variables are described as following:

Carbon dioxide emissions : I_{it} represents the carbon dioxide emissions (thousand tons) of province in the year of . In order to obtain the amount of carbon emissions, the quantities of energy consumption are converted into standard amounts, multiplied by the respective coefficients of carbon emissions, as in equation (4):

$$C_{it} = \sum_{j=1}^{9} e_{ijt} \eta_j \qquad (4)$$

Where C_{ij} is the carbon dioxide emissions of province *i* in the year *t*; e_{ijt} represents the *j* energy consumption of province *i* in year *t*; η_j

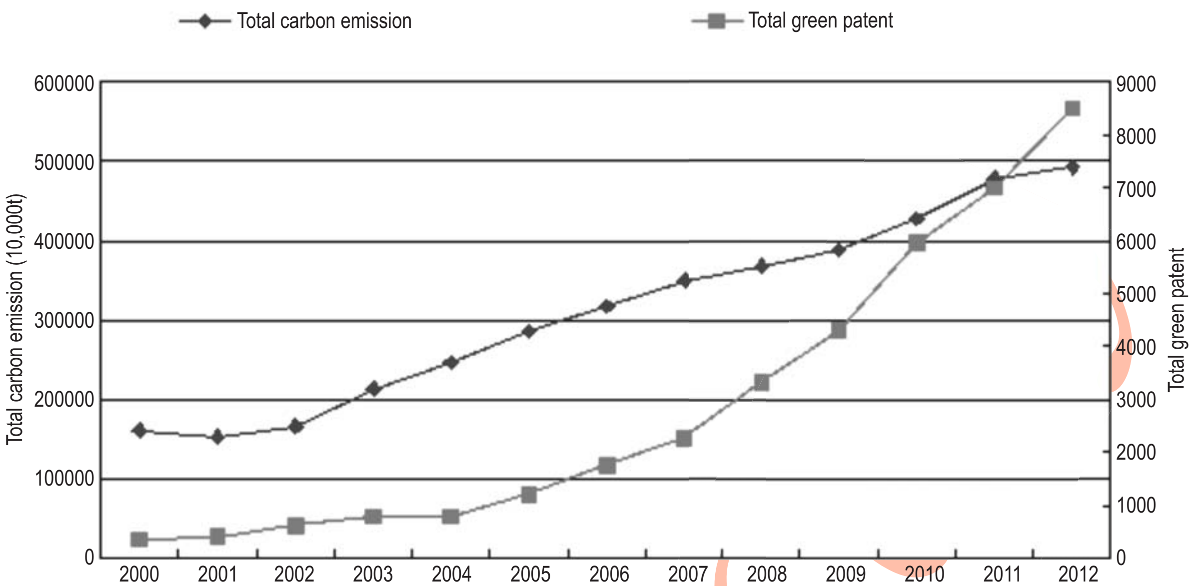

Fig. 1 : Total carbon emission and green patent of China from 2000 to 2012

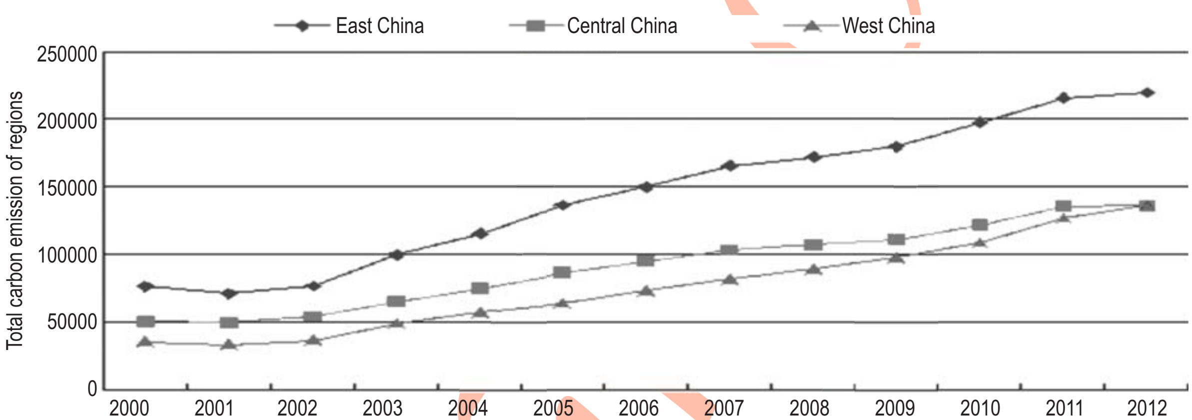

Fig. 2 : Carbon emission in three regions of China from 2000 to 2012

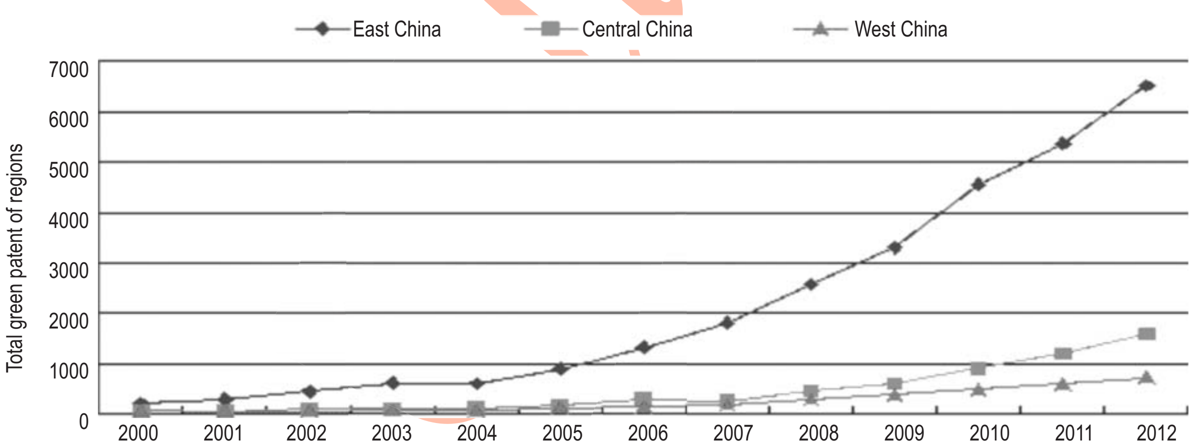

Fig. 3 : The amount of green patent in three regions of China from 2000 to 2012

is the coefficient of carbon emission of *j* energy. Taking a page from *China Energy Statistical Yearbook*, the energy consumptions could be related to nine categories, coal, diesel, petrol, kerosene, natural gas, crude oil, fuel oil, electricity and coke. The relevant coefficients are shown in Table 1 and Table 2.

Population : P_{it} denotes the population size of the province in the end of the year (unit: millions of people).

Per capita GDP : A_{it} denotes the per capita GDP in province i in the year t (yuan per person). In order to eliminate the impact of inflation, nominal per capita GDP will be translated into real per capita GDP at constant prices in 1995.

Technological level : T_{it} donates the technological change factor and the adopted number of green patent granted as proxy variable.

Most literature uses energy intensity, expressed as total energy use divided by GDP, as proxy variable for technology level. (Wang and Zhao, 2015; Fan *et al.,* 2006). This paper, however, seeks to find another reasonable variable to represent environmental related technology level. The use of patent data is well consolidated in literature (Jaffe and Palmer, 1997; Acs *et al.,* 2002; Johnstone *et al.,* 2010). However, despite that patent data present well known criticalities, we must also consider the following quantities. Firstly, the propensity to apply for patent protection may vary across country and across sector due to different cultural and legislative framework.

Secondly, the amount of patent cannot be equated with the quality, and cannot include all the inventions (Griliches, 1992). Despite these shortcoming, patent data have been tested using a quite reliable measurement index (Acs, *et al.*, 1994, 2002). Patent data are not just readily accessible and suitable to be used in a statistical analysis (count of patent data are collected in China Intellectual Property Office database), and according to Dernis and Guellec (2001), and Dernis and Khan (2004) there are very few examples of economically significantwhich have not been patented.

