Research Square

Preprints are preliminary reports that have not undergone peer review. They should not be considered conclusive, used to inform clinical practice, or referenced by the media as validated information.

The Decoupling of China's Economy-Carbon Emission and Its Driving Factors

Peng Kuai
Hefei University of Technology

Yao Cheng
Hefei University of Technology

Shu'an Zhang (ahepzhang@hotmail.com)
University of Accounting and Finance https://orcid.org/0000-0002-0954-6822

Research Article

Keywords: Economic growth, Carbon emission, Decoupling, Driving factors, Econometric model, Comparative analysis, China

Posted Date: July 12th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-651569/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License

The Decoupling of China's Economy-Carbon Emission and Its Driving Factors

Authors:

(1) Peng Kuai (First author)

School of Economics, Hefei University of Technology, Hefei 230601, P.R. China
E-mail addresses: pengkuai@hfut.edu.cn

(2) Yao Cheng

School of Economics, Hefei University of Technology, Hefei 230601, P.R. China

E-mail addresses: levis.charles@foxmail.com

(3) Shu'an Zhang *

Shanghai Lixin University of Accounting and Finance, Shanghai 201209, P.R. China
E-mail addresses: ahepzhang@hotmail.com
(Corresponding author)*

Abstract:

Decoupling between economic growth and carbon emission is a global hot topic. This paper studies China's economic-carbon decoupling and its driving factors. By using the panel data of 30 Chinese provinces from 2000 to 2016, the decoupling index of each province is calculated with the Tapio model. It is found that many provinces have progressed from no decoupling to weak decoupling and then strong decoupling. Then, the econometric models are used to explore the driving factors. Results show that energy structure is the most important factor, followed by GDP per capita and energy intensity, which all increase CO_2 emission significantly. The results are robust when tested with GMM, PCSE and FGLS estimation and LMDI decomposition. Further, we conduct a comparative analysis regarding the temporal and spatial characteristics of the above three driving factors to identify their relationship with decoupling, four groups of regions that represent different economic features are selected for the analysis. Heterogeneity effects of the factors among the regions has been observed, based on this

we provide targeted strategies for different regions.

Keywords: Economic growth; Carbon emission; Decoupling; Driving factors; Econometric model; Comparative analysis; China

Declarations:

(1) Note of preprint server

I have not submitted my manuscript to a preprint server before submitting it to *Environmental Science and Pollution Research.*

(2) Ethics approval and consent to participate

Not applicable.

(3) Consent for publication

Not applicable.

(4) Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

(5) Competing interests

The authors declare that they have no competing interests.

(6) Funding

National Natural Science Foundation of China.

(7) Authors' contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Peng Kuai, Shu'an Zhang and Yao Cheng. The first draft of the manuscript was written by Peng Kuai and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

(8) Acknowledgements

The study is financed by the National Natural Science Foundation of China under Grant NO. 71704044.

1. Introduction

Reducing carbon emissions to fight against global warming has become a consensus of many countries and regions. In "Joint Statement on Climate Change between China and the United States" released at the 2014 Asia-Pacific Economic Cooperation (APEC) meeting[1], China solemnly promised to achieve carbon dioxide emission peaks around 2030 and strive to reach an early peak. In order to fulfill this promise, China is promoting the economic transition to a green and low-carbon economy these years (Li and Qin, 2019), how to reduce carbon emissions while maintaining economic growth becomes a key issue for China's sustainable development (which is also important for many other developing countries).

Decoupling index is an important indicator to measure the relationship between carbon emissions and economic growth, it was originally used in the field of physics indicating that there is no corresponding relationship between two or more physical quantities. At present, it has been widely used in the field of sustainable development. Organization for Economic Co-operation and Development (OECD) (2001) regards it as one of the most important environmental strategies in the 21st century. United Nations Environment Programme’s "Green Economy Initiative (2011) " deems the decoupling of natural resource use and environmental impacts from economic growth as the heart of the Initiative. It also draws the interest of many researchers and has been

[1] The statement is available from the Xinhua Web: http://www.xinhuanet.com//world/2015-09/26/c_1116685873.htm.

employed to analyze the decoupling degrees in various countries, regions, cities, or sectors (Grand, 2016). By comparing the economic-carbon emissions decoupling relationships across regions and periods, we can determine whether the developing is following a sustainable path.

However, a more important question is what drives the decoupling? Although there are many studies expressed concerns to this problem, they mainly focus on two aspects: one is to obtain the decoupling state through direct calculation, such as Mikayilov et al. (2018), Wu et al. (2019); the other is to obtain factors affecting CO_2 emissions through decomposition or quantitative regression, such as Jeong and Kim (2013), Li and Qin (2019), etc. Obviously, further analysis should be made regarding the consistency between these factors and decoupling, because even with the same rate of change in CO_2 emissions, the decoupling index may vary with time and regions, however, this step is neglected in many studies. In this paper, besides identifying factors affecting CO_2 emissions, we will also analyze the dynamic relationship between the factors and the decoupling based on the economic characteristics of typical regions, so as to provide more targeted strategies.

Regarding identification of factors affecting CO_2 emissions, econometric models will be used in this paper. However, it is worth noting that the results of related studies often differ with each other. For example, Lin and Agyeman (2019) argued that change of energy consumption structure was the major driver for CO_2 emissions; while Nguyen, et al. (2020) pointed out that energy intensity is a main cause; the third different viewpoint issued by Chang, et al (2019) showed that economic growth is more

pronounced. This inconsistency may due to the lack of a unified framework for the choice of explanatory variables. Generally, many studies directly present their explanatory variables or just make simple qualitative descriptions (Lin and Agyeman, 2019; Nguyen et al., 2020), this may lead to missing variables or model setting errors, thus resulting in inaccurate estimation (Li, 2008). There are two approaches which may have potential, one is the Kaya identity approach (Leal et al., 2019), and the other is the SPIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) approach (Shuai et al., 2017), both use chain multiplication to decompose the factors that affect carbon emissions, so as to obtain a direct theoretical relationship between each factor and carbon emissions. This paper tries to employ the above two approaches for the selection of explanatory variables to make an improvement. In addition, we also use a variety of methods for robustness analysis; especially, we compare the regression results with that of the LMDI decomposition (this method is also widely used in related studies (Chang et al., 2019)).

In summary, this article intends to supplement the current research in the following aspects. First, we conduct a comparative analysis regarding the temporal and spatial characteristics of the driving factors to identify their consistency with decoupling, the results are more instructive for different region to obtain stable decoupling. Second, the chain multiplication of Kaya identity and SPIRPAT model are combined to make the selection of explanatory variables more theoretically. Third, the robustness analyses are carried out by using dynamic panel estimation, feasible generalized least squares (FGLS) estimation, panel corrected standard errors (PCSE) estimation, and LMDI

decomposition, to make our regression results more convincing.

The rest part of the study includes: Chapter 2 is about literature review; we focus on the factors affecting CO_2 emissions and the link between them and decoupling. Chapter 3 is about the overview of China's economy-carbon decoupling. Chapter 4 is method and data, which explains econometric model and related indexes and data; Chapter 5 is result analysis, which interprets the results revealed by the econometric model (including robustness analyses)； and a further analysis is conducted to identify the consistency between the key factors and decoupling; the last chapter is conclusion and suggestion.

2. Literature review

Decoupling between economy growth and CO_2 emission is one important indicator of sustainable development (OECD,2001). Many studies endeavored to find its driving factors, so as to obtain a steady decoupling relationship. For example, Jeong and Kim (2013) decomposed the changes of CO_2 emissions in the Korean manufacturing sector into five factors in terms of overall industrial activity, industrial activity mix, sectoral energy intensity, sectoral energy mix and CO_2 emission factors, they found that industrial activity mix (structure effect) played the biggest role in reducing GHG emissions, which was followed by the sectoral energy intensity (intensity effect). Li and Qin (2019) used a hybrid method combing LMDI and decoupling index approach to decompose carbon emissions of China into emission coefficient, energy intensity, industrial structure and economy growth, and found that changes of economic growth was the most prominently factor to the steady downward

trend of total CO_2 emission in China. Lin and Agyeman (2019) used a time series data spanning from 1980 to 2016 in an autoregressive distributed lag model to study the driving factors of energy-related CO_2 emissions, they found that change of energy consumption structure was the major driver for historical CO_2 emissions increase in Ghana, which is followed by energy intensity, carbon intensity changes and overall economic activity. Chang, et al (2019) use a dynamic panel data model where country-level carbon emissions are regressed against GDP, energy intensity, urbanization and trade openness, they found that both economic development and population size have a positive impact on carbon emission, and the magnitude of the former is higher than the later; they also found that energy intensity positively contributes to carbon emissions. For similar researches, see Mousavi et al. (2017), Leal et al. (2019). Huang et al. (2020).

Through reviewing the above literatures, we find that diversity factors such as industrial structure, energy intensity, energy structure, industrial structure and scale, population size, etc., have impact on carbon emissions. However, the results vary in different studies, which makes it difficult for us to understand the key drivers. An important reason for this inconsistency is that there is no unified standard for the selection of appropriate explanatory variables, and most studies mainly rely on the researcher's personal experience and previous literatures. Considering that the Kaya identity and the SPIRPAT model are potential to provide a proper framework for the selection explanatory variables (Ma et al., 2019), we try to employ them to provide a theoretical framework for the selection of explanatory variables. The other reason is

that some key variables may be omitted. For example, compared with the traditional impact factors mentioned above, the role of technological innovation has received less attention (Nguyen et al., 2020). Innovation (and its spillover) is important because it may have the effect of improving the technical efficiency of enterprises, which further improve the efficiency of resource and energy utilization at the industry level (Aldieri et al., 2020; Wang et al., 2020). In view of this, we will also consider the impact of innovation in subsequent analysis.

Another important question should be concerned is that only obtaining the factors affecting CO_2 emissions (many studies stop here) is not enough to explain decoupling, the economic situation also needs to be concerned. Because decoupling is exactly the ratio between growth in emissions relative to growth in GDP (Mikayilov et al., 2018). A more immediate piece of evidence is that China's carbon emission intensity has been declining in recent years, however, our calculations shows that not every region can be stably decoupled (see Table 1). The underlying logic of this heterogeneity is that: decoupling, or rather, the carbon emission elasticity of GDP growth will be affected by the economic foundations of different regions. This is also the key point of the environmental Kuznets Curve hypothesis. Steinberger and Roberts (2011) argued that there were strong correlations between energy and/or carbon and living standards at lower consumption levels (i.e., developing countries), and decoupling at higher levels (i.e., industrialized countries). Thus, besides identifying the factors affecting CO_2 emissions, we will further analyze the dynamic relationship between the factors and the economic status of typical regions, and then the consistency between the factors and

decoupling will be checked.

