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Determinants of stagnating carbon intensity in China

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Supporting Method and Data

Method and data for decomposition analysis

We employ decomposition analysis [1-4] to measure the significance of the two factors (sectoral carbon efficiency and production structure) in driving changes in regional carbon efficiency between 2002 and 2009. Carbon efficiency of a regional economy can be illustrated as follows: $c = \boldsymbol{f} \times \boldsymbol{p}$, where c represents carbon intensity of the entire economy (*scalar*),); $\boldsymbol{f}$ is row vector of sectoral carbon efficiency (amount of GDP per unit of CO_2 emission); and $\boldsymbol{p}$ is a column vector of the proportion of each sector's production output to total outputs of the regional economy (measured by percentages).

The absolute change of c (Δc) is decomposed between two time points, 2009 and 2002 into changes of the driving forces, $\boldsymbol{f}$ and $\boldsymbol{p}$. However, there is no unique solution for the decomposition[2,5-7]. Since our purpose only concerns two factors, the Marshall-Edgeworth index can be used to ensure a complete decomposition without any residual terms [8], which is shown in Eq. 1. In the case of n factors, the number of possible "complete" decompositions (without any residual terms) is equal to $n!$ [6].

$$\Delta c = \frac{1}{2}\Delta \boldsymbol{f} \times (\boldsymbol{p}_{2002} + \boldsymbol{p}_{2009}) + \frac{1}{2}\Delta \boldsymbol{p} \times (\boldsymbol{f}_{2002} + \boldsymbol{f}_{2009}) \quad (1)$$

We apply Equation 1 to conduct decomposition analysis for all 30 provinces in China. Two sets of data are collected and compiled for every province. First, the industrial output data for 42 economic sectors for the years 2002 and 2009 are obtained from provincial Statistical Yearbook 2003 and 2008. Second, in order to produce $\boldsymbol{f}$, we need to estimate CO_2 emissions for 42 economic sectors in each province based on provincial energy consumption by industry sector. The energy data were extracted and converted to emission data for the 30 provinces individually and stem mainly from three Chinese statistics sources: 1) Chinese Energy Statistics Yearbook [9,10] that provides energy balance sheets for every province; 2) China Economic Census Book 2008 [11] provides final energy consumption in industrial sector detail in 2008; and 3) Regional Statistics Yearbook 2003 providing final energy consumption in sectoral detail in 2002. However, the availability of final energy consumption data at sector level varies between Chinese provinces. We have implemented a set of compilation and normalization processes to configure energy datasets for every province that consists of 18 types of fuel, heat, and electricity consumption in physical units.

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Decomposition analysis and theoretical background

The principal idea of decomposition analysis can be illustrated as shown in Equation (1) in the case of a two determinant multiplicative function.

$$y = x_1 \cdot x_2 \quad \textbf{(1)}$$

The change of y (Δy) can be decomposed between two time points, t and t-1 into changes of the driving forces, x_1 and x_2 . However, there is no unique solution for the decomposition. For example, one can start the decomposition from the base year (e.g. t-1), which is referred to the Laspeyres index, whereas one can also begin the process from the target year (e.g. t), which is referred to as the Paasche index, as shown in Equation (2). Together using both Laspeyres and Paasche indices for decomposition analysis is referred to as so-called polar decomposition [12]. Heokstra and van den Bergh [5] examined that neither of the polar decompositions would lead to a complete decomposition (e.g. no residual terms), and the usual solution for this is to combine the two perspectives, so either Laspeyres- Paasche or Paasche-Laspeyres index.

$$\Delta y = y_t - y_{t-1} = \Delta(x_1 \cdot x_2)$$

or, **(2)**

$$\Delta y = y_{(t-1)} - y_t = \Delta(x_1 \cdot x_2)$$

Furthermore, the change of x_1 can be expressed as: $\Delta x_1 = x_{1(t)} - x_{1(t-1)}$; similarly, $\Delta x_2 = x_{2(t)} - x_{2(t-1)}$.

