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The impact of renewable energy and innovation on carbon emission: An empirical analysis for OECD countries

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Abstract

This paper employs a panel quantile regression method to study the impacts of economic growth, renewable energy, and development of patents on carbon emissions. Panel quantile regression is more useful method compared to the ordinary least squared (OLS) method because both individual heterogeneity and distributional heterogeneity are considered in a panel quantile regression, which provides comprehensive information of the relationship between carbon emissions per capita and different variables. To be specific, for economic growth, its impact on carbon emissions per capita is significant and positive, but its impact decreases for fast-increase emission countries. The results do not support the Environmental Kuznet Curve hypothesis. As for renewable energy, its impacts on carbon emission show an inverted U-shaped trend at different quantile levels. As for the development of patents, its effect is non-significant and positive at different quantile levels. Based on the results, we propose some policy recommendations to control carbon emissions per capita.

Keywords: CO_2 emissions; renewable energy; innovation; OECD

1. Introduction

Carbon emission is one of the leading causes of global warming and climate change. Therefore, it receives more and more attention from international organizations, governments from different countries, and environmentalists. In order to control carbon emissions, factors related to carbon emissions should be recognized firstly. Economic grow is an essential factor impacting carbon emissions (Zhu et al., 2016). Environmental Kuznet Curve (EKC) hypothesis suggests economic grow initially enhance carbon emissions; however, when economic levels exceed a turning point, economic growth will decrease carbon emissions, namely an inverted U-sharped relationship exist for economic growth and carbon emissions. Besides, renewable energy and development of patent are believed to have a significant

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impact on carbon emissions. Renewable energy is cleaner than fossil energy. Therefore, they are useful to reduce carbon emissions. As for patents, patents are related to technology, and technology are useful to improve the existing technology and reduce carbon emissions. However, few literatures investigate which factor is more important for carbon emissions, the expansion of renewable energy or the development of patents. Moreover, investment and exports are two crucial control variables in related studies because they also influence carbon emissions.

In summary, we hope to investigate two issues in this paper: 1) does the EKC hypothesis hold for OECD countries? 2) which factors have a more powerful impact on carbon emission, the expansion of renewable energy or the development of patents? In order to solve these two issues, we apply a panel quantile regression method, which takes distributional heterogeneity and individual heterogeneity into consideration. Panel quantile regression method provides comprehensive information on different variables and carbon emission. Besides, it does not order that the errors follow a normal distribution.

2. Data and Methodology

2.1. Data

Our data consist of panel data of CO_2 emissions per capita, GDP per capita, investment, renewable energy supply, export trade values and development of patent technologies in 35 OECD countries. The data are obtained from the OECD Environment Database. Our data covers the period from 1996 to 2015. The specific definition of each variable is provided here:

1. CO_2 emissions per capita (tonnes/capita) (CE): it refers to the units of CO_2 emissions from the consumption of fossil fuels divided by population. The data is obtained from the IEA's database of CO_2.

2. GDP per capita (USD/person) (GDP): it measures a country's economic wealth per capita of a nation in a million US dollars at current prices and purchasing power parity (PPPs). The economic growth has been considered as an essential factor for CO_2 emission intensity in previous research (Wang et al., 2013; Zhao et al., 2014).

3. Investment (million US dollars) (INV): it refers to the gross fixed capital formation, which is defined as the net increase in physical assets (investment minus disposals) in one year.

4. Renewable energy (thousand tonnes of oil equivalent) (RE): it refers to the equivalent production of primary energy for renewable energy, such as the hydro energy, solar energy, wind energy, geothermal energy, tide energy, biofuels energy and wave energy.

5. Export trade values (million US dollars) (ET): it represents the added values of exported goods and services which is transported from one country to other countries.

6. Development of patent (number) (DP): it refers to the triadic patent family, which is defined as a set of patents filed at three major patent offices. DP has been widely used to represent the innovative ability in one country in many literatures (see Popp, 2005; Wurlod and Noailly, 2018).