3. Overview of China's decoupling status

3.1 Sample description

As the largest developing country, China's rapid economic growth once relied on high consumption of resources and energy, and high emissions of pollutants and carbon dioxide. Since the 1990s, China has contributed the largest part to the increase in global carbon emissions, with a contribution rate of over 60%. According to our calculation, China's average annual growth rate of carbon emissions was 8.42% during year 2000 to 2016 (Figure 1), and the rapid growth of carbon emissions was mainly concentrated in the 10 years from 2002 to 2011, with an average annual growth rate of 12.2%. For this reason, China faces tremendous pressure to reduce carbon emissions. In order to promote the sustainable development of the economy, China vigorously promotes the low-carbon and green transformation of the economy, and actively responds to the "United Nations Framework Convention on Climate Change", the "Kyoto Protocol", the "Paris Agreement" and other international carbon reduction conventions. In 2014, China and the United States jointly issued the "Sino-US Joint Statement on Climate Change". China promised to reach its emissions peak of carbon dioxide by 2030 and will strive to reach the peak as soon as possible. At the same time, China also plans to increase the proportion of non-fossil energy in primary energy consumption to about 20% by 2030. These years, by implementing a series of strict policies, such as taking energy conservation and carbon dioxide emission reduction as binding indicators in the national economic development plan, reducing economic growth, adjusting the industrial structure, reducing backward production capacity, and continuously optimizing the energy structure, etc., the growth rate of carbon emissions has gradually

slowed, especially the intensity of carbon emissions, which has been showing a downward trend since 2011.

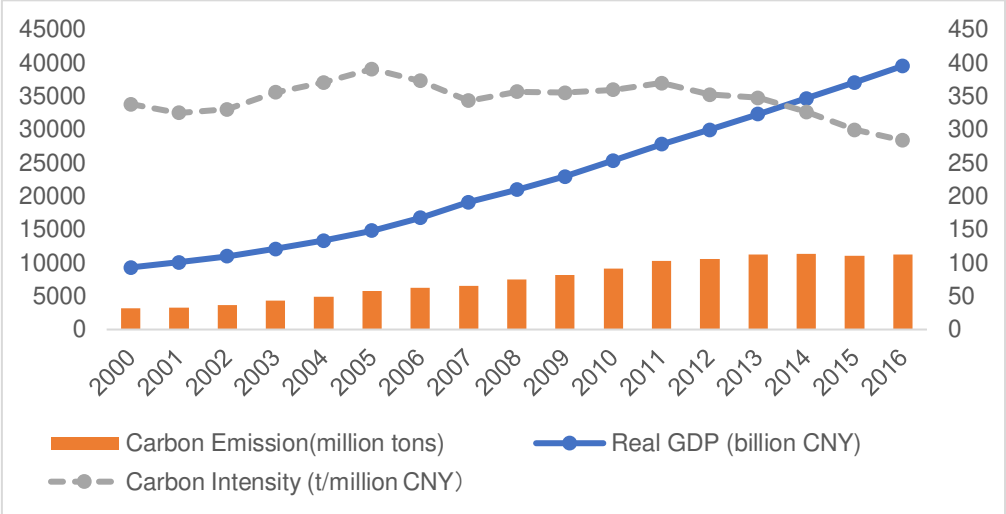


Fig.1 Trends in China's GDP, carbon emissions and carbon emission intensity[2]

Obviously, as a member of many developing countries, China's carbon reduction experience is of great demonstration significance. Therefore, taking China as the case can not only provide more scientific basis for domestic carbon reduction practices, but also provide a reference for other developing countries' carbon reduction policies.

3.2 Decoupling between economy growth and CO_2 emissions

According to the Tapio method, the decoupling indexes of economy-carbon emission of the provinces level during the study period are calculated, see Table 1. The results show that decoupling gradually increase in most provinces. During 2001-2005, weak decoupling is the most common status, but non-decoupling provinces also account for a considerable share. During 2006-2011, more provinces convert to weak decoupling which is dominant. It is worth noting that in 2009, some provinces returned to non-decoupling ("re-linking"). One possible reason is that after the global financial crisis in 2008, China increased its economic stimulus, a large number of projects had

[2] MS Excel 2019 was used to create Fig.1.

been launched which dramatically increased carbon emissions, meanwhile, economic recovery lagged because economic construction took more time. However, this "re-linking" soon turned into decoupling as the economy recovered and environmental regulations became stricter, as a result, more and more provinces turned to strong decoupling during 2012-2016， suggesting that China's carbon reduction work has achieved great results in recent years.

Meanwhile, it should be noted that decoupling is also heterogeneous in different regions[3]: After 2012, most regions have performed well, especially the developed northern and eastern regions such as Beijing, Tianjin, Shanghai, Jiangsu, and Zhejiang, which have basically maintained the decoupling status since 2006. In addition, Liaoning, Jilin, Henan, Hubei, Hunan and some other regions with good economic foundations also performed well. However, there are also some regions that performed poorly, such as Shandong, Gansu, Qinghai, Xinjiang, Heilongjiang, Fujian, Hainan, etc., most of these regions are in economically underdeveloped areas (except for Shandong and Fujian). Obviously, regional distribution of the decoupling status indicates that economic level is an important factor to decoupling.

[3] Based on the research of Li and Hou (2003), we divides the Chinese mainland into 8 major regions according to the characteristics of social and economic development: 1. Northeast China, including Liaoning, Jilin, and Heilongjiang; 2. Northern coastal areas: Beijing, Tianjin, Hebei , Shandong; 3. Eastern coastal areas: including Shanghai, Jiangsu, Zhejiang; 4. Southern coastal areas, including Fujian, Guangdong, and Hainan; 5. Middle Yellow River areas, including Shaanxi, Shanxi, Henan, and Inner Mongolia; 6. Middle Yangtze River areas, Including Hubei, Hunan, Jiangxi and Anhui; 7. Southwest China, including Yunnan, Guizhou, Sichuan, Chongqing, and Guangxi; 8. Great Northwest China, including Gansu, Qinghai, Ningxia, Tibet and Xinjiang.

Table 1 Decoupling analysis results

Decoupling state	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Beijing	-0.05	0.24	0.5	0.57	1.54	-0.9	0.07	0.11	0.27	0.08	-0.45	0.16	-0.85	0.44	-0.4	-0.47
Tianjing	-0.02	0.26	0.2	0.51	0.53	0.06	0.13	-0.01	0.63	0.96	0.43	0.06	0.25	-0.39	-0.39	-0.61
Hebei	0.4	0.97	0.71	0.62	0.65	0	0.2	0.23	0.87	0.42	0.65	0.17	0.02	-1.43	-0.7	0.01
Shanxi	0.26	8.41	2.13	0.18	-0.44	0.38	0.2	0.28	7.96	0.13	0.19	0.59	0.67	-2.92	-54.58	0.89
Neimeng	0.27	0.94	-0.19	2.42	0.61	0.48	0.55	0.59	0.61	0.51	1.08	0.37	-0.36	0.49	-0.71	0.65
Liaoning	-0.79	0.94	0.87	1.02	0.57	0.31	0.17	0.2	0.32	0.45	0.33	0.31	-0.47	0.02	-17.68	-0.02
Jilin	0.41	0.25	0.8	0.36	1.17	0.65	0.51	0.61	0.18	0.61	0.66	-0.09	-0.44	-0.15	-3.47	-0.44
Heilongjiang	-1.25	0.09	0.42	0.72	1.12	0.12	0.4	0.36	1.34	0.41	0.34	0.54	-1.15	0.34	-1.68	1.08
Shanghai	0.36	0.31	0.81	0.39	0.43	-0.19	0.19	0.44	-0.06	0.67	0.25	-0.28	0.55	-1.12	0.48	0.01
Jiangsu	0.05	0.57	0.89	0.83	0.96	0.5	0.03	0.08	0.4	0.58	0.82	0.21	0.21	-0.07	0.46	0.39
Zhejiang	3.33	0.64	0.6	1.3	1.01	0.76	0.09	0.14	0.56	0.36	0.35	-0.41	0.05	-0.16	0.17	-0.08
Anhui	0.77	0.38	1.13	0.47	0.31	0.69	0.48	0.71	0.73	0.26	0.31	0.36	0.67	0.38	0.04	-0.01
Fujian	-0.17	1.59	1.83	1	1.06	0.85	0.18	0.26	1.41	0.53	0.74	-0.07	-0.25	1.4	-0.46	-0.57
Jiangxi	0.27	0.54	1.41	0.99	0.48	0.64	0.02	0.08	0.48	0.71	0.43	0.05	0.61	0.2	0.69	0.13
Shandong	2.1	1.19	1.29	0.91	1.24	0.66	0.22	0.3	0.43	0.68	0.34	0.51	-0.29	0.91	1.05	0.88
Henan	1.46	0.45	3.08	0.13	1.83	0.16	0.1	0.16	0.27	0.44	0.62	-0.65	-0.18	0.13	0.04	-0.08
Hubei	0.09	0.76	0.88	0.67	-0.04	1.22	0.07	-0.09	0.51	0.63	0.6	0.01	-1.22	0.1	-0.11	0.02
Hunan	0.07	0.58	0.79	0.6	0.42	0.78	0.02	-0.05	0.4	0.27	0.51	-0.11	-0.32	-0.29	0.76	0.08
Guangdong	2.19	1.82	0.83	0.46	2.74	0.64	0.14	0.24	1.07	0.74	0.5	-0.23	-0.11	0.06	0.03	0.31
Guangxi	-0.48	-0.65	1.6	1.62	0.31	0.77	0.06	0.09	1.03	0.92	1.01	0.87	-0.1	-0.06	-0.69	0.63
Hainan	0.38	-6.99	63.09	0.37	-1.12	5.71	0.15	0.19	0.64	0.37	0.81	0.33	-0.69	0.98	1.75	-0.29
Chongqing	-0.62	0.2	-0.41	0.98	0.48	1.15	0.18	0.19	0.59	0.49	0.53	-0.09	-1.15	0.62	0.09	-0.09

Sichuan	0.12	0.79	2.08	0.81	-0.32	0.32	0.18	0.26	1.02	0.14	0.04	0.31	0.21	0.42	-1.16	-0.35
Guizhou	-0.99	2.87	5.98	0.51	1.36	1.07	0.08	0.1	0.96	0.04	0.44	0.47	0.21	-0.24	-0.06	0.51
Yunnan	0.39	0.56	2.18	-1.64	8.42	0.76	0.1	0.15	1.01	0.32	0.14	0.24	-0.1	-1.23	-1.69	-0.1
Shaanxi	0.13	1.68	0.71	1.07	3.63	-0.67	0.46	0.4	0.75	0.77	0.45	0.96	0.5	0.59	-0.46	0.38
Gansu	0.24	0.85	1.04	0.5	0.34	0.32	0.05	0.1	-0.18	0.53	0.71	0.24	0.27	0.09	4.23	-0.58
Qinghai	1.64	0.47	0.78	0.39	0.46	0.78	0.34	0.34	0.31	-0.01	0.76	1.44	0.8	-0.79	-1.57	2.57
Ningxia	0.51	1.48	18.81	2.96	1.48	0.61	0.39	0.38	0.81	0.74	1.36	0.64	0.62	0.28	0.61	-0.09
Xinjiang	0.52	-0.22	0.7	1.02	0.53	0.72	0.63	0.58	7.52	0.44	0.85	1.15	1.13	1.14	2.69	1.76

Note: The green shaded areas in the table indicate strong decoupling, the red shading indicates non-decoupling (or re-link), while the unshaded areas indicate weak decoupling.