One of the possibilities is to decompose Equation (2) is by using Laspeyres- Paasche index as shown in Equation (3):

$$\begin{aligned}\Delta(x_1 \cdot x_2) &= x_{1(t)} \cdot x_{2(t)} - x_{1(t-1)} \cdot x_{2(t-1)} \\ &= (\Delta x_1 + x_{1(t-1)}) \cdot x_{2(t)} - x_{1(t-1)} \cdot x_{2(t-1)} \\ &= \Delta x_1 \cdot x_{2(t)} + x_{1(t-1)} \cdot x_{2(t)} - x_{(t-1)} \cdot x_{2(t-1)} \\ &= \Delta x_1 \cdot x_{2(t)} + x_{1(t-1)} \cdot (\Delta x_2 + x_{2(t-1)}) - x_{(t-1)} \cdot x_{2(t-1)} \\ &= \Delta x_1 \cdot x_{2(t)} + x_{1(t-1)} \cdot \Delta x_2\end{aligned} \quad \textbf{(3)}$$

However, the other possibility to decompose Equation 2 is by using Paasche- Laspeyres index as shown in Equation 4:

$$\Delta(x_1 \cdot x_2) = \Delta x_1 \cdot x_{2(t-1)} + x_{1(t)} \cdot \Delta x_2 \quad \textbf{(4)}$$

Hereby, the core question is to examine whether the above two terms are congruent with the requirements of decomposition, which comprises the following three conditions in terms of Hoekstra and van der Bergh [5] and de Boer [12].

- complete, which means there are no residual terms
- “0” robust, which means it can deal with “0” values in the calculation
- time reversal, which means the decomposition produces a reverse result if the time period has been reversed, for example $\Delta y = y_t - y_{t-1} = -(y_{t-1} - y_t)$.

The method to examine the “complete” condition can be simply illustrated in Figure 2; Equation (3) covers the areas of “hdeg + bcda” with residual term “0” while the areas of Equation (4) covering is the “hafg + bcef” with residual term of “0”., Both decompositions cover the required areas (filled with dashed lines), which means they are qualified with the requirements of ‘complete’ and the condition of “0” robust for implementing calculations [5,12]. Equations (3) and (4) follow from each other by reverting base and comparison period. However neither of the above expressions satisfies the requirement of time reversal. A common approach is to take the average of these two equations to satisfy this requirement. Equation (3) and (4) is a “mirror pair” decomposition, which is the pair of permutations where the time period indication on the coefficients attached to each difference term is exactly the opposite [6].

As mentioned previously, either Laspeyres – Paasche or Paasche – Laspeyres index would fulfil the requirement of the “complete” requirement. The two approaches are equivalent and there is no reason why one of them should be preferred to the other [8]. Therefore, the decomposition of y is not unique; however the result (e.g. the covered areas in Figure 2) is unique in this two determinants case. The problem is referred to as non-uniqueness, which means that there exists a number of different decomposition forms and that it cannot be decided which one to prefer. Usually, the factors in SDA studies are more than three. Dietzenbacher and Los [6] proved that in the case of *n* factors, the number of possible "complete" decompositions (without any residual terms) is equal to *n!*.

Energy data compilation and normalisation

To perform the decomposition analysis, we calculate the sectoral efficiency changes and production structure changes. We require two sets of data for every province: sectoral economic output and energy/emission at sectoral level for both 2002 and 2009.

Sectoral economic outputs

We draw sectoral economic outputs from:

- Chinese Industry Statistics Yearbook for the manufacturing sectors for 30 provinces.
- Chinese Statistics Yearbook and Regional Statistics Yearbook for non-manufacturing sectors (e.g. agriculture, construction and services)

Energy and emission inventory in 2009

The provincial data for energy consumption for each sector in 2009 is constructed as follows:
First, The Chinese Economic Census Yearbook [11] lists total energy consumption for 39 industrial sectors (as shown in SI Table 2 – sector 1-39) in each province. The energy use covers 18 different types of fuel: Raw Coal, Cleaned Coal, Washed Coal, Briquette, Coke, Other Coking Products, Coke Oven Gas, Blast Furnace Gas, Other Gas, Natural Gas, Liquefied Natural Gas, Crude Oil Gasoline, Kerosene, Diesel Oil, Fuel Oil, Liquefied Petroleum Gas, Refinery Gas and Other Petroleum Products. The data is extracted from Chinese Energy Statistics Year Book (CESY) [9] to exclude the energy use for coal washing and coking, and re-allocated the energy used for power-generation/heating to the sector that combusts them. CO_2 emissions from combustion of fuels and industrial processes were calculated using the IPCC reference approach [13]. The allocation process has been proposed by and described in Peters [14]. Thus we got the provincial final energy consumption used for combustion from 39 industrial sectors in 2008.
Secondly, we scaled up the final energy consumption of 39 sectors to the year 2009 based on increase rate of final energy consumption from 2008 to 2009. The provincial final energy use data of 2008 and 2009 are available in Energy Balance Sheet from CESY.
Last, we extracted the provincial final energy use from "Agriculture, Construction, Transportation, Commercial Industry, Rural Residential consumption and Urban residential consumption" from Chinese Energy Statistics Yearbook in 2009, together with estimated final energy use of 39 sub sectors, and then constructed the final energy use of 44 economic sectors, the provincial final energy use of 44 sectors was used for our CO_2 emission inventory in 2009.

