Role of Low-carbon Technology Innovation in Environmental Performance of Manufacturing: Evidence From Oecd Countries

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Role of low-carbon technology innovation in environmental performance of manufacturing: evidence from OECD countries

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Abstract: Climate change disrupts the balance of natural ecosystems and threatens the sustainable development of human society. As the leading industry in many countries, manufacturing promotes economic development; unfortunately, it also emits large quantities of greenhouse gases. Thus, it is necessary to transform the production pattern of manufacturing into green production. Although technology innovation is the only way to tackle the issue, different types of technology innovation may lead to different environmental performances. We argue that low-carbon technology innovation (LCTI) is the key to green production. Using data of Economic Co-operation and Development (OECD) countries from 1990 to 2014, we use the patent-stock method to measure LCTI levels and analyze its development trend in OECD countries. Based on the shepherd distance function, we measure carbon efficiency and carbon productivity by the fixed-effect Stochastic Frontier Analysis (SFA) model. Then we investigate the effect of LCTI on carbon emission efficiency in manufacturing by the fixed-effect regression model. After controlling some variables, evidence shows a significant positive influence of LCTI on the environmental performance of manufacturing. The level of LCTI constantly increased in OECD countries during the study period. Among these countries, the level of low-carbon technology in the chemical industry is the highest; and in most of

the countries, the low-carbon technology of production process grows fastest. Policy implications are further discussed.

Key words: low-carbon technology innovation, carbon efficiency, carbon productivity, manufacturing

1. Introduction

For decades, evidence shows that the global climate is growing warmer and the cause is greenhouse gas (GHG) emissions. Global climate change has led to severe disasters, such as the rising global sea level, mass species extinction, and extreme weather events. Global climate warming disrupts the balance of natural ecosystems and threatens the sustainable development of human society (Tol, 2009). Under this background, countries in the world are trying to tackle climate change together. For instance, 197 countries signed the *Paris Agreement* in 2015, aiming to reduce GHG emissions and mitigate global warming. Getting to the core of the issue, the Intergovernmental Panel on Climate Change (IPCC) pointed out that human activity largely contributes to global climate change (IPCC, 2007) through manufacturing. Manufacturing, the leading industry in most countries, plays a significant role in human social activities. Manufacturing's production activities not only promote the social economy, but also consume considerable energy, emit enormous large amounts of GHG, and are the main factor contributing to climate change (Fysikopoulos et al., 2014). With the deterioration of the global climate environment, a low-carbon economic development pattern is increasingly attracting attention by countries the world over. Energy conservation and carbon reduction of manufacturing has become the key to realizing a low-carbon economy (Chen et al., 2017b). For this reason, it is necessary to change the production pattern of manufacturing from traditional to green production. In addition, national governments should try to control manufacturing GHG emissions while simultaneously promoting economic growth. In this sense, how to realize the dual goals of GHG reduction and a continuous growth of manufacturing output has attracted the attention of scholars and policy makers.

From the climate mitigation perspective, green production means achieving fewer GHG emissions under the same economic input and output levels, or reducing economic input and increasing economic output under the same GHG level, which is exactly the carbon efficiency (or carbon productivity) in the economic and management research fields. Carbon efficiency is an important indicator for measuring low-carbon economy and has been widely used by scholars (Beinhocker et al., 2008; Du & Li, 2019; Lin & Du, 2015; Yan et al., 2020). The improvement of carbon efficiency means that the goal of GHG reduction and the promotion of economic growth of manufacturing can be realized at the same time (Zhang et al., 2018). Beinhocker (2008) pointed out that the improvement of carbon emission efficiency is the key to reducing global carbon emissions, and the goal of reducing carbon emissions by 50% in 2050 can be realized if carbon efficiency is increased by at least tenfold of the 2005 levels. Also, some scholars think that carbon productivity is a core criterion of low-carbon economic development (Jiankun & Mingshan, 2011; Li et al., 2018). For example, Zhang (2018a) believes that carbon productivity is an important approach to measuring low-carbon development levels as it can integrate the dual goals of economic development and carbon reduction. Hence, improving the carbon productivity of manufacturing is the key issue; it is crucial to measure the carbon emission efficiency of manufacturing sectors and find out its influencing factors, which would not only be beneficial for dealing with the global climate change but also for realizing the low-carbon transformation of manufacturing sectors.

Today, society is looking for various ways to improve the carbon efficiency of manufacturing, such as institutional and organizational innovation (Zhang et al., 2018b; Sun et al., 2019), residents' demands, and energy use standards (Paksoy & Ozceylan, 2014). While technology innovation has been widely accepted as an effective way to reduce GHG emissions, it is also the fundamental way to increase carbon efficiency (Du & Li, 2019; Fan et al., 2021; Popp, 2012; Yan et al., 2020). Furthermore, because technology innovation was one of the three topics of the United Nation's climate change conference, COP24, policy makers pay special attention to the role of technology innovation in green transformation. The Porter Hypothesis states that stringent environment regulation can stimulate carbon reduction technology innovations and achieve the win–win situation of economic growth and carbon reduction (Porter, 1991). However, it is worth noting that different types of technology innovation may demonstrate different environmental performance. Theoretically, environment-friendly technology innovation (or low-carbon technology innovation) would promote carbon efficiency, while environment-unfriendly technology innovation (or high-carbon technology innovation) would inhibit carbon efficiency. Zhang (2017a) believes that LCTI is the key to reducing GHG emissions. Compared with traditional environmental regulation, LCTI plays a significant role in the improvement of carbon productivity by improving energy utilization efficiency and end-of-pipe treatment technologies, promoting industry upgrade, and improving human capital (Du & Li, 2019). In addition, LCTI might reduce the cost of mitigating GHG emissions, which is a key potential benefit (Popp, 2012). Green production in manufacturing means the improvement of carbon efficiency, which is highly related to the improvement of LCTI levels. To the best of our knowledge, few previous studies investigated the impact of LCTI on carbon emission efficiency. While there are distinctions in specific technology and industry, current literatures discuss the role of general technology innovation in economies or regions, and the role of LCTI in the green production of manufacturing sectors was seldom discussed in depth. In reality, different technology innovation may lead to different environmental performance, and the opposite effect would be generated if the development of green production were driven by high-carbon technology innovation. Therefore, to specialize the role of LCTI in green production manufacturing under the sustainable development goal has theoretical significance.

This study aims to evaluate the level of LCTI in manufacturing, discuss its theoretical links with green production, and make policy suggestions accordingly. The contributions of this study can be summarized in two points: First, the current study discusses the role of LCTI in the green production of the manufacturing sector, which focuses on specific industries and technology; existing studies focus on the relationship between overall technology innovation and environmental performance. This study excludes the interference of technology and industry heterogeneity in order to provide more stable empirical support for the results. Second, this study measures the specific LCTI of manufacturing sectors, which supplements the referring literature about LCTI indicators. Specifically, we use the "patent-industry" matching method, a global cutting-edge patent classification, to measure the patent stocks of LCTI of manufacturing in Economic Co-operation and Developing (OECD) countries from 1990 to 2014.

The study is structured as follows: Section one introduces the study's background. In section two, we briefly review the relevant literature on the measurements of technology innovation and carbon emission efficiency and the influential factors of carbon emission efficiency. Section three presents the methods of measuring LCTI and carbon efficiency: analysis models and data source. Section four provides descriptive analysis on the development trend of LCTI and discusses the results of regression. Section five concludes and provides policy implications to the analyses and future direction of the work.

2. Literature review

Up to now, a body of literature has investigated the impact of technology innovation on carbon emission efficiency. The current study reviews the relevant literature from three aspects: the measurement of LCTI, the measurement of carbon emission efficiency, and the influencing factors of carbon emission efficiency.