4. Econometric model and data

4.1 Econometric model

4.1.1 Basic model

Carbon emission is a key indicator that affects the decoupling index. Base on the slope of the Kuznets curve for carbon emissions (Mikayilov et al., 2018) (Figure 2), it is easy to find that the faster the relative increase in carbon emissions, the less likely it is that economic carbon emissions will be decoupled. Only when the growth of carbon emissions slows, the economy will transition to a weak decoupling state. Furthermore, only when carbon emissions begin to decline will there be a strong decoupling between economic growth and carbon emissions. Therefore, it is important to understand which factors drive the growth of carbon emissions. This paper takes carbon emissions as the explained variable, chooses appropriate indicators to explain the reasons affecting carbon emissions.

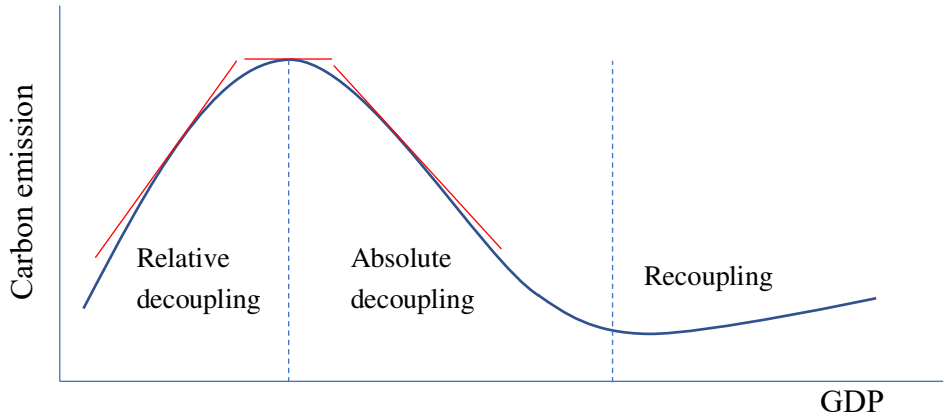


Fig.2 Carbon Emission Kuznets Curve (Mikayilov et al., 2018）

As for the selection of explanatory variables, we start with the decoupling formula itself. Base on formulas (1) to (3) in the Online Resource 1[4], it can be seen that the

[4] Online Resource 1 gives a description of the decoupling model.

decoupling index of carbon emissions is related to energy-carbon emission elasticity and GDP-energy consumption elasticity, and the two elasticities are affected by energy structure and energy intensity respectively. On the one hand, the higher the energy intensity (energy consumption per unit of GDP) of an economy, the greater its carbon emissions will generally be. On the other hand, it can be seen from Table 1 that there are differences in the carbon emission coefficients of various energy sources. In particular, the carbon emission coefficients of raw coal and coke are significantly higher than other types of fossil energy. Therefore, if the proportion of fossil energy such as coal and coke in an economy is higher, its carbon emissions tend to be greater. Based on the above considerations, this article first establishes the following basic model：

$$ln\, qc_{\mathrm{it}} = \beta_0 + \beta_1 ln\ \mathrm{inte}_{it} + \beta_2 \mathrm{stru}_{it} + u_i + \varepsilon_{it} \quad (5)$$

Where, *qc* represents the amount of carbon emissions, *inte* represents energy intensity, *stru* represents energy structure, *u* is individual effect, and *ε* is error term; the logarithm form is used to reduce the influence of heteroscedasticity.

Meanwhile, we extend the above basic model based on the Kaya identity formula. According to Tu et al. (2014), Wang (2017), carbon emissions are decomposed into several factors such as emission coefficients, energy structure, energy intensity, GDP per capita, and population size, etc. Among them, GDP per capita and population size are new influencing factors for the basic model, the relationship between the two and environmental impact has been extensive studied. According to Zhu et al. (2010), per capita GDP represents the level of national income, which directly affects the consumption level, and consumption is one of the “troikas” that drive economic growth and an important source of carbon emissions. And in the viewpoint of Moutinho et al. (2015), population size is also an important factor affecting environment quality. The larger the population of an economy, the more direct and indirect energy consumption

will be, thus leading to more increase in carbon emissions. Based on the above viewpoints, we further take per capita GDP and population size into consideration and expand the basic model to:

$$ln\, qc_{\mathrm{it}} = \beta_0 + \beta_1 ln\ \mathrm{inte}_{it} + \beta_2 \mathrm{stru}_{it} + \beta_3\, ln\, \mathrm{gdppr}_{\mathrm{it}} + \beta_4 ln\ \mathrm{p}_{\mathrm{it}} + u_i + \varepsilon_{it} \quad (6)$$

Where, *gdppr* and *p* represent per capita GDP and population size respectively. However, one important factor in terms of technological progress was not considered in the research of Tu et al. (2014) or Wang (2017). Fisher-Vanden and Wing (2008) argued that technological progress has carbon emission reduction effect while driving faster economic growth. Shuai et al. (2017) used a SPIRPAT model to decompose carbon emission into three factors in terms of population size, affluence per capita and technological progress, and they found that technology progress was the second most important key factor (the first was GDP per capita) affecting carbon emission. It is easy to find that the SPIRPAT model and the Kaya approach have some common decomposition factors, but the former also possesses technological progress while the latter doesn't. Thus, we combine the SPIRPAT model and the Kaya approach and add technological progress into Formula (6) as an extension, research and development (R&D) investment is employed as a proxy variable, see Formula (7).

$$ln\, q_{\mathrm{it}} = \beta_0 + \beta_1 ln\ \mathrm{inte}_{it} + \beta_2 \mathrm{stru}_{it} + \beta_3\, ln\, \mathrm{gdppr}_{\mathrm{it}} + \beta_4 ln\ \mathrm{p}_{\mathrm{it}} + \beta_5 ln\, \mathrm{rd}_{\mathrm{it}} + u_i + \varepsilon_{it} \quad (7)$$

Where, *rd* represents R&D. It is worth noting that China's environmental regulation has become increasingly strict in recent years. Relevant studies have shown that due to the homology of air pollutants and carbon dioxide, measures for the control of local air pollutants also has the effect of synergistically reduction of carbon emissions (Gao et al., 2014). Therefore, we choose the proportion of environmental protection

investment in GDP to measure the intensity of environmental regulation, and further expands formula (7) to:

$$ln\, qc_{\mathrm{it}} = \beta_0 + \beta_1 ln\ \mathrm{inte}_{it} + \beta_2 \mathrm{stru}_{it} + \beta_3\, ln\, \mathrm{gdppr}_{\mathrm{it}} + \beta_4 ln\ \mathrm{p}_{\mathrm{it}} + \beta_5 ln\ \mathrm{rd}_{\mathrm{it}} + \beta_6 ln\ \mathrm{iep}_{\mathrm{it}} + u_i + \varepsilon_{it} \quad (8)$$

Where *iep* represents the proportion of environmental protection investment in GDP. In summary, this article uses formulas (5) ~ (8) to analyze the influencing factors of carbon emissions, the main variables involved are as follows:

Table 2 Definition and description of the variables

Variable name	Symbol	Definition/Description
Amount of carbon dioxide emission	*qc*	See Formula (4)
Intensity of energy consumption	*inte*	Total energy consumption /Actual GDP
Structure of energy consumption	*stru*	Terminal consumption of fossil energy/Consumption of total energy
GDP per capita	*gdppr*	Total GDP of the province/total population
Population	*p*	/
R&D investment	*rd*	/
The proportion of environmental protection investment in GDP	*iep*	environmental protection investment /GDP

4.1.2 Modal screening

In equation (8), only the main driving factors are controlled. However, for individual province, there are generally variables that do not change with time but vary with individuals, which are difficult to observe, such as endowments (resources, locations, cultures, etc.) in various regions, which may be constant in a certain period of time but are closely related to each explanatory variable. Loss of these variables will lead to inconsistency in the estimation results. The individual effects of these missing variables are further divided into fixed effects and random effects. If these missing variables are related to explanatory variables, it is necessary to examine the individual fixed effects or time-fixed effects. If they are not related to explanatory variables,

random effects should be examined. Correspondingly, if there is no individual effect, it may be necessary to examine the mixed effect, that is, the entire panel model is regressed as a cross-sectional model.

The test process for model screening is as follows: first, the fixed effect and the mixed effect are compared and it is found that the fixed effect is more suitable than the mixed model through F test, it turns out that the value of the F statistic is 42.51, and the corresponding P value is less than 0.001, so the null hypothesis (H0: establish a mixed model) is rejected, and the individual effect is considered. On this basis, the HAUSMAN test is used to further compare individual fixed effects and individual random effects. The results are as follows:

Table 3 Results of HAUSMAN test

	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
lninte	0.769	0.559	0.210	0.059
stru	3.942	4.133	-0.190	0.055
lngdppr	0.940	0.883	0.056	0.053
lnp	0.674	0.769	-0.095	0.221
lnrd	0.116	0.079	0.037	0.029
iep	0.039	0.060	-0.021	.
chi2(6)= (b-B)'[(V_b-V_B)^(-1)](b-B) = 20.76			Prob>chi2 = 0.0020	

As can be seen from the above table, the value of the HAUSMAN test statistic chi2 is 15.80, and the corresponding p value is 0.0149, rejecting the null hypothesis (H0: establishing an individual random effects model), thus fixed effect is selected to carry out regression analysis.

4.2 Data explanation

The data involved in the decoupling analysis are mainly carbon emissions and GDP of 30 provinces in China from 2000 to 2016. The carbon emissions are calculated

by the author based on Formula (4). According to Formula (4), the specific data required include: various energy consumption E_i, conversion factor NCV_i for converting energy into standard coal, and carbon emission coefficient F_i of various energy sources. Among them, E_i corresponds to 8 types of energy such as raw coal, coke and crude oil, see Table 1, the data comes from China Energy Statistical Yearbook[5]. Data of NCV_i and F_i come from "2006 IPCC Guidelines for National Greenhouse Gas Inventories". Data of nominal GDP come from EPS database[6] supplemented according to China Statistical Yearbook[7]. Since actual GDP is used for analysis, we need to convert it to actual GDP. Specifically, using 2000 as the base period and based on the indicators of gross domestic product, we convert nominal GDP into actual GDP. The data of indices of gross domestic product (Last year=100) also comes from China Statistical Yearbook[5].