Table 1. Summary statistics (After logarithm)

Variable	CE	GDP	INV	RE	ET	DP
Minimum	1.2528	8.6141	6.8962	3.4261	8.1004	0.0000
Maximum	3.2426	11.5382	15.0936	11.9152	14.6120	9.8366
Q1(.25)	1.9315	9.9419	10.3947	7.2342	11.0046	2.8258
Q3(.75)	2.4159	10.5248	12.4454	9.3372	12.8779	6.6385
Mean	2.1847	10.1848	11.2339	8.2911	11.8234	4.9173
Standard deviation	0.4049	0.4949	1.5556	1.4935	1.3539	2.4000
Skewness	0.1370	-0.5230	-0.1226	-0.3711	-0.5003	0.1312
Kurtosis	-0.1925	0.3536	-0.0776	0.4208	-0.0932	-0.9150
Jarque-Bera	3.3541	37.6750***	1.9969	22.6074***	31.0049***	27.4380***

*significant at 10% level

**significant at 5% level

***significant at 1% level

Table 1 summarizes the statistical description of the minimum value, maximum value, 25th quantile, 75th quantile, mean value, standard deviation, skewness, kurtosis and Jarque–Bera test for the six variables. The skewed values, the kurtosis values and the values of Jarque-Bera test clearly show that the variables are not normally distributed (except CE and INV), which indicates OLS method is not suitable in this study.

2.2. Methodology

We apply a panel quantile regression model in this paper to study the effect of GDP per capita, investment, renewable energy supply, export trade values and development of patent on carbon dioxide emission per capita in OECD countries. By using this model, we can examine the driven factors of carbon emission in OECD countries at different quantile levels. In the energy and environment areas, the data often have a distinct peak or fat tails. In this situation, the quantile regression (Koenker and Bassett Jr, 1978) can provide more robust estimation results. To take the impact effects and unobserved individual heterogeneity into consideration, we consider the following model:

$$Q_{\Delta InY_{i,t}}(\tau|\cdot) = \alpha_{1,\tau}\Delta InGDP_{i,t} + \alpha_{2,\tau}\Delta InGDP_{i,t}^2 + \alpha_{3,\tau}\Delta InINV_{i,t} + \alpha_{4,\tau}\Delta InRES_{i,t} + \alpha_{5,\tau}\Delta InET_{i,t} + \alpha_{6,\tau}\Delta InDP_{i,t} + \beta_i, \quad i = 1,\dots,N, t = 1,\dots,T \tag{1}$$

The main problem on estimating the model (1) is that traditional linear approaches are impractical for quantile regression. To address such problems, Koenker (2004) proposed an appropriate method with a L_1-norm penalty term to eliminate unobserved fixed effects. Here, we will apply this method to estimate our model, which is as follow:

$$\underset{\alpha}{\operatorname{argmin}} \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{t=1}^{T} w_k \rho_{\tau_k}\{\Delta InY_{i,t} - \alpha_{1,\tau}\Delta InGDP_{i,t} - \alpha_{2,\tau}\Delta InGDP_{i,t}^2 - \alpha_{3,\tau}\Delta InINV_{i,t} - \alpha_{4,\tau}\Delta InRES_{i,t} - \alpha_{5,\tau}\Delta InET_{i,t} - \alpha_{6,\tau}\Delta InDP_{i,t} - \beta_i\} + \mu\sum_{i=1}^{N}|\beta_i|, \quad i = 1,\dots,N, t = 1,\dots,T \tag{2}$$

where $\rho_\tau(y) = y(\tau - \mathbf{1}_{y<0})$ is the traditional check function, $\mathbf{1}_A$ is the indicator function. $\Delta\, InY_{i,t}$ denotes the log return of carbon dioxide emission per capita in country *i* at time *t*. *K* is the index for quantiles. w_k equals to $1/K$, it represents the relative weight on *k*-th quantile, and is used to describe the contribution of different quantiles in this estimation (Koenker, 2004; Zhu et al., 2016). μ is the tuning parameter, which equals to 1 in this paper (Lamarche, 2011; Zhu et al., 2016).

3. Empirical results and analysis

In this section, the empirical results are presented. Before we start to estimate the variables, we first conduct panel unit root test to check whether the six variable are stationarity, including Levin-Lin-Chu Unit-Root Test (Levin et al., 2002), Choi's modified P Unit-Root Test (Choi, 2001), and Maddala-Wu Unit-Root Test (Maddala and Wu, 1999). The results indicate that the almost all of the variables (except DP) are non-stationary at 10% significance level. However, the null hypothesis for all variables at the first difference could be completely rejected at the 1% significance level (see Table 2), which implies that the data is stationary at first difference. Therefore, we use the first difference sequence in the subsequent empirical analysis.