First, existing studies have investigated the measurement methods of technology innovation. While in reality it is difficult to measure technology innovation levels directly, from an input–output production perspective, three indicators, which are research and development investment (R&D) data (Zhang et al., 2017b), patent data (Johnstone et al., 2010; Yan et al., 2017), and total-factor productivity data (Keller, 2010), are commonly used to estimate technology innovation levels indirectly (Wang, 2017). However, no perfect methods exist, and each measurement indicator has both advantages and disadvantages (Popp, 2012). As not all inventions can be patented in reality, the quality of these patented inventions remains uneven, which illustrates that patent data are not the perfect measurement of technology innovation (Griliches, 1998). Nevertheless, among these indicators, patent is the only indicator that provides adequate micro-information available for researchers to subdivide the research field in detail (Wang, 2017). For this reason, patent can be an appropriate measurement of LCTI, and it can promote the empirical research of LCTI (Dechezlepretre et al., 2011). In addition, due to the accessibility of patent data and further exploration by researchers, the impact evaluation of technology innovation has gone deeper into different areas, which provides an appropriate indicator for many econometric analyses and especially for a cross-regional comparative analysis—thus, patent data can be compared to the international standard indicator (Haščič et al., 2015).

Second, considering that carbon dioxide emission is the most important component in GHG emissions, and that it is also the main target of emission reduction, the majority of the existing studies considered carbon efficiency or carbon productivity as the key indicators of green production (Du & Li, 2019; Yan et al., 2020; Zhang et al., 2018a). At present, there are two main carbon emission efficiency indicators: single-factor and total-factor. Kaya and Yokobori (1997) initially defined single-factor carbon efficiency as the ratio of GDP to carbon dioxide emissions. However, the single-factor did not take other factors into account; besides, it cannot reflect the underlying technology efficiency, energy substitution effects, and other production factors. Under these circumstances, total-factor carbon efficiency has gradually been applied and can effectively overcome the shortcomings of single-factor indicator (Du et al., 2018). Currently, there are mainly two measurement methods of total carbon efficiency: Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). DEA is a non-parameter method that has no restriction in function form and is easily affected by sample data quality (Du et al., 2018). Considering that macroeconomic data tend to have big noise, the SFA method was suggested by some scholars because it divides the decision-making unit (DMU) deviating from the technical frontier into the efficient part and the random error part. Meanwhile, SFA eliminates data noise while calculating the efficiency value (Du et al., 2018). Wang and Ho (2010) thought that the traditional SFA regarded individual heterogeneity as an inefficient factor, reducing the accuracy of the result, while the improved fixed-effect SFA method not only eliminates data noise but also separates individual heterogeneity from the inefficient part.

At present, there are mainly two types of methods utilized to study the influencing factors of carbon emission efficiency. The first type is the decomposition method, namely the production theory method, logarithmic mean divisia index (LMDI) method, or Malmquist index method (Chen et al., 2017a; Jiankun & Mingshan, 2011; Hu & Liu, 2016; Li & Cheng, 2020; Sueyoshi et al., 2019; Yu et al., 2017; Zhou & Ang, 2008). Jiankun and Mingshan (2011) decomposed carbon productivity into three parts, industrial structure, energy structure, and energy technical efficiency, and then analyzed the influencing factor of carbon productivity. Chen (2018) investigated the impact factor of carbon productivity in China's power sector with the help of the LMDI method. Based on the production theory, Zhou and Ang (2008) develop a production theory method and decomposed total carbon dioxide into GDP, potential energy intensity, and technical factor. Using the Malmquist index, Yu (2017) studied the carbon productivity of the transportation industry. The second method is the econometric analysis method (Cole et al., 2013; Li & Wang, 2019; Yan et al., 2020; Yin et al., 2015; Zhang et al., 2018a; Du et al.,2019). Du et al. (2019) use panel data that included 71 economies to test if the effect of green technology innovation on carbon productivity is significant for economies with high income and not significant for less developed economies. Yan et al. (2020) use partially linear functional-coefficient models to investigate the effect of renewable technology innovation on green productivity and find that the significance of the effect depends on the relative income level China's provinces. Although the methods are different, most of the studies suggest that technology innovation is the main factor contributing to the increase of carbon efficiency (Du & Li, 2019; Yan et al., 2020; Yin et al., 2015; Yu et al., 2017; Zhou et al., 2019)

Considering that carbon emission efficiency is mainly used to measure green production in previous studies, we focus our research on the influencing factors of carbon emission efficiency on the impact of green production. Furthermore, the majority of existing studies focus on the influencing factors of carbon efficiency or carbon productivity from an economical or regional view; few studies mention a specific industry, especially manufacturing. Technology innovation can be divided into low-carbon technology and high-carbon technology, and different types of technology innovation may lead to different environmental performance. Opposite results would be obtained if the green production were promoted by high-carbon technology. This study aims to investigate the role of low-carbon technology innovation in the green production of manufacturing and to find the paths to improving carbon emissions efficiency in manufacturing.

3. Method and data

3.1. Shepard carbon distance function

Based on the study of Zhou et al. (2010), the Shephard carbon distance function is applied in this study to measure carbon efficiency, which can be defined as follows:

$$D_c(K, L, Y, C) = sup\{\theta : (K, L, Y, C/\theta) \in P\} \quad , \tag{1}$$

where K, L, Y, and C denote the capital input, labor input, manufacturing output, and manufacturing GHG emissions, respectively; P is defined as the possible production set:

$$P = \{(K, L) \ \ can \ \ produce(Y, C)\} \quad . \tag{2}$$

The Shephard carbon distance function describes the deviation of actual GHG emissions from theoretical GHG emissions when capital and labor are kept at the same technology level. Hypothetical GHG emissions can be calculated as $C/D_C(K, L, Y, C)$, denoted as C^*. The total-factor carbon efficiency formula can be used to estimate static carbon efficiency and is defined as follows:

$$TFCE = C^{*}/C = 1/D(K, L, Y, C) \quad . \tag{3}$$

Based on Shepard distance function, Zhou (2010) constructs the dynamic carbon emission model by a Malmquist index, which is also called carbon productivity. Moreover, the accumulated carbon productivity model in this study can be summarized as follows:

$$MCPI_i(t, t+1) = \left[\frac{D_t(K_{it}, L_{it}, Y_{it}, C_{it}) \times D_{t+1}(K_{it}, L_{it}, Y_{it}, C_{it})}{D_t\left(K_{i,t+1}, L_{i,t+1}, Y_{i,t+1}, C_{i,t+1}\right) \times D_{t+1}\left(K_{i,t+1}, L_{i,t+1}, Y_{i,t+1}, C_{i,t+1}\right)}\right]^{1/2} \tag{4}$$

and

$$MCPI_i(t, t+1) = \prod_{t=2}^{\tau} MCPI_i\left(t-1,\ t\right), \tau \geq 2, MCPI_i(0,1) = 1 \quad , \tag{5}$$

where i denotes the i-th DMU and t represents the period t. The dynamic change of carbon productivity from period t to $t+1$ can be estimated with equation (4), and the accumulated change of carbon productivity from 1 to t can be estimated with equation (5). Zhou (2010) proposes that $MCPI$ can be further decomposed into efficient effect ($EFFCH$) and technological effect ($TECHCH$) as

$$MCPI_i(t, \tau) = \frac{D_t(K_{it}, L_{it}, Y_{it}, C_{it})}{D_\tau(K_{i\tau}, L_{i\tau}, Y_{i\tau}, C_{i\tau})} \times \left[\frac{D_\tau(K_{i\tau}, L_{i\tau}, Y_{i\tau}, C_{i\tau}) \times D_\tau(K_{it}, L_{it}, Y_{it}, C_{it})}{D_t(K_{i\tau}, L_{i\tau}, Y_{i\tau}, C_{i\tau}) \times D_t\left(K_{i,t}, L_{i,t}, Y_{i,t}, C_{i,t}\right)}\right]^{1/2}$$

$$=: EFFCH_i(t, \tau) \times TECHCH_i(t, \tau) \quad . \tag{6}$$

Carbon efficiency cannot be calculated directly by equation (3). Following the study of Lin and Du (2015), the general Shephard carbon distance function in this study is hypothetically represented in equation (7); and translog function was used to construct the specific Shephard carbon distance function form. The improved model can be expressed as follows:

$$lnD_t(K_{it}, L_{it}, Y_{it}, C_{it}) = \alpha_i + f(lnK_{it}, lnL_{it}, lnY_{it}, lnC_{it}, t) + v_{it} \tag{7}$$