Indicators involved in the econometric model are shown in Table 2, where the carbon emission data is the same as the decoupling analysis. Data of other indicators such as intensity of energy consumption, GDP per capita, population, R&D investment, proportion of environmental protection investment in GDP come from the EPS database, also are supplemented according to China Statistical Yearbook. The calculation method of each indicator is shown in Table 2. It is worth noting that the energy structure is measured by the ratio of terminal consumption of fossil energy to the consumption of total energy, where fossil energy refers to the 8 types of energy in Table 1, their consumption data are from China Energy Statistical Yearbook, data of total energy consumption is also from the same source. Descriptive statistical characteristics of the

[5] National Bureau of statistics of China (NBSC). China Energy Statistics Yearbook. Beijing, China Statistics Press: 2001-2017.

[6] The EPS China Data. China Macroeconomic Database, China Science and Technology Database & China Energy Database, retrieved January 16, 2019. available from: http://www.epschinadata.com/

[7] National Bureau of statistics of China (NBSC). *China Statistical Yearbook*. Beijing, China Statistics Press: 2008-2017.

data are as follows:

Table 4 Statistical description of the variables

Variable	Sample	Mean value	Standard deviation	Least value	Maximum value
qc	510	251.91	225.26	0.81	1552.01
inte	509	1.95	3.46	0.27	29.53
stru	510	0.71	0.09	0.00	0.87
gdppr	510	29281.90	22973.96	2759.00	118198.00
p	510	4379.57	2640.65	517.00	10999.00
rd	510	2099668.00	3286476.00	8306.00	20400000.00
iep	510	1.30	0.68	0.30	4.24

5. Results

5.1 Results of the regression

The above analysis shows that decoupling has been making progresses in most of the Chinese provinces through reducing carbon emission speed and intensity. However, some provinces have experienced expensive negative decoupling, meanwhile, we are still far from the meeting the goal predetermined in the "Sino-US Joint Statement on Climate Change", so it is very necessary to explore which factors have a critical impact on China's carbon emissions, so as to provide a scientific basis for further carbon emissions reduction. Thus, amount of carbon emission is taken as the explained variable and several indicators such as intensity of energy consumption, GDP per capita, et al. (see Table 2) are selected as the explanatory variables to carry out the regression analysis. The logarithm of the variables (except for “stru” and “iep” which are essentially ratios) is used to reduce the effect of heteroscedasticity. Results are presented in Table 5, where Column (1) ~ (4) are directly corresponded to Function (5) ~ (8) respectively. Meanwhile, in Column (5) we controlled “area” effect and in Column (6) we controlled time effect, both regressions are also based on Function (8).

Table 5 Regression results of econometric model

	(1)	(2)	(3)	(4)	(5)	(6)
lninte	-1.367***	0.821***	0.783***	0.769***	0.524***	0.762***
	[0.1189]	[0.1262]	[0.1184]	[0.1307]	[0.1546]	[0.1560]
stru	5.375***	3.828***	3.879***	3.942***	4.173***	4.015***
	[1.1919]	[0.3972]	[0.3827]	[0.3524]	[0.4114]	[0.3836]
lngdppr		1.127***	0.949***	0.940***	0.877***	1.086***
		[0.0608]	[0.1519]	[0.1733]	[0.1645]	[0.3248]
lnp		0.855*	0.629	0.674	0.925***	0.875
		[0.4863]	[0.5607]	[0.4997]	[0.1070]	[0.7608]
lnrd			0.121	0.116	0.0655	0.127
			[0.1017]	[0.0945]	[0.0782]	[0.0758]
iep				0.0392	0.0603	0.0348
				[0.0870]	[0.0887]	[0.0852]
Individual fixed effect	Y	Y	Y	Y	N	Y
Regional fixed effect	N	N	N	N	Y	N
Time fixed effect	N	N	N	N	N	Y
_cons	1.656*	-15.94***	-13.99***	-14.28***	-15.24***	-17.52**
	[0.8311]	[4.0975]	[4.7764]	[4.3423]	[1.6114]	[8.4864]
N	510	510	510	510	510	510

Note: * p < 0.1, ** p < 0.05, *** p < 0.01；Standard errors in brackets.

The results in Table 5 show that: the sign of *inte* is generally positive, indicating that as the intensity of energy consumption increases, carbon emissions will also increase. The sign of *stru* is positive, indicating that the higher the proportion of fossil energy consumption in the total energy consumption, the greater the carbon emissions. The sign of *gdppr* is positive, indicating that as the income level of the economy increases, carbon emissions are also increasing. The positive sign of *p* is also in line with our expectation that the larger the population, the more carbon emissions. The sign of *rd* is positive, indicating that the more R&D investment, the more carbon emissions (this is not in line with people's expectations). The sign of *iep* is positive, indicating that environmental governance investment has failed to reduce carbon emissions (also is not in line with people's expectations). In terms of statistical significance, *inte*, *stru*, and *gdppr* are all highly significant among the 6 regressions, *p* is significant in Column (2)

and (5), while *rd* and *iep* are not significant in each regression.

Comparing the 6 regressions, *inte* in Column (1) is negative and do not meet people's expectations may be due to the fact that we used Equation (5) for regression, which, as a basic equation, missed some important variables. While the remaining five regressions are basically consistent in sign and significance level, indicating that it is necessary to extend the basic model, and also demonstrate the rationality of choosing explanatory variables based on the Kaya and SPIRPAT frameworks. Since the regression in Column (6) considers all explanatory variables and also controls the individual and time fixed effects, we interpret the regression results based on Column (6) as follows:

First，significant positive effects of energy intensity and energy structure are in line with peoples' prior knowledge: the higher the energy intensity and the larger the proportion of fossil energy are, the more carbon emission is. From the perspective of regression coefficients, while controlling other factors unchanged (the same below), for every 1% increase in energy intensity, carbon emissions will increase by 0.762%, this shows that energy intensity is an important factor influencing carbon emissions, which is consistent with the conclusions of many researchers (Chang et al.,2019; Huang et al., 2020; Nguyen et al., 2020). However, unlike the above researches, we also find that the impact of energy structure is more significant than energy intensity, that is: for every unit (1%) increase in energy structure (the proportion of fossil energy), carbon emissions will increase by 4.015%. This result is consistent with China's coal-based energy structure. Statistics show that coal accounted for more than 70% of China's energy consumption, which resulted in much higher carbon dioxide emissions than many developed countries (Hu et al., 2017). Fortunately, as China is promoting the adjustment of energy structure, the share of coal energy has gradually declined.

According to the "China Energy Big Data Report (2020)" released by the National Energy Information Platform, the proportion of coal consumption in China's total energy consumption has dropped from 70.2% to 57.7% during 2011 and 2019, and it will further decrease in the future. Therefore, as the proportion of coal consumption decreases, it is expected to have a significant carbon reduction effect.

Second, every 1% increase in per capita GDP will induce 1.086% increase in carbon emission, indicating that the impact of economic growth on carbon emissions is still dominated by a positive increase. Meanwhile, for every 1% increase in population size, carbon emissions will increase by 0.875% (not statistically significant). Obviously, the impact of per capita GDP is more significant than population size, which is consistent with the research conclusion of Chang et al (2019). In particular, if the carbon emission Kuznets hypothesis is also valid in China (Feng et al., 2017; Wang et al., 2018), the positive impact of per capita GDP means that China’s carbon emissions have not yet reached its peak, and since China's per capita GDP is still below the global average, it is expected that the positive impact of per capita GDP on carbon emissions will continue for some time.

Third, the proportion of environmental protection investment in GDP (*iep*) is used to represent environmental regulation, however, its result is not statistically significant, and the sign is positive, which do not seem to meet people's expectations. However, there were similar conclusions made in previous studies, for example, Xu and Liu (2016) studied the relationship between environmental protection investment and COD emissions, they found that the two are positively correlated indicating that environmental protection investment does not substantially reduce COD emissions. In this study, one reason for the unideal result of *iep* may be because it is not a suitable proxy variable for environmental regulation. However, there is currently no clear

definition of the intensity of environmental regulations, especially for carbon emissions (Kuai et al., 2019). Therefore, we can only use *iep* to indirectly represent the intensity of environmental regulations. However, China's environmental protection investment involves a wide range of content, including industrial and regional pollution prevention, environmental infrastructure (such as urban sewage treatment plants) construction, and environmental protection agency capacity building (Lu et al.,2010), while carbon reduction is only part of the content. In addition, although China's investment in environmental protection has been increasing in recent years, the scale is still relatively small, and utilization efficiency needs to be improved (Jie et al., 2010). For example, Jia and Zheng (2014) compared the utilization of environmental protection investment in China and the United States and found that in 2000, *iep* in the United States reached more than 2%, while China only reached 1.59% in 2012[8], they also pointed out various problems in China such as narrow sources of funds for environmental protection, irrational investment structure, and low investment efficiency. For the above reasons such as small investment scale, unreasonable structure, low utilization effect, etc., it is no wonder that the coefficient of *iep* is not significant in the regression of carbon emissions.

Fourth, like environmental investment, the coefficient of technology investment (*rd*) is also not significant, and the sign (positive) does not seem to meet people's expectations. Because it is generally believed that R&D investment will improve energy efficiency through technological advancement, thereby reducing carbon emissions (Nguyen et al., 2020). However, the research of Wang and Wang (2019) pointed out that the increase in R&D investment has increased carbon emissions. They

[8] We further searched through the EPS database and found that the proportion China's overall environmental protection investment in GDP has decreased since 2013. It was 1.67% in 2013 and had been gradually reduced to 1.15% in 2017 (Source: EPS DATA).

believe that the possible reason lies in the imperfect market development and the lack of relevant laws and regulations, leading to repeated R&D and low-level development that is relatively common in China and has not played a good role in reducing emissions. Churchill et al. (2019) studied the R&D effects on CO2 emission in Group of Seven (G7) countries and pointed out that the influence was time-varying, R&D had a positive impact in a quarter of the study period (1870-2014). Huang et al. (2020) believe that the impact of heterogeneous R&D on carbon emissions should be considered. As Kuai et al. (2019) pointed out that technology research could be divided into product type and environmental protection (green) type, the former may not have the same effects on pollution reduction. However, due to imperfect statistical method and caliber, it is difficult to distinguish the R&D of product type and green type. This is a direction that we need to improve in the future.

In summary, the impact of each indicator could be ranked based on the influence on carbon emission, the proportion of fossil energy is most worthy of our attention, followed by GDP per capita and energy intensity. Since the coefficients of population size, R&D investment, and environmental protection investment are not significant, we cannot rank them like energy structure, GDP per capita, etc.