Table 2. Results of panel unit root tests

Variable	CE	GDP	INV	RE	ET	DP
Levin-Lin-Chu Test	3.14	1.74	0.30	9.31	0.84	-3.92***
Choi's modified P Test	-2.41	-4.87	-2.92	2.74***	-2.45	6.12***
Maddala-Wu Test	41.46	12.42	35.43	102.41***	41.00	142.40***
First difference						
Levin-Lin-Chu Test	-22.07***	-14.95***	-14.95***	-22.74***	-18.69***	-25.43***

Choi's modified P Test	67.69***	28.15***	24.70***	76.30***	41.29***	75.13***
Maddala-Wu Test	870.95***	403.02***	362.30***	972.77***	558.60***	958.90***

***significant at 1% level

Table 2 shows the estimation results of the model (2) at the 5th, 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, 90th and 95th quantile levels. The estimation results imply that the effects of independent variables on log return of carbon dioxide emission per capita are clearly heterogeneous.

Table 3. Results of panel quantile regression

Variable	Quantiles										
	5th	10th	20th	30th	40th	50th	60th	70th	80th	90th	95th
Intercept	-11.10***	-8.65***	-5.74***	-4.12***	-3.00***	-1.66***	-0.58***	0.74	1.77	3.44***	5.19***
	(-9.55)	(-8.91)	(-8.50)	(-7.54)	(-6.10)	(-3.50)	(-1.09)	(1.42)	(3.67)	(6.34)	(6.26)
GDP	0.80***	0.64***	0.35**	0.35***	0.36***	0.23*	0.25***	0.18*	0.21***	0.31***	0.45***
	(5.53)	(3.45)	(2.23)	(2.61)	(2.74)	(1.91)	(2.47)	(1.96)	(2.61)	(3.29)	(3.58)
GDP^2	-0.03	-0.02	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00
	(-1.67)	(-1.13)	(-0.44)	(-0.78)	(-1.03)	(-0.54)	(-0.44)	(-0.13)	(-0.22)	(0.06)	(0.11)
INV	0.01	-0.05	-0.01	0.01	0.03	0.05**	0.03	0.01	0.00	0.00	0.03
	(0.18)	(-1.14)	(-0.17)	(0.39)	(1.66)	(2.21)	(1.20)	(0.66)	(0.16)	(0.12)	(0.70)
RE	-0.05	-0.10**	-0.08**	-0.08***	-0.07***	-0.06**	-0.05**	-0.07***	-0.07***	-0.09**	-0.10**
	(-0.92)	(-2.05)	(-2.55)	(-3.77)	(-3.08)	(-2.08)	(-2.16)	(-2.99)	(-2.97)	(-2.31)	(-2.49)
ET	-0.09	0.04	0.04	0.02	0.02	0.05	0.03	0.06*	0.07***	0.08	0.13
	(-1.20)	(0.56)	(1.03)	(0.81)	(0.76)	(1.62)	(0.85)	(1.91)	(2.97)	(1.49)	(1.63)
DP	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.02
	(1.13)	(1.11)	(1.16)	(0.98)	(0.64)	(0.16)	(0.39)	(0.95)	(1.06)	(1.02)	(1.54)

Note: Numbers in the parentheses represent t value.
*significant at 10% level
**significant at 5% level
***significant at 1% level

Firstly, we can find that the effect of the log return of GDP per-capita is clearly heterogeneous and significantly asymmetric in Figure 1 (a). The coefficient first decreases from 0.8 at the 5th quantile to 0.18 at the 70th quantile, and then increases to 0.45 at the 95th quantile. The positive coefficient means that the GDP per-capita increases will increase the carbon dioxide emission. This implies that promotion of economic development is accompanied by increasing carbon emission in OECD countries. The main reason is the development pattern of most OECD countries belong to the quantity-oriented development pattern, which does not pay sufficient attention to reducing the carbon emission. In addition, the decreasing trend shows that as the CO_2 emissions in OECD countries worsen, the governments have begun to change the pattern of economic development from the extensive development to the intensive development. The non-significant quadratic term of GDP per-capita indicates that there is no EKC curve in the OECD countries (See Figure 1 (b)). Besides, the high quantiles represent the countries whose changes of CO_2 per capita are large (denoted by large-change countries). The low quantiles represent the countries whose changes of CO_2 per capita are small (denoted by small-change countries). For large-change countries, they are high-income countries, people in these countries are used to consume more energy. Therefore, an increase in GDP will significantly improve CO_2 emissions per capita. As for small-change countries, they are less developed than high-income countries. Therefore, their economy still relies on secondary industry, and an increase in GDP will also greatly improve CO_2 emissions per capita.