$$lnD_t(K_{it}, L_{it}, Y_{it}, C_{it}) = \alpha_k k_{it} + \alpha_l l_{it} + \alpha_y y_{it} + \alpha_c c_{it} + \alpha\tau + \alpha_{kl} k_{it} l_{it} + \alpha_{ky} k_{it} y_{it} + \alpha_{kc} k_{it} c_{it} + \alpha_{lc} l_{it} c_{it} + \alpha_{ly} l_{it} y_{it} + \alpha_{yc} y_{it} c_{it} + \alpha_{kk} k_{it}^2 + \alpha_{ll} l_{it}^2 + \alpha_{yy} y_{it}^2 + \alpha_{cc} c_{it}^2 + \alpha_{tk}\tau k_{it} + \alpha_{tl}\tau l_{it} + \alpha_{ty}\tau y_{it} + \alpha_{tc}\tau c_{it} + \alpha_{tt}\tau^2 + (\alpha_i + v_{it}) \ , \tag{8}$$

where $k_{it} = lnK_{it} - ln\bar{K}$; $l_{it} = lnl_{it} - ln\bar{L}$; $y_{it} = lnY_{it} - ln\bar{Y}$; $c_{it} = lnC_{it} - ln\bar{C}$; $\bar{K}$, $\bar{L}$, $\bar{Y}$, and $\bar{C}$ represent the sample mean of K, L, Y, and C, respectively; α_i refers to the individual specific effect, which stands for the unobserved technological heterogeneity; and v_{it} indicates the random error.

According to equation (8), we can obtain

$$\frac{D_{t+1}\left(K_{i,t+1}, L_{i,t+1}, Y_{i,t+1}, C_{i,t+1}\right)}{D_t\left(K_{i,t+1}, L_{i,t+1}, Y_{i,t+1}, C_{i,t+1}\right)} = \exp[lnD_{t+1}\left(K_{i,t+1}, L_{i,t+1}, Y_{i,t+1}, C_{i,t+1}\right) - lnD_t(K_{i,t+1}, L_{i,t+1}, Y_{i,t+1}, C_{i,t+1})] = \exp[\alpha_t + \alpha_{tk} k_{i,t+1} + \alpha_{tl} l_{i,t+1} + \alpha_{ty} y_{i,t+1} + 2\alpha_{tt}(t+1)] \tag{9}$$

$$\frac{D_{t+1}\left(K_{i,t}, L_{i,t}, Y_{i,t}, C_{i,t}\right)}{D_t\left(K_{i,t}, L_{i,t}, Y_{i,t}, C_{i,t}\right)} = \exp[lnD_{t+1}(K_{it}, L_{it}, Y_{it}, C_{it}) - lnD_t(K_{it}, L_{it}, Y_{it}, C_{it})] = \exp\left(\alpha_t + \alpha_{tk} k_{it} + \alpha_{tl} l_{it} + \alpha_{ty} y_{it} + 2\alpha_{tt} t\right) \ . \tag{10}$$

Based on equation (9) and equation (10), $TECHCH$ can be calculated as follows:

$$TECHCH_i(t, t+1) = \{\exp\left[\alpha_t + \alpha_{tk} k_i^{t+1} + \alpha_{tl} l_i^{t+1} + \alpha_{ty} y_i^{t+1} + 2\alpha_{tt}(\mathrm{t} + 1\right) \times \exp\left(\alpha_t + \alpha_{tk} k_i^t + \alpha_{tl} l_i^t + \right.$$

$\alpha_{ty}y_i^t + 2\alpha_{tt}\mathrm{t})]\}^{1/2}$. (11)

According to equation (7), the Shephard carbon distance function is linearly homogeneous to carbon output, therefore equation (8) can be transformed as

$$-c_{it} = \alpha_k k_{it} + \alpha_l l_{it} + \alpha_y y_{it} + \alpha_c c_{it} + \alpha\tau + \alpha_{kl} k_{it} l_{it} + \alpha_{ky} k_{it} y_{it} + \alpha_{ly} l_{it} y_{it} + 0.5\alpha_{kk} k_{it}^2 + 0.5\alpha_{ll} l_{it}^2 + 0.5\alpha_{yy} y_{it}^2 + \alpha_{tk}\tau k_{it} + \alpha_{tl}\tau l_{it} + \alpha_{ty}\tau y_{it} + 0.5\alpha_{tt}\tau^2 + (\theta_i - u_{it} + v_{it}) , \quad (12)$$

where $\theta_i = \alpha_i - ln\bar{C}$, $u_{it} = lnD_t(K_{it}, L_{it}, Y_{it}, C_{it}) > 0$, $v_{it} \sim i.i.N(0, \sigma_v^2)$, and $u^* \sim N^+(\mu, \sigma_u^2)$; u_{it} is dependent of v_{it} . If $\mu = 0$, u^* follows half-normal distribution, and if $\mu \neq 0$, u^* follows non-negative truncated normal distribution and v_{it} follows the normal distribution. According to the study of Wang and Ho (2010), the equation (12) can be viewed as a fixed-effect SFA model. Also, according to the characteristics of the sample data in this study, the fixed-effect SFA model was the preferred model to measure total-factor carbon efficiency. Carbon efficiency and $EFFCH$ can be obtained by equations (13) and (14), respectively.

$$TFCE_{it} = E[\exp(-u_{it})\,|\varepsilon_{it}], \hat{u}_{it} = E[u_{it}|\tilde{\varepsilon}_i] , \quad (13)$$

$$EFFCH_i(t, t+1) = \frac{TFCE_{i,t+1}}{TFCE_{it}} = \frac{E[\exp(-u_{t,t+1})|\varepsilon_{i,t+1}]}{E[\exp(-u_{it}|\varepsilon_{it})]} . \quad (14)$$

According to equation (6), $MCPI$ can be calculated by $TECHCH$ and $EFFCH$.

3.2. LCTI estimating method

Because the development of LCTI is a cumulative process, patent stock can be a more proper index compared to patent quantity. Thus, the LCTI index in this study is constructed based on patent stock (Yan et al., 2017). The perpetual inventory method was employed to calculate low-carbon technology knowledge stock (Bottazzi & Peri, 2007; Verdolini & Galeotti, 2011). The estimation methods can be summarized as

$$LCT_{i,t} = PAT_{i,t} + (1-\delta)LCT_{i,t-1}, \tag{15}$$

where $LCT_{i,t}$ represents the low-carbon technology knowledge stock of economy i in t year, $PAT_{i,t}$ denotes the number of patent applications related to economy i in t year, and δ is the knowledge depreciation rate.

We set the initial value of knowledge stock by the following equation:

$$PF1_{i,t_0} = \frac{PAT_{i,t_0}}{(\bar{g}_s+\gamma)}\ , \tag{16}$$

where $\bar{g}_s$ represents the average growth rate of patent application number in the first five years, and γ is set as 0.1 according to the existing studies (Bottazzi & Peri, 2007; Keller, 2002; Verdolini & Galeotti, 2011). Based on the basic data of low-carbon patent technology combining with equation (15) and equation (16), this study calculated the patent stock of low-carbon technology in manufacturing then obtained the LCTI level in manufacturing industry.

How to measure the LCTI of manufacturing accurately is one of the key processes in this study. For this reason, both the patent classification industry matching method and the newly published "climate change mitigation for production processes" patent code (Y02P) in the Cooperative Patent Classification System (CPC) were employed as the identification standard of manufacturing low-carbon technology patents. The Y02P patent is mainly applied in the production process of manufacturing, and the intensity of technology innovation activities could be reflected through the patent number, which can fulfil the goal of GHG reduction during the production process. Referring to the secondary classification standard of Y02P, the climate change mitigation technology patent related to manufacturing was selected in this study to measure the LCTI of manufacturing.