5.2 Robustness analysis

5.2.1 Dynamic panel regression

Considering that there may be a time series correlation between carbon emissions in each period, we perform dynamic panel regression on equation (8) to test the robustness of the results in Section 4.2, the first-order lag terms of *rd* and *iep* are added in the regression to consider possible lag effects, results are shown in Table 6. Where,

Column (1) corresponds to OLS regression (as comparison base), Columns (2) ~ (4) correspond to generalized method of moments (GMM) regression. Differences between Columns (2) ~ (4) are as follows: (2) uses all lag items of L.*lnqc* as gmm-type instrumental variables (IVs), (3) adds the "collapse" command to optimize the number of IVs, (4) further uses the lag terms of *lnrd* and *iep* as gmm-type IVs, and their lags of 2 to 5 orders are considered.

Table 6 Results of dynamic panel estimation results

	OLS	GMM		
	(1)	(2)	(3)	(4)
L.lnqc	0.638***	0.619***	0.607***	0.373***
	[0.0440]	[0.1066]	[0.1046]	[0.0461]
L2.lnqc	0.0964**	0.0881	0.0653	0.214**
	[0.0416]	[0.0933]	[0.0952]	[0.0925]
lninte	0.0419**	0.0505	0.0622	0.0661
	[0.0167]	[0.0488]	[0.0557]	[0.0642]
stru	1.314***	1.628***	2.054***	2.140***
	[0.1270]	[0.5431]	[0.5804]	[0.5391]
lngdppr	0.153***	0.164*	0.210**	0.338*
	[0.0462]	[0.0850]	[0.0951]	[0.1688]
lnp	0.261***	0.275***	0.306***	0.460***
	[0.0352]	[0.0975]	[0.1035]	[0.1478]
lnrd	0.024	0.0847	0.022	-0.532
	[0.1041]	[0.0962]	[0.0954]	[0.6322]
L.lnrd	-0.0585	-0.114	-0.0583	0.442
	[0.1003]	[0.0940]	[0.0931]	[0.5573]
iep	0.0825***	0.0845**	0.0868**	0.13
	[0.0247]	[0.0384]	[0.0415]	[0.0933]
L.iep	0.0660**	0.063	0.0449	0.0741
	[0.0256]	[0.0406]	[0.0375]	[0.0659]
Time fixed effect	Y	Y	Y	Y
_cons	-2.984***	-3.237**	0	-5.438***
	[0.4631]	[1.3711]	[.]	[1.8009]
N	450	450	450	450

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Standard errors in brackets.

The above regression results show that the signs of the coefficients in the 4 regressions are consistent (except for *lnrd* and L.*lnrd* in column (4)), and they are also

consistent with the results in Table 5. In particular, the sign of L.*lnrd* is negative, indicating that there is a lag effect in R&D. From the perspective of statistical significance, the significance levels of the variables in the three GMM regressions are basically consistent. Compared with the results in Table 5, *stu* and *gdppr* are still significant, *rd* is still insignificant, but *inte* changes from significant to insignificant, *p* and *iep* from insignificant to significant. Judging from the ranking of the effects of each explanatory variable, *stru* is still the most prominent factor, followed by *gdppr*. In general, although the significance level of some indicators has changed, from the perspective of the signs of regression coefficients and the ranking of impact factors, the regression results of GMM and Table 5 are consistent. Therefore, it can be concluded that the results of main explanatory variables such as *stru*, *gdppr* are robust.

It should be noted that dynamic panel regression needs to satisfy the assumption that the error term sequence is not correlated, and meanwhile the IVs are not over-identified. In this paper, the Arrellano-Bond method is used to test the hypothesis of serial uncorrelation (H_0: the disturbance term of the differential model is not serially correlated), and the Hanson method is used to test the validity of IV (H_0: IV is not correlated with the error term), results are shown in Table 7, We can find that all three GMM regressions pass the corresponding test.

Table 7 Results of serial uncorrelated test and IV validity test

Regression model	Serial uncorrelated test		IV validity test		
	AR(1)	AR(2)	chi2(130)	chi2(12)	chi2(9)
GMM (2)	-2.38	-0.89	4.07		
	（0.017）	（0.372）	(1.000)		
GMM (3)	-2.37	-0.77		4.38	
	(0.018)	(0.443)		(0.976)	
GMM (4)	-1.80	-1.68			95.79
	(0.072)	(0.093)			(<0.001)

Note:1. GMM (2), GMM (3) and GMM (4) correspond to Column (2), (3) and (4) in Table 7, respectively; 2. P-value in brackets.

5.2.2 PCSE and FGLS regression

When using panel data for econometric analysis, the random error term of the model should meet the classic OLS assumptions, however, problems such as groupwise heteroscedasticity, cross-sectional correlation, and AR(1) serial correlation are quite often, if the model parameters are directly estimated, the result will be biased and inconsistent (Jiang et al., 2015). The commonly used methods to cope with the above problems are feasible generalized least squares (FGLS) estimation and panel corrected standard errors (PCSE) estimation (Zhao and Sui, 2015). The FGLS method substitutes the residual vector of each cross-section individual into the covariance matrix of cross-section heteroscedasticity, and uses GLS to obtain parameter estimates. This method can correct the problems of heteroscedasticity, contemporaneous correlation and sequence correlation exist in cross-sectional data, and improve the consistency and effectiveness of panel regression (Jiang et al., 2015). However, it is argued that FGLS method sometimes perform poorly in finite samples, particularly with respect to estimating standard errors SE (Chen et al., 2010). Beck and Katz (1995) proposed an alternative, two-step estimator (PCSE estimator) to make an improvement. In the first step, the data are transformed to eliminate serial correlation; in the second step, ordinary least square is applied to the transformed data, and the SE are corrected for cross-sectional correlation (Berk and Katz, 1995). Due to this advantage, PCSE is often deemed as the most suitable estimator when dealing with cross-sectional dependence (Gaspar et al., 2017).

This paper uses both PCSE and FGLS to estimate equation (8), meanwhile, time trend effect is controlled. It should be noted that the two estimates are usually applied to long panel data, however, subjecting to data availability constraints, we can only randomly select 35% of the samples (by province) for the regression. Twice random samplings are performed for each estimate to observe the robustness of the estimated results. It is worth noting that before using PCSE and FGLS estimators, we need to test for heteroscedasticity, cross-sectional correlation, and AR (1) serial correlation. The test results are shown in Table 8. It can be seen from this result that it is appropriate to use PCSE and FGLS for estimation. Results of the PCSE and FGLS for estimation are shown in Table 9.

Table 8 Model test for PCSE and FGLS for estimation

Test items	H0	Statistics	P-value	Conclusion
AR(1) serial correlation	No first-order autocorrelation	F(1,29)=17.505	0.0002	Reject H0
Heteroscedasticity	sigma(i)^2= sigma^2 for all i	chi2(30)=12137.52	<0.001	Reject H0
Cross-sectional correlation	No cross-sectional correlation	chi2(36)= 157.520 chi2(45)= 149.486	<0.001 <0.001	Reject H0

Note: The cross-sectional autocorrelation test needs to use a long panel. Therefore, 35% of samples are randomly selected from all provinces and cities to form the long panel. A total of two random samplings are performed, so there are two corresponding tests.

Table 9 Results of the PCSE and FGLS for estimation

	ols	xtpcse		xtgls	
	(1)	(2)	(3)	(4)	(5)
lninte	0.753***	0.869**	0.644	-0.110**	-0.145*
	[0.0947]	[0.4093]	[0.4263]	[0.0490]	[0.0811]
stru	3.942***	3.257***	3.872***	2.892***	2.867***
	[0.2023]	[0.5068]	[0.9510]	[0.0943]	[0.2877]
lngdppr	0.976***	1.483***	1.334***	0.805***	0.849***
	[0.1191]	[0.4090]	[0.4067]	[0.0813]	[0.0945]
lnp	0.732***	2.026**	3.425***	-0.371*	0.481**
	[0.2644]	[0.9819]	[0.9981]	[0.2124]	[0.2326]

lnrd	0.126*	-0.111	0.0667	0.117***	0.203***
	[0.0651]	[0.1770]	[0.2292]	[0.0357]	[0.0475]
iep	0.0393	-0.109	-0.123	-0.00557	-0.00771
	[0.0260]	[0.0716]	[0.0847]	[0.0098]	[0.0143]
Individual fixed effect	Y	Y	Y	Y	Y
Time trend	Y	Y	Y	Y	Y
_cons	-15.79***	-30.32***	0	-3.234	-10.63***
	[2.4955]	[11.5795]	[.]	[2.0602]	[2.3115]
N	510	187	170	187	170

Note: * p < 0.1, ** p < 0.05, *** p < 0.01；Standard errors in brackets；Column (2) and (4) correspond to the first random sampling. The ids of selected provinces and cities include: id1, id4, id8, id11, id14, id16, id17, id20, id24, id27, and id28; Column (2) and (4) correspond to the second random sampling, The ids of selected provinces and cities include: id2, id3, id4, id8, id11, id15, id17, id18, id23 and id25.

Compared with the results in Table 5, the regression results in Table 9 show that *rd* has changed from insignificant to significant in several regressions (Column (4) and (5)), but the sign remains the same; *iep* changes from a positive sign to a negative sign, but the significance remains the same; the symbol of *inte* has changed in several regressions (Column (4) and (5)), but the significance remains unchanged. The possible reasons for the above-mentioned changes include: using new method of PCSE and FGLS to correct cross-sectional correlation, heteroscedasticity, and serial correlation of the error term, meanwhile, random sampling leads to a reduction in sample size. In general, the results in Table 9 are consistent with that in Table 5: *stru* is still the most important driving factor, followed by *gdppr*; the positive symbol of *rd* and the insignificance of *iep* indicate that R&D investment and environmental protection investment failed to effectively reduce carbon. Based on the above consistency, we conclude that the results of the main variables such as *stru* and *gdppr* are still robust.

5.2.3 LMDI decomposition

LMDI decomposition is another commonly used method for identifying the factors affecting CO_2 emissions (Chang et al., 2019), we compare its results with that of the

regression for further robustness test. According to Ang(2015)[9], we decompose the variation of Carbon emission ($\triangle C$) into four parts according to the change rate of energy structure ($\triangle C_{CI}$), energy intensity ($\triangle C_{EI}$), per capita GDP ($\triangle C_{GDPpr}$) and population size ($\triangle C_P$), respectively. It is worth noting that, according to the decomposition framework of Ang (2015), we cannot examine the share of changes in carbon emissions corresponding to energy structure factors. The LMDI decomposition results based on national samples are shown in Table 11.