The following method was adopted to account for the green patent amount proposed by Chen (2013). Firstly, following the classification rules of OECD and Jaffe (1989), keywords of different green technologies were set to select and exclude green patents from the data of patent licensing registrations downloaded from SIPO. Secondly, survey of the addresses of the transferee and recipient of patent licensing were done which were the same places of the transferee and recipient of technology. All the annual data were selected in accordance with the recipients' locations.

Empirical Test : Referring to the regional features of China, the static model should be run initially, estimating the whole set of country, and then empirical analysis should be carried out on three typical regions, which are the East, Central and West regions, in order to analyze different influence of green patent on CO_2 emissions primarily.

Elhorst (2003) proposed that when the sample was randomly selected from the studied population, the choice of random effects model was more appropriate. Regression analysis focused on the Chinese provincial districts as particular individuals, thereby, using a fixed effects model was more reasonable theoretically. In Model I, the Green Patent Stock was used to account for technological change by a Fix-Effect (FE) model, while in Model II the robustness of this measure was controlled by employing the stock of total knowledge. Model III restrict the sample to eastern provinces only. Similarly, Model IV and V base the empirical analysis on Central and West sub-samples respectively and all these tests were run by STATA 12.0 version.

Table 1 : Coefficients of the amount of various energies are equivalent to one unit of the coal

Energy sources	Coefficients	Energy sources	Coefficients	Energy sources	Coefficients
Coal (kg)	0.7143	Kerosene (kg)	1.4714	Coke (kg)	0.9714
Diesel (kg)	1.4571	Oil (kg)	1.4286	Electricity (kWh)	0.1229
Gasoline (kg)	1.4714	Fuel oil (kg)	1.4286	Gas (m^3)	1.3300

Resources: China Statistical Yearbook 2013

Table 2 : Carbon emission coefficients of various energy sources

Energy sources	Coefficients	Energy sources	Coefficients	Energy sources	Coefficients
Coal (kg)	0.7476	Kerosene (kg)	0.3416	Coke (kg)	0.1128
Diesel (kg)	0.5913	Oil (kg)	0.5854	Electricity (kWh)	2.2132
Gasoline (kg)	0.5532	Fuel oil (kg)	0.6176	Gas (m3)	0.4479

Resources: IPCC (2007)

Table 3 : Classifications of green technology and the relevant keywords

Classifications	**Subclass**	**Keywords**
Industrial air pollution	B01D53/ C10K C10L F23	treat, scrub, remove
Water pollution	C02F-1 C02F-3 C02F-7 C02F-9 E03F	treat, waste, sew
Vehicle air pollution	F01N-3 F01N-5	Exhaust
Solid waste	B02C-8/40 B09B B65F C10B-53	treat, waste, refuse, garbage, remove
Alternative energy	C10J E04D 13/18 F03D F24J-2	wind, solar, waste, fuel, heat
Oil spills	E02B- 15/04	remove, spill
Radioactive waste	0G2 IF-9	hazard, radioactive
Recycling and reusing waste	A23K- 1/06 A23K- 1/08 B29B-17/00B30B-9/32 C04B-7/24 C04B- 11/26C05F C08J- 11 C10L-5/46 Cl0M-11/00C22B-7 D21 B- 1/32 D21 C- 11 D21 F- l/66	recycle, reuse, recover, waste, reuse

Resources: Based on the combination of the green technology patent search strategies of OECD and Jaffe (1989)