3.3. Influencing factors analysis methods

Based on the existing econometric study method, three panel fixed-effect econometric models considering time effect are employed in this study to analyze the impact of LCTI on carbon efficiency and carbon productivity, which can be constructed as follows:

$$TFCE_{it} = u_i + a_1 L.lnLCT_{it} + a_2 X_{it} + \delta_1 DT_t + \varepsilon_{it} \ , \tag{17}$$

$$TFCE_{it} = u_i + \beta_1 lnLCT_{it} + \beta_2 X_{it} + \delta_2 DT_t + \varepsilon_{it}, \tag{18}$$

$$MCPI_{it} = u_i + \gamma_1 L.lnLCT_{it} + \gamma_2 X_{it} + \varepsilon_{it} \ , \tag{19}$$

where $TFCE_{it}$ represents the carbon efficiency in economy i during period t; $MCPI_{it}$ stands for the carbon productivity in economy i from period t to $t+1$; $lnLCT_{it}$ indicates LCTI of manufacturing in economy i during period t; $L.lnLCT_{it}$ represents one-lag period of LCTI; DT_t refers to time fixed effect, which defines each period as a dummy variable and $t-1$ dummy variables are involved in the model; u_i stands for unobservable heterogeneity of manufacturing in economy i; ε_{it} indicates the disturbance that changes with time and individuals; and X represents control variables. The control variables are specified in the following aspects:

(1) Environmental regulation intensity

We select EPS, $EUETS$, $ETTG$, and $ENERT$, where EPS represents environment policy intensity, $EUETS$ stands for countries joining in the European

Emission-Trading Scheme, and the value of the participating countries is defined as 1; others are defined as 0. $ETTG$ indicates the ratio of environmental tax to GDP. $ENERT$ is the ratio of energy tax to GDP. All of these variables represent environmental regulation intensity, considering that regulation can affect carbon emission efficiency (Porter & Linde, 1995).

(2) Energy intensity and structure

Variables MEI and MIS represent energy intensity and structure. MEI is the ratio of energy use to output of manufacturing, representing energy use intensity. MIS is the ratio of low-energy density industry output to high-energy density output in manufacturing, representing manufacturing industry structure.

(3) Investment

Variables INV and $GDPK$ represent investment. INV is the ratio of gross capital information to GDP, representing investment level. $GDPK$ is the GDP per capital, representing capital intensity.

(4) Human capital

Variable HC represents human capital. Human capital facilitates learning and knowledge sharing among employees. As knowledge is part of innovation, human capital is beneficial for innovation (Ma et al., 2019).

(5) Trade level

Variable $TRADE$ stands for the ratio of total imports-exports to GDP, which indicated the foreign trade level. Zhang (2018) pointed out foreign trade can influence the carbon productivity.

(6) Economic development level (denoted as $lnGDP$ and $GDPK$)

Variable $lnGDP$ is the logarithm of gross domestic product; and $GDPK$ is gross domestic product per capital, representing economic development level.

(7) Government participation (denoted as GOV)

Variable GOV refers to the ratio of government consumption to GDP, representing government participation (Yan et al., 2018).

3.4. Data sources

The data used in this study are collected from World Input and Output Database (WIOD), including input and output of manufacturing in 28 OECD countries during the years 1995 through 2014. The statistical description of variables is shown in Table 1.

Table 1. Statistical description of the variables

Variable	Obs	Mean	Std. Dev.	Min	Max
$MCPI$	532	1.016	0.054	0.703	1.415
$TFCE$	560	0.878	0.063	0.553	0.979
LCT	560	4.642	2.267	-1.109	9.352
$EUETS$	560	0.375	0.485	0	1
$ETTG$	560	2.438	0.878	-1.501	5.372
$ENERT$	560	73.861	22.61	-53.852	346.472
$GDPK$	560	32293.13	13546.29	7894.748	92339.55
$lnGDP$	560	26.545	1.714	22.199	30.489
EPS	457	1.931	0.904	0.46	4.13
INV	558	3.504	10.495	-41.747	49.779
GOV	560	0.192	0.054	0.091	0.419
MEI	560	6.776	10.784	0.012	172.912
MIS	560	0.565	0.304	0	1
HC	560	3.127	0.403	1.854	3.734
$TRADE$	560	0.898	0.518	0.169	2.863

The data of the LCTI patent published by OECD statistics from 1990 to 2014 are obtainable; however, the 2014 specific data of the low-carbon technology patent of the production process are missing. So, for convenience, LCTI data of specific manufacturing from 1990 to 2013 were used for analysis in this study. The data of K, L, and Y in manufacturing used to calculate carbon efficiency were collected from World Input-Output Tables and underlying data. The data of GHG emissions in manufacturing originated from the OECD statistics database. The original patent data are from the OECD database. For control variables, the data of $EUETS$ are from European Emission-Trading Scheme. The data of HC, $TRADE$, and GOV were collected from PTW90. The data of INV and $lnGDP$ are originally from the WDI database. The data of EPS, $ETTG$, $GDPK$, and $ENERT$ were collected from OECD. The data of MEI and MIS were calculated based on the collected data.

4. Results and discussion

4.1. Environmental performance of LCTI in OECD manufacturing

Based on the patent stock method, both the aggregated LCTI and the LCTI of specific manufacturing in OECD countries were calculated in this study. Following the standard of YO2P first-level technology classification, low-carbon technology is mainly divided into eight types: metal processing, the chemical industry, the petrochemical industry, mineral processing, agricultural produce, the production process, integrated application, and potential emissions reduction.

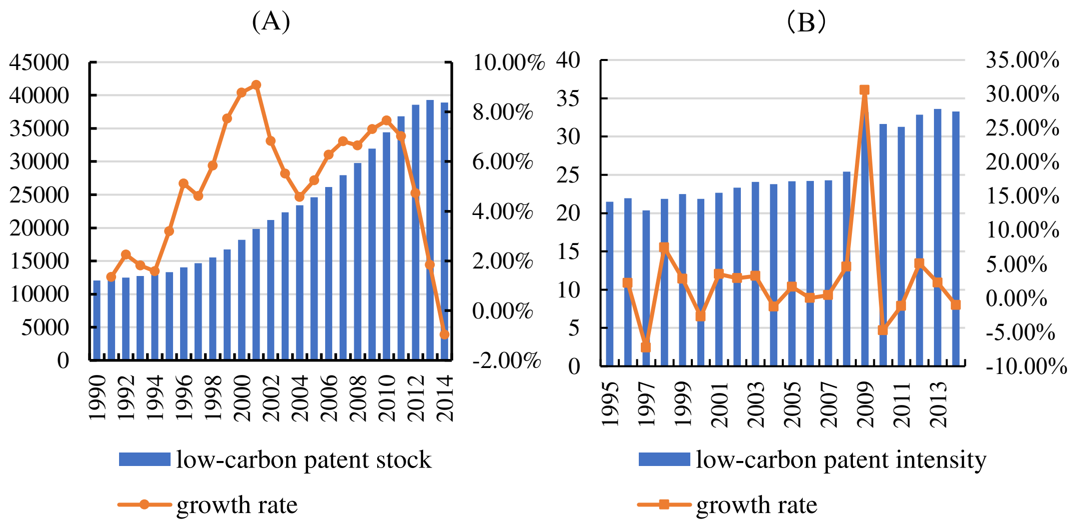


Figure 1. Patent stock and patent intensity of low-carbon technology in OECD manufacturing

Figure 1 (A) shows the development level of LCTI in OECD manufacturing and its growth rate. Patent stock represents the level of LCTI. It can be seen that the level of LCTI in OECD manufacturing is almost on the rise from 1990 to 2014, increasing by 323% in 2014. The growth rate of patent stock is increasing rapidly during the years 1992 through 2000, possibly as a result of signing the *United Nations Framework Convention on Climate Change* in 1992, which aims to reduce GHG emissions. The growth rate declines rapidly from 2001, mainly affected by Internet Economic Dot. The growth rate is negative in 2014, mainly due to the missing data of low-carbon technology patent of production process.

Figure 1 (B) illustrates the variation of low-carbon patent intensity in OECD manufacturing and its growth rate, wherein patent intensity refers to LCTI quality. The LCTI quality in OECD manufacturing increased by 55% in 2014 compared with the quality exhibited in 1995. The growth rate of patent intensity fluctuates around zero during the study period, reflecting an uncoordinated development of innovation and production in manufacturing. In 2009, the growth rate of patent intensity is abnormally high, mainly affected by the financial crisis of 2008, which has hysteresis effects on manufacturing production.