Table 11 Decomposing effect of various driving factors

Time	$\triangle C$	$\triangle C_{CI}$	$\triangle C_{EI}$	$\triangle C_{GDPpr}$	$\triangle C_P$
2000-2001	132.02	88.20	-317.02	338.49	22.36
2001-2002	354.68	-67.74	57.84	342.26	22.31
2002-2003	669.57	158.73	-63.76	550.79	23.81
2003-2004	638.17	-112.71	-105.88	829.64	27.13
2004-2005	862.17	152.37	-223.21	901.40	31.61
2005-2006	440.53	-149.13	-348.27	906.13	31.81
2006-2007	313.69	-284.33	-575.04	1139.97	33.10
2007-2008	922.85	522.56	-828.52	1193.18	35.64
2008-2009	667.62	228.32	-269.31	670.57	38.04
2009-2010	981.35	234.50	-796.12	1501.60	41.38
2010-2011	1141.13	357.43	-917.85	1655.10	46.45
2011-2012	288.88	-214.68	-531.54	983.49	51.61
2012-2013	678.88	1072.70	-1432.88	985.41	53.65
2013-2014	90.39	-233.81	-531.23	796.68	58.75
2014-2015	-227.05	-413.50	-427.77	558.58	55.64
2015-2016	116.69	-92.25	-635.46	778.89	65.52

[9] According to Ang(2015), $\triangle C=\triangle C_{CI}+\triangle C_{EI}+\triangle C_{GDPpr}+\triangle C_P$, the four items on the right side are corresponding share of $\triangle C$ according to the change rate of carbon emission intensity, energy consumption intensity, GDP per capita and population, respectively, where,

$$\begin{cases} \triangle C_{CI}=L(C^T,C^0)\ln\left(\frac{CI^T}{CI^0}\right)=\frac{C^T-C^0}{\ln C^T-\ln C^0}\ln\left(\frac{CI^T}{CI^0}\right) \\ \triangle C_{EI}=L(C^T,C^0)\ln\left(\frac{EI^T}{EI^0}\right)=\frac{C^T-C^0}{\ln C^T-\ln C^0}\ln\left(\frac{EI^T}{EI^0}\right) \\ \triangle C_{GDPpr}=L(C^T,C^0)\ln\left(\frac{GDPpr^T}{GDPpr^0}\right)=\frac{C^T-C^0}{\ln C^T-\ln C^0}\ln\left(\frac{GDPpr^T}{GDPpr^0}\right) \\ \triangle C_P=L(C^T,C^0)\ln\left(\frac{P^T}{P^0}\right)=\frac{C^T-C^0}{\ln C^T-\ln C^0}\ln\left(\frac{P^T}{P^0}\right) \end{cases}$$

Summation	8071.58	1246.65	-7946.02	14132.16	638.79

As we mentioned earlier, the essence of LMDI decomposition is to "distribute" changes in carbon emissions according to certain principles ($\triangle C = \triangle C_{CI} + \triangle C_{EI} + \triangle C_{GDPpr} + \triangle C_P$), which is the rate of change of each indicator. Based on Table 11, it could be found that GDP per capita possesses the largest share of carbon emissions change, and its value is positive, which means that GDP per capita has been increasing during the study period, thus always getting a positive share. Energy intensity follows closely, its value is negative for most of the period, this is because China's energy intensity continued to decrease during the study period. After that, it is energy-carbon emission intensity and population size. The above ranking is generally consistent with the regression results of Table 5, which indirectly demonstrates the robustness of the regression results.

5.3 Further analysis: consistency between the factors and decoupling

Through the above regression, we have found that energy structure, per capita GDP and energy intensity are the key factors affecting carbon emissions. To further identify the relationship between these factors and decoupling, we will analyze their trends over time & region to observe whether they are consistent with the decoupling changes; regional economic development will also be concerned during the analyses.

First, we draw Figure 3 to show the trend of the factors in the time dimension. By comparing the trends with that in Table 1, it is found that the factors keep pace with decoupling in the three-time intervals, namely, 2001-2005, 2006-2011 and 2012-2016. In general, China’s energy consumption structure and intensity have shown a steadily decreasing trend, while per capita GDP has shown a steadily increasing trend, which means a progress in sustainable development. Specifically, the median energy

consumption structure decreased from 0.73 in 2001-2005 to 0.68 in 2012-2016 (a decrease of 6.8%); in the same period, the median energy consumption intensity decreased from 1.5 tce per 10,000 CNY to 0.6 (a decrease of 60%); and the median per capita GDP increased from 8929.9 CNY per person to 42062.4 (an increase of 371.0%). Although China has made great progress, there is still a lot of room for improvement. According to the statistics of Global Energy Statistical Yearbook 2020[10], China's energy consumption intensity in 2019 is 0.128 koe/$2015p, but there is a big gap when compared to advanced economies, for example, United Kingdom (0.059 koe/$2015p), etc. At the same time, China's absolute per capita level is still low. According to the "World Economic Outlook Database[11]" released by the International Monetary Fund (IMF) in October 2019, China's per capita GDP ranks 65th in the world, which is far behind developed countries. However, from another perspective, this also means a "late-mover advantage", if China continues to make more progress in the economic and energy fields, there would be great potential for further decoupling.

Second, the aforementioned impact factors not only change over time, but also have differences over regions. Based on the decoupling results in Table 1, we select 9 typical provinces for further analysis. Among them, Beijing, Tianjin and Shanghai are economically developed regions; Jilin, Heilongjiang, Shandong and Hunan are moderately developed regions; Qinghai and Xinjiang are underdeveloped regions. The trends of each factor over the typical regions are shown in Figure 4 to Figure 6.

[10] https://yearbook.enerdata.net/total-energy/world-energy-intensity-gdp-data.html
[11] https://www.imf.org/external/chinese/index.htm

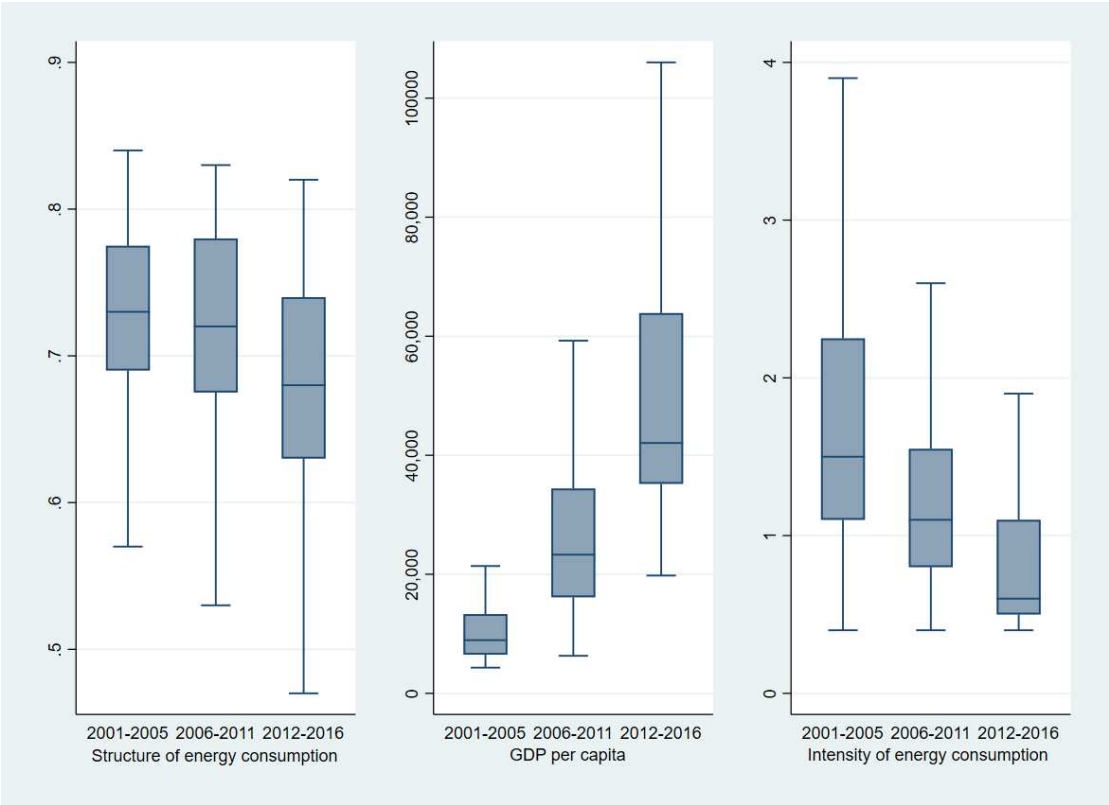
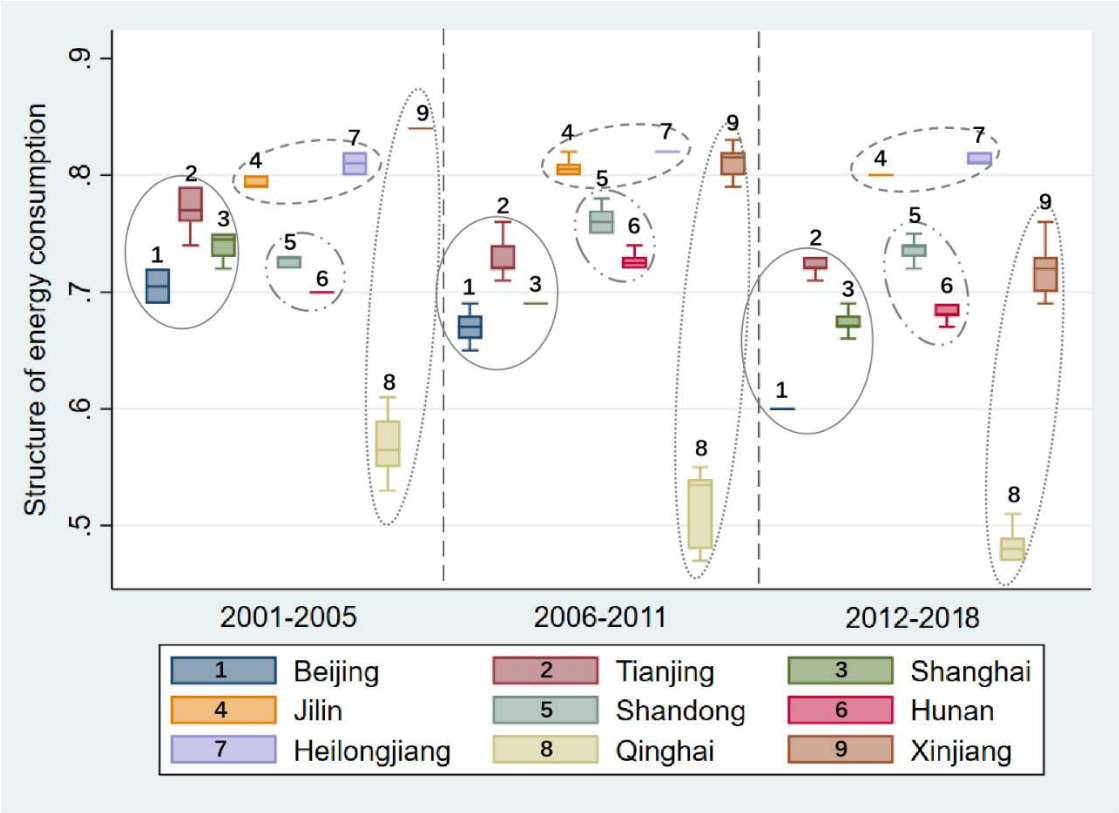


Fig.3 Trends of the three key factors over time [12]



[12] Stata MP 16 was used to create Fig.3, Fig.4, Fig.5 and Fig.6.