Energy and emission inventory in 2002

The energy data for 2002 we used in this paper was extracted and converted to emission data for the 30 provinces individually. The energy data were mainly from two official Chinese statistics sources: Chinese Energy Statistics Yearbook providing energy balance sheets for every province and Regional Statistics Yearbook providing final energy consumption in sectoral detail. The complete dataset for every province consists of 18 types of fuel, heat, and electricity consumption in physical units. CO_2 emissions from combustion of fuels and industrial processes were calculated following same approach as emission compilation for 2009.
However, energy data availability in some Chinese provinces is quite poor prior to 2005. Almost one-third of the provinces either only publish regional energy balance sheets without the details of sectoral final energy consumption pattern, or publish the final energy consumption data in a format different from the national classification. For example, there are no detailed final consumption data for Shandong province for the year 2002, but these are available for 2004. We calculate the energy consumption pattern assuming the same shares as in 2004 to the reported total of 2002. Many provinces such as Hubei or Yunnan only provide energy consumption for 4 or 5 categories of energy (e.g. coal, oil, gas, electricity and heat). We have to disaggregate these categories into the national standard of 18 types of energy consumption by applying national shares of fuel mix to total regional energy consumption volume. Some provinces such as Shanghai and Guangxi have never published

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energy consumption data in sectoral detail, thus we assume similar shares from other economically similar provinces as proxies. For instance, we assume that Shanghai has similar technology and fuel mix and thus industrial energy consumption patterns as Zhejiang, another highly developed region on China's east coast.

Supporting Tables

SI Table 1: Decomposition of change of regional carbon intensity among 30 Chinese provinces

Regions	Driven by sectoral carbon efficiency improvements	Production Structure carbonisation	**Overall economy's carbon efficiency changes**
Shanxi	49%	-13%	35%
Tianjin	71%	-42%	29%
Chongqing	37%	-9%	28%
Beijing	54%	-27%	27%
Hainan	45%	-20%	25%
Guangdong	22%	3%	24%
Shanghai	39%	-16%	23%
Anhui	65%	-45%	20%
Inner Mongolia	159%	-141%	18%
Jiangsu	10%	5%	16%
Shannxi	38%	-25%	14%
Zhejiang	46%	-35%	11%
Jilin	38%	-28%	10%
Ningxia	123%	-113%	10%
Hubei	26%	-17%	9%
Gansu	20%	-11%	9%
Liaoning	12%	-8%	4%
Qinghai	13%	-8%	4%
Hebei	72%	-78%	-6%
Heilongjing	41%	-47%	-6%
Shandong	8%	-17%	-9%
Jiangxi	3%	-14%	-11%
Henan	17%	-30%	-13%
Hunan	-10%	-5%	-15%
Fujian	10%	-26%	-16%
Sichuan	9%	-27%	-18%
Yunnan	24%	-43%	-19%
Xinjiang	-15%	-6%	-21%
Guangxi	18%	-40%	-22%
Guizhou	98%	-125%	-27%

SI Table 2: The energy and emission inventory sectors

	Sectors
1	Coal Mining and Dressing
2	Petroleum and Natural Gas Extraction
3	Ferrous Metals Mining and Dressing
4	Nonferrous Metals Mining and Dressing
5	Nonmetal Minerals Mining and Dressing
6	Other Minerals Mining and Dressing
7	Food Processing
8	Food Production
9	Beverage Production
10	Tobacco Processing
11	Textile Industry
12	Garments and Other Fiber Products
13	Leather, Furs, Down and Related Products
14	Timber Processing, Bamboo, Cane, Palm & Straw Products
15	Furniture Manufacturing
16	Papermaking and Paper Products
17	Printing and Record Medium Reproduction
18	Cultural, Educational and Sports Articles
19	Petroleum Processing and Coking
20	Raw Chemical Materials and Chemical Products
21	Medical and Pharmaceutical Products
22	Chemical Fiber
23	Rubber Products
24	Plastic Products
25	Nonmetal Mineral Products
26	Smelting and Pressing of Ferrous Metals
27	Smelting and Pressing of Nonferrous Metals
28	Metal Products
29	Ordinary Machinery
30	Equipment for Special Purpose
31	Transportation Equipment
32	Electric Equipment and Machinery
33	Electronic and Telecommunications Equipment
34	Instruments, Meters Cultural and Office Machinery
35	Other Manufacturing Industry
36	Scrap and waste
37	Electric Power, Steam and Hot Water Production and Supply
38	Gas Production and Supply
39	Tap Water Production and Supply
40	Agriculture
41	Construction