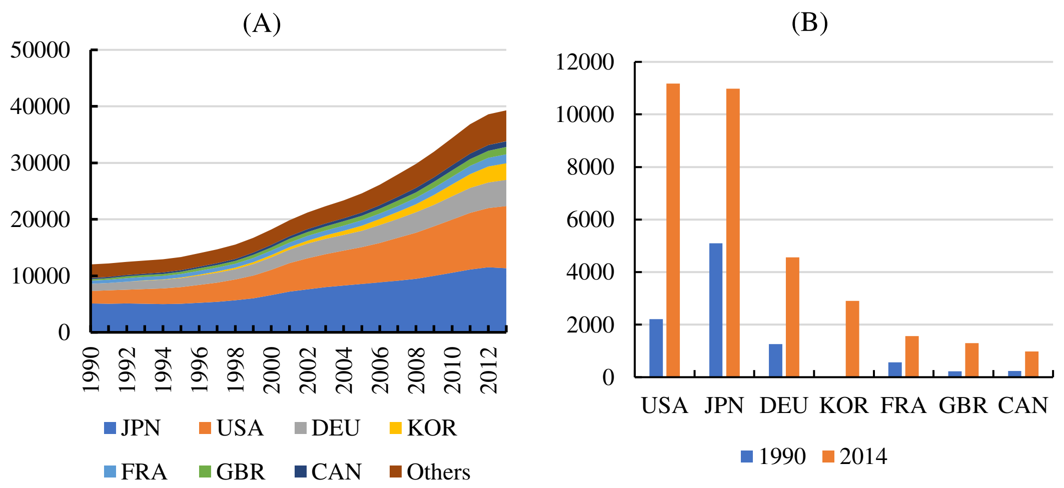


Figure 2. Low-carbon patent stock of manufacturing in seven OECD countries

Figure 2 (A) illustrates the development of low-carbon innovation in manufacturing in seven countries: Japan (JPN), America (USA), Germany (DEU), Korea (KOR), France (FRA), the United Kingdom (GBR), and Canada (CAN). These countries have the highest level of LCTI from 1990 to 2014, which accounts for approximately 70% of the total of OECD countries, and the proportion increased during the years 1990 through 2014, from 80% to 86%. It is noteworthy that JPN had the largest increase in low-carbon technology patent stock from 1995 to 2014, followed by the USA and DEU. These three countries are in the top tier of global manufacturing power, having relatively advanced technology innovation compared with the other countries. KOR has the fastest development speed of LCTI from 1990 to 2014, as it focused on the development of knowledge-intensive industry.

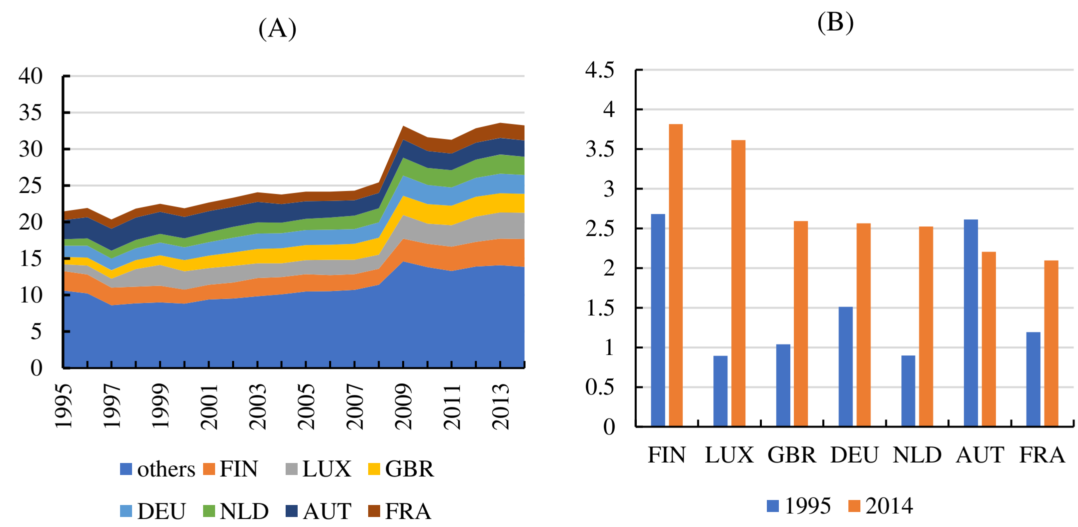
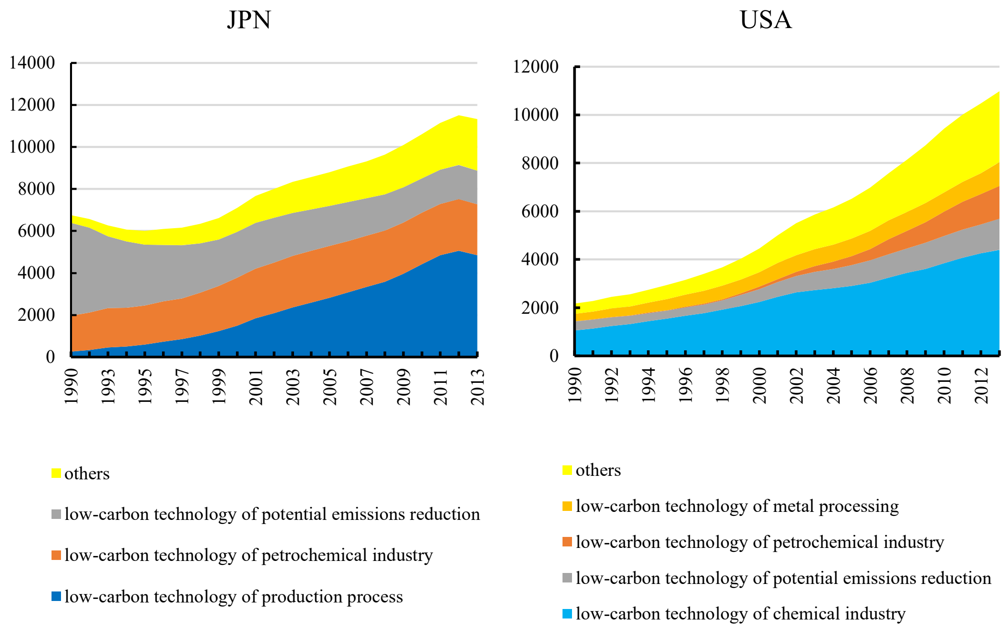
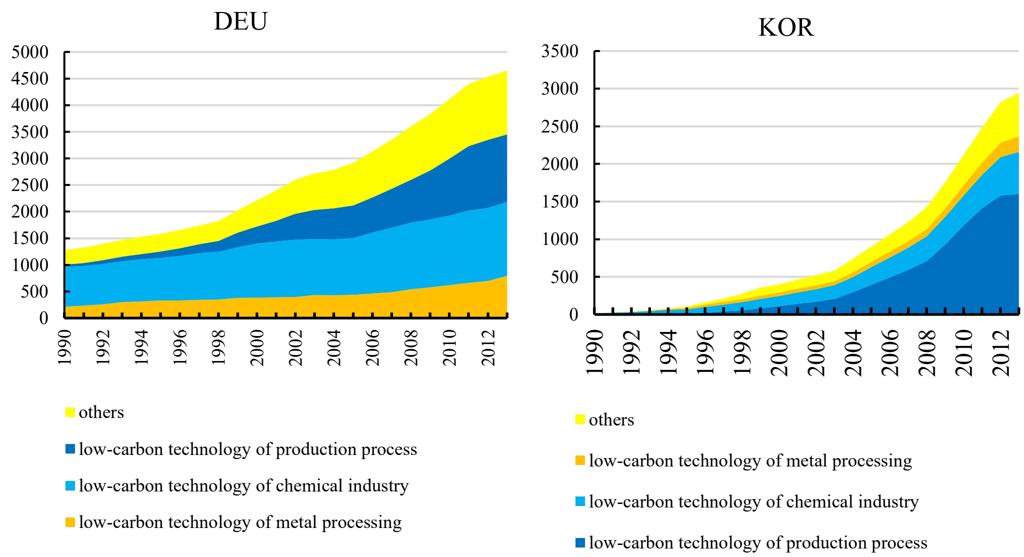


Figure 3. Low-carbon patent intensity of manufacturing in OECD countries

Figure 3 shows the development variation of low-carbon patent intensity of manufacturing in seven countries, Finland (FIN), Luxembourg (LUX), the United Kingdom (GBR), Germany (DEU), the Netherlands (NLD), Austria (AUT), and France (FRA). These countries had the highest level of low-carbon patent intensity in OECD countries from 1995 to 2014. The ranking of countries that have the highest LCTI quality differs from the countries that have the highest LCTI level, shown in Figure 2. It can be seen that DEU, GBR, and FRA demonstrate both high patent intensity and high patent stock, which implies that the level and the quality of LCTI in these countries are relatively high. It is noteworthy that although USA and JPN have high patent stock, these countries have relatively low patent intensity, suggesting that the LCTI level in these countries is unmatched with the scale of manufacturing industry. The aggregated patent intensity of LCTI of these seven countries accounts for more than 50% of the total OECD countries during the years 1995 to 2014. Among them, LUX shows the largest increase in low-carbon technology patent intensity, followed by Poland and

GBR. The patent intensity in LUX increased by 404% from 1995 to 2014, mainly caused by the rapid development of its steel industry.