Table 4 : Estimation results of the regression

Model	**I**	**II**	**III**	**IV**	**V**
Dependent Variable	*CO_2*	*CO_2*	*CO_2*	*CO_2*	*CO_2*
Green Patent Stock	-0.12^{***} (-0.03)		-0.11^{*} (-0.06)	0.04 (-0.04)	-0.15^{**} (-0.04)
Population	2.32^{***} (0.35)	1.99^{***} (0.36)	1.73^{**} (-0.6)	-0.65 (-0.63)	4.65^{***} (-0.5)
Per capita GDP	2.78^{***} (0.25)	2.58^{***} (0.25)	4.01^{***} (-0.57)	1.86^{***} (-0.59)	2.45^{***} (-0.36)
Per capita GDP^2	-0.09^{***} (-0.01)	-0.10^{***} (-0.01)	-0.18^{***} (-0.03)	-0.07^{*} (-0.03)	-0.09^{**} (-0.02)
Total Patent Stock		0.10^{***} (-0.03)			
Provincial FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	East	Central	West
N	429	435	165	120	144

* $p<0.1$; ** $p<0.05$; *** $p<0.01$. Standard errors in parentheses. All regressions include year and country effects

Results and Discussion

Following the model formulated by Dietz and Rosa (1994), the effect of technological change on CO_2 emission by STIRPAT model for a sample of 29 provinces of China have been estimated during the period 1999–2013. A stationary sequence test should be done before regression estimation to avoid the danger of spurious regressions. Considering the results displayed in Table A1 to A4 in Appendix, it can be concluded that these sequences are non-stationarity. This outcome fits the research undertaken in the time series literature since GDP series and population have normally a unit root. Nevertheless, all the variables present stationary character in first differential form. Therefore, differences of all the variables and re-estimated Model I were undertaken. All the regression results of STIRPAT models are displayed in Table 4 by estimating five different models.

Nationwide sample : Since the model is specified in natural logarithms, the coefficients of explanatory variables can directly be interpreted as elasticities. Model I shows a statistically significant and negative coefficient of Green K Stock (elasticity equal to -0.12), which confirms the hypothesis that an increase in country's green knowledge base, measured here via patent stock, had a positive effect on reduction of CO_2 emissions. Wei and Fang (2010) tested that the technology factor plays negative effect on emission, which the elasticities of R&D (measured by patent stock) was between -0.1 and -0.2. Shi and Zhou (2010) also drew conclusion that adoption of technology, which raises energy efficiency by enlarging investment on R & D, can contribute 64%-81% toward realizing the 2020 carbon intensity target. This evidence would provide certain suggestions and proof to the green innovations and research policy decisions, which supports enlarging the investment scale on green patents and formulating a policy to encourage the inventors.

Referring to other covariates, the elasticities of population and per capita GDP showed typically high performance as expected, which confirms the results of previous studies (Kaya, 1989). Affluence has become the prominent influence on increasing CO_2 emissions in China. (Feng *et al.,* 2009; Lin et al., 2009; Wang and Zhao, 2015). Population size has emerged as a persistent, major factor influencing the scale of national environmental impacts of all varieties (Rosa *et al.,* 2003).

Moving to EKC context, the positive elasticity of per capita GDP and the negative of its square form indicates that relationship between CO_2 emissions and economic growth is an inverted U-shape, which means that the classical EKC hypothesis does stand in China. The turning point can be calculated by the following equation, $\ln A^* = -c_1/(2C_2)$, the outcome being 15.4, which means that the per capita GDP would reach 5.10 million yuan (822328.4 USD), reversing the situation on a nationwide level. Li and Li (2010) calculated this turning point as 22.5 by using data from 30 provinces of China covering 1995-2007, which means per capita GDP would reach 5.5 billion yuan (8.87 billion dollar).

This result is quite different from the present result of this study. The primary cause for this large difference could be different time range of data. Specifically, the sample covered the latest five years (2009-2013) when China was dedicated to promoting reformation referring to the post economic crisis priorities such as adjusting economic structures and raising the efficiency of development, as opposed to eagerness to increase the rate of development as was the case in the years prior to economic crisis. Fang *et al*. (2008) proposed that the government could formulate more positive policies which could acquire

