***PREDICTION THE CO2 EMISSIONS OF CHINA AND IDENTIFY ITS DRIVERS***

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## Overview

China has pledged to peak the CO2 emission around 2030 and reduce it by 60%-65% compared with 2005 level at the Paris Conference on Climate Change in 2015, which would be used as a binding index of national economic and social development in its long-term planning. To achieve CO2 emission targets in China, each province should ensure that its carbon emissions at a reasonable level to avoid the short board effect.

## Methods

We proposed LSTM-STRIPAT, an integrated method, to identify the carbon emissions of 30 provinces and pointed out the important driving factor by combining prediction and empirical analysis. This research proposes LSTM-STRIPAT model to predict CO2 emissions and identify the drivers, we take consideration of urbanization, economic development, industry structure, energy consumption, energy intensity and population density on the basis of STRIPAT model, using the LSTM model to predict CO2 emissions for 30 provinces in China, identifying each province CO2 emissions peak situation. Then we empirically studied key factors influencing CO2 emissions through STRIPAT model to identify the work point for policy makers.



## Results

The results showed that: Beijing, Jilin, Heilongjiang, Shanghai, Fujian, Hubei, Guangdong, Guangxi, Yunnan, Tianjin, Hebei, Shanxi, Zhejiang, Liaoning, Shaanxi, Gansu have reached the CO2 emissions peak during 2008-2013 in succession, and Inner Mongolia, Jiangsu, Anhui, Jiangxi, Shandong, Henan, Hunan, Hainan, Chongqing, Sichuan, Guizhou, Qinghai, Ningxia, Xinjiang will keep the increase of CO2 emissions, and they cannot peak CO2 emissions before 2030. Besides, almost all provinces experienced a small peak in carbon emissions during 2008-2013, when a large scale of haze disaster broke out in China, air pollution began to cause wide attention. The empirical result shows that urbanization and population density have the significant negative effect on CO2 emissions, but the effect of urbanization is relevant weak. Consideration of lagged effect on CO2 emissions, GDP and energy intensity have significant negative effect on CO2 emissions. In addition, the lag effect is significant in dynamic model, which indicates that carbon reduction is not a tentative task, but a permanent goal. CO2 emissions are not only affected by the current factors, but also by the past.

## Conclusions

To achieve effective emission reduction, we need to work together and stick to it for a long time. Based on these prediction result and empirical findings, policy recommendations were provided as to abandon traditional economic development mode and seek the balance between economic development and carbon reduction; actively optimize and adjust the energy consumption structure in China; Promoting technological progress and reduce energy intensity and perfecting the laws and regulations to guarantee the implementation of these measures.

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