Secondly, Figure 1 (d) reveals that the impact of log return of renewable energy on the log return of carbon emission is also significantly heterogeneous. There is significant asymmetric in the response of carbon dioxide emission per capita to renewable energy at different quantiles. The coefficient of renewable energy has an inverted U-shaped trend at different quantile levels, from -0.1 at the 10th quantile to -0.05 at the 60th quantile and then increases to -0.1 at the

95th quantile. The negative coefficient indicates that renewable energy is an important factor in reducing carbon emissions because the production process of renewable energy release little carbon dioxide. Besides, the asymmetric coefficients indicate that the impact is larger in the higher or lower quantiles of carbon dioxide emission per capita. The results indicate that an increase in renewable energy supply can reduce more CO_2 per capita for large-change and small-change countries. This may be caused by that both large-change countries and small-change countries are more willing to reduce CO_2 emissions.

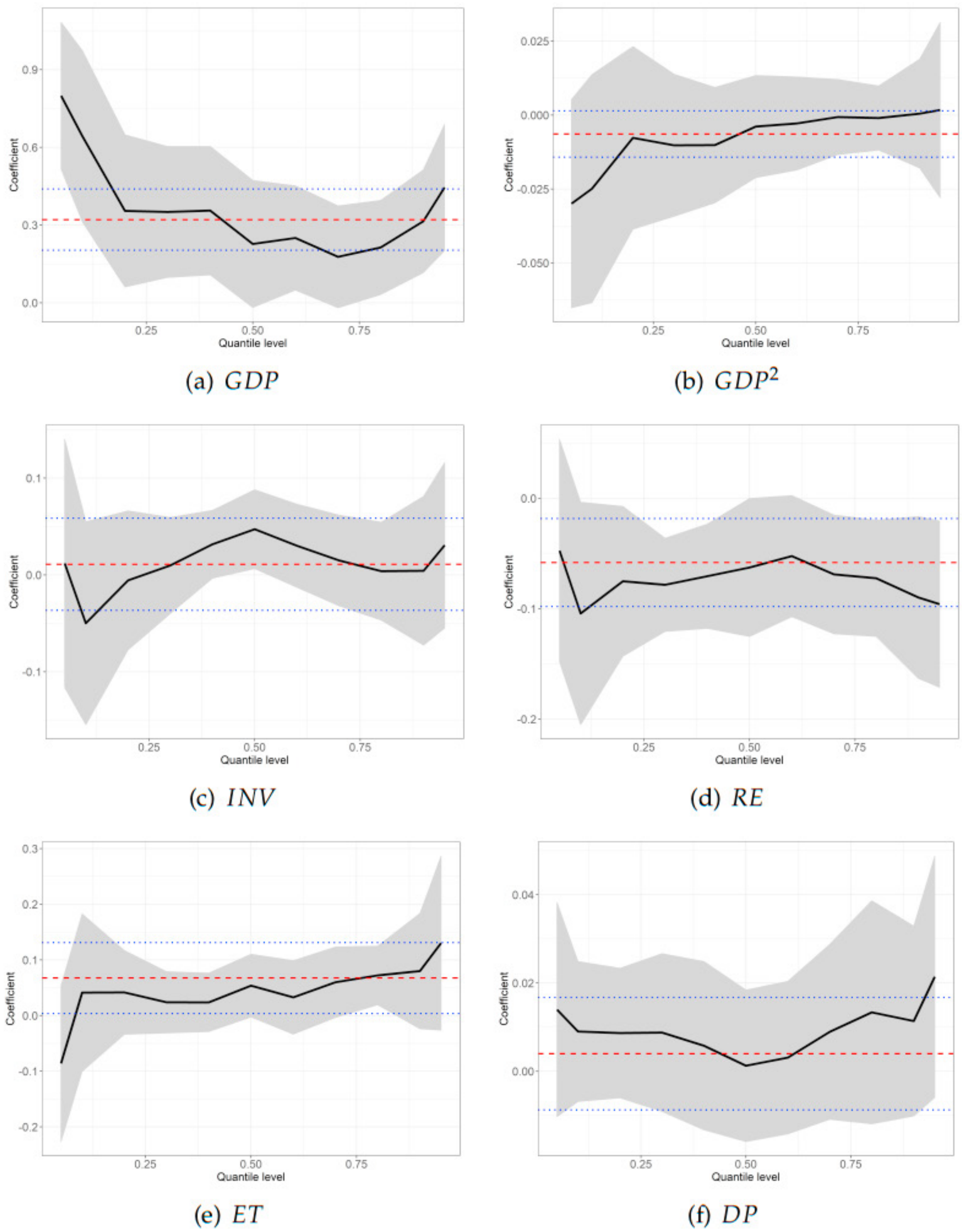

Fig. 1. Change in panel quantile regressions coefficients. Notes: Shaded areas correspond to 95% confidence intervals of quantile estimation. The red dashed line represents the corresponding OLS estimate with its 95% confidence interval (blue dashed line)

Thirdly, the impacts of development of patent on carbon emission per capita are illustrated in Figure 1 (f). Although its impacts are positive except for medium-change countries, indicating that growth in patents will increase CO_2 emissions except for medium-change countries. Moreover, as we can see from Figure 1 (f), its impacts are also heterogeneous across different quantiles, and the coefficients fluctuate between 0.00 and 0.02, which proves that OLS method can only provide the mean results. However, the coefficients are not significant for all quantiles, implying that the innovative activity cannot lead to a significant reduction in carbon emissions of the OECD countries.

The results for the effects of other variables are also heterogeneous at different quantile levels. First, the effect of log return of investment is statistically significant at 50th quantile (See Figure 1 (c)). The positive effect indicates that a higher investment increase leads to higher carbon emission growth. As for other quantiles, they are negative for small-change countries but start to become positive for medium-change and large-change countries. Although the coefficients are not significant, but they also prove that the OLS neglect the individual heterogeneity and can only provide the mean results. Second, the coefficient of log return of export trade is positive and statistically significant at upper quantiles (Figure 1 (e)), which implies that a larger increase in export trade can augment carbon emissions in OECD countries.

In summary, the results demonstrate that panel quantile model provides a much richer and more comprehensive picture of the effects of influence variables on per capita carbon dioxide emission in OECD countries than OLS panel data model.