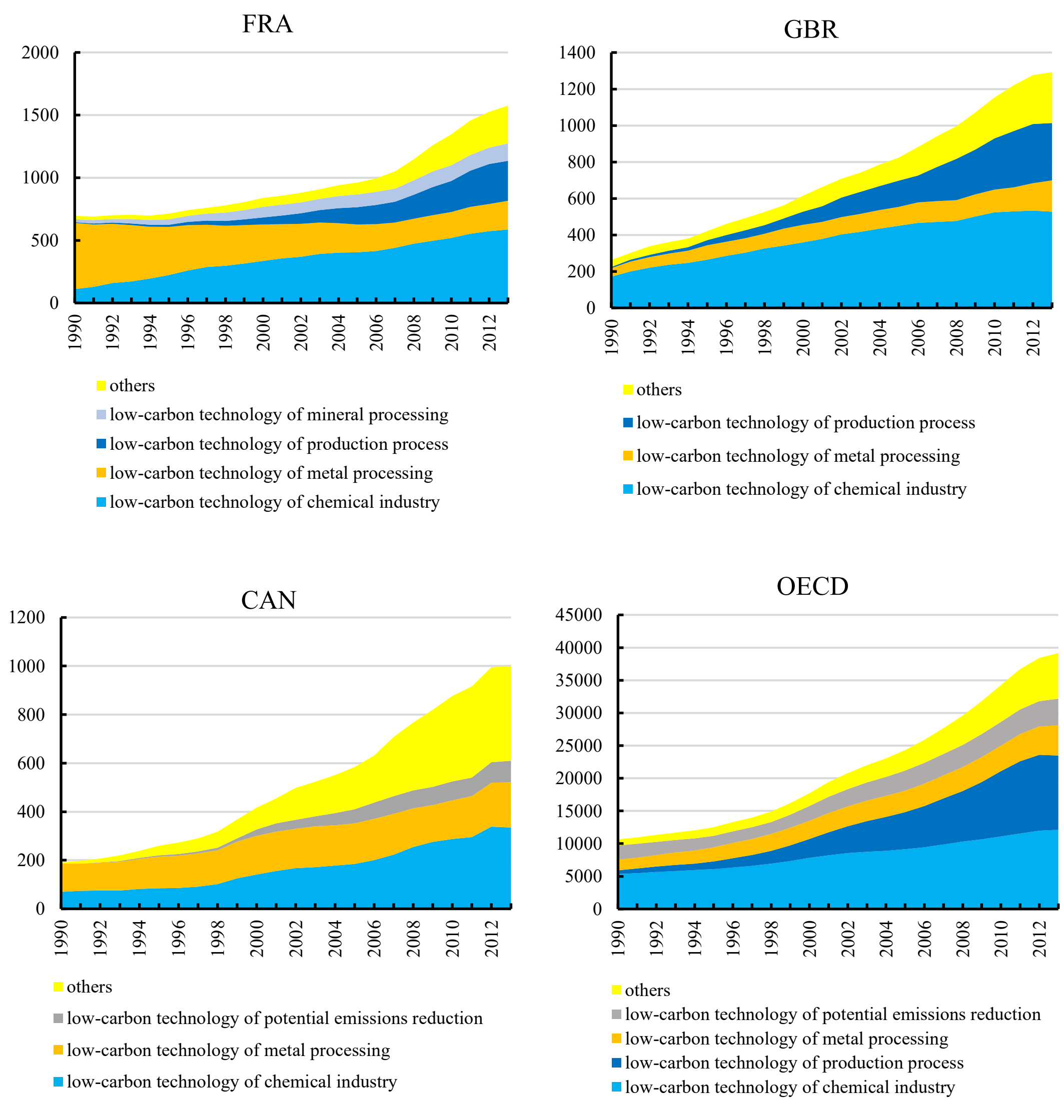


Figure 4. Level of specific LCTI in OECD countries

Figure 4 shows the level of specific LCTI in OECD countries that have the highest patent stock. It can be seen that the highest patent stock of specific low-carbon technology in OECD countries are low-carbon technologies of the chemical industry, the production process, metal-processing, and potential emissions reduction. In addition, patent stock of the four low-carbon technologies is consistently increasing during the study period, accounting for about 80% of the total low-carbon technology patent stock. Specifically, the proportion of patent stock of low-carbon technology of production process grew the fastest, from 5.5% in 1990 to 31.0% in 2013, while the proportions of other technologies decreased during the study period. Also noteworthy, most OECD countries have a high level of LCTI in the chemical industry and a rapid development speed of LCTI in the production process. The chemical industry is the major area in manufacturing to apply low-carbon technology from 1990 to 2013, and production process has the most potential to achieve low-caron manufacturing in most OECD countries.

4.2. Impact of LCTI on carbon efficiency

In order to investigate the role of LCTI in green production manufacturing, a two-way fixed model is employed in this study to investigate the impact of LCTI on carbon efficiency. The F values of the joint significance test on a time dummy variable are 12.51, 5.70, and 5.82; the P values are all zero; and there are time-fixed effects refusing the null hypothesis at the significance level of 1%.

Model 1 and model 2 were applied in this section to investigate the impact of the first order lag LCTI on carbon efficiency. As shown in Table 2, the coefficient of $L.\ln LCT$ in model 1 is 0.027 at the significant level of 10%, and the coefficient of $L.\ln LCT$ in model 2 is 0.023 at the significant level of 1%. Model 3 was employed to investigate the impact of the current LCTI on carbon efficiency, and the coefficient of $L.\ln LCT$ is 0.019 with the significant level of 5%. The results of Table 2 suggest that LCTI promotes carbon efficiency of manufacturing, and a lag effect is possible. The mean value of the coefficients of $\ln LCT$ and $L.\ln LCT$ is 0.02, which indicates that a 1% improvement of LCTI increases manufacturing carbon efficiency by 0.02 units.

Table 2. Estimate results of models with carbon efficiency

$TFCE$	Model 1	Model 2	Model 3
$L.\ln LCT$	0.027*	0.023***	
	(0.015)	(0.008)	
$\ln LCT$			0.019**
			(0.008)
$EUETS$	0.074***	0.073***	0.073***
	(0.022)	(0.011)	(0.011)
GOV	-0.476	-1.017***	-1.234***
	(0.347)	(0.285)	(0.272)
$TRADE$	0.041	0.015	0.016
	(0.040)	(0.022)	(0.021)
$lnGDP$	-0.078***	-0.104***	-0.102***
	(0.028)	(0.020)	(0.018)
HC	0.289**	0.400***	0.290***
	(0.126)	(0.062)	(0.063)
EPS		0.017***	0.016**
		(0.006)	(0.006)
INV	0.000		
	(0.000)		
$ENERT$	0.000	0.000	
	(0.000)	(0.000)	
$CONSTANT$	1.996***	2.355***	2.350***
	(0.776)	(0.533)	(0.495)

Notes: There is standard error in the parenthesis. *, ** and *** represent the significance of 1%, 5% and 10% respectively.