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42	Transportation
43	Commercial Industry
44	Rural residential consumption
45	Urban residential consumption

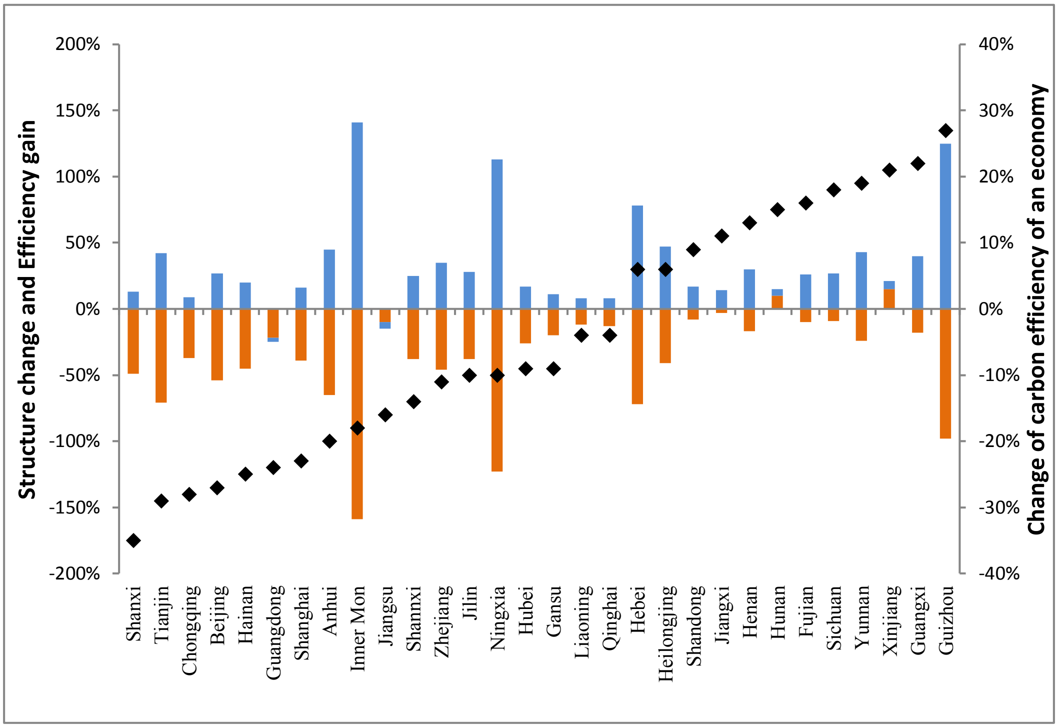
SI Table 3: Descriptive Statistics for Regressions

	Observations	Mean	Standard Deviation
Ratio of 2009/2002 Sectoral Emission Intensity	815	0.551	0.400
2002 Sectoral Emission Intensity	815	1.680	4.624
2002 Sectoral Output Share in Province	815	0.037	0.04
Ratio of 2009/2002 Sectoral Output	815	2.931	4.436

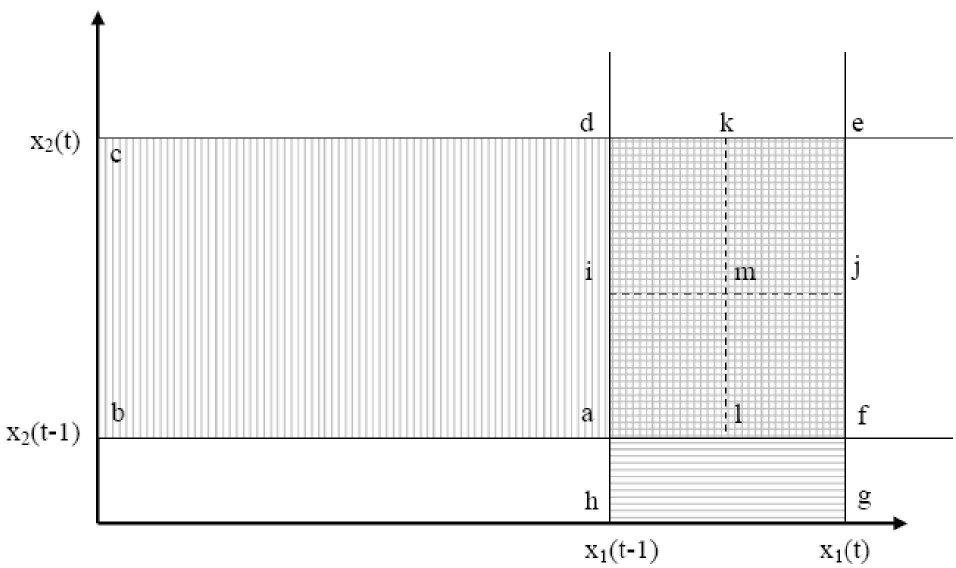
SI Table 4: Regional grouping of provinces for panel regression results discussion