4. Conclusions

The main purpose of this paper is to study the effect of economic growth, renewable energy, development of patents on the carbon emission in OECD countries. The data in this study consist of the annual sample period from 1996 to 2015 in 35 OECD countries. In order to find more useful information in limited data, we apply panel quantile regression method, which provides more details by taking unobserved individual heterogeneity and distributional heterogeneity into consideration. Compared with OLS regression, we believer panel quantile regression can discover more information by dividing carbon emissions into several quantiles.

The empirical results indicate that the impacts of the five different variables on carbon emission are heterogeneous and asymmetric at different quantiles. To be specific, the impact of GDP per capita on carbon emission is positive, but shows a decreasing tendency. That implies economic growth increase carbon emissions, but its positive impacts are decreasing for fast-increase emission countries. Besides, the EKC hypothesis is not valid in our samples. As for renewable energy, its impacts on carbon emission show an inverted U-shaped trend at different quantile levels, which increases from -0.1 at the 10th quantile to -0.05 at the 60th quantile and then decreases to -0.1 at the 95th quantile. This indicates that the impact is larger in the higher or lower quantiles of carbon dioxide emission per capita. As for the development of patents, its effect is non-significant and positive at different quantile levels, indicating that the innovative activity cannot lead to a significant reduction in carbon emissions of the OECD countries overall in the past.

Based on the results, several policy recommendations are proposed. Firstly, the GDP has a negative impact on carbon emission per capita. Therefore, in order to reduce CO_2 emissions, the government of the large-change countries should realize the importance of energy saving, and encourage the residents to cultivate a good habit of energy consumption, which is the most effective ways to reduce CO_2 emissions and has the least impacts on GDP. As for the small-change countries, the government should adjust their industry structures, aiming at building a low carbon economy structure. Secondly, as the use of renewable energy are helpful to reduce carbon emissions. The government in OECD countries should try to adjust their structure of energy consumption, to use more renewable energy. In order to do so, the government should provide policy support to the renewable energy industry, such as to provide a subsidy to the electricity generators of renewable energy, or to provide low-interest rate loans to the suppliers of renewable energy. Besides, the government should also facilitate the building of electricity infrastructure for renewable energy. As renewable energy belongs to distributed energy, therefore, it is very important for them to be connected to the main electricity network, which necessitates the construction of an auxiliary power system.

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