It can be seen that the coefficient $lnGDP$ is negative at the significance level of 1%, which means that economic development is not conducive to the improvement of carbon efficiency, possibly because countries pursue economic growth at the expense of environmental interests. The coefficients of $EUETS$ are positive in three models at the significance level of 1%, which denotes that joining Europe Union Carbon Trade markets possibly increases the carbon efficiency. The coefficients of EPS are positive in models 2 and 3 at the significance level of 1% and 5%, respectively, which means that increasing environmental regulation stringency improves carbon efficiency in manufacturing. The coefficients of HC are positive in the three models. The significance level of models 2 and 3 are 1%, and model 1 is 5%, which shows that improving human capital is helpful for increasing carbon efficiency. The coefficients of the control variable GOV in models 2 and 3 are negative, and the significance level is 1%, which shows that government participation in the market would hinder the improvement of carbon efficiency in manufacturing, possibly by distorting market competition.

4.3. Impact of LCTI on carbon productivity

Further investigations are carried out in this section to analyze the impact of LCTI on carbon productivity in manufacturing. Table 3 shows that the coefficient of first-order lag LCTI is distinctly positive, and the significance level is 5%, which indicates that LCTI is beneficial for increasing the carbon productivity in manufacturing and there exists a first-order lag effect. The coefficient of LCTI is 0.008, which shows that a 1% increase in the current LCTI leads to a 0.008 unit increase of carbon productivity in manufacturing in the next period.

Table 3. Estimate results of models with carbon productivity

$MCPI$	Coefficient	R-SE	T-value	Significance
$L.lnLCT$	0.008	0.004	2.15	**
MEI	0.000	0.000	-1.80	*
$TRADE$	-0.007	0.013	-0.49	
$GDPK$	0.000	0.000	-1.36	
$L.ETTG$	-0.010	0.006	-1.65	
$L.IVN$	0.000	0.000	1.97	*
MIS	0.065	0.015	4.44	***
HC	-0.005	0.038	-0.14	

$CONSTANT$	1.076	0.097	11.14	***

Note: *, ** and *** represent the significance of 1%, 5% and 10% respectively.

As shown in Table 3, the coefficient of control variable $L.IVN$ is positive at the significant level of 10%, meaning capital investment tends to increase the carbon productivity of manufacturing. The coefficient of variable MIS is positive at the significant level of 1%, which shows that optimizing industrial structure is beneficial for improving carbon efficiency in manufacturing.

5. Conclusions and policy implications

Currently, the world faces the huge challenge of climate change. As the leading industry in many countries, manufacturing plays a vital role in economic growth and social development. However, it also consumes a lot of energy and produces large quantities of carbon dioxide gas, one of the main causes of climate warming. Thus, it is necessary to shift the production model of manufacturing toward green production to reduce GHG emissions and improve the quality of atmosphere environment. At present, technology innovation is considered to be an effective way to improve carbon emissions performance. While different types of technology innovation may lead to different environmental performance, it is essential to analyze the impact of LCTI on green production of manufacturing. In an effort to investigate the aforementioned issues, the current study focuses on the development trend of LCTI in manufacturing using annual data from 1990 to 2014. Moreover, the role of LCTI on the environmental performance of manufacturing in OECD countries was investigated. For key indicators, the LCTI level was measured by patent stock, and environmental performance of manufacturing was measured by carbon efficiency and carbon productivity.

Through empirical analysis, we obtained four main conclusions. First, LCTI is conducive to improving the environmental performance of manufacturing in OECD countries. Improving LCTI can increase carbon efficiency and carbon productivity in manufacturing, and there exists a lag effect. Second, LCTI of manufacturing in OECD countries increased during the years 1990 through 2014. LCTI of the chemical industry demonstrated the highest level, and LCTI of production showed the fastest development in most OECD countries from 1990 to 2013. Third, countries DEU, GBR, and FRA demonstrated both high patent intensity and high patent stock, implying that the level and the quality of LCTI in these countries are relatively high. Although countries such as JPN and USA have high low-carbon patent stock, the patent intensity of these countries is relatively low, indicating that uncoordinated development exists between manufacturing production and LCTI. Finally, increasing environmental regulation stringency and human capital, joining carbon trade markets, and optimizing industrial structure can improve the environmental performance of manufacturing.

As a recap, the contributions of this study are twofold: First, compared with general technology innovation, we investigate the role of LCTI in the environmental performance of manufacturing, focusing on specific industries and technology. Theoretically, this study can provide stable empirical support that low-carbon technology improves the environmental performance of manufacturing by excluding the disturbance of heterogeneity on industries and technologies. Second, we measure the specific LCTI of manufacture sectors, supplementing the referenced literature concerning LCTI indicators and providing policy makers referent with data and indicators about the LCTI of manufacturing.

Based on the above results, the following policy implications can be drawn: First, OECD countries should invest more in the LCTI of manufacturing, focusing especially on the production process as it has the most potential for low-carbon technology. It is essential to increase R&D in low-carbon technologies, stimulate related low-carbon technology inventions, and introduce foreign advanced technology. It is noteworthy that OECD countries should pay attention to the coordinated development of LCTI and production of manufacturing, representing the quality of LCTI. Second, OECD countries should increase environment regulation stringency and improve the construction of the European carbon trading market. As the results show, environmental regulation is beneficial for green production of manufacturing. Previous studies also prove this hypothesis (Porter, 1991; Pei et al., 2019): It is necessary to implement environmental policies and increase policy stringency. Governments should intensify environmental supervision over manufacturing, such as raising taxes or fining polluting manufacturing production. In order to improve construction of the carbon trade market and stimulate green production of manufacturing, this study proposes controlling carbon emissions and carbon pricing. Finally, it is essential to increase the human capital level in manufacturing sectors, as the increase of human capital is conducive to promoting labor efficiency and producing knowledge beneficial for the development of LCTI manufacturing, which can also promote green production manufacturing indirectly. In addition, OECD countries should encourage and support schools, scientific research institutions, and enterprises in order to establish technology innovation training bases, create talent incentive systems, and improve talent flow mechanisms. Allocating qualified personnel to overseas training programs and stepping up efforts to attract more talent to the manufacturing sector are also recommended.

There are some limitations in our current study and some need further research. Further investigation needs to be conducted to analyze the role of low-carbon technology in green production of segmented manufacturing, which can exclude the heterogeneity of manufacturing industries. New methods need to be explored to classify low-carbon patents of segmented manufacturing and measure their LCTI level. In addition, the time range of the study period needs to be expanded. The patent data used in this study only cover the years from 1990 to 2014. A clear understanding of the history of low-carbon technology development requires a longer observation period; thus, data from a longer observation period are needed to clarify LCTI development from a historical perspective.

Ethical Approval

'Not applicable' for that section.

Consent to participate

'Not applicable' for that section.

Consent for publication

'Not applicable' for that section.

Availability of data and materials

The datasets generated and/or analysed during the current study are available in the OECD database, https://stats.oecd.org/.

Author competing interest

The authors declare that they have no competing interests.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Rui Shi: Conceptualization, Writing - original draft, Methodology, Formal analysis, Investigation, Software. **Yu Cui:** Investigation, Writing - review & editing. **Minjuan Zhao:** Funding acquisition, Project administration, Supervision.