Fig.4 Trends of energy consumption structure over region

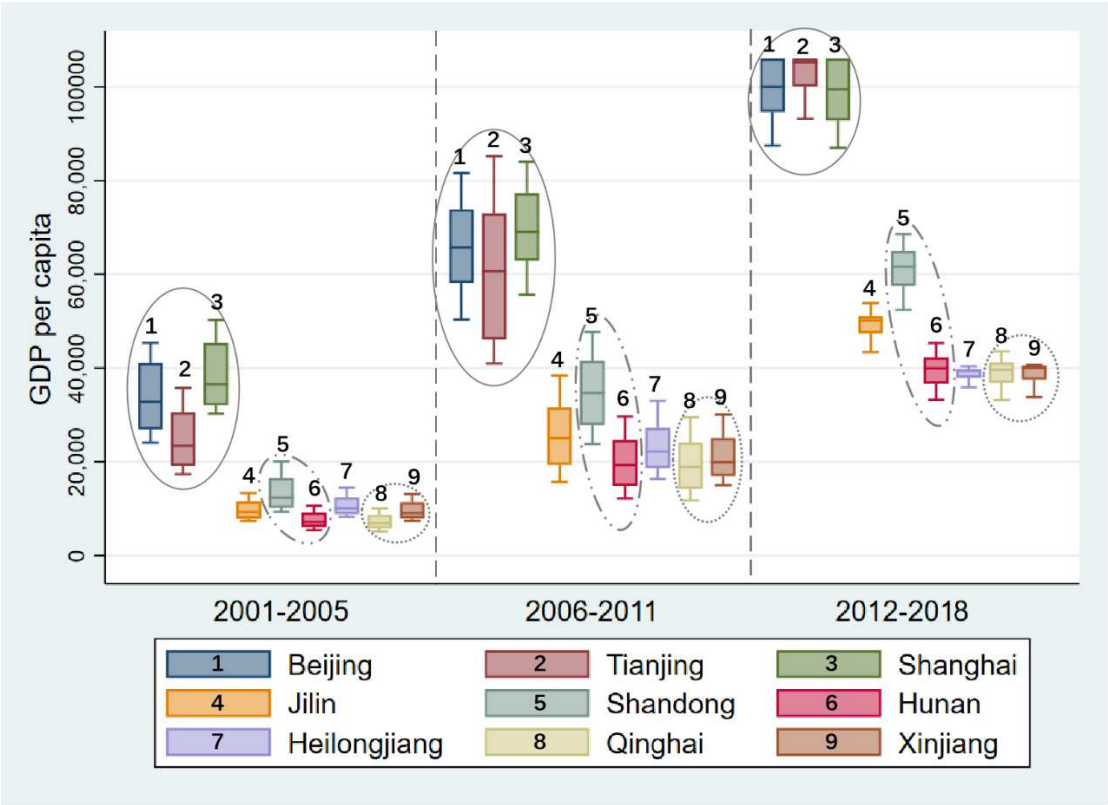


Fig.5 Trends of GDP per capita over region

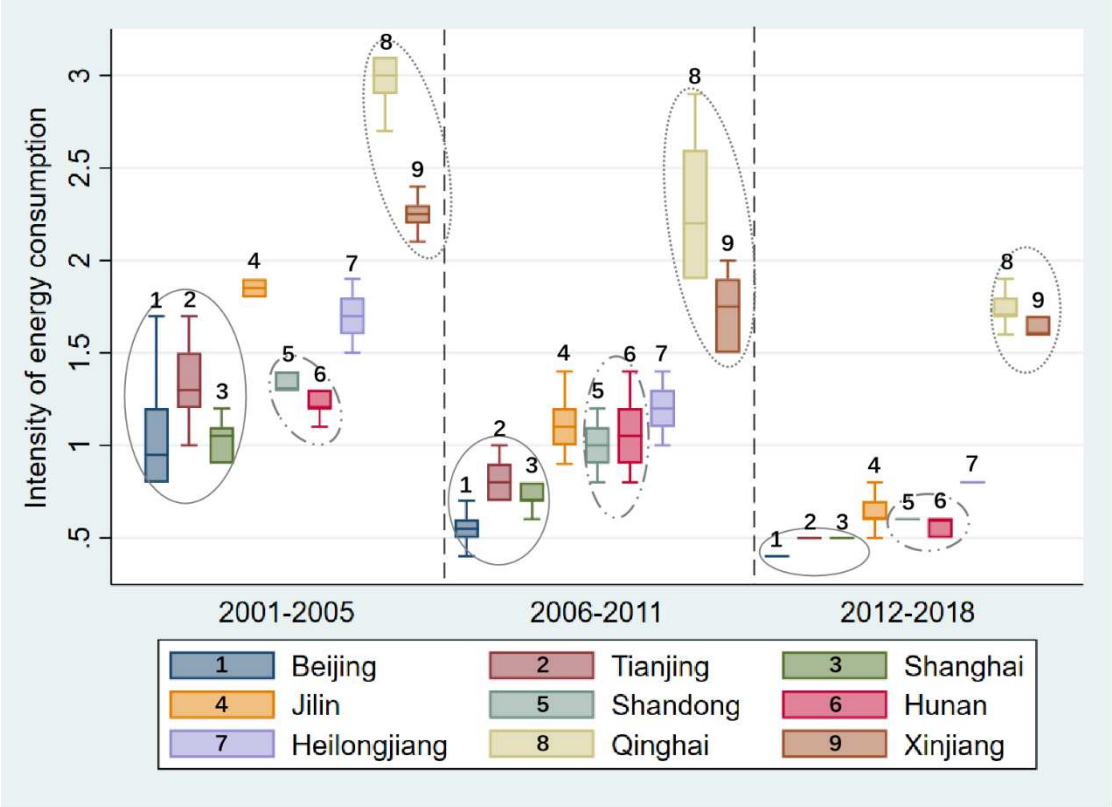


Fig.6 Trends of energy consumption intensity over region

Based on the economic features and Figure 4~6, the regions are divided into 4 groups. The first group includes economically developed regions such as Beijing, Shanghai and Tianjin. They possess high per capita GDP growth rate, at the same time, they are actively optimizing the energy consumption structure and reducing the energy intensity, thus a well decoupling status is obtained.

The second group includes the moderately developed regions such as Shandong and Hunan, which have faster economic growth and higher per capita GDP growth rate, their energy consumption intensity has also been reduced to a low level. However, as the adjustment of energy structure of Shandong is small but of Hunan is larger, Hunan has achieved a better decoupling status, but Shandong has not.

The third group includes Jilin and Heilongjiang, both belong to traditional resource-based provinces. Although the economic foundation was good, the economic growth rate has been declining in recent years (especially for Heilongjiang). Regarding the relatively high GDP per capita, the reason may not be economic growth but population loss. At the same time, adjustment of their energy structure is relatively small due to high dependence on fossil energy. Although energy consumption intensity has experienced a significant reduction, it is mainly due to the rapid economic recession, which reduces CO_2 emission and make Jilin decouples between economic growth and carbon emission (but this doesn't mean sustainable). Comparatively, Heilongjiang performs even poorer because it experiences much faster economic recession and slight increment in energy structure, which prevent it from decoupling.

The fourth includes Qinghai and Xinjiang, both belong to the underdeveloped regions with weak economic foundations in northwestern China. Due to the late-comer advantages, their per capita GDP growth rate is relatively high. Meanwhile, energy

structure and consumption intensity also fall sharply; however, this doesn't mean high energy efficiency, as we may see in Figure 6, the two possess the largest energy consumption intensity among the regions, this may be caused by the relaxation of environmental regulations because local governments face a huge challenge in terms of economic growth, making decoupling hard to achieve.

6. Conclusion and suggestion

The decoupling of economic-carbon emissions is a global hot topic, it is very important for many countries, especially some developing countries including China. They are often faced with the dual pressure of economic growth and resource environmental protection, and need to promote sustainable economic growth. In this study, based on the panel data of 30 provinces (cities) in China from 2000 to 2016, the decoupling indexes of each region are calculated with the Tapio model. It is found that many regions have progressed from no decoupling to weak decoupling and then strong decoupling, suggesting the effort of carbon reduction has achieved great results.

Then, we analyze the driving factors of carbon emissions using an econometric model. Six explanatory variables such as energy intensity, energy structure, GDP per capita, etc., are employed for the analysis, we found that energy structure is the most important factor, followed by GDP per capita and energy intensity, while the impacts of environmental protection investment and R&D investment are not significant. The results are robust when tested with methods such as GMM, PCSE and FGLS estimation and LMDI decomposition.

Further, we conduct a comparative analysis regarding the temporal and spatial characteristics of the driving factors to identify their consistency with decoupling, four groups of regions that represent different economic characteristics are selected for the analysis. By checking the trends of the driving factors and decoupling, we found a

strong consistency between them. But heterogeneity among the regions has also been observed: the economically developed regions perform well in all the three driving factors and obtain better decoupling status; the moderately developed regions should pay more attention on energy structure adjustment to maintain the decoupling status; the resource-based regions performs poorly in decoupling if their economic growth declines too rapidly and if there is too small adjustment of energy structure, the underdeveloped regions also perform poorly due to high energy intensity.

Based on these findings, it is suggested that targeted strategies be made for different regions: for the economically developed regions, focus is to consolidate the achievements in economic growth and energy management to ensure stable decoupling; for moderately developed regions, optimizing energy structure may be the most urgent task; for the resource-based regions where the economy begin to decline, the focus is on adjusting industrial structure to inspire economic growth; and for the underdeveloped regions, besides economic growth, the other focus is on improving energy efficiency to reduce energy consumption intensity.