Table A1 : Pool Unit Root tests results

Method	**$LNCO_2$**	**$LNCO_2$**	**LNT**	**LNT**	**LNP**	**LNP**	**LNA**	**LNA**	**LNEI**	**LNEI**
Null: All panels contain unit roots										
Fisher-ADF	2.57**	26.10***	-4.40	22.93***	-2.96	6.33***	-5.09	4.83***	-4.07	19.97***
Fisher-PP	-4.26	19.92***	-2.90	47.80***	8.51	5.39***	-5.29	8.24***	-1.87	20.85***
Levin, Lin & Chut	-10.89***	-14.87	-1.35	-13.87***	-0.20	-6.35***	3.48	-9.98***	1.51	-13.32***
Im-Pesaran-Shin	-2.31*	-6.65***	5.61	-7.78***	7.79	-1.72**	16.51	-4.81***	6.56	-5.84***
Nobs	319	290	319	290	319	290	319	290	319	290

Note : Automatic selection of lags: 0 to 2 maximum lags. *, **, *** Denotes rejection of the null hypothesis at 10% , 5%, 1% significance level respectively

Table A2 : Pool Unit Root tests results of East Region

Method	**$LNCO_2$**	**$LNCO_2$**	**LNT**	**LNT**	**LNP**	**LNP**	**LNA**	**LNA**	**LNEI**	**LNEI**
Null: All panels contain unit roots										
Fisher-ADF	2.78**	26.10***	-2.62	22.93***	-3.20	2.05*	-3.01	4.83***	-2.48	11.37***
Fisher-PP	-2.68	13.46***	-0.38	15.30***	-2.24	3.33***	-3.21	3.83***	-2.36	9.72***
Levin, Lin & Chut	-7.92***	-9.04***	0.74	-6.27***	1.51	-5.07*	0.773	-6.65***	-1.32	10.35***
Im-Pesaran-Shin	-2.35**	-6.03***	3.54	-3.22***	8.19	-1.53*	4.87	-2.64**	3.17	-3.46***
Nobs	121	110	121	110	121	110	121	110	121	110

Note : Automatic selection of lags: 0 to 2 maximum lags. *, **, *** Denotes rejection of the null hypothesis at 10% , 5%, 1% significance level respectively

Table A3 : Pool Unit Root tests results of Middle Region

Method	**$LNCO_2$**	**$LNCO_2$**	**LNT**	**LNT**	**LNP**	**LNP**	**LNA**	**LNA**	**LNEI**	**LNEI**
Null: All panels contain unit roots										
Fisher-ADF	2.32*	12.49***	-2.15	13.73***	-2.14	4.16***	-2.74	3.42***	-2.32	1.33*
Fisher-PP	4.76	9.17***	-2.60	31.71***	-1.31	2.31***	-2.80	5.46***	-2.14	5.39***
Levin, Lin & Chut	-5.89***	-7.09***	-1.75	-8.02***	0.25	-4.07***	3.3	-7.70***	-1.09	-3.17***
Im-Pesaran-Shin	-0.96	-4.61***	2.28	-4.76***	2.25	-2.26**	5.86	-2.28**	3.01	-1.54*
Nobs	88	80	88	80	88	80	88	80	88	80

Note : Automatic selection of lags: 0 to 2 maximum lags. *, **, *** Denotes rejection of the null hypothesis at 10% , 5%, 1% significance level respectively

Table A4 : Pool Unit Root tests results of West Region

Method	**$LNCO_2$**	**$LNCO_2$**	**LNT**	**LNT**	**LNP**	**LNP**	**LNA**	**LNA**	**LNEI**	**LNEI**
Null: All panels contain unit roots										
Fisher-ADF	0.11	16.09***	-2.81	20.27***	0.24	4.91***	-3.07	1.27*	-2.26	20.89***
Fisher-PP	-2.65	11.6***	2.21	36.99***	18.02***	3.61***	—2.8	5.12***	1.21*	20.48***
Levin, Lin & Chut	-5.21***	-9.72***	2.14	-10.08***	-2.06**	-5.08***	2.48	-5.05***	3.01	-9.16***
Im-Pesaran-Shin	-0.61	-6.22***	3.96	-6.71**	1.11	-2.75**	5.57	-1.69*	4.33	-5.99**
Nobs	110	100	110	100	110	100	110	100	110	100

Note : Automatic selection of lags: 0 to 2 maximum lags. *, **, *** Denotes rejection of the null hypothesis at 10% , 5%, 1% significance level respectively increasing environment quality along with economic growth.