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Figures

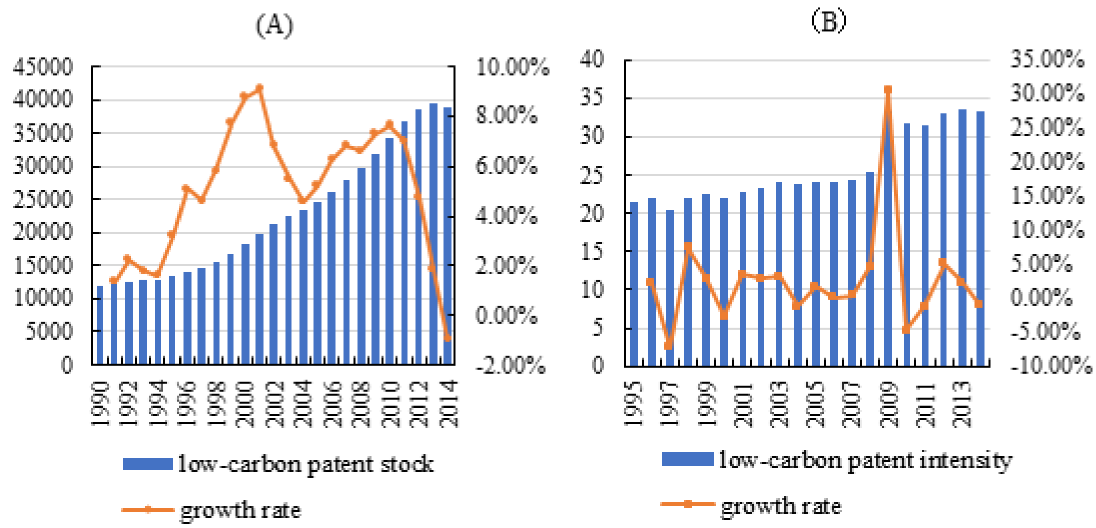

Figure 1

Patent stock and patent intensity of low-carbon technology in OECD manufacturing

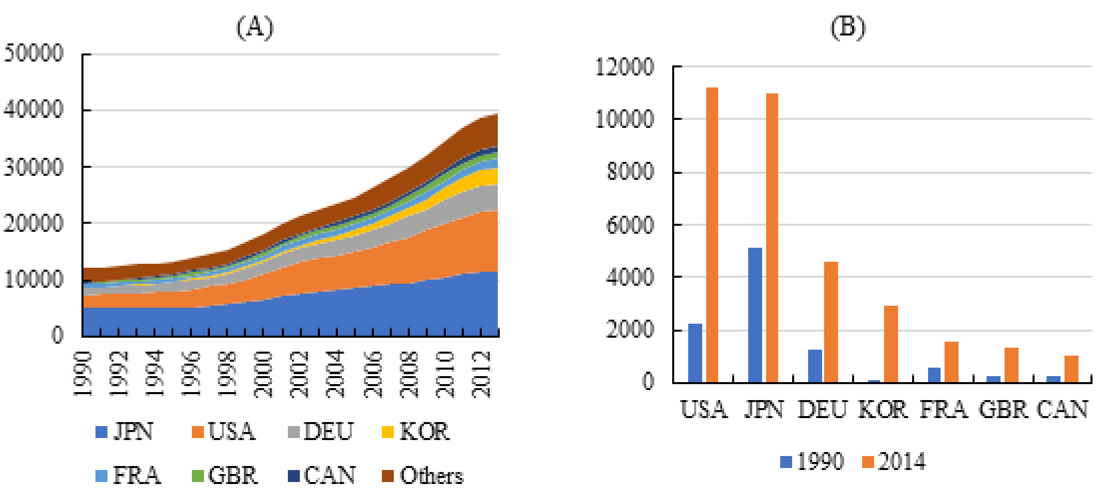

Figure 2

Low-carbon patent stock of manufacturing in seven OECD countries

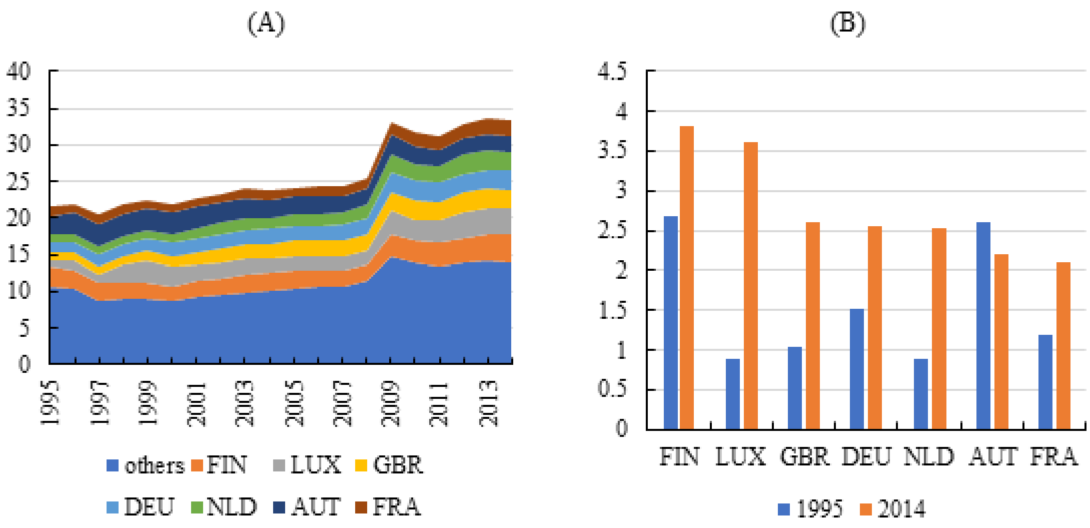

Figure 3

Low-carbon patent intensity of manufacturing in OECD countries

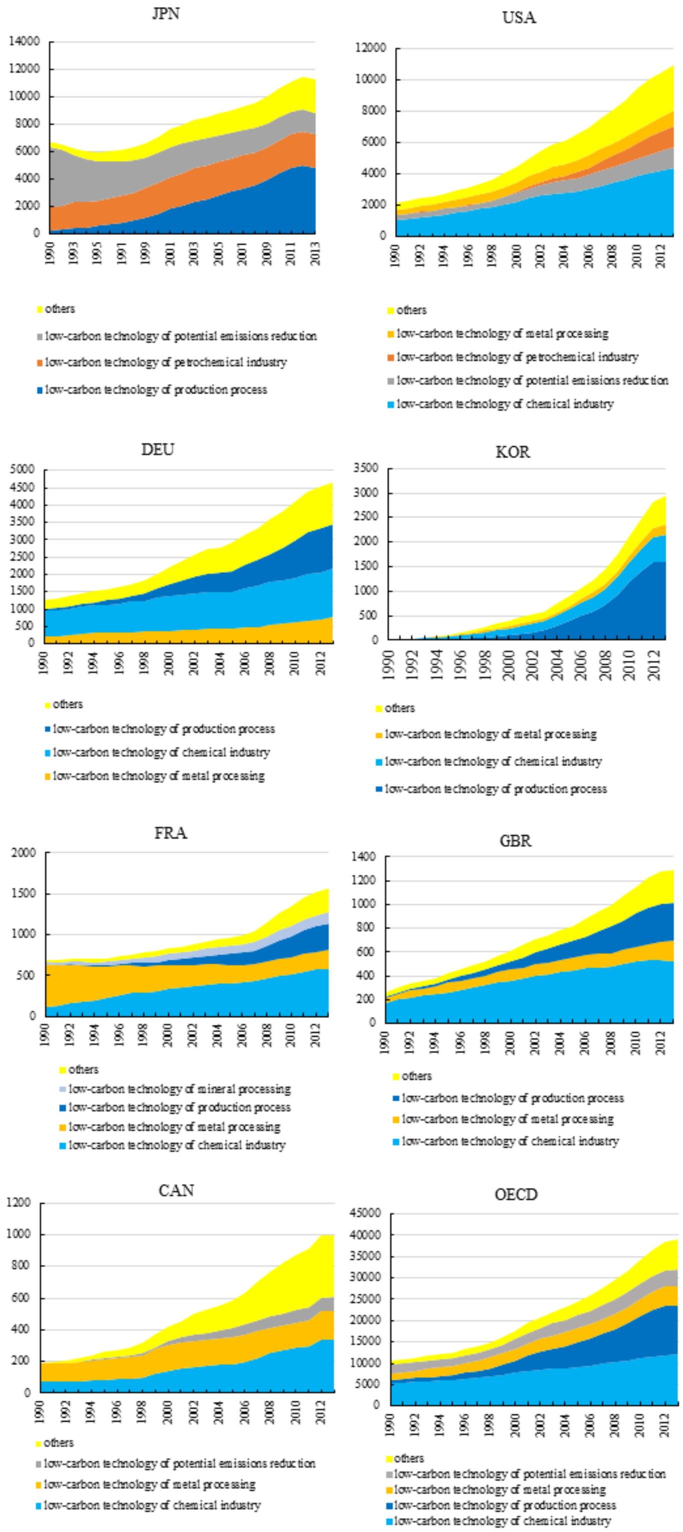

Figure 4

Level of specific LCTI in OECD countries