North East	Heilongjiang
	Jilin
	Liaoning
Coastal	Beijing
	Tianjing
	Jiangsu
	Zhejiang
	Shanghai
	Guangdong
	Fujian
	Hainan
Central	Hebei
	Shandong
	Anhui
	Henan
	Hubei
	Hunan
	Shanxi
	Jiangxi
West	Shannxi
	Gansu
	Ningxia
	Inner Mongolia
	Xinjiang
	Sichuan
	Guangxi
	Guizhou
	Chongqing
	Qinghai
	Yunnan

Supporting Figures



SI Figure 1: Change of carbon efficiency: race between efficiency gain and production structure change. The left y-axis represents the percentage changes of carbon efficiency would be driven by efficiency gains (blue columns) or rebound induced by production structure changes (orange columns). The right y-axis represents the net changes of carbon efficiency (efficiency gains minus production structure rebounds) of a provincial economy (black dots). The 30 provinces are ranked at x-axis from left to right in terms of net carbon efficiency gains during 2002 – 2009. The black dots below the x-axis represent the according provinces achieved net carbon efficiency gains while those above the x-axis stand for the according provinces made net carbon efficiency loss, during 2002 – 2009.



SI Figure 2: Additive decomposition of $y = x_1 \cdot x_2$, discrete time. *Source:* [8,15]

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References

1 Ang, B. W. Decomposition analysis for policymaking in energy: which is the preferred method? *Energy Policy* **32**, 1131-1139 (2004).

2 Ang, B. W. The LMDI approach to decomposition analysis: a practical guide. *Energy Policy* **33**, 867-871 (2005).

3 Ang, B. W. & Zhang, F. A survey of index decomposition analysis in energy and environmental studies. *Energy* **25**, 1149-1176 (2000).

4 Ang, B. W., Mu, A. R. & Zhou, P. Accounting frameworks for tracking energy efficiency trends. *Energy Economics* **32**, 1209-1219 (2010).

5 Hoekstra, R. & van der Bergh, J. C. J. M. Comparing structural and index decomposition analysis. *Energy Economics* **25**, 39-64 (2003).

6 Dietzenbacher, E. & Los, B. Structural decomposition techniques: Sense and sensitivity. *Economic Systems Research* **10**, 307-323 (1998).

7 Peters, G., Webber, C., Guan, D. & Hubacek, K. China's growing CO_2 emissions - A race between lifestyle changes and efficiency gains". *Environmental Science & Technology* **41**, 5939-5944 (2007).

8 Rørmose, P. & Olsen, T. in *15th International Input-Output Conference.*

9 National Bureau of Statistics. *China Energy Statistical Yearbook 2010*. (China Statistics Press, 2011).

10 National Bureau of Statistics. *China Energy Statistical Yearbook 2003*. (China Statistics Press, 2004).

11 China Economic Census Office of the State Council. *China Economic Census Yearbook 2008*. (China Statistics Press, 2011).

12 de Boer, P. Structural decomposition analysis and index number theory: an empirical application of the Montgomery decomposition. *Econometric Institute Report* **EI 2006-39** (2006).

13 IPCC. *2006 IPCC Guidelines for National Greenhouse Gas Inventories*. (Intergovernmental Panel on Climate Change, 2006).

14 Peters, G. P., Weber, C. & Liu, J. *Construction of Chinese Energy and Emissions Inventory*. (Norwegian University of Science and Technology, 2006).

15 Hoekstra, R. & van der Bergh, J. C. J. M. Structural decomposition analysis of physical flows in the economy. *Environmental and Resource Economics* **23**, 357--378 (2002).