References

Aldieri L., Makkonen T. and Vinci C. P. (2020). Environmental knowledge spillovers and productivity: A patent analysis for large international firms in the energy, water and land resources fields. Resources Policy, Vol. 69, 101877. https://doi.org/10.1016/j.resourpol.2020.101877

Ang, B.W. (2015) 'LMDI decomposition approach: A guide for implementation', Energy Policy, Vol. 86, pp.233 – 238. https://doi.org/10.1016/j.enpol.2015.07.007

Beck, N. and Katz, J.N. (2006) 'Nathaniel Beck and Jonathan N. Katz. 1995. "What to Do (and Not to Do) with Time-Series Cross-Section Data." "American Political Science

Review" 89 (September): 634-47', The American Political Science Review, Vol. 100, No. 4, pp.676-677. https://doi.org/10.2307/2082979

Chang, C.P., Dong, M.Y., Sui, B., and Chu,Y. (2019) 'Driving forces of global carbon emissions: From time- and spatial-dynamic perspectives', Economic Modelling, Vol. 77, pp.70 – 80. https://doi.org/10.1016/j.econmod.2019.01.021

Chen, X.J., Lin, S. and Reed, W.R. (2010) 'A Monte Carlo evaluation of the efficiency of the PCSE estimator', Applied Economics Letters, Vol. 17, No. 1, pp.7-10. https://doi.org/10.1080/13504850701719702

Churchill, S.A., Inekwe, J., Smyth, R. and Zhang, X.B. (2019) 'R&D intensity and carbon emissions in the G7: 1870–2014', Energy Economics, Vol.80, pp.30–37. https://doi.org/10.1016/j.eneco.2018.12.020

Feng, Y., Tang, X., Zhu, L.Y., Sun, B. and Zhang, D.H. (2017) 'Research on the relationship between carbon emission and development strategy in China', Soft Science, Vol. 31, No.12, pp. 34-38 (**in Chinese).** https://doi.org/10.13956/j.ss.1001-8409.2017.12.08

Fisher-Vanden, K. and Wing, I.S. (2008) 'Accounting for quality: Issues with modeling the impact of R&D on economic growth and carbon emissions in developing economies', Energy Economics, Vol. 30, No.6, pp. 2771-2784. https://doi.org/10.1016/j.eneco.2007.04.002

Gao, Y. B., Mao, X.Q., Corsetti, G. and Wei, Y. (2014) 'Evaluation of synergistic control effect of urban traffic air pollutants and greenhouse gases: a case study of Urumqi', China Environmental Science, Vol.34, No.11, pp.2985-2992 (**in Chinese).**

Grand, M.C. (2016). 'Carbon emission targets and decoupling indicators', Ecological Indicators, Vol. 67, pp.649 – 656. https://doi.org/10.1016/j.ecolind.2016.03.042

Hu, A.G., Yan, Y.L., Zhang, J.Y., Gao Y.N. and Liu, S.L. (2017) 'Carbon emission

trends in China: from relative emission reduction to absolute emission reduction (1990-2050)', National Conditions Report Vol. 18, 2015, pp.550-567 (**in Chinese).**

Huang, J.B., Luan, B.J., Cai, X.C. and Zou, H. (2020) 'The role of domestic R&D activities played in carbon intensity: Evidence from China', Science of the Total Environment, Vol. 708, 135033. https://doi.org/10.1016/j.scitotenv.2019.135033

Huang, Y., Zhu, H.M. and Zhang, Z.Q.Y. (2020) 'The heterogeneous effect of driving factors on carbon emission intensity in the Chinese transport sector: Evidence from dynamic panel quantile regression', Science of the Total Environment Vol. 727, 138578. https://doi.org/10.1016/j.scitotenv.2020.138578

IPCC 2008, 2006 IPCC Guidelines for National Greenhouse Gas Inventories – A primer, Prepared by the National Greenhouse Gas Inventories Programme, Eggleston, H.S., Miwa, K., Srivastava, N. and Tanabe, K. (eds). Published: IGES, Japan. https://www.ipcc-nggip.iges.or.jp/support/Primer_2006GLs.pdf

Jeong, K. and Kim, S. (2013) 'LMDI decomposition analysis of greenhouse gas emissions in the Korean manufacturing sector', Energy Policy, Vol. 62, pp.1245–1253. https://doi.org/10.1016/j.enpol.2013.06.077

Jia, L. and Zheng Guofeng. (2014) 'Comparative study on environmental protection investment between China and the United States and experience reference', Environment and Sustainable Development, Vol. 39, No. 6, pp.84-86 (**in Chinese).** https://doi.org/10.3969/j.issn.1673-288X.2014.06.021

Jiang, B., Xing, X.D. and Li, J. (2015) 'A study on the trade effect of China's reverse investment in EU under the "going out" strategy: a panel data model modified by FGLS and PCSE', Journal of International Trade, Vol. 9, pp.167-176 (**in Chinese).** https://doi.org/10.13510/j.cnki.jit.2015.09.015

Jie, M.H., Liu, X.W. and Bai, M.D. (2010) 'Empirical Study on environmental

protection investment efficiency and policy recommendations', China Population, Resources and Environment, Vol. 20, No.4, pp.100-105 (**in Chinese).** https://doi.org/10.3969/j.issn.1002-2104.2010.04.018

Kuai, P., Yang, S., Tao, A.P., Zhang, S.A. and Khan, Z.D. (2019) 'Environmental effects of Chinese-style fiscal decentralization and the sustainability implications', Journal of Cleaner Production, Vol. 239, 118089.

Leal, P.A., Marques, A.C., and Fuinhas, J.A. (2019) 'Decoupling economic growth from GHG emissions: Decomposition analysis by sectoral factors for Australia', Economic Analysis and Policy, Vol. 62, pp.12–26. https://doi.org/10.1016/j.eap.2018.11.003

Li, H.N. and Qin, Q.D. (2019) 'Challenges for China's carbon emissions peaking in 2030: A decomposition and decoupling analysis.' Journal of Cleaner Production, Vol. 207, pp.857-865. https://doi.org/10.1016/j.jclepro.2018.10.043

Li, S.T. and Hou, Y.Z. (2003) 'Analysis of the characteristics of regional social and economic development in China', China Development Review: Chinese edition, Vol. 5, No.2, pp.27-39 (**in Chinese).**

Li, Z.N. (2008) 'General regression model of Applied Research in econometrics', Economic Research Journal, Vol. 8, pp.136-144 (**in Chinese**). https://doi.org/CNKI:SUN:JJYJ.0.2008-08-019

Lin, B.Q. and Agyeman, S.D. (2019) 'Assessing Ghana's carbon dioxide emissions through energy consumption structure towards a sustainable development path', Journal of Cleaner Production, Vol. 238, 117941. https://doi.org/10.1016/j.jclepro.2019.117941

Ma, X.J., Wang, C.X., Dong, B.Y., et al. (2019) 'Carbon emissions from energy consumption in China: Its measurement and driving factors', Science of the Total

Environment, Vol. 648, pp.1411–1420. https://doi.org/10.1016/j.scitotenv.2018.08.183

Mikayilov, J.I., Hasanov, F.J., and Galeotti, M. (2018) 'Decoupling of CO2 emissions and GDP: A time-varying cointegration approach', Ecological Indicators, Vol. 95, No.1, pp.615 – 628.

Mousavi, B., Lopez, N.S.A., et al. (2017) 'Driving forces of Iran's CO2 emissions from energy consumption: An LMDI decomposition approach', Applied Energy, Vol. 206, pp.804–814. https://doi.org/10.1016/j.apenergy.2017.08.199

Moutinho, V., Moreira, A.C. and Silva, P.M. (2015) 'The driving forces of change in energy-related CO2 emissions in Eastern, Western, Northern and Southern Europe: The LMDI approach to decomposition analysis', Renewable and Sustainable Energy Reviews, Vol. 50, pp.1485–1499. https://doi.org/10.1016/j.rser.2015.05.072

National Energy Information Platform. [online] https://baijiahao.baidu.com/s?id=1668544235049445086&wfr=spider&for=pc

Nguyen, T.T., Pham, T.A.T., and Tram, H.T.X. (2020) 'Role of information and communication technologies and innovation in driving carbon emissions and economic growth in selected G-20 countries', Journal of Environmental Management, Vol. 261, 110162. https://doi.org/10.1016/j.jenvman.2020.110162

OECD. OECD Environmental Strategy for the First Decade of the 21st Century [EB/OL].http://www.oecd.org/env/indicators-modelling-outlooks/1863539.pdf (Accessed 16 May 2001)

Shuai, C.Y., Shen, L.Y., Jiao, L.D., Wu, Y. and Tan, Y.T. (2017) 'Identifying key impact factors on carbon emission: Evidences from panel and time-series data of 125 countries from 1990 to 2011', Applied Energy, Vol. 187, pp.310-325. https://doi.org/10.1016/j.apenergy.2016.11.029

Steinberger J K, Roberts J T. (2011) 'From constraint to sufficiency: The decoupling of

energy and carbon from human needs, 1975-2005'. Ecological Economics, Vol. 70, No.2, pp.425-433. https://doi.org/10.1016/j.ecolecon.2010.09.014

Tapio, P. (2005) 'Towards a theory of decoupling: degrees of decoupling in the EU and the case of road traffic in Finland between 1970 and 2001', Transport Policy, Vol. 12, No.2, pp.137-151. https://doi.org/10.1016/j.tranpol.2005.01.001

Tu, H.X., Xiao, X. and Xu, S.T. (2014) 'An analysis of Carbon Dioxide Emission by Chinese Industries Based on LMDI Method', Journal of Central South University (Social Science), Vol. 20, No.4, pp.31-36 (**in Chinese**).

Wang, F., Yang, X., Tian, Y. and Wang, S.P. (2018) 'Empirical study on the relationship between carbon emissions and economic growth based on EKC hypothesis', Ecological Economy, Vol. 34, No.10, pp.19-23 (**in Chinese).**

Wang H., Huang J., Zhou H., Deng C. & Fang C. (2020). Analysis of sustainable utilization of water resources based on the improved water resources ecological footprint model: A case study of Hubei Province, China. Journal of Environmental Management, Vol. 262, 110331. https://doi.org/10.1016/j.jenvman.2020.110331

Wang, L.Q. (2017) 'Investigation of NOx emissions reduction and its strategies over China's 30 provinces based on LMDI', Acta Scientiae Circumstantiae, Vol. 37, No.6, pp. 2394-2402 (**in Chinese**). https://doi.org/10.13671/j.hjkxxb.2016.0456

Wang, Z. and Wang, L.H. (2019) 'Research on the relationship between R&D input, industrial structure upgrading and carbon emission', Industrial Technology and Economy, Vol.38, No. 5, pp. 62-70 (**in Chinese).** https://doi.org/10.3969/j.issn.1004-910X.2019.05.008

Xu, H. and Liu, X. (2016) 'Co integration effect of environmental protection investment and economic growth and COD emission', Statistics & Decision, Vol.12, pp.134-138(**in Chinese).** https://doi.org/10.13546/j.cnki.tjyjc.2016.12.038

Zhao, W. and Sui, Y.H. (2015) ‘Agglomeration type, labor market characteristics and wage productivity difference’,Economic Research Journal, Vol. 50, No. 6, pp.33-45+58 (**in Chinese).**

Zhu, Q., Peng, X.Z., Chen, Z.M. and Yu, J. (2010) ‘Analysis Model and Empirical Study of Impacts from Population and Consumption on Carbon Emissions’, China Population, Resources and Environment, Vol. 20, No.2, pp.98-102 (**in Chinese).** https://doi.org/10.3969/j.issn.1002-2104.2010.02.017

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- OnlineResource1.pdf