Overall the results suggest that switching to more green technologies does exert a small effect in shrinking the level of total emissions so far, while a positive scale effect (partially confirmed by the significance of per capita GDP) seems to prevail on the technological effect on emissions. Moving to quantification of the results, a one standard deviation increase in Green K Stock leads to 0.12 standard deviation decrease in CO_2, while an increase of the same size in value added increases the dependent variable of about 2.78 st. Dev.

Model II basically confirmed previous results. Furthermore, the magnitude of coefficient was fairly similar except the positvie coefficient of total patent (equal to 0.10). This illustrates that introducing a broader concept of technological change does alter previous evidence. This evidence coincided with the discussion of brown and green patent and their effect on the environment by Aghion *et al.* (2012), considering that total knowledge stock also includes brown patents, which might have a negative effect on emissions if they increased the scale of pollution intense sectors.

Sub-samples of typical three regions : Models III, IV and V split the full data set into three sub samples of East, Central and West regions of China. Observing the results, the main evidence basically remained same except the Central region which showed no statistical significance. This is in keeping with the previous findings referred to as the Central downfall phenomenon in China, which is demonstrated by many Chinese economists from various angles, such as economics growth, population growth, knowledge spillovers effects. Specifically, it means that the growth in the Central region is slower than the East and the West, which has remained from 1997 until now (An and Ying, 2009; Zhu, 2007). The significant differences exist among the three regions due to the disparity of policies in China and varying possibilities for social mobility (Feng *et al.,* 2009).

The magnitude of the effects of green patent stock was stronger in West (-0.15-(-0.11)=0.04) than East. This suggests that the green innovation on the West region had a slightly greater influence on emissions reduction than the East, which was different from what was expected. This is due to the fact that the stock of green patents and the economic development level there is far lower than in the East region. Thus, when compared to the descriptive statistics of Fig. 1 and 2, which highlights the tendancy of the West to have a lower patent propensity, it can be seen that in this area even a small marginal increase in knowledge formation might have a strong effect on environmental performance. Thus, green patents in the West showed more sensitive elasticity on CO_2 emission than the East.

Referring to other factors, per capita GDP had prominent influence on CO_2 emissions in China. Furthermore, this confirms the evidence of most research on China among these three regions (Guo *et al.,* 2013; Fan *et al.,* 2006). While the ln A^2 coefficients -0.15, -0.07 and -0.09 indicates the existence of an inverted U-shape, with turning point of 11.1, 13.3, 13.6 indicating that the per capita GDP would reach 68,795 yuan (11,096 USD), 597,195.6 yuan (96,321.9 USD), 806,129.8 yuan (130,020.9 USD) respectively to reverse the current trend. Based on the same model, Li (2010) calculated the per capita GDP at turning points of 222,000 yuan (35,806 USD), 263,000 yuan (42,419 USD), 1,935,000 yuan (312,097 USD) for three regions respectively, which showed greatly differed from the present result. The possible reason for this difference, besides the one similar with the national sample result analysis, could be that they classified the three regions as GDP level factor, which shows a slight difference from the administrative areas of East, Central and West regions, which this paper adopted.

The second factor population had a positive effect on dependent variable in the East and West. This outcome concludes that the population impact plays bigger role in west than that in the east. Inevitably, the population of China will continue to contribute significantly to increasing the country's environmental impact, as it is large in size and cannot be reduced in short term (Lin *et al.,* 2009).

The main conclusions of this paper show that the switch to green technology has not yet played a dominant role in promoting environmental protection, while a scale effect (affluence and population) still prevails. Green patents show negative influence on CO_2 emissions in the whole country including the East and West regions, except the Central region. The analysis has significant meaning for policy makers, which supports enlarging the investment scale on green patents and encouraging international corporation with environment related innovations.

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